The Economics of Climate Innovation: Technology, Climate Policy, and the Clean Energy Transition*

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Abstract

This chapter examines the economics of climate innovation and its role in the clean technology transition. It outlines the incentives, market failures, and policy levers that shape the development and diffusion of clean technologies; traces global patterns in technology development and deployment; and highlights frontier challenges and open questions related to climate adaptation, critical mineral supply chains, artificial intelligence, and geopolitics. The analysis explores the role of effective climate policy, stressing the relevance of coordinated approaches that match instruments to technology maturity and local context.

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*A companion web application for exploring climate-relevant patent data and trends is available at https://patent-green-trends.streamlit.app/. We thank Anoushka Chopra, Li Jiang, Jade Sillere, Sanjana Subramanian, Sarayu Manoj, Rebecca Hausner, and Jiin Yun for exceptional research assistance. Jacob is also grateful to Karthik Sastry for greatly adding to and shaping his understanding of these topics. All errors and omissions are our own.

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1 Introduction

This chapter describes the interplay between climate change, innovation, and technological change. Despite the fact that global temperatures have already begun to rise, the progression of technology development and deployment will determine the full extent of environmental and economic harm. Innovation in renewable energy sources, for example, will shape future trends in carbon emissions and pollution, in addition to patterns of energy prices and access around the world. Even under the most optimistic emissions scenarios, however, economic damage from climate extremes is already rampant—ranging from crop failures to heat-related deaths to spikes in violent conflict—and will only continue in future decades. Here too, technology will shape the extent to which individuals, firms, and countries can adapt to new environmental challenges. The evolution of technology is a key factor shaping the full extent and economic consequences of global warming.

While innovation is a powerful force, however, there is no guarantee that it will evolve in any particular direction. History is rife with technological reversals, ranging from the global decline in nuclear energy investment during the 1990s following the Chernobyl meltdown to a large fall in US clean technology innovation during the 2010s. A large body of evidence has documented that the direction of innovation evolves endogenously, responding to economic and political incentives that may or may not push technology toward developing cheap renewable energy or new tools for climate adaptation. The political and geopolitical incentives that shape climate policy also shift over time, generating an important interplay between technology and politics. While some of the most dramatic advances in solar technology development were the result of a concerted policy agenda in China to build its solar sector, fossil fuel subsidies are still widespread around the world. Decision-making by policymakers and innovators will combine to shape the equilibrium pace and direction of technological change.

The technological transition required for averting the largest rise in global temperature is substantial, but it has already begun. This is outlined by Table 1. While growth around the world, especially in China and India, has led to a rise in global carbon emissions since 2000, the full effect of this increase in economic activity on emissions was offset by a substantial rise in renewable energy development and deployment (columns 1-2). The renewable share of electricity generation increased from 18% to 30%, driven in large part by innovation and declining prices in solar and wind power. While solar capacity increased around the world, its largest rise was in China, which skyrocketed to account for over a third of all global solar energy generation (610 GW today compared to just 0.03 GW in 2000). Over the same period, global electric vehicles rose from zero to 18% of global automobile sales.

That said, the world is far from reaching either the energy targets that existing policies hope to achieve by 2050 (column 3) or the energy targets that would be required to achieve net zero emissions by 2050 (column 4). To reach drafted policy goals, renewable capacity would

Table 1: The World in 2000 and 2025 vs 2050

Group	Subgroup	Metric	2000	2023 ≈ 2025	2050 IEA STEPS	2050 IEA NZE
ΔT		Global mean ΔT (°C)	0.6°C	1.2°C	1.9°C	1.5°C
Global Emissions and Energy Use		Global CO_2 emissions (Gt)	26 Gt	39 Gt	36 Gt	0 Gt (net)
Global Emissions and Energy Use		Global GHG emissions (Gt CO_2-eq)	36.2 Gt	53 Gt		0 Gt CO_2 + 0.3 Gt CH_4
Global Emissions and Energy Use		Global oil demand (Mb//d)	77 Mb/d	102 Mb/d	97 Mb/d - 105 Mb/d	24 Mb/d
Global Emissions and Energy Use		Fossil-fuel share of primary energy (%)	85 %	81 %	67 %	20 %
Renewable Capacity		Renewable capacity - total (GW)	800 GW - 808 GW	4,448 GW	23,217 GW	33,178 GW
Renewable Capacity	Breakdown	Hydro Capacity (GW)	790 GW	1,283 GW - 1,410 GW	2,027 GW	2,685 GW
Renewable Capacity	Breakdown	Solar Capacity (GW)	1 GW	1,609 GW - 1,865 GW	16,445 GW	15,468 GW -21,618 GW
Renewable Capacity	Breakdown	Wind Capacity (GW)	17 GW	1,133 GW	4,189 GW	7,795 GW
Renewable Capacity		EV share of car sales (%)	0	18 %	25 %	100 %
Renewable Capacity		Renewables share of electricity (%)	18 %	30 %	55 %	88 %
Top countries by GHG Emissions	USA	Total (Mt CO_2e)	7,203 Mt	5,960 Mt	2,016 Mt*	
Top countries by GHG Emissions	USA	Global Share (%)	20 %	11.25 %	7%*	
Top countries by GHG Emissions	USA	Per Capita (t CO_2e)	26t	18 t	5.4 t*	
Top countries by GHG Emissions	China	Total (Mt CO_2e)	5,243 Mt	15,944 Mt	6,356 Mt*	
Top countries by GHG Emissions	China	Global Share (%)	14.5 %	30 %	22.2 %*	
Top countries by GHG Emissions	China	Per Capita (t CO_2e)	4 t	11 t	4.9 t*	
Top countries by GHG Emissions	EU27	Total (Mt CO_2e)	4,481 Mt	3,222 Mt	746 Mt*	
Top countries by GHG Emissions	EU27	Global Share (%)	12.4 %	6 %	2.6 %*	
Top countries by GHG Emissions	EU27	Per Capita (t CO_2e)	10 t	7.2 t	1.75 t*	
Top countries by GHG Emissions	India	Total (Mt CO_2e)	1,845 Mt	4,134 Mt	3,184 Mt*	
Top countries by GHG Emissions	India	Global Share (%)	5.1 %	7.8 %	11 %*	
Top countries by GHG Emissions	India	Per Capita (t CO_2e)	2 t	3 t	1.9 t*	
Top Cpuntries by Renewable Capacity	USA	Solar PV Capacity (GW)	0.59 GW	139 GW -170 GW	1,895 GW	
Top Cpuntries by Renewable Capacity	USA	Wind Capacity (GW)	2.4 GW	148 GW	528 GW	
Top Cpuntries by Renewable Capacity	China	Solar PV Capacity (GW)	0.03 GW	610 GW	9,433 GW	
Top Cpuntries by Renewable Capacity	China	Wind Capacity (GW)	0.34 GW	442 GW	1,516 GW	
Top Cpuntries by Renewable Capacity	EU27	Solar PV Capacity (GW)	0.18 GW	257 GW	1,078 GW	
Top Cpuntries by Renewable Capacity	EU27	Wind Capacity (GW)	12.3 GW	219 GW	597 GW	

Note: Data sources are shown in Appendix Section A.1

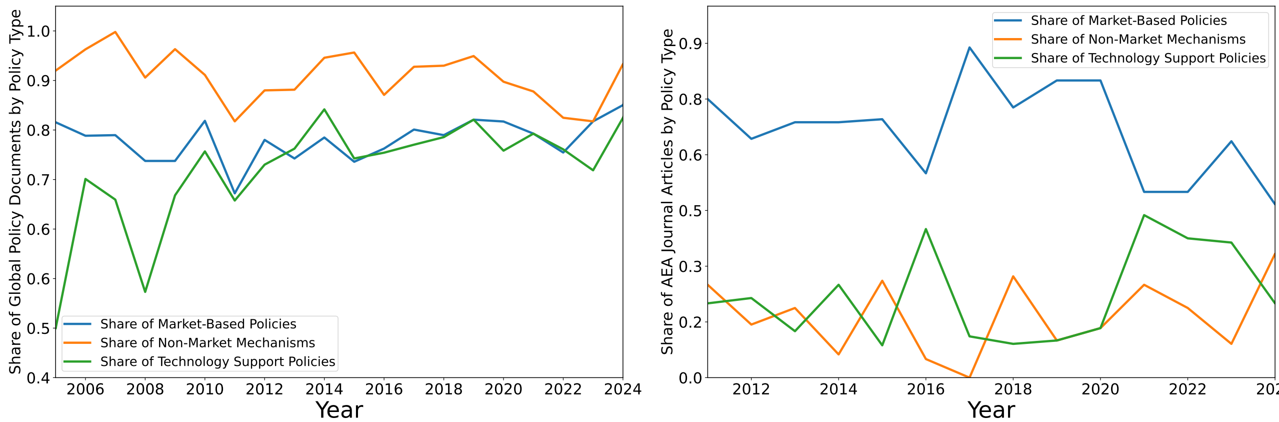
need to increase by over fourfold over the next 25 years, with a large share of this increase coming from a rise in solar capacity (column 3). Even this transformation, however, would be well below what the latest International Energy Agency (IEA) estimates suggest is required to achieve net zero emissions by 2050 and limit the rise in global mean temperature to 1.5°C (column 4). While these numbers all come with substantial uncertainty, they highlight the full scale of the energy transition that has already begun and the potential paths that technology may take going forward.

Throughout the chapter, we emphasize the key role that economics can play in understanding the intersection and interactions between technology, climate policy, and environmental change. While it is possible to estimate the technological requirements for limiting ever larger increases in global temperatures (see Table 1), how technology and policy evolve in practice requires understanding the political and economic incentives that shape innovator decision making, the equilibrium direction of innovation, and the two-way relationship between politics and technological change. The importance of new technology development to policy makers around the world is captured by the substantial rise over the past two decades in policies that explicitly support technology development to accelerate a transition to clean energy (see Figure 1a).[1] As we describe below, regulations and market-based interventions can also affect technology development by shifting technology demand; however, this explicit focus on subsidizing the technology of the future is a clear and growing goal. Yet when we studied all articles that reference environmental policy published in American Economics Association (AEA) journals since 2011, the vast majority—roughly 80%—focused on market-based interventions and few referenced technology or non-market regulation, the most common policy structure in practice (see Figure 1b). This strikes us as a major missed opportunity.

The goal of this chapter is to present a broad overview of the intersection between climate change and technology, reviewing core concepts, mechanisms, and existing research, as well as describing topics that strike us as important and exciting areas for future work. Each section is meant to be self contained and does not assume substantial prior knowledge of either environmental economics or the economics of innovation, both of which are important for understanding the subject matter of this chapter. Our hope is that this chapter serves as a resource for students interested in pursuing research in these areas, economists of all academic backgrounds, or policymakers interested in research in economics and related fields.

The next section of this chapter (Section 2) describes the key concepts that are needed

1. To measure characteristics of global climate law and policy, we downloaded the full "Climate Change Laws of the World" database from https://climate-laws.org/. We download the full text of each document and classify all documents based on whether they include market-based policies, non-market based polices, or technology support policies (or combinations thereof). In particular, we first use DeepSeek to classify a subset of the documents and then used this labeled training dataset to fine-tune RoBERTa, which provided the remaining classifications. We use a related method to categorize all articles published by American Economics Association (AEA) journals since 2011, which we scraped from https://www.aeaweb.org/journals. See Appendix A.2.



(a) Climate Laws and Policies

(b) AEA Journal Articles

Figure 1: The Focus of Climate Policy

Note: Figure 1a plots trends over time in the share of global climate laws and policies from Climate Change Laws of the World (https://climate-laws.org/) that we categorize as market-based policies, non-market regulatory mechanisms, and technology support policies. Figure 1b plots trends over time in the share of articles about environmental economics and published in American Economics Association (AEA) journals since 2011 that reference market-based policies, non-market regulatory mechanisms, and technology support policies. Additional methodological details are described in Appendix A.2.

to study the economics of innovation and the environment. These range from micro-level mechanisms that drive decision making by innovators to macroeconomic models of directed technological change that provide a framework for understanding the aggregate direction of technological change. In describing these economic forces, we also document how they emerge using data on recent trends in technology development, review existing theoretical and empirical work on these topics, and highlight potential areas for future research.

The third section of this chapter (Section 3) presents a detailed examination of the clean technology landscape and a description of recent innovation trends. First, we describe a taxonomy of the full set of technologies relevant for the energy transition, ranging from power generation to battery and grid development to building and transportation infrastructure. This provides context for many ideas and examples that come up later in the chapter and is designed to serve as a reference for readers about the various ways in which technology development and use are evolving. Second, we provide an overview of the key data sources and empirical approaches that can be used to measure innovation. We offer a descriptions of the pros and cons of each strategy, as well as provide examples from recent empirical work. Third, we use some of these data sources to describe key developments in energy technology over the past decades, from the take-off of green innovation during the 1990s to China's surge in recent years and geographic patterns of technology diffusion.

The fourth section of the chapter (Section 4) describes the relationship between technology and climate policy. We outline how policy—from environmental regulation that shapes demand for new technologies to the more recent rise of industrial policies and direct technology support—affects the level and direction of innovation. We also describe challenges associated with climate policy evaluation, a series of case studies of recent policy experiments, and the countervailing effects of government support for the fossil fuel industry.

The fifth section of this chapter (Section 5) turns from mitigation innovation to adaptation innovation, the development of new technologies that allow economic actors to adjust to more extreme environmental conditions. We introduce a theoretical framework that describes the incentives driving adaptation innovation before discussing existing work and open questions about adaptation, technology diffusion, and interactions between adaptation and mitigation.

Finally, the sixth section of this chapter (Section 6) describes a series of additional areas that cut across topics or have received more limited attention in economics research to date but that are increasingly central to modern debates about technology and the environment. These topics include the importance of critical minerals to clean technology supply chains; the incentives that shape innovation across clean technology areas; the dual impacts of artificial intelligence on energy use and innovation; and the geopolitical consequences of the clean energy transition. While there are many additional topics that we do not cover in this section, our hope is to highlight the number of fascinating and essential topics left to be explored.

We also provide a companion web application at https://patent-green-trends.streamlit.app/. The app offers interactive visualizations of patenting trends across various clean and dirty technologies from 1980 through 2020.[2] It serves as an accessible extension of this chapter, allowing readers to view and compare trajectories by technology and country

2 The Fundamental Economics of Clean Technological Change

2.1 Microeconomic Mechanisms

This section examines the microeconomic mechanisms that shape clean technological change: how innovation unfolds, who participates, which market failures arise, and the policies used to address them. Table 2 links stages of the innovation process to the main externalities—knowledge spillovers, environmental externalities, financial frictions, and coordination problems—and to the instruments commonly deployed in response. We build on prior reviews of innovation and the environment (Jaffe et al. 2003; Popp et al. 2010; Popp 2019; Armitage et al. 2024), aiming not to restate them in full but to draw out key mechanisms and highlight recent contributions. Broader surveys of innovation economics offer additional context and describe many of these forces in additional detial with applications beyond climate-related technologies (Bloom et al. 2019; Bryan and Williams 2021; Jones 2021; Howell 2024).

2. Additional details are described in Appendix A.3.

2.1.1 Technology Readiness Levels (TRLs)

Table 2 organizes the discussion of the economic mechanisms underpinning innovation across technology readiness levels (TRLs). Organizing innovation by TRLs is a standardized method of measuring the maturity of a particular technology, which was originally developed by NASA in the 1970s and is often used to assess technological progress across various streams of clean energy development. For each stage, Table 2 provides definitions, main actors, key activities, expected outputs, and illustrative examples drawn from the International Energy Agency (IEA) Clean Energy Technology Guide.[3] Although often depicted as a linear sequence, innovation in practice is iterative, with feedback loops and reversals. Still, successful diffusion usually requires moving through the stages outlined in Table 2. For clean technologies, this journey is especially demanding. Market failures arise at multiple points leading to persistent underinvestment in development and deployment.

The TRL framework allows these failures to be mapped to distinct phases, clarifying which policy tools are most relevant. Examples of policies to address each potential market failure are listed in the bottom section of Table 2. Levels 1 through 9 are the original stages first developed by NASA. The IEA extends this by adding TRLs 10 and 11: TRL 10 covers technologies that are commercial and competitive but need further innovation efforts for the technology to be integrated into energy systems and value chains when deployed at scale. We label this as "early adoption." TRL 11 represents technologies that have achieved predictable growth. We further distinguish between TRL 11 and TRL 11+ to capture the difference between technologies that are still scaling and those that have achieved widespread market dominance, especially relative to dirtier alternatives. While the distinctions between TRLs 9, 10, 11, and 11+ can be subtle, since all refer to technologies considered mature, they differ in the extent of market uptake and integration. In our examples, we consider technologies with only niche deployment to fall below TRL 11. TRL 11 corresponds to broad diffusion across markets, while TRL 11+ reflects full market transformation, marked by robust sales, especially relative to dirtier alternatives.

3. The IEA TRL data tool is available at https://www.iea.org/data-and-statistics/data-tools/etp-clean-energy-technology-guide

<table>
<tr><th colspan="2"></th><th>TRL 1</th><th>TRL 2</th><th>TRL 3</th><th>TRL 4</th><th>TRL 5</th><th>TRL 6</th><th>TRL 7</th><th>TRL 8</th><th>TRL 9</th><th>TRL 10</th><th>TRL 11</th><th>TRL 11+</th></tr>
<tr><th colspan="2"></th><th colspan="3">Concept</th><th colspan="3">Prototype</th><th colspan="2">Demonstration</th><th colspan="2">Early Adoption</th><th colspan="2">Mature</th></tr>
<tr><td colspan="2">Definition</td><td>Initial idea, basic principles defined</td><td>Concept and application formulated</td><td>Experimental proof-of-concept demonstrated</td><td>Small prototype proven in lab under test conditions</td><td>Large prototype proven in relevant conditions</td><td>Large prototype partially integrated with existing systems proven in relevant conditions</td><td>At or near full scale prototype proven in operational environment with most functions available for demonstration and test</td><td>FOAK (First-of-a-Kind) commercial prototype completed (full scale) and tested in simulated and operational scenarios</td><td>Solution is commercially available; Commercial operation in relevant environment (e.g., niche markets)</td><td>Commercial and competitive but needs further innovation efforts for the technology to be integrated into energy systems and value chains when deployed at scale</td><td>Market Scaling; volume manufacturing ramp; mainstream lenders comfortable; standards published & adopted; supply-chain build-out</td><td>Market Transformation: robust sales; established global standards; commoditisation & service ecosystems mature</td></tr>
<tr><td colspan="2">Climate-Tech Examples (2024)</td><td>Nuclear Fusion (TRL 1-3)</td><td>Li-Air battery, Ammonia as reductant (DRI) for iron and steel production</td><td>Aluminium smelting with chloride electrolysis, Pre-combustion carbon capture</td><td>Algae-based Biofuels, Post-combustion carbon capture</td><td>Light-water small modular reactor, Biofuels with CCUS</td><td>Propane heat pumps for buildings, Battery passport, Onboard carbon capture for ships</td><td>Electricity in the Bayer process for Aluminium production, High-temperature gas-cooled small modular reactor</td><td>Direct Air Capture, Floating offshore wind, Hydrogen fuel cell electric vehicle</td><td>Utility-scale Li-ion battery storage, Battery electric vehicles, Electrolyser for H2 production, CO2 sequestration in inert carbonate materials (mineralisation)</td><td>Crystalline-silicon solar PV, Smart meter, Li-ion batteries, Seabed fixed offshore wind turbine, Onshore wind, Biofuels (enzymatic fermentation without CCUS)</td><td colspan="2">Conventional LED, Hydropower, Pumped Storage, Geothermal, Pyro/hydro-metallurgy battery recycling</td></tr>
<tr><td colspan="2">Main actors, activities and outputs</td><td>Universities & national labs – fundamental research, preliminary physical and computational models</td><td>Universities & labs – conceptual designs, refine theoretical models</td><td>Universities, start-ups, and early corporate R&D — build lab-scale prototypes, test feasibility, generate proof-of-concept data.</td><td>Corporate R&D teams and start-ups — assemble early subsystems, test integrated components under lab conditions.</td><td>Corporate R&D teams and start-ups — construct large-scale prototypes, validate in simulated or relevant environments.</td><td>Engineering teams and component manufacturers — test full-scale prototypes, demonstrate functionality in operational settings.</td><td>Project developers, component manufacturers, and infrastructure developers — integrate systems, validate performance at or near full scale, assess risks.</td><td>Technology vendors and investors — deploy first commercial prototypes, secure funding, assess bankability.</td><td>Utilities, manufacturers, and lead customers — begin commercial production, operate under real conditions, monitor reliability.</td><td>Lead adopters, standards bodies, and lenders — scale operations, standardise processes, support market readiness.</td><td>Multiple manufacturers, infrastructure developers, and commercial banks — expand manufacturing, stabilise supply chains, reduce unit costs.</td><td>Mass-market producers, distributors, and lenders — support full market rollout, ensure after-sales service, maintain quality.</td></tr>
<tr><td colspan="2" rowspan="6">Market Failures</td><td colspan="11">Knowledge Spillovers</td><td rowspan="5">Unpriced Environmental Externalities</td></tr>
<tr><td colspan="3">Knowledge from basic and applied R&D</td><td colspan="3">Knowledge from prototyping</td><td colspan="2">Knowledge from demonstration</td><td colspan="3">Learning-by-Doing/Learning-by-Using</td></tr>
<tr><td colspan="3" rowspan="2"></td><td colspan="8">Financial Frictions</td></tr>
<tr><td colspan="3">Technological Valley of Death
High Perceived Technology Risk</td><td colspan="2">Commercialization Valley of Death
High Capital Intensity, Information Asymmetry (with financiers)</td><td colspan="2">Profitability Valley of Death
High Capital Intensity, Information Asymmetry (with financiers)</td><td>Capital-market imperfections for giga-projects</td></tr>
<tr><td colspan="6">Path Dependency in R&D</td><td colspan="5">Coordination Failures, Switching Costs and Path Dependency
Supply-Chain development, Complementary Infrastructure, Workforce Skills, Network Externalities, Standard-setting</td></tr>
<tr><td colspan="10"></td><td colspan="2">Information Asymmetry (with consumers)</td></tr>
<tr><td rowspan="3">Policies</td><td>Supply-Push</td><td colspan="3">Public R&D funding, University & Lab grants, R&D tax credits, Exploratory and “moon-shot” prizes</td><td colspan="3">Public co-funding for pilots, Seed funding & grants for start-ups, Access to public testing facilities, Innovation prizes</td><td colspan="2">Grants for FOAK commercial-scale projects, Concessional or blended-finance loans & loan guarantees, Public-Private Partnerships</td><td colspan="2">Production Tax Credits (PTCs), Investment Tax Credits (ITCs), Advance Market Commitments or volume-guarantee platforms</td><td colspan="2">Support for supply-chain development, Workforce training & development programs, Low-cost financing for manufacturing expansion</td></tr>
<tr><td>Demand-Pull</td><td colspan="6">Not Applicable</td><td colspan="2">Public procurement of demonstration units, Initial off-take agreements</td><td colspan="2">Feed-in Tariffs, Contracts for Difference (CfDs), Consumer subsidies & rebates, Renewable Portfolio Standards (RPS)</td><td colspan="2">Broad carbon pricing (e.g., ETS, Carbon Tax), Public green procurement mandates, Auctions and reverse auctions for deployment</td></tr>
<tr><td>Systemic & Regulatory</td><td colspan="3">Intellectual property (IP) protection frameworks</td><td colspan="3">Streamlined permitting for pilot projects</td><td colspan="2">Clear regulations for demonstration, Risk-sharing frameworks</td><td colspan="2">Information campaigns & consumer labeling, Interconnection standards, Early-stage grid & infrastructure planning</td><td colspan="2">Performance standards & mandates, Public investment in enabling infrastructure (e.g., grid, pipelines), International collaboration on standards</td></tr>
</table>

Table 2: Technological Readiness, Market Failures, and Policies

Note: The table summarizes key stages of technology readiness (TRLs) and links them to the main economic mechanisms shaping clean innovation. For each level, it identifies principal actors, typical activities, expected outputs, and illustrative clean-energy technologies (based on the IEA Clean Energy Technology Guide, available at https://www.iea.org/data-and-statistics/data-tools/etp-clean-energy-technology-guide). The framework highlights that market failures occur at multiple stages—ranging from knowledge spillovers and financial frictions to coordination problems—leading to systematic underinvestment in development and deployment. For clean technologies, advancing through these stages is especially challenging given their long timelines, capital intensity, and dependence on enabling infrastructure.

2.1.2 Unpriced Environmental Externalities

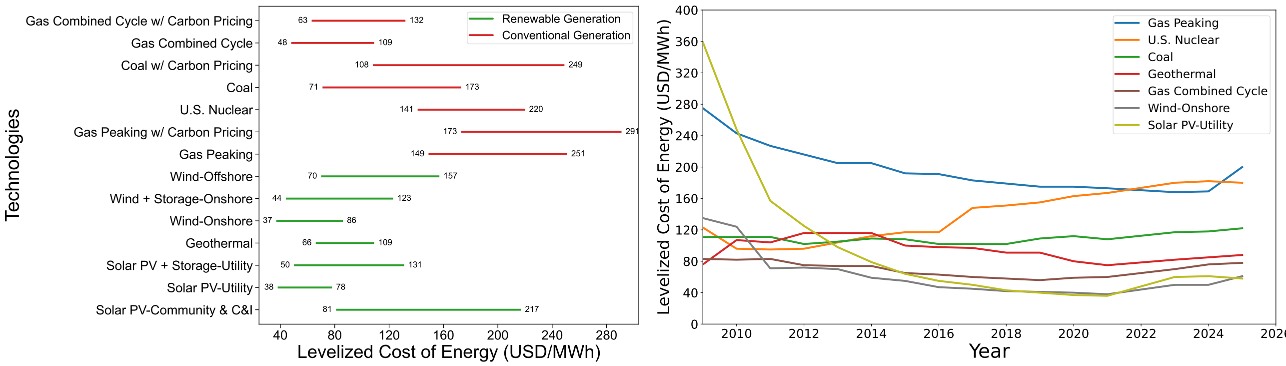
One of the most fundamental market failures affecting clean technology development is the negative environmental externality associated with fossil fuels, represented by the green box at the right end of Table 2. These include not only the global climate impacts of greenhouse gas emissions, but also the local health damages from air pollution caused by the combustion of fossil energy sources. These societal costs are not reflected in market prices, which means fossil fuels are systematically under-priced. Although air pollution is a more localized externality than climate change—and might therefore seem easier to internalize—the benefits of cleaner air are often diffuse, delayed, or not immediately visible. This makes societies more likely to undervalue pollution control and, as a result, underinvest in abatement technologies or in the development of new, low-pollution production processes.

This underpricing of pollution distorts the innovation playing field. It gives fossil-based technologies a cost advantage and makes it harder for clean technologies to compete. The problem is often worsened by explicit fossil fuel subsidies, which remain in place in many parts of the world (see Section 4.6). In Table 2, this externality appears in the downstream part of the technology development process where it directly suppresses demand for clean technologies relative to dirty alternatives. However, the effects of these unpriced externalities go much deeper. By weakening expected market size and profitability, this externality discourages private investment from the earliest stages of clean technology development. It reduces incentives to engage in research and development (R&D), shrinking the pipeline of future innovation. In this way, it interacts with and amplifies other market failures further upstream. It can indeed be considered, in effect, as the "mother of all externalities"—with cascading effects throughout the entire innovation chain.[4]

This mechanism is captured in the induced innovation hypothesis: when the relative price of clean technologies increases (for example, via carbon pricing), firms have stronger incentives to invest in innovation that improves their performance and cost-effectiveness. The dynamic efficiency argument for carbon pricing rests on this logic, and we provide a longer discussion of this topic in Section 4.1. Some clean technologies—including solar photovoltaic or electric vehicles—have reached or are approaching cost parity in certain markets. This is clearly illustrated by the current level as well as recent trends in the levelized cost of clean energy sources, displayed in Figure 2).[5] However, their diffusion remains limited in many sectors. This suggests that unpriced externalities and other barriers continue to hold back adoption even where clean tech is already economically viable. Anticipating these commercialization

4. We are aware that this phrase is most often used in reference to the scope and scale of greenhouse gas externalities. Here we use it in a different, but in our view equally fitting, sense to describe the cascading effects of pollution externalities throughout the innovation chain.

5. A "levelized cost" is a metric that aggregates the entire cost of a project over its lifespan and divides it by the total output, typically measured in a unit of energy like dollars per megawatt-hour.



(a) Levelized Cost Ranges

(b) Levelized Costs Over Time

Figure 2: Levelized Cost of Electricity

Note: Reproduced from Lazard LCOE+ 2025. In Panel 2a, drawn from page 11 of the report, Lazard applies an illustrative carbon price range of $40–$60/ton for Gas Combined Cycle, Coal as well as Gas peaking, to highlight sensitivity across technologies. In Panel 2b, drawn from page 14 of the report, historical values are constructed using the midpoint of Lazard's reported high and low LCOE estimates for each technology-year. For nuclear, figures reflect Lazard's LCOE v14.0 (inflation-adjusted) based on then-estimated costs for the Vogtle Plant, given limited public data on new-build projects. Together, the panels underscore the narrowing cost differentials between certain clean technologies and fossil-based alternatives.

challenges, upstream innovators are less likely to invest in new clean technology development.

2.1.3 Knowledge Spillovers

Knowledge spillovers occur when the benefits of new knowledge extend beyond the individual or firm that made the original investment in creating it. This is common because new knowledge has many of the characteristics of a public good: it is non-rival (one firm's use does not diminish another's ability to use it) and often non-excludable (others can access and apply it even when formal intellectual property protections exist).

These spillovers take different forms at different stages of the innovation process, and are represented by the blue row in Table 2. Early-stage research often generates ideas and methods that diffuse widely through publication, collaboration, or informal exchange. At later stages, firms benefit from learning by doing (LBD) and users from learning by using (LBU), often in ways that create knowledge others can exploit. Opportunities for knowledge creation exist throughout the technology lifecycle—but in nearly all cases, that knowledge is difficult to fully appropriate, contributing to underinvestment across the innovation chain.

R&D Spillovers. When a firm invests in research and development—for example, to discover a more efficient catalyst for green hydrogen or a more durable material for wind turbine blades—it inevitably generates knowledge that benefits others. The beneficiaries could be future innovators in he same technology area, who are now able to build on a larger body of existing knowledge, or innovators in other areas who are able to apply the new knowledge in different ways. While intellectual property rights such as patents are intended to help innovators capture the returns on their inventions, they are imperfect tools and often imperfectly enforced in large parts of the world. Patent protection does not prevent others from learning from disclosed information and developing alternative approaches—so-called "inventing around" existing intellectual property protection. In fact, patent filings themselves often serve as valuable inputs for follow-on R&D efforts by competitors and researchers.

This leads to a fundamental misalignment between private and social returns to R&D (e.g., Acemoglu et al. 2012). The innovating firm typically bears the full cost and risk of the R&D investment, but captures only a fraction of the total economic benefit it creates. The remaining value spills over to others. Because the social return to R&D is much higher than the private return, private firms tend to invest less in R&D than is socially optimal.

The extent of these spillovers from R&D investments can vary widely across applications. Some empirical studies have argued that clean energy technologies generate larger knowledge spillovers than fossil-based ones, adding to their inefficient under-supply since these spillovers are not internalized by innovators and investors. Dechezleprêtre et al. (2013), for example, find that clean patents receive up to 60% more forward citations, implying higher social returns. Studying variation in citation patterns across sections, Noailly and Shestalova (2017) show that solar and storage patents spill over widely to unrelated domains such as semiconductors and electrical machinery, suggesting they have high knowledge value beyond their immediate applications. Spillovers from other areas also shape clean technology development. Andres et al. (2022) find, for example, that clean technologies draw far more spillovers from AI and ICT than dirty ones, underscoring complementarities between innovation in clean technology and knowledge from other areas. However, up and down the "knowledge supply chain," the presence of spillovers means that private R&D investment will be below the efficient level.

The fact that knowledge spillovers generate a mismatch between private and social benefits of R&D investment implies that public R&D can have substantial benefits. Governments can address underinvestment by directly funding research and by creating incentives for private actors to invest. Instruments range from support for national laboratories and university-based research, to competitive grant programs such as those run by the US Department of Energy or Horizon Europe, to broad-based measures like R&D tax credits. Evaluating US Department of Energy Small Business Innovation Research (SBIR) grants, Myers and Lanahan (2022) estimate that each patent by a funded firm gives rise to about three additional patents by others, with roughly 60% of these spillovers occurring within the United States. Howell (2017) shows that funding from the SBIR program has large positive effects on patenting and future revenue, especially for the most financially constrained innovating firms. More generally, a number of studies investigate the economic impacts of public R&D investment across different areas of the economy and often estimate high benefit-cost ratios for these investments (e.g., Griliches

1958; Jones and Summers 2020; Fieldhouse and Mertens 2023; Akerman et al. 2025).

Learning by Doing and Learning by Using. Two important sources of knowledge creation outside formal R&D are learning by doing and learning by using. These processes generate cost reductions and performance improvements through experience, both on the supply and demand sides of the innovation process. Learning by doing refers to cost declines that occur as firms gain experience in manufacturing and deployment. As production scales, firms improve workflows, optimize supply chains, reduce waste, and identify process innovations—lowering unit costs. These effects are captured in the widely observed "learning curves" or "experience curves" that characterize many clean energy technologies, showing that costs decline substantially with experience; however, as discussed in Section 2.2.5, they likely also reflect cost reductions driven by additional research, development and demonstration (RD&D).

Learning by using, by contrast, originates on the demand side. As households adopt new technologies, they acquire know-how that can diffuse through social networks and feed back to producers. Evidence from residential solar photovoltaics (PV) illustrates these dynamics. Bollinger and Gillingham (2012) first documented strong neighbor effects in California, showing that the presence of nearby adopters increased the probability of adoption. Building on this, Gillingham and Bollinger (2021) analyze Connecticut's "Solarize" campaigns and find that community outreach and volunteer ambassadors sharply boosted adoption, with effects far larger than could be explained by price discounts alone, consistent with social learning. Complementing these results, Bollinger et al. (2022) use high-resolution data on panel visibility and show that households are significantly more likely to adopt when they can *see* neighbors' panels, with an effect size comparable to a large price reduction. Beyond high-income contexts, Alem and Dugoua (2022) provide experimental evidence from East Africa that peer communication raises willingness to pay for solar lanterns, again highlighting the role of information flows in early adoption.

It is useful, however, to distinguish between learning by using and peer effects. Learning by using refers specifically to the informational spillovers generated as early adopters gain experience operating a technology and share that knowledge. Peer effects are a broader phenomenon: they include social learning, but also other channels such as conformity, status signaling, or network externalities that increase the value of adoption as more users join. In practice, it is often difficult to disentangle these mechanisms. For instance, the Solarize campaigns point to information as the key driver (Gillingham and Bollinger 2021), while visibility effects may reflect either improved information or social influence. In this sense, peer effects encompass learning by using but also extend to non-informational channels (Bollinger et al. 2022).

The resulting knowledge from both learning by doing and learning by using, however, is difficult to fully appropriate. Manufacturers and users alike rarely capture the full value of the learning they generate. As with knowledge spillovers in R&D, this can lead to underinvestment: rational actors have incentives to wait and free-ride on the learning generated by others. Thus, there may be substantial value in policy support not only for innovation but also for early deployment, through instruments such as feed-in tariffs, production tax credits, and other mechanisms that reward early adopters or subsidize early production. Such tools aim to correct underinvestment driven by learning spillovers and help accelerate the emergence of cost-competitive clean technologies. See also Langer and Lemoine (2022), who show that the optimal time profile of deployment subsidies depends on forward-looking adoption decisions and heterogeneous private values: efficient schedules tend to rise over time to price discriminate across adopters, though anticipated cost declines and spending-smoothing considerations can flatten this trajectory.

Figuring out the appropriate design of such policies and subsidy amount requires quantifying the magnitude of learning effects and the external benefits they generate. Several recent papers have made important contributions on this front. Van Benthem et al. (2008) examine California's solar PV market and show that subsidies are warranted only if learning-by-doing is strong. They estimate that unit costs fall by about 10% every time cumulative production doubles. At this rate, the subsidy path that maximizes welfare is very close to the program California implemented in the mid-2000s, which offered rebates of roughly $2 per watt. The key insight is that these subsidies are not justified by the environmental benefits from reduced emissions alone—those are too small on their own—but by the additional future cost reductions that today's installations make possible through learning spillovers. Covert and Sweeney (2022) study the global wind turbine industry and show that a doubling of cumulative experience reduces costs by 14–29%, while spillovers across models and firms are very limited. This explains why larger, more efficient turbines require substantial "experience investments" before becoming competitive. Barwick et al. (2025) estimate a 7.5% learning rate in electric vehicle (EV) batteries, with learning accounting for more than a third of recent cost declines. They demonstrate that EV subsidies strongly reinforce learning and generate cross-country spillovers.

Contracting-Related Spillovers. An important but often overlooked form of spillover arises in how clean technologies are financed. Novel technologies often require new types of contracts and project structures, but commercial lenders may lack the expertise to finance unfamiliar assets—especially large-scale infrastructure (see Armitage et al. (2024) for a longer discussion). Green banks and public financial institutions can help by piloting financing models and sharing what works. By developing standardized contract terms—such as those used for rooftop solar or residential mortgages—they reduce transaction costs, build market confidence, and make it easier to bundle projects and attract institutional investors (OECD 2016). This contracting knowledge lowers barriers for future market participants, but is not easily monetized by early pioneers. Like other learning spillovers, it justifies early public involvement to create and diffuse financial know-how.

2.1.4 Financial Frictions

Clean technologies face significant financing challenges as they progress from laboratory innovation to market dominance, summarized in the orange box in Table 2. These challenges manifest as a series of critical funding gaps, commonly known as "Valleys of Death," where promising technologies stall due to a lack of capital. Understanding these valleys and the underlying financial frictions is essential for developing effective policy interventions.

The Technological Valley of Death. The first valley occurs between laboratory research and field demonstration. At this stage, entrepreneurs must bridge the gap between promising research results and working prototypes that can demonstrate technical performance under real-world conditions. While capital requirements are smaller than in later phases, they remain substantial and risky—too large for personal networks but often too uncertain for traditional venture capital. The key challenge is convincing investors that an innovation represents genuine commercial potential rather than merely scientific curiosity.

The Commercialization Valley of Death. The second valley represents an even more formidable challenge: the transition from successful pilot projects to first-of-a-kind commercial-scale facilities. For clean technologies, this stage typically requires investments ranging from tens of millions to billions of dollars. The scale far exceeds typical venture capital capacity, while risks remain too high for conventional project finance. In fact, early venture capital investments in green technology were due to the combination of uncertainty and heavy capital requirements for which venture firms were unprepared (see Mallaby 2022). Institutional investors and banks, who normally fund large infrastructure projects, are reluctant to invest in unproven technologies lacking established revenue streams. For clean technologies, this valley might be better characterized as a "Grand Canyon" given its depth and breadth.

The Profitability Valley of Death. Even once a clean technology has proven itself technically and found early commercial niches, it often enters a profitability Valley of Death. Reaching the commercial stage often means entering niche markets where high costs are less of a barrier—for example, early solar panels used in satellites, or luxury EVs like Tesla's early models (Nemet 2019). But mass markets require major capital outlays at precisely the point where revenues remain low and risks high. Private investors are reluctant to finance this stage because projects may seem unprofitable until scale is reached or until the clean technology or production process receives policy support, which can include production tax credits, carbon pricing, or guaranteed demand. This third valley underscores how market structure and policy expectations shape the return profile for late-stage clean tech.

These funding gaps reflect structural frictions in innovation finance. Understanding these frictions is key to designing effective policy instruments that go beyond filling temporary capital shortfalls. Two mechanisms in particular—information asymmetries and elevated risk profiles—may explain why private finance often fails to support clean technologies at critical stages.

Information Asymmetry. A fundamental friction stems from the knowledge gap between entrepreneurs and financiers. Clean technology entrepreneurs typically possess highly specialized technical expertise, while investors—whether venture capitalists or bank loan officers—often lack the in-house knowledge to properly evaluate underlying science or engineering viability. This asymmetry makes accurate risk assessment extremely difficult. While information asymmetry exists across all innovation sectors, it may be particularly acute in clean technology compared to areas like software, where investors have greater familiarity with products and business models (Armitage et al. 2024). The problem is compounded by the asset-light nature of many clean tech startups, which limits their ability to offer traditional collateral.

Elevated Risk Profiles. Clean technologies carry inherently higher risk levels due to their capital intensity, long timelines, and exposure to uncertain regulatory environments. Unlike software startups, which may require little more than laptops and server space, most clean tech ventures involve building and testing physical systems—factories, equipment, and infrastructure. These projects often take a decade or more to reach commercial maturity (e.g., Mallaby 2022). Moreover, as described in Section 2.1.2, clean technologies are often priced above the efficient level and as a result, their future profitability depends on policy decisions—such as carbon pricing or subsidy regimes—that are difficult to predict and can change rapidly. The combination of technological and market risk deters conventional lenders, particularly those providing project finance, which has traditionally favored established technologies with stable cash flows and low perceived risk. Noailly and Smeets (2021), for example, provide firm-level evidence that renewable-energy firms are significantly more sensitive to cash-flow shocks than fossil-fuel firms, underscoring how financing constraints distort the direction of innovation.

These structural challenges in clean technology financing were dramatically illustrated during the "Cleantech 1.0" wave between 2006 and 2011. Venture capital firms invested over $25 billion USD in clean technology during this period, often achieving disappointing returns

(Gaddy et al. 2017; Mallaby 2022). This experience revealed a fundamental mismatch between the requirements of capital-intensive, slow-maturing technologies and venture capital preferences, which typically favor high-growth, short-horizon opportunities. As research by Nanda (2020) demonstrates, venture capital is more likely to support scale-ups that have already resolved significant technical uncertainty rather than early-stage firms still navigating basic development and demonstration challenges. These dynamics are particularly relevant because a significant share of green R&D is conducted by small, young firms lacking the substantial capital reserves of established incumbents (Nanda et al. 2015)[6]. This makes traversing the valleys of death especially difficult without external support mechanisms.

Policy Responses to Financial Frictions. There are several potential policy solutions to the financial frictions that limit technology development. Loan guarantee programs—such as the US Department of Energy's Title 17 program—allow governments to use their creditworthiness to absorb part of a project's default risk, enabling riskier projects to access low-cost debt from private lenders. While these programs have successfully financed major clean technology projects, they remain politically contentious. The bankruptcy of Solyndra, a solar panel manufacturer that received federal loan guarantees, became a rallying point for critics who argued that the government was "picking winners" (or rather "losers") (Groom 2014). The concern is that public agencies may lack better information than private markets about which technologies will succeed, yet by directing large sums to a few projects they magnify the fiscal and political cost of failure. More broadly, this debate reflects wider disagreements about the appropriate role of the state in allocating capital under technological uncertainty.

Green banks and other public financial institutions offer a complementary approach. Seeded with public funds, these institutions can co-invest in projects that are in the national interest but are unable to secure adequate private financing (Mazzucato and Semieniuk 2018). While early US green banks focused on financing deployment of already-commercial technologies at the community level (e.g., community solar), they are increasingly involved in utility-scale and first-of-a-kind projects. The distinction between traditional loan programs and green bank activities is narrowing (Armitage et al. 2024). Instrument design also matters: Pless (2024) finds that R&D grants and tax credits are complementary for smaller, financially constrained firms—where grants relax liquidity constraints and enable fuller use of credits—while for larger incumbents with easier access to finance the two instruments behave more like substitutes.

Finally, public-private demonstration funding remains a widely accepted and effective way to bridge the early-stage gap. Governments can offer cost-sharing grants and support for pilot-scale projects that allow firms to prove their technical and commercial viability. These programs

6. Nanda et al. (2015) documents that renewables patenting by startups grew from less than 5% in 2000 to about 20% in 2009.

are relatively uncontroversial and can generate critical data and operational experience needed to attract later-stage private capital. Recent research formalizes this intuition: Kotchen and Costello (2018) show that subsidizing pilot projects can often be the most efficient use of public climate finance. Because pilots generate information about whether larger investments are likely to succeed or fail, they help avoid wasteful full-scale failures and can expand the set of projects that are socially worthwhile. In this way, pilots create value not only when they succeed but also when they reveal that a costly project should be abandoned.

2.1.5 Path Dependency and Coordination Failures

Beyond financial barriers, clean technology innovation is also shaped by deeper structural forces—-namely, path dependency and coordination failure. These two concepts are closely related but analytically distinct, and are represented by the gray boxes in Table 2.

Path dependency explains why one particular path—once chosen—becomes increasingly difficult to leave. Over time, early steps can lock in a particular technology or system—even if superior alternatives emerge later. The modern economics of path dependency was formalized by David (1985) and Arthur (1989), who demonstrated how increasing returns, historical contingencies, and small early advantages can cause one technology to dominate, not because it is the best but because it got a head start.

Coordination problems explain why multiple paths may be available but difficult to coordinate on. Coordination failures occur when the actions of multiple agents are complementary—each actor's decision depends on what others do—but no one moves first. Without a credible mechanism to coordinate beliefs or actions, however, the system can become stuck in a suboptimal equilibrium. In the clean technology context, such failures are pervasive. Adoption of a new technology may depend on simultaneous investments in infrastructure, supply chains, services, and regulation—none of which are worthwhile unless the others also materialize. Each actor hesitates, waiting for others to act.

Both path dependency and coordination failures are underpinned by parts of the innovation process that exhibit increasing returns, sunk costs, network effects, and complementarities:

- Increasing returns to adoption arise when technologies become cheaper or more valuable as they scale. These returns may stem from learning by doing, economies of scale, or R&D spillovers. In clean technology, early adopters face high costs while late adopters benefit from cumulative improvements. This dynamic discourages early investment unless coordinated or subsidized.

- Sunk costs in physical infrastructure (pipelines, refineries, transmission grids) or human capital (specialized skills, routines) create inertia because past investments cannot be recovered. Retiring a coal plant or retraining a specialized workforce means writing off capital already paid for, making actors reluctant to switch even when cleaner options become competitive.

- Network effects occur when the value of a technology increases with the number of users. Fossil-based systems benefit from mature networks of suppliers, users, and norms. Clean technologies must build these networks from scratch.
- Complementarities mean that one technology is more valuable when others are also in place. Clean technologies rarely function in isolation—they depend on specialized components, compatible standards, infrastructure, and user practices. These complementarities raise the value of simultaneous action from multiple actors, creating fertile ground for coordination failure.

While coordination failures can exist without path dependency, they are typically less problematic: if actors are initially uncoordinated, they may still coordinate in the future, especially with better information. In contrast, path-dependent lock-in may be much harder to escape. Once entrenched, the system itself tips the scales against change. A particularly subtle form of coordination failure involves self-fulfilling expectations. Beliefs about a technology's future adoption shape present-day investment and policy decisions. If firms or financiers expect clean technologies to remain niche, they will underinvest, thereby ensuring their own pessimism becomes reality. Smulders and Zhou (2025) show that when clean and dirty technologies are close substitutes, expectations alone can determine which one dominates in the long run.

In practice, the underlying mechanisms—increasing returns, sunk costs, network effects, and complementarities—often reinforce each other. For example, increasing returns, which drive path dependence, can interact with complementarities to make coordination failure more likely. Still, it is analytically useful to distinguish them. The distinction clarifies where policy should aim to break incumbent lock-in and where it should instead focus on synchronizing actions and shaping expectations. Effective industrial climate policy must often do both. In what follows, we explore several concrete mechanisms of path dependence and coordination failure. Some of these are also reviewed in Armitage et al. (2024) and Pia and Dumas (2025).

Path Dependency in R&D. emerges through the specialization of human capital. Once researchers invest time and resources in building expertise within a specific technological domain, switching fields is costly—both in terms of retraining and in lost productivity during transition. These sunk costs of training, combined with increasing returns to specialization, create a strong incentive to continue working within a familiar research trajectory. Empirical evidence supports this. Aghion et al. (2016) show that auto firms' past patenting strongly predicts whether they continue in clean or dirty technologies. Dugoua and Gerarden (2025) find that higher gas prices spur more clean patenting, but almost entirely from incumbents already specialized in clean fields. We return to these mechanisms in Section 2.2.2, in the broader context of directed technological change.

Path Dependency in the Workforce. Related dynamics play out in the broader labor market. As fossil fuel assets shut down, workers in these sectors face the risk of stranded human capital—skills that are no longer in demand. Without effective retraining or compensation, this can create significant political resistance to transition, particularly in regions heavily dependent on fossil employment. Even in the absence of geographical mismatch, the energy transition is likely to produce frictions: labor shortages in clean sectors, displaced workers in carbon-intensive ones, and institutional gridlock (Popp et al. 2024).

Path Dependency in Infrastructure. Infrastructure represents one of the most powerful sources of path dependency due to its capital intensity, long lifespans, and high sunk costs (see Hawkins-Pierot and Wagner 2023, for recent empirical evidence). Coal-fired power plants, for example, can operate for 40 to 60 years, making it economically irrational to retire them early, even if cleaner alternatives are available. Another example is the electricity grid, which was designed around large, centralized, dispatchable generation and one-way power flows to consumers. This setup is poorly suited to high shares of variable, decentralized renewables like wind and solar. Upgrading the grid to a flexible, smart, bi-directional system with storage and demand response capabilities requires not only capital but also institutional coordination. Legacy infrastructure can lock societies into outdated technological models for decades, even when they are no longer efficient or aligned with policy goals. For a detailed review of how such dynamics create stranded assets in the transition to a carbon-free economy, see Van der Ploeg and Rezai (2020).

Path Dependency in Consumer Behavior. Habits, norms, and preferences embed path dependencies that persist long after conditions change. Formative shocks can leave deep imprints: US cohorts exposed to higher gasoline prices in their teenage years continue to drive less and use transit more decades later (Severen and Van Benthem 2022). Food consumption patterns also adjust only slowly—regional taste preferences in India constrain caloric gains from cheaper or more nutritious alternatives (Atkin 2016). When shocks force consumers to experiment, hidden inefficiencies are revealed: a London Underground strike led many commuters to discover and permanently adopt better routes (Larcom et al. 2017). Inertia can likewise undermine adoption of new technology: households given improved cooking stoves in India often reverted to traditional practices, erasing anticipated health and environmental benefits (Hanna et al. 2016). These examples highlight how routines, learned familiarity, and social norms function as a kind of sunk cost, slowing the uptake of even cost-competitive or environmentally superior innovations.

Path Dependency in Institutions. Perhaps the most entrenched source of path dependency is institutional inertia, particularly the political and economic power amassed by fossil fuel incumbents. Over time, these actors have embedded themselves in policymaking processes, using tools such as lobbying, campaign contributions, and influence over regulatory agencies to maintain favorable treatment—a dynamic often described as "regulatory capture." These institutions are not neutral arbiters of transition but active participants in defending the status quo. As a result, rules, incentives, and oversight structures may be slow to adapt or may even reinforce fossil fuel dependence.

Coordination Failures in EV Charging. A classic form of coordination failure arises around technical standards. In the early phases of electric vehicle (EV) deployment, car manufacturers adopted incompatible charging connectors and protocols—CHAdeMO, CCS, Tesla's proprietary standard—fragmenting the market. Without a common standard, EV users faced uncertainty about charger compatibility, while infrastructure providers were reluctant to invest in charging stations that might quickly become obsolete. Each firm waited for others to move first. This low-investment equilibrium, driven by a lack of coordination, slowed the rollout of public charging infrastructure and dampened consumer adoption (Li 2023).

The issue was not technological but institutional. Charging standards exhibit classic strategic complementarities: the value of a given plug or protocol rises with the number of compatible vehicles and stations. As with other network goods, expectations matter: firms hesitate to commit to a standard unless they expect others to follow. In this setting, standardization bodies or government mandates can play a catalytic role. In the US, a turning point came when several manufacturers voluntarily adopted Tesla's NACS standard in 2023–2024, followed by federal policy that conditioned charging infrastructure funding on interoperability requirements. Similar challenges have played out in the EU, though with earlier harmonization via the Type 2 Mennekes standard. The lesson is clear: left to the market, coordination on standards may emerge too late or not at all—stalling the clean technology transition. More generally, Gregoire-Zawilski and Popp (2024) study the effect of technology standards on innovation in grid technology and find that they (intuitively) reduce patenting activity by large incumbent firms, but at the same time increase firm entry and overall patenting quality.

Complementary Investments: The Chicken-and-Egg Problem of EVs and Charging Infrastructure. Another persistent coordination failure arises from the need for complementary investments across different actors in the clean technology ecosystem. EVs again offer a textbook example: widespread adoption depends on a dense network of public charging stations, while investment in that infrastructure depends on a sufficiently large EV user base. This creates a chicken-and-egg problem. Consumers hesitate to buy EVs due to "range anxiety"—the fear of being unable to find a charger when needed—while infrastructure providers hesitate to build chargers without a guaranteed flow of users.

From an economic perspective, this is a classic case of interdependent expectations: each actor's willingness to invest is contingent on what others are expected to do. Without coordination, all parties delay action, resulting in systemic underinvestment. Moreover, the problem spans multiple domains: utilities must plan for grid upgrades to handle rising demand from chargers; local authorities must permit and support infrastructure roll-out, and automakers must commit to EV production at scale. Each of these investments only pays off if the others materialize. In such a setting, public investment and clear policy signals—such as national infrastructure plans, EV sales mandates, or consumer purchase incentives—can help synchronize decisions across actors and shift the system to a high-uptake equilibrium.

Coordination Under Competing Clean Technology Options. Coordination failures can also emerge in the context of technological competition between incompatible clean technology paradigms. A prominent example is the early-stage rivalry between fuel cell electric vehicles (FCEVs) and battery electric vehicles (BEVs). Both were seen as plausible alternatives to internal combustion engines, yet each required a distinct ecosystem of inputs, infrastructure, and complementary capabilities. Fuel cells required investment in hydrogen production, storage, and refueling networks; batteries required scaling lithium-ion manufacturing and a charging infrastructure. These technologies are systemically incompatible—investments in one do not support the other—creating a situation where coordination on a dominant design was necessary for scale and cost reductions to materialize.

In this setting, firms faced a strategic coordination problem: each had an incentive to delay investment until it became clear which technology others would back. For years, no dominant standard emerged. The resolution did not come through deliberate coordination, but rather from an exogenous technological shock. Rapid improvements in lithium-ion battery performance dramatically lowered battery costs, shifting expectations and investment decisively toward BEVs. As documented by Dugoua and Dumas (2024), national innovation systems then realigned accordingly, reallocating R&D support and industrial policy tools away from hydrogen and toward battery platforms.

This episode illustrates a key feature of clean technology transitions: coordination problems do not only concern infrastructure or standards. They also arise between alternative clean energy paths, especially when technologies are not interoperable. Without a salient coordinating signal—whether from policy or external technological change—firms may rationally underinvest in all options, delaying convergence and the emergence of scalable industrial ecosystems.

Conclusions on Path Dependency and Coordination Failures. The policy response depends on which dynamic is more binding. Where path dependence dominates, intervention must counteract the built-in advantages of incumbent technologies. This can involve early-stage R&D support for clean alternatives, de-risking initial investments, or compensating for stranded assets, with the aim of overcoming sunk costs and giving new technologies a foothold. Where coordination failures are more salient, policy works best as a coordination device. Credible long-run targets, backed by public investment, and institutions such as procurement schemes, standards, or infrastructure plans can help synchronize expectations and actions across firms, financiers, and consumers.

2.1.6 Information Asymmetries in Consumer Adoption

Information asymmetries present a major barrier to the early adoption of clean technologies. Consumers often lack the expertise to assess product quality, evaluate long-term performance, or verify vendor claims—particularly for complex technologies like rooftop solar, heat pumps, or energy-efficient appliances. This uncertainty leads to risk aversion and reinforces a status quo bias toward familiar options, even when cleaner alternatives may offer better value over time (Samuelson and Zeckhauser 1988; Gillingham and Palmer 2014; Sallee 2014; Allcott and Knittel 2019). Evidence from vehicle and housing markets illustrates the point: car buyers substantially undervalue future fuel savings (Gillingham et al. 2021), while homeowners tend to fully capitalize fuel costs (Myers 2019), and tenants in rental markets often remain uninformed about energy expenditures, leading to under-investment by landlords (Myers 2020).

The challenge is further exacerbated by "greenwashing," the practice of making exaggerated or misleading environmental claims. When consumers are repeatedly exposed to low-quality or deceptive "green" offerings, trust erodes, making it harder for genuinely superior products to gain traction. Even well-intentioned consumers may struggle to distinguish between truly impactful innovations and marketing spin (Lyon and Maxwell 2011).

Government and third-party certifications can help reduce these asymmetries by offering trusted, standardized signals of product quality and environmental performance. Yet their effectiveness depends on credibility, consumer awareness, and the extent to which the information is accessible and understandable. Labels can act as heuristics that substitute for detailed information, leading some consumers to pay a large premium for certification while ignoring operating costs (Giraudet et al. 2018; Houde 2018). Coarse certification may even crowd out higher-quality signals and create bunching at thresholds, with ambiguous welfare effects under imperfect competition (Houde 2025).

This discussion is closely related to the broader economics of energy efficiency, which surveys mechanisms behind the so-called "efficiency gap" and the roles of information, split incentives, and behavioral frictions (Allcott and Greenstone 2012; Gerarden et al. 2017; Fowlie and Meeks 2021; Gillingham and Myers 2025).

2.1.7 Conclusion: Interconnected Market Failures

The unpriced carbon externality resulting from dirty production and knowledge spillovers that result from innovation are often treated as the central market failures in clean technology development. The goal of this section was to describe these market failures but also to show that a broader set of frictions—including demand-side uncertainty, financing constraints, and coordination problems—also hinders investment and deployment across the innovation supply chain. While we have discussed each of these issues largely in isolation, it is important to emphasize that they are not isolated problems. Rather, they form a tightly linked and mutually-reinforcing chain of barriers (see Table 2).

Any factor that weakens demand for clean technologies—such as the failure to price negative externalities—also dampens incentives to supply clean technologies in the first place. Lower expected demand reduces firms' willingness to invest in knowledge creation, shrinking the pipeline of R&D projects and limiting the number of technologies that advance to demonstration or commercialization. Weak or uncertain demand—which can be exacerbated by coordination challenges—also raises the perceived risk for private investors, making it harder for clean technologies to cross the so-called "Valleys of Death" between stages. And any clean technology brought to market must still compete in a system characterized by infrastructural and institutional inertia—often against incumbent technologies that benefit from explicit (see Section 4.6) or implicit subsidies by not paying their full social costs.

The scale and complexity of these barriers often mean that no single instrument—whether R&D funding or carbon pricing—can address the full set of market failures. Effective strategy requires enabling conditions for clean technologies to emerge, scale, and compete. This includes demand-side measures, infrastructure investment, institutional capacity, and credible long-term signals. Recent policies reflect this broader approach (see Section 4 and more specifically Sections 4.1 and 4.2). Subsidies, green banks, and production tax credits are not only tools for correcting market failures but also for constructing markets where none exist. When integrated into a coherent mix, such instruments can reduce uncertainty, mobilize investment, and enable clean technologies to scale and mature within competitive markets.

These mechanisms also have a strong spatial dimension: the concentration of activity—from R&D and demonstration to production and deployment—shapes how market failures manifest, as co-location reduces frictions, knowledge spillovers travel more readily, financing is easier to secure, and some coordination problems may be less severe; the literature on innovation ecosystems and clusters shows how interactions among universities, firms, investors, and public bodies influence research productivity and commercialization (Guzman et al. 2024), regional clusters promote entrepreneurial entry and start-up employment by lowering search, input, and information costs (Delgado et al. 2010), and comparative evidence highlights that these territorial dynamics differ systematically across contexts, with the U.S. benefiting from higher mobility and integrated markets while Europe faces barriers that limit diffusion (Crescenzi et al. 2007).

2.2 Macroeconomic Modeling

The previous section described the process of clean technology innovation, including the various market frictions and failures that emerge over the course of the innovation process. In this section, we turn to macroeconomic models that describe the forces that shape the overall rate and direction of technological change. While economists and policymakers have long recognized that the progression of climate change and its economic damage will be shaped by technological progress, most early models at this intersection assumed that technological change was "exogenous" and progressed at some pre-specified rate (e.g., Nordhaus 1994). More recent approaches directly model how economic incentives shape the direction of technological change (see e.g., Acemoglu 2002) and take into account the fact that innovation can respond dynamically to changing market conditions and policies (see e.g., Acemoglu et al. 2012; Acemoglu et al. 2016). This endogeneity of technological progress can change the costs and benefits of different policies, as well as the timing of optimal policy, in dramatic ways.

Directed technological change models in environmental economics have been described extensively in recent review articles (see e.g., Hémous and Olsen 2021; Dechezleprêtre and Hémous 2022). Here, we summarize the main modeling approaches and several empirical applications, before describing frontier areas that could be the subject of future work.

2.2.1 Baseline Directed Technological Change Model

This section summarizes the baseline directed technological change model applied to the development of clean technology, largely based on the model presented in Acemoglu et al. (2012). A key goal of these models is to understand the implications of endogenous technological change for optimal policy. Pre-existing views of optimal policy had fallen into different camps, with some advocating for limited and gradual intervention in order to limit the growth costs of an energy transition (the "Nordhaus approach") and others advocating for large, immediate, and permanent intervention (the "Stern" or "Al Gore" approach) or even zero growth policies (the "Greenpeace approach") in order to ward off climate catastrophe. Directed technological change models make it possible to evaluate these different proposals, taking into account how innovation shifts in response to policy and, in turn, shapes the economic consequences of an energy transition.

The model features production with both "clean" and "dirty" inputs and two key externalities. The first is an environmental externality, which came up in Section 2.1.2: production using dirty inputs leads to environmental degradation. The second is a knowledge externality, which also came up in Section 2.1.3: advances in clean (dirty) inputs make future innovation in that area more productive (i.e., innovation "builds on the shoulders of giants"). While Section 2.1.3 described the many sources of knowledge spillovers that can exist during the innovation process, directed technological change models typically focus on dynamic knowledge spillovers within a particular technology area as the main externality. Policy intervention is then motivated by the fact that private innovators ignore both the environmental harm of innovation in dirty technology and the positive knowledge spillovers from innovation.

Model Set Up. We first describe the production side of the economy, before turning to consumption (where the environmental externality lives) and innovation (where the knowledge spillover externality lives). There is a final good Y produced competitively with a clean input Y_c and a dirty input Y_d:

$$Y = (Y_c^{\frac{\epsilon-1}{\epsilon}} + Y_d^{\frac{\epsilon-1}{\epsilon}})^{\frac{\epsilon}{\epsilon-1}} \tag{1}$$

Most analyses assume that $\epsilon > 1$ so that the two goods are substitutes (e.g., a gasoline versus an electric car, or a clean versus dirty manufacturing production process). For $j \in \{c, d\}$, the input Y_j is produced with labor L_j and a continuum of machines x_{ji}:

$$Y_j = L_j^{1-\alpha} \int_o^1 A_{ji}^{1-\alpha} x_{ji}^{\alpha} di, \qquad 0 < \alpha < 1 \tag{2}$$

The A_{ji} are themselves an outcome of endogenous choices made by innovators. Optimal use of a given intermediate x_{ji} is increasing in the productivity A_{ji} of that intermediate.

There is a unit mass of infinitely lived representative consumers with utility:

$$\sum_{t=0}^{\infty} \frac{1}{(1+\rho)^t} u(C_t, S_t) \tag{3}$$

where C_t is consumption of the final good at time t, S_t is the quality of the environment at time t, and $\rho > 0$ is the discount rate. Utility is increasing in both consumption of the final good and the quality of the environment (e.g., absence of pollution, lack of extreme heat, etc.). Further assume $S_t \in [0, \bar{S}]$ where utility is $-\infty$ when S approaches zero and utility is flat at $S = \bar{S}$.

Production of the dirty input causes environmental harm:

$$S_{t+1} = -\xi Y_{dt} + (1+\delta) S_t \tag{4}$$

for $S \in (0, \bar{S})$. In the case of environmental harm from pollution, $\bar{S}$ can be thought of as the unpolluted level and $S = 0$ as the absorbing lower bound, while $\delta > 0$ is the rate of environmental regeneration. Absent policy intervention, this environmental harm is not taken into account by producers using the dirty input.

Finally, innovation takes place in each period as scientists s of unit mass choose to work in either the clean or dirty sectors. Once they make their sector choice, they are randomly allocated to a machine. Each scientist has a probability η_j of successfully improving an existing machine. If successful, this leads to a quality improvement of $\gamma > 0$ (i.e., $A_{jit} = (1+\gamma)A_{ji,t-1}$) and the innovator gains monopoly rights to sell the machine for one period. This could be thought of as having patent rights over the machine, making it possible for the innovator to capture some of the benefits of their knowledge creation. If they are unsuccessful, then there is no improvement in the technology (i.e., $A_{jit} = A_{ji,t-1}$) and monopoly rights are allocated randomly.

Laissez-Faire Equilibrium. Absent policy intervention, innovators choose which sector to enter by maximizing profits, taking into account final machine demand in each sector. Profits are given by:

$$\pi_{ij} = (p_{ij} - \psi)x_{ij} \tag{5}$$

where p_{ij} is the price of the machine and ψ is marginal cost. From the final producer profit maximization problem, machine demand x_{ij} is given by:

$$x_{ij} = (\frac{\alpha p_j}{p_{ji}})^{\frac{-1}{1-\alpha}} A_{ji} L_{ji} \tag{6}$$

and taking into account the probability and impact of technology quality improvement in each technology line, the law of motion of input quality in each sector j is given by:

$$A_{jt} = (1 + \gamma\eta_j s_{jt})A_{j,t-1} \tag{7}$$

This directly captures the knowledge externality and the idea that existing innovation builds on the quality of previous machines. Technology advances in previous periods increase the potential technology quality today (and in the future).

Combining equations (5)-(7) with the convenient normalization $\phi = \alpha^2$ we can derive expected profits from entering sector j:

$$\Pi_j = \eta_j(1+\gamma)(1-\alpha)\alpha p_{jt}^{\frac{1}{1-\alpha}} L_{ji} A_{j,t-1} \tag{8}$$

The key object that determines the direction of innovation, however, is not total profits that can be expected from entering either sector, but the relative profits from entering the dirty versus entering the clean sector. This ratio will determine the area in which scientists choose to invest their time and resources. The ratio in expected profits between the clean and dirty sectors is given by the following expression:

$$\frac{\Pi_{ct}}{\Pi_{dt}} = \underbrace{\frac{\eta_c}{\eta_d}}_{\text{Chance of success}} \times \underbrace{\left(\frac{p_{ct}}{p_{dt}}\right)^{\frac{1}{1-\alpha}}}_{\text{Price effect}} \times \underbrace{\frac{L_{ct}}{L_{dt}}}_{\text{Market size effect}} \times \underbrace{\frac{A_{c,t-1}}{A_{d,t-1}}}_{\text{Productivity effect}} \tag{9}$$

When this ratio exceeds one, it is more profitable to enter the clean sector; when this is below one, the dirty sector is more attractive. There are four key forces shaping this trade-off.

1. **Chance of success:** Innovation is directed to the sector with the higher probability that R&D efforts yield a successful improvement.

2. **Price effect:** Innovation tends to flow to the sector that is technologically behind (with higher prices), because a quality improvement there leads to a larger proportional reduction in production costs and prices. This force is stronger when ϵ is small, i.e. when clean and dirty goods are poor substitutes.

3. **Market size effect:** A larger customer base increases the returns to innovation. When $\epsilon > 1$, the more advanced sector attracts more demand, amplifying its advantage.

4. **Productivity effect:** Innovation yields larger private gains in sectors that are already more productive. A higher past productivity level $A_{j,t-1}$ means that each new step on the quality ladder multiplies a larger base, so the payoff from successful R&D is greater. This captures the idea of "standing on the shoulders of giants" and also generates path dependency, since it will lead new innovation to concentrate in the sector that is already more productive (see Section 2.1.5).

Expressing prices in terms of technology levels and letting $\varphi = (1-\alpha)(1-\epsilon)$ (which will be negative in the usual case when $\epsilon > 0$), we can express the ratio between expected profits in the two sectors as:

$$\frac{\Pi_{ct}}{\Pi_{dt}} = \frac{\eta_c}{\eta_d}\left(\frac{1+\gamma\eta_c s_{ct}}{1+\gamma\eta_d s_{dt}}\right)^{-\phi-1} \frac{A_{c,t-1}}{A_{d,t-1}}^{-\phi} \tag{10}$$

An immediate implication of this formulation is that innovation always takes place in the relatively more advanced sector, so long as $\epsilon > 0$ and hence $\varphi < 0$. This path dependency implies that if the initial technology level is higher in the dirty input or production process compared to the clean input or production process (i.e., if $A_{d,0} > A_{c,0}$), innovation always takes place only in the dirty technology. Moreover, due to the environmental externality from production using the dirty input (equation (4)), this will always lead to an environmental disaster, defined as a situation where S_t reaches zero in finite time.

One clear takeaway is that there is no reason that clean technology should develop on its own and absent policy intervention. In this baseline model, assuming that the productivity of dirty technology had an initial advantage—as was surely the case—there would be little incentive for scientists to enter clean technology development at all. In other words, innovation incentives in the laissez-faire path can lock the economy into dirty innovation and makes an eventual environmental disaster unavoidable.

The Role of Policy. The disaster that emerges from the laissez-faire equilibrium immediately suggests that there is an important role for policy. When can a temporary research subsidy ward off environmental disaster? Increasing innovation in the clean sector has two competing effects. First, by making clean production relatively more efficient, it reduces labor allocated to the dirty sector. This is because, as clean inputs now deliver more output per unit of effort, firms have an incentive to reallocate workers and resources toward clean production, reducing the share of activity in the dirty sector. Second, by making clean production relatively more efficient, it lowers the overall cost of the final good and can thereby increase production in the dirty sector. Because cheaper clean inputs reduce production costs economy-wide, the final good's price falls. The lower price raises aggregate demand and expands total output. As output grows, demand increases for both clean and dirty inputs, so efficiency gains in the clean sector may indirectly boost dirty production.

The elasticity of substitution between the clean and dirty inputs determines which effect dominates. When the two inputs are strong substitutes (i.e., $\epsilon > 1/1-\alpha$), a temporary clean research subsidy will prevent environmental disaster by reducing Y_d over time. When the two inputs are weak substitutes (i.e., $\epsilon < 1/1-\alpha$), a temporary research subsidy cannot prevent environmental disaster since increasing clean innovation increases Y_d over time, generating further environmental degradation.

The social optimum can always be achieved, however, through the combination of a carbon tax on the use of the dirty input, a clean research subsidy, and a subsidy for the use of all machines (where subsidies are financed by lump sum taxes). Intuitively, two policy levers are needed in order to correct for the two market failures. First, the (intra-temporal) environmental externality means that firms producing using the dirty input do not take into account their impact on the environment. Second, the (inter-temporal) knowledge externality means that firms innovating in both clean and dirty technology do not take into account their impact on future innovators. A carbon tax fixes the environmental externality without affecting the knowledge spillover. Research subsidies can correct the under supply of clean innovation and prevent directed innovation from locking the economy into into the dirty technology state, but does not correct the environmental externality. Only both instruments in concert can correct the static distortions from the environmental externality and the dynamic distortions from the knowledge spillover.

Finally, policy intervention can be temporary, since once A_{ct} catches up to A_{dt}, innovators will choose to advance clean technology instead of dirty technology on their own. However, during the period of time that it takes A_{ct} to catch up, growth is reduced and environmental degradation continues. The longer the intervention is delayed and the gap between A_{dt} and A_{ct} is allowed to grow, the worse the environmental outcome and the longer the necessary period of reduced growth so that A_{ct} can catch up.

Directed vs. Undirected Innovation. The model with directed technological change that directly accounts for innovation investment decisions departs in important ways from models that do not take this into account. Under laissez-faire and without optimal policy, environmental disaster arises earlier with directed technological change than in an equivalent economy without directed technological change. This is because innovator incentives push toward further technological advancement of the dirty technology, which has an initial productivity advantage. This process leads to a doom loop in which directed innovation accelerates environmental destruction.

However, when clean and dirty inputs are strong substitutes, a temporary research subsidy can prevent environmental disaster in a model with directed technological change, but not in an otherwise identical model without directed innovation. With directed innovation, the research subsidy shifts research focus toward clean technology. Once A_{ct} overtakes A_{dt}, innovators will continue to increase clean technology quality on their own and the research subsidy can be removed. This positive feedback loop between quality improvements and innovative investments is absent in models without directed technological change.

Thus, models with directed innovation are neither more nor less "optimistic" in all cases. Incorporating directed innovation increases the potential costs of inaction but also highlights the powerful role of policy—even temporary policy—in spurring technological change.

Quantification and estimation. A few studies have estimated directed-change models on US data. Acemoglu et al. (2016) show that the optimal policy relies on a large, front-loaded subsidy to clean R&D combined with a carbon tax that rises and then declines; this mix keeps warming below 2°C, while delaying action by 50 years lowers welfare by 1.7% of permanent consumption and using only a carbon tax instead of the mix raises costs by 1.9%. Fried (2018) calibrates a three-sector model with US R&D and energy data, finding that endogenous innovation reduces the carbon tax needed to cut emissions by 30% in 20 years by about one-fifth and shifts R&D strongly toward green technologies.

2.2.2 Empirical Analysis of Directed Technological Change

Several papers have investigated the key components of the directed technological change model empirically (see Popp 2019, for a recent review). These studies highlight that technology development responds dynamically to changing market incentives, including prices and policy interventions. They also provide evidence of the knowledge spillovers that are central to the Acemoglu et al. (2012) model and justification for clean R&D subsidies.

Aghion et al. (2016) study how price effects and knowledge spillovers shape innovation in the automotive industry. They combine data on all patenting in automotive technology classes, and further use the patent technology classification scheme to classify each patent as either clean or dirty. They then investigate how clean and dirty innovation are affected by both the relevant knowledge stock (i.e., capturing the knowledge spillovers that can be targeted by R&D policy) and fuel prices (i.e., capturing the margin that can be targeted by tax policy). They measure each firm's fuel price exposure by constructing a weighted sum of the fuel price across all countries, where the weights are the share of each firm's patents filed in each country. They parameterize the knowledge stock in both clean and dirty technology using the history of patenting in that area by other firms and by the firm in question.

The main finding is that patenting responds strongly both to changes in fuel prices and to knowledge stocks. Increased fuel prices lead to more clean technology patenting and less dirty technology patenting. A higher clean technology knowledge stock is associated with more clean technology patenting (while a higher dirty technology stock has the opposite effect), and a higher dirty technology knowledge stock leads to more dirty technology patenting (while a higher clean technology stock has no discernible effect). Recall from the previous section that the key question is whether and when the clean technology stock overtakes the dirty technology stock — this is the point at which innovators will choose to invest in clean technology even absent policy intervention. In simulations, the authors investigate how fuel price increases will affect the timing of this transition. The estimates suggested that a fuel price increase of 20% would have been required for the clean stock to overtake the dirty stock by the 2020s.

This study echoes findings from earlier work on induced innovation, showing that both market prices and the supply of knowledge are important drivers of clean energy innovation. Newell et al. (1999) use a product-characteristics model of consumer durables to show that increases in energy prices shifted innovation toward greater energy efficiency and accelerated the adoption of more efficient technologies. Popp (2002) shows that both supply-side factors, captured by the existing stock of scientific knowledge, and demand-side forces, such as higher energy prices, drive energy-efficient patenting.

More recent work has further documented how policy can tilt the direction of innovation between clean and dirty applications. Calel and Dechezleprêtre (2016) show that the introduction of a European carbon market increased low-carbon patenting by regulated firms with no evidence of crowd-out (see also Benatti et al. 2023). Relatedly, Moore et al. (2025) show that a carbon tax on transport fuel in Sweden led to a rise in low-carbon transportation patenting. Analyzing policy differences across countries, Popp (2006) shows that pollution regulation spurs the development of pollution-control technologies (with limited cross-border spillovers); Johnstone et al. (2010a) analyze how a variety of renewable energy policies affect clean innovation at varying levels of market-readiness; and Noailly (2012) focuses on regulations and energy efficiency of buildings. Finally, Calel (2020) finds that while the European carbon market increased low-carbon patenting, cap-and-trade programs primarily encourage the adoption of existing technologies (rather than new technology development). Further exploring firm-level trade-offs between innovation and technology adoption, as well as how both are affected by policy, could be an important area for future work.

It is important to remember that, absent policy intervention, there is no guarantee that innovation will push in the direction of greater energy efficiency—the exact opposite can happen. Knittel (2011) shows that from 1980 to the early 2000s, the US automobile sector prioritized advancements in power and size instead of fuel efficiency. Had power and size been held at their 1980 levels, fuel economy could have increased by 60% during the same period of time. Moreover, while the evidence cited above suggests that innovation can dynamically shift in response to policy changes, there are also forces constraining rapid shifts in technology. One is technology lock-in, introduced in Section 2.1.5. For example, Hawkins-Pierot and Wagner (2023) show that the electricity price when US manufacturing plants open has long-run effects on their energy intensity and technology use. This technology lock-in limits changes in technology use by incumbents. Dugoua and Gerarden (2025) show that increased clean technology development following natural gas price spikes is primarily driven by inventors already working in clean technology. Thus, early career specialization decisions can have long-run consequences for the direction of innovation and for the overall technological response to policy change.

Finally, it is worth pointing out that the fact that the direction of innovation shifts in response to market and policy incentives does not necessarily mean that the new induced innovation is impactful. Technological change induced by changes in demand may just not be where the most transformative innovations come from. Nemet (2009), for example, argues that the rise in demand for wind power led to only incremental new technology development. This is a key challenge for empirical work in this area and raises the importance of measuring the direction of innovation not only in terms of the number of new technologies (e.g., new patents) but also in terms of the *impact* of those technologies. We describe potential approaches to this measurement challenge in Section 3.2

2.2.3 Extensions of the Baseline Framework

Recent work has extended the baseline framework to include important additional features of reality. Many of these topics remain open and essential areas for future research.

Intermediate Technologies. The baseline model considers only clean and dirty technology; however, in practice, energy sources can also have intermediate levels of carbon intensity. This can lead to more complicated and nuanced dynamics (see Dechezleprêtre and Hémous 2022; Lemoine 2024). For example, Acemoglu et al. (2023) study the impact of the shale gas revolution in the United States, driven by advances in horizontal drilling and hydraulic fracturing ("fracking") methods that made natural gas much cheaper. The production of natural gas from shale deposits increased twelvefold from 2007 to 2018. What was the impact of this on carbon emissions? On the one hand, natural gas emits much less carbon than coal per unit of energy. On the other hand, the greater energy efficiency of fossil fuels could discourage innovation targeting cleaner (green) energy sources and boost long-run emissions. The authors show that the shale gas boom led to a decline in clean energy patenting and use a model of directed technological change to show that this led to an increase in US carbon emissions, pushing the US into a "fossil fuel trap." While shale gas is one example of an intermediate technology, moving beyond models with a simple dichotomy between clean and dirty technologies could be an important area of future work (see also Section 6.1).

Richer Technology Spillovers. The baseline directed technological change model has a single inter-temporal spillover: a knowledge spillover within clean and dirty technology areas. However, in practice, the pattern of knowledge spillovers could be much more complicated (see Section 2.1.3) and shape both the direction of innovation and optimal policy. These could be important to understand given how central uninternalized knowledge spillovers are to policy design and the overall impact of investments in R&D.

One recent example of work in this area is Donald (2023), which builds a model that incorporates cross-technology knowledge spillovers (e.g., from dirty to clean technology) and not only within-technology, dynamic spillovers. This incorporates the idea that many new technology areas do not start from scratch but build on existing technology in other areas. Advances in clean technology are no different, and often build on earlier advances in dirty technology; as Donald (2023, p. 1) notes, "[T]he first Tesla prototype—the Mule 1— was a combustion engine car that the engineers at Tesla reconfigured by ripping out the engine and stuffing the engine compartment full of batteries." These spillovers can limit the value of temporary, big push policies highlighted by the baseline directed technological change model, since clean innovation always builds on the existing stock of dirty technology. Jee and Srivastav (2024) also use patent data to investigate knowledge spillovers between clean and dirty technology—including indirect links that pass through other "bridging" technologies—and document cross-sector heterogeneity in these links.

Other studies have investigated the importance of dynamic knowledge spillovers within the firm and highlighted how the market structure of innovation can affect its focus and direction, including the speed of technology transitions (Lensman 2025). Analyses that focus only on sector-level changes in innovation could miss these important forces.

In future work, economists could do more to document the prevalence of knowledge spillovers—including spillovers between distinct lines of clean energy research, not only between clean and dirty research, as well as spillovers along the supply chain—and investigate how these shape the role of policy and policy design. Using firm-level data and digging into the market structure of technology development in clean and dirty industries could also be important. Methodologically, while most existing work has used patent citation information to capture knowledge spillovers across time and technologies, other studies have highlighted that citation flows take place only between a small set of firms and often represent business partnerships rather than the actual flow of ideas (Fadeev 2024). Therefore, new approaches to capture knowledge spillovers—how new knowledge in one area affects the rate of innovation in another—would be very valuable.

Supply Chains. While the baseline model incorporates a single clean and dirty input, real-world production takes place in the context of increasingly complicated and globalized supply chains. Reducing carbon emissions requires not only developing renewable sources of energy supply, but also low-emission enabling technologies, like batteries and grids, as well as end-use technologies that can use renewable or low-carbon inputs, like electric cars and new building structures. There are currently substantial differences in clean technology investment and innovation at different parts of the supply chain, and within each stage of the supply chain (IEA 2021c). New work by Aghion et al. (2025) builds a model of a green technological transition that spans an entire supply chain, from upstream inputs to final production. The authors argue that carbon taxation alone is insufficient to drive the energy transition and make the case for industrial policy tailored to the supply chain, highlighting that coordination along the production chain is critical and that targeted subsidies can shift the economy toward sustainable growth.

Despite its clear importance, research at this intersection is limited. Existing empirical work studying drivers of clean versus dirty innovation is insufficient to explain why there are such vast differences between investment in certain upstream versus downstream clean technology, or why innovation differs so drastically across various clean technology areas. Another area to explore could be the international nature of supply chains and how the green transition shifts supply chain links across countries. The role of policy could be very different depending on the extent to which (and which part of) the supply chain is domestic versus international. Moreover, by shifting which parts of the energy supply chain are controlled by each country, the energy transition could shift the distribution of economic power and energy supply chokepoints across countries. This could motivate the use of industrial policy as a political tool to control foreign access to sources of energy or other key inputs. We return to this topic when discussing the potential global winners and losers from the green transition in Section 6.4.

Alternative Drivers of Innovation and Policy. New work has highlighted alternative drivers of the direction of innovation, beyond the trade-off between price and productivity effects highlighted above. For example, Casey (2023) shows how efficiency standards can shift research incentives, and Alsina-Pujols and Hovdahl (2024) study how differentiated patent protection alters relative profitability of clean versus dirty innovation. Aghion et al. (2023) study the impact of consumer preferences on clean innovation in the automobile sector. This work highlights the role that narratives could play in shifting the direction of innovation and the interplay between cultural trends and technological change (see Acemoglu and Johnson 2023).

This would all be interesting to explore in future work, especially given the cultural divides that exist when it comes to certain renewable technologies and changes over time in the cultural value of conservation. Moreover, the incentives that drive innovation in upstream parts of the innovation network, including basic science, could be different from the incentives that shape downstream technology development, which is closer to commercialization. Exploring these social and political determinants of the direction of innovation—and showing how much they matter in different parts of the innovation network—could greatly add to our understanding of technology development. These alternative drivers of innovation could also limit the effectiveness of standard policy levers or motivate new policy ideas that act on these non-market forces.

Clean-Dirty Substitutability. The results of the baseline directed technological change model hinge on the substitutability between clean and dirty technologies. In most models, this elasticity of substitution is assumed to be greater than one and fixed over time. Using panel data from 26 countries, Papageorgiou et al. (2017) estimate elasticities of substitution between two and three depending on the sector, suggesting relatively high levels of substitutability and potentially large effects of temporary clean research subsidies. Jo and Miftakhova (2024) re-examine the common assumption in climate-growth models that the elasticity of substitution between clean and dirty energy is constant. Instead, they propose a dynamic, endogenous elasticity that evolves with the share of clean energy in the economy. They argue that as clean technology progresses and its capabilities increase, the extent to which dirty inputs can be substituted with clean ones increases as well. This leads to a greater elasticity of substitution over time, which lowers the economic costs of climate change mitigation. A richer framework could allow elasticities of substitution to vary across areas of the economy or over time, and more work is needed to understand the key drivers of changes in these elasticities as technological capabilities evolve.

2.2.4 Directed Technological Change in a Global Context

So far, we have focused on the interactions between policy and the direction of innovation in a single country. However, different parts of the world are connected both by trade and by knowledge spillovers. Trade linkages between countries, alongside uneven regulatory and innovation capacities, can complicate the conclusions from the baseline directed technological change model. Several papers have investigated how directed technological change can affect carbon leakage and the international consequences of unilateral climate policy (Di Maria and Smulders 2005; Di Maria and Valente 2008; Acemoglu et al. 2014; Hémous 2016). For example, Acemoglu et al. (2014) highlight how trade between a regulated North and un-regulated South can lead to the South to fully specialize in production of the dirty input, thereby reducing all incentive to imitate clean technology development from the North. Thus, coordinated policy is preferable, especially when clean and dirty inputs are complements in production (Di Maria and Smulders 2005). Hémous (2016) goes so far as to argue that the combination of directed innovation and international trade can increase reliance on dirty technology, to the extent that dirty technology has an initial advantage and foreign markets provide an even larger potential market size for new technology. In this context, unilateral policy can make matters worse if the unregulated country speeds up innovation in dirty technology; for this reason, optimal policy also includes a clean technology subsidy and pollution trade tax.

There is much left to explore at the intersection of directed innovation, trade, and international knowledge spillovers. First, to what extent are foreign market opportunities an important driver of the direction of innovation? While global markets are often much larger than domestic markets, Dechezleprêtre and Glachant (2014) use data on country-level policy and innovation in the wind industry and find that the effect of domestic demand on innovation is an order of magnitude larger than the effect of foreign demand. This is consistent with work in other contexts documenting strong home bias in technology development (Costinot et al. 2019; Moscona and Sastry 2025). That said, foreign markets still clearly matter; as one clear example, Chinese R&D in solar technology and other clean energy sources is clearly oriented toward developing low-cost products that could serve other emerging markets. While this process is likely driven both by financial incentives and the desire to accumulate soft power through the deployment of energy technology, it suggests that international trade could accelerate the development of certain technologies (in this case, clean technologies). However, more work is needed to understand the impact of these global economic and political incentives.

Second, what forces shape knowledge spillovers across countries? And how strong are these spillovers to begin with? Dechezleprêtre et al. (2011) show that clean technologies flow disproportionately among high-income countries and almost never to low-income countries. Parts of this analysis would surely be turned on its head by the recent take-off of climate mitigation innovation in China; nevertheless, there are many barriers to the flow and applicability of knowledge across countries. One example is that advances in mitigation technology from high-income countries may be less appropriate elsewhere. They may prioritize certain auxiliary functions over cost reduction; they may rely on complementary infrastructure or capital, including the existence of a well-functioning grid, that does not exist in low-income contexts; they could be designed for temperate environmental conditions and fail in tropical or desert conditions (e.g., solar cells that respond poorly to thermal and irradiance stresses, decay quickly in tropical humid conditions, or lose functionality without frequent dust and sand cleaning in desert conditions). Thus, even for a given technology area, knowledge developed in one country may not be applicable elsewhere. This issue compounds once you take into account that there are many renewable technology areas—solar, wind, nuclear, geothermal, etc.—and countries may be differentially suited to each one (see Figure 18 below). Thus, understanding the determinants and impact of international knowledge spillovers on climate mitigation technology could be an important area for future work.

Third, there is relatively little work about the coordination and diffusion of R&D policies across countries. In theory, what should this coordination look like? Should countries specialize in different technologies or each invest in a portfolio of technologies? Politically, R&D support policies may have greater opportunities for international agreement than taxes on production or trade, where no country wants to unilaterally place itself at a productivity disadvantage and policy intervention is more inherently zero-sum. In practice, how does one country's support for climate-mitigating R&D affect support policies in all countries? Could action by a small set of countries lead to a "race to the top" effect, to the extent that other countries also feel compelled to support their clean energy sectors to compete? Or could support for clean technology by one country perversely lead others to double down and specialize in dirty technology, as has been argued is currently the case of China and the US (Gelles et al. 2025)? These all strike us as very important and open areas for research.

2.2.5 Integrated Assessment Models and Learning Curves

While directed technological change models highlight the mechanisms that govern how innovative effort is allocated between clean and dirty technologies, much of climate policy analysis relies on a different class of models: integrated assessment models (IAMs). IAMs take a more aggregate perspective, linking economic activity, emissions, and the climate system in a single framework. Their main strength is the ability to connect economic dynamics with physical climate processes to provide internally consistent projections of emissions, climate change, damages, and mitigation costs.

IAMs are used extensively in practice, for example in major policy assessments such as the Intergovernmental Panel on Climate Change (IPCC) reports, as well as in national and international policy evaluation exercises. They are employed to estimate the social cost of carbon, to project the costs of meeting temperature targets, and to explore optimal carbon price trajectories. Early IAMs treated technological change as exogenous: productivity growth or cost reductions followed fixed schedules, unaffected by market conditions or policy. Later models introduced limited forms of endogeneity, most often through learning by doing or reduced-form representations of R&D. These mechanisms allow costs to decline with deployment or investment, but remain highly stylized.

This contrasts with the directed technological change framework, where innovation is modeled as an explicit decision and policy can directly redirect innovative effort through instruments such as carbon pricing or R&D subsidies. The empirical evidence described in the previous sections highlights the potential importance of treating innovation as endogenous, subject to changes in both rate and direction as economic incentives evolve. IAMs generally represent innovation only in aggregate terms, allowing productivity or cost to respond to policy intervention in a more mechanical way. Conversely, directed technological change models often have a highly stylized representation of the environment (see equation (4)), and have been difficult to fully quantify.

The aim of this section is not to provide a comprehensive survey of how IAMs treat technology. Readers seeking such coverage can consult Gillingham et al. (2008), Nordhaus (2010), Grubb et al. (2021b), and Dietz (2024). The objective here is to offer a concise overview before turning to the role of learning curves, the main approach by which IAMs represent cost reductions in clean technologies.

Technological Change in IAMs. IAMs that allow innovation to evolve in response to policy typically focus on one of two mechanisms: R&D-based innovation and learning by doing. Both create feedback from policy to technology costs, but in stylized form.

R&D-based models introduce a knowledge stock that accumulates through research spending and reduces abatement costs. The ENTICE model is the canonical example: it augments the original DICE model (Nordhaus 1992) with an explicit energy R&D sector, so that carbon pricing or subsidies induce research effort that lowers future costs (Popp 2004). A different extension by Dietz and Stern (2015) embeds endogenous growth in a DICE model, allowing climate policy to affect long-run productivity, and combines this with convex damages and fat-tailed risks. While both approaches extend the same framework, their focus differs: Popp (2004) emphasizes sectoral energy R&D, while Dietz and Stern (2015) emphasize growth dynamics and risk.

Learning-by-doing models link cost declines to cumulative deployment in a mechanical way, most often through an experience curve in which each doubling of capacity reduces costs by a fixed learning rate. Policy that accelerates deployment thus directly reduces costs, creating path dependence in technology choice. This formulation is widely used in large-scale IAMs, particularly for renewables and storage (e.g., Stehfest et al. 2014; Luderer et al. 2015).

Some models combine both mechanisms. WITCH, for example, is a multi-region dynamic growth model with an explicit energy system. It includes two R&D channels: one for economy-wide energy efficiency, where knowledge stocks accumulate through research with spillovers across regions, and another for technology-specific backstops, where dedicated R&D lowers costs alongside learning by doing from deployment (Bosetti et al. 2006; Bosetti et al. 2014; Emmerling et al. 2016). This dual structure captures both the incentives for strategic free-riding on others' R&D and spillovers from early deployment. Model runs highlight how carbon pricing, R&D support, and deployment policies interact in shaping long-run costs.

Recent work by Coppens et al. (2025) provides a systematic comparison of these representations. Using an analytical IAM and estimation from hundreds of scenarios, they show that assuming exogenous cost trends lowers near-term carbon prices and backloads abatement, while incorporating learning-by-doing creates a deployment externality that justifies stronger early action. By contrast, R&D-driven change delivers results close to the exogenous case only if R&D costs are modest. Their Table 1 is especially valuable: it surveys 22 major IAM families, showing that most still rely on exogenous assumptions, with few incorporating R&D explicitly. This divergence in modeling approaches explains much of the variation in IAM projections of mitigation costs and policy stringency.

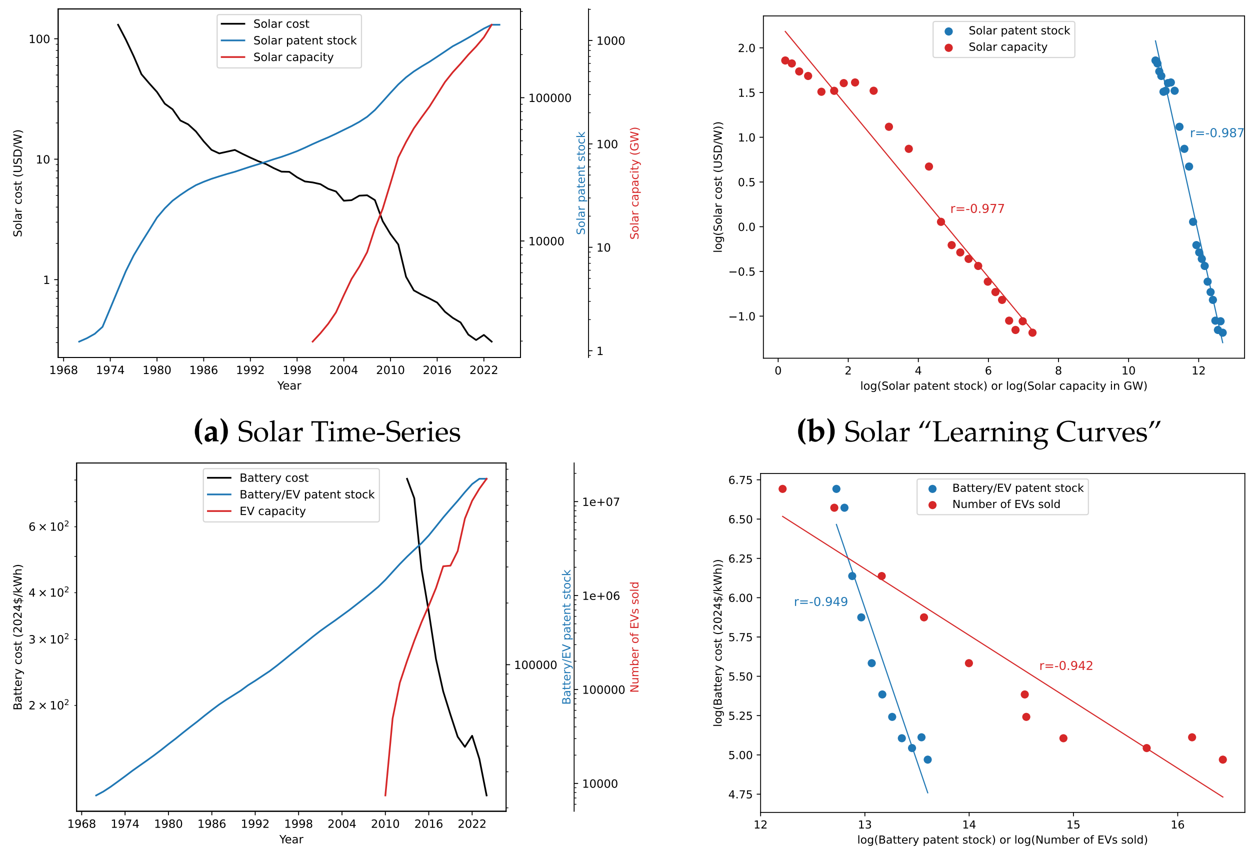
Earlier work by Hart (2019) explicitly embeds a directed technological change mechanism within an IAM-style growth model, thereby linking the two traditions. The model shows that clean-research subsidies should be front-loaded and decline over time, while optimal carbon prices rise monotonically. Hart finds that carbon pricing alone can deliver about 91% of the welfare gains of the full policy mix, whereas subsidies alone achieve only 36%.

Learning Curves: Evidence and Interpretation. A widely used approach to modeling innovation in IAMs is through technology learning curves. In their standard form, unit costs are assumed to decline as a power law in cumulative deployment:

$$C_t = C_0 \, Q_t^{-\alpha},$$

where C_t is the unit cost at time t, C_0 is the initial cost, Q_t is cumulative installed capacity or output up to time t, and $\alpha > 0$ is the learning elasticity. Each doubling of cumulative deployment reduces costs by a fixed percentage, known as the learning rate. This functional form is attractive for large-scale models because it is simple, empirically grounded, and creates a feedback in which early deployment lowers future costs.

While stylized, learning curves of this form are often a reasonable representation of real-world data. Figure 3 illustrates this for solar photovoltaics and lithium-ion batteries. The costs of both solar photovoltaics and batteries have declined substantially over time, coinciding



(a) Solar Time-Series

(b) Solar "Learning Curves"

(c) Battery Time-Series

(d) Battery "Learning Curves"

Figure 3: Learning Curves for Solar Photovoltaics and Lithium Ion Battery

Note: Panels (a) and (c) plot costs, cumulative deployment, and patent stocks over time for solar PV and lithium-ion batteries. Panels (b) and (d) show learning curves by plotting costs against cumulative deployment and against cumulative patent stocks on log–log axes. In both technologies, costs decline steadily as deployment and patenting rise, producing near-linear relationships.
Patent data are from PATSTAT (DocDB families, year = first filing). Patent stocks are calculated as the undiscounted cumulative sum of patent flows over time, starting from the earliest patents observed in the PATSTAT dataset (dating back to the late 19th century). For details on patent data construction and processing steps, see Appendix A.3. Cost and deployment data come from multiple sources. Solar module costs are from OWID et al. (2025), accessed via Our World in Data, and containing earlier series from Nemet (2009) and Farmer and Lafond (2016). Battery pack costs are from Bloomberg NEF (2024). Solar deployment refers to installed PV capacity from IRENA (2024a), accessed via Our World in Data. For batteries, deployment is proxied by the number of electric cars sold, taken from IEA (2025c), also via Ritchie (2024b) at Our World in Data.

with large increases in patenting activity (Figures 3a and 3c). When costs are plotted against cumulative deployment, they follow an almost linear trend on log–log axes (Figures 3b). A similar pattern emerges when costs are plotted against cumulative patent stocks, used here as a proxy for knowledge accumulation (Figure 3d). These figures show clear cost reductions in these technologies that coincide with increases in both R&D activity and deployment. This dual relationship is consistent with decomposition studies showing that, alongside deployment, innovation was a major contributor to recent solar and battery cost reductions (Kavlak et al. 2018; Ziegler and Trancik 2021).

Some work has investigated the mechanisms underlying these cost decline curves, which are used as a catch-all proxy for innovation trends in IAMs. Engineering-based decompositions of photovoltaics find that increased cell efficiency, reductions in silicon use, lower input prices, and economies of scale all contributed, with public and private R&D identified as the single most important high-level mechanism over 1980–2012 (Nemet 2006; Kavlak et al. 2018). More recent studies emphasize how hardware innovations spilled over into "soft" balance-of-system costs, so that improvements in modules and inverters indirectly lowered installation and permitting costs as well (Klemun et al. 2023; Kavlak et al. 2025). For lithium-ion batteries, engineering analyses show that global price declines of more than 90% since commercialization can be explained both by cumulative production and by inventive activity, with estimated learning rates of roughly 20–25% per doubling of output and "inventive-activity rates" of around 40% per doubling of patent filings (Ziegler and Trancik 2021). These findings suggest that experience and innovation interacted: deployment expanded markets, while sustained R&D in chemistry and materials science produced stepwise improvements in performance.

The appeal of learning curves in IAMs is that they provide a tractable way to incorporate real-world technology cost declines into climate modeling and allow the rate of these cost declines to respond to policy. At the same time, they fully abstract from the many mechanisms that underlie this cost decline—including experience, R&D, scale economies, and input markets—and parameterize technological change using only a single time-series correlation. This makes it challenging to model more detailed interactions between policy, innovation, and technology deployment; moreover, this framework also abstracts from any changes in the direction of innovation and how that can mediate the relationship between technology development and environmental damage. Developing frameworks that take innovation incentives and directed technological change seriously, while also allowing for clear and tractable policy simulation, seems like a potentially impactful area for future research.

3 The Clean Technology Landscape: Data and Trends

3.1 A Taxonomy of Clean Technologies

3.1.1 Overview

Economic models often reduce technology choice to a binary: "clean" versus "dirty." While analytically convenient, this framing obscures the diversity within clean technologies. The portfolio spans multiple sectors, stages of maturity, and modes of impact. Even just focusing on technologies that increase renewable energy efficiency, restricting attention to solar, wind, and electric vehicles, understates both the range of available options and their role in meeting climate targets.

Our aim in this section is pragmatic: to give economists a compact, sector-by-sector map of mitigation and adaptation technologies that exist, and to extend this taxonomy beyond the usual suspects. Readers are encouraged to approach this section *à la carte*: skim areas you know, slow down in areas that are new, and use it to understand which technologies exist and where existing technological holes remain. Another goal of this section is to make clear the energy transition is a result of innovation across a range of different areas, all of which are linked by knowledge spillovers and coordination challenges outlined in Section 2.1. Moreover, we hope that this taxonomy also makes clear how the impact of policy could also be different across technology areas and clarifies where in the innovation ecosystem specific policies may have particular bite.

Why breadth matters. The importance of looking beyond the "usual suspects" becomes clear in the IEA's scenario analysis (IEA 2020a, 2020b). Two contrasting pathways illustrate the point. The *Stated Policies Scenario* (STEPS) reflects current and announced policies; in this world, emissions decline only modestly, with progress driven largely by mature and early-adoption technologies such as efficiency improvements, deployment of solar PV and wind, incremental electrification of transport and buildings, and associated grid reinforcement (see Table 1). STEPS relies little on technologies that have not yet reached the market.

The *Sustainable Development Scenario* (SDS), in contrast, is a normative pathway consistent with bringing energy-sector CO_2 emissions to net zero around 2070, with residual emissions of roughly 3 Gt balanced by removals. In the near term, efficiency and renewables account for about 70% of the gap between SDS and STEPS through 2040. Beyond 2040, however, further reductions depend increasingly on technologies that are not yet mature: (i) deeper electrification supported by advanced batteries and heat pumps; (ii) carbon capture, utilization and storage (CCUS), including negative-emissions options such as bio-energy with CCS (BECCS) and direct air capture; (iii) low-carbon hydrogen and hydrogen-derived fuels for industry and long-distance transport; and (iv) sustainable bio-energy.

In total, more than one-third of the cumulative emissions reductions, according to these projections, come from technologies that are today at the demonstration or large-prototype stage (see Figure 4). A further 41% come from technologies in the early adoption phase, while only 25% derive from technologies that are already mature. Heavy industry and long-distance transport are projected to be especially dependent on technology in its early stages (e.g., hydrogen-based steel or low-carbon chemicals in the case of the former and sustainable aviation fuels or ammonia- or methanol-based shipping in the case of the latter).

The IEA also explores a Faster Innovation Case consistent with net zero by 2050. Here the reliance on immature technologies rises even further: by 2050, CO_2 savings from technologies currently at prototype or demonstration stage would need to be about 75% higher than in

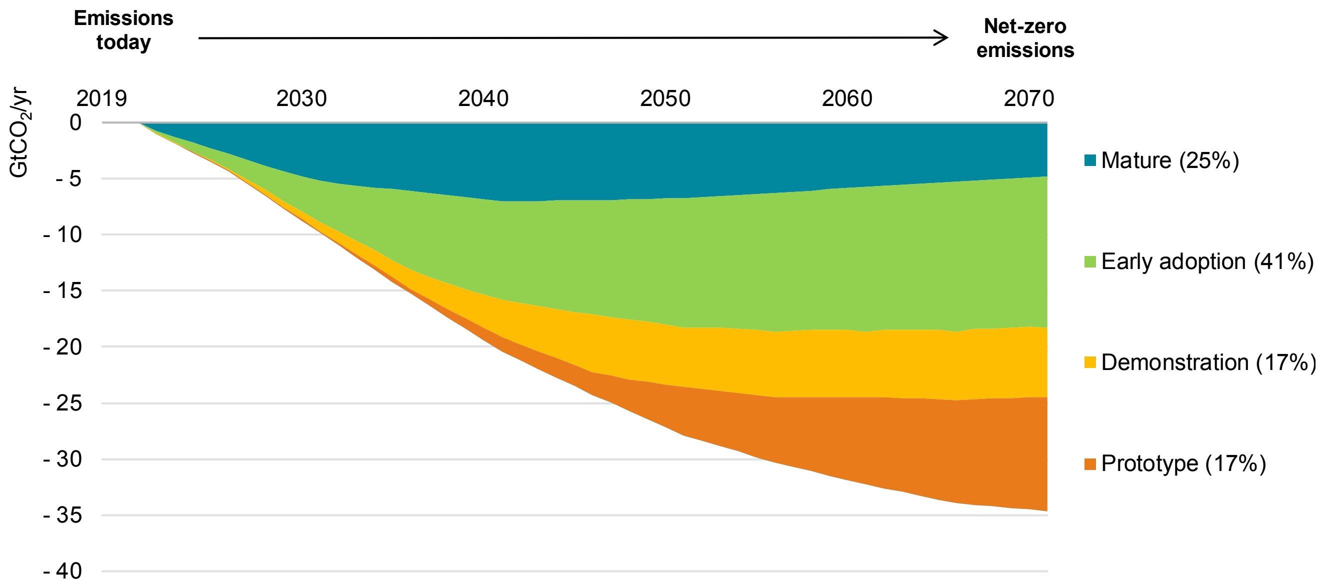


Figure 4: Energy Sector CO2 Emissions Reductions by Current TRL

Note: Reproduced from Figure 3.1 in IEA (2020b). The figure decomposes cumulative CO_2 reductions in the IEA's Sustainable Development Scenario (SDS) relative to the Stated Policies Scenario (STEPS) by the maturity of the underlying technologies. "Mature" refers to technologies already widely deployed (around TRL 11), "early adoption" to those with at least one commercial design but competing variants still emerging (TRL $\geq$9), "demonstration" to designs proven at pilot or demonstration scale but not yet commercial (TRL 7–8), and "large prototype" to technologies currently at prototype stage (around TRL 5). The key insight is that only about one-quarter of the SDS reductions come from mature options, while more than one-third depend on technologies that are today at the demonstration or prototype stage, highlighting the central role of innovation in achieving net zero.

the SDS, and roughly 45% of all reductions would come from options not yet commercially deployed. Together, these estimates suggest that understanding the full technology landscape could be key to understanding both clean innovation today and the energy transition over the coming decades.

Roadmap for what follows. The sections that follow map mitigation options by sector—power, transport, industry, buildings, and cross-cutting systems such as storage, hydrogen, grids, and carbon management—linking them to emissions profiles where possible (see Table 3 for reference). We then turn to adaptation technologies, whose role is increasingly intertwined with mitigation (see Table 4 for reference). Throughout, we return to the technology readiness level (TRL) framework introduced in Section 2.1.1 to describe the current state of maturity of each technology area.

3.1.2 Power Generation

The power generation sector accounts for around 28% of global greenhouse gas (GHG) emissions, driven primarily by coal (20%) and natural gas (6%). It is also the sector where decar-

Table 3: Taxonomy of Mitigation Technologies and Associated GHG Emissions.

Sector	**Category/Subcategory**	**Global GHG emissions in 2020 (%)**	**Example technologies (TRL)**
	Renewable		
	Solar Power	–	Crystalline Si PV (10); Thin
	Wind Power	–	film PV (5-6); Floating offshore
Power Generation	Hydropower	–	wind (8); Hydropower (11);
28%	Geothermal Power	–	Ocean salinity gradient and
Coal 20%	Ocean Power	–	thermal (4-5); Small modular
Nat. Gas 6%	**Other**		reactors (5); CCUS
Oil 1%	Nuclear Power	–	Post-combustion chemical
	Biomass Power	–	absorption (8); CCUS
	Fossil Power with CCUS	–	supercritical CO2 cycle (5-6)
	Energy Storage	–	Grid-forming inverter with PV
	Grid Technologies	–	or wind (7-8); Superconduct.
Cross-Cutting	Critical Minerals	–	high-voltage (7); Lithium-ion
Technologies	Carbon Management	–	battery storage (9); Direct air
	Hydrogen	–	capture (6–7); Direct lithium
			extraction from brine (7-8)
Buildings	Building Envelopes	–	Dynamic glazing (8); LED
7%	Lighting		lighting: Conventional (11),
Residential 5%	Appliances and Equipment	–	Polymer (9); Induction cooking
Commercial 1%	Heat Pumps	–	appliances (11); Air-to-air heat
Refrigerants 1%	Cooling		pumps (10); Membrane heat
	Data Centers and Networks		pumps (5);
	Road	**12%**	
	Fuel Economy of Cars/Vans	–	Biofuels Micro-algae (3-4);
	Biofuels	–	Battery electric cars (9);
Transport	Electric Vehicles	–	Sustainable aviation fuel:
16%	Trucks and Buses		HEFA (9-10), e-fuels (4-6);
	Rail		Methanol/ammonia-fuelled
	Aviation	1%	ships (6–7)
	International Shipping	2%	
	Cement and Concrete	5%	
	Chemicals and Plastics	4%	Cement kiln with CCUS (4-8);
	Pulp and Paper		Alternative materials for
Industry	Iron and Steel	5%	cement (3-9); Hydrogen direct
31%	Aluminium		reduced iron (4–7); Blast
	E-waste Recycling		furnaces with CCUS (5-9);
	Oil and Gas	5%	High temperature heat
	Cross-cutting Industry	–	electrification (3)
	Crops	7%	
Agriculture, Land-Use	Livestock	6%	
and Landfills	Landfills and Waste	4%	Cultured meat (5-9);
18%	Land Use and Forests	1%	plant-based meat (9)
	Agriculture Fuel Combustion	<1%	

Note: This figure groups technologies largely based on the Cooperative Patent Classification of patented technologies. Data on the shares of global GHG emissions are from the Rhodium Group, available at https://rhg.com/research/global-greenhouse-gas-emissions-2021/.

bonization is most advanced, owing to rapid cost declines in renewable energy technologies. The central challenge is shifting from demonstrating the technical feasibility of renewable-based systems to managing the complexities of large-scale deployment and integration.

Mature Renewables: Solar Photovoltaics and Onshore Wind. Solar photovoltaics (PV) and onshore wind are the main pillars of global power sector decarbonization. Both have moved from niche applications to mainstream energy sources. The IEA assesses crystalline-silicon PV and onshore wind at TRL 10: commercially established and competitive, but requiring continued innovation to support integration into energy systems at scale. Deployment has been expanding at a historic pace, with PV and onshore wind expected to dominate renewable capacity growth through 2030. The primary driver has been a sustained and dramatic reduction in costs: Lazard estimates indicate that the levelized cost of electricity (LCOE) from utility-scale solar PV fell by more than 80% between 2009 and 2025, from $359/MWh to $58/MWh (see Figure 2). Onshore wind followed a similar, though less steep, trajectory, with costs falling to around $61/MWh in 2025. By comparison, new-build gas combined cycle plants have an LCOE of about $78/MWh (versus $31/MWh for marginal operating costs of depreciated plants), while coal averages $122/MWh for new build and $73/MWh for marginal operation. These figures highlight the competitiveness of renewables in new capacity additions.

With cost competitiveness largely achieved, the main barriers now lie in integration. Variability, seasonal dependence, and geographic constraints limit the extent to which solar and wind can replace fossil generation without complementary technologies. Institutional and infrastructural barriers—including lengthy permitting processes and grid connection delays—have emerged as significant bottlenecks. Further innovation remains critical in cross-cutting areas such as grid technologies and large-scale storage, which are essential for system-level flexibility and reliability.

Emerging Renewables: Offshore Wind and Ocean Energy. Offshore wind is less mature than its onshore counterpart but is poised for rapid growth, benefiting from stronger and more consistent wind resources at sea. Fixed-bottom offshore wind is commercially established (TRL 10), but innovation is advancing in floating turbines (TRL 5–7), which could unlock the vast resource potential of deep waters. Offshore projects face higher upfront costs and are vulnerable to inflation, high interest rates, and supply chain challenges, yet they remain central to many national decarbonization strategies (e.g., EC 2020). Beyond electricity, offshore wind is increasingly explored as a source for low-emissions hydrogen production (TRL 5). Other experimental designs, such as airborne wind systems, remain at early prototype stages (TRL 4–5).

Ocean energy encompasses a portfolio of less mature technologies, including tidal, wave, salinity gradient, and thermal energy. Their predictability is an advantage, but high costs and technical risks in harsh marine environments constrain commercialization. Tidal range and tidal stream systems are approaching readiness (TRL 9), while wave energy converters are at TRL 7–8 but not yet cost-competitive. Salinity gradient and ocean thermal remain at the prototype stage (TRL 4–5).

Firm and Dispatchable Low-Carbon Power: Nuclear, Geothermal, and Hydropower. A system dominated by variable renewables will likely require complementary sources of firm, dispatchable low-carbon electricity to ensure grid stability and energy security.

Hydropower remains the largest renewable source globally and is a fully mature technology (TRL 11). Its principal value lies in its flexibility: reservoirs can operate as large-scale storage, balancing fluctuations in wind and solar output. However, opportunities for new large-scale projects are limited by site availability and social and environmental concerns. Nearly 40% of existing global capacity is more than 40 years old (IEA 2021a), highlighting the need for refurbishment and modernization to enhance flexibility.

Geothermal energy exploits subsurface heat for electricity and direct use. Conventional hydrothermal systems (dry steam and flash plants) are commercially established (TRL 11) but geographically constrained. Enhanced Geothermal Systems (EGS), currently at TRL 6–7, aim to create artificial reservoirs, offering the potential to expand geothermal deployment far beyond favorable natural sites.

Nuclear power provides zero-carbon, dispatchable electricity at scale. Large Generation III/III+ light-water reactors are mature (TRL 10–11), but in many advanced economies the sector is constrained by high capital costs, long construction times, and challenges of public acceptance and waste disposal (see Rauch 2023, for a recent discussion). Innovation efforts increasingly focus on Small Modular Reactors (SMRs), a diverse class of advanced designs (TRL 4–9) that aim to reduce costs and construction risks through modularity and factory fabrication. While proponents emphasize their potential for flexibility and industrial heat applications, SMRs have yet to demonstrate commercial deployment.

3.1.3 Cross-cutting Technologies

Technologies in this category underpin decarbonization across the energy system. They are essential to support the large-scale integration of renewables in power generation, but their role extends well beyond the power sector to both transport and industry.

Battery storage. Electrochemical batteries provide critical short-term flexibility for electricity systems and are also central to electrified transport. Lithium-ion is the dominant technology (TRL 9), with costs having fallen dramatically over the past decade. However, costs are increasingly linked to volatile mineral markets for lithium, cobalt, and nickel (see Section 6.3). This has accelerated innovation in alternative chemistries. Sodium-ion batteries (TRL 7), for example, use abundant and inexpensive materials and are beginning to reach the market, particularly for stationary storage. Leading designs contain no lithium, cobalt, or graphite and often replace copper with aluminum as the current collector, reducing cost and supply-chain risks (IEA 2025c). Their lower energy density makes them especially suited to stationary storage and urban micro-mobility. Progress has been rapid, from TRL 3–4 in 2021 to TRL 8–9 by 2023–24. Metal–air systems, such as zinc–air or iron–air (TRL 7–8) are attracting interest for long-duration storage, with designs targeting discharge times of 100+ hours. These could provide a cost-effective solution for balancing renewables over multi-day periods.

Smart Grids. If batteries provide the physical capacity for flexibility, smart grids provide the digital infrastructure. Advanced sensors, communications, and control software allow grid operators to monitor and manage electricity flows in real time. This enables demand response, coordinated charging of EVs, and the seamless integration of distributed resources such as rooftop PV. Core technologies—–including smart meters and advanced control systems–are largely mature (TRLs 7–11). The main challenge is not technical feasibility but investment and deployment, which remain far below what is needed in net-zero pathways (Davis et al. 2023).

Critical Minerals. The clean energy transition depends on secure supplies of critical minerals, including lithium, cobalt, nickel, and rare earths, essential for batteries, motors, wind turbines, and grid equipment (see Section 6.3). These supply chains are highly concentrated geographically and vulnerable to geopolitical, environmental, and market risks. Innovation efforts focus on mineral substitution, efficiency improvements, recycling, and new extraction methods (Andersen and Noailly 2022). Direct lithium extraction from brines is at TRL 7–8, phytomining (using plants to accumulate metals) is at TRL 5–6, and deep-sea mining remains at an early stage (TRL 3).

Carbon Management. Carbon capture, utilization, and storage (CCUS), direct air capture (DAC), and bioenergy with CCS (BECCS) are critical to address emissions that are otherwise hard to abate. In industry, CCUS is indispensable for process emissions (e.g., clinker production); in power, it can decarbonize residual fossil capacity or enable BECCS as a carbon removal option; in transport, captured CO_2 can be converted into synthetic fuels. Capture technologies are technically demonstrated across a wide range of applications (e.g., post-combustion amine systems for biomass power with CCUS at TRL 8–9; direct air capture at TRL 6–7). Storage pathways likewise span a broad spectrum, from early-stage approaches such as mineralisation of supercritical CO_2 (TRL 3) to CO_2-enhanced oil recovery, which is well-established and deployed commercially (TRL 11). Project announcements for 2030 exceed 430 $MtCO_2$/year of capture capacity, yet this remains far below the 1.6 $GtCO_2$/year required in the IEA Net Zero Scenario (IEA 2024f). Key challenges are high costs, the need for shared transport and storage networks, and the establishment of stable policy frameworks.

Hydrogen. Hydrogen is a cross-cutting zero-carbon energy carrier and feedstock with uses in industry (e.g. ammonia, refining, emerging roles in ironmaking), heavy transport, and shipping, and as a candidate for long-duration energy storage. Today, however, over 99% of hydrogen production uses unabated fossil fuels (without carbon capture) (IEA 2024e). Scaling low-carbon supply requires either *green* hydrogen via electrolysis powered by low-emissions electricity or *blue* hydrogen via fossil-based production with CCUS (see above). Technology readiness spans TRL 4–11: electrolysis overall ranges from TRL 4–9, with polymer electrolyte membrane (PEM) and alkaline systems commercial (TRL 9); wastewater electrolysis remains at prototype stage (TRL 4); seawater electrolysis is emerging (TRL 5); fossil-based hydrogen with CCUS varies by configuration (TRL 4–6). The binding constraints are cost and infrastructure: access to low-cost clean electricity and high utilization for electrolyzers; CO_2 transport and storage for blue hydrogen; and hydrogen networks for production, storage (e.g. salt caverns), and transport (pipelines or carriers such as ammonia).

3.1.4 Buildings

Buildings account for about 7% of global GHG emissions from direct on-site combustion (space and water heating, cooking). Their climate impact is larger once *indirect* emissions from purchased electricity and heat are reallocated to the sector, lifting the total to the mid-teens (see Table 3). A broader lifecycle view, which includes emissions from producing construction materials such as steel and cement, raises the contribution further and underscores how tightly buildings are coupled to the wider energy system.

Decarbonization relies on improving energy efficiency and electrifying end uses. Efficiency lowers the energy required to deliver comfort and services; electrification shifts the remainder to low-emissions power. The long lifetime of buildings creates lock-in: poor performance at construction can persist for 50–100 years, so high standards for new builds are essential, and deep retrofits may be the only decarbonization option for the existing stock. Managing non-CO_2 emissions from refrigeration and air conditioning through leak reduction and lower-GWP refrigerants is also important.

On the *building fabric*, high-performance envelopes reduce heating and cooling loads at source. Advanced fenestration (high-performance glazing, frames, and shading) is commercially established (roughly TRL 8–9) and can cut heat losses and solar gains substantially. Wall and façade systems span a range of designs from conventional high-R insulation to modular prefabricated panels (mid- to high-TRL), with the choice driven by climate, heritage constraints, and retrofit logistics.

For *lighting and appliances*, efficient luminaires (notably LEDs) are fully mature (TRL 9–11) and deliver large savings with short payback periods, while advanced controls (occupancy and daylight sensors) reduce peak loads and smooth demand. Direct-current lighting for building microgrids is emerging (around TRL 7); its value rises where on-site PV and storage are present by avoiding conversion losses. Clean cooking is increasingly electric (TRL 11), with solar solutions available in specific contexts (TRL 9).

Heat pumps are central to electrifying space and water heating. Modern units typically deliver about 2–4 kWh of heat per 1 kWh of electricity (higher in mild climates, lower in very cold ones) (IEA 2022c). Designs serve different needs and sit at different maturity levels. Air-to-air systems (split/packaged units) provide room or zonal heating and cooling where no hydronic system exists and are fully commercial (TRL 9–10); heat-recovery VRF/VRV variants suit multi-zone homes and commercial buildings needing simultaneous heating/cooling (TRL 10). Air-to-water systems feed radiators or underfloor loops and supply domestic hot water (TRL 9–10), while cold-climate air-source models extend reliable operation well below $0°$C (TRL 8–9). Central heat-pump water heaters serve multi-family and commercial hot-water loads (TRL 9–10). For harder retrofits, high-temperature air-to-water units deliver about 70–90°C to legacy radiators without full emitter upgrades (mid-TRL, $\sim$7). Membrane heat pumps target dehumidification and latent-load control in hot–humid climates or ventilation-led retrofits (TRL 5–7). Integrated heat-pump plus thermal storage concepts aim to shift loads to off-peak periods and support the grid (early, TRL 3–4). Where drilling is feasible, ground-source systems offer the highest seasonal efficiency for large or cold-climate loads (TRL 9).

Cooling demand is rising rapidly with incomes and heat exposure. Mature options include efficient vapour-compression units and evaporative cooling in suitable climates (TRL 4-9). Solid-state concepts (thermoelectric, electrocaloric) remain early-stage (TRL 4-6) and are not yet cost-competitive. Desiccant-based systems for dehumidification (TRL 9) are commercially available and can be valuable in humid regions when coupled with ventilation strategies. Across cooling, better envelopes and shading materially reduce peak loads, easing pressure on grids during heat waves.

Overall, better envelopes and efficient devices cut loads; heat pumps electrify residual thermal demand; improved refrigerant management reduces F-gas emissions. Because buildings are the largest electricity consumer, raising performance in this sector eases the scale and speed required from power-sector decarbonization while improving comfort and lowering operating costs for households and firms.

3.1.5 Transport

Transport is the second-largest source of energy-related CO_2 and accounts for roughly 16% of global GHG emissions (see Table 3). Options and constraints differ sharply by mode. Road transport is moving quickly, whereas aviation (about 2%) and shipping (about 1%) remain harder to decarbonize because of long asset lifetimes, international operations, and the need for energy-dense fuels. Within road transport (about 12%), electrification leads for light-duty vehicles, with heavier-duty cycles and weak-grid settings requiring a broader toolkit.

Biofuels. Liquid biofuels delivered the earliest reductions by cutting emissions from conventional cars already on the road and they continue to matter where electrification is slow (e.g. in regions with under-developed grids) and for aviation and shipping. The climate benefits of biofuels vary widely and depend on their full lifecycle impacts. First-generation fuels, produced from food crops such as corn (ethanol) or soy and palm oil (biodiesel), are commercially mature (TRL 9–11) but raise the greatest sustainability concerns. Their cultivation competes with food production and can drive deforestation or peatland drainage, leading to large direct and indirect land-use change emissions that may negate the climate benefit for decades (Fargione et al. 2008; Keeney and Hertel 2009). Second-generation (advanced) fuels rely on wastes, residues, or lignocellulosic feedstocks. Some routes, such as hydrotreated vegetable oil (HVO) and HEFA for aviation, are already commercial (TRL 9–10), while others such as cellulosic ethanol and biomass-to-liquids Fischer–Tropsch remain less mature, as noted above. Lifecycle performance is generally stronger than first-generation fuels, since feedstocks do not directly compete with food and land-use pressures are lower, though production costs remain high. Third-generation fuels such as algae are at the basic research and early pilot stages (TRL 3–4). They offer advantages—high yields without land competition—but remain far from large-scale deployment.

Electrification of Road Transport. Electrification is the main pathway for decarbonizing road transport, but it is not a one-size-fits-all solution. It dominates light-duty applications; in heavy-duty, it competes with other options depending on duty cycle, terrain, and infrastructure.

Battery Electric Vehicles (BEVs) have become the dominant technology pathway, with rapid market growth driven by supportive policies—such as vehicle efficiency standards, purchase subsidies, and phase-out dates for internal combustion engines (IEA 2023a)—alongside significant technological progress, especially in lithium-ion battery performance and cost reduction. While the core vehicle technology is mature (TRL 9), challenges remain, particularly around the widespread deployment of public charging infrastructure and the integration of millions of EVs onto the grid. Smart charging solutions and grid upgrades are needed to manage new loads and leverage EVs as grid resources. Moreover, the security and sustainability of battery supply chains, heavily dependent on a few critical minerals, are key concerns (see Section 6.3).

Charging technologies are evolving alongside vehicle advancements. Battery swapping (TRL 8–9) offers rapid exchange of depleted batteries, particularly in regions with high EV adoption. Conductive charging (TRL 8) remains the standard, while fast and ultra-fast charging (TRL 7–8) is being deployed in public stations to reduce charging time. Smart charging (TRL 7) optimizes grid interactions, preventing overload during peak hours. Inductive charging (TRL 5), while promising for wireless charging, is still in the early stages of deployment.

Several innovations are emerging to address specific challenges related to battery chemistry. Sodium-ion batteries (TRL 8) offer a lower-cost, more abundant alternative to lithium-ion, beginning to enter markets for stationary storage and some vehicles. Solid-state batteries (TRL 6) promise higher energy density and safety but remain in early development. Lithium-sulfur batteries (TRL 5–6) have potential for higher energy density, while lithium-air batteries (TRL 2) are still at the research stage with major technical hurdles to overcome.

Another alternative is *Fuel Cell Electric Vehicles (FCEVs)*, powered by hydrogen. While less mature than BEVs, fuel cell technologies (TRL 8–9) show promise for applications like long-haul trucking, where the weight and refuelling time of large batteries are prohibitive (IEA 2025c). However, the development of FCEVs is tied to the broader hydrogen economy, which faces challenges like the high cost of low-carbon hydrogen and the lack of widespread hydrogen refuelling infrastructure.

Aviation and Shipping. Aviation has limited near-term options for decarbonization. The leading pathway is sustainable aviation fuels (SAF)—liquid fuels that are chemically almost identical to kerosene and can be used directly in current aircrafts. The most advanced SAF route is HEFA (hydroprocessed esters and fatty acids), which converts waste oils and animal fats into jet fuel. HEFA fuels are already commercial (TRL 9–10), but their supply is constrained by limited feedstocks and high costs. Other SAF options are earlier in development. Power-to-liquid "e-fuels" combine green hydrogen with captured CO_2 to make synthetic fuels (TRL 4–6). Biomass gasification followed by Fischer–Tropsch synthesis, with carbon capture and storage, is another pathway (TRL 5). Airframe and propulsion efficiency improvements have also continued: ultra-high bypass ratio engines are at advanced development (TRL 6–7) while open-rotor concepts and blended-wing bodies are earlier (TRL 3–4).

Multiple alternative marine fuels are being tested; however, unlike aviation, no single drop-in solution exists. Biofuels, methanol, ammonia, and hydrogen span applications from pilot to early commercial, depending on engine and vessel class (roughly TRL 4–9). Production, on-board storage, engines, and global bunkering will require large, coordinated investment. In the interim, operational measures reduce fuel use now: dynamic route, trim, and draught optimization are mature (TRL 9–10); engine waste-heat recovery is advanced (TRL 8–9); windassisted propulsion—kites and rotor/sail systems—is at demonstration to early commercial stages (TRL 7–9); and increased automation/connected systems remain earlier (TRL 6).

3.1.6 Industry

The industrial sector, encompassing manufacturing, mining, and construction, accounts for roughly one-quarter of direct global CO_2 emissions and remains among the most difficult to decarbonize (see Table 3). Challenges stem from the diversity of industrial processes, the need for high-temperature heat, and emissions arising directly from chemical reactions ("process emissions"), particularly in cement, steel, and chemical production. According to the IEA, more than half of the emissions reductions required in heavy industry to achieve net zero depend on technologies that are not yet commercially available at scale (IEA 2021b).

Cross-Cutting Strategies and Technologies in Industry. Several decarbonization strategies apply across multiple sub-sectors. These include improvements in energy and material efficiency, electrification of processes, the substitution of fossil fuels with low-carbon fuels and feedstocks, and the deployment of carbon capture. A central cross-cutting challenge is the provision of industrial heat, which is typically classified by temperature level. Low- to medium-temperature heat, up to around 400°C, accounts for about half of industrial heat demand. A portfolio of increasingly mature technologies is available here: heat pumps, which are highly efficient for applications up to 200°C (TRL 7); electric boilers, which are commercially mature and can operate up to 300°C (TRL 9); and other electric and electromagnetic heating options (TRL 9). Bio-coal and biomethane are also mature substitutes for fossil fuels (TRL 8–9). In contrast, high-temperature heat above 400°C presents a greater challenge. Options include combustion of low-carbon fuels such as green or blue hydrogen (TRL 8–9) and biomass, while direct electrification technologies like electric arc or plasma heating remain at earlier stages of development (TRL 3–4). Thermal batteries, capable of storing heat in insulated materials, are an emerging solution for applications up to 1500°C.

Decarbonization Pathways for Key Industrial Sectors. Decarbonization will likely require major changes to the production processes in the most emissions-intensive sub-sectors. In cement and concrete, over half of total emissions are process emissions from limestone calcination. Mitigation options include deploying CCUS on cement kilns, which range from demonstration to pre-commercial stages (TRL 4–8), electrifying kilns (TRL 5), and shifting to alternative cementitious materials. Some alternatives, such as alkali-activated binders, are already commercially mature (TRL 9), whereas others, including materials derived from magnesium silicates or non-carbonate calcium sources, are in early research phases (TRL 3–4).

In iron and steel production, decarbonization can occur through retrofitting blast furnaces with CCUS (TRL 5–9) or by replacing coking coal with biomass-based reductants (TRL 9). A more transformative option involves Direct Reduced Iron (DRI) using low-carbon hydrogen as the reducing agent (TRL 4–7). Several breakthrough technologies, including ore electrolysis and flash ironmaking, are at the prototype stage (TRL 4–5) and could offer longer-term solutions.

The chemicals and plastics sector faces dual challenges, as fossil fuels are used both for energy and as feedstock. Potential strategies include applying CCUS to ammonia and methanol production (TRL 5–11), switching to bio-based feedstocks (TRL 5–8), and using low-carbon hydrogen to produce ammonia and methanol (TRL 7–8). Electrification of steam crackers, a central process in plastics production, is a key innovation at the large prototype stage (TRL 5). Advanced recycling methods such as pyrolysis and gasification, which convert waste plastics into feedstocks, are moving from demonstration to commercial scale (TRL 6–9).

In aluminum production, emissions are driven primarily by electricity use in smelting and by the consumption of carbon anodes. Decarbonization pathways include the use of renewable electricity and the development of inert anodes, which release oxygen instead of CO_2 and are currently at the pre-commercial demonstration stage (TRL 7). Additional innovations include electrifying high-temperature heat in alumina refining (TRL 3) and exploring hydrogen-based heating options (TRL 5).

The pulp and paper industry is distinctive in its extensive use of biomass residues such as black liquor for energy. Opportunities for further decarbonization include increasing efficiency, electrifying heat, and deploying CCUS. Waste-to-energy systems such as black liquor gasification are already mature (TRL 9), while high-temperature heat pumps (TRL 7) and electric boilers (TRL 9) can provide fossil-free heating. Innovations in dewatering and drying, including processes based on supercritical CO_2, are still at very early research stages (TRL 2) but could deliver large efficiency gains.

E-waste Recycling. The rapid growth of electronic waste represents both a challenge and an opportunity. Collection and sorting technologies are largely mature and commercially deployed (TRL 10–11). Pre-processing and disassembly, by contrast, span a wide range of readiness levels: robotic disassembly techniques are still in early stages (TRL 3), while conventional mechanical and thermal processes are well established (TRL 11). Processing technologies such as hydrometallurgy and pyro-smelting are commercially available (TRL 11), although more advanced variants, including direct recycling and novel hydrometallurgy, remain at intermediate stages (TRL 5–6). Digital innovations, including battery passports (TRL 6) and the use of digital twins (TRL 10), are being deployed to improve tracking and process efficiency.

Emissions Management in Fossil Fuel Operations. Finally, reducing methane emissions from oil and gas operations represents a critical near-term mitigation opportunity. Methane is a potent greenhouse gas, and emissions occur through both leaks and deliberate venting. A suite of mature technologies exists to address these emissions. Monitoring and repair programs are well established (TRL 9–11), satellite-based systems now provide wide-area detection capabilities (TRL 10), and low-emission equipment such as dry-seal compressors and electric motors is fully commercial (TRL 11). Methane that cannot be recovered can be destroyed using flares (TRL 11) or ventilation air methane oxidisers (TRL 10), which convert it into less potent CO_2.

3.1.7 Agriculture, Land Use, and Landfills

The agriculture, forestry, and other land use (AFOLU) sector, together with waste, is responsible for roughly 18% of global greenhouse gas emissions (see Table 3). These emissions are dominated by the potent non-CO_2 gases methane (CH_4) and nitrous oxide (N_2O). Decarbonization in this domain may require a multi-faceted approach, encompassing shifts in food production and consumption, improvements in on-farm practices and land management, and the effective control of emissions from waste.

Alternative Proteins: Shifting Production and Consumption. Livestock production is a central driver of agricultural emissions, and shifting protein sources away from conventional animal agriculture could be a powerful mitigation lever. A diverse set of alternative protein technologies is emerging at different levels of technological maturity (Smith et al. 2024). Plant-based meat alternatives are fully mature and commercially available (TRL 9). They deliver substantial climate benefits, requiring far less land and water and producing up to 90% lower GHG emissions than conventional beef. Insects, long consumed in many regions, are also a mature option (TRL 9), offering highly efficient feed conversion ratios and significantly lower resource requirements compared to livestock. However, cultural and political barriers may limit the adoption of these low-carbon food sources.

Other alternative proteins are less mature but rapidly advancing. Algae, a highly productive and versatile source of protein and oils, can be cultivated on non-arable land with non-potable water, thus avoiding competition with traditional agriculture; current systems are at demonstration to early commercial stages (TRL 8–9). Microbial fermentation encompasses both biomass fermentation and precision fermentation. The former, used to produce mycoproteins, is commercially mature (TRL 9), while the latter—precision fermentation that programs microorganisms to produce specific animal proteins such as casein or egg white—spans a wider maturity range from prototype to early adoption (TRL 5–9). Cultured meat, produced by cultivating animal cells in bioreactors, remains at the pre-commercial stage (TRL 5–8). Its long-term climate impact is uncertain and depends critically on the carbon intensity of the energy used in production. If powered by a fossil-heavy grid, its lifecycle emissions may exceed those of conventional beef, since CO_2 is longer-lived in the atmosphere than methane.

On-Farm Mitigation and Land Management. Beyond shifting consumption, significant reductions in agricultural emissions can be achieved through changes in production practices and land use. Precision agriculture constitutes a suite of mature technologies (TRL 8–9), including GPS-guided equipment, remote sensing, and satellite imagery, that enable variable-rate application of fertilizers, water, and pesticides. These practices reduce nitrous oxide emissions, cut fuel consumption, and maintain yields while lowering overall input use, though they require investment in data, skills, and equipment (Balafoutis et al. 2020).

Livestock emissions can also be mitigated through feed additives that inhibit enteric methane formation. The synthetic compound 3-NOP (marketed as Bovaer) is commercially available in several markets (TRL 8–9) and consistently reduces methane emissions by around 30% (Kebreab et al. 2023; Global Methane Hub 2024). Seaweed-based additives, such as Asparagopsis, show higher potential—up to 80% reductions in trials—but remain less mature (TRL 6–7) due to challenges in large-scale cultivation, durability, and safety. Another option is the application of biochar, a carbon-rich product generated through pyrolysis of biomass. Adding biochar to soils creates a stable carbon sink with storage timescales of decades to centuries, while also improving soil health and yields. Biochar is considered a mature technology (TRL 8–9), though its net climate benefits depend on the sustainability of feedstocks and the cleanliness of the pyrolysis process (Chiaramonti et al. 2024; Kammann and Cowie 2024).

Landfill Emissions Management. Methane from the anaerobic decomposition of organic waste in landfills is another significant source of emissions. Landfill gas capture is a fully commercial and widely deployed technology (TRL 9) (Bogner et al. 2007). Gas collection systems—comprising wells, covers, and piping—capture methane for flaring or for use as a renewable energy source, displacing fossil fuels. Modern engineered landfills can achieve capture efficiencies above 85%, with performance improving as sites are capped and operated over time (U.S. EPA, Office of Air and Radiation, Climate Change Division 2024).

3.1.8 Adaptation Technologies

Adaptation technologies reduce vulnerability to climate hazards by addressing risks from heat, drought, flooding, storms, and other physical impacts. Their scope is largely distinct from mitigation, but there are notable overlaps. For example, nature-based solutions such as mangrove restoration protect coastlines while also sequestering carbon; distributed renewable energy

Table 4: Taxonomy of Climate Adaptation Technologies

Area		Description
Agriculture and Forestry	Agriculture	Development of crops tolerant to abiotic stresses (e.g., heat, drought, salinity); improved land and water use efficiency; precision agriculture tools (e.g., soil moisture monitoring, variable rate irrigation); climate-informed planting and harvesting systems; and resilient greenhouse technologies for controlled environment agriculture.
	Ecological corridors	Design and implementation of habitat corridors and buffer zones to facilitate species migration, maintain landscape connectivity, and enhance ecosystem resilience to climate change.
	Livestock or Poultry	Improved shelter and ventilation for heat stress; heat-resilient breeds; modified feeding strategies to account for forage loss or nutritional shifts; and water storage and delivery systems adapted to drought and high temperatures.
	Fisheries	Heat- and salinity-tolerant species and strains; recirculating aquaculture systems (RAS) to reduce exposure to climate-sensitive water conditions; alternative protein feeds (e.g., insect- or algae-based); and monitoring systems for water temperature, oxygen levels, and disease risk.
	Food Processing	Off-grid cold storage and refrigeration powered by renewable energy; improved insulation and packaging to preserve food under high temperatures; and decentralised processing technologies to reduce spoilage and maintain food quality during climate-related disruptions.
Coastal and Rivers		Hard infrastructure (e.g., dams, dykes, breakwaters); nature-based solutions such as dune restoration, cliff stabilisation, artificial reefs, and coral protection; and systems for flood control, stormwater management, and flood or hurricane risk monitoring and mapping.
Water Conservation		Rainwater harvesting; desalination (including reverse osmosis powered by renewable energy); grey water reuse (e.g., from basins or showers); leak detection and reduction in distribution systems; water filtration and off-grid purification; wastewater treatment (including solar-powered systems); aquifer recharge; and saltwater intrusion barriers to protect freshwater resources.
Infrastructure		Underground or reinforced power lines to reduce storm vulnerability; high-performance insulation materials (e.g., vacuum glazing, natural or recycled materials); green and reflective roofs to mitigate urban heat; solar- or waste heat-powered HVAC systems; and urban green infrastructure to manage flood risk and reduce heat exposure.
Health	Pollution	Emission reduction technologies (e.g., catalytic converters), particulate matter capture systems, advanced air quality monitoring networks, low-cost sensors for pollutants like PM and ozone, adaptive emission controls, and real-time pollutant mapping platforms.
	Diseases	Integrated disease surveillance systems, climate-driven epidemiological forecasting models, mobile diagnostics, rapid response units for outbreaks, and biocontrol innovations targeting climate-sensitive vector-borne diseases (e.g., mosquitoes and ticks).
Monitoring	Weather	High-resolution local forecasts, extreme event early warning systems, seasonal climate outlooks, and downscaled climate projection tools.
	Water	Watershed and groundwater sensor networks, remote sensing for surface water extent, real-time flood/drought mapping and water quality monitoring.
	Species	Biodiversity inventories using eDNA and camera traps, GPS telemetry for migratory species, AI-driven species identification, and invasive species alert platforms.

Note: Largely based on the Y02A section of the Cooperative Patent Classification systems can provide resilient power during extreme weather events; and sustainable land management practices can improve soil moisture retention while enhancing carbon storage.

Table 4 summarizes key adaptation technology areas, ranging from water management and climate-resilient agriculture to health systems, infrastructure resilience, and ecosystem-based approaches. Priorities vary across regions, reflecting differences in exposure, adaptive capacity, and development objectives. While mitigation pathways are often global in orientation, adaptation is inherently place-specific, requiring locally tailored technological solutions supported by context-appropriate policy and investment frameworks. We describe adaptation technology development in more detail in Section 5.

3.2 Measuring Innovation and Where it Comes From

Before describing key patterns and trends in clean technology innovation, we present a brief introduction to innovation data and strategies for measuring new technology development. Each measurement strategy comes with its own trade-offs, and there are often benefits to combining multiple measurement strategies in order to understand the process of innovation and technological change.

Patents. The most common strategy for measuring new technology development is using new patent applications or awards.[7] This strategy has several appealing features, including the fact that it uses fully public and standardized data, allows for long time series, and provides a wealth of information about each technology, including characteristics of the inventor and of the patented technology itself. The categorization of each patent into a series of patent technology classes makes it relatively straightforward to identify all patents related to specific technology areas, including clean energy or climate adaptation (see Veefkind et al. 2012b, on the identification of patent classes related to climate mitigation technology). Patent citation information can be used to approximate the "importance" of each technology, and the full citation network can be used to understand knowledge flows and spillovers across inventors, firms, or technology areas (e.g., Donald 2023; Lensman 2025). Since patents are required to reference all relevant prior art, the patent citation network paints a clear picture of the earlier inventions on which new technologies are built. The way in which innovation builds on past knowledge is a key feature of many models of directed technological change (see Section 2.2).

With recent advances in using language as data, patent text is increasingly exploited both to develop new proxies for the importance of each technology (e.g., Kelly et al. 2021) and to

7. A useful open source tool for exploring US patent data is PatentsView since it has also harmonized a range of patent-level information, including inventor names, inventor locations, etc. For global coverage, PATSTAT is widely used and includes data from most major patent authorities. Another resource is Lens.org, which allows users to browse patent data directly through a web interface, filter by technology codes (e.g., Y02E 10/50 for solar PV), and generate summary statistics about applicants, inventors, and countries via its "Analysis" tab.

delve into further detail about what each technology accomplishes (see Dugoua et al. 2022; Ganguli et al. 2024). The fact that individual patented technologies are often protected in multiple countries (referred to as "patent families") also makes it possible to track international technology diffusion in a systematic way (e.g., Dechezleprêtre et al. 2011; Probst et al. 2021; Touboul et al. 2023, on the international diffusion of mitigation and adaptation technology).

Patent data also has several drawbacks. First, patented inventions may or may not lead to commercialized products or new technologies that ultimately are adopted and increase productivity. There is no guarantee that changes in the number of patents correspond to changes in what the researcher may ultimately care about. Second, patenting propensities can differ substantially across firms (e.g., because of differences in the use of trade secrets), sectors (e.g., because of differences in characteristics of technology), and countries (e.g., because of differences in legal support or access), making these comparisons challenging. Third, patent quality can be highly skewed, and strategic or defensive patents add to this challenge since they likely represent limited technological advance. Changes over time or across technology areas in these strategic incentives can lead to major differences in measured patenting rates. Finally, there are many technological advances that are never patented, including trade secrets and other information kept within the firm, new ideas in parts of the world where patent protection enforcement is limited, and a range of new knowledge that is not patentable, including a large share of service-sector innovation.

R&D expenditures. Another approach is using R&D investment statistics. For example, the International Energy Agency (IEA) maintains detailed statistics of public investment in energy technology research, development, and demonstration.[8] Compustat maintains systematic data on R&D investments made by public firms. An advantage to measuring R&D investment is that, unlike measuring patenting or other "outputs" of research investment, there is no time lag between when the firm or public entity decides to invest in innovation and when it is observed in the data. Moreover, R&D information captures investments in technologies that may never be patented or made public but that could nevertheless represent important advances in the area of interest. The downside to R&D data, however, is that innovation *inputs* are not the same thing as innovation *output*, and it is challenging to link changes in research budgets to changes in new technology development or productivity. This is especially true given the varied incentives, tax-related and otherwise, to increase reported R&D expenditure.

Scientific publications. Data on scientific publications are useful for measuring the "upstream" scientific advances that often underlie new technology development.[9] The advantage

8. The IEA data can be accessed and analyzed at this link.

9. A useful open source data source for publication information is OpenAlex, which compiles a range of earlier data efforts and has conducted a lot of useful data processing and labeling.

of this approach is that it is often the only way to observe frontier knowledge production and the arrival of completely new scientific ideas and approaches. Fundamental scientific advances are often published in scientific journals, but often not directly linked to a new patent or product. Moreover, as with patent data, citation and authorship information make it possible to directly measure knowledge spillovers and collaboration patterns. Also similar to patent data, article text can be used to probe the nature of new ideas further. The downsides are that publication information often fails to capture proprietary or applied research, and there is often a long time lag between scientific publication and the development of a new product or process. As with the patent data, differences in publication conventions across fields and countries can make these comparisons challenging.

Venture capital and start-up investment. Venture capital investment has been responsible for some of the most transformative technologies of the last several decades, both in developed (Lerner and Nanda 2020) and developing (Lerner et al. 2024) countries. New start-ups are often highly commercially oriented, and investment databases can make it possible to observe valuations of different business models, stages of development of different products, and investor networks and characteristics. However, these databases are often proprietary and costly and can have limited coverage outside of the largest entrepreneurial ecosystems.[10] Start-ups — and venture-backed businesses in particular — also represent only a subset of innovative firms and, as we described above, venture capital has a checkered past when it comes to investing in clean technology (see Mallaby 2022). That said, venture firms are increasingly investing in climate adaptation start-ups that help individuals, firms, or governments cope with climate hazards (see e.g., Tailwind Futures 2024). A study of recent trends suggests that entrepreneurial start-up firms may play a more prominent role in the future than they have in the past (Van Den Heuvel and Popp 2023). One prominent example is the case of small modular nuclear reactors, which are gaining steam in the US (Rauch 2023).

New product development or commercialization. A shortcoming to all the strategies above is that they can fail to perfectly capture what researchers may often care about, which is the development of a new technology or product that is brought to market and used directly in production or by consumers. Most patented technologies are never brought to market; scientific publications and research investments are often far upstream from commercializable technologies; and start-up business models often fail, and the ones that survive represent only a subset of the market. Therefore, some studies attempt to measure new product development or commercialization directly; however, this approach does not lend itself naturally to all contexts

10. Common venture investment databases include Pitchbook, Crunchbase, and Refinitiv. Especially outside the US, Pitchbook seems to have the most comprehensive coverage (see Lerner et al. 2024, who compare the coverage of these sources in a large sample of countries).

and can be challenging or impossible in many settings.

One example of this approach comes from agriculture, where studies have used the release of new seed varieties in order to understand how technology development and adoption respond to worsening climate trends (see Butler and Huybers 2013; Singh et al. 2020; Xiong et al. 2021; Moscona and Sastry 2023; Moscona 2025). Another example is studies of innovation in the biomedical sciences that investigate how different forces affect the development of new drugs or diagnostics (e.g., Williams 2013; Budish et al. 2015) The exact approach to measuring for-market products will likely vary across contexts, but the value of developing such an approach for understanding the process of technology development, energy efficiency, or production resilience could be high.

Downstream efficiency or productivity. When studying clean technology investments or climate adaptation innovation, the researcher may ultimately care about the impact on downstream energy costs and efficiency or on production resilience. In the context of energy technology development, it is possible to directly measure the prices of different energy sources. For example, in an influential paper, Way et al. (2022) uses cost reduction patterns across many technologies to forecast the economic impact of the energy transition (see also Figure 2). It may also be possible to directly measure technology improvements (e.g., solar cell efficiency, wind blade size, battery cost, etc.). When studying climate adaptation technology, it can be important to estimate how new technology affects actual production resilience or human health to understand its real-world impact. Some papers, for example, have shown that exposure to air conditioning—the most prominent climate adaptation technology—reduces the marginal effect of extreme heat on mortality (Barreca et al. 2016). Others have shown that exposure to climate-induced adaptation technology development in agriculture reduces the marginal effect of extreme heat on agricultural productivity (Moscona and Sastry 2023; Moscona 2025). New approaches to connect new innovations and technology development to their downstream consequences for producers and consumers could be very valuable.

3.3 The Dynamics and Geography of Clean Innovation

In this section, we use the data described above—especially data on patenting—to describe key trends in climate mitigation innovation over the course of the past several decades. First, we track the early take-off of green innovation starting in the 1990s. Second, we discuss the drop-off in innovation during the 2010s, known as the "Green Drop." Third, we describe the rise of China in clean technology development, perhaps the most dramatic change in the innovation landscape in recent years. Finally, we describe the process of clean technology diffusion.

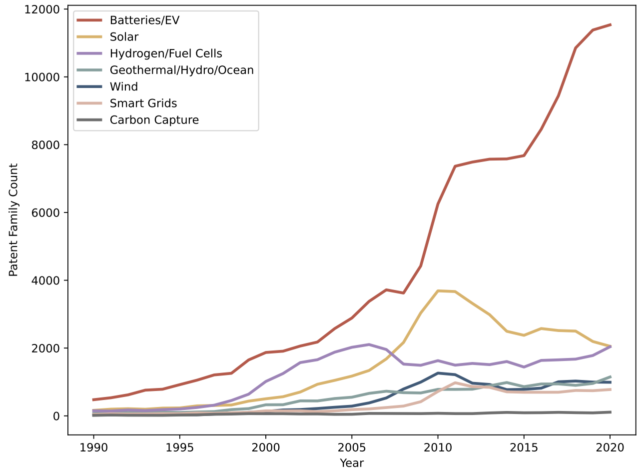
3.3.1 The Takeoff of Green Innovation: 1990-2010

The two decades from 1990 to 2010 marked a break in the trajectory of energy technology. Unlike the clean technology response to the 1970s oil-shock response (Popp 2002)—a wave of research that receded when fuel prices fell—this period saw a sustained, policy-led shift toward low-carbon innovation. New climate institutions, domestic markets for clean technologies, and targeted industrial policies moved emerging clean technologies from high-cost niches to the edge of large-scale deployment. The period incubated a new generation of technologies and established the conditions for later diffusion.

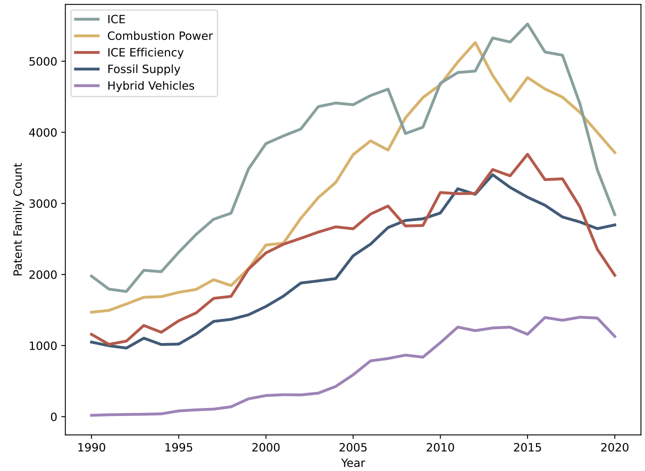
Patents provide clear evidence of the shift. Figure 5 shows that patenting on clean technologies rose continuously throughout the period, and especially sharply towards the end of the 2000s. Solar and batteries increased most strongly, while carbon capture grew from a small base. Fuel cells and hydrogen displayed a different cycle: rapid growth to a mid-2000s peak followed by decline, reflecting the well-documented boom and bust in this sector (Melton et al. 2016; Dugoua and Dumas 2024). Fossil-related technologies—combustion power, fossil supply, and internal combustion engines—also grew. Thus, the clean-technology surge of this era may be better seen as largely *additional* to, rather than *substitutive* of, fossil innovation. That said, by the end of the period, the number of new patents related to dirty technologies began to level off or even decline in some areas.

Public research, development, and demonstration (RD&D) funding followed a comparable pattern, a first indication that public support drove part of the increase in clean technology development. Section 2.1 describes a range of market failures, chief among them the externalities from production using dirty technology, that can justify public intervention. Figure 6 shows that funding rose steeply around 1980 in response to the oil crises, with nuclear capturing a large part of the increase, especially in Japan. Spending then declined through the 1990s before rising again from the early 2000s. The composition also shifted: nuclear RD&D fell sharply, while funding for energy efficiency and renewable technologies increased. In the United States, the sharp spike in 2009 reflects the stimulus package under the American Recovery and Reinvestment Act. Venture capital also entered the sector during this period. Cleantech investment, negligible in the 1990s, grew quickly after 2004 but collapsed with the 2008 financial crisis (Gaddy et al. 2017). We examine this collapse in greater detail in Section 3.3.2.

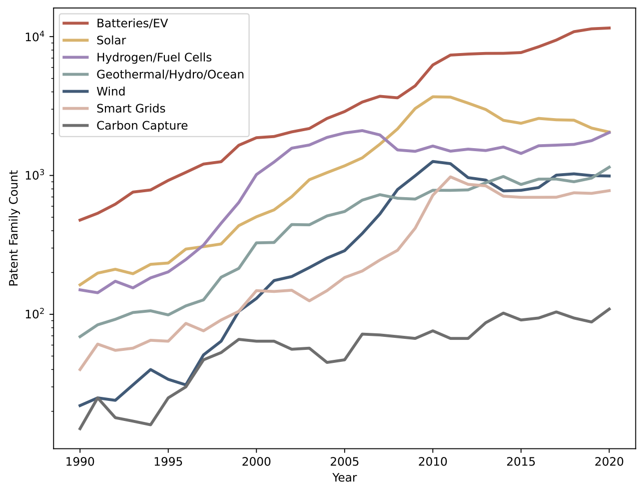
Policy changes from 1990–2010 also strengthened incentives for clean technology innovation. What changed in this period was the introduction of demand-pull measures that created more stable markets for clean technology and reduced investment risk. International agreements set the broader context. The UNFCCC in 1992 created a framework for cooperation, and the Kyoto Protocol in 1997 (in force 2005) introduced binding targets. Kyoto lacked strong enforcement mechanisms, and the United States did not ratify it, but the agreement nonetheless encouraged several countries to adopt more ambitious domestic measures. The most influen-



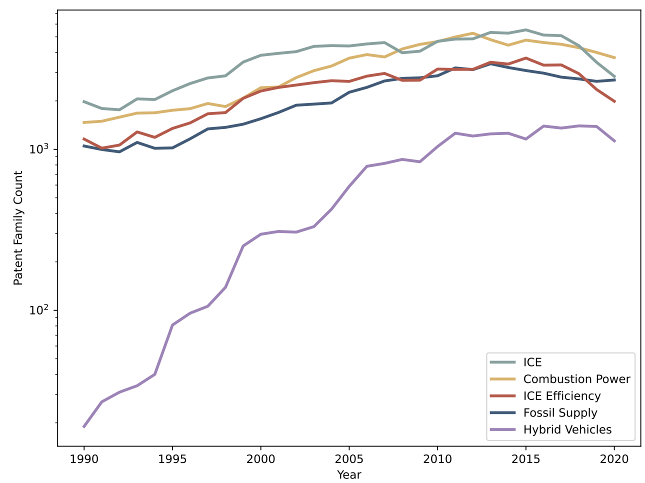
(a) Clean technologies (levels)



(b) Dirty technologies (levels)



(c) Clean technologies (log)

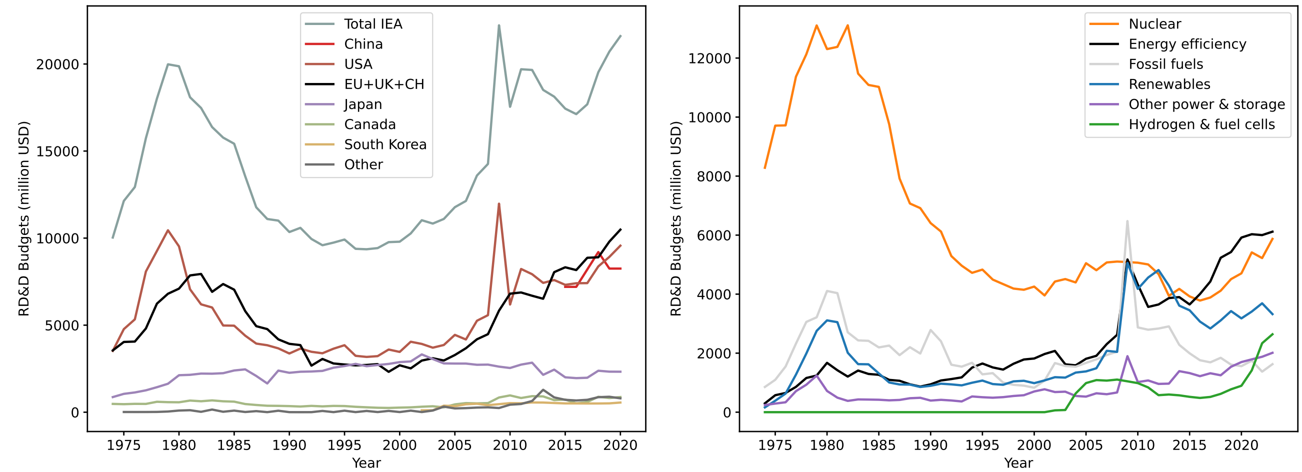


(d) Dirty technologies (log)

Figure 5: Patenting Trends in Energy Technologies

Note: Panels (a) and (b) plot annual patent family counts for clean and dirty energy technologies in levels, while panels (c) and (d) use a log scale. These figures show international patent families, defined as DocDB families in PATSTAT with applications filed in at least two different countries. The year refers to the filing date of the first application in the family. For details on patent data construction and processing steps, see Appendix A.3.
The log panels highlight proportional growth, making it possible to observe the expansion of small but important categories such as carbon capture and storage (CCS), which remain limited in absolute terms. Clean patenting rises strongly after the mid-2000s, led by solar and batteries, with wind and smart grids also increasing. There is a clear drop across many clean technologies around 2012, a phenomenon we return to in Section 3.3.2. In contrast, dirty technologies continued to grow through about 2015, after which some categories—especially transportation-related ones—show sharp declines.

tial policies were national interventions that guaranteed prices or sales volumes. Germany's Renewable Energy Sources Act of 2000 established long-term, technology-specific feed-in tariffs with priority grid access. By eliminating price and market risk, it unlocked investment and triggered large-scale deployment, particularly in photovoltaics. In the United States, state-level Renewable Portfolio Standards mandated rising shares of renewable electricity, creating pre-



(a) Key Countries

(b) Key Technologies

Figure 6: Public RD&D Spending on Clean Energy

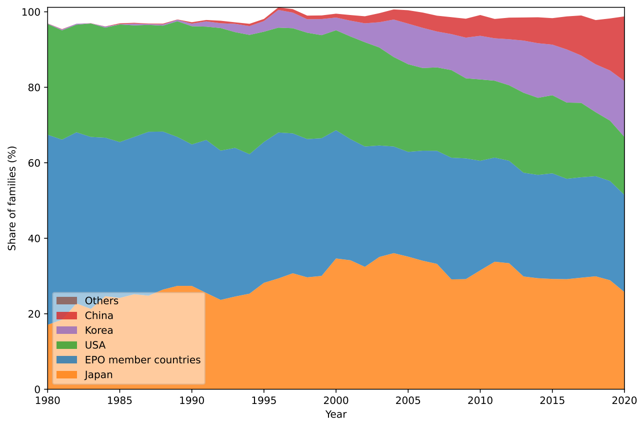
Note: Data are from the IEA Energy Technology RD&D Budget database (2025) and reported in constant USD. Values cover public budgets classified as "Research, development and demonstration." "Total IEA" is the aggregate across all reporting countries, and technology categories follow IEA definitions.
Trends across countries (Panel a) show that spending rises steeply after the 1970s oil shocks, declines through the 1990s, and climbs again from the mid-2000s, with a sharp US spike in 2009 under the American Recovery and Reinvestment Act. Since 2010, China has expanded rapidly and now ranks alongside the US and EU+UK+CH as a leading funder, while Japan and Korea remain significant but below past peaks.
By technology (panel b), nuclear still absorbs the largest share, but recent growth comes from renewables, energy efficiency, hydrogen and fuel cells, and power/storage technologies. Fossil RD&D has fallen relative to its 1980s peak; note that this category includes CCS funding. The overall pattern shows that while the early surge was nuclear-led, recent increases are broader, with clean energy technologies steadily gaining weight in public RD&D portfolios.

dictable demand that drove growth, especially in wind. The EU Emissions Trading System, launched in 2005, provided a broad carbon price signal. In its first phase, allowance prices were low and volatile, which limited the impact. In the second phase (2008–2012), however, higher and more stable prices emerged, and evidence shows that the ETS did stimulate innovation in regulated sectors (Calel and Dechezleprêtre 2016).

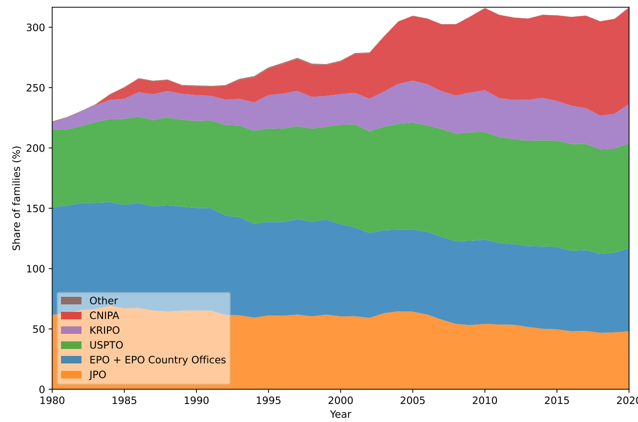
Two factors reinforced these trends. Niche markets provided early opportunities for learning and scale. In photovoltaics, Japanese firms built reliable demand by integrating solar cells into consumer electronics and later expanded under Japan's first residential subsidy program. This foundation made the technology ready for large-scale deployment once German feed-in tariffs created a mass market (Nemet 2019). Rising oil and gas prices in the mid-2000s also improved the competitiveness of alternatives and coincided with the cleantech venture boom.

Innovation during this period was highly concentrated (see also Dechezleprêtre et al. 2011). A small group of advanced economies (Japan, the United States, and Europe, with Germany particularly prominent) accounted for the majority of climate-mitigation inventions. Figure 7 displays clean technology patenting over time, grouped by both the country or region of the

International families

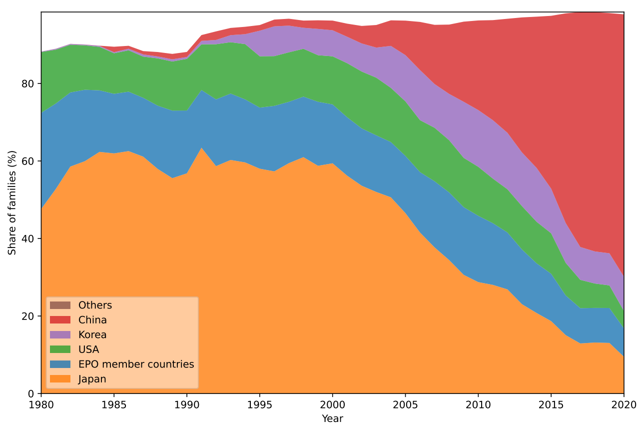


(a) Key Origin Countries

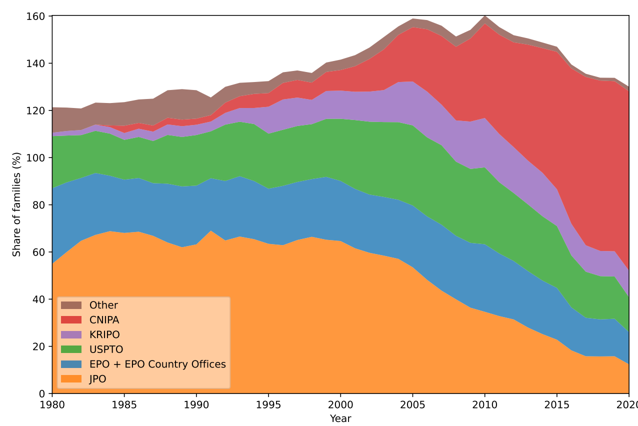


(b) Key Authorities

All families



(c) Key Origin Countries



(d) Key Authorities

Figure 7: Geography of Clean Energy Patenting Over Time

Note: Panels (a) and (b) show *international* patent families, while panels (c) and (d) show *all* families. International families are PATSTAT DocDB families with applications filed in at least two countries. "Origin country" is assigned hierarchically: inventor country; if missing, applicant country; if missing, the country of the authority of the family's first filing. "Authority" refers to the office of the family's first filing. Years correspond to the first filing year of the family. See Appendix A.3 for data processing details.
Among international families, the vast majority originated with inventors in the United States, Japan, and Europe. This pattern still holds, but since 2010, Chinese inventors have claimed a growing share. The shift is far more dramatic when all families are considered: because many Chinese patents are filed only domestically, China's share rises steeply from around 2005 and reaches nearly 70% by 2020.
Filing authorities show a parallel evolution. The USPTO, EPO, and JPO were the main destinations through the 2000s, but by 2020, CNIPA had become one of the largest offices even when counting only international families. Taken together, the figure illustrates both the globalization of clean innovation and the central role of China's domestic patent system, while also showing that the geography of origin and the geography of protection are fairly aligned.
JPO = Japan Patent Office; EPO = European Patent Office; USPTO = United States Patent and Trademark Office; CNIPA = China National Intellectual Property Administration.

inventor (Figures 7a and 7c) and by the patent office in which the patent was filed (Figures 7b and 7d). We display the results both for patents that were filed in multiple patent offices, often indicating that it is a particularly high-quality or broadly applicable technology (Figures 7a and 7b) and for the full sample of global patents filed in any authority (Figures 7c and 7d). Before 2010, the vast majority of patents originated from Japan, the United States, and Europe, and most patents were also filed in those authorities, indicating that mitigation technologies were designed for these high-income markets. The dramatic rise of China, both in terms of both where new technologies are developed and where they are commercialized, is apparent across all sub-figures. We return to this rise in Section 3.3.3.

Within each country, regional clusters reinforced progress. In Japan, national agencies such as NEDO (the New Energy and Industrial Technology Development Organization) and AIST (the National Institute of Advanced Industrial Science and Technology) coordinated large-scale programs with industry and academia, supporting advances in photovoltaics, efficiency, and hybrid vehicles (Yamaguchi 2001; Åhman 2006; Suzuki et al. 2014). In Germany, manufacturing centered in the "Solar Valley" of Bitterfeld–Wolfen/Thalheim, while Fraunhofer ISE in Freiburg provided applied research capacity (Brock et al. 2021; Llanos-Paredes 2023). Denmark built a strong wind industry around firms such as Vestas, supported by suppliers, universities, and national test facilities that enabled rapid iteration (Lema et al. 2014) (see also Section 4.2 for examples of successful case studies of climate industrial policies). In California, venture capital and entrepreneurship targeted energy hardware and materials, catalyzing rapid firm entry (Gaddy et al. 2017; Lerner and Nanda 2020).

International patenting patterns confirm this concentration. Figure 8 shows the origin–by-destination flows of foreign-oriented patent families, groups of patents that are related to the same focal technology but protected in multiple countries (e.g., a patented technology first protected in the US and subsequently protected in Japan and South Korea). These flows indicate an intent to commercialize or license technologies in other markets. Japanese inventors filed extensively at the USPTO, with additional flows to the EPO and CNIPA of roughly similar size. US inventors frequently patented in Europe, reflecting its importance as a destination market. Within Europe, Germany hosted the largest pool of clean inventors, followed by France, the United Kingdom, and Italy. Overall, these cross-filings highlight how a small group of economies acted both as the principal sources of clean innovation and as the main targets for international protection, further reinforcing the patterns highlighted by Figure 7.

3.3.2 A Pause in Clean Energy Innovation: The 2011–2014 Patenting Dip

Between 2011 and 2014, clean energy patenting fell sharply. This decline has been documented before–most clearly by Popp et al. (2022), who showed that filings for a wide range of clean technologies dropped across major patent offices during this period. With the benefit of several

(a) 2005 **(b)** 2020

Figure 8: Flows of Foreign-Oriented Clean Energy Patent Families

Note: The figure shows *foreign-oriented* patent families, defined (following WIPO) as families with inventors or applicants in one country that are filed in at least one other country. Origin is taken as the inventor country; if missing, the applicant country; if still missing, the authority country of the first filing. The destination is the office of the foreign filing(s). For readability, European national offices and the EPO are grouped together. Note that a family with German inventors filed in France is considered foreign-oriented in this context. For details on patent data construction and processing steps, see Appendix A.3.
In both 2005 and 2020, the United States, Japan, and the main European countries (Germany, France, the UK) account for the bulk of foreign-oriented families, while East Asia stands out as a second major hub with Japan, South Korea, and Taiwan all highly visible. The largest flows are Japan→USPTO, Japan→China, and US→Europe, and these remain prominent throughout the period. China was already significant in 2005, as an important destination, with CNIPA among the main authorities alongside USPTO and EPO. By 2020, its importance had grown sharply on the inventor side, making it one of the leading origins of foreign-oriented families. We also note that India appears by 2020 as one of the top ten origin countries. Together, these flows highlight the enduring dominance of the US, Japan, and Europe, the central role of East Asia, and the rapid rise of China as both a source and destination of foreign-oriented clean patenting.
JPO = Japan Patent Office; EPO = European Patent Office; USPTO = United States Patent and Trademark Office; CNIPA = China National Intellectual Property Administration.

years of additional data, we can now revisit this episode to see how persistent it was and what happened next.

Figure 9a shows trends in international clean patent families across the four major patent offices. The patterns are broadly similar: counts rose steadily until peaking around 2011–2012, then declined to a low point in 2014 before recovering. The size of this "green patenting drop" varies by office: about 11% at the JPO, 8.6% at the EPO, 2.8% at the CNIPA, and only 2% at the USPTO. This figure focuses only on international families. If instead we consider all clean families (i.e., including those filed only in a single patent office), the picture in China looks very different: domestic clean patenting continued to grow during this period, though at a slower pace than in the 2000s.

The green patenting drop is also not confined to one or two clean technologies. It shows up in solar, wind, batteries, and many other low-carbon technologies alike[11]. However, the recovery was relatively quick across all regions. By 2020, each major authority recorded more clean technology filings than before the dip. The rebound was weaker in Japan, while China recovered rapidly and now rivals the USPTO in the number of clean patent families. In contrast, fossil-related patenting shows no similar rebound. In all authorities, dirty technology filings held steady or continued declining.

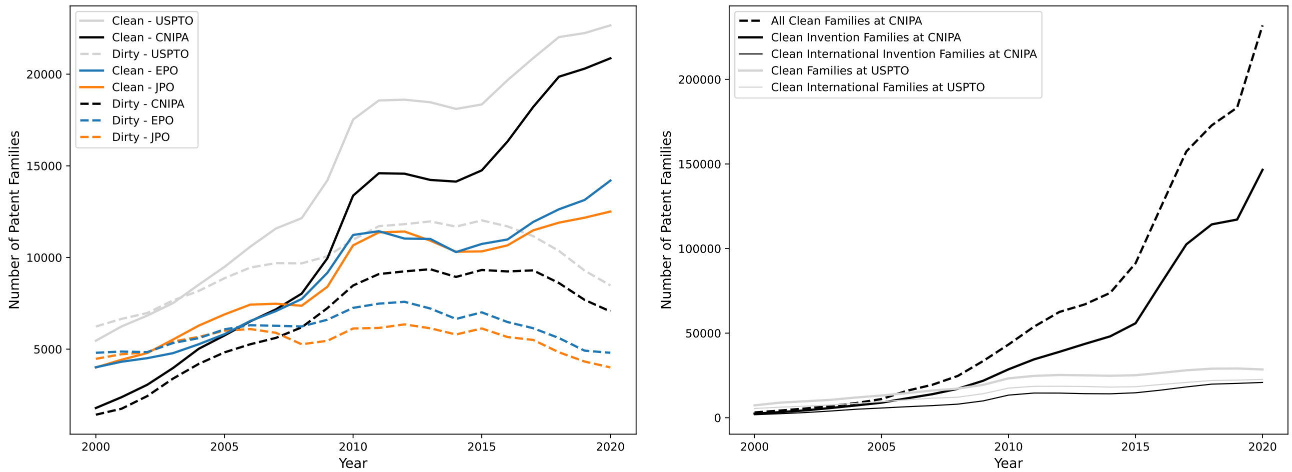
So what happened? The causes are likely multiple and overlapping. First, the timing coincides with a cleantech VC bust. Following a wave of investment into capital-intensive clean technologies, cleantech venture funding collapsed after 2011. More than half the capital invested from 2006–2011 was never recovered (Gaddy et al. 2017). By 2013, annual VC flows into the sector had fallen by over 80%. The bust was reinforced by the post-2008 credit crunch, which left young cleantech firms especially vulnerable; tight financial conditions disproportionately curtailed green patenting during this period (Aghion et al. 2024).

Second, policy support weakened or became more uncertain. Tax credits and feed-in tariffs were cut or allowed to expire in key markets such as Germany or Spain, undermining incentives to invest in new technology. International negotiations also faltered in Copenhagen in 2009 (Reuters 2009). There were also shifts in relative prices for reasons unrelated to these policy changes. The post-2008 shale boom in the United States pushed gas prices to record lows, making renewables relatively less competitive and re-directing technical effort toward fossil extraction (Acemoglu et al. 2023; Dugoua and Gerarden 2025).

China's rapid scale-up of solar manufacturing may have also put pressure on international firms and may have discouraged further innovation in places like the US and Europe. Massive industrial support for domestic solar manufacturing led to global oversupply and plunging PV prices, squeezing margins and innovation budgets in Europe and the US (Hart 2020; Banares-Sanchez et al. 2024). Technological maturity may have played a role, too. With the manufacturing scale-up initiated by China, both wind and solar may have converged on dominant designs with a greater focus on process improvements rather than a rise in the number of newly patented technologies.

These mechanisms likely reinforced each other. Policy pull weakened just as private investment collapsed, while Chinese scale-up accelerated as incumbents retrenched. The result was a temporary but broad-based contraction in clean energy patenting. The rebound that followed suggests this was not a structural break in innovation capacity but a pause driven by short-term financial, policy, and market shifts. More broadly, as described in Section 2.2, it shows how responsive innovation is to short-term changes in the alignment of investment, policy, and industrial dynamics.

11. These trends can be explored via our companion web app here.



(a) Clean vs Dirty Patenting Drop

(b) Chinese Clean Patent Families

Figure 9: The "Green Drop" and the Rise of Chinese Patenting

Note: Panel a shows trends in *international* patent families between 2000 and 2020 across clean and dirty technologies, while panel b zooms in on clean patenting at CNIPA and USPTO, distinguishing between all families and the international subset. "International" refers to PATSTAT DocDB families filed in at least two jurisdictions; year = first filing. The figure shows more lines for CNIPA because it distinguishes between invention families and all families. CNIPA records also cover weaker forms of patent protection that do not exist at the USPTO. The USPTO lines, by contrast, capture only standard invention families. For details on patent data construction and processing steps, see Appendix A.3.
The data highlight two patterns. First, a sharp "green drop" in international clean patenting occurred in the early 2010s, visible across major offices, whereas dirty patenting continued to rise until the mid-2010s before flattening or declining (see Section 3.3.2 for more details). Second, when looking at all clean families, CNIPA has become the dominant venue for clean filings. Clean families at CNIPA surge from the mid-2000s, far outpacing USPTO counts, though most remain domestic. Even among international families, however, CNIPA shows strong growth. This may not be immediately visible in the figure, since the graph also includes Chinese-only clean families whose very high counts push the scale upward. If those lines were excluded, the lower curves would appear more clearly, and the CNIPA international families in particular would stand out as having grown substantially from their low base in the early 2000s. This underscores both the rapid rise of China as the central hub of clean patenting (see Section 3.3.3 for more details).
JPO = Japan Patent Office; EPO = European Patent Office; USPTO = United States Patent and Trademark Office; CNIPA = China National Intellectual Property Administration.

3.3.3 The Rise of China in Clean Technology

After the 2011–2014 slowdown, clean innovation resumed growth in all major economies. What most clearly marks the post-2015 period, however, is the dramatic rise of China. Its surge in patenting and deployment rapidly altered the global balance, placing China alongside—and in some areas ahead of—the US, Europe, and Japan. This ascent was the product of a deliberate, multi-decade strategy that combined innovation, industrial policy, and large-scale deployment. It unfolded along three dimensions: the expansion of new technology development (which is apparent in the patent data), unprecedented increases in R&D investment, and a large-scale increase in manufacturing and adoption that reshaped global markets.

China's rise is most evident in clean patenting. Figure 9b reports families filed at CNIPA, distinguishing invention families, utility models and designs, and international invention families (filed in at least two jurisdictions). For comparison, filings at the USPTO are also shown. The growth at CNIPA is striking.

Patent quality remains contested, though. Critics point to the prevalence of utility models (i.e., weaker forms of protection for less novel technologies), the large share of patent applications that are never granted, and the presence of government subsidies that encourage increasing filing volume. Others argue that the surge reflects genuine inventive activity, noting its coincidence with rising R&D spending and rapid industrial upgrading. Figure 9b shows that, even excluding utility models, invention families expanded quickly, with China surpassing the US around 2008. Evidence from *granted* invention families (not plotted) confirms this pattern: China overtook the US around 2012 and by 2020 was filing about twice as many. Similar results are found for highly cited families.[12] Grant rates also differ markedly across offices. At the USPTO, about 89% of applications filed in 2017 were eventually granted. At CNIPA, the comparable share was only around 50%, though it had risen to nearly 58% by 2020.[13] The lower CNIPA grant rate has reinforced concerns that many Chinese filings are strategic or of limited quality.

In response to these criticisms, the Chinese government launched reforms beginning in 2021. The most prominent step was the cancellation of local subsidies that directly rewarded filing (Xinhua 2021), which likely encouraged volume over substance. These were replaced by performance-based incentives tied to commercialization and technological contribution. Stricter examination guidelines and higher fees for low-quality applications were also introduced to deter opportunistic behavior. Taken together, these measures were designed to shift the system away from patent counts and toward quality and economic relevance.

International patent families present a different picture from the trends using all patent data (see Figure 7). The total number of patents filed by Chinese inventors has long surpassed that of US inventors. After 2005, patenting in China accelerated sharply, and by 2020 nearly 70% of clean technology families were filed at CNIPA. This reflects China's emergence not just as a prolific filer but as the central locus of global clean technology patenting. When we focus on international families, on the other hand, Chinese inventors still trail US inventors by a small margin. While international families are often used as a proxy for higher-quality inventions, however, it is not obvious that domestic-only patents are inherently low quality. Could China's clean-tech market now be large enough that many inventors see little need to patent abroad? Might recent geopolitical frictions and strategic decoupling further reduce the business case for foreign filings? Treating single-country families as uniformly weak may be misleading.

12. These trends can be explored via our companion web app here

13. We calculate these rates by dividing the number of clean families filed at authority j in year t that PATSTAT records as *granted*. A caveat is that PATSTAT codes a family as granted if at least one application in the family is granted in any office, so our measure does not account for *where* the grant occurred.

More empirical work is needed to provide a nuanced assessment of the quality of domestic clean-technology patents in China.

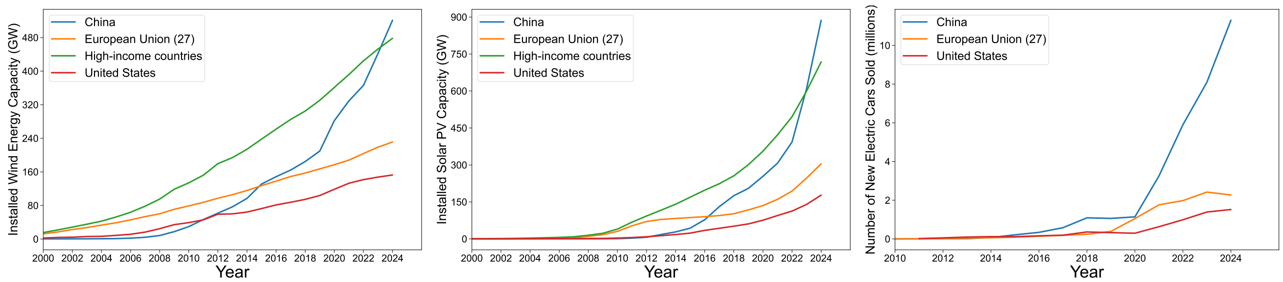
China's patenting outcomes come with equally extraordinary investment in research and development. Figure 6a shows that China is now among the top investors in public clean energy RD&D, roughly on par with the United States and Europe. By 2023, its gross domestic expenditure on R&D reached about $700 billion, or 26% of global R&D spending, up from only 4% in 2000 (Bonaglia et al. 2024). R&D intensity rose to 2.6% in 2023, nearly matching the OECD average of 2.7% (OECD 2025). Although most of the R&D is funded by the business sector[14], much of this is conducted by state-owned enterprises or firms backed by state-directed funds, underscoring the blurred boundary between public and private capital (China Power Team 2018).

Beyond innovation, the size of China's manufacturing sector has enabled the deployment of clean technologies at scale, reshaping the global market as the center of clean technology adoption. This could help explain why such a large share of Chinese inventors choose to only protect their technology in China—in many areas, it represents the largest market. Figure 10 tracks installed capacity in solar photovoltaics, wind, and electric vehicles (EVs). In short, China now has more solar and wind capacity and EVs than all high-income countries combined. For solar, deployment in high-income countries began to scale around 2010, led by Europe. From 2015 onward, however, China accelerated sharply and by 2023 had overtaken the combined total of high-income economies. Wind deployment in high-income countries expanded before 2010, but China ramped up quickly in the early 2010s and is now the largest market. The most dramatic case is EVs. After 2020, China experienced a dramatic increase, moving from fewer than 2 million EVs to more than 11 million in just four years—a scale-up that left the EU and United States far behind.[15]

China's dominance in clean technology innovation and adoption is reinforced by its control over supply chains. In solar photovoltaics, in 2022, it held more than 80% of global market share across all stages, from polysilicon to finished modules (IEA 2022b). In wind, by 2024 Chinese firms accounted for 70% of new global installations (GWEC 2025), with the top four of the largest turbine manufacturers based in China (BloombergNEF 2025). In electric vehicles and batteries, China produced 12 million EVs in 2024—over 70% of the world total (Aranca 2025)—and CATL alone supplied nearly 40% of global batteries (SNE Research 2024). In Section 6.3, we describe in greater details China's control of the supply chain for minerals, key ingredients in a large share of clean technologies. China has also consistently met or exceeded

14. 78% in 2025 compared to 69% in the US and 57% for the EU (Eurostat 2024)

15. On a per capita basis, China still lags behind in solar and wind but is far ahead in EVs. Solar capacity stands at 0.63 kW per person in China, compared with 0.68 in the EU and 0.51 in the US. Wind capacity is 0.37 kW per person in China, 0.51 in the EU, and 0.44 in the US. For EVs, China leads by a wide margin, with about 8 per 1,000 inhabitants, compared with 5.0 in the EU and 4.4 in the US. EVs now represent almost half of all new passenger vehicle sales in China (IEA 2025c).



(a) Wind **(b)** Solar **(c)** Electric Vehicles

Figure 10: Clean Technology Deployment Across Regions

Note: Panel 10b has been reproduced from IRENA (2024a), Panel 10a from IRENA (2024b) and data for Panel 10c are from the *IEA's Global EV Outlook 2025*, processed and visualized by *Our World in Data*. Panel 10b reports total installed solar electricity capacity (on- and off-grid), including both photovoltaic and concentrated solar power, measured in gigawatts. Panel 10a reports total installed wind electricity capacity (on- and off-grid), including both onshore and offshore, also in gigawatts. Panel 10c reports annual sales of electric cars, defined as fully battery-electric vehicles and plug-in hybrids. The figures illustrate the rapid global expansion of these technologies, with China emerging as the dominant market for solar, wind, and EV deployment.

its own deployment targets, reaching its 2030 goal for installed wind and solar capacity six years early, in 2024 (L. 2025).

These outcomes rest on an aggressive and evolving policy framework. In the early 2000s, China's accession to the WTO provided the external pressure and political justification to restructure state-owned enterprises, liberalize input markets, and attract foreign direct investment, building the industrial foundation for future growth (Zhu 2012). During the mid-2000s, binding energy-intensity and pollution-reduction targets, together with the 2005 Renewable Energy Law and wind procurement rules, created predictable home-market demand and protection for domestic suppliers in efficiency technologies, flue-gas desulfurization, and wind (Cao et al. 2009; Price et al. 2011). The solar sector remained export-oriented until the 2008 crisis. When European demand collapsed, China introduced a suite of domestic support programs, including subsidies and a national feed-in tariff (2011), which redirected excess capacity to the home market, stabilized the industry, and entrenched its cost advantage (Zhang and He 2013) (Nahm 2023).

Since the mid-2010s, this ambition has broadened to securing global primacy and supply chain control. Industrial strategies such as *Made in China 2025* and the 14th Five-Year Plan mobilized vast financial resources for R&D, promoted vertical integration from raw materials to final products, and fostered intense domestic competition followed by consolidation (Wübbeke et al. 2016; Institute for Security and Development Policy 2018; Aglietta et al. 2021). Firms such as BYD and CATL emerged from this process as globally competitive champions, battle-tested in domestic price wars and equipped with the scale and integration to dominate international markets (IEA 2024d).

Taken together, while there is room for debate about the full extent of China's rise, the evidence suggests that China has become a global leader in clean technology innovation, manufacturing, and deployment. This process involved a combination of state investment, industrial capacity, and large domestic markets. China's patenting and R&D investment intensity either match or have surpassed that of advanced economies, and manufacturing scale has lowered global costs and accelerated worldwide deployment. In many ways, China has become both the largest clean technology market and a central driver of global innovation, cost reduction, and supply chain control.

3.3.4 Geographic Gap between Innovation and Diffusion

Clean-tech innovation is concentrated in a few global hubs, with China's rapid rise alongside established leaders in the United States, Japan, and Europe (see Probst et al. 2021). This concentration highlights an important asymmetry: while invention is geographically concentrated in a small set of countries, the challenge of emissions reduction is global. For mitigation to succeed, technology diffusion must occur wherever energy demand is growing, including across the low and middle-income countries in Africa, Asia, and South America.

Innovation and diffusion are distinct stages of technological change. Patents and R&D expenditures show where ideas are created and where inventors anticipate markets. Diffusion is about adoption and use, which depend on local infrastructure, financing conditions, and institutions in addition to the technology itself. In environmental settings, policy influences both invention and adoption, but the drivers of diffusion are broader than price or performance alone. Existing evidence using global patent data suggests that the diffusion of climate-mitigating technology is limited in practice, especially diffusion to low and middle-income countries (Dechezleprêtre et al. 2011; Probst et al. 2021)

One force shaping technology diffusion (or the lack thereof) is the broad set of market frictions in the adopting locations that can constrain technology adoption. The earlier Technology-Readiness-Level-market-failure framework, presented in Table 2, highlights many of these barriers. That framework traced the path of technologies from the first appearance of an idea through to mass-market adoption, with different barriers binding at different points along the way. As technologies move toward widespread use, other frictions become decisive: high costs of capital, inadequate infrastructure, coordination failures, regulatory risk, and information asymmetries.

Another force shaping technology diffusion is the direction of technology itself and potential mismatch between frontier technology and technology requirements around the world (see also Section 2.2.4). Frontier R&D portfolios often reflect the conditions of high-income economies. In transport, innovation has concentrated on battery electric vehicles, which presuppose reliable grids and high purchasing power. Rapson and Muehlegger (2023) point out that, by contrast, in lower-income settings, near-term decarbonization may be more feasible through liquid biofuels that make use of the existing vehicle stock and distribution infrastructure. In the power sector, advanced economies have focused on deploying large-scale renewables supported by expanded transmission networks. By contrast, many low- and middle-income countries face severe grid constraints and instead depend on off-grid and mini-grid solar solutions. Even in the United States, delays in building new transmission lines have become a major obstacle, showing that infrastructure is often the binding constraint on diffusion (Davis et al. 2023).

Barriers to diffusion are compounded by the fact that costs vary widely across sectors and regions. A technology that is competitive in one setting may not be economical in another. Capital-intensive options are particularly sensitive: where financing is scarce or interest rates are high, projects that look viable on paper cannot be built. Learning by doing and learning by using require sustained deployment at scale, so countries with limited rollout may never capture these cost reductions. Expectations about future demand also matter, since firms direct investment toward markets where policy signals and procurement create credible opportunities. Taken together, these dynamics rule out the idea of a single global technology hierarchy. Instead, effective decarbonization strategies require portfolios tailored to local financial, institutional, and infrastructural conditions (Gillingham and Stock 2018).

We think that there are three main lessons from this discussion. First, invention and diffusion indicators both need to be taken into account. Patent counts or R&D expenditures measure where ideas are generated, but they cannot be taken as evidence of technology adoption. Tracking deployment, investment flows, and complementary infrastructure is equally important to understand where emissions will actually fall. Second, a major role of policy is to address the barriers that bind on the diffusion side of the TRL scale. This includes lowering financing costs, expanding infrastructure and standard-setting, reducing regulatory risk, and building local skills and institutions. Such measures are not substitutes for innovation policy but necessary complements. Without them, concentrated invention remains trapped in a few markets and fails to deliver global emissions reductions. Third, full deployment of mitigation technology may not be possible without shifting the direction of technological change toward applications that are relevant and economical, and low- and middle-income countries and other settings where existing frontier technology is not being adopted.

For comprehensive reviews of diffusion in clean technologies, see Popp et al. (2010) and Corey et al. (2014). Broader surveys of technology diffusion can be found in Stoneman and Battisti (2010) and Stokey (2021). Recent evidence on concentrated invention and uneven international transfer is provided by Probst et al. (2021). Since international trade is a major channel shaping technology diffusion, we also direct readers to the chapter on this topic in this volume (Farrokhi et al., Forthcoming).

4 Climate Policy and Technology

For much of the past three decades, climate policy was framed as a textbook market failure: greenhouse gas emissions are an externality best corrected by a technology-neutral carbon price. A tax or cap-and-trade system would internalize the social cost of carbon, markets would steer capital toward the lowest-cost abatement opportunities, deliver least-cost abatement, and provide continuous incentives for innovation. This logic was powerful and elegant, and it inspired an extensive literature focused on market-based policy instruments (see Figure 1), including many papers showing how they induce innovation and shape technological change.

In practice, political resistance has constrained carbon prices, and other failures—including knowledge spillovers, coordination problems, capital-market imperfections, and technology lock-in—further limit the effectiveness of pricing alone. These limits have been reinforced by geopolitical rivalry, supply-chain vulnerabilities exposed by recent crises, and the sentiment that existing policies were too slow to deliver decarbonization. For all these reasons, governments have moved beyond a carbon-price-only paradigm. Many countries are now adopting a more interventionist model of green industrial policy. This approach is not only about internalizing an externality; it is about deliberately building, scaling, and in some cases relocating clean energy innovation and manufacturing.

This section examines how policy shapes innovation through several complementary lenses. We begin with a brief discussion of the effect of demand-side instruments such as carbon prices and standards on innovation. We then turn to the rise of green industrial policy, outlining its rationales, risks, and the lessons from historical and contemporary case studies. Next, we describe the new wave of large-scale initiatives—the IRA, the EU Green Deal, China's 14th Five-Year Plan, India's PLI schemes, and others—and discuss why rigorous *ex post* evaluation will be essential. We then assess the balance between RD&D and deployment subsidies, highlighting the risks of premature lock-in. We also explore how political and policy design-driven uncertainty can undermine credibility and chill investment. Finally, we remind the reader that not all policy changes push in the direction of greater investment in clean technology; in fact, recent years have seen the rise of fossil fuel subsidies that could do the exact opposite. Together, these subsections trace the evolution from first-best prescriptions to the messy but unavoidable pragmatism of other policy mixes.

Climate policy is a broad domain, spanning decades of economic theory and an extensive empirical literature. Much of this work is already well surveyed elsewhere (Stavins 2003; Goulder and Parry 2008; Aldy et al. 2010; Sterner and Robinson 2018; Metcalf 2021; Timilsina 2022; Kotchen 2024, e.g.,). See also Moore and Rising (Forthcoming) in this volume for a review of central critiques of climate policy in economics. The aim here is therefore not to provide an encyclopedic review but to offer an entry point for readers new to the field, to highlight the main debates as they relate to technological innovation and diffusion, and to distill lessons from emblematic cases.

4.1 Demand-Side Policy Instruments

A central concern in environmental economics is how different instruments affect incentives for innovation. Market-based instruments (MBIs)—carbon taxes and cap-and-trade systems—are widely considered superior to command-and-control (CAC) standards in terms of dynamic efficiency. Because pollution always carries a price under MBIs, firms profit from any innovation that lowers abatement costs: adopting cleaner inputs reduces tax bills or frees permits for sale. This incentive is continuous and does not diminish once a compliance threshold is met. By contrast, under CAC standards, incentives typically end once the firm meets the mandated emissions rate or technology requirement. Indeed, stringent CACs can even discourage disclosure of innovation if regulators tighten the standard in response.

Greaker and Popp (2022) make this distinction concrete with a simple model using the familiar marginal abatement cost (MAC) and marginal environmental damage (MED) curves. In their setup, the laissez-faire equilibrium generates excessive emissions because firms ignore the external damages. Introducing a pollution tax equal to marginal damages aligns private and social costs: firms abate until $MAC = t$, and any innovation that shifts the MAC curve downward immediately raises profits by lowering tax payments or freeing allowances. Under a fixed performance standard, by contrast, firms are required to reduce emissions to a given level e^*. Once this target is met, the private gain from further cost-reducing innovation is flat: lowering the MAC below the compliance point does not generate additional benefit. This simple framework illustrates why MBIs, in theory, provide stronger dynamic efficiency than uniform CAC rules.

This dynamic efficiency argument is closely related to the theory of induced innovation. As first noted by Hicks (1932), changes in relative factor prices direct inventive activity: when a resource becomes more expensive, innovation is stimulated to economize on its use. Applied to the environment, this implies that when policies raise the effective price of emissions, firms have an incentive to search for abatement technologies. Milliman and Prince (1989) formalized this intuition by showing how environmental regulation shifts firms onto a higher marginal abatement cost curve, creating an incentive to innovate in order to shift the curve back down. In this way, environmental policy affects not only the rate but also the direction of technical change. The literature on directed technical change develops this insight further, stressing that innovation responds to relative prices, market size, and regulatory signals (Acemoglu 1998).

A large empirical literature provides strong support for the induced innovation hypothesis. Across a wide range of settings, higher energy prices and more stringent regulations are consistently associated with increases in patenting and R&D directed toward renewables, energy efficiency, and other clean technologies. Comprehensive reviews of this evidence are

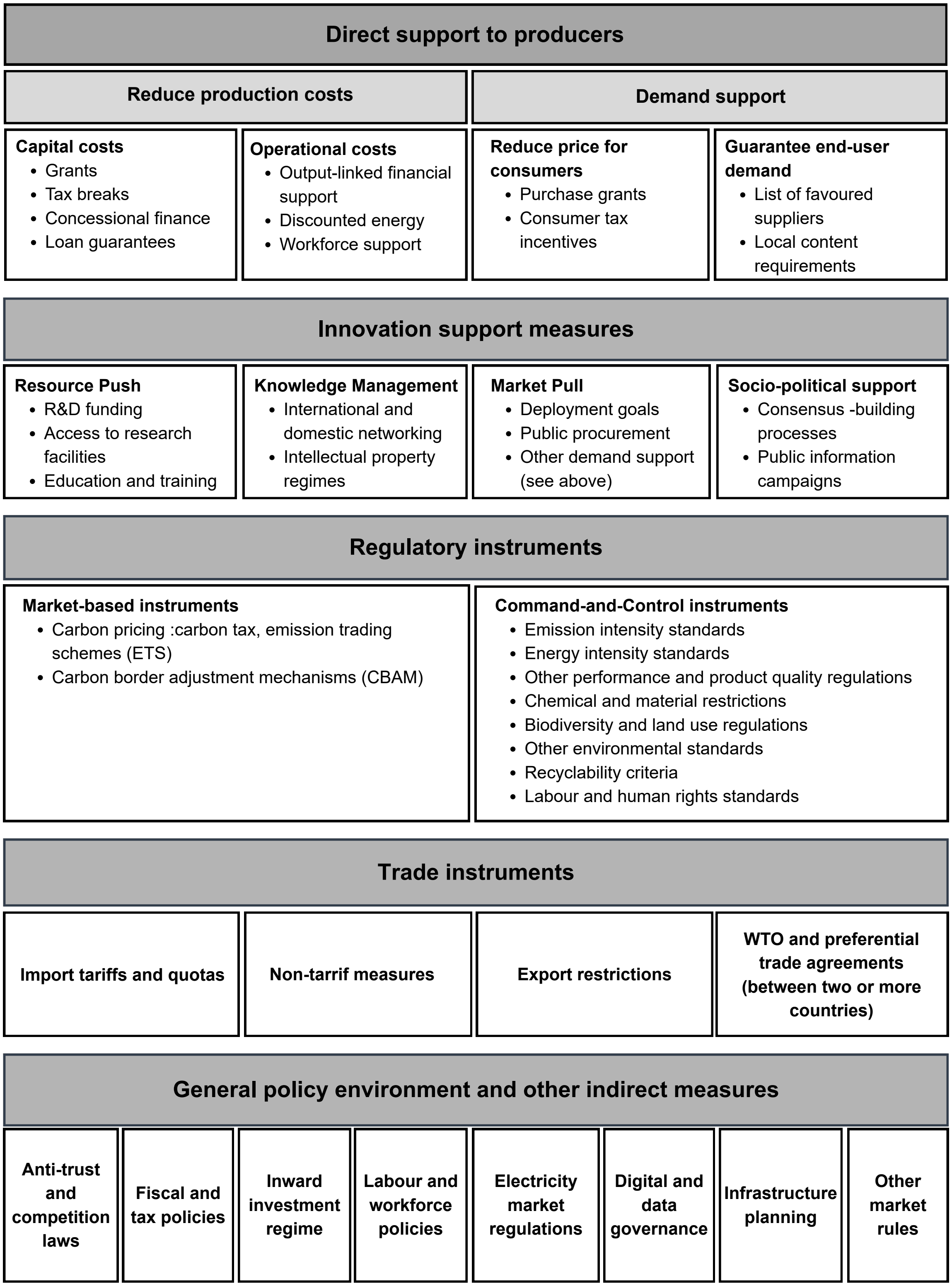


Figure 11: Industrial Strategy Policy Instruments

Note: Reproduced and adapted from the IEA ETP 2024 report (IEA 2024a, Fig. 1.37) provided by Popp (2019) and Grubb et al. (2021a). This literature reinforces the case for instruments that make the cost of emissions visible, credible, and predictable over time.

The *Porter Hypothesis* builds on the same logic. In its "weak" form, it holds that environmental regulation induces innovation that would not otherwise occur. In its "strong" form, it claims that this innovation can more than offset compliance costs by raising productivity and competitiveness (Porter and Van Der Linde 1995). The weak version is well established and overlaps with the induced innovation literature, while evidence for the strong version is mixed and context dependent, though case studies show instances where regulation-driven innovation produced net gains (Ambec et al. 2013). In both cases, the mechanism is the same as in the dynamic efficiency argument: by shifting relative costs and expected market size, policy directs innovative effort toward cleaner technologies.

Textbook treatments draw a sharp contrast between CAC and MBIs, but in practice, the boundary is often blurred. Many policies combine elements of both, with hybrid designs emerging as pragmatic responses to uncertainty about abatement costs and damages. Figure 1a highlights this fact in the data: roughly 80% contain some market-based intervention while 90% contain some non-market regulation, indicating that most contain some combination of the two. A well-known example is the tradable performance standard, which sets an emissions-intensity benchmark (for example, tons of CO_2 per MWh) and allows firms that exceed the benchmark to sell credits. Such systems retain some marginal incentive to improve while avoiding the political costs of an explicit carbon tax (Fischer and Newell 2008).

Despite the theoretical appeal of MBIs, they have not dominated in practice. In the US, policymakers have repeatedly turned to such standards and hybrid instruments rather than comprehensive carbon pricing. Some of the most prominent environmental policies follow this pattern, including the Corporate Average Fuel Economy (CAFE) standards, state-level Renewable Portfolio Standards (RPS), and the federal Clean Power Plan.

The CAFE program, in place since the 1970s, has raised average fuel efficiency but with mixed economic efficiency and welfare outcomes. Manufacturers complied by improving engines but also by shifting the fleet mix and exploiting attribute-based loopholes (Klier and Linn 2011). The standards spurred adoption of fuel-saving technologies, yet often at higher cost than equivalent gasoline price increases (Klier and Linn 2016). Because attribute-based formulas link stringency to vehicle footprint, they created incentives to enlarge vehicles; the resulting rise in weight not only undermined efficiency gains but also imposed additional external costs (Anderson and Auffhammer 2014). Welfare analyses show that alternatives such as feebates would have achieved the same fuel-economy gains more efficiently, while attribute-based designs created distortions and "attribute gaming" that reduced cost-effectiveness (Durrmeyer and Samano 2018; Ito and Sallee 2018; Feldman and Levinson 2023).

A similar reliance on standards appears in the power sector. State-level renewable portfolio standards (RPS) require utilities to source a rising share of electricity from renewables. Compliance is tracked through renewable energy credits (RECs): utilities that generate or purchase renewable power receive credits, which can be traded to meet portfolio targets. RPS helped create markets for wind and solar, but their impacts have been modest and design-dependent. Using an instrumental-variables approach, Feldman and Levinson (2023) show that higher REC demand reduced coal use and CO_2 emissions, but with small magnitudes, mixed effects on natural gas, and little evidence that RPS drove most renewable growth. Broader modeling and review studies find that RPS can cut emissions but at relatively high cost compared with technology-neutral carbon pricing (Lyon 2016; Young and Bistline 2018; Borenstein and Kellogg 2023). Overall, RPS illustrate that while politically durable, they are second-best instruments relative to broad carbon pricing.

In Europe, binding renewable targets and vehicle CO_2 standards have been central to the policy mix. Firm-level evidence shows that stringent standards redirected innovation toward clean technologies such as electric vehicles and hydrogen drivetrains, and away from incremental improvements to combustion engines (Rozendaal and Vollebergh 2025). This is consistent with the basic theory which shows that market-based instruments provide stronger incentives than standards, but not that standards have no effect. When standards are demanding and require technologies not yet in use, they also induce innovation by shifting relative costs and expected market size. Despite their higher static costs, standards can therefore play an important role in steering innovation toward next-generation technologies.

Some recent theoretical work also goes further and suggests that market-based instruments may not always be sufficient to trigger the deep technological shifts required for decarbonization. When incumbent "dirty" technologies benefit from strong economies of scale, entrenched infrastructure, or network effects, a carbon price on its own may leave clean alternatives unprofitable. In such cases, standards that directly mandate a shift—such as bans on new internal-combustion vehicles or clean electricity requirements—can help overcome lock-in by guaranteeing demand for emerging technologies and altering firms' expectations about the future trajectory of markets (Yeh et al. 2021; Ambec and De Donder 2022).

Fischer (2019) makes this point in the context of industrial decarbonization, arguing that sectors such as steel, cement, and chemicals face particularly high abatement costs and limited near-term technological options. For these "hard to abate" activities, a carbon price may not provide a strong enough or credible signal to induce investment in novel processes. Market-based performance standards, by setting benchmarks for emissions intensity and rewarding improvements beyond them, can offer a more practical way to stimulate innovation and capital investment in low-carbon industrial technologies. Well-designed standards thus provide greater certainty for firms undertaking costly, long-lived investments, complementing both carbon pricing and R&D support.

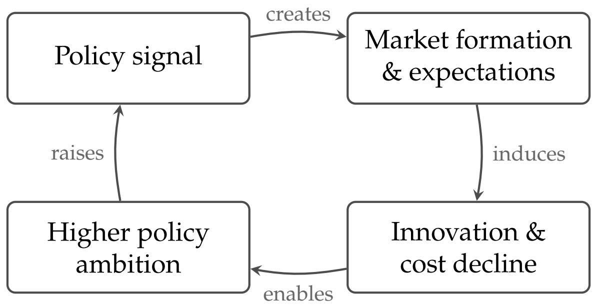


Figure 12: Policy–Innovation Feedback Loop

Note: The diagram illustrates the bidirectional feedback loop between policy and innovation. Policy signals create markets and expectations, which in turn induce innovation and cost reductions. These technological advances then enable higher levels of policy ambition, completing a virtuous cycle. Historical examples include the Montreal Protocol and the gradual tightening of the Dutch carbon tax, both of which show how innovation lowers costs and makes stronger regulation feasible.

Importantly, the relationship between policy and innovation is bidirectional. While policy induces innovation, subsequent technological advances reduce costs and thereby broaden the scope for more ambitious regulation. This feedback loop has been central to the progressive ratcheting of climate ambition. The Montreal Protocol illustrates the mechanism clearly: as substitutes for ozone-depleting substances became available, policymakers were able to tighten standards further (Dugoua 2023). A similar pattern is visible in the Netherlands, where an initially modest carbon tax was gradually raised as firms adjusted and clean technologies became cheaper (Anderson et al. 2021). This dynamic can operate as a virtuous cycle (see Figure 12): policy signals create markets and expectations, markets in turn stimulate innovation and cost declines, and these declines make stronger policy both politically acceptable and economically efficient.

The discussion above shows that while market-based instruments provide strong dynamic incentives, and standards can also redirect innovation when sufficiently stringent, both approaches face limits. Political resistance constrains the scope of carbon pricing, and standards often achieve change only incrementally or at high cost. Moreover, neither tool alone addresses the wider set of barriers to clean technology: financing gaps, coordination failures, supply-chain dependencies, or the strategic aims of governments in a world of geopolitical rivalry. These limits have pushed climate policy beyond a narrow focus on pricing and regulation toward a broader agenda of industrial strategy.

4.2 The Rise of Industrial Policies

Industrial policy, broadly defined, refers to deliberate state interventions to reshape the structure of an economy by channeling resources into targeted sectors or technologies. Green industrial policy applies this logic with an explicit climate objective. Figure 11 illustrates how the green industrial policy toolkit now extends far beyond the demand-side instruments reviewed in the previous subsection. It spans subsidies, tax credits, concessional finance, loan guarantees, public procurement, local-content rules, standards, and large-scale investments in infrastructure and R&D. The aim is to accelerate clean-technology deployment, foster domestic manufacturing capacity, and create the virtuous cycle in which policy support drives down costs, reinforces political coalitions, and enables more ambitious climate action.

The return of industrial policy has reignited foundational debates in economics. Proponents argue that it is justified because the net-zero transition is hampered not just by the unpriced carbon externality but by multiple, interacting failures: knowledge spillovers, financing frictions, coordination problems, and infant-industry dynamics (see Section 2.1 for an overview of market failures in clean technologies). According to this argument, if left alone markets would underprovide investment, leaving critical technologies stranded in "Valleys of Death."

Critics emphasize that industrial policy is highly vulnerable to government failure. Information deficits mean that states often lack the capacity to identify which firms or technologies will ultimately succeed, leading to costly bets on the wrong pathways. Rent-seeking and political capture can redirect public resources toward well-connected incumbents rather than innovative challengers, entrenching inefficiency. Large subsidy programs risk fiscal waste if they lack clear sunset clauses or cost controls, while local-content rules and "buy national" provisions can trigger subsidy races and trade disputes. Poorly designed schemes can also create asset bubbles and overcapacity, with painful collapses once support is withdrawn.

This widening of policy scope has already been studied extensively. Reviews in the climate and energy fields examine rationales, instruments, and outcomes of industrial policies (Rodrik 2014; Wu and Salzman 2014; Harrison et al. 2017; UN Environment and German Development Institute 2017; Newell et al. 2019; Tagliapietra and Veugelers 2021; Criscuolo et al. 2023; Hahn et al. 2024; OECD 2024b; Gerarden et al. 2025). Other surveys in trade and development economics provide a broader perspective (Rodrik 2008; Harrison and Rodríguez-Clare 2010; Juhász et al. 2024). Our purpose is not to repeat those debates but to build on them, using emblematic cases to identify design lessons for green industrial policy.

A key challenge is that the criteria for judging success in industrial policy are multiple and contested, particularly when applied to climate goals. Traditional assessments focused on outcomes such as productivity growth, export performance, or the creation of globally competitive firms. Green industrial policy, by contrast, pursues multiple and sometimes conflicting goals: lowering technology costs for global mitigation, accelerating domestic deployment to meet national climate targets, fostering innovative ecosystems, and securing local jobs or supply chains. China's solar expansion, for example, sharply reduced global module costs while also creating international trade frictions. Evaluating effectiveness, therefore, requires attention to which goals are being prioritized and at what scale.

Historical precedents outside the climate field provide the benchmarks against which many current debates about industrial policy are framed. Airbus, for instance, is often remembered as the archetypal European project: a coordinated multinational effort that created a global champion in civil aviation, showing how sustained public backing and cross-border cooperation could succeed in a high-tech, capital-intensive industry (Hodge et al. 2024). In East Asia, targeted state support for semiconductors and shipbuilding—through directed credit, technology acquisition, and export discipline—demonstrated how industrial planning could propel latecomer economies into world leadership (Wade 1990; Chu 2016). In the United States, defense procurement, especially through the Defense Advanced Research Projects Agency (DARPA), showed how mission-oriented public funding and demand-pull contracts nurtured breakthroughs in computing and information technology (Fuchs 2010; Mazzucato 2013; Azoulay et al. 2019). These emblematic cases have left a deep imprint on how policymakers and scholars conceive of industrial strategy today.

Failures and mixed outcomes also loom large. The Concorde program produced a technological marvel but revealed the dangers of pouring vast public resources into projects lacking a viable commercial market (EC 2018). Japan's Fifth Generation Computer project, launched in the 1980s with the aim of leapfrogging US computing, illustrates how state-led bets can falter when technological trajectories shift unexpectedly. Several US semiconductor consortia of the same period likewise struggled to translate government coordination into competitiveness (Center for a New American Security 2022). France's Minitel offers a more ambiguous lesson: it enabled an early nationwide digital network, familiarizing households with online services well before the Internet era, but also created lock-in that slowed the shift to open global standards (Benghozi and Licoppe 2003).

These precedents continue to loom in the background of contemporary debates on industrial policy. They provide the backdrop against which current strategies for the clean energy transition can be interpreted. In Table 5 (which also includes all relevant references), we present a set of emblematic cases and assign them broad labels—"success," "failure," or "mixed." These labels should be read with caution. They are intended as shorthand to reflect how the economics and policy community has generally come to view these cases, based on our reading of the literature, not as definitive verdicts. A case judged a "success" may still contain significant shortcomings, just as a "failure" may have produced lasting benefits. The classifications represent a high-level, on-net assessment rather than a full evaluation. We encourage more detailed reviews of these experiences, since learning from history is indispensable for designing effective policy today.

Denmark's wind sector is a frequently cited success story. From the 1980s onward, a combination of feed-in tariffs, community ownership schemes, and public investment in grid capacity created a stable environment for deployment. These policies supported the growth of domestic

Table 5: Green Industrial Policy Case Studies

Case	Type	Core instruments	Outcome & design lessons	Sources
Denmark—Wind	Success	Public R&D; early feed-in tariffs with degression; grid planning; community ownership	Created global OEMs (e.g., Vestas) and now sources about half of domestic electricity from wind. Lesson: sustained, adaptive policy—combining R&D, market creation, and social licence—supports long-term success while avoiding over-subsidy.	Elliott et al. (2023) and UNFCCC (2023)
China—Solar	Success	Export-led manufacturing, then subsidies for R&D, production and adoption; state-backed credit; JV/FDI and tech transfer; cluster-based scale-up.	Pushed module costs below \$0.25/W and captured $>$ 80% of global manufacturing. Lesson: state-backed scale-up drives steep cost declines, but risks overcapacity and international trade frictions.	IEA (2022b), Gerarden (2023), Banares-Sanchez et al. (2024), and OWID et al. (2025)
China—EVs & Batteries	Success	Purchase subsidies and tax breaks (with local top-ups); other city-level incentives (license plates); public procurement pilots; mandate requiring automakers to meet EV sales quotas; charging and swapping infrastructure; R&D support; subsidy eligibility tied to approved domestic battery suppliers.	Built the world's largest EV market and fostered globally competitive firms (BYD, CATL). Lesson: a coordinated toolkit addressing supply, demand, and infrastructure can rapidly create markets; subsidies should taper as sectors mature to sustain competition. Also risks of overcapacity and trade frictions.	UN Environment and German Development Institute (2017), IEA (2023a), Barwick et al. (2024), and Barwick et al. (2025)
United States—DOE Loan Program (incl. Solyndra & Tesla)	Portfolio success (with failures)	ARRA-era loan guarantees for first-of-a-kind (FOAK) projects; portfolio, VC-like approach	Enabled Tesla and the first utility-scale PVs. Despite Solyndra's collapse (after polysilicon price collapse), portfolio losses were only ~2.3%, with interest income exceeding losses. Lesson: frontier technology finance requires portfolio diversification, tolerance for some failures, and adaptive review; success is measured at the portfolio level, not project by project.	Groom (2014), Rodrik (2014), and Sivaram (2020)
Spain—Solar FIT boom–bust	Failure	Extremely generous feed-in tariffs without caps or automatic degression; retroactive tariff cuts	Triggered a 2008 installation surge but subsequent paralysis (2012–2016) and waves of investor-state lawsuits. Lesson: cost-control mechanisms (auctions, tariff degression) are essential, and credibility must be preserved—retroactive changes destroy investor confidence and raise future capital costs.	D. Couture (2011), Río and Mir-Artigues (2014), and Keeley (2022)
Norway—EV uptake	Success	Large tax exemptions (VAT, purchase tax); non-price perks (bus lanes, free parking/tolls); charging infrastructure support	Achieved the world's highest EV market share, with EVs exceeding 80% of new car sales. Lesson: a comprehensive incentive package—combining major financial benefits with practical perks—can rapidly shift consumer markets toward new technologies.	IEA (2023a) and Nolan (2025)
UK—Offshore wind CfDs	Success	Competitive auctions; long-term contracts-for-difference (CfDs)	Associated with steep declines in offshore wind LCOE during the 2010s. Lesson: stable long-term market signals combined with competitive allocation are highly effective in driving technology cost reductions.	Energy Transitions Commission (2024)
Germany—Energiewende	Mixed	Generous feed-in tariffs (later auctions); binding renewable targets; nuclear phase-out	Delivered rapid expansion of wind and solar capacity, but costs were shifted to consumers, producing some of Europe's highest retail electricity prices. Lesson: manage ambition and pace with attention to cost distribution to preserve public and political support.	UN Environment and German Development Institute (2017), IEA (2020c), and OECD (2024b)
US—Biofuels	Failure	Renewable Fuel Standard (RFS); blending mandates; tradable credits; tax incentives; procurement; concessional finance; import protection	Scaled first-generation corn ethanol but with limited net climate gains. Unintended effects included food-price increases, adverse land-use change, volatile permit markets, and stalled progress on advanced biofuels. Lesson: avoid locking in specific pathways before lifecycle impacts are known; prefer technology-neutral, performance-based standards with realistic targets.	Wright (2014) and Stock (2015, 2018)

Note: The table presents illustrative case studies of green industrial policy, along with a brief description and relevant references. For a more extended description of each case and the lessons they highlight, see Section 4.2.

manufacturers such as Vestas, while early planning for transmission reduced curtailment and enabled large-scale integration of wind power.

China's solar strategy illustrates the impact of coordinated state direction (see Section 3.3.3). Generous credit from state-owned banks, subsidies for both producers and consumers, and a deliberate effort to build an end-to-end supply chain drove massive domestic demand and rapid cost declines. Globally, this led to steep reductions in the price of photovoltaics. At the same time, however, the strategy generated overcapacity, created intense international trade frictions, and exposed the risks of relying on a single country for critical inputs.

China's electric vehicle and battery sectors also show the effects of a coordinated industrial strategy. National and local governments combined consumer subsidies, purchase-tax exemptions, and public procurement with non-price measures such as license-plate advantages in major cities. At the same time, large public investment expanded charging networks, while industrial plans backed battery production through credit, land, and permitting. A dual-credit system later linked support to vehicle efficiency and range. Subsidies were gradually reduced as volumes expanded and costs fell. The outcome was the world's largest EV market and globally competitive firms such as BYD and CATL at the technology frontier.

The US Department of Energy's Loan Programs Office illustrates how a portfolio model can be applied to industrial policy. By extending loan guarantees and direct loans, it aimed to finance first-of-a-kind projects that private lenders considered too risky. Some failures were inevitable, and Solyndra became a prominent and politically charged example. But this outcome in part reflected the program's logic: individual losses were expected as part of a wider portfolio. Other loans, including early support for Tesla and utility-scale solar, seemed to have long-run benefits, and overall the portfolio generated positive returns. The case shows that public finance can tolerate failure while enabling technologies that reshape industries.

Spain's PV program highlights the risks of unstable policy. High feed-in tariffs triggered a rapid surge in installations, but retroactive cuts to subsidies undermined investor confidence. The initial boom left behind a legacy of litigation and damaged credibility, illustrating how retroactivity can raise financing costs long after the policies themselves have ended.

Norway's EV rollout is a clear demand-side success aimed at rapid uptake rather than domestic industry building. A stable package of VAT and registration-tax exemptions, CO_2-based taxation of internal combustion vehicles, reduced tolls and parking charges, selective bus-lane access, and municipal procurement created a strong cost advantage for electric cars. Early investment in nationwide fast-charging and reliance on a low-carbon power system reduced infrastructure and range concerns. As adoption expanded, incentives were phased down gradually—for example, by reintroducing VAT above certain price thresholds and normalizing tolls—while avoiding retroactive changes.

The UK's offshore wind sector demonstrates the value of competitive pull mechanisms. Contracts-for-difference (CfDs), allocated through regular auctions with transparent schedules, created strong incentives to reduce costs. This framework underpinned one of the fastest cost declines of any major energy technology. Recent inflationary shocks, however, exposed vulnerabilities in program design, as strike prices failed to keep pace with rising input costs and some planned projects stalled.

Germany's Energiewende combines long-term feed-in tariffs under the Renewable Energy Act (EEG) with priority grid access and dispatch for renewables. Fixed 20-year tariffs triggered a surge in solar PV between 2009 and 2012 and strong growth in onshore wind. The costs of support were recovered through the EEG surcharge on retail electricity bills. Large industrial consumers were widely exempted, leaving households and small businesses to shoulder most of the burden. While wholesale prices fell through the merit-order effect, retail prices rose as surcharges and network charges increased. Delays in expanding north–south transmission and local siting conflicts added curtailment and redispatch costs. Later reforms introduced tariff degression, volume caps, and competitive auctions to contain expenditures, and part of the financing was shifted to the federal budget.

The US biofuels program, introduced in 2005 and expanded in 2007, mandated rising blending volumes enforced through tradable Renewable Identification Numbers (RINs), and was supported by tax credits, import protection, and loan guarantees. It spurred the rapid growth of corn ethanol and biodiesel, which by the mid-2010s supplied about 10% of US gasoline consumption and provided income support for rural producers. The outcomes were mixed and considered by some as a failure. The net climate benefits remain disputed once indirect land-use change is considered. Advanced biofuels consistently fell short of mandated targets, leading regulators to issue repeated waivers. RIN price volatility also created compliance uncertainty for refiners and blenders. And increased demand for corn and soy contributed to higher food and feed prices, raising concerns over distributional impacts.

Lessons from the cases. The cases above point to a set of practical design lessons. Stable and predictable rules are essential: retroactive changes, as in Spain's PV program, undermine investor confidence for years, while transparent calendars and competitive allocation, as in UK offshore wind auctions, can anchor investment and drive down costs. Cost discipline also matters. Degression rules, volume caps, and indexation prevent overspending and reduce exposure to macroeconomic shocks, while portfolio approaches, as seen in the US Loan Programs Office, allow some failures without jeopardizing the program as a whole. Early investment in infrastructure is critical, as Denmark's wind expansion showed, whereas delays in grid reinforcement during Germany's *Energiewende* imposed high redispatch costs. Finally, adaptability seems important. China's EV and battery support illustrates how subsidies can be tapered as volumes rise and performance requirements tighten.

A contested territory. Despite these lessons, the role of industrial policy remains highly contested. Supporters emphasize its ability to overcome coordination failures, accelerate learning, mobilize finance for risky technologies, and address resilience and distributional goals. Critics warn of fiscal costs, rent capture, market distortion, and the danger of locking in incumbents or inefficient technologies. Trade partners also raise concerns over spillovers and subsidy races. These debates underscore that industrial policy is not a settled consensus but a policy space where evidence, political priorities, and institutional design continue to collide.

4.3 Looking Ahead: What (and How) to Evaluate

A central task in the coming years is to evaluate the wave of large-scale industrial and climate policies now being implemented. Table 6 highlights the most prominent cases. In the United States, the *Inflation Reduction Act (IRA)* combines tax credits with manufacturing incentives to accelerate deployment and reshore supply chains. In the European Union, the *Green Deal* and the *Net-Zero Industry Act (NZIA)* aim to scale clean-tech manufacturing, while the *Carbon Border Adjustment Mechanism (CBAM)* introduces a new trade instrument against carbon leakage. China's *14th Five-Year Plan* continues its strategy of intensity targets combined with state-directed industrial support. India's *Production–Linked Incentive (PLI)* schemes target domestic production in solar, batteries, and EVs. France's *France 2030* program directs investment toward nuclear, hydrogen, and other strategic technologies. The *Just Energy Transition Partnerships (JETPs)* link concessional finance and policy commitments in coal-dependent economies.

These initiatives employ varied instruments—subsidies, tax expenditures, procurement, loan guarantees, trade measures, and concessional finance—and pursue multiple objectives: emissions reduction, cost declines, innovation, domestic value creation, and distributional goals. Their diversity creates a natural laboratory for evaluation.

Rigorous evaluation must go beyond tracking investment flows or installed capacity, however. It is equally, if not more, important to know how the causal impacts of these policies affect emissions, innovation, technology costs, industrial outcomes, and political durability (Pless et al. 2020). Existing research on environmental policy and innovation has already begun applying empirical tools developed more broadly in economics. Using these methods to study industrial policy raises several core questions:

- *Additionality*: Did the policy induce investment, jobs, and innovation that would not otherwise have occurred?
- *Cost-effectiveness*: What is the public cost per unit of outcome (e.g., per ton of CO_2 reduced, per job created, per unit of capacity)?
- *Innovation effects*: Did the policy drive technological advance or mainly subsidize mature deployment?
- *Distributional impacts*: How are costs and benefits shared across groups, regions, and sectors?
- *Unintended consequences*: Did the policy create bubbles, lock-in, or trade frictions?

Evaluation is not merely important to get to an overall assessment of whether the program was a "success" or "failure." It is to provide evidence that allows policies to be improved over time. Because technology costs and performance remain uncertain, programs should include review points and mechanisms for adjustment.

Table 6: Overview of Recent Climate and Industrial Policies

Country/Region	Policy/Act	Overarching Objective	Core Mechanisms	Target Sectors	Budget/Scale	Observed/Projected Impact	Sources
United States	Inflation Reduction Act (IRA, 2022)	Re-shore manufacturing; accelerate clean deployment; compete with China	Uncapped ITC/PTC (base + bonus; 30% ITC if labour rules); 10% Domestic Content & Energy Community adders; Direct Pay (tax-exempt) & Transferability; 45X mfg. credit; 45V H_2; 45Q CCUS; tech-neutral clean electricity credits from 2025	Power, EVs, batteries, H_2, CCUS, SAF, manufacturing	$\sim$\$369 B in tax expenditures (official)	$\sim$\$2 T private capex (2025–2035); $\sim$1.2 M jobs/yr; U.S. GHG 32–42% below 2005 by 2030	Bistline et al. (2023), Allcott et al. (2024), ICF (2024), and Aldy (2025)
European Union	Net-Zero Industry Act (NZIA, 2024)	Scale EU clean-tech manufacturing; reduce strategic dependencies	Benchmark of $\sim$40% EU manufacturing of deployment needs by 2030; fast-track permitting for "strategic projects"; non-price criteria in procurement/auctions; regulatory sandboxes	Solar, wind, batteries, heat pumps, electrolysers, grid tech, CCUS	No single envelope; leverages EU/national funds & state-aid flexibility	Projected up to $\sim$3 M additional energy-sector jobs by 2030	Karagianni and Davis (2023), Blenkinsop (2024), and Strategy& (n.d.)
European Union	Carbon Border Adjustment Mechanism (CBAM, 2023–2026)	Prevent carbon leakage; level carbon-cost playing field	Import levy linked to EU ETS price; transitional reporting (Oct 2023–2025); certificates required from 2026; deduct foreign carbon price; phased with ETS free-allowance phase-out	Cement, iron & steel, aluminium, fertilisers, electricity, hydrogen	Revenue mechanism (not spending)	Modelled import reduction of covered goods by 4–26% by 2030; induces wider carbon-pricing adoption	Evans et al. (2023), Hlavackova (2025), and Taxation and Customs Union, EC (2025)
China	14th Five-Year Plan (2021–2025)	Energy security + emissions peaking; tech self-reliance	Intensity targets (energy/GDP -13.5%, CO_2/GDP -18% by 2025); NEV subsidies/procurement; industrial plans; national ETS with intensity benchmarks (no hard cap)	Renewables, NEVs, batteries, industrial efficiency	State-directed investment via budgets, SOEs, state banks (no single envelope)	$\sim$70% of global EV sales; $\sim$73% Li-ion capacity; record renewables build alongside continued coal approvals	Rapier (2019), Etcetera Language Group, Inc.(Translator) and Xinhua News Agency (Original Source) (2021), Greenpeace East Asia (2025), and NZero (2025)
India	Production-Linked Incentive (PLI, 2020–)	Boost domestic manufacturing; reduce import dependence	Performance-linked subsidies on incremental sales; sector schemes for solar modules, ACC batteries, auto/EVs, green H_2 & electrolysers	Electronics, auto/EVs, solar, batteries, H_2	$\sim$\$23 B across 14 sectors	Mixed execution in green tech (delays vs. targets); stronger results in electronics	Kumar et al. (2024) and Reuters (2025)
France	France 2030 (2021–)	Tech sovereignty via targeted industrial champions	Direct state investment/calls for projects; focus on SMRs, green H_2, low-carbon aviation; critical minerals supply chains	Nuclear (SMRs), H_2, aviation, batteries/materials	EUR 54 B plan	Backs specific domestic projects & supply chains (state-as-investor model)	Ministry of Ecological Transition (2022), Service d'Information du Gouvernement (2024), and Agence Nationale de la Recherche (2025)
South Africa	Just Energy Transition Partnership (JETP, 2021–)	Coal-to-clean power transition with social protection	\$8.5 B concessional package; grid & renewables investment; worker/community support; partnership with donors	Power system; workforce transition	\$8.5 B initial commitment	Early-stage implementation; template for transition finance with equity safeguards	Imelda (2023)

Note: The table provides a comparative overview of major recent climate and industrial policy packages across key economies, summarizing objectives, instruments, target sectors, and expected impacts. For more details, see Section 4.3. Acronyms: ITC = Investment Tax Credit; PTC = Production Tax Credit; CCUS = Carbon Capture, Utilization and Storage; SAF = Sustainable Aviation Fuel; NEV = New Energy Vehicle; ETS = Emissions Trading System; SMR = Small Modular Reactor; ACC = Advanced Chemistry Cell. Reported budgets are official estimates or commitments; realized expenditures may differ. Impacts reflect government and third-party modeling.

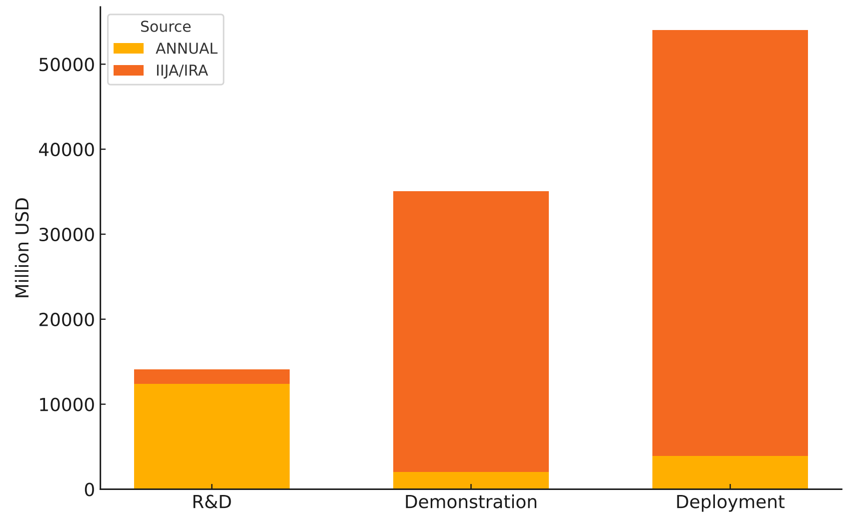


Figure 13: DOE Clean Energy Appropriations: RD&D vs. Deployment

Note: Appropriations in million nominal USD. The bars on the left show annual DOE budgets in FY21–23, which devoted the bulk of resources to R&D ($12.4bn) and only modest sums to demonstration ($2.0bn) and deployment ($4.0bn). The bars on the right show one-time IIJA/IRA funding, which reversed this pattern: only $1.7bn for R&D but very large allocations for demonstration ($33.0bn) and deployment ($50.1bn). The figure highlights the contrast between steady annual appropriations focused on upstream research and exceptional stimulus packages skewed toward later-stage support. Source: Figure 3 in O'Rear et al. (2025).

4.4 RD&D vs Deployment Investments

The examples above highlight potential synergies between new technology development and technology deployment. A notable feature of recent US appropriations is the sharp imbalance between research, development, and demonstration (RD&D) and deployment support. As Figure 13 shows, annual appropriations channeled most resources to R&D ($12.4 billion), with only modest sums for demonstration ($2.0 billion) and deployment ($4.0 billion). By contrast, one-time funding from the IIJA and IRA was heavily weighted toward later stages: just $1.7 billion for R&D against $33.0 billion for demonstration and $50.1 billion for deployment (O'Rear et al. 2025). This pattern reflects a broader tilt toward supply-side industrial policy aimed at scaling domestic manufacturing and subsidizing adoption rather than expanding the knowledge base.

The case for public R&D enjoys broad consensus: knowledge spillovers, appropriability problems, and long lead times ensure systematic under-provision by the private sector (see Section 2.1). Demonstration activities also face persistent financing gaps. By contrast, the rationale for large-scale deployment subsidies is more contested. They can accelerate uptake and generate learning by doing, but also risk locking in incumbent designs, crowding out alternative technological options, and transferring rents to mature producers.

What constitutes an appropriate "balance" between stages of the innovation chain remains an unanswered question. There is no accepted benchmark for the optimal allocation of resources, and cross-technology heterogeneity further complicates matters. What is clear is that many promising options remain at low TRLs, as highlighted earlier in this chapter. In this setting, a portfolio strategy—maintaining strong support for upstream R&D while targeting deployment support more selectively—is essential to avoid premature lock-in and to keep multiple technological pathways open for deep decarbonization.

4.5 The Chilling Effect of Policy Uncertainty

Recent green industrial policies have mobilized record levels of investment, yet their long-term effectiveness is undermined by a pervasive and often underestimated threat: policy uncertainty. The energy transition relies on capital-intensive, long-lived assets—from multi-billion-dollar battery giga-factories to offshore wind farms—whose viability depends on predictable and credible policy frameworks. Shifts in subsidies, regulations, energy, or carbon prices can generate a chilling effect, deterring projects and weakening the very objectives such policies aim to achieve.

Economic theory highlights the option value of waiting: when investments are irreversible, and the policy or market environment is uncertain, firms rationally delay commitment until risks are resolved (Bloom et al. 2007). This effect is especially pronounced for R&D, where uncertainty dampens responsiveness to shocks, prolongs persistence, and slows adjustment (Bloom 2007). In clean technologies, the result is slower deployment and weaker innovation incentives precisely when rapid scaling is most urgent. Uncertainty also elevates financing costs by increasing perceived project risk, raising the cost of capital, and limiting access to funding. The bias then shifts investment toward short-payback projects that are less effective in driving long-run decarbonization.

Industrial policies are particularly exposed to political sources of uncertainty. Unlike standards or market-based instruments, which impose costs on firms without drawing directly on public budgets, subsidy and tax-credit programs rely on appropriations or foregone revenue. Their fiscal visibility makes them more vulnerable to reversal when political priorities or budget conditions change. Large-scale subsidy schemes, such as those in the US Inflation Reduction Act (IRA), are therefore contingent on electoral cycles. President Trump has already acted aggressively: on his first days in office, he ordered agencies to halt IRA disbursements, froze grants and loans under an executive order, and directed the EPA to terminate $20 billion in awards from the Greenhouse Gas Reduction Fund (Britton and Runyon 2025; Guarna and Turner 2025). These freezes and cancellations have triggered at least sixteen lawsuits and left major programs in limbo. Additional legislation—the "One Big Beautiful Bill Act"—has begun to eliminate incentives for EVs and to tighten deadlines for renewable projects (Storrow 2025). The prospect of continuing rollbacks is already priced into investment decisions, raising financing costs and chilling project pipelines.

Uncertainty does not only stem from political reversals. Even when policies are politically stable, their design can blur the demand signals on which innovators and investors rely. Carbon markets are a prominent example. While cap-and-trade provides quantity certainty, it leaves allowance prices highly volatile and unpredictable. In California's program, Borenstein et al. (2019) show that uncertainty about baseline emissions and the interaction with complementary policies meant that allowance prices were often expected to hit regulatory floors or ceilings rather than settle at a stable interior equilibrium. Such volatility undermines the credibility of the price signal as a long-run guide for innovation.

Standards and mandates can create similar ambiguity. The US Renewable Fuel Standard, for instance, has been characterized by high and volatile credit prices and frequent discretionary adjustments by the Environmental Protection Agency. Stock (2018) argues that these structural features—annual rulemakings, waiver authorities, and litigation—have politicized what should be a technocratic process, generating persistent uncertainty about compliance trajectories and discouraging investment in second-generation fuels. In this sense, instruments that look durable on paper may still fail to provide innovation incentives if the demand trajectory they imply remains uncertain. The Mercury and Air Toxics Standards provide a clear example: perceived enforcement probabilities fell sharply during the rule's rollout, leading many firms to postpone compliance investments. Resolving uncertainty earlier would have reduced compliance expenditures but at the cost of higher pollution damages (Gowrisankaran et al. 2025).

A growing body of empirical work now quantifies the effects of policy uncertainty on clean investment and innovation, often using new text-as-data approaches (Baker et al. 2016; Dugoua et al. 2022). Noailly et al. (2024) construct a news-based index that captures the salience of environmental and climate policy in US newspapers, showing that greater salience is associated with stronger clean investment. Noailly et al. (2022) develop an Environmental Policy Uncertainty index and find that higher uncertainty reduces the probability that clean technology start-ups attract venture capital and increases volatility for firms with green revenues, highlighting the need to distinguish policy attention from policy uncertainty.

Basaglia et al. (2025) take a narrower focus, creating a Climate Policy Uncertainty index that tracks articles linking climate, policy, and uncertainty terms. Their index distinguishes between uncertainty about policy tightening and weakening. They show that higher uncertainty depresses capital spending, R&D, employment, and clean patenting in carbon-intensive sectors, with the largest effects when policy rollbacks are anticipated. Cross-country evidence also indicates that uncertainty shocks reduce renewable-energy patenting more sharply than other forms of innovation, with the impact amplified during recessions or periods of financial stress (Bettarelli et al. 2024). Market-based evidence points in the same direction. Using option prices in the EU Emissions Trading System, Fuchs et al. (2024) measure expected carbon price volatility and show that higher volatility lowers firms' decarbonization investment. The effect is economically large: an increase in uncertainty reduces expected investment by about as much as an actual drop in the carbon price itself.

Finally, Chen (2025) documents how repeated expirations and renewals of the US wind Production Tax Credit generated boom–bust investment cycles. These lapses pushed firms to rush projects before deadlines, leading to poorly timed entry relative to technological advances and demand growth, causing large welfare losses.

4.6 Fossil Fuel Subsidies

While much of the previous sub-sections described new policies designed (at least in part) to encourage the development of new clean technologies, there is also a large set of existing policies that do the exact opposite. Chief among them are fossil fuel subsidies, which tilt relative prices towards carbon-intensive energy, thereby slowing reallocation to clean technologies and absorbing fiscal space that could otherwise fund social protection, innovation, and infrastructure. The 2022 energy crisis made their role unusually visible: governments responded to higher prices with large-scale subsidies to households and firms. Fiscal costs rose to record levels before easing somewhat in 2023, underscoring both the magnitude of intervention and the political difficulty of reform.

This section focuses on *explicit* subsidies—direct budgetary transfers, tax expenditures, and price-gap support that hold retail energy prices below supply cost—distinct from implicit subsidies such as the underpricing of externalities. Figure 14 illustrates the sharp post-2020 increase, driven largely by petroleum, natural gas, and electricity subsidies. Estimates by the IEA and OECD place explicit subsidies at USD 1.6 trillion in 2022, declining to USD 1.1 trillion in 2023 but still well above pre-crisis norms. A central concern is that temporary crisis measures could become entrenched, undermining long-term phase-out efforts (OECD 2024c).

Subsidies take diverse forms, from tax breaks for producers to price caps and direct transfers for consumers. Among OECD economies, 77% of support is channeled through the tax system—such as rebates or deductions for exploration and production—while the remainder comes through direct budgetary measures (Elgouacem 2020). Globally, consumption dominates: 90% of subsidies go to end-users versus just 7% to producers (OECD 2024a). By fuel type, electricity (36%), natural gas (32%), and oil (31%) account for almost all support, with coal receiving less than 1% (Institute for Energy Research 2023).

There are also large differences in fossil fuel subsidies across countries (Table 7). Fossil fuel–rich exporters such as Saudi Arabia and Russia spend over $500 USD per capita to keep domestic energy below market rates. While most European countries usually spend less than $100 USD per capita, the 2022 crisis pushed several—including the Netherlands, France, and the UK—into the top subsidy spenders. Future global competition in energy markets may lead

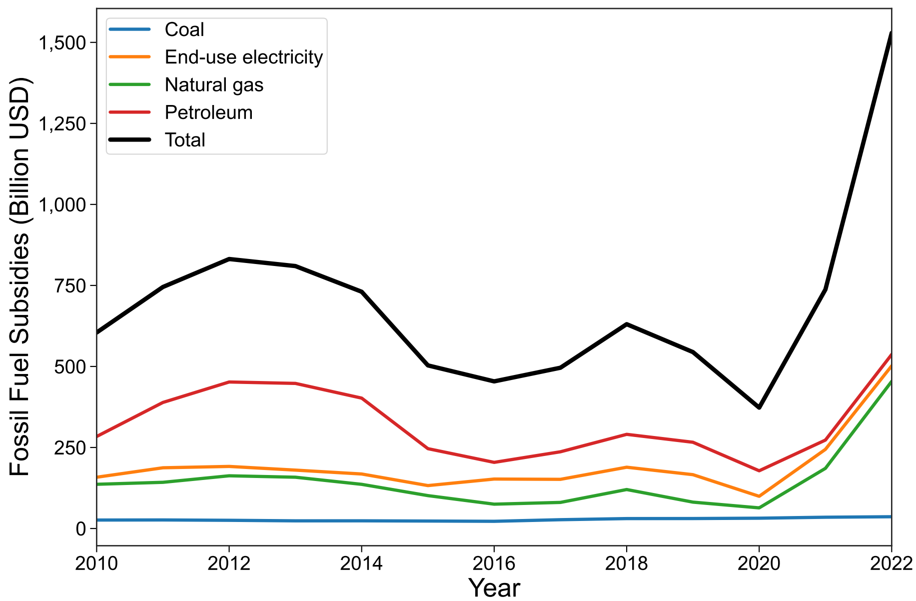


Figure 14: Fossil Fuel Subsidies Over Time.
Note: Reproduced from the *Fossil Fuel Subsidy Tracker*, which compiles estimates from the OECD, IEA, and IMF for 195 economies through 2022. The figure documents the surge in explicit fossil fuel subsidies after 2020—measured in billions of USD——highlighting the persistence of elevated support levels in the wake of recent global crises.

to even more aggressive subsidies, as some countries double down on fossil fuel production as an economic and political strategy (see Section 6.4).

The standard rationale for subsidies is affordability, yet empirical evidence consistently shows they are regressive. Wealthier households consume more energy and thus capture a disproportionate share of benefits. The richest quintile typically receives more than six times the subsidy value of the poorest quintile (Potdevin and Wu 2024). The poor, often disconnected from formal infrastructure, may receive little to no benefit. As a social protection tool, subsidies are highly inefficient: one IMF study found that only USD 1 of every USD 33 spent on gasoline subsidies reaches the poorest 20% (Harruch 2024).

Reform is politically challenging once these subsidies are in place; however, there are a handful of examples of it taking place (Rentschler and Bazilian 2017). Indonesia's experience shows that gradual reforms, backed by communication and targeted cash transfers, can succeed (Nozaki and Shang 2013). The political costs of removal are real but often short-lived: evidence from Mexico and Bolivia shows temporary approval dips, with more persistent backlash when trust in government is low (Oca Leon et al. 2024). Survey experiments in Malaysia suggest that framing reforms in redistributive terms raises support, whereas environmental framing reduces opposition among skeptics (Innocenti and Bharadwaj 2025). From a macroeconomic perspective, broad consumption subsidies can also worsen a country's terms of trade in tight markets—the EU's 2022 gas subsidies being a case in point (Gros 2022).

Building on these insights, many questions remain open. How are the benefits and costs

Table 7: Fossil Fuel Subsidies by Country and Type in 2022

Country	Natural Gas		Petroleum	
	Per Capita (USD)	Total (USD bn)	Per Capita (USD)	Total (USD bn)
France	112.57	7.65	279.25	18.97
United Kingdom	503.67	33.73	108.93	7.29
Indonesia	1.79	0.49	131.18	36.14
India	1.76	2.49	30.37	43.04
Iran	511.03	45.25	589.43	52.19
Russia	681.36	97.81	0.00	0.00
Saudi Arabia	454.95	16.56	963.51	35.08
Italy	303.18	17.84	302.94	17.83
Netherlands	774.22	13.71	61.52	1.09
United States	12.39	4.13	23.09	7.69

Note: Reproduced from the *Fossil Fuel Subsidy Tracker*, which compiles estimates from the OECD, IEA, and IMF. Figures are reported in nominal terms, both on a per capita basis (USD per person) and as total national subsidies (USD billions). The table shows that fossil fuel–rich exporters spend substantially more per capita on energy subsidies than most European or Asian countries, while the 2022 crisis temporarily raised subsidies in several high-income European economies.

of subsidies distributed across households, and what determines the extent of pass-through to consumers? How do subsidies shape firm behavior, sectoral competitiveness, and long-run patterns of energy intensity? What kinds of pricing rules or smoothing mechanisms can governments adopt to balance political durability, fiscal risk, and inflationary pressures in volatile markets? When subsidies are reformed, which forms of social protection—cash transfers, in-kind support, or public services—best shield vulnerable groups, and under what conditions? At the international level, how do large-scale subsidies spill over through trade, prices, and investment, and is there scope for coordination to avoid collective inefficiencies? And finally, what are the long-run industrial consequences: does persistent support lock in carbon-intensive capital and slow down the transition to cleaner technologies, or can it sometimes provide a bridge to managed structural change?

5 Innovation and Climate Adaptation

Major temperature increases have already taken place, and will continue to do so regardless of the path of mitigation technology and future emissions. Adaptation technology may play an important role in shaping the consequences of this disruption, making it possible for individuals, firms, cities, or countries to adapt *ex post*. While mitigation technology development can be organized around a key and quantifiable central goal—reducing emissions involved in economic production and consumption—adaptation technology can be more varied and hard to pin down.

Early in the chapter, we describe a wide range of adaptation technologies (Table 4). Some are related to infrastructure and engineering, including developing lower-cost strategies for coastal and flood protection or more advanced cooling infrastructure. Others are related to biotechnology, including developing more heat or pest-resistant crop varieties, stress-resistant livestock, or new antiviral therapies as changing temperatures affect the pattern of human disease outbreaks (e.g., Hotez and LaBeaud 2023). The development of tracking and early warning systems, both for climate hazards themselves and also for knock-on effects like disease outbreaks, may also become relevant. These technologies could give individuals the time and ability to adapt to these threats in other ways.

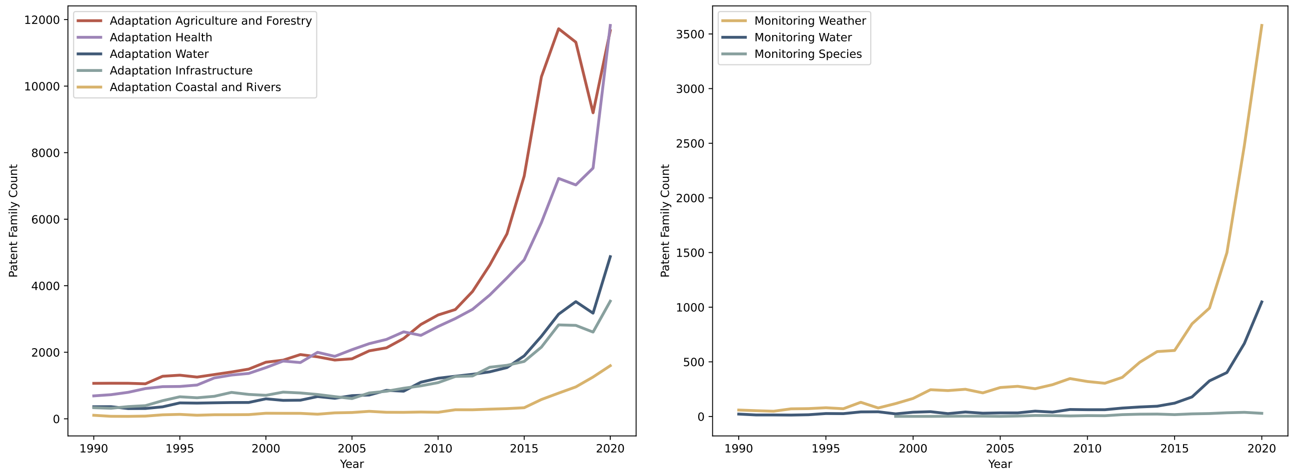
In addition to crossing technology areas, different adaptation technologies may facilitate very different types of adaptation responses. On the one hand, technology might allow individuals or producers to "adapt in place," increasing local resilience to climate damages. This can include directly changing production technology, for example, via the development of heat-resistant seed varieties that make agricultural production possible as temperatures rise. Climate monitoring and early warning systems can also facilitate other forms of preparation for environmental extremes. It can also include changing the local environment to protect from environmental extremes, without directly changing production technology; examples of this are expanded use of air conditioning, changes in city or building design, other forms of geoengineering that alter the local environment, or the development of sea walls and other defensive investments.

On the other hand, technology can also drive adaptation-via-reallocation. In addition to reducing the damage that climate change can do to productivity or health, it can also facilitate the movement of firms and individuals across space and toward regions that are less directly exposed to damaging climate trends. In agriculture, for example, new technology can make it possible to expand production to new or *ex ante* less fertile land. More generally, this can include anything that facilitates the efficient and productive movement of firms and individuals toward regions that are less exposed to climate damage, and discovering or exploiting new economic opportunities in those regions. Thus, the exact direction that adaptation innovation takes—and the rate of adaptation technology development in the first place—may play a major role in shaping human responses to climate change.

Despite the many ways that technology can shape and reshape the impacts of climate change on well-being, there is relatively little existing research investigating the forces that drive climate adaptation technology development, or the extent to which this technology development mitigates the economic consequences of global warming[16]. Hötte and Jee (2022) show that overall adaptation technology patenting is rising at a much slower rate than clean energy patenting and than patenting in the economy as a whole, even though economic damage from climate extremes is accelerating.

Breaking overall innovation down by topic, Figure 15a displays adaptation patent trends

16. For a broader review of the literature on the economics of adaptation and climate damages, see Carleton et al. (2024) and Auffhammer (2018).



(a) Adaptation **(b)** Monitoring

Figure 15: Adaptation Technology Patenting Over Time

Note: The figure plots the number of *all* patent families (PATSTAT DocDB), where "all families" include those filed only domestically as well as those filed in multiple jurisdictions; years correspond to the first filing year. A patent family is defined following PATSTAT's DocDB family definition, which groups together all applications covering the same invention.
Adaptation technologies include patents related to agriculture and forestry, coastal protection, water management, infrastructure resilience, and health. Monitoring technologies cover weather forecasting, water and species monitoring, and other information systems. For detailed category definitions, see Table 4, and for patent data construction and processing steps, see Appendix A.3.
Patenting in both adaptation and monitoring increased through the 2000s, with adaptation showing higher levels of activity during that period. After 2015, both categories display a sharp uptick, reflecting a recent acceleration in innovation. This surge is driven largely by growth in Chinese filings, though patent families also expand steadily across all other major jurisdictions. The pattern holds when restricting attention to international families or to granted families only.

over time for the five main technology categories identified by the USPTO: coastal protection, agriculture, infrastructure, water use, and monitoring and information technology. There are large differences across technology areas; while adaptation-relevant patents in agriculture have risen sharply, there has been little change in adaptation-relevant patents in coastal protection. One reason for this gap could be large differences in private-market demand for adaptation technologies. As we describe below, worsening climate change could increase farmer demand for more resilient technology, thereby incentivizing new technology development; however, coastal investment decisions rely on government investment and policy change, which could be slower, less predictable, and less lucrative. But what truly drives differences in investment across adaptation technologies in practice, and what is the role of government policy in this process? And to what extent do these different investments crowd each other in or out? The answers to these questions could have important implications for estimating climate damages and understanding optimal policy responses to environmental change.

Beyond understanding trends in innovation, the most important question might be the extent to which new innovation mitigates economic damages from climate change, especially in the most climate-exposed parts of the world. However, there are few studies investigating the impact of new technologies on climate resilience, and those that exist focus on individual sectors in fixed locations, abstracting from the ways that technology could facilitate production reallocation or mitigate the knock-on effects of rising temperatures (e.g., via disease emergence). One common theme is that global diffusion of adaptation technology is limited, especially to developing countries where expected climate damages are largest (Touboul et al. 2023). Taking all of this into account, what forces shape the development and (global) consequences of climate adaptation technology?

5.1 Adaptation Technology Development: A Theoretical Framework

We first provide one potential framework for modeling private incentives to invest in adaptation technology development, based on Acemoglu (2010) and its recent application in Moscona and Sastry (2023). A key conclusion of the theory is that — as is the case for green technology development (see Section 2.2) — there is no guarantee that the progression of climate change leads to stronger incentives for developing adaptation technologies. In fact, under reasonable conditions, the exact opposite can happen, and there is no clear reason to assume that the development of adaptation technology will increase as climate damages become more severe.

Model Set Up. The goal is to build as simple a framework as possible that homes in on the economic mechanisms that drive the relationship between climate change and adaptation technology development. Consider an economy in which a continuum of producers $i \in [0, 1]$ can produce a single good. The quality of the climate or environment in each location is $A_i \in [A', A'']$ with cumulative distribution $F(.)$ across locations. This can capture the extent of extreme heat, which reduces agricultural output (Schlenker and Roberts 2009), or the extent of flooding, which disrupts manufacturing production (Castro-Vincenzi 2022; Balboni et al. 2023), among other sources of climate damage.

There is a technological input, and the producer uses T_i of this input. The productivity of this input in location i reflects both local fundamentals A_i (i.e., local environmental quality) and the state of the aggregate technological frontier θ, which are combined in the function $G(.)$. In particular, the production function of producer i is:

$$Y_i = \alpha^{-\alpha}(1-\alpha)^{-1}G(A_i, \theta)^{\alpha}T_i^{1-\alpha} \tag{11}$$

where Y_i is total output and $\alpha \in [0, 1]$ captures the relative importance of technology in the production function. $\alpha^{-\alpha}(1-\alpha)^{-1}$ is a normalization added only to simplify the analysis. Assume that $G(.)$ is concave and twice continuously differentiable. Let G_1 and G_2 denote the partial derivatives of G with respect to local innate productivity A_i and technological quality

θ, respectively. Imposing $G_1 \geq 0$ and $G_2 \geq 0$ ensures that output is (weakly) increasing in both local productivity and the technological level of the economy.

Each producer maximizes profits taking output price p and input cost q as given. Taking the first order condition of the farmer's maximization problem:

$$T_i = \alpha^{-1} p^{\frac{1}{\alpha}} q^{\frac{-1}{\alpha}} G(A_i, \theta)$$

Thus, use of the technological input is directly increasing in $G(A_i, \theta)$.

Suppose that climate change represents a worsening of climate conditions everywhere. That is, a damaging climate shift is one in which the climate productivity distribution shifts from $F(.)$ to $F^{CC}(.)$, where $F()$ first-order stochastically dominates $F^{CC}()$. The key question will be how this shift affects the equilibrium technology level θ and ultimately production resilience in the face of the worsening environmental conditions.

To model innovation, we assume there is a representative innovator that determines both the price of T_i and the aggregate level of technological progress (θ) in order to maximize profits. The innovator faces a marginal cost of technology development $1 - \alpha$ and a convex cost $C(\theta)$ of expanding the technological frontier. Substituting for technology input use from the producer's maximization problem, the innovator's maximization problem becomes:

$$\max_{q,\theta} (q - (1 - \alpha)) \alpha^{-1} p^{\frac{1}{\alpha}} q^{\frac{-1}{\alpha}} \int G(A_i, \theta) dF(A) - C(\theta) \tag{12}$$

The first order condition for q is satisfied for any θ if $q^{-\frac{1}{\alpha}} - (q - (1 - \alpha)) \frac{1}{\alpha} q^{-\frac{1}{\alpha} - 1} = 0$; thus, the profit maximizing technology price is $q = 1$. Plugging this into the original maximand, the innovator's problem simplifies to one-dimensional optimization over the technology level θ:

$$\max_{\theta} p^{\frac{1}{\alpha}} \int G(A_i, \theta) dF(A) - C(\theta) \tag{13}$$

Finally, assume that the price of the production good is determined by an inverse demand function $p = D(Y)$, where D is continuous and non-increasing and Y is total output in the economy: $Y = \int Y_i(A_i) dF(A)$. An equilibrium is defined as price p, output Y, and technology level θ such that both producers and innovators maximize profits and the crop price lies on the demand curve.

Before turning to the results, it is important to define two key cases for the role of technology in production. It will turn out that the distinction between these cases is central for determining whether overall technology development increases or decreases in response to climate damage, as well as how endogenous technology development shapes production resilience:

Definition 1. *Innovation is climate-substituting if $G_{12} \leq 0$ and a climate-complementing if $G_{12} \geq 0$.*

Here G_{12} denotes the cross-partial derivative of $G(\cdot)$ with respect to local productivity A_i and the technological frontier θ and captures whether technological progress increases or decreases the marginal impact of local climate conditions on output.

In words, Definition 1 means that new technology is a *climate substitute* if it reduces the marginal impact of climate damage on output. This would be the case if new technology development, on average, makes production less sensitive to climate hazards. One example could be the development of heat-resistant seeds that lessen the impact of high temperatures on crop production. Another could be factory floor designs that include barrier walls to guard against flood damage (e.g., Leitold et al. 2021).

New technology is a *climate complement* if it increases the marginal impact of climate damage on output. While this may seem counterintuitive, there are a range of examples of new technologies increasing productivity at the expense of climate resilience. Recent evidence on US agriculture, for example, suggests that much of recent breeding efforts increases yields *at the expense of* resilience to drought, in part because seed varieties can be finely tuned to specific environmental characteristics and, as a result, are more sensitive to fluctuations (Lobell et al. 2014). Relatedly, in the case of manufacturing, many new processes involved in battery production require very specific temperature and humidity ranges (Volta Foundation 2024), and exposure to extreme heat or humidity can shut down battery production. These new technologies become much less productive when the environment changes.

Key Theoretical Results. We next describe the main results of the model. The effect of worsening climate damage on innovation hinges crucially on whether technology tends to be a climate substitute or a climate complement.[17]

First, consider a small open economy (i.e., a world with fixed prices). If the climate shifts in a damaging way, then the technology level (θ) will rise when technology is a climate substitute and fall when it is a climate complement. When technology is a climate substitute, producers are more willing to pay for new technology under worse climate conditions, since improvements are especially valuable in offsetting damage. When technology is a climate complement, the opposite is true. Thus, whether the equilibrium level of technology rises or falls in a damaged market depends on how the marginal benefit of technology responds to climate conditions. In the climate-substituting case, innovation can still increase in a "shrinking" or "damaged" market because demand for technological improvements rises. The climate-complementing case, on the other hand, recovers the more common intuition that innovation concentrates in large or growing markets.

Next, we allow for flexible prices by assuming that equilibrium quantities lie along a downward-sloping demand curve. In this case, a damaging climate shock reduces output

17. See Moscona and Sastry (2023) for a full discussion and derivation of all results. Here, we just summarize the results and provide basic intuition.

and therefore raises prices. Higher prices increase the marginal product of technology for producers and, as a result, the returns to technological improvement for innovators. In the climate-substituting case, this reinforces the incentive to improve technology after climate damage. In the climate-complementing case, price effects work against the marginal-product channel described in the previous paragraph. Thus, the overall impact of damaging climate change on the equilibrium level of technology depends on the relative strength of these two forces.

Finally, consider the extent to which endogenous technology development affects production resilience (i.e., the negative of profits' sensitivity to weather). In the case of climate-substituting technology, climate damage always increases technology improvement, which, in turn, increases production resilience. This is true regardless of the strength of price effects. The climate-complementing technology case, however, is more complicated because the direction of innovation and the marginal product of new technology can be misaligned. When price effects are weak, innovation retreats in response to climate damage; however, this paradoxically increases production resilience since, in this case, technological advancements make production more sensitive to weather fluctuations. When price effects are strong, general equilibrium effects can lead innovation to increase in response to climate damage even though the marginal product of new technology has declined. In this case, production resilience declines even though technology development has increased.

Thus, even in a simple theoretical framework, the response of technology development to climate damage is ambiguous. Depending on specific characteristics of technology improvement, technology development can either advance or retreat in response to damaging climate trends. As a result, directed technological change can either increase or decrease production resilience, dovetailing with the fact that directed innovation can accelerate both climate catastrophe and a transition to clean technology in the model presented in Section 2.2.1.

Extensions. In the baseline model, there is a single technology, and it is either a climate complement or a climate substitute. A more realistic setting may be one in which the innovator can choose the extent to which technology is a climate substitute (i.e., reduces the marginal effect of negative climate shocks on output). The extent to which this is possible in practice might vary substantially across contexts; for example, technological features of battery development might make it infeasible to make production less sensitive to variation in temperature and humidity without sacrificing efficiency. The same could be true for crop yields. Regardless of these different circumstances, adding this feature to the model will weakly push toward directed innovation *increasing* resilience in response to climate shocks.

A second question is the extent to which climate-induced innovation is efficient. The fact that innovation increases in response to climate damage (e.g., in the climate-substituting case of the baseline model) does not necessarily imply that it increases by the "right amount," or that a planner's solution would coincide with equilibrium technology development. In the framework above, the only market failure is innovator market power, which leads to the under-provision of innovation in general but does not lead the *direction* of innovation to deviate from the solution to the planner's problem. This is not the case, however, in a model with dynamic externalities in which innovation today has uninternalized benefits for technology development tomorrow. While these dynamic returns to scale are often emphasized in models of growth and endogenous technological change (e.g., Romer 1990), they could be especially relevant in the present context since adaptation technology development is just beginning to ramp up (see Figure 15) and climate damages are expected to get substantially worse in the near future. More generally, Acemoglu (2023) explores the forces that might prevent the market from getting "the direction of technology right."

One shortcoming of this framework is that a key determinant of future profitability is future government decision-making, which is beyond the scope of this model. For example, incentives to invest in improved sea wall technology are determined by whether, when, and where governments will decide to build sea walls, which can be shaped by complicated political incentives and dynamics (see Hsiao 2023). Incorporating political economy and expectations about future government actions into a model of investment in adaptation technology seems like an interesting area of future work.

5.2 Climate Damages and Innovation: Empirical Evidence

The fact that the impact of climate damages on adaptation technology development is ambiguous—and that innovation could *either increase or decrease* production resilience to climate shocks—makes it all the more important to investigate this relationship in the data. However, as noted above, empirical work at this intersection is limited, in part because the set of adaptation technologies and their potential impacts are so varied.

One sector in which this question has been explored empirically is agriculture. Moscona and Sastry (2023) investigate how exposure to climate change in the US has affected the direction of innovation by exploiting heterogeneous exposure to climate damage across crops.[18] In particular, they measure the extreme heat exposure of each crop in each decade since 1950, driven both by differences in crop geography at baseline and the differential sensitivity of each crop to extreme heat. First, using data on all new crop variety releases in each year, they find that new variety development has been directed toward crops with increasing exposure to

18. The importance of adapting technology to specific environmental conditions is a key feature of agricultural innovation more generally, even absent systematic changes in the environment due to global warming. For reviews of the economics technology development and diffusion in agriculture, see Sunding and Zilberman (2001), Pardey et al. (2010), and Alston and Pardey (2021). Many of the microeconomic forces governing climate adaptation technology development are also common features of agricultural innovation more generally.

extreme heat; the mean in-sample extreme heat exposure is associated with a 20% increase in variety development. Second, using data on the universe of agricultural patenting, they show that the shift in technology development toward more heat-exposed crops was driven by technologies that would be relevant for climate adaptation, measured using both the text of the patent abstract and using the technology class of the invention (e.g., soil treatment might help with climate adaptation while mechanical harvester technology would not).

Finally, they show that this new technology development has offset some of the economic damage from extreme heat trends: the marginal effect of extreme heat on agricultural profits and land values is muted for counties growing crops that were more exposed to induced innovation in the national market. Combined with a model, these estimates imply that directed innovation has offset only about 20% of the potential economic damage from extreme heat on US agriculture. That is, innovation to date has been only an incomplete guard against productivity losses from global warming, even in the US, which has the largest agricultural markets and R&D ecosystem, making it perhaps the best case scenario for adaptation-via-innovation.

These findings suggest that the "climate substitutes" case of the theory seems to dominate in this context, and that innovators shift focus toward more adaptation-relevant technologies as climate damage worsens. Cui and Zhong (2025) find similar results studying the relationship between extreme heat shocks and crop variety development in China; in China, however, the results are smaller in magnitude, and the development of the most widely-adopted temperature-induced varieties is driven by the public sector, perhaps reflecting the different nature of innovation incentives and institutions. Looking farther back in history, Moscona (2025) studies the response of innovation to the American Dust Bowl of the 1930s, perhaps the worst environmental catastrophe in US history, that caused widespread damage to the Plains region. There too, technology development shifted toward the most climate-damaged crops—the crops planted in areas that the Dust Bowl hit hardest—consistent with historical accounts that the Dust Bowl was partly responsible for the early take-off of the US agricultural biotechnology sector (e.g., Crabb 1947; Crow 1998; Sutch 2011).

Zooming out across many natural disasters and countries, Miao and Popp (2014) show that country-level exposure to natural disasters (e.g., floods, earthquakes) leads to a sharp uptick in patenting to mitigate disaster risk. Thus, existing evidence seems to suggest that in response to negative climate realizations, innovation shifts in the direction of offsetting climate damage. These findings are consistent with evidence from other contexts that negative supply shocks — or "scarcity" — can drive technological change (e.g., Habakkuk 1962; Acemoglu 2010; San 2023; Flynn et al. 2025). The extent to which this induced innovation offsets economic damage from climate change, however, is largely an open question. Moreover, much more evidence is needed to understand whether these findings generalize to other sectors and contexts.

5.3 Climate Damages and Adaptation Technology Adoption

Other studies take the state of technology development as given and estimate whether the adoption of new technology can mitigate the productivity and health consequences of climate change. According to existing estimates, the impact of rising temperatures on mortality represents a substantial share of overall climate damages since extreme heat substantially increases mortality, especially for the elderly (e.g., Deschênes and Greenstone 2011; Hsiang et al. 2017). In the US, however, the relationship between temperature and mortality has declined substantially over time, driven in large part by the widespread adoption of air conditioning (Barreca et al. 2016). Air conditioning adoption can also substantially reduce the marginal effect of heat on firm productivity (Zivin and Kahn 2016; Somanathan et al. 2021; Costa et al. 2024). Beyond air conditioning, other cooling technologies, like "cool" high-albedo roofing (Rawat and Singh 2022), can drastically reduce workplace exposure to extreme heat.

Another set of technologies that mitigate climate damage by altering the local environment is coastal protection. Benetton et al. (2025) study the construction of a sea wall to protect Venice and find that, while the sea wall does protect the city and increase local land values, it is far from paying for itself when these hedonic benefits are compared to the costs. Hsiao (2023) studies the construction of a sea wall in Jakarta and finds that, paradoxically, the ability of the government to fund a sea wall can complicate adaptation to climate change. Absent the ability to commit to future policy, the potential construction of a sea wall can create coastal moral hazard. Migration away from the coast is inefficiently suppressed by the expectation of future sea wall construction, and the government is likely unable to commit to never building a sea wall, especially if a large share of firms and individuals are concentrated in at-risk areas.

This is one example of adaptation-via-technology interacting with other mechanisms of adaptation (in this case, migration), which we return to below. In this case, the prospect of a sea wall reduces migration, thereby leading to substantial and unnecessary government expenditure to finance defensive technology investments.

Other studies directly investigate the adoption of more resilient production technology. For example, Taraz (2017) shows that Indian farmers increase investment in irrigation in response to droughts; however, these investments ultimately do little to reduce the effect of climate extremes on crop yields. Other work finds that irrigation adoption reduces the effect of rainfall shortages on conflict (Gatti et al. 2021) or output (Balana et al. 2024). Some studies have shown that improved climate forecast and monitoring technology can also reduce agricultural damages by affecting insurance uptake (Suarez et al. 2008) and input choice (e.g., seed) (Kayamo et al. 2023). More generally, better weather tracking can substantially lower overall economic damages from natural disasters, including hurricanes and floods (e.g., Perera et al. 2019; NOAA 2020); investing in these technologies has a high estimated benefit-cost ratio across contexts, even in low-income countries (Martinez 2020; Islam et al. 2024).

5.4 Interactions with Mitigation and with Other Adaptation Mechanisms

Adaptation technology might have important interactions with mitigation technology development or with other mechanisms of adaptation. One prominent example of these feedback mechanisms is the case of geoengineering, large-scale manipulation of Earth's climate to counteract the effects of climate change (e.g., reflecting sunlight back into space, directly removing carbon from the atmosphere, etc.). The Fifth Assessment Report of the Intergovernmental Panel on Climate Change (IPCC) even argued that investments in geoengineering and possible future deployment of techniques ranging from aerosol injections to carbon capture could reduce current mitigation efforts. Acemoglu and Rafey (2023) formalize this relationship. They show, in a model with a social planner who can set a carbon tax but not commit to future tax rates, that geoengineering breakthroughs reduce future damages and hence future Pigouvian carbon taxes. Anticipating lower carbon taxes in the future, firms reduce their investments in clean technology development because the lower carbon tax will reduce the future profitability of these investments. Thus, advancements in geoengineering technology can lead to underinvestment in socially valuable mitigation technologies. This logic need not only apply to geoengineering. Any technological advances that reduce economic harms from a given change in temperature—from heat-resistant seeds to affordable sea wall technology—can reduce expected profits from clean technology investments.

The development of adaptation technologies is often cited as one rationale for limiting emissions regulation or public investments in clean technology. For example, in a meeting of the US House Committee on Science, Space & Technology, Committee Chairman Lamar Smith stated that the committee should "look to technological innovations that increase resilience and decrease vulnerability to inevitable climate change" instead of imposing regulation (U.S. House Committee on Science, Space, and Technology 2018). In this telling, technology development will *inevitably* make the economic impacts of global warming less severe, reducing the need to reduce emissions today. Understanding how beliefs about the current and future potential of adaptation technology shape decision making—by voters, politicians, and firms—could be important to explore. The quote referenced above may not represent a sincere belief and instead be political cover, but it nonetheless raises important questions: what *do* individuals believe about the potential impacts of climate adaptation technology, the timing of its development, and who will benefit? Is this variation in beliefs explained by actual differences in the potential of new technology to offset climate damages?

While these examples suggest that adaptation technology (or even beliefs about future adaptation technology) may reduce investment in mitigation, there may also be technological synergies between adaptation and mitigation technology. In their patent data analysis, Hötte and Jee (2022) find that 26% of climate adaptation technologies also facilitate mitigation; a large share of these are related to infrastructure, including the fact that greater insulation technology both maintains moderate temperatures during extreme weather events and increases energy efficiency. Another example is that more resilient crop varieties also tend to sequester more carbon. Other papers explore single technologies in greater detail, including work on how high-albedo roofing can also reduce temperatures (e.g., Bamdad 2023). Exploring the full set of interactions between adaptation and mitigation technology development seems like an important avenue for future research.

Adaptation technology development may also interact with *other mechanisms of adaptation*. These interactions could be important to take into account. For example, in the case of agriculture, Miao (2020) shows that crop insurance can mediate the extent to which technology development responds to droughts (i.e., the development of drought-tolerant crop traits). In particular, the study finds that the rise in innovation in response to drought is substantially reduced by subsidized crop insurance. This is related to other work showing insurance coverage reduces climate adaptation in US agriculture across the board (Annan and Schlenker 2015).

The response of innovation could be mediated by endogenous responses beyond insurance take-up. A number of papers suggest that production re-allocation (e.g., crop switching in the case of agriculture) could be an important mechanism of adaptation to climate change (e.g., Costinot et al. 2016; Rising and Devineni 2020; Sloat et al. 2020). On the one hand, production reallocation and innovation could be substitutes, meaning that fewer crop switching frictions could reduce innovation incentives, or alternatively, new technology development may limit the need for production reallocation by reducing the costs of continuing to produce in the same place. On the other hand, new technology development may be required to adapt agricultural production to new land and facilitate the production of specific crops in areas where they had not been grown previously (see Olmstead and Rhode 2008, on this process in the US). To our knowledge, however, there is no work studying the interaction between these two main potential drivers of climate adaptation: production re-allocation and innovation (i.e., changing the production possibilities frontier).

5.5 Global Outlook: Who Benefits from New Adaptation Innovation?

A major question is who will benefit from adaptation innovation and technology development. The specific climate threats faced by different parts of the world are distinct, meaning that the technologies most useful for limiting economic damage will also be different. This suggests that not only the amount of adaptation technology *in general*, but also the *specific focus* of that new technology, will determine how it re-shapes the global impacts of climate change.

Most global innovation concentrates in a handful of wealthy countries (Boroush 2020) and the development of climate adaptation technology is no different (Touboul et al. 2023, see also Sections 3.3.1 and 3.3.4 on the concentration of mitigation innovation). Do innovators also respond unevenly to climate challenges and damages in different parts of the world? Moscona and Sastry (2023) show that while US innovation responds sharply to the cross-crop pattern of extreme heat exposure in the US — whereby technology development rises for crops that are most exposed to damaging climate trends — there is no evidence that innovation responds to damaging climate trends in other parts of the world, especially in low-income countries. Incentives pulling innovators toward investing in technologies that could allow farmers in developing countries to adapt to climate change seem limited or absent outside the US.

Still, a remaining possibility is that the technology developed in response to demand from US producers may itself also be relevant for adaptation in other parts of the world. While this may be true in some contexts, it does not seem to be the case in agriculture. One way to see this is to plot US crop-level exposure to damaging climate trends, either in the past or projected into the future, against crop-level exposure to damaging climate trends in other parts of the world. The relationship is essentially flat, implying that even the set of crops for which heat-resistant seeds will be in highest demand—never mind adapting those seeds to differing ecological conditions—is vastly different. This pattern may generalize to other sectors. For example, it seems unlikely that the high-cost sea wall approach studied by Benetton et al. (2025) could be implemented outside a small set of high-income cities.

Another example is related to disease outbreaks. Both slow-moving warming, which can shift the range of disease vectors and microbes, as well as extreme climate events, can lead to disease outbreaks (e.g., Zell 2004; McMichael 2015). Many emerging outbreaks take place in developing countries; however, research investment focusing on either treating the pathogens that drive these outbreaks or developing monitoring and warning techniques remains limited (Hotez 2016). Extreme weather warning systems are an important adaptation tool (see above); however, Linsenmeier and Shrader (2023) document that weather forecasts are substantially more accurate in rich compared to poor countries.

Zooming out from individual industries, Touboul et al. (2023) study the global diffusion of climate adaptation technology around the world. They make use of a new patent data classification system that enables the identification of all patented technologies relevant for climate adaptation (Angelucci et al. 2018), which makes it possible to track the development and international transfer of specific adaptation technologies using the patent family system described in previous sections. The authors show that while there has been a rise in the development of adaptation-relevant technologies since the 1990s, it has not outpaced overall patenting growth (i.e, there has not been a major shift toward adaptation-relevant innovation), and the vast majority of this growth has been concentrated in only a few countries. For example, 23.6% of inventors of adaptation-relevant patents reside in the United States, followed by Japan (15.8%), Germany (10.8%), South Korea (7.0%), and China (6.5%).

Moreover, this technology is rarely transferred across borders, especially to low-income countries: the cross-border patent transfer rate for adaptation technologies is lower than both the all-technology average or the average for climate change mitigation technologies, and patent transfer to low-income countries is virtually absent. This absence of adaptation technology diffusion to developing countries is particularly concerning in light of the fact that, as the authors show, they are often the places where the incidence of climate hazards, like extreme temperatures, is most severe.

One potential explanation for the slow or absent diffusion of adaptation technologies is precisely the role of "technology mismatch" described above. It is possible that adaptation technology developed in one environment is simply not applicable (or not as productive) elsewhere; this may be more true for adaptation, which may be more finely linked to specific production processes or climate threats, than for mitigation technology, which may be more general-purpose. Understanding the determinants of adaptation technology diffusion seems like an important area for future work.

Pavanello et al. (2021) and Davis et al. (2021) study international diffusion patterns of perhaps the most impactful adaptation technology to date: air conditioning. The spread of air conditioning can explain a large share of the decline in the temperature-mortality relationship in the United States (Barreca et al. 2016). However, air conditioning adoption rates remain substantially lower outside the United States, particularly in developing countries, especially in commercial buildings, where cooling systems may be particularly important for mitigating the effects of global warming on economic output and productivity. Pavanello et al. (2021) focus on large emerging economies—Brazil, India, Indonesia, and Mexico—and show that, within each country, temperature and income jointly predict adoption alongside education, urbanization, and dwelling quality. While projections suggest that tens of millions of households may be in a position to adopt air conditioning, current trends imply that access to electricity will be insufficient to support this higher demand for cooling.

Not all forces push in the direction of greater inequality in the availability of appropriate adaptation technology, however. One consequence of rising temperatures is that high-income, innovating countries will begin to experience some of the productivity and health threats that currently disproportionately affect low- and middle-income countries. This includes exposure to higher temperatures and extreme climate conditions, but also exposure to agriculture-damaging plant pathogens (Bebber et al. 2013) and to human diseases (Hotez 2018) that have historically not affected high-income regions. As global warming progresses, pathogen ranges shift to include new parts of the world where they previously did not exist. To the extent that global innovation concentrates disproportionately on threats to production and health that are present in high-income countries, this process might lead innovation to focus on a more common set of threats and lead to technology development with widespread benefits. Moscona and Sastry (2025) show that, in the case of agriculture, while pest and pathogen range shifts are likely to cause substantial disruption, they may also coordinate technology development around more globally-damaging threats to production that partially offset the negative direct effects of global warming on productivity. Much more research is needed to understand how innovation shapes the global economic consequences of climate change.

6 Frontier and Cross-Cutting Topics

This final section describes a series of topics about which there has been less research to date but that strike us as important areas for future work. These topics are related to themes that cut across previous sections of the chapter and are at the center of ongoing political and economic debates about climate change and technology.

6.1 The Direction of Clean Technology

A broad range of different technologies and potential technological pathways underlie the "green technology transition." Most work to date has focused on understanding drivers of innovation in clean versus dirty technologies, both in theory and in practice. Much less attention has been devoted to understanding *which* clean technologies have been the focus of innovation, why certain technologies have been favored over others, and what the optimal distribution of innovation across clean technologies and energy sources "should" be. Especially as "green industrial policy" becomes more common around the world (see Section 4.2), answering these questions will become crucial.

Section 3.1 describes the wide range of technologies that can reduce reliance on fossil fuels—while some are substitutes for one another, meaning that success in only one is required for reducing carbon use in that particular area, others rely on complementary knowledge or are linked in complicated supply chains that reduce reliance on carbon only when functioning together. Moreover, each particular technology area comes with its own uncertainties about the progression of future technological breakthroughs and future policy support or political backlash, all of which could have major effects on potential inventor profits and hence investment. Understanding how innovators navigate these questions, and the role of policy design in a context with many potential technological trajectories, strikes us as an important area for future work.

One feature of innovation that complicates answering these questions is the important role of knowledge spillovers. Existing work has focused on the impact of dynamic knowledge spillovers, and these effects have been documented at an aggregate level (for more detail, see Section 2.2.2). However, knowledge spillovers could vary drastically across technology areas and, moreover, they could be accompanied by cross-technology spillovers, where innovation in one area increases the productivity of future innovation in another. This full pattern of knowledge spillovers shapes the direction of innovation across different clean technology areas *and* helps determine the areas where policy intervention is most relevant. However, little is known about how this all works in practice.

A second feature of innovation that complicates answering these questions is the role of uncertainty, both about future technological progress and about future policy intervention (see Section 4.5). In a simple world with two potential sources of renewable energy that are substitutes for one another, the clear policy solution may be to focus innovation in one of the two sources in order to avoid duplicated innovative effort. In fact, models like Acemoglu et al. (2012) suggest that innovators themselves will endogenously focus on the technology area that is more productive. However, even in this simple setup, the answer is no longer so simple once certain technology areas may be subject to unexpected policy intervention or political backlash, at home or abroad. The recent and sudden policy reversal in US wind energy is a clear example (e.g., Gelles 2025). These policy swings are especially relevant given the stark political divides when it comes to renewable energy investments. Section 6.3 describes the complicated and changing policy landscape around critical minerals, which are key inputs for many renewable energy technologies. Volatility and policy-driven uncertainty in mineral supply translate directly into uncertainty about future technology costs.

Moreover, future technological progress may alter which clean technology is most productive and lowest cost, thereby increasing the value of knowledge in areas that are currently less competitive. The future pace and scale of cost reductions remain highly uncertain, and experts have repeatedly underestimated the speed of decline in renewable energy costs. These underestimates can vary across technologies; for example, cost reductions in photovoltaics beat projections by a wide margin (Ghadim et al. 2025). Innovation therefore may become inefficiently concentrated in a few technology areas since innovators are unlikely to internalize the benefits their discoveries create after these future breakthroughs take place (Acemoglu 2011). These forces may justify spreading clean energy research across applications and for policy measures that limit the (potentially) inefficient concentration in a narrow set of applications.

Studying the forces that drive the distribution of innovation across clean technology areas is also important because, in practice, innovation across these areas does not act and react as a monolith. Technology development across different applications is subject to unique constraints, opportunities, and dynamics, all of which affect the direction of innovation. Nuclear energy is a clear example. Figure 16 presents trends over time in patenting of technologies related to nuclear energy across a range of markets. The rise in nuclear energy innovation during the 1970s and 1980s, driven in large part by Japan, when nuclear was seen as the future of energy production, was followed by a sharp decline following the Three Mile Island and Chernobyl nuclear incidents. In recent years, patenting in nuclear energy has taken off again, driven to a large extent by a state-led push and large-scale investment in China. This rise in

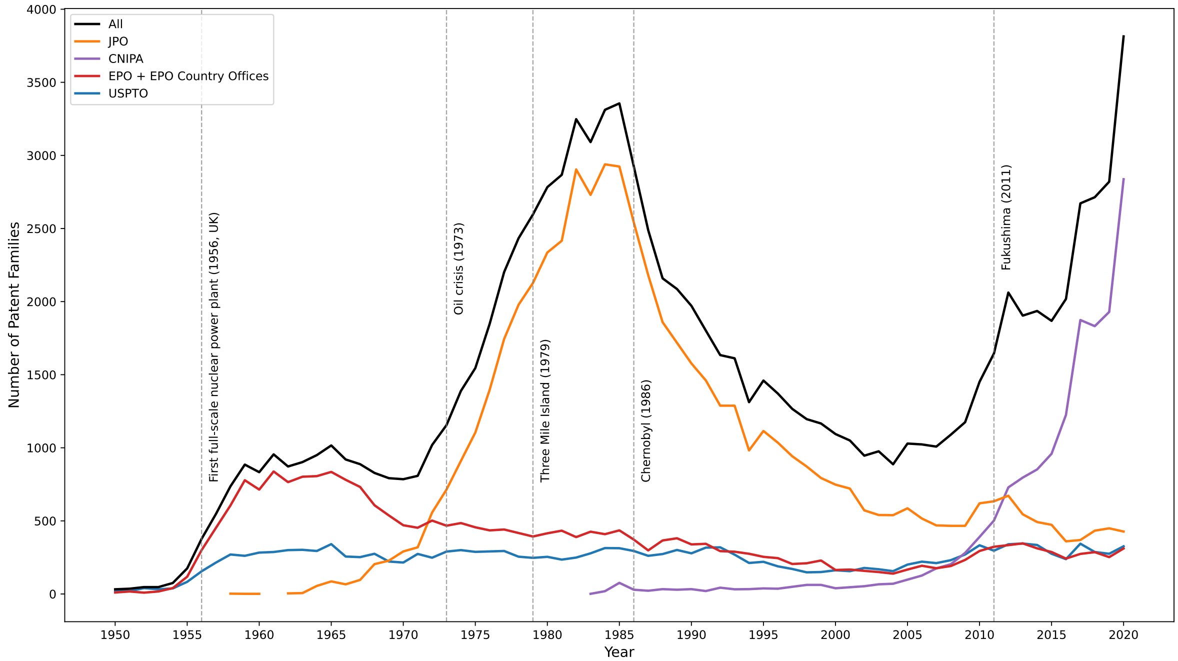


Figure 16: Nuclear Energy Patenting Over Time

Note: The figure reports counts of all nuclear patent families (PATSTAT DocDB), including domestic families, international families, and families that were never granted. Years correspond to the first filing year.
Nuclear patenting expanded rapidly from the 1960s through the 1980s, with a striking peak at the JPO. Much of this peak disappears when restricting to granted families, but Japan still dominates granted nuclear patents in that period. At the USPTO, EPO, and JPO, the basic pattern is robust whether we look at all applications, granted families, or international families: activity drops sharply in the 1990s after the Three Mile Island and Chernobyl accidents, then begins to recover toward the late 2000s before stabilizing at lower levels.
China follows a different trajectory. When considering all families or granted families, CNIPA filings rise extremely quickly from the mid-2000s. When focusing only on international families, the increase is steadier but still substantial: by 2020, Chinese international filings reach volumes comparable to those at the USPTO, EPO, and JPO. This contrast highlights the difference between China's very large domestic filing surge and its more measured—but still significant—internationally relevant nuclear innovation.
For details on patent data construction and processing steps, see Appendix A.3. JPO = Japan Patent Office; EPO = European Patent Office; USPTO = United States Patent and Trademark Office; CNIPA = China National Intellectual Property Administration.

China would likely have been hard to foresee in 2005, when nuclear patenting was at its nadir and patenting in China was well below that in both Europe and the US.

This pattern illustrates several features of energy innovation. First, it is subject to wide swings in market opportunities that are often specific to individual technology areas and challenging to anticipate—in this case, major shifts in public opinion and changes in top-down policy that may be more extreme than other areas of innovation and technology development. Second, while potentially conducive to substantial knowledge spillovers and learning by doing, concentrating innovative resources in one area comes with major risks. Japan concentrated a large share of its research investment in nuclear technology and, after the 1990s, its fortunes fell with that of the global market for nuclear energy (see Figure 6). Third, understanding the focus of innovation *within* each energy source may be as important as understanding the focus of innovation across them. Within nuclear energy, some advocate for concentrating investment in expanding conventional reactor development and deployment. This has been the major focus of investment in China. Others advocate for advanced and small modular reactors (SMRs)—the main focus of new US nuclear start-ups—which have a broader set of potential applications and could be mass produced at lower cost, but which rely on substantially newer and less-proven technology. This trade-off—versions of which exist across renewable technology areas—is challenging to quantify, especially given the large costs associated with delays in decarbonization.

More generally, each clean technology and energy source has unique market opportunities and (political) challenges. Certain parts of the world have high solar energy potential while others do not (and the same is true for wind). While nuclear energy provision is less reliant on local weather conditions, SMRs (should they eventually be deployed at scale) may be much more useful in remote regions where extending transmission lines is difficult or costly. They may also be attractive in contexts where financing large-scale reactors is prohibitively difficult. This financing challenge is present even in high-income countries, and is typically even more severe in low- and middle-income settings. Politically, both renewable energy and carbon-intensive energy sources are highly polarized in the US, with the former receiving substantially more support from the Left than the Right and vice versa (Leppert and Kennedy 2024). While nuclear energy receives largely bipartisan support (perhaps surprisingly, given its controversial history), political tensions remain when it comes to disposing of nuclear waste. How do all these forces combine to shape the focus of innovation across clean energy sources, up and down the supply chain? What should the optimal policy be in this complex technology landscape, taking spillovers and uncertainty seriously? How do political incentives across technology areas shape technological progress and the set of feasible policy interventions? These all seem like important questions for future research.

6.2 Economics of Clean Artificial Intelligence

6.2.1 AI as a General-Purpose Technology

Artificial intelligence shows the classic traits of a general-purpose technology: it is widely applicable, improves quickly, and reshapes complementary activities (Cockburn et al. 2018). Like electricity or the internet, it has the potential to transform how other technologies are developed and deployed. AI could help accelerate decarbonization by optimizing power grids, speeding up clean-tech research, or reducing waste. At the same time, it creates new demand for electricity, water, and critical minerals, and may also increase the productivity of fossil-based technologies. Recent work on the economics of AI cautions against overly optimistic projections. Productivity effects often arrive with a lag as organizations invest in complementary changes at the so-called productivity curve (Brynjolfsson and Li 2024). Simple task-based accounting also suggests that the macroeconomic impact depends on how many tasks are affected and by how much, not on headline model performance (Korinek 2024; Acemoglu 2025). This suggests that AI's climate significance will be shaped less by a sudden aggregate boost and more by the specific domains in which it is deployed.

6.2.2 AI and Energy Use

Energy use is the aspect of AI's environmental footprint that is drawing the most attention and concern. The energy use of AI is a fast-moving and uncertain space. Reliable estimates are difficult to come about, since companies release little data and models differ widely in their resource intensity. A widely circulated estimate suggests that training GPT-4 required around 50 GWh of electricity—about 0.02% of California's annual generation and more than fifty times the electricity needed to train GPT-3 (The Economist 2024).[19]

Once a model is deployed, inference typically dominates its lifetime footprint. Experts estimate that billions of daily queries mean that inference may account for 80–90% of total energy use (O'Donnell and Crownhart 2025). Recent disclosures from Google provide some of the first official per-prompt estimates of a major LLM. According to Google, the median Gemini text prompt consumes about 0.24 Wh of electricity, with associated emissions of 0.03 gCO_2e and 0.26 mL of water (Vahdat and Dean 2025). Google notes that this is roughly five to ten times more than a standard search query, but still comparable to running a light bulb for less than a minute.

The IEA estimates that global electricity demand from data centers, cryptocurrencies, and AI could grow from 416 TWh in 2024 to between 700 and over 1,700 TWh by 2035, depending on how things unfold (IEA 2025a). That's a wide range—roughly the difference between the annual electricity use of Brazil and all of Latin America and the Caribbean (Ember 2024). Still, even the upper end would be about 4% of global electricity demand in 2035 (IEA 2024h, Table A.3a, p. 299), less than what the world already uses for air conditioning, which was 2,111 TWh in 2022 (Ritchie 2024a). Yet the local and systemic effects can be large. Data centers are predicted to consume as much as 9.1% of all US electricity by 2030, with some regions like Virginia potentially reaching up to 50% (EPRI 2024). Modeling studies show that if AI growth outpaces grid decarbonization or capacity expansion, it could raise both electricity prices and emissions (Bogmans et al. 2025).

19. No data has been released by OpenAI itself; the number traces back to a simple back-of-the-envelope calculation (Minde 2023), based on the information that training reportedly cost about $100 million, lasted 100 days, and used roughly 25,000 NVIDIA A100 GPUs.

6.2.3 Environmental Impacts: Carbon, Water, and Materials

Carbon emissions—not raw electricity demand—are what ultimately matter for AI's climate footprint. A kilowatt-hour from coal has a vastly different impact than one from hydro, solar, or nuclear. In principle, the technologies to run AI on clean power already exist: firms can co-locate near low-carbon resources, invest directly in renewables and storage, or sign long-term power purchase agreements (PPAs) to guarantee carbon-free supply. Microsoft's deal to source electricity from the Three Mile Island nuclear plant is a striking example: pairing always-on zero-carbon generation with the fast-growing load from AI data centers (BBC 2024). Other cases, such as Iceland's geothermal- and hydro-based facilities, show that siting decisions alone can produce near-zero-carbon operations.

The central challenge is understanding the incentives that firms face. Will companies face the right mix of carbon prices, disclosure rules, and contractual opportunities to align AI expansion with investments in clean energy? For economists, this motivates several potential research questions. How effective are power purchase agreements (PPAs) and corporate procurement in driving additional clean generation, rather than simply reshuffling existing supply? What forms of carbon accounting—hourly, regional, global—most strongly influence firm behavior? Do carbon prices, tariffs, or grid-congestion charges provide efficient signals for siting and operating AI infrastructure? And what are the distributional consequences if clean-energy access for AI comes at the expense of other consumers?

Beyond electricity, other environmental costs are less well measured. Data centers often rely on millions of liters of water for cooling (Ren 2023), but reporting is sparse—the latest Google release being the exception. Hardware depends on critical minerals such as copper, gallium, and rare earths, most of which are mined in developing countries under weak environmental and labor standards (DOE 2023). Rapid hardware turnover creates mounting e-waste: AI-related infrastructure could generate up to 5 Mt annually by 2030, in a world where less than a quarter of e-waste is properly recycled. These lifecycle impacts are unevenly distributed and remain poorly integrated into most climate scenarios.

6.2.4 Will AI Accelerate Clean-Tech Discovery and Deployment?

AI is emerging as a potentially powerful enabler of innovation in climate technologies. In batteries, where development has historically been slow and empirical, machine learning can shorten discovery cycles from decades to years or even months. Models trained on large datasets of material properties now screen millions of candidates for electrodes and electrolytes, predicting stability, voltage windows, conductivity, and mineral criticality. In one case, AI-driven screening reduced a set of over 100,000 hypothetical battery materials to just a few hundred promising contenders within weeks (Dave et al. 2022). AI can also forecast degradation and cycle life from the first 100–150 charge cycles with about 9% average percentage test error, avoiding thousands of hours of testing (Severson et al. 2019). Robotic "self-driving" labs close the loop by autonomously synthesizing and testing new chemistries, as demonstrated in recent solid-state electrolyte experiments (Chen et al. 2024; Yik et al. 2025). These advances not only improve performance but also help identify alternatives to scarce minerals like cobalt and nickel, expanding the frontier toward sodium-ion and long-duration storage options (IEA 2025a).

AI may also help optimize energy systems already in place. Grid operators are applying AI to forecast demand, integrate renewables, and rebalance networks in real time. The IEA estimates that such improvements could unlock up to 175 GW of global transmission capacity by 2030 without building new lines (IEA 2025a). AI is also being deployed to improve predictive maintenance for wind and solar fleets and to enhance efficiency in buildings and industry.

Energy demand from AI data centers could be a separate driver of clean technology development. Amazon, Google, and Microsoft are all making large investments in nuclear energy, motivated by demand for a powerful energy source without intermittency that can fuel AI data centers (Penn and Weise 2024). The long-run effect of new energy demand from AI on the direction of innovation remains to be seen.

It is unlikely that AI's benefits will flow only to clean technologies. Fossil-fuel industries are already experimenting with AI to optimize exploration and production, raising the risk that these tools could also reinforce carbon-intensive activities. At the same time, evidence from patent data shows that clean-energy technologies absorb AI knowledge spillovers more effectively than fossil-based ones (Andres et al. 2022; Verendel 2023). This asymmetry suggests that while both sectors will adopt AI, the relative gains may tilt toward clean technologies.

6.2.5 Rebound Effects

By increasing task efficiency, AI deployment could lead to rebound effects that increase overall energy demand. For example, the energy required per computation has fallen steadily with advances in hardware, software, and data-center operations (Cowls et al. 2021); yet efficiency does not automatically translate into proportional reductions in overall demand. As compute becomes cheaper, larger models are trained, queries multiply, and applications proliferate. The result is a potential rebound effect in which the realized savings are smaller than the engineering gains would suggest. These device-level rebounds are relatively well understood and can be represented in demand models using standard elasticities. Much harder to assess are the broader, system-wide rebounds. AI can reduce emissions in existing activities, for example, by improving grid management or logistics, while at the same time enabling entirely new services such as generative media, synthetic content, or autonomous assistants that add to energy demand. Whether these new uses substitute for existing activities or add to them remains uncertain. Reviews emphasize that such indirect effects could in fact be larger than the direct ones, yet they are rarely included in mainstream climate and energy models (Luers et al. 2024). For economists, the central questions concern how large these rebounds really are in practice, how elastic demand for AI services is across different sectors, at what point efficiency gains enable scale expansion rather than savings, and how indirect effects can be credibly represented in economic and climate models.

6.2.6 Evolving Policy Landscape

In principle, if electricity markets priced carbon fully and consistently, AI could be treated like any other source of demand. In practice, emissions remain underpriced, siting decisions create local bottlenecks, and voluntary pledges have not prevented rising data-center emissions. Governments have begun to act: Ireland and Singapore have paused new facilities in grid-constrained regions; California has introduced disclosure rules (Patrizio 2023; IEA 2025c); China has announced long-term clean-power targets (Enviliance 2023); and the EU AI Act embeds environmental provisions, including requirements for documentation of energy use (EC 2024). These efforts are fragmented, but they reflect a growing recognition that AI infrastructure is too significant to ignore.

A central question is what kind of information is most useful for guiding decisions. Industry currently reports metrics such as Power Usage Effectiveness (PUE)—the ratio of total facility electricity use to the electricity consumed by computing equipment. A PUE of 1.1 means that for every kilowatt-hour used by servers, an additional 0.1 kWh is consumed by cooling and other overheads. While widely adopted, PUE focuses only on energy efficiency within the facility; it says nothing about the carbon intensity of the power consumed, nor about the system-wide effects of data-center growth. Economists can help by assessing which metrics—PUE, emissions per unit of compute, or time- and location-specific carbon intensity—are most relevant for modeling demand, designing policy, and shaping incentives.

Beyond measurement, there are broader uncertainties. How can rebound effects, which are difficult to quantify, be incorporated into projections? How should mineral supply risks be accounted for, given the overlap between AI hardware and clean-energy technologies? What regulatory designs are adaptive enough to keep pace with rapid hardware change and deployment cycles? And how should labor and skills constraints enter the analysis, given the overlap between AI expertise and the needs of the green economy? Economists are well positioned to answer these questions. Developing forward-looking scenarios that integrate AI into climate pathways and models that capture both direct and indirect effects will also be essential. Only with such tools can policymakers judge whether AI is likely to accelerate decarbonization or reinforce existing constraints.

6.3 Critical Minerals

Critical minerals (CMs) are essential inputs for clean technologies such as batteries, wind turbines, and electricity networks. Their importance has grown as electrification accelerates: lithium, cobalt, nickel, copper, graphite, and rare earths now underpin the core hardware of the energy transition. Under the IEA Net Zero scenario, metals production is projected to increase in value by almost a factor of four, amounting to roughly USD 11 trillion between now and 2040. Boer et al. (2024) show that this would put transition metals on a par with crude oil in macroeconomic importance, with production values similar to those of the entire oil market.

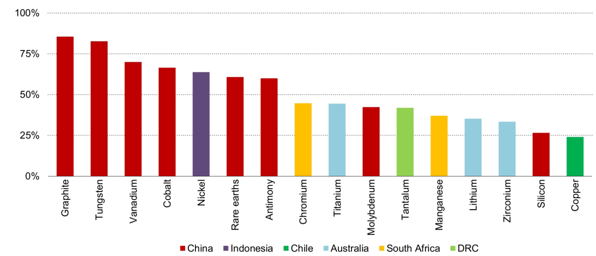
Recent data from the IEA (IEA 2024b, 2025b) confirm that clean energy technologies are now the main source of demand growth. From 2022 to 2024, clean energy accounted for most of the increase in demand for battery metals, roughly 70–90% of the total. In 2024, energy applications made up 62% of lithium demand, about one-third of cobalt and graphite, 29% of copper, and 17% of nickel. Projections show these shares rising quickly: by 2040 in the Net Zero scenario, demand from clean technologies more than triples, with lithium use rising more than tenfold and copper nearly twenty times.

Three points stand out. First, demand growth is rapid and policy-driven. Second, supply chains are highly concentrated, with more than 40% of strategic minerals having a single top producer responsible for over half of global output, and refining even more dominated by China (Figures 17a–17b). Third, prices are also highly volatile, often more so than oil and gas (Figure 17d), with recent boom-bust cycles across battery metals (Figure 17e). This all means that CMs are not only a technological input but also a source of macroeconomic and geopolitical risk. They will shape the trajectory and costs of decarbonization, while also raising fundamental questions for economics on innovation, political economy, and industrial policy design.

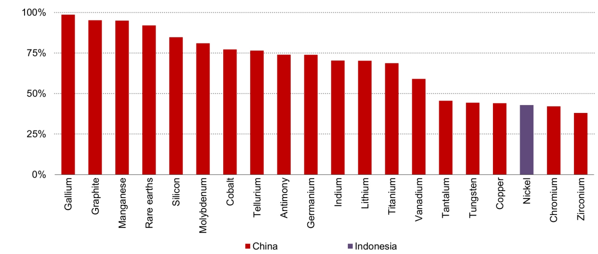
6.3.1 Supply, Concentration, and Geopolitics

Geographic concentration in critical minerals is extreme. If supply from the largest producer of any major mineral were disrupted, only half of global demand could be met (IEA 2025b). In over 40% of strategic minerals, a single producer accounts for more than half of global output (Figure 17a). Mineral refining is even more concentrated. China dominates nearly all of the twenty minerals analyzed, with an average market share of about 70%. The only exception is nickel, where Indonesia has leveraged its large reserves and heavy Chinese investment to move rapidly up the value chain (Figure 17b).

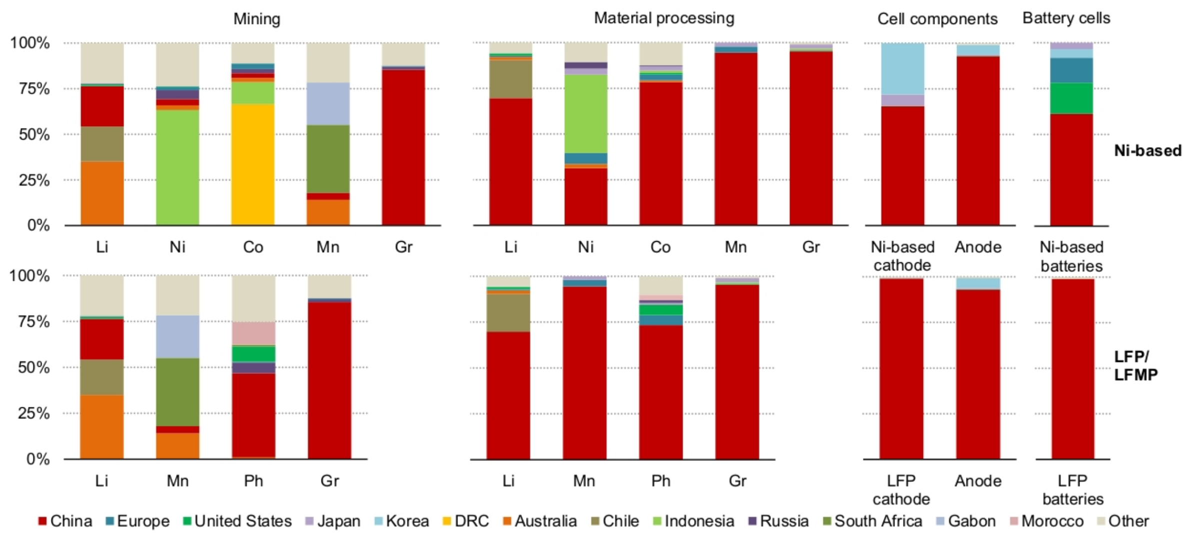
Concentration has deepened over the past two years (IEA 2025b). The lithium-ion battery supply chain illustrates the trend. Nickel-based chemistries, which use cobalt and nickel to achieve higher energy density, are still traded across global markets. In contrast, lithium iron



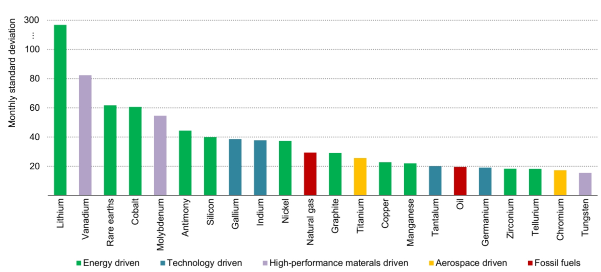
(a) Share of top producers in mining



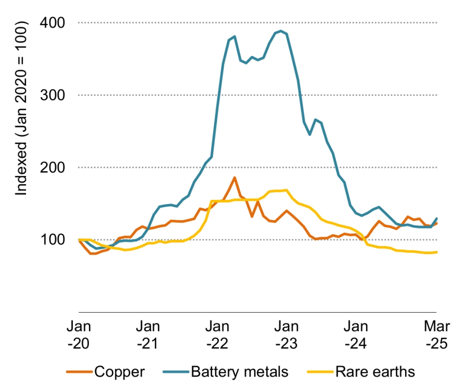
(b) Share of top producers in refining



(c) Geographical distribution of the lithium-ion battery supply chain



(d) Price volatility



(e) Price over time

Figure 17: Critical Minerals: Concentration and Volatility

Note: Reproduced from the IEA GCMO 2025. The specific page numbers are indicated below. Panel 17d (page 250) shows the monthly price volatility for selected minerals and fossil fuels, January 2014-March 2025. The IEA notes that due to data availability, the volatility values for some minerals were calculated over differing time frames: January 2020 to March 2025 for graphite, January 2018 to March 2025 for manganese, March 2017 to March 2025 for titanium, and September 2019 to March 2025 for indium. Panel 17e (page 19) shows the annual average price developments for selected minerals, 2020-2024 Panel 17a and 17b (page 251 and 252) show the share of top producers of, respectively, mined or refined energy-related strategic minerals. The IEA specifies that these are based on the most recent year for which data are available. On Panel 17a, the figure for silicon refers to silica mining; Gallium, germanium, indium, and tellurium are not shown as they are almost entirely produced as by-products. On Panel 17b, the figure for titanium refers to titanium metal; manganese to high-purity manganese sulfate, and molybdenum to ferromolybdenum. Panel 17c (page 209) shows the geographical distribution of the LFP and nickel-based lithium-ion battery supply chain for the year 2024. Ni-based = nickel-based cathodes. Li = lithium; Ni = nickel; Co = cobalt; Gr = graphite, Mn = manganese, Ph = phosphate; Material Processing: Mn = battery- grade Mn sulfate, Ph = battery-grade phosphoric acid, Gr = battery-grade graphite. DRC stands for Democratic Republic of the Congo.

phosphate (LFP) batteries—cheaper and free of nickel and cobalt, though lower in energy density and largely suited to smaller cars—have expanded rapidly. This growth has not diversified supply but instead reinforced dependence on China, which dominates LFP production (Figure 17c). Even in recycling—where new entrants might have been expected—most new capacity since 2020 has also been built in China.

This persistent concentration is reshaping the energy security debate. In the fossil fuel era, the clean transition was framed as a way to reduce dependence on oil and gas imports from specific foreign suppliers. Today, however, attention has shifted: the mineral supply chain itself has become a new source of vulnerability. The analogy with fossil fuels is only partial. Whereas oil and gas disruptions could halt flows overnight, minerals are embodied in capital goods, so existing BEVs or wind farms continue to operate. The challenge instead lies in scaling future capacity. For countries aiming to achieve net-zero emissions, this means that concentration threatens to slow the roll-out of clean technologies.

Evidence from scenario analysis reinforces this concern. Naegler et al. (2025) combine integrated assessment modeling with material flow analysis to construct indicators of supply concentration and weighted country risk. Their results show that while raw-material costs fall under ambitious decarbonization pathways, geopolitical supply risks remain high. This finding points to concentration as a structural feature of mineral supply, not a temporary bottleneck. It also raises a broader policy question: how should countries evaluate the trade-off between minimizing energy costs and limiting geopolitical risk?

6.3.2 Policy Responses

The geographic concentration of critical minerals has triggered a wave of industrial policies across major economies. Governments are using diverse instruments, ranging from traceability systems and recycling mandates to export restrictions and subsidies.

A relatively uncontroversial area is transparency and data sharing. A key example is the EU's new battery passport, mandated under the Batteries Regulation for all large-format batteries by 2027. The passport is a digital record that follows a battery through its life cycle, covering composition, critical mineral content, origin, performance history, and ownership. This improves prospects for second-life applications: accurate metadata on state-of-health can reduce diagnostic labor by up to 40% and lower liability barriers to repurposing and recycling (Weng et al. 2023; Rizos and Urban 2024). Implementation hurdles remain, however—data formats differ and firms remain cautious about sharing sensitive information—but the passport shows how industrial policy can support both resource recovery and market efficiency.

More contentious are export restrictions and subsidy-led strategies. Indonesia's nickel policies illustrate the former. By banning ore exports and requiring domestic processing, the country became the world's largest nickel refiner in under a decade, largely with Chinese capital and technology (Wu and Bird 2025). This secured greater domestic value capture but also reinforced global midstream concentration. China has extended export controls beyond minerals such as gallium, germanium and graphite to processing technologies themselves (IEA 2025b), raising supply risks and spillovers for downstream industries.

Subsidy-led policies are especially visible in the EU and the United States. The case of Northvolt, Europe's flagship battery start-up, illustrates the risks. Despite extensive public support, the firm filed for bankruptcy in 2024 after failing to scale production and reduce defect rates. Commentators have called it a modern "Solyndra moment," highlighting the dangers of betting on national champions without addressing structural cost disadvantages relative to incumbents in China and Korea (Milne 2025; Thomas 2025).

Policy responses are thus mixed. Initiatives such as the battery passport may strengthen supply chain efficiency and sustainability. Others, such as export bans and poorly designed subsidies, risk reinforcing concentration or wasting public funds. For economists, the central questions are: how should governments weigh diversification, efficiency, and competitiveness; what forms of industrial policy avoid "picking losers"; and how do measures in one jurisdiction spill over internationally, influencing innovation and comparative advantage elsewhere?

6.3.3 Price Volatility and Market Structure

Critical mineral prices are highly volatile. Across twenty strategic minerals, about three-quarters have been more volatile than oil and half more volatile than natural gas (see Figure 17d). The dynamics of the past few years illustrate this clearly. In 2021–22, demand for battery metals surged while supply lagged, triggering a sharp spike in prices. By 2023–24, however, new supply came onstream more quickly than expected, and prices fell back across many key materials (Figure 17e) (IEA 2025b).

These swings are rooted in the way critical mineral markets are structured. They are small, thin, and often opaque. Trade is dominated by bilateral contracts rather than deep, liquid exchanges; reliable benchmarks are missing for many battery-grade products; inventories are patchily reported; and variations in product quality further fragment already thin markets (IEA 2025b). Moreover, supply cannot respond quickly: projects involve long lead times and high capital costs, while many minerals are by-products of other ores, which severs their supply from movements in their own price. Geographic concentration further amplifies shocks, as disruptions in just a few places can ripple through global markets.

Volatility in raw material prices translates directly into volatility in technology costs and investment timing. A striking example came in 2021–22: the surge in mineral prices was large enough to halt—and even reverse—a decade-long decline in battery pack costs. For the first time in more than ten years, battery prices rose rather than fell. When mineral prices corrected in 2023, costs resumed their downward path, but not enough to return to their pre-surge trajectory (Kim 2022). With limited scope for rapid supply responses, Boer et al. (2024) show that Net Zero pathways could sustain "peak-like" prices unless new technologies and capacity are deployed quickly.

6.3.4 Innovation, Substitution, and Recycling

Innovation can help relax mineral bottlenecks, though the extent and direction depend on prices, policy, and research effort. It acts on two margins: raising supply elasticities upstream through better exploration, extraction, and processing, and lowering material intensity downstream via substitution, thrift, and reuse. Elasticities are not fixed technological constants, and they can be shifted by both policy and technology. As a result, uncertainty about their true values widens the set of plausible possible future scenarios and complicates modeling. A simple illustration is lithium, where combining right-sizing of EV batteries, alternative chemistries, and recycling might be able to cut the projected 2030 demand pathway by roughly a quarter—close to today's production—without loss of service (IEA 2025b).

Dugoua et al. (2025) provide an overview of the role and scope for innovation across the supply chain of critical minerals. On the supply side, three types of innovation stand out. First, in discovery and extraction, new targeting techniques, advanced geophysics, and approaches such as direct lithium extraction promise faster and more precise identification of reserves. Second, in processing, low-carbon and modular methods—for example, hydrometallurgical routes for nickel and cobalt or improved rare-earth separation—can reduce permitting hurdles and allow plants to be deployed closer to deposits. Third, in process integration, technologies that improve coproduct recovery (gallium, germanium, indium) or raise yields make existing resources go further. Collectively, these innovations lower costs and, more importantly, shorten development timelines, steepening effective supply elasticities.

What makes these innovations powerful is not only their impact on expected costs but their effect on risk. Exploration tools that raise the probability of successful discovery reduce the variance of outcomes. Modular plants shorten lead times and reduce exposure to delays. Flowsheets built from proven unit operations lower the risk of failure when scaling from pilot to commercial production. And coproduct recovery diversifies revenues, dampening the exposure to swings in any single market. For firms, these reductions in uncertainty can matter more than small shifts in average costs: a project with a shorter and more predictable payback horizon is far likelier to attract investment.

On the demand side, substitution and thrift are already shifting exposures. Lithium iron phosphate (LFP) has spread rapidly, lithium–manganese–iron phosphate (LMFP) is emerging, and sodium-ion is entering early niches. Motor and magnet designs economize on dysprosium and terbium, while copper thrifting and high-voltage DC grids reduce the metal intensity of transmission. These shifts do not remove dependence; they relocate it to different minerals and stages of the chain, creating new geopolitical and price risks. For firms, the challenge is portfolio management: balancing exposures across chemistries and platforms when both prices and policy signals are volatile. Analyzing these decisions requires linking engineering substitution possibilities with stochastic price and policy paths, and studying how firms hedge through contracts, product design, and geographic diversification.

Recycling represents a third lever. High-temperature and hydrometallurgical routes are scaling, and design-for-disassembly together with traceability initiatives (such as battery passports) reduce frictions for reuse and second-life applications. But two frictions are structural. First, feedstock arrives with a lag, as products reach end-of-life only after years in use. Second, growing chemistry diversity fragments the scrap stream, lowering average value-in and raising sorting costs, especially as cobalt content falls. This makes recycling uniquely sensitive to the combination of volatile prices and shifting policy incentives: while innovation clearly responds to shocks, uncertainty about direction can create moving targets for R&D.

Evidence on induced innovation confirms that innovation responds strongly to shocks. Alfaro et al. (2025) studies Chinese export restrictions on rare earths and documents that these shocks spurred patenting and entry abroad in separation technologies and magnet substitutes. The mechanism is consistent with standard induced innovation theory: price and policy signals redirect inventive effort. Flynn et al. (2025) find that there is a substantial increase in mineral-specific innovation following a rise in political risk (e.g., internal conflict, military takeover) where that mineral's deposits are concentrated. Price volatility and the rapid pace of policy change—sometimes driven by rapidly-changing political events—combine to make mineral supply highly volatile and hence make the direction of induced innovation less predictable. Policy can accelerate innovation, but it can also create moving targets that dissipate effort or entrench lock-in.

Mineral projects are capital-intensive and highly exposed to price swings, which makes downside risk a central barrier to investment in new technologies and capacity. For innovation to take hold, firms need a more predictable revenue horizon. One possible avenue comes from electricity markets—especially wind power in the UK and Europe—where contracts for difference (CfDs), cap-and-floor schemes, and proxy revenue swaps have been used to stabilize cash flows, reduce financing costs, and still preserve market signals (Beiter et al. 2023; Ason and Dal Poz 2024; Kitzing et al. 2024). Whether such mechanisms can be adapted to critical minerals remains an open question. Options include long-term sales contracts that guarantee producers a minimum and maximum price linked to transparent market indices, or public price-support programs that cushion the revenues of first-of-a-kind refining and recycling plants. A key research and policy agenda is to identify which tranche of risk is most binding—exploration, scale-up, or commodity revenue—and to assess whether instruments of this type could ease those risks without imposing excessive fiscal cost.

6.3.5 Competing demand and strategic uses

The clean-energy transition is not the only major driver of critical mineral demand. A powerful combination of defense rearmament and AI infrastructure deployment is reshaping material markets, creating potential tensions with climate goals. Military and data-center hardware rely on many of the same minerals that underpin wind turbines, electric vehicles, and solar photovoltaics. This overlapping demand raises a key question: will it crowd out clean-energy deployment by straining already thin markets, or will it catalyze supply-chain expansion by anchoring investment?

Defense and AI are becoming major new sources of mineral demand. Military expenditure reached record levels in 2024, and AI-related investment is driving a rapid build-out of data centers and high-performance computing. Both sectors rely on many of the same inputs as clean energy—rare-earth magnets, gallium and germanium semiconductors, titanium alloys, high-purity silicon, and copper—creating significant overlap. These pressures are already visible in policy: the US DoD is funding domestic rare-earth separation (IEA 2025b), and NATO has prioritized stockpiling and recycling of critical materials (NATO 2025).

Overlapping demand from defense and AI could either crowd out clean technologies by tightening supply in thin markets, or crowd in new investment by anchoring long-term offtakes and stimulating innovation (see Dugoua et al. 2025). Overlapping demand can crowd out clean technologies when sectors with a greater willingness to pay can raise prices and absorb scarce supply in thin markets, such as gallium or heavy rare earths. Defense procurement also secures long-term contracts or strategic reserves, effectively pre-empting capacity before civilian buyers can access it. Policy carve-outs—exemplified by China's restrictions on gallium and germanium—create segmented markets that raise transaction costs and limit coordination across supply chains. In such an environment, shocks transmit quickly, and the macroeconomic consequences can resemble those of oil or gas price spikes.

At the same time, several mechanisms could generate crowding in. High-value, state-backed procurement reduces investment risk and improves project bankability, encouraging new refining and recycling projects outside China. The 2025 US DoD–MP Materials agreement, which set a price floor and guaranteed long-term offtake for a new rare-earth magnet plant, illustrates how military demand can underwrite civilian supply (Sangita Gayatri Kannan and Lange 2025). Technological spillovers further blur the boundary between sectors: gallium nitride chips developed for radar now improve EV inverters (Oncea 2024; Rahman et al. 2024), while defense logistics chains built around traceability can pioneer standards later adopted in civilian recycling.

Which of these dynamics dominates depends on where AI and defense demand intersect with existing bottlenecks. Minerals such as gallium, dysprosium, and high-purity silicon are already under pressure due to limited refining capacity and geographic concentration, making them especially vulnerable to crowding out. Others, like lithium, are less affected because they are not heavily used in these applications. The implication is that governance of cross-sector flows—through monitoring, procurement design, and reserve-release protocols—will be crucial. Without coordination, clean-tech deployment could slow; with it, strategic demand might help diversify supply and stabilize investment.

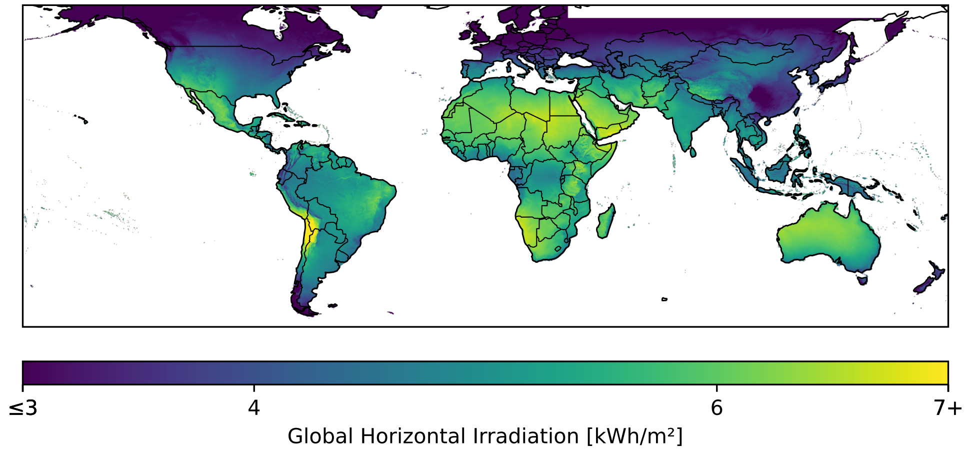
Looking further ahead, the frontier option of off-Earth extraction highlights the uncertainty of long-run supply. Launch costs have fallen by roughly a factor of twenty in the past decade, and some argue that continued declines could make asteroid or lunar mining technically feasible. Fleming et al. (2023) suggest that such a shift could sustain metal use while reducing terrestrial environmental and social costs. The economics and governance of space mining remain highly uncertain, but the debate illustrates the need to account for long-term options when designing today's supply strategies. Anticipation of future frontier supply could discourage near-term diversification, yet ignoring option value risks over-committing to expensive terrestrial pathways.

6.4 Global Winners and Losers from the Clean Energy Transition

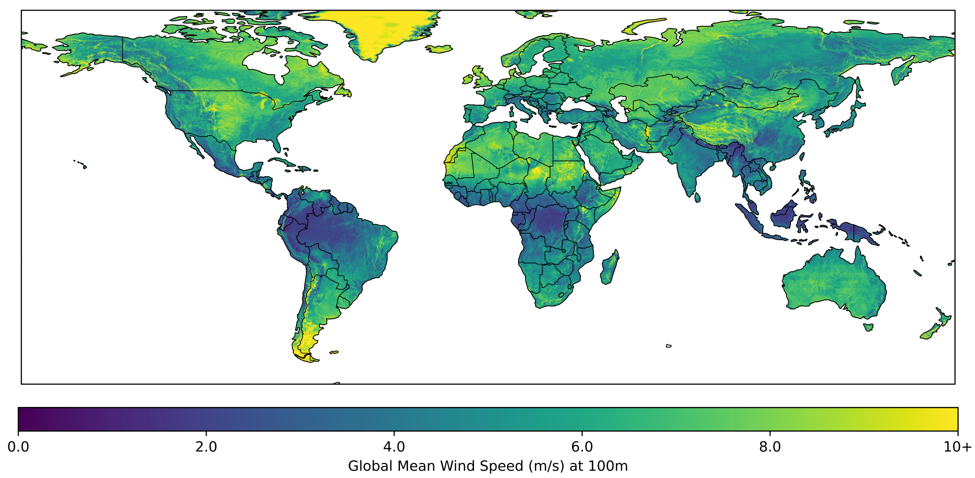
A global shift away from high-carbon sources of energy creates winners and losers, leaving certain nations well-positioned to profit from a transition toward clean energy. Government policy can further allow countries to exploit the potential opportunities of a clean transition for political or geopolitical gain. At the same time, other countries and interest groups, especially those with greatest control over the supply of dirty energy, stand to lose both revenue and international influence (Andres et al. 2023), and may respond with policies designed to curtail a global shift toward clean energy sources over which they would have little control.

There are two reasons that these issues should be at the center of research in climate economics. First, energy policy is deeply linked to geopolitics and security, both of which are referenced as a key justification for a majority of the policy changes described in Section 4. This link between energy policy and international influence is likely to only continue as geopolitical tensions rise. Second, the energy transition is among the most important forces that are shaping and will shape international relations and international politics over the coming decades. Environmental and energy economists are uniquely positioned to study this transition, combining an understanding of energy and resource markets with models of economic, political, and geopolitical incentives.

The energy transition shifts the key natural resources that undergird global production, and these resources are distributed unevenly both within and across nations. The global oil deposits that shaped international conflict during the 20th and early 21st centuries—and perhaps also the countries that control them—will likely decline in political importance (see e.g., Yergin 2020). They will be replaced, however, by new resources whose demand will grow



(a) Solar Energy Potential



(b) Wind Energy Potential

Figure 18: Renewable Energy Potential Around the World

Note: Panel 18a, reproduced from Global Solar Atlas, reports the long-term average of daily global horizontal irradiation (GHI) in kWh/m² for 1994–2024, based on the Solargis global solar model. Panel 18b, reproduced from Global Wind Atlas, measures Global Mean Wind Speed (m/s) at 100m.

with a transition to renewable energy sources. This includes mineral resources, described in detail in Section 6.3, which are key ingredients to almost every modern technology. It also includes access to renewable energy sources themselves, which varies across space and shapes the extent to which each region can generate local renewable energy. Figure 18 displays the global distribution of the geographic potential of solar and wind energy, driven by variation in solar irradiation and wind speed, respectively. While some regions could potentially harness both energy sources, others—including parts of South America, Central Africa, and Southeast Asia—have limited geographic potential in either. These differences in clean energy potential could shift the balance of economic power within countries and reshape energy dependencies across countries.

Natural resources themselves do not determine economic or political outcomes; instead, they interact with policy choices, political decisions, and state capacity, often in complex ways. While local mineral deposits may become a potential source of wealth, recent research has also shown that lootable mineral resources can cause large spikes in violent conflict, spurring political turmoil (Berman et al. 2017). Meanwhile, a peace agreement between the Democratic Republic of Congo (DRC) and Rwanda was secured with US backing in part due to the fact that the US was able to secure critical mineral access for US companies (Faucon et al. 2025; Mureithi 2025). More generally, mineral resources are increasingly being used as a bargaining chip in international negotiations (Chothia 2025). Thus, access to key mineral reserves may be a factor in global conflict in future years—and innovation will endogenously shape mineral reliance and the potential for substitution across different potential mineral sources.

While mineral resources themselves are essential, they are only the most upstream component of new supply chains that build clean technology. Through concerted policy intervention, China has gained control of a large share of the processing and refining stages of most minerals. Despite the environmental and health harms associated with these processes—one reason that little of this activity takes place in most high-income countries—China has achieved almost complete control of global mineral supply chains (see Figure 17).

Other countries are also drafting policies to exploit their mineral resources, which have grown in value in recent years. Indonesia, for example, is attempting to exploit its abundance in deposits of nickel—a key mineral for EV batteries—with an industrial policy aimed to develop a vertically integrated domestic EV supply chain, from mineral deposits all the way to vehicle manufacturing (Wu and Bird 2025). While this approach has already led (with large strategic investments from China) to the development of a domestic refining industry, the overall impact of Indonesia's nickel-oriented industrial policy (and others like it) is unclear. While essential for many batteries, nickel only represents a small fraction of the cost of EV production, and many EV models (including those that are gaining global market share) rely on alternative battery designs (e.g., lithium-iron-phosphate). Manufacturing competition from regional neighbors may also limit Indonesia's ability to compete in the downstream parts of the EV supply chain. Together, these examples highlight how geography and policy combine to shape the global consequences of the energy transition.

Beyond the role of natural resources, certain countries—due to a combination of targeted policies and early technological advancements—are already positioning themselves as technological leaders in clean energy production. Again, China is the best example of this (see Section 3.3.3). While the scale of China's renewable energy investments and the resulting cost reductions have accelerated the global energy transition, they are also leading large parts of the world—especially low and middle-income countries—to rely on Chinese infrastructure, technology, and energy. This grants China substantial geopolitical and geo-economic power, which it has already begun to exercise during international disagreements (e.g., Bradsher 2010).

Thus, China's rise may provide cheap and renewable energy for large parts of the world, and it also allows China to accumulate geopolitical power in a way that would not have been possible prior to the energy transition.

Other countries that lack domestic sources of fossil fuel are aiming to capitalize on the transition to a renewable-based energy system, where the ability to develop new technology may be (on the margin) more impactful when it comes to developing control of energy supply chains than was the case when most economic activity was dependent on oil (as the French saying dating back to the 1973 oil crisis goes, "We don't have oil, but we have ideas"). This is exemplified by large-scale European investments in hydrogen and solar investments in Japan.

Russia is angling to become a global leader in the provision of nuclear energy. In doing so, the government hopes to extend its geopolitical influence, and Russian plants are currently under construction in Bangladesh, China, Egypt, India, Iran, and Turkey, among several other countries (Mooney and Hancock 2024). Russia is also developing plans to help process the nuclear waste from countries that operate its plants; given that waste disposal is a key political obstacle to nuclear deployment, this is likely a very enticing deal, but one that comes with potentially long-term dependence on the Russian government.

While, in principle, a global transition away from fossil fuels should generate substantial global welfare benefits, competition over the control of that transition and the resulting economic and political gains may involve substantial conflict and new opportunities for coercion. Understanding the geopolitical impacts of the clean energy transition—including how policy and technology both shape and are shaped by political incentives—may be the most important area for future work described in this chapter.

7 Conclusion

This chapter has examined the economics of innovation, technology, and climate policy. We began with the microeconomic foundations of technological change, where multiple market failures interact to slow clean innovation. We then turned to macroeconomic models of directed technological change, which show how policy shapes the focus of new technology development and its resulting environmental impact. The following sections described the landscape of clean technology development and recent trends in the rate, direction, and geography of innovation. We then described adaptation technology development and its impacts before turning to frontier topics, including critical minerals, artificial intelligence, and the geopolitics of the energy transition.

This chapter's primary lens has been economics, with a focus on the role of policy in shaping incentives to develop and adopt new technology. We have surely left many important facets of technology and climate change unexplored. Some of these require bridging the gap between economics and other fields. For example, we provided a high-level taxonomy of mitigation technology, but did not attempt the detailed engineering or climate science assessments needed to judge technological feasibility, or model how the development of these new technologies interacts with climate projections. We did not delve into the political economy of policy implementation, where questions of vested interests, public opinion, and institutional structures determine which policies are adopted and maintained. Our treatment of consumer adoption emphasized economic concepts such as information asymmetries, but a richer account would also draw on sociology and behavioral science to explain how norms, cultural values, and cognitive biases influence technology uptake. Finally, while many sections referenced the interplay between geopolitics and the energy transition, we did not cover the international law and governance frameworks that regulate climate agreements, technology transfer, or trade disputes. Answering many of these questions will likely require cross-field collaboration and draw on contributions from political science, law, engineering, and other social sciences.

We hope the chapter is useful for scholars and policymakers curious about innovation, technology, or climate policy, whether new to the field or long engaged with it. Our aim is that readers leave with fresh ideas on how to apply the rich and expanding toolbox of economics to the broad set of important questions at the intersection of climate change and technology. The stakes are high, but with data becoming easier to collect and analyze, the scope for rigorous and relevant research has never been greater.

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A Data and Methodology

A.1 Sources for Table 1

Table A.1: The World in 2000 and 2025 vs 2050 (with sources)

Metric	2000	2025 ≈ 2023	2050 IEA STEPS	2050 IEA NZE
Global mean ΔT (°C)	0.6°C[1]	1.2°C[2]	1.9°C[2]	1.5°C[3]
Global GHG emissions (Gt CO_2-eq)	36.2 Gt[4]	53.0 Gt[4]		0 Gt $C0_2$ + 0.3 Gt CH_4[6]
Global CO_2 emissions (Gt)	26 Gt[5]	39 Gt[5]	36 Gt[6]	0 Gt (net)[6]
Top GHG emitters (As of 2023)				
China				
Total (Mt CO_2e)	5,243 Mt [4]	15,944 Mt [4]	6,356 Mt* [18]	
Global Share (%)	14.5 % [4]	30 % [4]	22.2 %* [18]	
Per Capita (t CO_2e)	4 t [4]	11 t [4]	4.9 t* [18]	
USA				
Total (Mt CO_2e)	7,203 Mt [4]	5,960 Mt [4]	2,016 Mt* [18]	
Global Share (%)	20 % [4]	11.25 % [4]	7 %* [18]	
Per Capita (t CO_2e)	26 t [4]	18 t [4]	5.4 t* [18]	
India				
Total (Mt CO_2e)	1,845 Mt [4]	4,134 Mt [4]	3,184 Mt* [18]	
Global Share (%)	5.1 % [4]	7.8 % [4]	11 %* [18]	
Per Capita (t CO_2e)	2 t [4]	3 t [4]	1.9 t* [18]	
EU27				
Total (Mt CO_2e)	4,481 Mt [4]	3,222 Mt [4]	746 Mt* [18]	
Global Share (%)	12.4 % [4]	6 % [4]	2.6 %* [18]	
Per Capita (t CO_2e)	10 t [4]	7.2 t [4]	1.75 t* [18]	
Fossil-fuel share of primary energy (%)	85 %[7]	81 %[7]	67 %[6]	20 %[6]
Renewables share of electricity (%)	18.30 %[8]	30 %[8]	55 %[6]	88 %[6]
Global oil demand (Mb/d)	77 Mb/d[2]	102 Mb/d[2]	97 Mb/d[2] - 105 Mb/d[6]	24 Mb/d[6]
Renewable capacity – total (GW)	800 GW[9] - 808 GW	4,448 GW[12]	23,217 GW[10]	33,178 GW[10]
Renewable Energy Breakdown				
Hydro (GW)	790 GW[11]	1,283 GW[8] - 1,410 GW[10]	2,027[13]	2,685 GW[13]
Solar (GW)	1 GW[14]	1,609 GW[10] - 1,865 GW[12]	16,445 GW[10]	15,468 GW[13]- 21,618 GW[10]
Wind (GW)	17 GW[14]	1,133 GW[12]	4,189 GW[10]	7,795 GW[13]
Top Countries by Renewable Capacity (As of 2023)				
Solar PV Capacity (GW)				
China	0.03 GW [15]	610 GW [15]	9,433 GW [18]	
EU27	0.18 GW [15]	257 GW [15]	1,078 GW [18]	
USA	0.59 GW [15]	139 GW [15] - 170 GW [18]	1,895 GW[18]	
Wind Capacity (GW)				
China	0.34 GW [17]	442 GW [17]	1,516 GW [18]	
EU27	12.3 GW [17]	219 GW [17]	597 GW [18]	
USA	2.4 GW [17]	148 GW [17]	528 GW [18]	
EV share of car sales (%)	0	18%[16]	25%[6]	100%[6]

*Only pertains to CO_2 emissions.

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A.2 Policy and Article Classification

A.2.1 Collecting Textual Data

The database used for source URLs of environmental policy briefs around the world is the Climate Change Laws of the world database (Radar 2025). This database contains metadata and links to national environmental policy briefs around the world since 1947. Using these URLs, we implemented an adaptive scraping pipeline using Selenium (Adam et al. 2025) that handles heterogeneous sources—direct PDF downloads and diverse HTML webpages—and extracts all textual content from the source URL. In the case of URLs relating to HTML webpages, the primary scraping package used was BeautifulSoup (Richardson 2007), and in the case of URLs relating to PDFs, the primary scraping package used was PyMuPDF (Artifex Software, Inc. 2025).

Given the large volume of text for each brief, the texts were then chunked using a semantic chunking strategy for at most 4,500 character-sized chunks. This approach splits each text into character segments, which are at most 4,500 characters long in semantically-coherent chunks. The algorithm does this by breaking the text into sentences, encoding them into embeddings, and computing cosine similarities between adjacent sentences. Semantic similarity is measured using the cosine similarity of textual embeddings by comparing the angle between their vector representations, where smaller angles indicate greater similarity. We selected a multilingual embedding model - paraphrase-multilingual-MiniLM-L12-v2 from the Sentence Transformers package (Reimers and Gurevych 2019) - to account for the non-English texts in our corpus. This step resulted in almost a million chunks for about ∼7,800 documents.

Once the texts were chunked, further processing, such as translating and cleaning for gibberish, required knowledge of the language of the source text. For robustness, we used two packages for detecting the source language of each chunk[20]: langid (Lui and Baldwin 2012) and langdetect (Shuyo 2010). To be overly-cautious, we considered as non-english any text which either package flagged as being non-english. If there was a contradiction in the original language, we prioritized the classification of langid.

After text preprocessing, we implemented a pipeline to detect and filter out gibberish, which often arises when non-Latin scripts (e.g., Chinese or Japanese) are misencoded, producing unreadable characters (mojibake). Another source of gibberish occurs in the presence of headers, footers or banners present in the source website or PDF. The pipeline combines character- and word-level heuristics with frequency statistics: each chunk is normalized to remove formatting or other unusual characters, then assessed by criteria such as unusual character and symbol character ratios, long consonant runs (for Latin scripts), and word frequency profiles based on Zipf scores[21] from the wordfreq library (Speer 2022) across a defined set of languages. A chunk was flagged as gibberish if these measures crossed set thresholds, with the overall stringency-related parameters determined through extensive trial and error on random samples of the dataset. For this task, source language identification was necessary as word frequencies vary across languages; without constraining to the appropriate language set, valid sentences in languages like Finnish could have been misclassified as gibberish when judged against English norms.

Once the chunks were filtered for gibberish, we implemented an automated translation pipeline to translate non-English text into English using the GoogleTranslator interface from the deep-translator package, which accesses the Google Translate API (Google). This marked the final stage of the pre-processing pipeline.

A.2.2 Classification

To classify environmental policy documents into three categories—market-based instruments (MBIs), non-market-based instruments (NBMIs), and technological support (TECH) — we first generated labeled data using DeepSeek's API. We designed the following context and structured prompt that asked the model to return binary dummy variables for each type of environmental policy instrument, along with a short justification note. Before designing the

20. The language detection was made at the chunk-level, as many documents contained text in several languages.

21. Zipf scores are a way of expressing how common a word is in natural language, based on Zipf's law which says that a few words make up most of language usage, while most words are rarely used.

prompt, we consulted DeepSeek for its interpretations of the instrument types and found its definitions sufficiently clear, removing the need to explicitly define them in the output structure and reducing attention due to a lengthier prompt. The final prompt design was as follows:

```
You are an expert in environmental policy.

Classify the input text into three possible categories:
- Market-based instruments (MBIs)
- Non market-based instruments (NBMIs)
- Technological support (TECH)

Rules:
- For each category, output a dummy variable: 1 if present, else 0.
- Return a single CSV row with the following columns in order:
  dummy_mkt,dummy_non,dummy_tech,notes
- The first field (row_index) will be added by the caller; you should not include it.
- Use only 0/1 for the dummy flags. Keep notes concise (<= 120 characters).
```

User Prompt:

```
Classify the following text:

Text:
---
{chunk}
---
Return exactly: dummy_mkt,dummy_non,dummy_tech,notes
```

This request was run iteratively on a representative subset of the dataset—spanning multiple languages, countries, and time periods — across five days. This process yielded ∼18,000 labeled text chunks that served as a training dataset for fine-tuning a pre-trained Large Language Model (LLM). We then fine-tuned a RoBERTa model[22] on this labeled dataset, training it for two epochs. Training and validation losses both decreased between the first and second epoch, suggesting the model was learning without overfitting; we stopped after two epochs to avoid the risk of overfitting. Performance metrics for RoBERTa showed that strict subset accuracy (requiring all three labels to be predicted correctly) reached 54.2%, substantially above the 12.5% baseline expected by random guessing. Micro and macro precision–recall–F1 scores indicate the model was conservative, tending towards false negatives more than false positives, which is arguably

22. This is a transformer-based language model, based on BERT, which was developed by Facebook AI.

appropriate for this policy classification context. We trained a single multiclass model instead of building separate binary classifiers, as it allows the model to learn shared patterns across classes and account for correlations between the dummy variables.

The final fine-tuned RoBERTa model was then used to predict the classifications of the three dummy variables for the unclassified text.

A.3 Patent Data

We use the **PATSTAT Global 2024 Spring Edition** (Version 5.23), a worldwide patent database maintained by the European Patent Office and available here. The dataset covers applications from all major patent offices and is designed for cross-country statistical research. We classify both energy and broader clean technologies, as well as fossil-based technologies, using a combination of Cooperative Patent Classification (CPC) and International Patent Classification (IPC) codes together with targeted keyword searches.

The classification has three parts:

1. *Energy/Clean technology categories*: high-level groupings such as solar, wind, hydro, geothermal, transport, industry, and other climate-relevant areas. See Tables A.2.

2. *Patent codes*: specific CPC and IPC codes, with keywords inclusion and exclusion rules to improve precision.

3. *Keyword queries*: Lucene-style search strings that capture fossil and other non-renewable technologies not fully covered by codes.

The detailed list of codes used is downloadable through our companion web application at https://patent-green-trends.streamlit.app/. These CPC and IPC code strategies build mainly on the CPC Y02 classification (Veefkind et al. 2012a), the IPC Green Inventory (WIPO) and the codes used in Dugoua and Gerarden (2025) and Dugoua and Dumas (2024). For identifying fossil technologies, we implemented the methodology described by EPO and IEA (2021). We also reviewed and completed our classification schemes based on prior work in this area (Aghion et al. 2016; Dechezleprêtre et al. 2013; Johnstone et al. 2010b; Lanzi et al. 2011; Popp et al. 2022).

The PATSTAT Global data are first restricted to invention applications, excluding utility models, designs, and other non-invention filings. Applications are then aggregated to DOCDB simple families, which group together filings that share the same priority set. This avoids double-counting the same invention when it is filed in multiple jurisdictions. The year of each patent family is defined as the year of the first filing among all applications within the family, regardless of the country of filing.

Table A.2: Patent Indexing Strategies for Clean, Dirty and Adaptation Technologies

Technology	Aggregate	CleanDirtyLabels
Solar	Renewable	Clean Electricity
Geothermal	Renewable	Clean Electricity
Wind	Renewable	Clean Electricity
Hydro	Renewable	Clean Electricity
Ocean	Renewable	Clean Electricity
Other Renewable	Renewable	Clean Electricity
Nuclear		Clean Electricity
Nuclear Fusion		Clean Electricity
Nuclear Fission		Clean Electricity
Smart Grids	Enabling	Clean Electricity
Other Energy Storage	Enabling	Clean Electricity
Oil and Gas Supply		Dirty Electricity, Dirty Transportation
Traditional Combustion		Dirty Electricity
Combustion Efficiency		Dirty Electricity
Coal Supply		Dirty Electricity
Gas Supply		Dirty Electricity
Electric Vehicles		Clean Transportation
Fuel Cells	Enabling	Clean Transportation
Batteries	Enabling	Clean Transportation, Clean Electricity
ICE Efficiency		Dirty Transportation
Oil Supply		Dirty Transportation
Internal Combustion Engine		Dirty Transportation
Hybrid Vehicles		Dirty Transportation
Non-Road Transport		Other Clean
Building Efficiency		Other Clean
Biofuels and Waste		Other Clean
Carbon Capture and Storage	Enabling	Other Clean
Other Enabling	Enabling	Other Clean
Chemical and Petrochemical		Other Clean
Hydrogen	Enabling	Other Clean
Clean ICT		Other Clean
Other Industry		Other Clean
Other Road Transport		Other Clean
Metals and Minerals		Other Clean
Monitoring Species		Adaptation
Adaptation All Health		Adaptation
Monitoring Water		Adaptation
Monitoring Weather		Adaptation
Adaptation All Indirect		Adaptation
Adaptation Diseases		Adaptation
Adaptation Pollution		Adaptation
Adaptation Food		Adaptation
Adaptation All Agri-Env		Adaptation
Adaptation Livestock		Adaptation
Adaptation Ecological		Adaptation
Adaptation Agriculture		Adaptation
Adaptation Infrastructure		Adaptation
Adaptation Water		Adaptation
Adaptation Coastal and Rivers		Adaptation
Adaptation Fisheries		Adaptation
Solid Waste		Waste
Waste Water		Waste
Bio Packaging		Waste

We define *international families* as those comprising applications filed in at least two distinct national jurisdictions. The European Patent Office (EPO) and the World Intellectual Property Organization (WIPO/WO) are not treated as separate jurisdictions, as they represent administrative filing routes rather than countries. Thus, a family with filings in France (FR) and Germany (DE) qualifies as international, while one filed in France (FR) and at the EPO does not.

The *country of origin* of a family is assigned in several steps. Ideally this is based on the address of the inventors, but these fields are often missing. When inventor information is unavailable, we fall back on the country of applicants. To improve coverage, we merge in two external datasets: Seliger et al. (2019), which provides inventor-based origins up to 2014 and falls back on applicants where needed, and Seliger and de Rassenfosse (2020), which adds applicant country codes for 2015. For the remaining families with no recorded origin, we assign the country where the first filing in the family was filed.

For *foreign-oriente* families, we follow the World Intellectual Property Organization (WIPO) definition: a family is foreign-oriented if at least one member is filed at an office outside the family's country of origin. Patent Cooperation Treaty (PCT) receiving offices are not considered, as they act only as intermediaries. Under this definition, a German-origin family with filings at the German office and the EPO is not foreign-oriented; it would need a filing at another national office, such as in France or Italy, to qualify.

B Additional TRL Figures

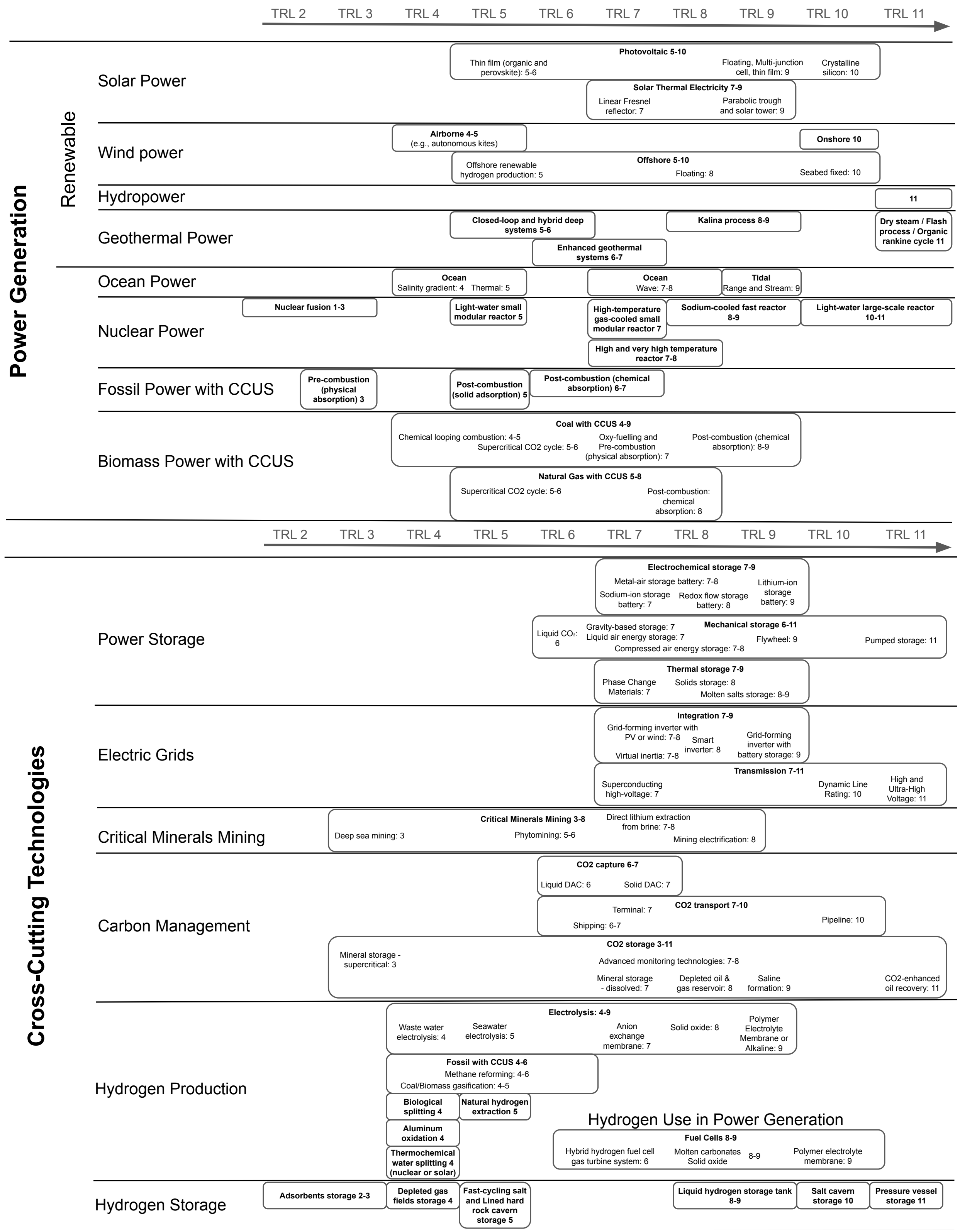

Figure A.1: Key technologies along the TRL Scale: Power and Cross-Cutting

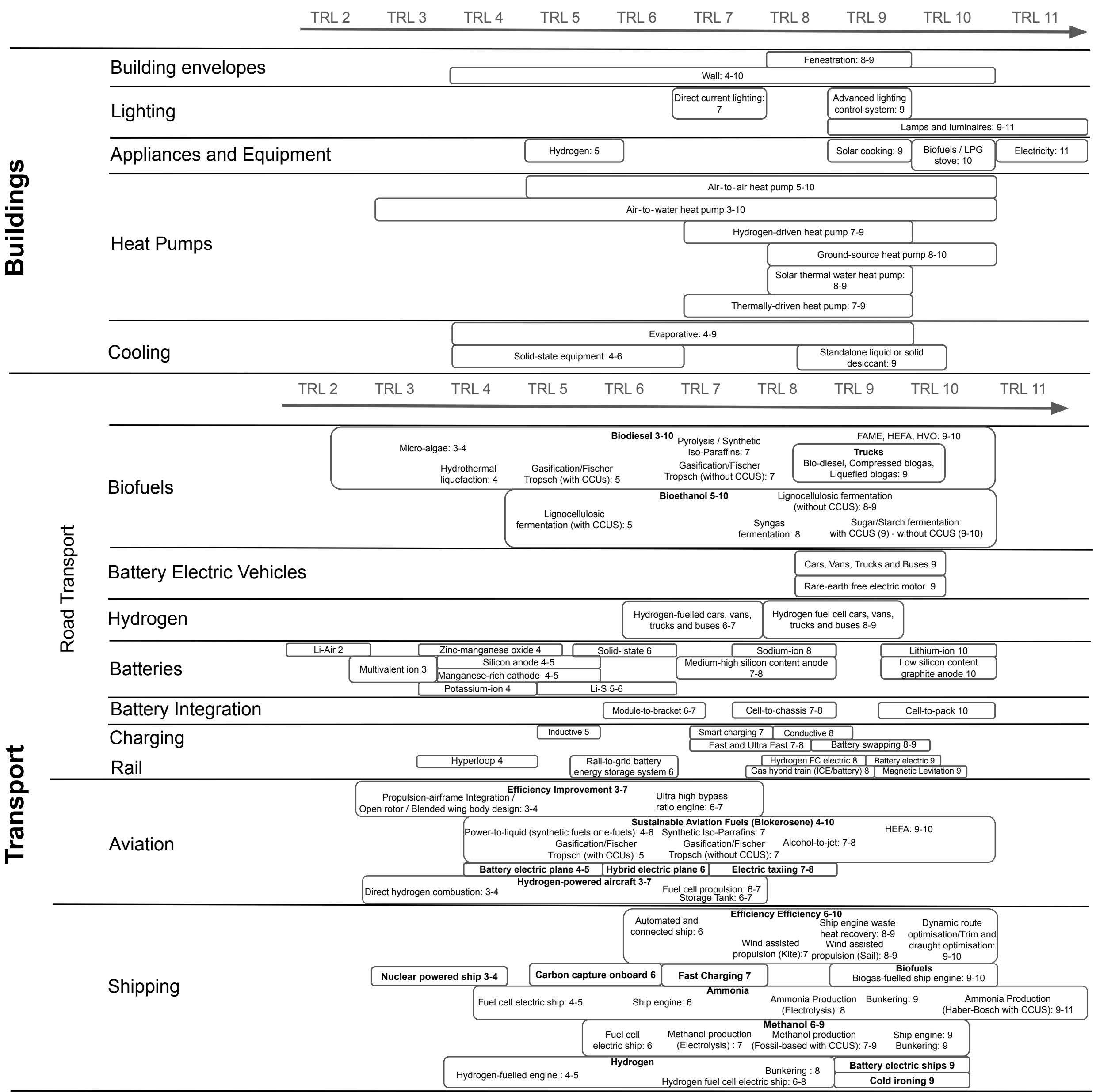

Figure A.2: Key technologies along the TRL Scale: Building and Transport

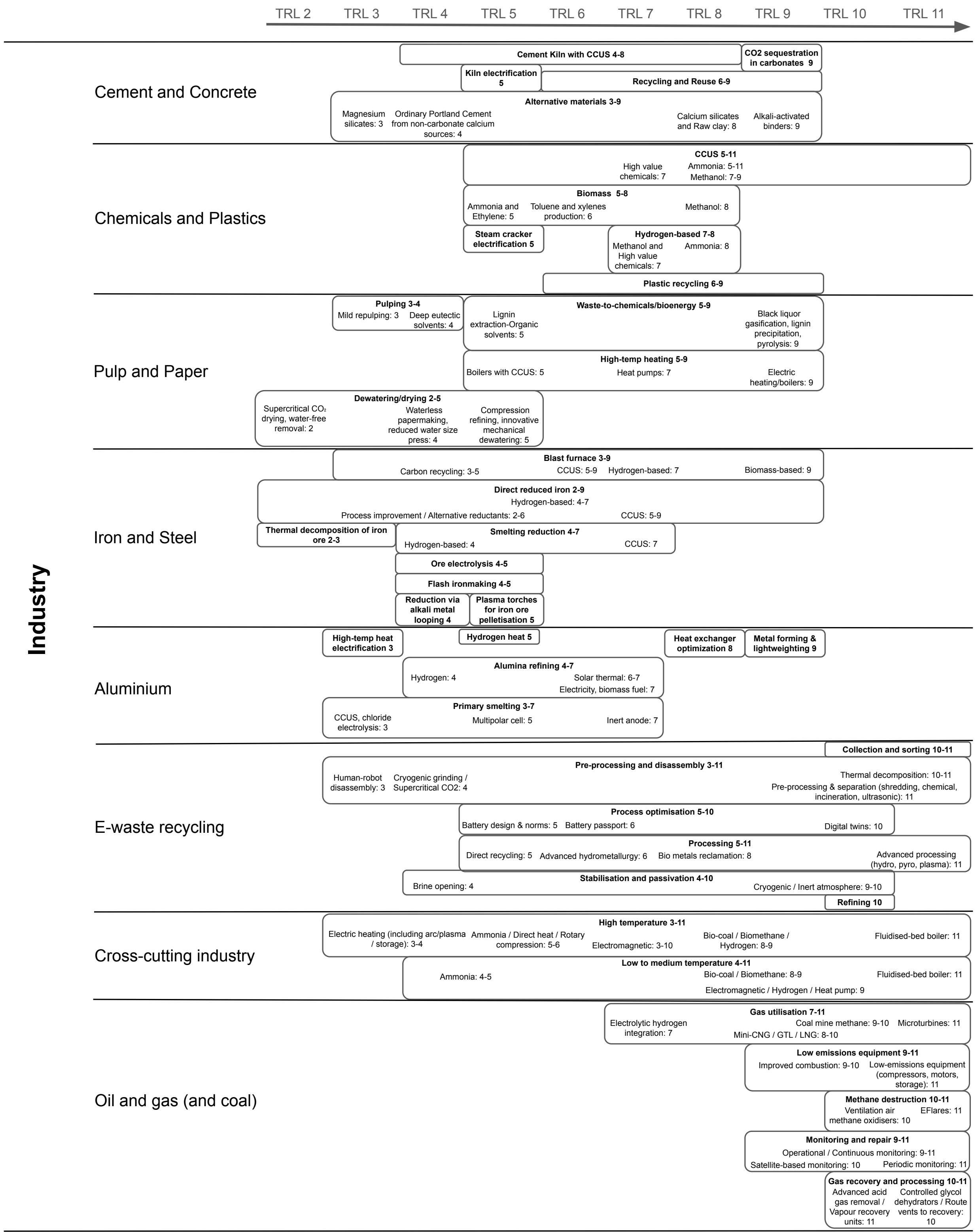

Figure A.3: Key technologies along the TRL Scale: Industry