Final Report

A Model for Clean Energy Innovation

How Corporate Buyers Can Accelerate the Development and Commercialization of Technologies Needed for Net Zero

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ABSTRACT

This report is designed to help guide corporate energy buyers seeking to accelerate the development and commercialization of technologies that will be needed in a zero-emission, reliability-optimized electric system. It develops an innovation model combining key questions and considerations to guide corporate decisions on interventions to accelerate the development of emerging technologies (Chapter 1). It is based on detailed case studies of the development of solar photovoltaic (PV) (Chapter 2), on-shore wind (Chapter 3), and nuclear generation (Chapter 4) technologies; a review of the literature on innovation; and an independent report on *Forecasting the Cost of Clean Energy Technologies* prepared by University of Cambridge Professor of Climate Change Policy, Laura Diaz Anadon (Appendix B).

The report explores the critical question: How can corporations accelerate the development and reduce the costs of technologies that will be needed in a low carbon future but today are not cost-effective or in widespread use and, in many cases, have not been demonstrated at commercial scale? Its analysis suggests that accelerating the development of these technologies requires looking beyond simple learning curves to better understand and influence the innovation process.

The report reviews the history of PV since its invention in 1954 and analyzes the factors contributing to the 90% reduction in PV costs since 2009. It discusses the development of wind technology, focusing on the period since the development of three-blade, upwind facing turbines in the late 1970s, and analyzes factors contributing to the recent 70% reduction in wind energy costs. We find that both the inference that "learning by doing" was a primary cause of these cost reductions and the claim that "any deliberate effort to scale up a new technology might reasonably be expected to lead to falling costs" are not supported by the available evidence.

The report examines the effects of purchasing strategies at different stages in a technology's development and the impact of market dynamics. It describes five distinct sets of technology characteristics and associated patterns of innovation. For PV, wind, and nuclear energy, we identify specific information exchanges that have the potential to be used, expanded, or optimized to accelerate innovation. Similar innovation patterns and opportunities may be available to technologies with comparable characteristics.

Accelerating the development of emerging technologies complements corporate commitments to reduce emissions and the support available for deploying clean energy following the 2022 Inflation Reduction Act. This report explores five high-level questions and several more detailed issues for corporate energy buyers to consider when evaluating opportunities to accelerate the development of emerging technologies.

Innovation is a process of gathering observations, analytical studies, developing prototypes to validate changes, demonstrations in an operational environment, gathering additional data, and incorporating new learnings. The report also recommends additional research on how improvements in data access and analysis, including virtualization and AI, have started and may be able to accelerate the tempo innovation, creating an emerging pathway we have called Learning by Feedback.

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EXECUTIVE SUMMARY

This report is designed to help guide corporate energy buyers seeking to accelerate the development and commercialization of technologies that will be needed to achieve a zero-emission, reliability-optimized electric system. It is based on detailed case studies of the development of solar photovoltaic (PV), on-shore wind, and nuclear generation; a review of the literature on innovation; and a report on *Forecasting the Cost of Clean Energy Technologies* prepared by University of Cambridge Professor of Climate Change Policy, Laura Diaz Anadon. Professor Diaz Anadon is the lead author for Working Group III on Climate Change Mitigation for the 6th Assessment Report of the International Panel on Climate Change (IPCC). We describe key questions and considerations for evaluating emerging clean energy technologies and interventions to accelerate their development.

Tabors Caramanis Rudkevich (TCR), with its partner ADL Ventures, Inc., prepared a companion report, *Strategies for Investing in Clean Energy Technologies,* that describes proven and novel ways to support the development and deployment of clean energy technologies. Together, these reports address how energy buyers can accelerate the development and availability of technologies that currently are not widely available or economically-competitive but may be needed to achieve a low carbon energy future. This approach is a complement to reductions in corporate greenhouse gas emissions.[1]

<u>Why Build an Innovation Model: The limitations of Learning by Doing</u>

Avoiding the worst impacts of climate change requires achieving net zero carbon dioxide emissions globally by the early 2050s, just 30 years from now.[2] Such a reduction in economy-wide emissions will need to rely on a zero-emission, reliability-optimized electric system that has been expanded to support the electrification of transport, heating, and industrial end uses, is resilient to the effects of climate change, including increasingly frequent severe weather, and remains affordable for consumers. While deployment of solar, wind, and battery storage technologies represents an essential step towards that objective, the further development of emerging technologies is also needed. The system will have to provide reliable, affordable power during extended periods of low wind and solar output. A critical question is: How can we accelerate the development and reduce the costs of technologies that today are not cost-effective or in widespread use and, in many cases, have not been demonstrated at commercial scale?

One unfortunately common answer is to increase the deployment of technologies that currently are not cost-effective. This suggestion is based on an inaccurate interpretation of learning curves – that deployment causes learning. A learning curve is a simple statistical correlation between historical production quantities and costs. It does not imply a causal relationship between deployment and cost

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[1] TCR also advises energy buyers on how they can increase emission reductions by selecting clean electric resources that will displace the output of the highest emitting electric generators based on long-term nodal and hourly forecasts of marginal emission rates. For an illustration of this strategy, *see* He et al., 2021.

[2] IPCC Newsroom Post, 2022; IPCC Summary for Policymakers, 2022.

reduction or that a further deliberate increase in the deployment of an early-stage technology will produce a corresponding reduction in its costs.

Most learning curve studies estimate a one-factor progress rate based on a correlation between cost reductions and cumulative deployment in a model that does not include other explanatory variables. Other two- or multi-factor studies include only a small number of additional variables. This approach has the advantage of simplicity but has little explanatory value. These studies have an "omitted variable bias." Omitted variable bias occurs when one or more explanatory variables that have been left out of the statistical model have a non-zero regression coefficient and are correlated with a variable in the model. Multiple factors, including research and development (R&D), economies of scale, input prices, collaborations, knowledge spillovers from other industries, technological advances, changes in global trade and manufacturing, and the accumulation of general knowledge over time, may reduce technology costs. By failing to consider additional variables, most learning curves significantly overstate the impact of deployment. Other studies have shown that time-based models (Moore's Law) perform approximately as well as models based on deployment.[3] This similarity suggests that it is difficult to distinguish the incremental impacts of deployment from that of variables associated with the simple passage of time.

The argument for deployment rests on an inference that cost reductions are the result of learning by doing. However, detailed bottom-up studies identifying the specific changes that reduced the costs of PV and lithium-ion batteries have found that learning by doing played little or no role in reducing their costs.[4] Other studies have identified learning by doing in the installation or operation of wind turbines. However, these studies found that the benefits of learning by doing did not persist over time, often did not transfer between projects, and, at least on their own, had little impact on producing non-incremental changes in performance.[5]

Moreover, two- and multi-factor learning curve studies that include variables for R&D or patent production (learning by searching) reduce the explanatory value of deployment. They reach a consistent conclusion that R&D is significant at all stages of technology development and generally makes a larger contribution than learning by doing.[6]

Accelerating the development of emerging technologies that currently are not competitive or widely deployed requires looking beyond learning curves and focusing on how to increase the pace of innovation. Innovation is a process of gathering observations, analytical studies, modeling improvements, developing prototypes to validate changes, demonstrations in an operational environment, gathering additional performance data from deployments, and cycling back to

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[3] Meng et al., 2021; *See also* Nagy et al., 2013 and Lafond et al., 2018.

[4] Pillai, 2015; Nemet, Beyond the Learning Curve, 2005; Kavlak et al., 2018; Trancik et al., 2020; Bollinger & Gillingham, 2019; and Ziegler et al., 2021.

[5] Nemet, 2012 and Anderson et al., 2019.

[6] National Academies of Sciences, Medicine, and Engineering, 2016; Jamasb, 2007; Rubin et al., 2015. *See also* Louwen et al. 2022 and Zhou & Gu, 2019.

incorporate new learning into the process. Accelerating the development of an emerging technology requires recognizing its stage of development and understanding the issues that need to be addressed to advance its development.

Buyer Strategies at Different Stages of Technology Development

Emerging technologies move through different stages of development. These stages are associated with Technology Readiness Levels (TRLs), originally a 9-level taxonomy that NASA developed for the space program. In 2020, the International Energy Agency modified and extended TRL classifications to 11 levels, recognizing that commercially available technologies may need additional development or support to be integrated into existing systems and broadly adopted.[7] Stages of development and related TRLs include:

- **Research**: Concept development and laboratory experimentation (TRLs 1 – 3)
- **Development**: Investigations of achievable performance, testing prototypes in laboratory conditions, validating components in semi-integrated systems, and producing and demonstrating early prototypes in a relevant environment (TRLs 4 – 6)
- **Demonstration**: Systems or prototypes verified in an operational environment, followed by production and validation of full-scale system in final commercial form (TRLs 7 – 8)
- **Deployment**: Early adoption occurs in this stage. The technology is commercially available and may have been deployed to multiple users, but needs evolutionary improvements to become or remain competitive and/or further efforts to enable its integration at scale
- **Diffusion**: At this point, the technology is mature, further growth is predictable.

It is important to distinguish technologies that are in the development or demonstration stages from those that have reached the deployment or diffusion stages.

For technologies in the development or demonstration stages (TRLs 4 – 8) and technologies that are far from becoming competitive, the primary focus should be on development, demonstration, and/or innovation to reduce costs and improve performance. Some early-stage technologies may benefit from moderate levels of deployment or sales in niche markets to generate revenue for continued development and test improvements. However, buyers and policy makers should be cautious about accelerating the deployment of early-stage technologies:

- **Subsidizing deployment of technologies that are not cost competitive can be expensive and unsustainable.** This happened with California's short-lived 1983 to 1985 standard offer contracts for wind generation and in Japan's early efforts to subsidize residential rooftop solar.[8]
- **Subsidizing deployment may divert resources from more productive R&D activities.** The 1983 to 1985 California wind subsidies coincided with a decline in wind technology patents.[9]

[7] International Energy Agency, 2020, *Energy Technology Perspectives 2020*.

[8] *See* chapter 3, section 3.3 and chapter 2, section 2.2.3.

[9] Nemet, 2009.

During the rapid growth of U.S. wind generation from 2004 to 2009, wind energy costs increased, and technology development stagnated.[10] Higher Feed-in Tariff prices under Germany's 2000 Renewable Energy Law (Erneuerbare-Energien-Gestz) provided over 200 billion euros in PV subsidies but, contrary to expectations, was not associated with an increase in patent activity.[11]

- **A rapid increase in deployment can disrupt supply chains and industry structures.** As European Feed-in Tariffs increased the demand for PV, the price of polysilicon, a basic input, spiked, resulting in a ten-fold price increase from 2003 to 2008. This price increase undermined the financial condition of the German PV firm, Q-Cells, which had been world's leading manufacturer.[12]

As an alternative to greater deployment, buyers should consider the use of prizes, conditional purchase commitments, advanced market commitments, and support for R&D including joint development agreements, test beds, and accelerator programs, as described in our companion report, *Strategies for Investing in Clean Energy Technologies.*

Deployment is a unique stage in a technology's development. If the technology is becoming competitive, additional deployment may induce entrepreneurs to increase their investments in R&D to become or remain competitive and create economies of scale, which in a competitive market may reduce prices. However, buyers need to be aware that in paying for accelerated deployment they may be assuming risks and costs that the technology's investors would assume in an efficient market without externalities.

Market Dynamics: Lessons Related to Risk and Displacing Incumbents

In the 1970s, global energy markets were disrupted by the Arab oil embargo and later reductions in oil supplies related to the Iran – Iraq War. Today, global markets face comparable disruptions and risks given Europe's dependence on Russian oil and natural gas, a Russian monopoly on the supply of the high-assay low-enriched uranium (HALEU) fuel needed for advanced reactors, China's dominance of the solar energy industry, the world's dependence on developing nations and China for critical minerals, and the potential impacts of a changing climate. Investors should take such risks into account both by seeking to develop a range of options and accounting for the real option costs of large capital-intensive investments.

The on-going transformation of the U.S. electric generation fleet – from one in which electricity was primarily provided by coal-fired generation to one powered primarily by natural gas, wind, and solar resources – illustrates the potential for rapid adoption of lower cost clean energy resources. At the same time, the continued operation of coal-fired generators that would be uneconomic at markets prices shows how incumbents can use regulation to protect their market share.

[10] *See* chapter 3, section 3.6.

[11] Böhringer et al., 2014; Böhringer et al., 2017.

[12] Nemet, 2019.

How Technology Characteristics Impact Progress

Based on our case studies of PV, wind, and nuclear generation, we identified five sets of technology characteristics, each associated with a typical pattern of innovation. These patterns may help identify opportunities to accelerate the development of technologies with similar characteristics. Table ES-1 summarizes the characteristics and related innovation patterns.

Table ES-1: Technology Characteristics and Innovation Patterns

Technology Characteristics	Typical Innovation Patterns
Modular – encourages component innovation, **Granular –** allows rapid low-cost experimentation, and **Mass-Produced –** enables economies of scale and knowledge being embedded in production equipment, e.g., PV modules, LED lighting	**Rapid:** Innovation occurs through: • Integration of scientific advances • Independent component innovation • Supply chain coordination and design standardization • Manufacturing process improvements • Economies of scale enabled by embedding knowledge in production equipment
Moderately complex standard platforms – many components, requires integration of key components, e.g., wind & gas turbines	**Moderate:** Innovation occurs in new models: • Basic design persists, e.g., three-blade, upwind facing wind turbine developed in 1970s • Integration of component innovations • Upscaling unit size • Standard platform adapted to varying conditions[13]
Customization of construction or installation – affects components and processes for multiple technologies, e.g., construction of large nuclear reactors, wind farm site work, installation of residential rooftop PV	**Variable:** Differences in conditions limit the transferable knowledge and can retard the diffusion of innovation • Equipment is modified to simplify installation • Workforce development
High design complexity – requires tight integration of critical components and system level design, e.g., nuclear power, commercial aircraft	**Long:** Innovation introduced in new standard designs: • Innovation requires lengthy periods of design, testing, and systems integration

[13] The term "platform" is used to identify a technology with standard configuration that can be installed in and adapted for different local conditions.

Technology Characteristics	Typical Innovation Patterns
High regulatory complexity – environmental, safety, and other regulatory issues affect design, deployment, and/or the ability to make changes, e.g., nuclear, potentially hydrogen storage at scale	**Impeded:** Designs & deployment plans subject to detailed regulatory requirements, review, and litigation • Designs and deployment plans are completed up front • Regulators may have access to design and/or testing

For PV, wind, and nuclear, we used these innovation patterns to identify specific information exchanges that have the potential to be used, expanded, or optimized to accelerate innovation. Other technologies with similar characteristics might benefit from comparable exchanges, although we have not extended our analysis to additional technologies.

Our approach differs from others[14] in that it is based on detailed case studies of key clean energy technologies and focuses on identifying innovation patterns and opportunities to accelerate the development of technologies with different characteristics.

A Model for Clean Energy Innovation

The 2022 Inflation Reduction Act significantly increased support for the deployment of clean energy technologies. If successful, such support could move the U.S. much of the way towards meeting its near-term carbon reduction targets. However, the possibility that tax credits may disproportionately benefit mature technologies, with the effect of locking out potentially superior emerging alternatives, underscores the value of a corporate clean energy innovation model.

The innovation model combines a set of key questions and related considerations to guide corporate decisions regarding interventions to accelerate the development of technologies needed for a zero-emission, reliability-optimized future. There are five high-level questions. Each should lead buyers to examine a set of additional considerations reflected in the framing of the question.

- Are the technologies that may be required to achieve a reliable zero-emission electric system being developed in a timely manner?
- What is the probability that a technology under consideration will successfully compete for a role in an affordable, reliable, low carbon future?
- Can the pace of innovation for this technology be accelerated, such that it can more effectively compete?
- What risks and unknowns could impact the technology's development and commercial opportunities?
- Considering the alignment of a broader set of factors, is the technology on a path that will enable it to be successfully adopted and integrated into the power system?

[14] *See* Abernathy & Utterback, 1978; Davies, 1997; Huentler et al., 2016; and Malhotra & Schmidt, 2020.

The last of these questions recognizes that a technology's adoption, integration, and widespread use depends on more than its cost and performance. Diffusion of the technology may require aligning organizational and supply chain capabilities, user preferences and demand, financial resources, regulation, industry institutions, standards and infrastructure and pursuing development paths along each of these dimensions. Additional questions are provided for technologies at different stages of development.

Greater data availability, improvements in information technology, and advances in modeling and virtualization may be accelerating the pace at which information and learning is exchanged and optimizing the tempo of innovation. This is a new innovation path that we call Learning by Feedback. It differs from Learning by Doing in that it relies on gathering sufficient data to analyze potential improvements but is not directly related to maximizing deployment. We suggest further research on this topic.

Case Studies: Solar PV, On-shore Wind, and Nuclear Energy

The report includes detailed case studies of the development of PV, on-shore wind, and nuclear energy. Each case study includes its own more detailed executive summary.

The study of PV traces the development of the technology from its invention at Bell Labs in 1954 and early applications in the space program to the present. It addresses the growth of Chinese PV firms, which today control more than an 80% market share at each stage in the production of PV modules. Chinese PV firms got started in the 1990s by importing talent, technology, and Western capital. They were prepared for and benefited from the growth of the European market in the 2000s. And, unlike leading PV companies in Germany and Japan, the Chinese responded to increasing silicon prices by developing their own domestic supplies. Starting around 2010 and coinciding with the increasing market share of Chinese PV companies, the industry experienced a rapid decrease in manufacturing costs, more than 15% per year on average. The reduction was driven by a combination of improvements in crystalline silicon PV technology and reductions in manufacturing costs. It reflected increased collaboration between manufacturing partners and even competitors facilitated by the development of a cluster of vertically integrated Chinese companies.

The case study of on-shore wind focuses on the period after the development in the late 1970s of three-blade, upwind facing turbines, which remains a basis for today's standard turbine platforms. It traces both technological advances and the impacts of deployment subsidies, noting that periods of accelerated deployment often have not coincided with improvements in the technology. For example, U.S. and, as a result, global additions of wind generation capacity increased dramatically from 2004 to 2009. However, this was also a period in which the per-megawatt cost of wind turbines increased and technological progress stalled. In 2012, a resurgence of technological improvements, accompanied by the reversal of a trend toward declining wind site quality, started a multi-year trend of declining average per-megawatt capital costs and increasing average capacity factors. Newer models were taller and had much wider rotor diameters, enabling operation at lower wind speeds. The per-megawatt capital costs also declined back to 2003 levels. After several years of steady decline, the average levelized cost of energy (LCOE) for U.S. on-shore wind generators has not decreased since 2018. This stagnation is a combination of two factors – the average capacity factor flattened out at about 40% and capital costs ceased to decline. Although experts expect a further decline in costs, it remains to be seen whether this reduction will materialize.

Nuclear is a highly complex technology, constructed on-site over multiple years, and subject to significant regulatory oversight. The case study for nuclear power examines industry experience across multiple countries. Costs have varied by country and period but have generally increased as more reactors have been deployed. The best case for controlling nuclear construction costs has been in South Korea. Korean nuclear plant construction has been undertaken by a single utility, sequentially constructing standard designs, in multi-unit facilities. For a time, this led to a small improvement in overnight construction costs, which do not include financing costs or reflect construction durations. However, when one accounts for the ten-year or longer construction durations of recent Korean reactors, doubling the construction durations of earlier plants, the trend is one of increasing total plant costs.

Forecasting the Cost of Clean Energy Technologies

Professor Diaz Anadon's report describes energy technology innovation as a complex adaptive process consisting of interconnected stages and feedbacks. She describes two main approaches to forecasting technology costs: expert-based approaches, which may be particularly valuable for emerging technologies in the early stages of the innovation process, and model-based forecasts, including models based on deployment or on time. Her report includes the following key observations:

- Given the complexity, interdependencies, and uncertainties characterizing technology innovation, energy technology cost forecasting should, when at all possible, be conducted on a probabilistic basis.[15]
- Using past data, when available, in a probabilistic manner, model-based forecasts have out-performed expert elicitation. Expert-based methods of forecasting energy costs have resulted in overconfident and in many cases pessimistic estimates.
- The use of model-based approaches does not imply attributing all improvements to learning by doing.
- Not all energy technologies evolve in the same way. Some of the differences may be attributable to changes in material or input costs, technologies having a high fraction of variable and fuel costs that experience increases because lower-cost resources are extracted first, differences in the characteristics of technologies such as complexity or granularity, or differences between the development of newer and dominant technologies within a particular category.

The report also summarizes recent research on patterns of innovation for technologies with different characteristics.

Organization of the Report

Chapter 1 describes key findings and guidance for corporate buyers seeking to accelerate the development of clean energy technologies. Chapters 2-4 present detailed case studies of the development of solar PV, on-shore wind, and nuclear technology, respectively. Supplemental data for

[15] Diaz Anadon, Appendix B; Diaz Anadon et al., 2017.

the nuclear case study can be found in Appendix A. Professor Diaz Anadon's report is attached as Appendix B.

CHAPTER 1: Building a Clean Energy Innovation Model: Lessons Learned from the Development of Key Clean Electricity Technologies

1.1: Introduction

Developing additional clean electric resources that displace the output of the highest emitting electric generators can accelerate emission reductions, increase reductions per dollar invested, and ensure greater cumulative reductions. Solar, wind, and battery storage have become increasingly cost-effective and can be sited and operated to reduce generation from higher emitting resources. However, solar, wind, and battery technologies alone are insufficient for meeting the requirements of an affordable, reliable, resilient, net zero energy future. Thus, the key question this project addresses is: How can corporate energy buyers supplement existing purchasing with targeted strategies that will accelerate the development, commercialization, and wider adoption of the additional clean energy technologies needed to achieve net zero emissions? To answer this question, we conducted a detailed review of the development of three key clean electric technologies: solar photovoltaics (PV), on-shore wind, and nuclear. We examined their development to better understand their varied outcomes, identify lessons learned that may be transferable to other clean energy technologies with similar characteristics, and provide an empirical foundation for developing a model of energy technology development and innovation. We complemented these case studies with an assessment of technology forecasting prepared by University of Cambridge Professor Laura Diaz Anadon. Professor Diaz Anadon also discusses drivers of innovation and the patterns of innovation associated with different technology characteristics. Using this background, we develop an innovation model and a set of considerations to guide corporate decision makers who are looking for opportunities to accelerate the development of clean energy technologies. These considerations can help buyers identify:

- Which new technologies are likely to develop in a timely manner, successfully compete to be part of a portfolio of clean energy technologies, and contribute to a low carbon electric system and a net zero energy future?
- When can actions by corporate buyers help to accelerate the development, commercialization, and wider deployment of needed technologies?
- What strategies could accelerate innovation and the development and commercialization of needed resources?

Corporate purchases and deployment incentives can increase the adoption of existing clean energy technologies that are mature and cost-effective. However, our focus is on accelerating the development and commercialization of emerging technologies that are not yet cost effective but that will be needed, in addition to solar, wind, and battery storage, in net zero energy future. Our objective is to find ways to complement existing government deployment incentives and encourage the development of additional strategies that target accelerating the development of these technologies. The case studies of solar, wind, and nuclear technologies and recent detailed bottom-up studies indicate that learning by doing has had a limited impact on the costs of solar, wind, and nuclear power.

Multi-factor learning curve models also suggest that the role of deployment and learning by doing are often overstated.

A modest level of early deployment, e.g., participation in a niche market, may be beneficial for some emerging technologies. However, rapidly accelerating their deployment may increase costs and divert resources from productive research and development activities. Moreover, large deployment subsidies have proven to be costly and difficult to sustain. We identify key considerations in this report and, in a companion document, describe approaches that support technology development while linking the achievement of development milestones to future purchase commitments.[16]

This report identifies five categories of technology characteristics that tend to exhibit different patterns of innovation and rates of progress. It treats innovation as a product of knowledge discovery, exchange, analysis, and application. The pace of innovation is a function of the speed with which information both moves forward in this process and cycles back through feedback loops to confirm earlier hypotheses and create new learning. For each technology that we reviewed, we identify information paths that, if optimized, could accelerate innovation. We describe and distinguish from learning by doing an innovation pathway that we call "learning by feedback," which can be facilitated by greater access to data and improved modeling capabilities and can be supported by carefully targeted strategies.

1.2: Why Build a Clean Energy Innovation Model

This transition to a net zero energy system presents multiple major challenges. The first is time. Corporate and national commitments have set the objective of achieving net carbon neutrality no later than 2050 – twenty-seven years from now. To put this in perspective, the first solar cell was developed by Bell Labs in 1954. It was not until 2016 that PV began to provide 1% or more of electric generation in the U.S.[17] The first electric wind turbines were developed in the 19th century and the earliest upwind facing three-blade turbines, comparable to the design of modern wind turbines, were built in the late 1970s.[18] Yet it was not until 2008 that wind turbines produced more than 1% of total U.S. electric generation.[19] The next generation of clean energy technologies needs to be developed, commercialized, and deployed much more rapidly.

Second, to achieve economy-wide decarbonization, the transition to clean energy must support widespread electrification of transport, building energy uses, and other current uses of fossil fuels. This could require a massive increase in our electrical infrastructure. Given the electrification needed

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[16] *See also* Tabors Caramanis Rudkevich, 2023. *Strategies for Investing in Clean Energy Technologies: Traditional and Novel Mechanisms for Accelerating Development and Deployment.*

[17] Chapter 2 – Case Study 1: Solar Photovoltaic

[18] Chapter 3 – Case Study 2: On-shore Wind

[19] EIA, 2011.

to meet carbon objectives, total U.S. electricity usage could be as much as two to four times current levels by 2050.[20]

Third, as the economy and essential end uses, including heating and transportation, become dependent on electricity, the power system will need to be highly reliable at virtually every location where power is being used. This will require compensating for the intra-day ramping and volatility of intermittent solar and wind resources as well as supplying power during extended periods of limited solar and wind output. In addition, the power system will need to adapt to the effects of climate change and be resilient in the face of increasingly frequent extreme weather events.[21]

Finally, energy must remain affordable. If prices or customer costs rise sharply, a backlash could thwart the achievement of clean energy objectives. Consumers, corporations, and societies have limited resources, which should be used efficiently.

Given this combination of challenges, it is appropriate to maintain a healthy skepticism with respect to simple solutions. We have heard the argument that since 2009 corporate purchases have driven down the cost of solar by more than 90% and wind energy by more than 70% and that purchasing 24/7 clean energy can have a similar transformative effect on clean firm resources.[22] However, the facts do not support the premise of this argument. Voluntary corporate procurement of renewable energy did not begin in earnest until around 2015, when the World Resources Institute and World Business Council for Sustainable Development's Greenhouse Gas Scope 2 Reporting Guidance allowed companies to use renewable energy purchases to offset emissions.[23] However, by 2015, the levelized cost of PV had already fallen from 2009 levels by more than 80% and wind by nearly 60%. By 2015, in Lazard's analysis, the unsubsidized levelized cost of new wind and solar was already below that for gas combined-cycle generators.[24] Corporate purchases did not drive but, rather, largely *followed* the reductions in solar and wind costs.

The argument is also being made that purchasing clean energy technologies that are not yet cost-effective will inevitably reduce their costs with every doubling of their cumulative deployment as emerging technologies inevitably ride down the "learning curve." One way in which the argument appears is in the form of unsupported assumptions that deployment will produce learning by doing, learning by doing has been responsible for the reductions in the cost of solar and wind energy, and that the same progress rates can be applied to other technologies. These assumptions are, in large part, unfounded and addressed in greater detail throughout this report.

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[20] Larson et al., 2021. This increase includes some flexible demand that could shift to off-peak periods.

[21] Electric Power Research Institute, 2021; Centolella et al., 2023.

[22] Jenkins et al., 2022; Jenkins, 24/7 Carbon-free Electricity Procurement: The Next Frontier?, 2022.

[23] Chapter 3 – Case Study 2: On-shore Wind

[24] Chapter 2 – Case Study 1: Solar Photovoltaics; Lazard, 2021.

The argument also appears with the invocation of "Wright's Law." This is named for Theodore Wright, an engineer who in the 1920s worked for the Curtiss Aeroplane and Motor Company. Wright recognized that as the Company's employees repeated the tasks, they became more proficient and the amount of wasted material declined. He observed that costs dropped more rapidly with initial repetitions and numbers of planes, then started to level off.[25] Because the trend line Wright found showed the relationship between unit cost and cumulative production, learning was assumed to be the main driver.[26] In the same article, Wright also commented on plant level economies of scale, noting that overhead costs initially fall as a percent of total costs as the size of a factory increases before, at some point, increasing with further expansion.[27] Later commentators, discounting the contribution of learning to declining manufacturing costs, briefly changed the name from learning curve to the manufacturing progress function. By the 1980s, it was being called an experience curve to better reflect the impact of technological change. Today, the terms learning curve and experience curve are often used interchangeably.[28]

Contemporary advocates have generalized Wright's observations on employee proficiency and plant level economies of scale far beyond the types of data on which they were based, stating, for example, "any deliberate effort to scale up a new technology might reasonably be expected to lead to falling costs. And remember that what matters for the learning rate is *cumulative* production, not time. The faster production doubles and doubles again, the faster costs ought to fall."[29] It may be reasonable to expect improvements in employee proficiency up to some number of task repetitions and plant level economies of scale within certain ranges. Economies of scale also may be found at a firm level. Larger firms can spread administrative and general expenses over additional units of production and can transfer production processes from one plant to another. However, as one shifts from employee productivity and plant-level analysis to aggregate experience curves for an entire industry, "the conceptual story begins to look stretched, as one must make assumptions about the extent to which experience is shared across firms. In the strictest interpretation of the learning by doing model applied to entire industries, one must assume that each firm benefits from the collective experience of all. The model assumes homogeneous knowledge spillovers among firms."[30] Why would individual employee learning and plant or even firm level economies of scale provide the causal basis for a statistical relationship between the doubling cumulative industry wide capacity and industry wide unit

[25] Wright, 1936.

[26] Grafström, 2021.

[27] Wright, 1936.

[28] Grafström & Poudineh, 2021. Some commentators limit their use of the term "learning curve" to changes in the unit cost of a specific product and use "experience curve" with respect to changes in the unit costs of industry output, including changes resulting from the introduction of new technology. Most sources do not maintain this distinction. Reflecting common practice, we will use the terms interchangeably and default to the term "learning curve."

[29] Harvey & Gillis, 2022.

[30] Nemet & Husmann, 2012.

costs? Why would learning by doing be related to megawatts of capacity rather than the number of units produced or installed? Why would economies of scale benefit from the doubling of cumulative capacity rather than increases in annual output? The logical gaps in the learning curve argument suggest the presence of missing links, which, if understood, might lead to superior strategies for accelerating the development of clean energy technologies.

The problem is that learning curves are simply a statistical association between historical production quantities and unit costs or prices. A statistical correlation does not necessarily imply a causal relationship. Because development of the curve starts with identifying a statistical relationship between cumulative capacity and unit cost and given that it is called a learning or experience curve, the inference is that deployment leads to learning and cost reductions. However, this inference is not well founded. First, this statistical approach creates an omitted variable bias. Multiple factors are contributing to the trends reflected in learning curves. However, if one or more explanatory variables are omitted from the statistical model, and they both have a non-zero regression coefficient and are correlated with a variable in the model, the learning curve will provide a biased result. To the extent a learning curve analysis does not analyze other potential variables, it risks significantly overstating the impact of learning by doing. Yet, most learning curve studies rely on a one-factor learning curve, based on cumulative capacity produced or installed, or on a two-factor or multi-factor learning curve that includes only a small number of additional variables. Factors such as increases in the knowledge stock produced by RD&D, exogenous technological advances, knowledge spillovers from other industries or technologies, deliberate initiatives to increase learning by interacting and knowledge spillovers between partners, unit economies of scale, production economies of scale, changes in the cost and use of material or labor inputs, changes in regulations or incentives, and other market dynamics often are not included in the statistical models. Data availability for some factors may be limited and, in the absence of sufficiently large data set, it may be difficult to address any collinearity among explanatory variables.[31] One- and two-factor learning curve models have the advantage of simplicity. However, given the potential impact of omitted variables it is inappropriate to assume that the doubling of capacity caused a reduction in costs or that further deployments will accelerate cost reductions. Second, one variable commonly omitted in learning curve studies is time. Yet, time-based models, following Moore's law, fit the data and provide forecasts that are very similar to those based on deployment or Wright's law.[32] The similarity of the two approaches indicates that it is difficult to distinguish the incremental impacts of changes in deployment from the exogenous accumulation of knowledge or other explanatory variables that are correlated with the passage of time.[33]

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[31] Samadi, 2018. *See also* Elia et al., 2021; Söderholm & Sundqvist, 2007.

[32] Meng et al., 2021; *See also* Nagy et al., 2013; and Lafond et al., 2018.

[33] Lafond et al., 2020 argues that the increase in the wartime production levels during WWII provides a natural experiment in which deployment contributed to cost reductions. They find that changes in war time production were associated, independent of time, with about half of the contemporaneous productivity improvements. However, the productivity improvements that occurred during the national mobilization to build, at virtually any cost, the ships, planes, tanks, and guns needed for the war effort may not be representative of the effects of

Third, both of these "model-based approaches explicitly use one or more variables from available observed data to approximate the impact of the full set of drivers of innovation on technology costs, implicitly assuming that the rate of change in the past will be the best predictor of the rate of change in the future."[34] This assumption may not be accurate: the rate of progress may change over time, be impacted by exogenous shocks, or simply reflect different combinations of drivers from one period to the next. Finally, as a technology becomes cost competitive in one or more market segments, causality may start to move in the opposite direction of the common inference, with affordable prices and price elastic demand causing an increase in deployment. Very few learning curve studies have tested for such a reversal of causality.

Given the objective of accelerating the development of pre-commercial energy technologies, it is essential to determine to what extent a change in the rate of deployment causes reductions in technology costs. To the extent deployment or learning by doing is merely statistically associated with but does not cause cost reductions, there is little reason to have faith that accelerating deployments will lower the cost of technologies that are yet not competitive. Additionally, if deployment has only an indirect effect, inducing other changes that lower costs, it may be possible to achieve the same cost reductions with a lower level of investment by targeting the direct contributors to reducing technology costs. A later section will examine what more detailed models tell us about the impacts of learning by doing.

An additional concern with the use of learning curves is unacknowledged uncertainty. Although studies have cautioned users to consider potential discontinuities and uncertainty regarding future learning rates, learning curves are often used to develop point forecasts without acknowledging these concerns. This is a particularly significant concern in longer term forecasts where a small change in initial data or assumptions may have a large impact over time.[35]

It may not be possible to fully separate the contributions of different innovation policies or to track all the relationships between different innovation mechanisms. Nonetheless, looking beyond single factor explanations, understanding the lessons of the past, asking key questions, and using the best available data are essential for accelerating the pace of innovation to meet climate objectives. Corporate buyers and policymakers face the specific question of how best to *accelerate* the development of emerging technologies that are not yet cost competitive but will be needed to complement solar, wind, and battery storage in a net zero energy future. The International Energy Agency has estimated that shifting to a sustainable path will require that 35% of cumulative CO_2 reductions come from prototype or demonstration stage technologies and an additional 40% from technologies that are not widely

subsidizing the early deployment of emerging energy technologies. Moreover, the authors note that available data, "does not allow us to evaluate deeper channels of causality. For instance, a higher productivity that follows a rise in experience can be due to direct learning by doing, or to any productivity-enhancing factor that tends to scale with experience, such as R&D."

[34] Meng et al., 2021.

[35] Nemet & Husmann, 2012; Nordhaus, 2009.

deployed.[36] In this context, acceleration requires increasing the pace of technological progress and cost reductions and doing so in way that is cost effective. Our objective is to look beyond learning curves to better understand the drivers of technology development and commercialization and how they might be influenced to accelerate the availability of technologies needed in a low carbon future.

1.3: Approach Part One: Case Studies

To untangle the factors that have contributed to cost reductions and advances in technology, we developed case studies of three key clean energy technologies. We examined technologies with different characteristics and histories to understand how such differences contributed to their varied outcomes and may affect the potential contributions of similar technologies. We considered how larger market dynamics and external events impacted their development. We were interested in studies on the impacts of purchases and demand subsidies at different stages in the technology's development and studies that sought to break out the impact of learning by doing from other factors.

Subsequent chapters present case studies of:

> **Solar PV:** PV is modular. The boundaries between its components can be clearly defined. This allows greater flexibility for independent component innovation and enables specialization. Throughout much of its history, this modularity enabled the development and use of global supply chains. However, in the last decade Chinese companies have dominated PV production and created a cluster of vertically integrated firms. This cluster has fostered standardization and facilitated the exchange of knowledge within and even between competing firms. PV is also granular, composed of small-scale cells and modules that are assembled into larger arrays and facilities. This granularity enables rapid, low risk experimentation. The production of billions of units creates opportunities for rapid learning. Granular technologies – technologies that are available in smaller units, have lower dollar per unit investment costs, are modular, and scale through repetition – allow innovations to be more easily introduced and are associated with faster learning.[37] Finally, PV modules are a manufactured technology. Many of the lessons learned in one factory can be embedded in production equipment and readily transferred to a production facility somewhere else. This enables major suppliers to benefit from economies of scale. Parts of our analysis focus on the more cost-effective utility-scale installations. However, we note that residential and small commercial rooftop installations may require customization and create opportunities for learning by doing among local installers.
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> **On-shore Wind:** Wind turbines are a moderately complex technology. They have many components and a significant level of design integration. Some key components cannot be readily modified without changing other components of the design. For example, a turbine manufacturer generally cannot install a longer blade without reengineering other parts of the turbine, such as the gearbox and bearing components. Significant changes are implemented by developing a new model of an otherwise standard turbine platform. Wind turbine technology has advanced through the integration of component innovations and upscaling of turbine

[36] International Energy Agency, 2020, *Special Report on Clean Energy Innovation.*

[37] Wilson et al., 2020; Sweerts et al., 2020; Dahlgren et al., 2013.

capacity and rotor size.[38] However, standard turbine platforms are sited in different locations that may require customization in the siting of turbines, considerations of site topology and wind conditions, transportation logistics, and compliance with local regulatory requirements.

Nuclear: Nuclear power is a highly complex technology with a multitude of safety critical components that require tight design integration. In addition to complex design requirements, nuclear power is subject to significant regulatory oversight and limited by detailed regulatory requirements addressing safety and environmental issues. A design change can require years of regulatory review and litigation before it is approved and can be implemented. Moreover, nuclear reactors are constructed on site, not manufactured, and take years to complete. Costs have varied by country and over time but generally have increased as more reactors have been deployed. The United States experienced rapid cost escalation beginning in the mid- to late-1960s. Other countries with large reactor fleets, including France, have experienced more moderate cost increases. However, even under the best-case conditions, with a single utility sequentially building a standard design in multi-unit plants, South Korea was able to achieve only modest cost declines. More recently, South Korea has adopted a new reactor design, which has doubled construction times, likely increasing per-megawatt costs compared to historical levels. High capital costs, long construction durations, and the risk of cost overruns have limited attempts to develop additional nuclear plants in the U.S. and other countries. We also considered the development of small modular reactors (SMRs), which represent an attempt to control costs and risk by reducing on-site construction requirements and limiting unit size. However, small reactors give up the cost advantages that historically led to the development or larger units and remain subject to rigid regulatory oversight. To date, the U.S. has not yet built any commercial SMRs.

Each of these technologies developed over a period of decades, enabling us to track changes in costs, technological advances, market developments, incentives, rates of adoption, and other factors impacting their development. Documenting lessons learned from the development of these technologies provides insights into the characteristics of technologies that are likely to succeed in the competition to decarbonize the power system and paths for accelerating their development and deployment.

One of our objectives when reviewing the development of these technologies was to consider the different pathways for technology development that may contribute to cost reductions. The innovation literature has identified the following pathways:

Learning by Searching or Researching, including Research, Development, and/or Demonstration (RD&D) Activities: Learning by searching produces changes in the properties and engineering of products or processes, which typically require laboratory research and/or testing and non-routine changes to manufacturing settings or processes. RD&D can lead to breakthroughs and significant technological advances.

[38] Huenteler et al., 2016. *See also* Surana et al., 2020.

Learning by Interacting or Knowledge Transfer: The adaptation of technologies or transfer knowledge from other fields or industries or through collaborations among firms or individuals.

Supply Chain Development: Enabling different firms to utilize their respective comparative advantages to produce overall value.

Learning by Doing: Learning by doing is the direct result of repeated experience. It generally does not involve significant changes in the properties or engineering of products or processes. It may occur at the level of an individual employee, a firm, or given the diffusion of knowledge over time within a cluster of firms or an industry. Learning by doing tends to produce incremental improvements over time.

Learning by Using: Learning by using refers to improvements by customers in the use, operation, or maintenance of a technology.

Production Economies of Scale: Production economies of scale benefit a specific firm that can reduce unit costs by expanding its production capacity and/or use of existing capacity. Economies of scale are often realized without outside intervention when the benefits to the firm of increasing production exceed the costs and risks associated with making the necessary investments. Production economies of scale may or may not benefit an entire industry depending on the extent of knowledge transfer, competition, and supply chain relationships. Scale economies may reduce prices if the production of the firm is marginal and the market is competitive, may increase firm profits with little impact on prices, or may increase prices if it results in the firm gaining market power.

Unit or Installation Economies of Scale: Unit or installation economies of scale occur when building larger units reduces costs per unit of output. Examples include building a larger wind turbine or developing utility-scale PV instead of multiple residential rooftop PV installations.

We think this list is incomplete in that it does not fully capture the potential impacts of increasing data availability, information and communications technology, and modeling capabilities to accelerate innovation. In a later section, we will introduce the concept of learning by feedback as an area for future research.

1.4: Approach Part Two: Analysis of Technology Forecasting

We complemented our examination of case studies with an analysis of methodologies for forecasting the cost of clean energy technologies and a review of the academic literature on innovation and energy technology costs. A report on *Forecasting the Cost of Clean Energy Technologies* was prepared for this project by a leading expert, University of Cambridge Professor Laura Diaz Anadon,[39] and is attached as

[39] Professor Diaz Anadon holds the chaired Professorship of Climate Change Policy at the University of Cambridge. She is also Director of the Cambridge Centre for Environment, Energy and Natural Resource Governance, a Fellow at St. John's College, Cambridge, a long-standing affiliate of the Belfer Center for Science and International Affairs at the Harvard Kennedy School, and the Lead Author for Working Group III on Climate Change Mitigation for the 6th Assessment Report of the International Panel on Climate Change.

Appendix B. The report examines the drivers of innovation, describes empirical evidence regarding different approaches to forecasting the cost of energy technologies, and discusses patterns in data on energy innovation trajectories and their relationship to technology characteristics. It points out that while most research indicates that the societal benefits of the clean energy transition far outweigh the costs, greater investment will be required in the short- to medium-term. It recognizes that "all public and private organizations have budget constraints," such that, "it becomes essential to ensure that investments in innovation are made to deliver the greatest returns in terms of cost reductions and climate mitigation, among other goals."

Professor Diaz Anadon describes energy technology innovation as a complex adaptive process consisting of interconnected stages and feedbacks. Figure 1 illustrates the process in a condensed form, including metrics commonly used to study technology evolution or activities at different stages. A more holistic representation would also include a representation of a range of actors and broader socioeconomic factors.[40] The report cites research highlighting the role of different drivers of innovation: demand induced innovation, knowledge spillovers from other areas of technology or across different actors and geographies, learning by doing or learning by using, research and development, and economies of scale.

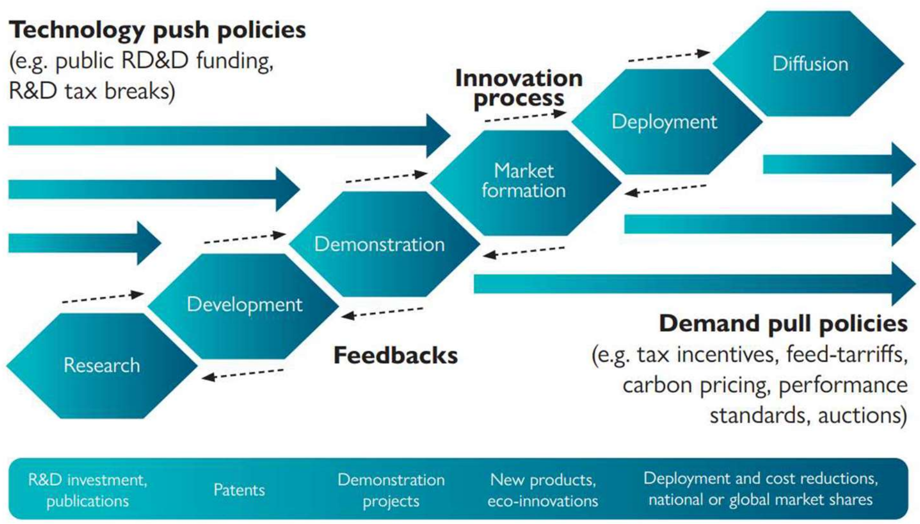

Figure 1: Partial Overview of the technology innovation process

Credit: Diaz Anadon, Appendix B

Professor Diaz Anadon describes two main approaches to forecasting technology costs: expert-based approaches, which may be particularly valuable for emerging technologies in the early stages of the innovation process, and model-based forecasts. Her report cites prior work by Professor Diaz Anadon and her colleagues finding that model-based methods based on using deployment (Wright's law) or time (Moore's law) as a proxy for the innovation process outperformed expert elicitations both in terms of capturing and producing median forecast values that were closer to observed values. Except for

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[40] Diaz Anadon, Appendix B. *See also* Diaz Anadon et al., 2016; and section 1.9, below.

forecasts for nuclear energy, all methods tended to underestimate technological progress.[41] The report also discusses different approaches for reflecting uncertainty in technology forecasts.

The report offers five key observations regarding forecasting the cost of energy technologies:

- Given the complexity, interdependencies, and uncertainties characterizing technology innovation, energy technology cost forecasting should, when at all possible, be conducted on a probabilistic basis.[42]
- Using past data, when available, in a probabilistic manner, model-based forecasts have out-performed expert elicitation. Expert based methods of forecasting energy costs have resulted in overconfident and, in many cases, pessimistic estimates.
- The use of model-based approaches does not imply attributing all improvements to learning by doing. They may assume that underlying drivers of innovation continue as in the past or become stronger or weaker.
- The use of more and more up-to-date data increases the likelihood of probabilistic forecasts generating ranges that will capture future trajectories.
- Not all energy technologies evolve in the same way, some of the differences may be attributable to changes in material or input costs, technologies having a high fraction of variable and fuel costs that experience increases as a result of lower cost resources being extracted first, differences in the characteristics of technologies such as complexity or granularity, or differences between the development of newer and dominant technologies within a particular category.

Professor Diaz Anadon's report also summarizes recent research on patterns of innovation for technologies with different characteristics, which are discussed in section 1.8.

The next sections draw on case studies and the academic literature to address specific questions:

- To what extent has learning by doing contributed to reductions in the cost of key clean energy technologies?
- How have accelerated purchasing strategies impacted clean energy technologies at different stages in their development?
- How have market dynamics and other exogenous factors impacted the development of key clean energy technologies?
- How do the characteristics of different technologies impact the pace of their development and their potential to contribute to a net zero energy future?

The final section of this chapter describes an innovation model, a set of considerations to guide decision makers seeking to accelerate the development of clean energy technologies. It is structured as a series of questions that corporate buyers should consider when identifying technologies that could

[41] Diaz Anadon, Appendix B; Meng et al., 2020.

[42] Diaz Anadon, Appendix B; Diaz Anadon et al., 2017.

contribute to achieving a net zero energy future, evaluating specific technologies, and considering specific purchases or other interventions.

This section also introduces a hypothesis that the development and commercialization of clean energy technologies is being and can be to a greater degree accelerated by optimizing the pace at which observations and information are gathered from both existing implementations and new research, analyzed, and modeled including with advanced tools such as virtualization and AI, integrated into product and process development, and then implemented. This emerging pathway, which we call *learning by feedback*, potentially could increase the tempo of innovation and provide a cost-effective way to accelerate the development of needed clean energy technologies. We recommend further research on how advances in information technology could be used to accelerate the development of clean energy technologies.

1.5: The Contribution of Learning by Doing to Cost Reduction

In contrast to top-down learning curve studies, several detailed studies have isolated the impacts of learning by doing from other factors that contributed to changes in the cost of clean energy technologies. We identified studies addressing this issue for PV, batteries, wind, and nuclear technologies.

Consistent with the innovation literature, we have used a specific definition for learning by doing based on the repeated execution of specific tasks. We recognize that others may treat any improvement or reduction in cost statistically associated with industry experience to be learning by doing. However, this broad definition is an impediment to identifying specific strategies for accelerating technology development.

In chapter 2 on PV, we review five detailed attribution studies, four that examine the causes of reductions in the cost or price of PV modules or systems and one that examines the impact of learning by doing on balance of system costs for installing rooftop solar panels. One of the best studies is by Professor Unni Pillai, the Head of Nanoengineering at SUNY Polytechnic Institute, whose research focuses on drivers of technological innovation. Using firm level cost data from 2005 to 2012 reported to the U.S. Securities and Exchange Commission (SEC) by 15 PV-only companies, together with industry data on cumulative output, polysilicon prices, and the fraction of panels produced in China, Pillai examined the impact of eleven different variables on year-to-year changes in the firms' unit costs. In contrast to other less detailed studies, Pillai's analysis of firm level data found that learning by doing and economies of scale "…do not have any significant effect on cost once four other factors are taken into account, namely, (i) reduction in the cost of silicon, a principal raw material, (ii) increasing presence of solar panel manufacturers from China, (iii) technological innovations, and (iv) increase in investment at the industry level."[43] Pillai analyzes variables identified in our PV case study that are not considered in most learning curve studies. The introduction of a series of technological improvements often by Chinese companies and the development of a cluster of vertically integrated Chinese firms have changed the PV industry. Additionally, Pillai associates annual changes in industry investment with its impact on economies of scale in equipment manufacturing. Equipment investment has two

[43] Pillai, 2015.

potential impacts on costs. First, the investment is an input cost. Second, with knowledge embedded in production equipment, equipment investment is a way of updating and spreading that knowledge.[44]

Gregory Nemet, currently a Professor at the University of Wisconsin, identified specific factors that led to the reduction in PV costs during the period 1976 – 2001. The result of his bottom-up analysis is that the impact of learning by doing, "is small compared to those of expected future demand, risk management, R&D, and knowledge spillovers. This weak relationship suggests careful consideration of the conditions under which we can rely on experience curves to predict technical change."[45] Both Nemet and two groups of researchers at the Massachusetts Institute of Technology (MIT), who used a bottom-up approach to look at later periods, found that the impact of learning by doing on the price of PV modules or systems was small, accounting for no more than 15% of the price reductions in the periods they studied. Each of these four studies also found that R&D or technological changes likely resulting from R&D to have been a significant driver of cost reductions.[46]

This type of bottom-up analysis, which starts by identifying specific component causes of cost reductions, is receiving increasing attention as researchers seek to better understand the drivers of clean energy innovation and how they might be influenced. Ziegler et al. performed a similar detailed bottom-up study of lithium-ion batteries finding that public and private R&D and economies of scale contributed to a large majority of the decline lithium-ion cell costs between 1995 and 2015. Given the high level of automation in the manufacturing process, learning by doing contributed only 2% of the cost reduction over the two decades. This type of analysis can both identify specific factors that have contributed to past reductions in costs and guide future development efforts.[47]

Another detailed study by Kenneth Gillingham of Yale and Bryan Bollinger, at the time at Duke and now at the New York University Stern School of Business, looked at data on 76,838 installations of small rooftop solar systems in California from 2002 to 2012. They examined the extent to which the level of experience of firms installing the panels reduced balance of system costs because of learning by doing. They found that the magnitude of learning is small and that learning by doing "can account for just a $0.12 per watt decline in non-hardware costs" over the study period.[48]

As the PV chapter suggests, local learning by doing among installers might be one of the reasons that the cost of installing residential rooftop solar is lower in Germany than in the United States. In their review of PV costs, Nemet and Hausman suggest, "Learning by doing plays a much more important role in reducing installation costs. An important aspect of this learning is that it is a local phenomenon."[49]

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[44] *See* chapter 2, sections 2.2.5 and 2.3.

[45] Nemet, Beyond the Learning Curve, 2005.

[46] Nemet, Beyond the Learning Curve, 2005; Kavlak et al., 2018; and Trancik et al., 2020.

[47] Ziegler et al., 2021.

[48] Bollinger & Gillingham, 2019.

[49] Nemet & Husmann, 2012.

The PV chapter also describes two multi-factor learning curve studies that included explanatory variables related to research and development, Louwen et al. that represented R&D based on PV patent filings and Zhou and Gu that reflected the impacts of R&D based on prior government PV R&D expenditures. In each case, the learning rate associated with the R&D variable exceeded that of capacity deployment, suggesting that although many learning curve studies do not account for R&D, its impacts are significant.[50]

The cost of purchasing wind turbines is the dominant cost in wind power. We have not identified detailed studies that specifically isolate the role of learning by doing in wind turbine manufacturing. However, there are studies that examine learning by doing in the installation and operation of wind turbines. Studies find evidence of learning by doing in project development and operation. However, the resulting benefits appear to rapidly depreciate as personnel move, new projects are undertaken, and technology changes. The studies do not indicate that such learning contributed to significant advances in wind technology.

It is reasonable to expect learning by doing in the construction and operation of wind farms given the need to customize site-specific installations and the degree of variability in operating conditions. For example, learning by doing could occur in the siting, permitting, design, and construction and the operation of wind farms. Developers need to:

- Identify suitable sites based on wind conditions, access to transmission lines, and other infrastructure.
- Comply with federal, state, and local regulations governing siting, construction, and transmission interconnection.
- Arrange for the transport of thousands of oversized cargos to remote project sites.
- Manage complex, site-specific construction operations including how to build tower foundations in different types of terrain.
- Developers also manage the maintenance and operation of the wind facilities based on expected wind and market conditions.

A study by Professor Nemet examined the extent of learning by doing in the development and operation of all 312 wind power projects built in California from 1982 to 2003. It found that experience in project development and in the operation of specific projects improved performance. However, the knowledge gained from such experience depreciated rapidly and did not persist over time. Moreover, operational knowledge gained from learning by doing did not transfer from one project to another within a firm. Nemet concludes that, "This finding is consistent with much of the work on learning by doing. In this case, as in previous ones, the knowledge gained from experience is useful for the refinement of existing systems. It seems much less useful, at least on its own, to producing radically different designs that could lead to non-incremental changes in performance."[51]

[50] Louwen et al., 2022; Zhou & Gu, 2019.

[51] Nemet, 2012.

Anderson, Leslie, and Wolak studied installation costs for 408 wind projects in the U.S. during the period of 2001 to 2015. Their objective was to investigate the empirical evidence for within-firm learning by doing and across-firm learning by doing in the design and construction of wind power projects, after controlling for all other potential sources of wind project cost differences over time. Like Nemet, they found some evidence of firm-specific learning by doing in the design and construction of wind power projects, which depreciated rapidly with time and with distance from where the experience originated. However, unlike Nemet, they found no evidence for inter-firm knowledge spillovers. A spillover of knowledge across firms would have implied a positive externality that could warrant additional policy interventions.[52]

In his 2012 review on the prospects for nuclear power, Lucas Davis of the University of California Berkeley cites two studies finding evidence for learning by doing during the building of early nuclear power plants, but no evidence of industry-wide learning by doing; a study identifying learning by doing in a nuclear construction company; and a longer term 1996 study (McCabe) finding evidence of learning by doing by both the construction companies and the utilities managing these projects that was, however, reduced by design variations and cost uncertainty. Given the long construction durations and the complexity in nuclear plant construction, it is not surprising that there could be learning by doing in the construction process. However, whatever relative advantages such learning might have provided, they were far from sufficient to stem the high and rising costs of nuclear plant construction. Davis suggests, as others have, that if one wanted to take advantage of learning by doing, France offers a useful point of comparison:

> "Development of nuclear power in France began later and with much less design variation. When Electricité de France began seriously building reactors in the 1970s, it adopted a single design for all of its reactors. With one exception, all nuclear power reactors currently in operation in France are of exactly this same design.... In addition, Electricité de France has long enjoyed a high degree of regulatory stability due to its close relationship with the French National Safety Authority and broad public support for nuclear power. Given this high degree of standardization, the apparent cost *escalation* in French construction costs is particularly striking."[53]

Despite the potential learning by doing benefits of a standard design, Davis concludes, "At a minimum, it seems clear that the French approach supporting a single reactor design is not going to be adopted in the United States."[54] In Chapter 4, section 4.3.1.2, we provide data on the rising overnight capital costs and lengthening construction durations of French nuclear power plants.

To summarize, there is evidence of learning by doing in limited circumstances involving customization or adaptation to varying local conditions, as in the installation of a technology platform in varying conditions, such as PV installation for rooftop solar or wind turbine construction, in the operation of wind resources again under varying conditions, and during the customized and lengthy construction of

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[52] Anderson et al., 2019.

[53] Davis, 2012; McCabe, 1996.

[54] Davis, 2012.

U.S. nuclear plants. However, there is no evidence that learning by doing produced the significant technological advances needed to materially accelerate the development of these technologies.

Additionally, there is a consistent conclusion among two- and multi-factor learning curve studies that examine the relative importance of R&D (learning by searching) and capacity deployment (learning by doing) for different technology categories. The results generally show higher learning by research than learning by doing progress rates.[55] For example, Tooraj Jamasb, Director of the Copenhagen School of Energy Infrastructure, developed two-factor learning curves comparing the relative importance of R&D and capacity deployment for eleven different electric generation technologies, "The results generally show higher learning by research than learning by doing rates. We do not find any technological development stage where learning by doing is the dominant driver of technological change."[56] Similarly, Rubin et al. conducted a literature review identifying learning rates for eleven power generation technologies. He finds that, "The most prevalent multi-factor model for energy technologies is a "two-factor learning curve" where the key drivers of cost reduction are assumed to be the cumulative expenditure for R&D as well as the cumulative installed capacity or production of the technology. … Empirical tests of this two-factor formulation find that R&D contributes significantly to cost reductions in all stages of technological development, often more so than learning by doing."[57]

1.6: Effects of Purchasing Strategies at Different Stages in Technology Development

Emerging technologies move through different stages in the process of technology development, commercialization, and wider adoption. Economists have broadly classified these stages as: invention – the generation of new knowledge and ideas; innovation – the further development of inventions and their transformation into products; deployment – early commercial operation; and diffusion – the widespread adoption of new products.[58] These stages roughly correspond to the stages of research, development, deployment, and diffusion in the innovation literature. Within these stages, technologies and products can be at different technology readiness levels (TRLs). To support the development of technologies for space exploration, NASA devised a taxonomy to classify the technical readiness level of different technologies, adopting a nine-level classification system. It was not an indication of economic cost-effectiveness or commercial viability.

In 2020, the International Energy Agency (IEA) recognized that, "arriving at a stage where a technology can be considered commercially available (TRL 9) is not sufficient to describe its readiness to meet energy policy objectives, for which scale is often crucial. Beyond the TRL 9 stage, technologies need to be further developed to be integrated within existing systems or otherwise evolve to be able to reach scale; other supporting technologies may need to be developed, or supply chains set up, which in turn

[55] National Academies of Sciences, Medicine, and Engineering, 2016.

[56] Jamasb, 2007.

[57] Rubin et al., 2015

[58] Schumpeter, 1934; Schumpeter, 1942.

may require further development of the technology itself."[59] For this reason, IEA extended the TRL scale, adding TRL 10 for technologies that are commercial and competitive but need further innovation to be integrated in energy systems and value chains at scale and TRL 11 for mature technologies that have achieved predictable growth. Descriptions of the Technology Readiness Levels (TRLs) including the extensions and modifications proposed by IEA are summarized in Table 1. TRL descriptions, titles, and level groupings include both the designations used in the innovation literature, e.g., Research, Development, Demonstration, Deployment, and Diffusion and those used by the IEA, e.g., Initial idea, Prototype, Demonstration, Early Adoption, and Mature.

Table 1: Technology Readiness Factors

TRL	Description	Examples
Research / Concept		
1	Basic Principles Observed / Initial idea	Scientific observation and studies of basic properties / Basic principles have been defined
2	Technology Concept Formulated / Application formulated	Applications envisioned and limited analytical studies / Concept and application of solution have been formulated
3	Experimental Proof of Concept / Concept needs validation	R&D initiated with studies and laboratory measurements to validate analytical predictions / Solution needs to be prototyped and applied
Development / Prototype		
4	Technology validated in lab / Early prototype	Designed investigation providing evidence that required performance might be achievable / Prototype proven in test conditions
5	Technology validated in relevant environment / Large prototype	Reliability significantly increases. Validation in semi-integrated system in a simulated environment / Components proven in conditions to be deployed
6	Technology demonstrated in relevant environment / Full prototype	Prototype produced and demonstrated in a simulated environment / Prototype proven at scale in conditions to be deployed
Demonstration		
7	System or prototype demonstrated in an operational environment / Pre-commercial demonstration	A major increase in maturity, performance of a system or prototype verified in an operational environment / Solution working in expected conditions

[59] International Energy Agency 2020, *Energy Technology Perspectives 2020*.

8	System complete and qualified / First-of-a-kind commercial	System is produced/manufactured, its performance is validated in the operational environment / Commercial demonstration, full scale deployment in final form
Deployment / Early Adoption		
9	Actual system proven in operational environment / Commercial operation in relevant environment	System proven ready for full commercial deployment, and being successfully deployed by multiple users / Solution is commercially available, needs evolutionary improvement to stay competitive
10	Integration needed at scale	Solution is commercial and competitive but needs further integration efforts
Diffusion / Mature		
11	Proof of stability reached	Predictable growth

For an illustrative classification of clean electric technologies by NASA TRL levels, please see Appendix D of the 2016 National Academies report.[60]

Technologies do not always move through these classifications in a straight line. One version of a technology might be at TRL 9 or 10, but not yet commercially viable for broader application without a component or potential improvement that is still under development in TRL 4, 5, or 6. We introduce these concepts as a foundation for exploring two questions:

- Under what conditions can accelerated purchasing strategies support the advancement of emerging clean energy technologies through the stages of development and deployment to wider adoption?
- Are there novel strategies that might better support and accelerate this process?

While corporate purchasing of clean electric technologies to advance environmental objectives is a comparatively recent development, we can examine the impacts of accelerated purchasing – purchases that would not be made based solely on the private net benefits to the buyer – by reviewing the impacts of niche markets and government support programs. Our case studies and observation of other technologies lead to the following findings:

The value of niche markets to some emerging technologies: For some emerging technologies that are not yet sufficiently advanced for broad application in the power industry, sales in niche markets may sustain the continued development of the technology. This occurred for PV where early applications in the space program and remote terrestrial locations sustained the industry until the energy crises of the 1970s focused government and corporate attention on the need for energy alternatives. Similarly, lithium-ion battery technology advanced with support from the consumer electronics market before moving into applications in electric vehicles and grid

[60] National Academies of Sciences, Medicine, and Engineering, 2016.

storage. Technology developers and entrepreneurs are often encouraged to look for a niche market to provide a revenue stream for supporting continued technology and product development. On the other hand, pursuit of a niche can divert resources from the development of the technology for its ultimate target market. Deciding whether to pursue niche markets is an important strategic decision.

Deployment subsidies can have an immediate and significant impact on technology adoption: Wind energy deployment provides clear evidence of the potential impact of subsidies, with deployment increasing rapidly with enactment or extension and falling with the expiration of federal tax credits and changes in European feed in tariffs and subsidies; *see* chapter 3, section 3.4. If the policy objective was simply to deploy technologies, financial incentives could accelerate deployment. However, the ability to sustain such policies and the impact of subsidies on innovation will depend on other factors. Supporting early deployment of technologies that are not yet ready to compete, particularly pre-TRL 9 technologies, requires careful consideration of the likely costs and benefits.

Early deployment programs may be unsustainable: When the cost of an emerging technology is well above the level at which the technology would be able to compete on an unsubsidized basis, subsidizing adoption is expensive. In cases of early subsidies for adoption of emerging technologies, a political response has often led to early termination of the program. The California 'Wind Rush" is one example. In 1983, the California Public Utilities Commission (CPUC) began offering generous standard offer fixed price contracts to wind developers (Standard Offer 4), on top of federal and state tax credits. By 1984, California had 75% of global wind energy capacity, with 17,000 wind turbines installed by 1985. By 1985, it became clear that Standard Offer 4 contracts were too expensive, and the CPUC terminated the program. The federal credit expired in 1985. California ended its tax credit in 1987. The rush was over, and the U.S. market would not pick up again until the late 1990s; *see* chapter 3, section 3.3. In 1994, Japan began offering rebates for residential rooftop PV with the objective of installing one million rooftop systems by 2010. In the first three years, rebates were available for 50% of system costs, then were gradually reduced. Although sustained for a longer period than California's wind subsidies, Japan's rooftop solar rebate program encountered political opposition, had its budget cut by more than half in 2003, and was terminated in 2005. The program had spent the equivalent of $1.1 billion dollars to support the installation of 200,000 systems representing 800 MW of capacity. This was well below the targeted number of installations and far below the government's initial goal that solar might supply as much as 50% of Japan's electricity requirements; *see* chapter 2, section 2.2.3.

Accelerating deployment can divert resources away from innovation: When market economics or subsidies provide a strong incentive for accelerating deployment, firms have an incentive to focus their resources on expanding production and deployment. The result may be that scarce resources are shifted away from more productive R&D activities.[61] The case studies of PV and wind provide examples where this appears to have occurred. California implemented aggressive policies to promote the deployment of wind power in the late 1970s and 1980s. At

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[61] Jamasb, 2007.

the time, California accounted for over 90% of the market for wind turbines. However, an analysis of the impact of California's deployment incentives on innovations in wind technology found that, "Inventors filed almost all of the highly cited wind power patents well before there was any substantial market for wind power equipment and before the important details of strong policy instruments could have been anticipated. Moreover, patenting activity declined precipitously just as demand for wind power created a multi-billion dollar market." The California wind rush did not lead to an increase in innovation.[62] Similarly, annual additions to wind capacity grew rapidly in the period from 2005 to 2011, peaking in 2009 at a level globally that was more than two and a half times and, in the U.S., more than double the amount capacity added in 2005. However, U.S. wind turbine prices, capital costs, and the levelized cost of wind energy increased from 2005 to 2009, and wind capacity factors did not improve from 2005 to 2011. Innovation stagnated as the industry focused on expanding deployment; *see* chapter 3, section 3.6. High German feed-in tariffs rapidly accelerated PV adoption, supporting the development of more than 30 GW of PV in Germany between 2004 and 2012. However, Professor Christoph Böhringer and his colleagues' analysis of the tariffs' impact on innovation failed to find any statistically significant relationship between the increases in feed-in tariff rates and innovation as reflected in patent filings.[63] Söderholm and Sundqvist also suggest that high German feed-in-tariffs may have discouraged competition among renewable energy sources and deterred innovation.[64] To the extent the objective is, in part, to improve technology and reduce costs, rapidly accelerating deployment is not only insufficient but may divert resources from R&D activities focused on technology improvement. Going forward, it may be important to align industry capabilities with the pace of deployment and to continue to support R&D as deployment increases.

Rapid acceleration in the deployment of emerging technologies may disrupt supply chains and industry structures: The escalation in Feed-in-Tariff (FiT) prices in Germany and other European nations increased demand for PV, outstripping the supply of PV grade silicon, a basic raw material input. The result was a ten-fold increase in polysilicon prices from 2003 to 2008. The German company, Q-Cells, at the time was the world's largest PV manufacturer. To maintain production, Q-Cells purchased silicon at high prices and sought to diversify into thin-film technology. With the spike and subsequent drop in silicon prices, Q-Cells suffered a $1.9 billion loss. It lost its market share as Chinese firms entered the market. The escalation in German FiT prices was an expensive policy that disrupted rather than helped German PV manufacturing; *see* chapter 2 at section 2.2.4.

The risk of premature lock-in to an inferior technology: Significant deployment incentives or early support for a particular technology option may create a risk of path dependence and lock-

[62] Nemet, 2009.

[63] Böhringer et al., 2014; Böhringer et al., 2017.

[64] Söderholm & Sundqvist, 2007.

in to a potentially inferior technology. Firms with more mature technologies can benefit from policy-induced market growth. However, this is not usually the case for firms producing less mature technologies. Strong policy induced market growth may thus raise the barrier to entry for less mature technologies and increase the risk of a technological lock-in.[65] Early government support can also lead to lock-in and was a factor in the development of the nuclear power industry. Light water reactors are considered by many to be inferior to other potential reactor designs. Yet light water reactors dominate nuclear power in the U.S. and many other countries. This is largely due to the early adoption and heavy development of light water reactors by the U.S. navy for submarine propulsion.[66] Similarly, individual companies may lock into a particular technology based upon support from a secondary market. There may be evidence of this in the response of Japanese PV companies to the 2008 spike in polysilicon prices. Many of the Japanese PV companies also produced consumer electronics and had focused thin film PV that could be applied in their consumer products. In response to the increase in polysilicon prices, Sharp and other Japanese manufacturers doubled down on thin film PV and aggressively pursued the emerging amorphous silicon (a-Si) thin film technology, which would prove to be inferior to rapidly improving crystalline silicon technology.

For technologies that are not yet in a position to compete including, but not limited to, pre-commercial technologies that have not yet reached TRL-9, buyers and policymakers should focus on accelerating technology development and consider alternatives to support early deployment. TCR's companion report, *Strategies for Investing in Clean Energy Technologies: Traditional and Novel Mechanisms for Accelerating Development and Deployment,* describes recent experience with contingent purchasing, advanced market commitment, and joint development models in which buyers may support the development process, including by making purchasing commitments contingent on the achievement of performance and price milestones. Deployment, TRLs 9 and 10, is a unique stage where a technology is in commercial operation and is addressing issues that need to be resolved for integration at scale. For technologies in this stage and mature technologies (TRL 11), accelerating deployment may offer cost reduction benefits:

- Given an expectation of sustained future growth, support for accelerated deployment may increase returns and induce entrepreneurial R&D.[67] R&D induced by a growing market demand may be different from the R&D that would be undertaken because of direct government or corporate buyer support. This potential benefit should be evaluated on a case-by-case basis.
- For technologies that are becoming competitive, accelerated deployment could help achieve production economies of scale. Whether economies of scale produce a public benefit, reducing the price of technology, or only private benefits for one or a few producers depends on the extent of market competition and whether the benefiting firms are or may become marginal producers. This issue also may require a case-by-case assessment.

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[65] Hoppmann, 2013. *See also* Battke, 2015; and Schmidt, 2016.

[66] Cowan, 1990.

[67] Grubb et al., 2021.

- By expanding the technology's track record of performance and attracting additional investors, greater deployment may modestly reduce financing expenditures. Egli et al. suggests that increased deployments may be associated with reducing financing expenditures, between a baseline period of 2000 to 2005 and 2017, by an amount sufficient to reduce the levelized cost of energy for on-shore wind in Germany by 4% and solar PV by 1%.[68] Given this modest impact, at some point, additional deployment may provide diminishing returns in terms of reducing financing expenses.

For technologies that have achieved TRLs 9 through 11, the innovation process does not stop. Further development may be required before the technology can be integrated at scale and widely adopted. Moreover, continuing improvements may be needed for the technology to remain competitive in a net zero energy future.

1.7: The Impacts of Market Dynamics on Technology Development

In the case studies for solar, wind, and nuclear technology, we identify major changes in market dynamics and the external events that contributed to these changes. Looking across these case studies it is helpful to focus on two different periods and the lessons that they may offer for the future.

The first is the decade of the 1970s. It featured major disruptions to global energy markets including the Arab oil embargo of 1973 and the reductions in oil production during the 1979 Iranian revolution and the 1980s Iran – Iraq War. These events would increase global oil prices and lead to a recognition of our vulnerability to external events, including in nations that could become hostile to the U.S. and its allies. The U.S. responded with the creation of the Department of Energy (DOE), new research and development programs including what would later become the National Renewable Energy Laboratory (NREL), and long-term goals of energy independence. The basic upwind three-blade wind turbine design that continues to be the dominant architecture today was developed in the 1970s, and many of the innovations that shaped PV development also grew out of research started in this period.

The West faces similar vulnerabilities today given Europe's dependence on Russian oil and natural gas, and the current Russian monopoly in the commercial supply of the high-assay low-enriched uranium (HALEU) fuel needed for many advanced nuclear reactors, China's dominance of the solar energy supply chain, and the world's dependence on developing nations and China for minerals critical to the transition to a clean energy economy. In response, greater attention is being given to supply chain risks and the development of domestic supply chains and supplies from allied countries.[69] Less clear is whether the current recognition of energy vulnerability will lead to accelerated research and development and creation of a next generation of secure clean energy technologies that can avoid issues of supply chain vulnerability and support the development of a low carbon future.

Another major development was the 1979 accident at the Three Mile Island nuclear plant. The accident exposed gaps in then existing safety standards and regulation. It would lead to changes in regulatory oversight that contributed to large escalations in costs and construction durations for nuclear plants then under construction. The large cost increases damaged the prospects for nuclear

[68] Egli et al., 2018.

[69] See, for example, International Energy Agency, 2022; U.S. Department of Energy, 2022.

energy in the U.S. However, more generally they illustrated the risks of pursuing large, capital-intensive projects where safety and environmental requirements are integral to design specifications. This was a particularly difficult challenge for plants that had begun construction prior to the completion of engineering and final regulatory sign-off on plant design. There are two important generalizable lessons from this experience. First, there are significant real opportunity costs associated with making large, irreversible capital investments that need to be considered when evaluating alternative resource options.[70] Second, in implementing complex technologies with critical safety and/or environmental protection components, it is essential to analyze and minimize risks upfront. The consequences of not doing so may range from extensive and costly rework to permanently damaging the future of an otherwise promising energy technology.

The second period with market dynamics that would prove important for key clean electric technologies began in the early 2000s and extended into the early 2010s. In the first half of the period the deployment of solar and wind rapidly increased with higher feed-in tariffs in Europe and tax incentives, renewable portfolio standards, and favorable market economics for wind development in the U.S. This was also a period in which North American electricity markets became more transparent and open to competition with the development of RTO/ISO LMP energy markets and several large states opening their retail markets to competition. China was also open to private sector investment and the development of competitive enterprise.

Significant market disruptions occurred, headlined by the 2008 financial crisis and the "great recession," which followed. There were also sector-specific disruptions affecting clean energy. Brought on in part by high European feed-in tariffs, the demand for PV grade polysilicon exceeded available supply, creating a ten-fold increase in the price of polysilicon – the basic raw material for production of crystalline silicon cells – from 2003 to 2008. This was followed by a collapse in polysilicon prices as demand fell during the recession. Mistakes in the management of the price spike and reduced access to capital following the 2008 financial crisis led to losses for Japanese and German PV manufacturers and the rise of the Chinese firms that now dominate all stages of PV production. Wind and other energy technologies also experienced increasing input costs with the near tripling of iron and steel prices from 2001 to 2008, followed by a temporary decline during the recession. These developments underscore the importance of understanding market risks.

The late 2000s was a period characterized by a changing generation mix and increasing attention to climate change risks. Congress considered but failed to pass bipartisan climate change legislation. However, another major change in U.S. energy markets, the shale gas revolution, would lead to reductions in electric sector carbon emissions. New shale rock fracturing and horizontal drilling techniques sharply reduced natural gas and electricity prices starting near the end of 2008. Lower electricity prices have contributed to the retirement of more the 100 GW of U.S. coal-fired capacity since 2011 with an additional 50 GW scheduled to retire by 2029.[71] Two primary lessons of this change are that:

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[70] Dixit & Pindyck, 1994.

[71] Energy Information Administration, 2022.

- The development of less expensive natural gas and renewable generation technologies has had a dramatic impact on the U.S. electric supply mix, with coal-fired units having produced 52% of U.S. generation in 2000 with gas, wind, and solar together accounting for 16%, to 2020 when natural gas, wind, and solar were responsible for 52% of U.S. electricity production and coal 19%. The development of low-cost resources can have a significant impact on electric generation and ultimately on electric sector emissions.
- Many legacy coal-fired generators that might have retired if their economics were based solely on efficient market prices have continued to operate.[72] This is, in part, because state regulated vertically integrated utilities, which otherwise would stop earning a return on and have to write-off major assets, continue to operate these units, and, in part, due to changes in ISO/RTO capacity pricing that favored baseload resources. The tension between economic efficiency and the incumbents' ability to influence regulation will impact the transition to a clean energy economy.

With recent increases in the cost of solar and wind, the impacts of the war in Ukraine, disruptions in the Chinese economy, greater onshoring of supply chains, and changes in U.S. energy policy, clean energy could be entering another transition period. The effects of these developments deserve further attention as additional information and analysis becomes available.

1.8: How Technology Characteristics Impact Progress

In our case studies of PV, which exhibited rapid cost reductions and technological advances, on-shore wind, where cost reductions accompanied improvements in different components of standard turbine design, and nuclear power, which has been subject to increasing costs over time and with the deployment of additional reactors, different technology characteristics are associated with distinctive patterns of innovation. We identified five generic sets of technology characteristics and related innovation patterns. These patterns may be useful for evaluating the potential to accelerate the development of technologies with similar characteristics. Table 2 summarizes these characteristics and associated patterns of innovation.

Table 2: Technology Characteristics and Innovation Patterns

Technology Characteristics	Typical Innovation Patterns
Modular – encourages component innovation, **Granular –** allows rapid low-cost experimentation, and **Mass-Produced –** enables economies of scale and knowledge being embedded in production equipment, e.g., PV modules, LED lighting	**Rapid:** Innovation occurs through: • Integration of scientific advances • Independent component innovation • Supply chain coordination and design standardization • Manufacturing process improvements • Economies of scale enabled by embedding knowledge in production equipment

[72] Gimon et al., 2021.

Technology Characteristics	Typical Innovation Patterns
Moderately complex standard platforms – many components, requires integration of key components, e.g., wind & gas turbines	**Moderate:** Innovation occurs in new models: • Basic design persists, e.g., 3 blade, upwind facing wind turbine developed in 1970s • Integration of component innovations • Upscaling unit size • Standard platform adapted to varying conditions
Customization of construction or installation – affects components and processes for multiple technologies, e.g., construction of large nuclear, wind farm site work, installation of residential rooftop PV	**Variable:** Differences in conditions limit the transferable knowledge and can retard the diffusion of innovation • Equipment is modified to simplify installation • Workforce development
High design complexity – requires tight integration of critical components and system level design, e.g., nuclear power, commercial aircraft	**Long:** Innovation introduced in new standard designs: • Innovation requires lengthy periods of design, testing, and systems integration
High regulatory complexity – environmental, safety, and other regulatory issues affect design, deployment, and / or the ability to make changes, e.g., nuclear, potentially hydrogen storage at scale	**Impeded:** Designs & deployment plans subject to detailed regulatory requirements, review, and litigation • Designs and deployment plans are completed up front • Regulators may have access to design and/or testing

This categorization treats customization and regulatory complexity as separate characteristics that may apply to components of different clean energy technologies. Considering these characteristics separately rather than as attributes of a given clean energy system may offer opportunities to work around some of the challenges that these characteristics may present.

For the three technologies that we studied, we were also able to identify potential flows of data and information, which together with analysis, modeling, and validation studies could support and potentially accelerate innovation. The opportunities were different for each of these technologies.

The following paths for the gathering and exchange of information have the potential to be used, expanded, or optimized to accelerate innovation in PV technology:

- Between researchers and PV and inverter companies identifying and implementing advancements in science and technology.
- Among researchers, PV and inverter companies, and facility operators who provide performance data on PV modules and inverters and their interactions with the power grid.
- Among companies at different levels in the supply chain to enable standardization.
- Among manufacturing companies, process engineers, and equipment manufacturers to embed process knowledge in production machinery.

- Among PV companies, installers, and users to develop features that facilitate customization and reduce installation, operating, and maintenance costs.
- Knowledge management practices, including the development of communities of practice, within installation companies to further reduce the cost impacts of customization where required.[73]

For wind power, the following paths for the gathering and exchange of data and information have been or have the potential to become the basis for flows that could contribute to or accelerate innovation:

- Providing turbine manufacturers, engineers, researchers, and facility managers detailed data on turbine performance, operation, and power production.
- Between turbine manufacturers, engineers, researchers, and project developers to develop features and tools that could facilitate project development and platform installation in different terrains and conditions.
- Between turbine manufacturers, project developers, researchers, and affected communities to develop features and processes that facilitate project development consistent with community standards.
- Knowledge management practices, including the development of communities of practice, within project developers and operating companies to improve performance given variable development and operating conditions.

Nuclear power is a more challenging technology involving high levels of design and regulatory complexity and requiring on-site construction that can require significant customization. The best case for progress in controlling nuclear construction costs has been the South Korean experience. Korean nuclear plant construction has been undertaken by a single utility, sequentially constructing standard designs, in multi-unit facilities. The Korean data include an initial small improvement in overnight construction costs, which do not include financing costs or reflect construction durations. However, when one accounts for the ten-year or longer construction durations of recent Korean reactors, doubling the construction durations of earlier plants, the trend becomes one of increasing total plant costs given, a reasonable allowance for financing during construction.

A high level of complexity, regulatory requirements, and a necessary degree of customization have impeded innovation in nuclear power. It is not clear to what extent SMRs may be able to reduce the impact of design and regulatory complexity, even if a greater proportion of the cost is shifted to factory-based manufacturing. This may suggest an innovation strategy for new reactors that is based on optimizing system design, minimizing risks, and addressing regulatory concerns in a test bed environment before starting commercialization and deployment. The following paths for the gathering and exchange of data and information have the potential to become the basis for innovation given such a strategy:

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[73] The design of specific data and information exchanges and feedback mechanisms is beyond the scope of this paper.

- Early and on-going observation of system design and testing by regulatory staff and exchanges of data and information between the companies developing advanced systems and their regulators.
- Between companies developing advanced nuclear systems and potential customers and representatives of communities where early reactors may be located to help address potential customer and community concerns.

We identified types of information exchanges that could be used, expanded, or optimized to accelerate innovation for PV, wind, and nuclear energy. Other technologies that have similar characteristics might benefit from similar types of information exchanges, although we have not extended our analysis to cover additional technologies.

Two different models, which are discussed in Professor Diaz Anadon's report, are commonly used to describe patterns of innovation. The Abernathy and Utterback model (A-U model) suggests that in the early years of an industry firms focus on product innovation to exploit the performance potential of discontinuous innovation and compete against alternative product designs. Following this stage, which they call an era of ferment, a dominant design emerges leading to the standardization of components and supply chains. In this second stage, they argue that the focus of innovation tends to be on process innovations and specialized materials.[74] A second model, the Davis model, characterizes innovation patterns in complex products and suggests that for these products the focus of innovation activity moves across components over time.[75] Huenteler et al. have sought to apply these theories to the energy sector through the addition of two dimensions: first, the scale of the production process (or what might be better described as the potential to scale production), which is characterized by system modularity and homogeneity of user demand, and second, the complexity of the product architecture, which is understood to be a function of the number of sub-systems and components and the complexity of their interactions. Based on a comparison of patent citation networks, Huenteler et al. argues that PV has a scale of production process that is higher than that of wind turbines, is mass produced, and is better described by the A-U model. They posit that PV should exhibit a shift over time from product to process innovation. They also argue that the product architecture of wind turbines is more complex than that for PV. Their analysis illustrates, as Davis would suggest, a shifting of patent activity from one wind turbine component to another over time.[76]

Our PV case study suggests that Huenteler, which was based on patent citations from the period 1963 – 2009, may be incomplete. Over the last decade, PV companies have implemented significant technical advances in the architecture of PV cells and modules, in addition to making innovative improvements in the production process.[77] This may be a period in which science and technology are enabling continuing improvements in some mass-produced clean energy technologies, such that firms

[74] Abernathy & Utterback, 1978.

[75] Davies, 1997.

[76] Huenteler et al., 2016.

[77] *See* chapter 2, section 2.2.5.

manufacturing these technologies cannot simply shift their focus to the production process and remain competitive.

A subsequent paper by Malhorta and Schmidt focuses on technology complexity and customization and the implications of these characteristics in energy systems for innovation. Malhorta and Schmidt propose a 3-by-3 matrix with one axis based on measures of the complexity and the other on the customization in different energy systems. Technologies are assigned to cells within the matrix based, in part, on differences in the results of learning curve studies. We agree that complexity and customization have an impact on the pace of innovation. However, our approaches differ in other respects. Our innovation model is the result of detailed case studies on the development of key clean energy technologies. It is designed to help corporate buyers explore the potential for cost reductions and encourage their consideration of a range of technology specific strategies for accelerating innovation. We want buyers to look beyond the learning curves. By avoiding the inference that innovation is a function of deployment, we encourage buyers to consider innovative mechanisms for accelerating innovation, many of which are likely to be less costly and more effective than increasing deployment of technologies that are not yet competitive. In contrast to the much less specific way Malhorta and Schmidt use the term, we evaluate learning by doing, as it has been traditionally defined, and find that it has had a comparatively limited role in reducing the costs of clean energy technologies. Additionally, given our background in systems analysis, we would approach analysis of system complexity somewhat differently, considering both the number of components in a system and their interdependence, specifically focusing on the definition of sub-system boundaries and requirements for tight integration of sub-systems and components. Finally, we suggest treating customization as a characteristic of specific system components and of construction or installation processes, not as an inherent characteristic of an entire energy system.[78]

1.9: A Model for Clean Energy Innovation

The combination of the Energy Act of 2020, the 2021 Infrastructure Investment and Jobs Act, the 2022 CHIPS and Science Act, and the 2022 Inflation Reduction Act have transformed U.S. energy policy and significantly increased support for the deployment of clean energy technologies. If successful, these bills will move the U.S. much of the way towards meeting its near-term carbon reduction targets. However, ultimately realizing global environmental and development objectives will require accelerating development, commercialization, and broad adoption of additional technologies.

Achieving a net zero energy future will require substantial electrification of transport, heating, and industrial end uses and a zero-emission electric system with the reliability needed to meet increasing customer requirements. This future will require accelerating the development of emerging electric technologies that are not widely available and, in many cases, at an early stage in their development. To achieve this objective, we are proposing an innovation model and specific strategies that complement both existing deployment incentives and corporate clean energy purchases designed to displace the operation of high emission sources. This model is a set of considerations that can help guide corporate decisions on interventions to accelerate the development and deployment of clean

[78] Malhotra, & Schmidt, 2020.

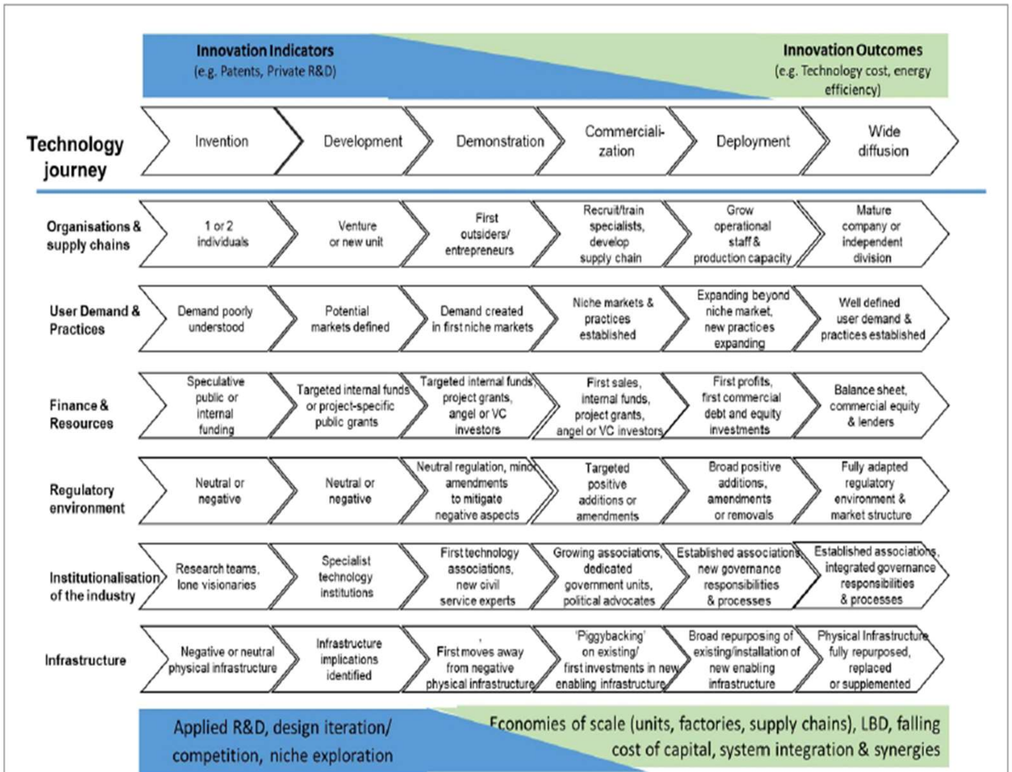
energy technologies. A companion report addresses proven and novel strategies that corporate buyers might use in such interventions.

The considerations are framed as a set of key questions to be explored. When evaluating technologies, corporate buyers should ask:

- **Are technologies that may be required to achieve a reliable zero emission electric system being developed in a timely manner?** – Asking this question highlights the need to identify, first, the requirements of a reliable zero-emission power system and, second, the gap between those requirements and existing technologies. It recognizes that technology development is a process and encourages corporate buyers to evaluate where needed technologies are in the process. It adds a time dimension: development is timely if it enables deployment and diffusion of the technology in time to meet environmental objectives. It asks about technologies that *may be* required, recognizing that one goal of the innovation process is to address the unknown. It may be important to develop a portfolio of options, not knowing which will succeed and prove to be cost-effective and reliable. Starting with this question also recognizes the possibility that existing policies and institutions may be locking in an inferior solution, supporting the deployment of a more mature technology to such an extent that a potentially better but less mature technology may be unable to compete.
- **What is the probability that the technology will successfully compete for a role in an affordable, reliable, low carbon future**? – In framing this question, we are acknowledging that different technologies may be needed to meet different requirements, e.g., short-term balancing vs. supplying power for long periods of limited wind and solar output. We are accepting that there may be multiple ways in which those requirements could be met and that there is likely to be competition among different options. We are recognizing uncertainties about both the future costs of competing technologies and future requirements and suggesting the importance of probabilistic analysis. Finally, we conditioned the question by using the terms "affordable" and "reliable" in recognition that both corporate and societal resources are limited and that a low carbon future will rely on electricity to meet a growing proportion of critical needs. If a low carbon future is not pursued in an affordable and reliable manner, the likelihood of achieving emission reduction objectives may be significantly reduced.
- **Can the pace of innovation for this technology be accelerated, such that it can more effectively compete?** – In answering this question, corporations can start by considering characteristics of the technology and its components and their impact on the likely pattern and pace of innovation. However, the inquiry should not stop there. The pace of innovation may not be fixed and potentially could be accelerated. Innovation depends on a flow of observations, information, and analysis; *see* Figure 1. Can corporate support help optimize, consistent with the capabilities of participating organizations, and accelerate the pace with which information moves through the innovation process? The reference to competition is added to point out the probability of innovation in other competing technologies.
- **What risks and unknowns could impact the technology's development and commercial opportunities?** – This question asks about both risk, factors that can be statistically analyzed, and unknowns, relevant futures for which we have no empirical basis on which to calculate probabilities. It recognizes the impact that different market shocks have had on the development of solar, wind, nuclear, and other clean energy technologies. It invites decision

makers to consider a range of future scenarios, including cases that could have positive and negative implications and to identify and track any early indicators that would make key scenarios more or less likely. Additionally, corporate buyers should ask if the possibility of a given scenario changes their assessment of a given technology, e.g., is there a high impact future in which the availability of this technology would be critically important?

- **Considering the alignment of a broader set of factors, is the technology on a path that will enable it to be successfully adopted and integrated into the power system?** – The adoption and integration of the technology and its broader diffusion and growth, depend on more than the technology's cost and performance. The market success of new technology will require an alignment of organizational and supply chain capabilities, user preferences and demand, financial resources, regulation, industry institutions, standards and infrastructure. An emerging technology may have to pursue development paths in each of these areas. Figure 2 illustrates potential development journeys along multiple dimensions.[79] Corporate buyers should consider the technology status and progress toward achieving the necessary alignment of these additional factors and what, if any, contributions they could make to facilitating such development.



Source: Grubb et al. 2021

Figure 2: Expanded Innovation Framework: Alignment of Additional Factors

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[79] Grubb et al., 2021; *see also* Geels et al., 2017.

Interventions should consider the stage of the technology's development. If a technology is not yet approaching a competitive level of cost and performance or is in a pre-deployment stage (prior to TRL 9), advancing and accelerating its development should be the primary objective. A niche market that supports a moderate level of deployment may in some cases contribute to development without unduly diverting resources from more beneficial R&D. However, to the extent an early acceleration of deployment may be proposed at this stage several questions should be asked:

- In what specific ways and by what mechanisms, would increased deployment accelerate the technology's development? What alternatives have been considered? What evidence suggests this increased deployment is likely to be a more cost-effective and successful option?
- What will be the cost of accelerating deployment? How will the costs be allocated? Will support for increasing deployment be sustainable?
- Does the industry have the capacity to support the increase in deployment without diverting talent and resources from more productive activities?
- Can the supply chain support a rapid increase in deployment?
- How might existing industry and market structures be changed or disrupted?

If the technology and necessary supporting components have reached the deployment or early adoption stage of development (TRL 9 or 10), the case for accelerating deployment becomes more credible. However, it is still important to consider: What are the costs and benefits? How will incumbents respond, and what will be the impacts of their response? Can the technology be integrated at scale into existing energy systems?

These questions are designed to focus attention on accelerating innovation and technology development, complement existing deployment policies, and encourage the consideration of a strategies that may be more effective than accelerating the deployment of still pre-commercial technologies.

Accelerating innovation requires a recognition that innovation is not a linear process. It requires gathering observations and data, analyzing that information, modeling components and systems, using the models to identify and test potential improvements, validating the impacts of these changes, demonstrating the advances in relevant and operational environments, deploying the new systems, gathering more data on their performance, and continuing to cycle through this innovation loop. Interventions that incent or facilitate effective improvements in the tempo of this innovation cycle have the potential to accelerate innovation.

Based, in part, on our PV and wind case studies, together with anecdotal reports on turbine manufacturer monitoring existing wind turbines, the development of a PV cluster in China that might have an impact on innovation like what Silicon Valley had for information technologies, and apparent increases in the pace of technology improvements in PV and wind during the last decade, we could be observing a new innovation pathway. With an increase in available data, improvements in information technology, and greater modeling capabilities, manufacturers, entrepreneurs, and researchers can gather information from technology demonstrations and deployments, analyze unknowns and impediments, design, test, then deploy improvements, in an iterative innovation loop, at a level of detail and pace that previously was not possible. Further advances may be possible with the availability of real-time data, virtualization, and the application of AI. We call this pathway *learning by* *feedback*. It differs from and supplements the conventional linear path view of RD&D. It also is different from learning by doing because it relies on gathering sufficient data to analyze potential improvements but is not directly related to maximizing deployment.

Focusing on the tempo of innovation, rather than on the pace of deployment, has three important benefits. First, we can look for and develop strategies specifically designed to facilitate or incent improvements in the pace of innovation. The accompanying TCR report on prizes and purchasing and on novel strategies identifies targeted strategies to support and encourage increasing the pace of innovation in addition to strategies that reduce barriers to deployment. Second, strategies that focus on improving the tempo of innovation may have a larger impact and may be more cost-effective than approaches that emphasize accelerated deployment of not yet cost-effective technologies. Finally, understanding the pace of innovation for different technologies may avoid an ineffective investment in a technology that will not be able to successfully compete for a role in a low carbon economy. Among otherwise comparable technologies, those that can innovate more rapidly will have an evolutionary advantage.

CHAPTER 2: Case Study 1: Solar Photovoltaics

2.1: Executive Summary

This chapter examines the evolutionary development of solar PV technology, from its origins in the 1950s to its status today as a low-cost source of energy; changing market dynamics; and the causes for the decline in PV costs.

The modularity and granularity of PV technology facilitated its development and large decline in costs. Solar PV systems consist of modular components: crystalline wafers, PV cells, modules, inverters, and electrical and balance of system equipment. Modularity and standard interfaces enabled independent component innovation, in which suppliers and developers could specialize and create optimized supply chains for each component. Additionally, the small scale of individual PV cells and modules enables rapid, low risk experimentation. Moreover, the major components are manufactured, not built on site, which enables individual firms to benefit from manufacturing economies of scale and supply chain globalization. These attributes characterize a specific innovation model which suggests lessons that may be applied to accelerate the development of technologies with similar characteristics.

1950s – 1970s: Early Development and Applications

The earliest working PV cells were developed by Bell Labs in 1954. Early applications were in the space program and military communications, offshore drilling platforms, and telecom repeater stations.

1970s – Early 1990s: Energy Market Disruptions and Policy Responses

This was a transitional period with terrestrial applications overtaking space-based uses by 1980. Interest in solar increased when energy markets were disrupted by the 1973 Arab oil embargo, the 1979 Iranian Revolution, and cuts in global oil production during the 1980 Iran-Iraq War. Starting in the mid-1970s, the U.S. DOE and its predecessors funded solar research and a limited block buy program for early applications, although these programs were cut back or phased out in the early 1980s.

Many of the most important improvements in PV technology occurred in the U.S. in the decade from the mid-1970s to the mid-1980s. In the United States, over a billion dollars was invested in solar PV R&D during this period. In 1978, Congress passed an Investment Tax Credit (ITC) benefiting solar, as well as the Public Utility Regulatory Policies Act (PURPA), which required public utilities to allow renewable generators to connect to the utility's grid and make "avoided cost" payments to so-called Qualifying Facilities (QFs), the value of which was set by the states based on the cost of alternative technologies. California authorized among the most generous payments to QFs and resulted in the development of wind, geothermal, and solar thermal resources, however, PV remained prohibitively expensive for widespread use in power generation.

Other countries also initiated R&D programs. During the 1973 Arab Oil Embargo, OPEC blocked oil shipments to Japan. Japan has few domestic energy resources and the Arab embargo on oil sales to Japan led the country's Ministry of International Trade and Industry (MITI) to initiate the "Sunshine

Project" in 1974. The Project supported R&D on solar with the goal of reducing Japan's dependence on foreign oil. From 1980s to the early 2000s, the Sunshine Project provided stable funding for PV R&D at a level that was comparable to the average of (the more inconsistent) U.S. government support for such R&D during the same period. MITI partnered with leading Japanese electronics firms, which also made major R&D investments. Most of the research in Japan focused on thin-film PV, including a-Si PV, which could be used in consumer electronics. By 1990, aside from the already saturated consumer electronics market and limited publicly funded demonstrations, there were few opportunities for Japanese companies to expand solar cell production.

Despite R&D efforts, PV remained too expensive to compete with conventional technologies in most applications. The period from 1984 to the early 1990s was a lull in the pace of global PV deployment.

Early 1990s – 2009: Market Development and Dynamics

Additional policy initiatives to expand the market for solar power began in 1993 when Japan launched its "million roof" rebate program. The program targeted the development of 1 million residential PV systems by 2010. Over 11 years, the program supported the installation of 200,000 systems, totaling 800 MW of capacity. However, political support for the subsidies waned and the program ended in 2005. Although net metering tariffs remained in place, without the rebates PV was too expensive for widespread adoption. The million rooftops target was not met until 2013, by which point PV had become cost-effective given Japan's high electricity rates.

Germany introduced a modest feed-in tariff (FiT) in 1991, but it had little impact on PV adoption. The German FiT was revised in 2000 to substantially increase the prices paid to PV generation and offer 20-year contracts. The FiT price remained at a level that was nearly double electricity prices until 2009 and above the average electricity price until 2012. This program supported adoption of over 30 GW of PV in Germany between 2004 and 2012 with subsidies totaling over 200 billion euros. In 2013, the surcharge supporting the direct cost of the FiT accounted for approximately one-fourth of the German average household electricity price.

By early 2013, Germany, which has only one-third the number of households as the U.S., had installed 2.5 times more residential PV capacity than the U.S. In 2012, residential PV systems were twice as expensive in the U.S. as in Germany. An analysis by Lawrence Berkeley National Laboratory attributes over 85% of the cost difference to non-hardware costs, such as customer acquisition and installation labor. Local installers in Germany may have benefitted from learning by doing and may have achieved some firm-level economies of scale because of a less fragmented German market. However, the German experience may not be transferable to the U.S. due to structural differences in the two markets.

While reducing installation costs, the German FiT was not associated with fundamental innovations in PV technology. An analysis by Christoph Böhringer and colleagues failed to find a statistically a significant relationship between the high FiT prices for PV and patent applications. One explanation is that the FiT may have provided incentives to make incremental improvements in installation costs for residential PV, but limited incentives for pursuing significant technological innovations. In response to the FiT production subsidy, firms may have shifted resources from R&D toward increasing output.

In the 2000s, other countries also instituted FiTs, rapidly increasing global demand and altering market dynamics. Between 2003 and 2008, the price of silicon, a basic raw material for solar PV modules, grew by an order of magnitude. The spike in silicon prices led some manufacturers to pursue improved crystalline cells and others to focus increasingly on thin-film cells. By 2010 crystalline silicon PV cells had emerged as the technology of choice for most PV modules.

In Japan, Sharp had increased its global market share from 2% in 1993 to 30% by 2003, the largest in the industry. In Germany, Q-Cells rode the wave of demand created by the high FiT. It began operating a 10 MW production facility in 2001, expanded its production capacity to nearly 300 MW by 2005, and became the largest cell producer in the industry by 2008. However, both Sharp and Q-Cells made strategic mistakes. Sharp had not closely followed developments in Europe and appeared to be surprised by the size and rapid growth of the German market. Sharp lost market share in large part because, seeking to reduce its exposure to polysilicon prices, it made a large bet on a thin-film amorphous silicon (a-Si) production facility. However, a-Si was never able to achieve the efficiency needed to compete with improving crystalline technologies.

Q-Cells also made mistakes. To expand production capacity, they over committed to silicon supply contracts when prices were high. With the crash in silicon prices in late 2008, these contracts became an expensive burden on the company. In addition, Q-Cells simultaneously chose to diversify into an expensive thin film production facility. Together, these factors led to a $1.9 billion annual loss in 2009 that placed Q-Cells at a competitive disadvantage.

Underlying the failures at both Sharp and Q-Cells was a series of rapid improvements in crystalline silicon technology that would benefit Chinese producers. The small scale, modular characteristics of PV can enable one form of the technology to rapidly evolve and start to dominate other branches on the evolutionary tree of PV technologies.

2010 – Present: The Rise of Chinese Manufacturing

Since 2010, PV manufacturing has moved from Japan, Europe, and the United States to China. Today, the collective market shares of Chinese producers exceed 80% at each major stage of the production process, including the production of polysilicon, monocrystalline or polycrystalline ingots, wafers, cells, modules, and panels. About 97% of the world's production of silicon wafers occurs in China. Based on the manufacturing capacity under construction, China's share of the polysilicon market is also expected to reach almost 95% of global production.

Four factors helped position Chinese companies to succeed in this period. First, China was able to import talent and technology. The first Chinese PV companies grew out of relationships with the world's leading research laboratory developing advanced crystalline silicon PV technology at the University of New South Wales (UNSW) in Australia. The founder of the first significant Chinese PV manufacturer, Suntech, had been a researcher in the UNSW lab. Many of the other major Chinese PV companies have Chief Technology Officers who trained at UNSW. This Australian connection, together with the ability to initially source production equipment in the West, gave Chinese manufacturers an opportunity to take advantage of advanced technology.

Second, the Chinese firms acted adroitly to take advantage of changing market dynamics and manufactured to meet increasing German demand. Suntech was founded in 2001, a time when the Chinese government was trying to increase exports by encouraging private investment to take advantage of lower labor costs domestically. By September 2002, Suntech was operating its first production line, and made an important technical advance by recognizing that it could obtain the monocrystalline silicon needed to produce more efficient cells from Chinese producers of monocrystalline silicon for computer chips at a lower cost than importing the polycrystalline silicon used abroad. Suntech opened a new monocrystalline production line in 2004. Additionally, Suntech was able to secure $100 million in venture capital investment in 2004. These accomplishments helped Suntech respond to the rapid growth of the German market and lead the development of the Chinese PV industry. Others would follow a similar path, with nine Chinese PV companies raising capital on U.S. exchanges prior to the 2008 financial crisis. Six of these firms remained among the top ten global manufacturers more than a decade later. Moreover, using this period to establish their technical capabilities, Chinese firms began producing much of the equipment used in the production of crystalline silicon PV, reducing equipment costs relative to what was available from foreign equipment suppliers. By 2009 China was the largest producer of solar PV cells and had passed the United States, Japan, and South Korea to become the most prolific originator of solar PV patents.

Third, unlike Sharp and Q-Cells, Chinese companies responded to the silicon shortage by creating the capacity to produce polysilicon. While Chinese companies would suffer losses from their purchases of expensive silicon or investments in the furnaces needed to produce polysilicon when the prices dropped, the development of polysilicon production would help grow local supply chains and support vertical integration that would both reduce margins in each segment of the production process and promote rapid integration of technical and market knowledge.

Finally, as the financial crisis and reductions in PV incentives abroad impacted Chinese manufacturers, the Chinese government took steps to support the industry and grow a domestic market. In 2009, the government launched rebate programs for rooftop PV, initiated a demonstration program that provided a 50% upfront subsidy for grid systems, and began soliciting bids for large scale PV power stations. In 2011, China initiated its own PV FiT. While these steps were motivated in part by U.S. and EU tariffs on Chinese PV imports, PV was becoming increasingly affordable, which reduced the subsidies required to promote PV adoption. By 2013, China had become the largest national PV market.

Starting around 2010, the silicon PV industry experienced a rapid decrease in manufacturing costs, more than 15% per year on average. The reduction was driven by increased collaboration between manufacturing partners and even competitors. This collaboration produced a standardization of the technology, alignment of the supply chain, greater automation, and a significant increase in labor productivity. It also reflected the vertical integration of Chinese solar companies and the development of co-located supply chains, which had the effect of creating a production cluster and accelerating the exchange of knowledge within and among Chinese firms.

Most of the decline in PV costs since 2010 has been a result of specific improvements in crystalline silicon PV technology, based on the combination of a shift to higher quality mono-crystalline silicon and the development of more efficient, lower cost cells and modules.

Attribution Studies

Four detailed studies have examined the impacts of specific changes in component costs, key inputs, and other factors affecting module or system costs or prices. Starting from detailed bottom-up analyses, these studies have been able to evaluate the extent to which mechanisms such as R&D, learning by doing, and economies of scale impacted cost reductions. The results present a sharp contrast to the inferences often drawn from top-down learning or experience curve studies. Each study found that learning by doing, defined as increased efficiency in manufacturing or installation resulting from the repetition of tasks, had only a limited or no statistically significant impact in reducing PV costs. Each of the studies also identified R&D as a significant factor in cost reductions.

2.2: History of Development and Deployment

2.2.1: Introduction

This paper examines the evolutionary development of PV technology and the causes for the decline in PV costs.[80] As shown in Figure 3, PV costs have been declining rapidly, making solar a least-cost energy supplier when it operates.[81] As the unsubsidized levelized cost of solar energy began to drop below the cost of power from gas combined-cycle generation in the middle of the last decade, there was an increase in the deployment of PV globally, as shown in Figure . In the U.S., the lower costs attracted greater investor interest.

Growth in the U.S. was reflected first in increasing transmission interconnection requests starting in 2015. With the unsubsidized cost of PV dropping below that of fossil generation, utility-scale PV and hybrid combinations of PV and battery storage have come to dominate the interconnection queues of U.S. RTOs/ISOs and grid operators. For the first time, PV provided more than 1% of net generation in the U.S. in 2016.[82]

The interconnection queues provide an indicator of relative investor interest, although not all the capacity proposed in the interconnection queues will ultimately be built. Actual U.S. PV installations grew in 2015 and 2016, then stagnated from 2017 to 2019, before increasing again in 2020 and 2021, driven primarily by utility-scale installations.

[80] Costs for PV are often measured in terms of $/Watt (CapEx) of modules or entire systems or in $/MWh (LCOE). LCOE is the fundamental metric that is the cost of a module or system divided by the module's output under standard conditions. LCOE is a useful metric for comparing solar to other power system technologies, but one must normalize for differences in or assume a given plant configuration (e.g., tracking or no tracking), a location, and a weather-dependent annual insolation pattern.

[81] Figure 3 includes only data for utility-scale PV. The costs for residential and commercial rooftop PV are significantly higher. Lazard's 2021 LCOE calculations for renewable resources are based on capacity factors that reflect favorable siting of solar and wind generators and for natural gas combined cycle generation use fuel costs that are significantly below near-term natural gas prices.

[82] Energy Information Administration, *Electric Power Monthly*, 2022.

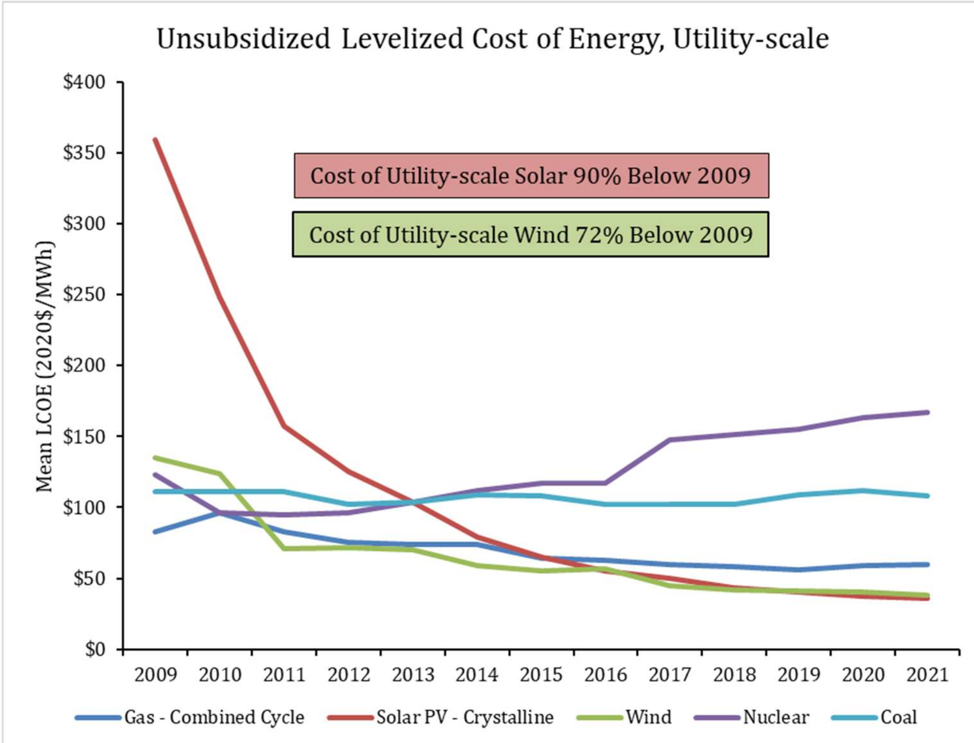

Figure 3: Unsubsidized Levelized Cost of Energy (LCOE) – Utility Scale Generation

Credit: *Lazard, 2021*

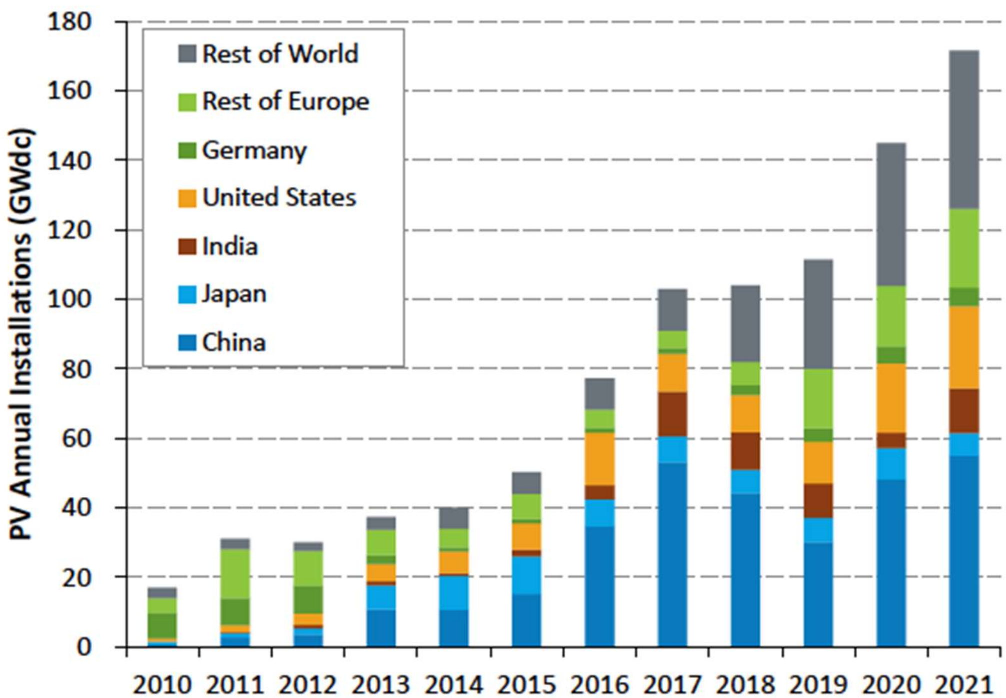

Figure 4: Global PV Capacity Additions by Country

Credit: *Feldman et al. 2022*

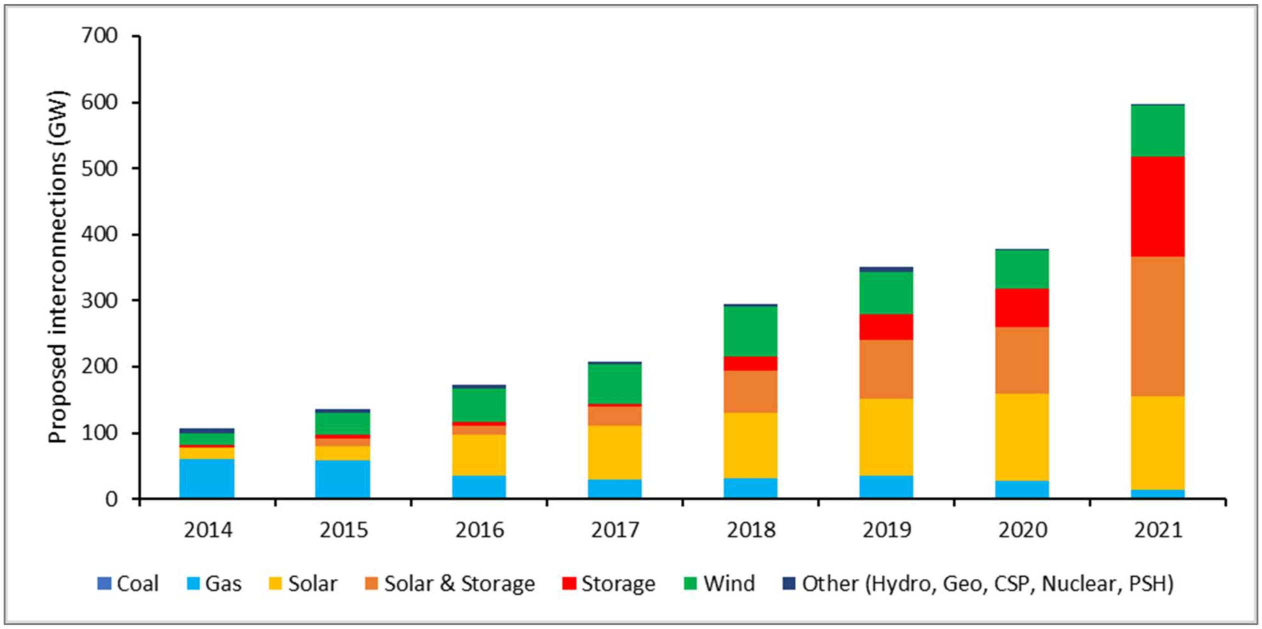

Figure 5: ISO, RTO, and Utility Interconnection Queues

Credit: *Rand et al. 2022*

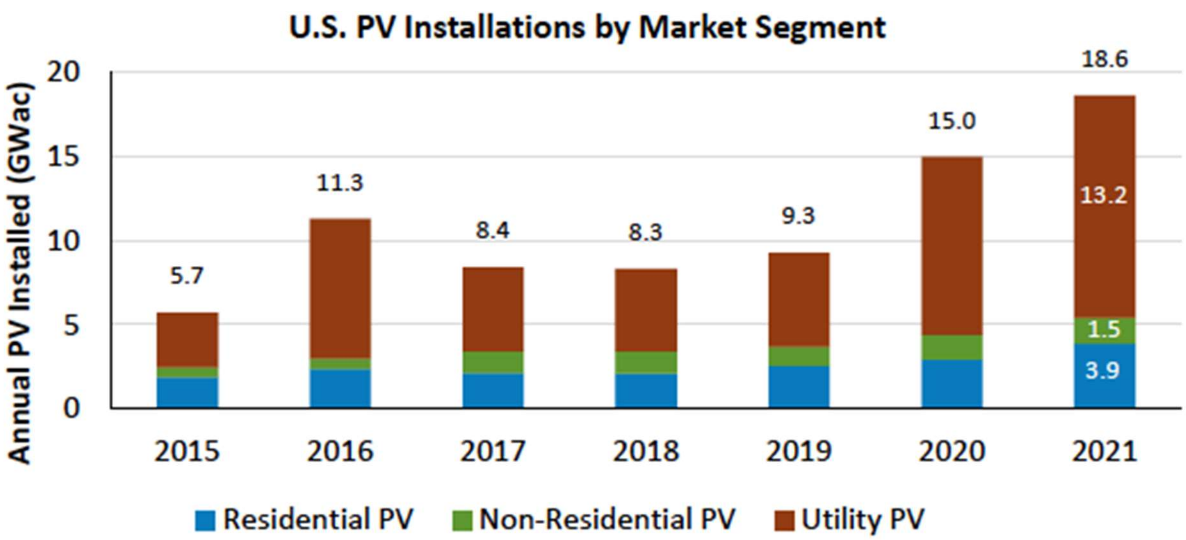

Figure 6: U.S. PV Installation Breakdown by Market Segment[83]

Credit: *Feldman et al. 2022*

[83] Based on Energy Information Administration (EIA) data from "Electric Power Monthly" and forms EIA-023, EIA-826, and EIA-861 (April 2022, February 2021, February 2019). Consistent with the preceding chart on interconnection queues, data is shown in GW of alternating current capacity. Solar industry sources often present capacity additions in direct current.

Most of the increase in investor interest, corporate purchases, and utility-scale development of PV in the U.S. has occurred after 2015 when solar electricity was already competitive with or less costly than other forms of electric generation independent of tax credits and other subsidies.

U.S. PV installations benefit from an ITC initially set at 10% in the Energy Tax Act of 1978; sequentially extended and modified; made permanent and raised to 30% by the Energy Policy Act of 2005; phased down to 26% in 2020 and 22% in 2021; then increased back to 30%, extended into the 2030s, and made transferrable by the 2022 Inflation Reduction Act. Prior to 2015, the ITC appears to have had only a modest impact on investment and Federal tax revenues with annual tax expenditures well below a billion dollars per year.[84] Smaller scale rooftop is much more expensive than utility-scale PV installations[85] but has enjoyed significant benefits from rate designs that allow PV owners to avoid paying for a portion of fixed grid costs, and Net Energy Metering subsidies that commonly set payments for power exported to the grid at levels that exceed applicable market prices and in many cases the total of market prices plus grid and societal benefits.[86]

Figure and Figure above reflect only the most recent portion of PV's development. The first operating solar cell was built nearly seventy years ago. Cost reductions have been gradual. For most of its history, PV has been too expensive to achieve widespread adoption outside of limited niche markets, which helped support its development.

The modularity and granularity of PV technology facilitated its development and the ultimate decline in its cost. Solar PV systems are built out of modular components: crystalline wafers, PV cells, modules, inverters, and electrical and balance of system equipment. Modularity and standard interfaces enabled independent component innovation, in which suppliers and developers could specialize and create, often international, supply chains specific to each component that maximize the comparative advantages of different organizations. Additionally, PV is a granular technology. When compared to conventional generation, the small scale of individual PV cells and modules enables rapid, low risk experimentation. Moreover, the major components are manufactured, not built on site, which enabled individual firms to benefit from manufacturing economies of scale and supply chain globalization. These characteristics define an innovation model that could be applied to accelerate the development of technologies with similar characteristics. However, technologies with different characteristics may require very different strategies and policies to facilitate their development, commercialization, and adoption.

We will trace the development and commercialization of PV technology from 1954 to today, noting significant technological advances, the formation of markets, and efforts to accelerate PV adoption. We will investigate various incentive mechanisms designed to drive the adoption of solar power. We will also refer to the use of different pathways for learning, technological development, and reducing costs described in the preceding chapter.

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[84] Congressional Research Service, 2021; Sidley Austin, 2022.

[85] Lazard, 2021.

[86] Borenstein, 2015; Verdant, 2021.

2.2.2: 1950s – 1960s: Early Development

Silicon-based PV solar cells were first demonstrated in 1954 by Bell Laboratories.[87] The first Bell Labs solar cell had an efficiency of 4.5%, which was increased to 6% within a few months. The first application of the Bell Labs silicon cell was in charging a battery used to power a telephone repeater in 1957. The development of radiation-proof cells enabled their use in the Vanguard 1 satellite in March 1958 and subsequent spacecraft. Early applications in spacecraft required a light-weight power source with maximum possible reliability. Vanguard 1 operated continuously for eight years.[88] Between 1958 and 1969, the U.S. space program had spent more than $150 million for solar cells and related equipment.[89] By 1972 approximately one-thousand spacecraft had been launched using solar cells.[90] NASA has continued to support PV R&D and views PV as critical to NASA missions. For example, the NASA developed Roll Out Solar Array (ROSA) technology is a flexible, light weight, autonomously deploying, and high efficiency solar array that was successfully deployed on the International Space Station in 2021 and could be applied in other missions.[91]

In the 1960s, other niche applications requiring reliable long-term operation in remote locations began to appear, including for military communications and navigational lighting, on offshore drilling platforms, and in remote railroad crossings and telecom repeater stations. Over time, technological improvements and less rigid requirements would enable the development of lower cost PV for terrestrial power production.

2.2.3: 1970s to Early 1990s: Energy Market Disruptions and Policy Responses

This was a transitional period. With the development of niche markets for navigation, telecommunications, and remote residences, terrestrial applications became dominant over space-based uses by 1980.

Policymakers and then corporations started to become interested in solar as energy markets were roiled by a series of disruptions. When Egypt and Syria launched the Yom Kippur War in October 1973, the U.S. provided arms to Israel, and the Organization of Arab Petroleum Exporting Countries (OAPEC) boycotted oil sales to the U.S. and allied countries. By the end of 1973, OAPEC countries had cut their oil output by 25%.[92] In 1973, the U.S. obtained 17% of its electric power from oil-fired generators and relied on oil for 46% of its total energy consumption.[93] The ban on oil sales to the U.S. resulted in fuel shortages and higher gasoline prices. The embargo was lifted in March 1974 following negotiations

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[87] APS News Archives, 2009.

[88] Lenardic, 2022.

[89] National Research Council, 1972.

[90] Nemet, 2019.

[91] National Research Council, 1972.

[92] Nemet, 2019.

[93] EIA, 2011; Nuclear Energy Institute, 2022.

and reported U.S. consideration of using military force to seize Arab oil fields. A second energy crisis followed the Iranian Revolution in January 1979, coincided with the Three Mile Island nuclear accident in March 1979, and intensified with additional cuts in global oil production during the 1980 Iran-Iraq War.

The 1973 crisis would lead President Nixon to call for Project Independence to develop the potential for the U.S. to meet its own energy needs without depending on foreign sources. A Project Independence Blueprint was released in January 1974, after Gerald Ford became President. The Blueprint envisioned a very limited role for PV and emphasized the potential of nuclear. Plans called for 1,000 new reactors in the U.S. by 2000, although only about 30 U.S. nuclear reactors started and completed construction after the Blueprint was issued.[94]

In October 1974, the Energy Reorganization Act created the Energy Research and Development Administration (ERDA), and the Solar Energy Research, Development, and Demonstration Act authorized the creation of a solar research institute. ERDA's solar energy program would be expanded under President Carter starting in 1977.

In 1977, the Solar Energy Research Institute (SERI), which would later become the National Renewable Energy Laboratory, was founded, and ERDA was merged with the Federal Energy Agency to form the DOE. These new federal agencies had R&D budgets for solar. These efforts were expanded by the Solar PV R&D Act of 1978, which authorized a 10-year $1.5 billion R&D program on crystalline solar at NASA's Jet Propulsion Laboratory (JPL), thin film and high efficiency silicon at SERI, and concentrating PV at Sandia National Laboratory with the goal of near-term commercialization. Much of the JPL funding for crystalline solar development was used to sponsor R&D in private organizations and at universities, facilitating rapid advances in PV technology. However, just as PV R&D was ramping up in the early 1980's, the Reagan Administration cut the PV R&D budget from $130 million per year to $50 million and made clear that the government would focus on basic, not "applied" research.

To encourage and support manufacturers in the development of solar technology, ERDA initiated and DOE continued a Block Buy public procurement program. The buys were staged in a series of "blocks" with increasingly demanding technical specifications. Three of five planned block purchases were completed – a $9 million planned purchase of 46 kW of PV capacity in 1975-76, a $1.7 million planned buy of 90 kW in 1976-77, and a $2.2 million planned 200 kW block in 1978-79 – before the program was phased out with small public purchase, approximately 40 kW, through the mid-1980s. While PV remained too expensive for widespread use, the combination of government R&D funding and the Block Buy program supported entrepreneurs, gave the private sector a stake in PV development, and enabled specialization.[95, 96]

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[94] Kelly & White, 1974; Nemet, 2019.

[95] Nemet, 2019.

[96] The 1970s would see major U.S. Oil Companies invest in solar energy for both use on offshore drilling platforms and diversification. However, the companies had sold their investments in solar by the end of the 1990s and before the subsequent increase in PV adoption. Jones and Bouamane 2012.

The R&D spending in this period would lead to multiple breakthroughs. Husmann and Nemet (2012) found that, "Almost every one of the 20 most important improvements in PV occurred during a 10-year period between the mid-1970s and the mid-1980s, most of them in the United States where over a billion was invested in PV R&D during that period." They used a combination of patent analysis and expert elicitation to identify "breakthroughs," which they defined as technical achievements representing a new combination of technologies that either open a new area of technology for exploration and use or that create specific improvements that spread to become an industry standard.[97]

In 1978, Congress passed an ITC benefiting solar and PURPA, which required public utilities to allow renewable generators to connect to the utility grid and to make "avoided cost" payments to QFs of a capacity less than or equal to 80 MW. It was left to the states to determine the avoided cost payments. Avoided cost calculations are generally based on the cost of alternative technologies, but specific methodologies vary widely among states.

California authorized among the most generous payments to QFs. In 1985, the California Public Utilities Commission transitioned to multi-year fixed price contracts for Interim Standard Offer Four (ISO4), which would provide a model for other efforts to encourage PV adoption. The California program would result in the development of wind, geothermal, and solar thermal resources. Solar thermal generation facilities, such as those developed by Luz during the 1980s in California's Mojave Desert, used mirrors to concentrate sunlight to many make steam and drive turbine generators. These facilities did not use PV technology, although some would later be retired and replaced by PV. Even with the benefits of the ITC and generous fixed price QF contracts, PV remained too expensive for widespread adoption in this period.

Starting in the 1970s, other countries would begin solar R&D programs. During the 1973 Arab Oil Embargo, OAPEC blocked oil shipments to Japan. Japan had few domestic energy resources. In response, the Ministry of International Trade and Industry (MITI) initiated the "Sunshine Project" in July 1974. The Project would support R&D on solar and other energy technologies, including coal gasification, geothermal, and hydrogen, but not nuclear given continuing post-World War II anti-nuclear sentiment. The goal was to reduce Japan's dependence on foreign oil.

Within the Project, MITI funded PV R&D and induced greater industry investment in R&D and inter-company knowledge spillovers. Japanese companies had been involved in PV R&D since the 1950s. By the 1960s, Japan was piloting the use of PV in communications relay stations, lighthouses, navigation buoys, and satellites. The Sunshine Project increased government support of PV R&D and from the early 1980s until the early 2000s provided stable funding for PV R&D at a level that was comparable in size to the average of the more inconsistent U.S. government support PV R&D during the same period.[98] Approximately 40% of MITI's PV R&D budget was allocated to eight major conglomerates and leading PV firms, which responded by more than matching the government's commitment with their

[97] Nemet & Husmann, 2012; Husmann and Nemet also identify earlier and additional breakthroughs. *See also* Green, 2005 and Louwen et al., 2022.

[98] Nemet, 2019.

own R&D investments.[99] Government and private sector R&D led to an increase in the knowledge stock of leading Japanese companies reflected in a greater number of PV related patent applications and lower cost Japanese solar cells.[100]

Most of the research focus of Japanese companies was on the development of thin-film PV, including a-Si PV, which could be used in consumer electronics. In 1982, 80% of Japan's 1.7MW of annual PV production was for consumer electronics.

Technology development and demonstrations were managed by Japan's New Energy Development Organization (NEDO) in cooperation with major industrial partners, including Sharp, Sanyo, and Kyocera. NEDO funded demonstration programs designed to reduce PV costs. However, by 1990, aside from the already saturated consumer electronics market and limited publicly funded demonstrations there appeared to be few opportunities to expand solar cell production.

While R&D efforts would continue, PV remained too expensive to compete with conventional energy technologies in most applications. The period from 1984 to 1994 globally was a lull in efforts to expand PV deployment. During this period the U.S. market for PV remained limited.

2.2.4: Early 1990s to 2009: Market Development and Dynamics

Efforts to create a broader market for solar power began in Japan. Electric rates in Japan were much higher than in the U.S. MITI had originally set extremely ambitious goals for solar, projecting that as much as 50% of Japan's energy could come from solar by 1990. Feeling pressure to enable PV adoption, in 1992, Japanese utilities began offering voluntary net metering, allowing residential customers to sell excess PV output back to the utility. In 1993, Japan launched its "million roof" program targeting the development of 1 million residential PV systems by 2010.[101] MITI began with a market experiment offering subsidies for 700 rooftop solar installations. It received 1,000 applications. MITI expanded the program to 1,000 rooftops in 1994 and received 5,000 applications. Based on this experience, MITI offered a program of rebates starting at 50% of costs for 1994-96 and 33% for 1997-99. Thereafter rebates were fixed at yen per Watt levels that declined in each subsequent year and that phased out in 2005. Installations grew from 539 in 1994 to 15,879 in 2000 and 54,475 in 2004. With a total budget of $1.1 billion, subsidy programs supported the installation of a total of 200,000 systems with 0.8 GW of capacity over 11 years. However, political support for the subsidies had waned and the program budget was cut by over half in 2003 and ended in 2005. Although utility net metering remained in place,[102] without rebates PV remained too expensive for widespread adoption. PV did not reach a million rooftops or start to provide more than 1% of Japan's electricity

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[99] Sanyo Electric, Kyocera Corp., Sharp Corp., Kaneka Corp., Fuji Electric, Hitachi, Mitsubishi Electric, and Sumitomo Electric.

[100] Watanabe et al., 2000.

[101] Green, 2019.

[102] Nemet, 2019.

until 2013.[103] However, the combination of R&D support and demand subsidies enabled the leading Japanese solar company, Sharp, to achieve economies of scale and become at one point the world's largest PV manufacturer.

Programs to incent solar deployment also began in Europe. In 1991, Germany started the first notable FiT program, the Electricity Feed-In Law of 1991 (in German, the Stromeinspeisungsgestz or SEG), with only minor uptake. The payments made for solar and wind were set at 90% of the average electricity prices paid by all customers in the preceding year, which was not nearly enough to incent PV entry.[104] With PV module costs at approximately $10/W, the LCOE would have been about $750/MWh. The SEG was replaced in 2000 by a substantially higher FiT, following the passage of the Renewable Energy Law (Erneuerbare-Energien-Gestz or EEG in German).[105] Drawing on the experience with municipal programs in Germany, the Japanese rebate program, as well as Standard Offer 4 PURPA incentives in California, the EEG substantially increased German FiT prices for PV and provided guaranteed 20-year contracts for renewable energy. It set somewhat lower contract prices for mature technologies such as wind and paid higher prices for less mature technologies including PV. In 2001, rooftop PV systems up to 5 MW could receive .99DM or 50¢/kWh over twice the retail electricity rate. Initially, EEG subsidies for PV were capped at 350MW. After Germany's Green Party gained seats in the 2002 German parliamentary election, the PV capacity cap was raised to 1,000 MW. The new government passed the Renewable Sources Act Amendment in July 2004, which set a more aggressive renewable energy target of 20% by 2020 and increased FiT rates available to PV. Subsequent policy changes would further lift the cap on PV capacity and raise German renewable energy targets to 35% by 2020, 50% by 2030, and 80% by 2050.[106] The FiT price for residential PV declined over time but would be at a level that was nearly double electricity prices until 2009 and above the average electricity price until 2012.[107] The program supported adoption of over 30 GW of PV in Germany between 2004 and 2012 with subsidies totaling over 200 billion euros.[108]

By early 2013, Germany, which has only one-third the number of households as the U.S., had installed 2.5 times more residential PV capacity than the U.S. With a much larger proportion of households in Germany having installed PV, a significant price gap emerged for residential PV between Germany and the U.S. In 2012 residential PV systems were twice as expensive in the US as in Germany. An analysis by Lawrence Berkeley National Laboratory attributed over 85% of the cost difference to non-hardware costs. The largest differentials were in customer acquisition and installation labor. German installers also had lower profits and overhead costs and lower expenses related to permitting, interconnection, and inspection procedures. There were additional costs in the U.S. due to state and local sales taxes,

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[103] Green, 2019; Matsubara, 2018.

[104] IEA, Electricity Feed-In Law of 1991. *See* International Energy Agency, 2013.

[105] Significant solar FiTs were also adopted in France, Spain, and Portugal among other countries.

[106] Nemet, 2019.

[107] Seel et al., 2014.

[108] Nemet, 2019.

smaller average system sizes, and longer project-development times. Local installers in Germany may have benefitted from learning by doing and may have achieved some firm level economies of scale because of a less fragmented German market. However, the study finds that the transferability of the German experience to the U.S. may be limited due to structural differences between the two markets that are unlikely to change.[109]

While reducing installation costs, the German FiT was not associated with fundamental innovations in technology. An analysis by Christoph Böhringer and his colleagues failed to find a statistically significant relationship between the high EEG PV FiTs and innovations documented in patent applications. One economic explanation is that the FiT may have provided incentives to make incremental improvements, such as those evident in installation costs for residential PV, but limited incentives for significant technological innovations. In response to the FiT production subsidy, firms may have shifted resources from risky explorative research toward increasing output.[110] This risk previously had been identified by Jamasb in an analysis of learning rates for twelve different electric generation technologies. Jamasb found that policies based on overestimates of learning by doing, such as those in single factor learning curves, particularly in the case of emerging and evolving technologies, "can shift the scarce resources earmarked for innovation resources from more productive R&D activities to less productive and more costly capacity deployment policies."[111]

By 2013, the EEG surcharge, which supported the direct costs of the German FiTs, accounted for roughly one-fourth of the national average household electricity price.[112] As the surcharges increased, the German FiTs became controversial. They were curtailed through a series of legislative actions from 2010 to 2013.[113]

Other countries instituted FiTs, most notable Spain. Those programs resulted in expanded global PV production.

With the increase in global demand created by FiTs, market dynamics changed. By the end of 2004, the price of PV grade polysilicon, a basic input to cell production, had started increasing. In 2008, the price of silicon surged to $475/kg, 10 times the 2003 price, as shown in Figure 7.[114] This increased global PV module prices and triggered significant changes in PV supply chains.[115] Although prices

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[109] Seel et al., 2014. It is also possible that some installation firms in Germany may have enjoyed firm level economies of scale.

[110] Böhringer et al., 2014.

[111] Jamasb, 2007.

[112] Böhringer et al., 2014.

[113] Nemet, 2019.

[114] Ibid.

[115] Louwen & van Sark, 2020.

would fall back to 2005 levels by 2010 and ultimately decline to $8/kg by 2020, these price swings would impact the plans and market positions of major producers.

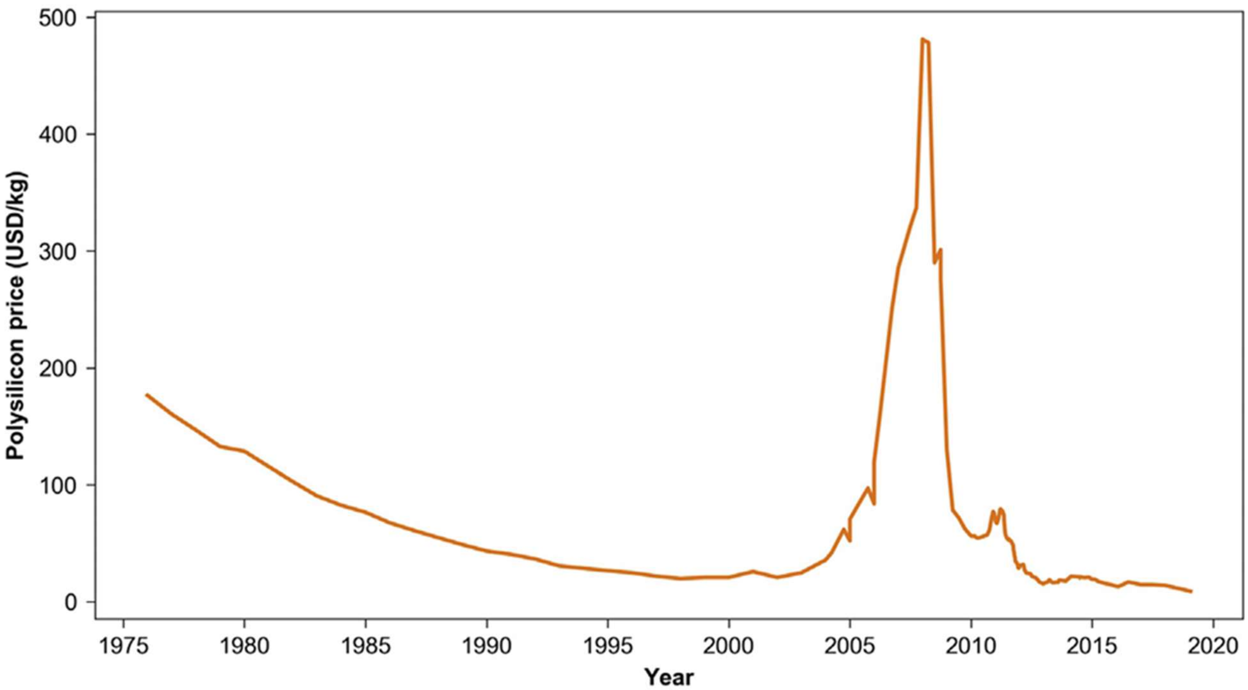


Figure 7: Polysilicon Prices 1975 to 2018

Credit: *Louwen & van Sark 2020*

In Japan, Sharp, in particular, benefited by building additional production capacity for the Japanese PV rebate program. Sharp increased its global market share from 2% in 1993 to 30% by 2003, the largest in the industry. By 2005 it had 500 MW of production capacity.[116] In Germany, a start-up Q-Cells was founded in 1999 to produce high-quality PV cells. It would ride the wave of demand created by the EEG FiT. It began operating a 10 MW production facility in July 2001, expanded its production capacity to nearly 300 MW by 2005, and became the largest cell producer in the industry by 2008. However, both Sharp and Q-Cells would make mistakes in responding to the rapidly increasing price of silicon.

Sharp's market share would drop to 10% by 2007, then sink into the low single digits. Initially Sharp may have been less well positioned than others to respond to changes in the market. They had not closely followed developments in Europe and appeared to be surprised by the size and rapid growth of the German market. They were disadvantaged being in Japan, a high-cost location, and by the Japanese quality philosophy that made cost-saving compromises less attractive. However, Sharp lost market share in large part because it made a large bet on the wrong technology. Sharp invested $1 billion in a thin-film a-Si production facility to avoid paying high prices for crystalline silicon and providing silicon producers the forward purchase commitment they needed to expand production. However, a-Si was never able to achieve the efficiency required to compete with improving crystalline technologies.

[116] Nemet, 2019.

Q-Cells also made mistakes. First, to ensure their ability to expand production capacity they over committed to silicon supply contracts when prices were high: purchasing 900 tons in 2006, the equivalent of 740 MW or nearly three years of production; making a 10 year/2,000 ton per year fixed price purchase commitment starting in 2008, sufficient to produce 10 GW of cells; and buying an additional 13,400 tons at fixed prices for 2008 and 2009 and the average of a fixed contract a spot prices for the subsequent 8 years. With the crash in silicon prices in late 2008, these contracts, totaling around $2 billion, became an expensive burden on the company. Second, Q-Cells simultaneously chose to diversify into alternatives to crystalline silicon, apparently doubting that the cost of crystalline silicon PV could drop in the manner that it subsequently did. Like Sharp, from 2005 to 2008, Q-Cells invested in developing thin-film production capacity. The additional thin-film investments further placed the company's competitive position in jeopardy. Third, despite its apparent aggressiveness, Q-Cells was relatively slow to incorporate technological innovations, cautious about qualifying new materials and preferring to invent their own solutions rather than borrow from others. Together, these factors placed Q-Cells at a competitive disadvantage. The company reported a loss of $1.9 billion in 2009, at a time when the financial crisis shut off access to capital. Production volumes declined after 2010 and, in 2012, the business was sold to Hanwha Solar.

Underlying the failures at both Sharp and Q-Cells was a series of rapid improvements in crystalline silicon technology that would benefit Chinese producers. Small scale, modular characteristics of PV can enable one form of the technology to rapidly evolve and start to dominate other branches on the evolutionary tree of PV technologies.

2.2.5: 2010 to Present: The Rise of Chinese Manufacturing

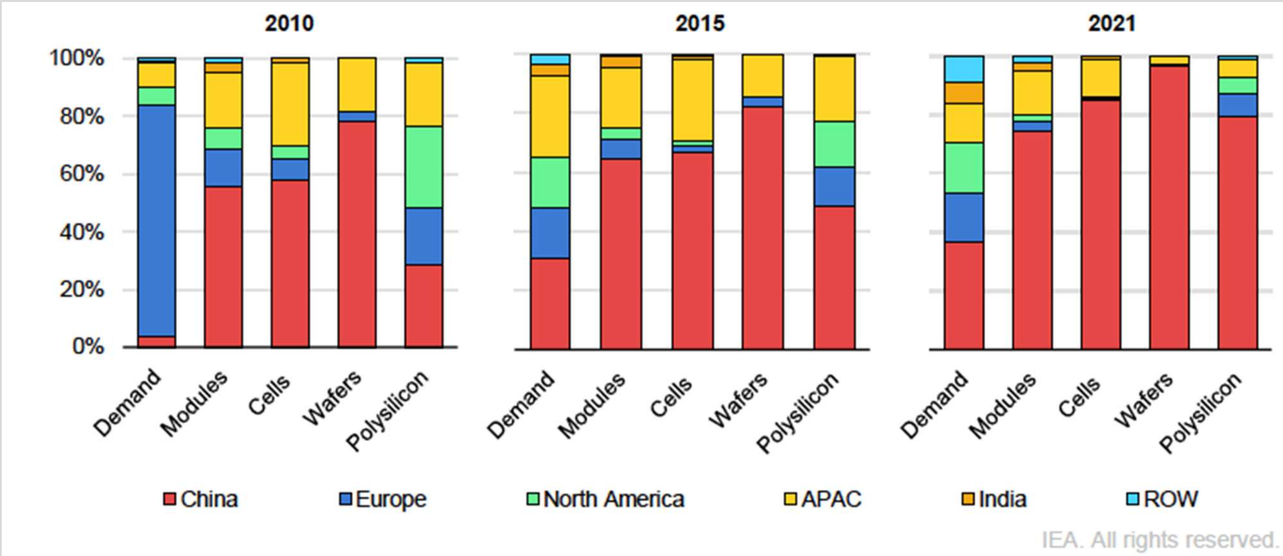
Since 2010, PV manufacturing has moved from Japan, Europe, and the United States to the Peoples Republic of China. Over the last decade, China invested over $50 billion in new PV supply capacity. Today, the collective market shares of Chinese producers exceed 80% at each major stage of the production process, including the production of polysilicon, monocrystalline or polycrystalline ingots, wafers, cells, modules and panels, as shown in Figure 8.[117] As illustrated in Figure 9, about 97% of the world's production of silicon wafers occurs in China.[118] Based on manufacturing capacity under construction, China's share of the polysilicon and ingot market is also expected to reach almost 95% of global production.[119] In 2020, Chinese firms and institutions originated 84% of global solar PV related patents, as illustrated in Figure .[120]

[117] International Energy Agency, 2022.

[118] U.S. Department of Energy, 2022. DOE also estimates that China produces more than 70% metallurgical-grade silicon, which is produced from high grade quartz and is the key raw material for crystalline silicon production.

[119] International Energy Agency, 2022.

[120] Our World In Data, 2022. We cannot exclude the possibility that the quantity of patent filings may reflect differences between national patent systems.



Notes: APAC = Asia-Pacific region excluding India. ROW = rest of world.

Figure 8: PV Demand and Manufacturing Capacity by Country and Region 2010-2021

Credit: *International Energy Agency, 2022*

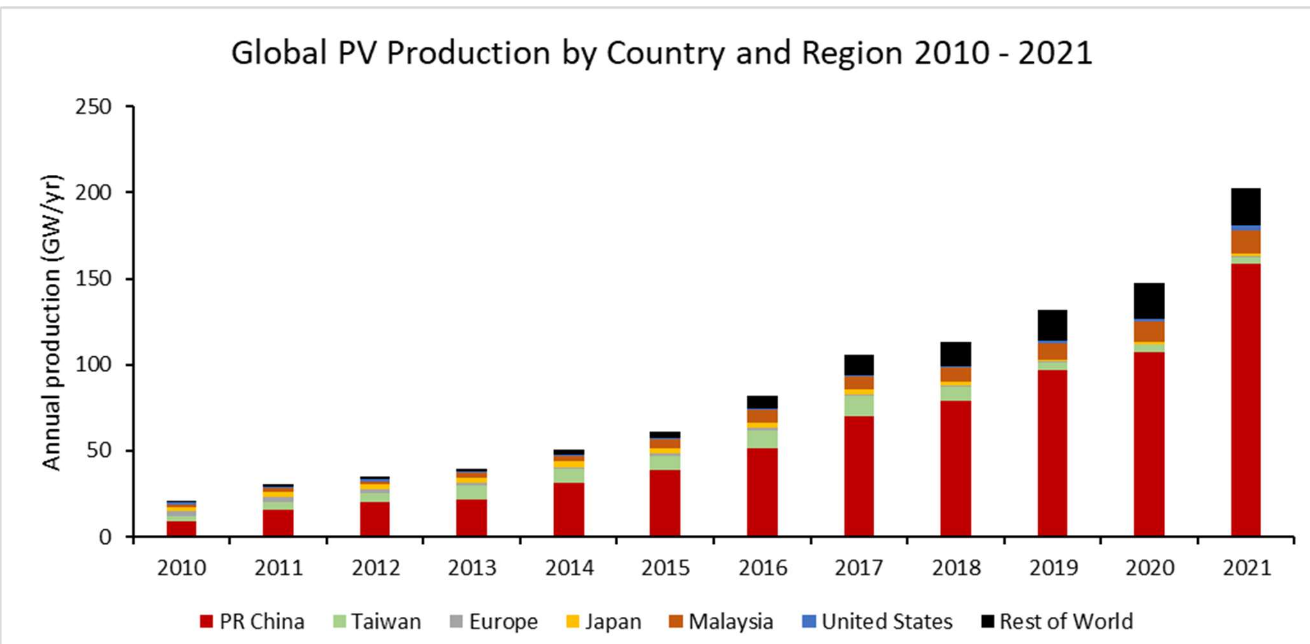


Figure 9: Global PV Production by Country and Region 2010-2021

Credit: *Helveston, He & Davidson, 2022*

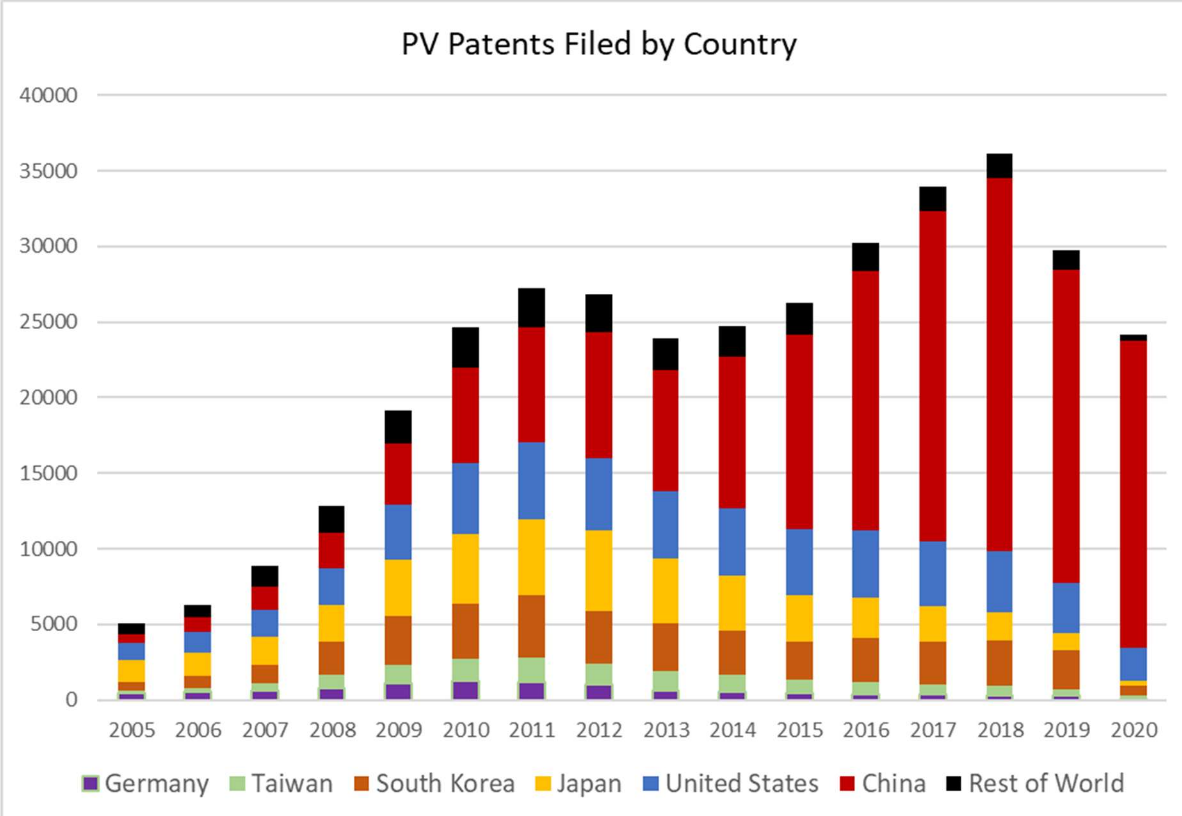


Figure 10: Solar PV Patent Filings by Country 2005-2020

Credit: *Our World in Data, 2022*

Four factors helped position Chinese companies to succeed in this period. First, during the earliest stages of its development, China relied on the importation of talent and technologies from abroad. For example, the founders of the Chinese PV industry had strong relationships with the leading research laboratory developing crystalline silicon PV technology at the UNSW in Australia. Zhengrong Shi, the founder of the first significant Chinese PV manufacturer, Suntech, had been a researcher in the UNSW lab before coming to China to start his company. Other early entrants, Trina and Canadian Solar, started assembling modules using Suntech's technology. The next three Chinese companies Solarfun, JA Solar, and Sunergy purchased technology from Suntech or used technology supplied by an Australian-Chinese joint venture. Moreover, many of the major Chinese PV companies continue to have Chief Technology Officers who trained at UNSW.[121] The UNSW team was instrumental in achieving a 50% improvement in the relative efficiency of silicon cells and held the record for having produced the highest efficiency crystalline cells for 30 of the 36 years from 1984 to 2019.[122] Moreover, to develop their initial production capacity, Chinese firms were able to purchase technology

[121] Nemet, 2019; Green, 2019.

[122] Green, 2019; National Renewable Energy Lab, 2022.

in the West.[123] These connections gave Chinese manufacturers an opportunity to utilize advances in technology that would help drive down costs.

Second, the Chinese firms acted adroitly to take advantage of changing market dynamics and manufacture to meet increasing German demand. Suntech was founded in 2001 at a time when the Chinese economy was encouraging private investment and taking advantage of lower costs to increase exports. By September 2002, Suntech was operating its first production line. Recognizing the importance of convincing global markets of Suntech quality, the company also pursued International Standards Organization 9001 certification – the first Chinese company to do so, certifications from the International Electrotechnical Commission, and with European Conformity quality standards, which it achieved in 2003. Around this time, Suntech also made an important technical advance, recognizing that it could obtain the monocrystalline silicon needed to produce more efficient cells from Chinese sources who were producing monocrystalline silicon for computer chips at a lower cost than importing the polycrystalline silicon used abroad, Suntech opened a new monocrystalline production line in 2004. Additionally, Suntech was able to secure a $100 million in Western venture capital investment in 2004 and in December 2005 raise $400 million from Wall Street with an Initial Public Offering. These accomplishments helped Suntech respond to the rapid growth of the German market and lead the development of the Chinese PV industry. Others would follow a similar path with nine Chinese PV companies being listed on U.S. exchanges prior to the collapse of Lehman Brothers triggered the 2008 financial crisis. Six of these firms remained among the top ten global manufacturers more than a decade later.[124] Moreover, using this period to establish their technical capabilities, Chinese firms began producing much of the equipment used in the production of crystalline silicon PV, reducing equipment costs relative to what was available from foreign equipment suppliers. By 2009 China was the largest producer of solar cells and had passed Japan and the United States, Japan, and South Korea to become the most prolific originator of solar PV patents with over 21% of global patent filings.[125]

Third, unlike Sharp and Q-Cells, the Chinese companies responded to the silicon shortage by creating the capacity to produce PV grade polysilicon. In 2005, silicon production in China accounted for only 0.5% of global production. By 2010, China was producing 32% of global PV grade polysilicon supplies.[126] While Chinese companies would suffer losses when the prices dropped from their purchases of expensive silicon or investments in the furnaces needed to produce silicon, the development of polysilicon production would help grow local supply chains and support vertical

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[123] Nemet, 2019.

[124] Nemet, 2019; Green, 2019. Other Chinese firms raising capital in U.S. markets would include Yingli raising $319 million, Trina $420 million, CSI $250 million, and JA Solar $225 million in 2007. *See* Reuters Staff, 2007; Investor Ideas, 2007.

[125] Zhang & Gallagher, 2016; Our World In Data, 2022.

[126] Gallagher & Zhang, 2013.

integration that would both reduce margins in each segment of the production process and promote rapid integration of technical and market knowledge.[127]

As the financial crisis and reductions in PV incentives abroad impacted Chinese manufacturers, the Chinese government took steps to support the industry and grow a domestic market. First, the Chinese Development Bank provided lines of credit worth $30 billion to PV manufacturers. Second, in 2009, the government launched rebate programs for rooftop PV, initiated a demonstration program that provided a 50% upfront subsidy for grid systems, and began soliciting bids for large scale PV power stations. Third, in 2011, China initiated its own PV FiT. The government's commitment to support the Chinese domestic market, in part, was motivated by the U.S. imposing in 2012 a 31% tariff on solar panels imported from China and the EU implementing similar measures in 2013.[128] However, PV was becoming increasingly affordable, which reduced the subsidies required to promote PV adoption.[129] As a result, by 2013, China had become the largest national PV market, as shown in Figure 11.[130]

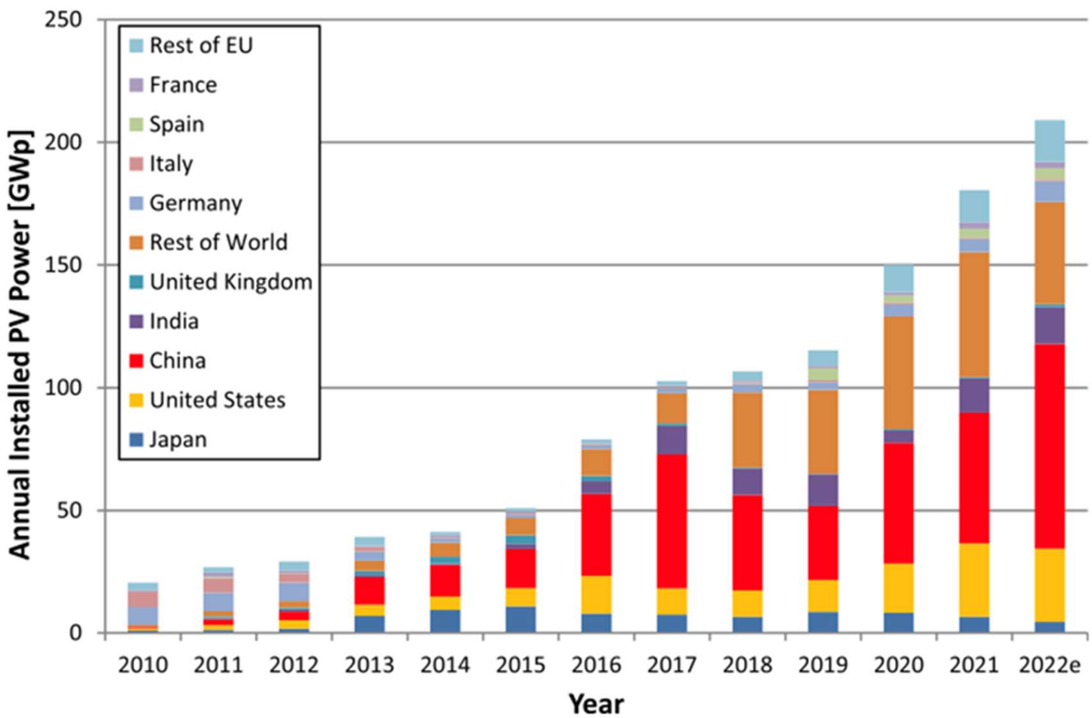

Figure 11: Annual PV Installations by Country 2010 to 2021 with Estimates for 2022

Credit: *Jäger-Waldau, 2022*

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[127] Nemet, 2019; Zhang & Gallagher, 2016.

[128] Gallagher & Zhang, 2013.

[129] Nemet, 2019.

[130] Jäger-Waldau, 2022.

Since 2010, declining costs have made PV competitive with conventional power production. While other component costs have also declined, in part because of improvements in the module power and efficiency, lower module costs have been the largest factor in the reduction in overall PV system costs since 2010.[131] The integration and standardization of production, primarily in China, and specific improvements in crystalline silicon PV technology played major roles in lowering PV costs. Changing market dynamics also moved PV prices in different directions at times during this period.

Starting around 2010, the silicon PV industry went through a period of significant changes, including a rapid decrease in manufacturing costs, more than 15% per year on average. The reduction in manufacturing costs was driven by increased collaboration between manufacturing partners and even competitors. This collaboration produced a standardization of the technology, including standardization of cell and module designs and production processes, a complete alignment of the supply chain (equipment, materials, and chemicals), greater automation, and a significant increase in labor productivity.[132] This standardization developed despite fierce competition in the Chinese market. Major Chinese companies pursued vertical integration to improve their profitability, achieve cost reductions, and control quality. Moreover, vertically integrated suppliers could diversify their risk and compensate for any losses in one segment of the supply chain through profits in another.[133] The development of vertically integrated and co-located supply chains had the effect of creating a production cluster and a learning network within and among Chinese firms. It facilitated knowledge communication among engineers in different plants, which induced rapid process improvements in some firms.[134]

Most of the cost reductions were driven by improvements in crystalline silicon PV technology, which combined a shift to higher quality mono-crystalline silicon cells and the development of more efficient, lower cost cells and modules.

By 2021, mono-crystalline silicon accounted for 84% of PV module production, up from around 25% of module production in 2016.[135] The shift to mono-crystalline silicon took advantage of improvements in mono-crystalline silicon ingot fabrication and the ability to achieve a greater reduction in material losses during wafer production using mono-crystalline silicon. The shift to mono-crystalline silicon produced direct cost savings. Mono-crystalline cells generally are more efficient and have a higher power output. The shift to mono-crystalline silicon also enabled the cutting of wafers with diamond wire saws that are one-third the width of those used a decade ago, significantly reducing kerf loss, the loss of material during the cutting of ingots into wafers. It led to the production of larger cells. An

[131] Fu et al., 2018; Feldman et al., 2021; Ramasamy et al., 2022.

[132] Wilson et al., 2020.

[133] International Energy Agency, 2022.

[134] Gallagher & Zhang, 2013; *see also* Goodrich et al., 2013.

[135] Fraunhofer Institute for Solar Energy Systems, 2022.

increase in wafer size from 125 mm^2 in 2010 to as much as 210 mm^2 today, which has increased cell power output.[136]

Moreover, the shift to mono-crystalline silicon also enabled the change in cell design. The dominant cell design shifted from Aluminum Back Surface Field (Al-BSF) to higher efficiency Passivated Emitter and Rear Contact (PERC) cells. By 2013, the efficiency of Al-BSF cells had plateaued at around 20%.[137] PERC cells move contacts to the rear of the cell, eliminating shading from front-side contacts, and improve the cells' optical and electrical properties. Typical cell efficiency for PERC cells is 23.6%.[138] With this change, the entire supply chain was aligned and standardized on PERC technology; it became the "workhorse" of the PV industry.[139] In parallel with mass production of PERC cells, other high-efficiency cell structures – interdigitated back contact, heterojunction, and TOPcon cells – have also moved into mass-production and could account for larger shares of production in coming years.[140]

In addition to improving efficiency, the shift to mono-crystalline PERC cell modules reduced costs by lowering the requirements for key inputs. Polysilicon usage has fallen from 7g/Wp in 2010 to approximately 2g/Wp in 2021.[141] Moreover, despite the increase in the size of commercial cells, silicon usage fell from approximately 20g/cell in 2009 to less than 15g/cell in 2020. The other major input cost is the sliver used in contacts. Silver use has declined from 0.4g/cell in 2009 to 0.09g/cell.[142]

In the last ten years, typical power output per PV module has increased from 250W to a shipment weighted average of around 450W and the average efficiency of commercial crystalline silicon modules has increased from about 15% efficient to a shipment weighted average efficiency of 20.4% in 2021, with the most efficient crystalline silicon commercial modules produced by the top 10 manufacturers having an efficiency of 22.4%.[143]

Changing market conditions also impact PV prices, tending to increase prices in some periods and accelerating the long-term decline in PV prices in others. For example, the decline in polysilicon prices from their peak of $475/kg in 2008 to $17/kg in 2014 has been attributed to an oversupply of polysilicon in the period from 2009 to 2013 resulting from large expansions in production capacity.[144]

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[136] Wilson et al., 2020.

[137] Ibid. Note cell efficiencies will be higher than module efficiency for module containing equivalent cells.

[138] Svarc, 2022.

[139] Wilson et al., 2020.

[140] Ibid.

[141] Fraunhofer Institute for Solar Energy Systems, 2022.

[142] Louwen & van Sark, 2020.

[143] Wilson et al., 2020; Fraunhofer Institute for Solar Energy Systems, 2022.

[144] Louwen & van Sark, 2020.

Similarly, the accelerated decline in PV prices from 2017 to 2019 has been attributed to slowing growth in global deployments coincident with a rapid increase in supply. A 2021 paper suggests, "Although the result of a variety of mechanisms, it is likely that this fast decline in the last years is mainly a result of increased competition in the PV market due to oversupply…."[145] However, PV prices stabilized in 2019 and 2020, then increased in 2021 and 2022, following significant increases in input prices.[146] The direction and pace of near-term changes in PV prices is uncertain and could be impacted by changes in the balance of global supply and demand, input prices, trade restrictions, as well as, U.S. domestic content requirements and deployment incentives.

2.3: Attribution Studies

Learning curves, also known as experience curves, are used to model the pace of technological improvement in PV and other energy technologies. The most common form of learning curve is a single factor model that reflects an historical correlation between a production quantity, typically the cumulative MW of PV capacity that has been manufactured or deployed, and unit costs or, as a proxy for cost, unit prices. Other models may introduce a second or small number of additional independent variables.[147] The implicit assumption is that industry experience represented by cumulative capacity is driving a reduction in costs. However, to better understand the innovation process and how to accelerate the development and commercialization of clean energy technologies, it is important to test the assumption that cost reductions can be attributed to cumulative experience. In this section, we describe studies of PV costs that have done so by examining cost drivers in greater detail and introducing variables that have not been included in simpler learning curve studies. We have identified and reviewed four detailed attribution studies for the cost of PV modules and systems and an additional study addressing the costs of installing rooftop PV.

Multiple changes in inputs, components, and other factors have contributed to the remarkable reduction in the cost of PV. Detailed studies have examined how different technological changes contributed to the reductions in PV costs or prices and based on that analysis, which high-level drivers, including R&D, learning by doing, and economies of scale are likely to have impacted the reductions. While available studies produce somewhat different results, each of these more detailed studies finds that R&D or changes likely to have resulted from R&D, such as improvements in cell efficiency, have been a significant driver of cost reductions. Moreover, each study found that learning by doing, defined as increased efficiency in manufacturing or installation resulting from the repetition of tasks, had at most only a limited impact on reducing costs or prices.

Nemet 2005 introduces the limitations of top-down learning or experience curve models, which examine the statistical correlation between capacity deployment and cost reductions. To take a deeper look at the factors causing cost reductions, the study then examines the drivers behind improvements in PV technology, disaggregating historic year-by-year changes in PV prices and tracing these changes

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[145] Louwen et al., 2022.

[146] Louwen et al., 2022; International Energy Agency, 2022; PVXchange, 2022.

[147] For a review of the use and development of learning curves for PV and generally, *see* Louwen et al., 2022; Louwen & van Sark, 2020; Nemet & Husmann, 2012; Rubin et al., 2015; and Jamasb, 2007.

to observable technical factors.[148] The study examines the factors driving reductions in the global price of crystalline silicon PV modules from 1975 to 2001. It identifies seven key factors that changed over time and had an impact on PV module costs:

Module efficiency: power output per square meter, which nearly doubled over the study period;

Plant size: economies of scale resulting from the increase of more than two orders of magnitude in the average annual output of PV manufacturing plants, which he based on an estimated impact of plant size on operating costs that was borrowed from studies of the semi-conductor industry;

Yield: the proportion of functioning cells at the end of the production process to potential number of cells per silicon wafer, an indicator of manufacturing efficiency;

Poly-crystalline silicon share: During this period poly-crystalline silicon was less expensive than mono-crystalline silicon and the then growing use of poly-crystalline silicon was a potential contributor to cost reductions;

Silicon cost: Silicon was the largest component of raw materials used in producing crystalline silicon PV and its price fell by nearly a factor of 12 during the study period;

Silicon consumption: The amount of silicon used per Watt of capacity in PV modules, which had fallen by a factor of 1.5 during the period as manufacturing changes reduced wafer thickness from 500 to 250 µm, then from 250 to 190 µm, and reduced kerf losses due to improvements in sawing wafers;

Increased wafer size: Larger wafers facilitated savings in cell production and module assembly costs.

The study used a time series model to identify the extent to which year-to-year changes in these factors explained changes in module prices. Three factors cell efficiency, plant size, and silicon prices had a significant impact in explaining price changes. Nemet evaluated the impact of these factors both over the entire 26-year period and, recognizing that terrestrial applications became dominant after 1980, in two sub-periods 1975 to 1979 and 1980 to 2001. In the 1980 - 2001 subperiod, the seven factors together could explain 95% of annual changes in module prices, with:

- Changes in plant size associated with 43%;
- Module efficiency 30%;
- Silicon prices 12% of the total observed change in average module prices.

Professor Nemet concludes that, "*Learning derived from experience is only one of several explanations for the cost reductions in PV. Its role in enabling changes in the two most important factors identified in this study — plant size and module efficiency — is small compared to those of expected future demand,*

[148] Nemet, Beyond the learning curve, 2005; *See also* Nemet, Technical Change in Photovoltaics and the Applicability of the Learning Curve Model, 2005.

risk management, R&D, and knowledge spillovers. This weak relationship suggests careful consideration of the conditions under which we can rely on experience curves to predict technical change."[149]

Pillai 2015 is among the most rigorous of the four studies. It analyzed firm level data during the period of 2005 to 2012 for 15 major PV only companies. This study examines the impact of multiple factors on each firm's average unit production costs for crystalline silicon panels. It differs from most other studies, which rely on module prices as a proxy for costs. Its use of firm level unit costs as reported to the U.S. SEC, recognizes that this metric that is closely watched by industry analysts.[150]

Pillai's analysis is based on independent measurements of each firm's delivered panel average conversion efficiency, its publicly reported silicon consumption per Watt of capacity produced, and, as a proxy for production economies of scale, the firm's average manufacturing plant size, as well as industry data on the market price of polysilicon, the increasing fraction of panels produced in China, and the sum of all the firms' capital expenditures. Unit production cost and capital expenditure data are based on the firms' annual reports to the SEC on the cost of goods sold and on Form 10-K filings. The use of data on the cost of goods sold excludes from the analysis changes in profit margins in response to changing market conditions.

This study found that changes in polysilicon prices were associated with one-third of the annual change in unit production costs, industry capital investment with 25%, polysilicon usage with 24%, and improvements in panel efficiency with 10% of year-to-year changes in unit costs.[151]

The independent variables for Chinese production and industry capital investment proved to be significant:

- The production costs of Chinese firms were 22.4% lower than those of firms from other countries, such that the shift of production to China had a statistically significant impact on year-to-year changes in PV costs.[152]
- During this period, capital expenditures, which enable the automation of production, were a significant input to costs. Year-to-year changes in industry capital expenditures had a statistically significant impact on firm level costs. Pillai notes that the average price of capital equipment in dollars per MW of capacity purchased was lower in years when the firms in total purchase a higher amount of capacity. Professor Pillai suggests decreases in purchase price of capital equipment could be a result of economies of scale in the production of capital

[149] Nemet, Beyond the learning curve, 2005.

[150] Pillai, 2015.

[151] Ibid.

[152] Pillai, 2015; *see also* Goodrich et al., 2013 for a discussion of the manufacturing advantages of Chinese PV firms.

equipment in years when industry purchases are higher and proposes further investigation of the upstream capital equipment market.[153]

While learning curve analyses often attribute cost reductions to learning by doing and several studies identify economies of scale as an important driver, Professor Pillai's detailed firm-level analysis finds that *learning by doing and economies of scale "do not have any significant effect on cost once four other factors are taken into account, namely, (i) reduction in the cost of a principal raw material [silicon], (ii) increasing presence of solar panel manufacturers from China, (iii) technological innovations, and (iv) increase in investment at the industry level.*"[154]

Kavlak, McNerney, and Trancik 2018 analyze how changes in cost related variables (low-level mechanisms) impacted the price of crystalline silicon PV modules. They then associate each of these mechanisms to one of more high-level process drivers – R&D, learning by doing, economies of scale, or other. The study analyzes changes in costs from 1980 to 2012 and for two subperiods from 1980 to 2000 and from 2001 to 2012.[155] Kavlak's analysis includes factors for module efficiency, polysilicon prices, silicon usage, wafer area, manufacturing plant size, and yield, and adds a variable for non-silicon material costs based on estimated material costs less the cost of silicon.

In addition to considering non-silicon material costs, Kavlak's approach differs from Nemet's model in certain other respects. For example, Kavlak represents plant size in modules produced per year, rather than Watts per year, such that plant size is no longer impacted by improvements in module efficiency. Similarly, silicon usage is represented in estimated grams per module, not grams per Watt, which increases the relative contribution of silicon usage to module prices. These differences change the relative contribution of cost factors to module price reductions. For example, both Kavlak and Nemet model the period 1980 to 2001, with Kavlak attributing 8% of cost reductions to plant size, not the 43% cost reduction estimated by Nemet. Kavlak estimates that 24% of the reduction from 1980 to 2001 in attributable to module efficiency, 22% to non-silicon material costs, 18% to silicon prices, 15% to silicon usage, and 11% to wafer size.[156]

Kavlak distinguishes their approach from that of Pillai by arguing for a separation between low level mechanisms and the attribution of these mechanisms to high level process drivers. However, this point is not altogether persuasive because Pillai's inclusion of variables for production by Chinese

[153] Pillai, 2015. Firm specific capital expenditures did not have a statistically significant impact, indicating that the associated cost reductions were not a function of expanded firm specific production capacity or automation. Cumulative industry capital expenditures also did not have a statistically significant impact suggesting that cumulative experience was not the cause of the related cost reductions.

[154] Pillai, 2015.

[155] Kavlak et al., 2018.

[156] Kavlak et al., 2018; Nemet, Beyond the learning curve, 2005.

firms and industry level investment both represent proxies for more difficult to quantify lower-level variables and have a significant impact on model results.[157]

Additionally, Pillai models impacts on year-to-year changes in production costs from 2005 to 2012, a period in which there was a large spike and decline in polysilicon prices. Not surprisingly Pillai finds that over 57% of the changes in year-to-year production costs are associated with polysilicon prices or usage. Kavlak models an overlapping period from 2001 to 2012 and represents silicon price and usage making only about a 10% contribution to the change in module costs.[158] This difference appears as though it might be based on Kavlak using data from only 1980, 2001, and 2012 to calculate changes in module cost components and missing the large increase in poly-silicon prices that started in 2004, peaked in 2008, and had returned to 2004 levels by 2012.[159]

In a subsequent stage of analysis, Kavlak attributes each low-level explanatory variable to a high-level mechanism, either: R&D, economies of scale, learning by doing, other, or a 50%/50% split between R&D and economies of scale. Based on this attribution, public and private R&D contributed to nearly 60% of the overall change in module prices from 1980 to 2001 and 1980 to 2012 with economies of scale accounting for approximately 20% of cost reductions in each of these periods. For the period from 2001 to 2012, the study attributes approximately 40% of the reduction to R&D and about 40% to economies of scale. In both the overall study period and each of the subperiods, Kavlak concluded that learning by doing has responsible for less than 10% of the reduction in module prices.[160]

Trancik 2020 reports the results of a multi-part study undertaken by Professor Trancik's lab at MIT for the U.S. Department of Energy's Office of Energy Efficiency and Renewable Energy.[161] This study included estimates of the effects of changes in specific low level cost variables and high level mechanisms on the costs of PV systems, including impacts on the costs of PV modules, how changes in PV modules impact balance of system costs, and mechanisms that directly impact balance of system costs. The low-level cost model included twelve different explanatory variables impacting module costs and a total of thirty-one explanatory variables for the overall cost of PV systems. Explanatory variables included both hardware and soft cost related variables. One or more variable was used to in estimating each of fourteen hardware or soft cost components. Additionally, each explanatory variable was associated with one or more of the following high-level mechanisms that likely changed the variable over time: R&D, economies of scale, learning by doing, other, pricing strategy, or financial

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157 Kavlak et al., 2018; Pillai, 2015.

158 Kavlak et al., 2018.

159 Kavlak et al., 2018; *see also* Kavlak, 2018. Neither the published paper nor the dissertation on which it appears to be based include data on the statistical significance of reported contributions.

160 Kavlak, 2018.

161 Trancik et al., 2020. The publication page for Professor Trancik's Lab at MIT lists several yet unpublished papers, some of which may be related to this project.

incentives.[162] Addressing PV system prices, this is a more comprehensive and, in some respects, more detailed analysis than that presented in the other studies.

As described in the report, "The central idea behind this approach is to ground estimates of the high-level drivers of cost change in a combination of engineering knowledge on the improvement efforts different features are amenable to, and in empirical accounts of these efforts."[163] The analysis distinguishes low-level cost changes that are the result of R&D from learning by doing. Low-level variables that describe engineering properties and require laboratory and non-routine manufacturing settings to change are associated with R&D. Variables describing processes that can change due to the repetition of similar work steps and result in incremental improvements are assigned to learning by doing. Pricing strategy is included as a high-level mechanism to capture companies' responses to market pressures, such as imports of less expensive products from China. The effects of regulatory changes, including fees and taxes that affect consumer costs, are grouped under the high-level mechanism of financial incentives. The assignment of low-level variables to one or more high-level mechanisms enables the authors to provide a "rough estimate" of the historical contributions of different high-level drivers.

The study identifies public and private R&D as contributing 50% or more of the decrease in PV system costs in the U.S. over the 1980 to 2017 period. During that period the contributions of economies of scale were placed in the range of 20% to 30% and learning by doing at approximately 10% to 15%.[164]

The study also includes an observation that module and hardware improvements have had a significant impact on balance of system and soft such as installation costs. Trancik found that modules and inverters were responsible 85% of the reduction in PV system costs from 1980 to 2017, "approximately one third of which was achieved through hardware-soft cost interactions, … where changes to hardware, such as increased module area, reduced the cost of soft technology, such as installation."[165]

Each of the four studies summarized in this section used a detailed bottom-up approach to better understand the factors driving reductions in PV costs. In contrast to top-down learning curve models, these studies describe the contributions of specific engineering and process improvements to PV module and system costs.

The costs most directly impacted by learning by doing are PV balance of system (BOS) costs, which may be reduced as installers learn how best to install panels on different roof layouts, modify hardware to facilitate installation, improve site-visit data collection, and accelerate permitting. An additional study focused directly on the impacts of learning by doing on BOS costs. Bollinger and Gillingham analyzed BOS costs for 76,838 small rooftop solar installations receiving incentive payments in California

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[162] Ibid.

[163] Ibid.

[164] Ibid.

[165] Ibid.

between 2002 and 2012.[166] The study reviewed the impacts of the California Solar Initiative (CSI), a $2 billion state program providing substantial upfront rebates for rooftop PV. The economic justification for the CSI was based on reducing environmental externalities and compensating for what are called "non-appropriable" learning by doing benefits, learning that was not just appropriated by the firm installing the panels, but which would spillover and benefit the California solar industry generally. The spillover of learning by doing, like spillover benefits from research, was treated as a positive externality justifying public investment. Earlier studies indicated that the CSI could not be easily justified on economic efficiency grounds based on environmental externalities alone, making the existence of non-appropriable learning benefits essential to an economic justification.[167] Analyzing detailed county level data, Bollinger and Gillingham found evidence that an installation contractor's internal – appropriated – learning impacted their non-hardware costs and statistically weaker evidence of spillover benefits based on installations by competitive installers. They conclude:

> "However, the learning is small in magnitude; LBD [learning by doing] can account for just a $0.12 per watt decline in non-hardware costs over the data period. As a reference point, during this period, hardware costs declined from over $7 per watt to less than $3.50 per watt. … [T]he balance-of-system … which includes both the non-hardware costs (customer acquisition, labor, permitting, etc.) and the firm markup, declined by less than a dollar, from $3 per watt to a little over $2 per watt, only 15% of which we can attribute to LBD. Thus, it is hard to justify the substantial CSI incentives from an economic efficiency argument alone."[168]

Even without the detailed data used in the studies discussed above, a comparatively straight forward inclusion of annual patent volumes in a multi-factor experience curve analysis supports the importance of R&D and modifies the statistical association between capacity deployment and learning rates. In Louwen et al., the inclusion of patents in a three-factor experience curve model of factors impacting average PV module selling prices between 1975 and 2018 results in:

- Improving the fit of the model to actual experience;
- Compared to a two-factor model (including silicon prices), reducing the learning rate for deployed capacity from 19.8% to 15.6%; and
- Produced an estimated learning rate associated with the level of patent activity of 17.5%.

The Louwen et al. study notes that, "it is generally difficult to accurately separate learning by doing from learning by searching in multifactor experience curves, hence, it is likely that the effect of learning by doing in the experience curve shown in [this study] includes the technological progress in areas that Kavlak et al. deem the result of R&D activities."[169] Kavlak is one of the bottom-up attribution studies summarized above.

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[166] Bollinger & Gillingham, 2019.

[167] Borenstein, 2008; van Benthem et al., 2008; Burr, 2014.

[168] Bollinger & Gillingham, 2019.

[169] Louwen et al., 2022.

A similar, but more pronounced pattern was identified in a learning curve analysis of high-level drivers of recent improvements in U.S. PV and wind costs. Zhou and Gu used a two-factor learning curve model based on cumulative installed capacity and cumulative public sector R&D spending, fitting the model to account the lag between R&D expenditure and integration of the resulting knowledge into practice. For U.S. utility-scale PV from 2009 to 2016 they found a learning by doing progress rate of 6.78% per doubling of capacity and for R&D a learning by searching (R&D) progress rate of 75.21% with a time delay of four years.[170]

The more detailed analysis presented in these attribution studies raises important questions about the inference commonly drawn from learning or experience curve analyses that increased deployment reduces costs.

[170] Zhou & Gu, 2019.

CHAPTER 3: Case Study 2: On-shore Wind

3.1: Executive Summary

The earliest electric wind turbines were developed in the 19th century. Innovation continued through the 1930s in northern Europe and the U.S. and was useful in some niche applications like rural electrification. Interest and government funding for wind turbines revived during the energy crisis of the 1970s, and small (~30-60 kW) turbines began to be manufactured by multiple companies, especially in Denmark and the U.S. In the early 1980s, federal and state tax credits and new regulations for utilities such as PURPA and guaranteed standard offer contracts created a boom in wind power in California – the California wind rush. By 1985, there were 17,000 turbines installed in California, which had 75% of the world's wind capacity. In the mid-1980s, the tax credits expired, California ended the standard offer contracts, and the boom ended.

Focus shifted to Denmark and northern Europe, and innovation in wind turbine design continued at a rapid pace. Vestas, a major turbine manufacturer, first mass-produced turbines in 1980 and sold hundreds of small (~50 kW) turbines in the California wind rush. Throughout the 1980s and 1990s, they developed multiple control technologies that increased generator efficiency and reduced turbine stress and reduced turbine blade weight by a factor of 4. Throughout this period, they manufactured bigger and bigger turbines. In 1994, their V44 model had a rated capacity of 600 kW, a massive increase from the turbines of the early 1980s. In 1997, they introduced the V66, with a rated capacity of 1.65 MW. Two years later, they introduced the V80-2.0, with a rated capacity of 2 MW.

Rapid growth in turbine size and steady deployment in California and Europe corresponded with a significant decline in capital costs. From 1983 to 1998, global capacity-weighted average capital cost for wind turbines decreased from ~$5,200/kW in 1983 to ~$2,400/kW, with 10 GW of wind capacity installed globally by 1998, as shown in Figure .

These cost declines towards the turn of the century combined with new wind-friendly policies to spur rapid growth in global wind capacity in the 1998-2005 time period. FiTs, production tax credits (PTCs), renewable portfolio standards (RPS), and other subsidies for renewable energy in the U.S. and Europe made wind energy profitable and competitive, especially in newly forming deregulated electricity markets. Data from the U.S. and several countries in Europe show that growth and stagnation in wind capacity coincide with policy changes such as the introduction and expiration of tax credits and FiTs. Globally, wind capacity grew from 5 GW in 1995 to 58 GW by the end of 2005, with the bulk of that growth happening in Europe (41 GW by 2005). This rapid deployment coincided with further increases in turbine size and further decreases in cost. In the U.S., average installed turbine nameplate capacity doubled from 1998-2005, and globally, capital cost declined from $2,350/kW to $1,910/kW.

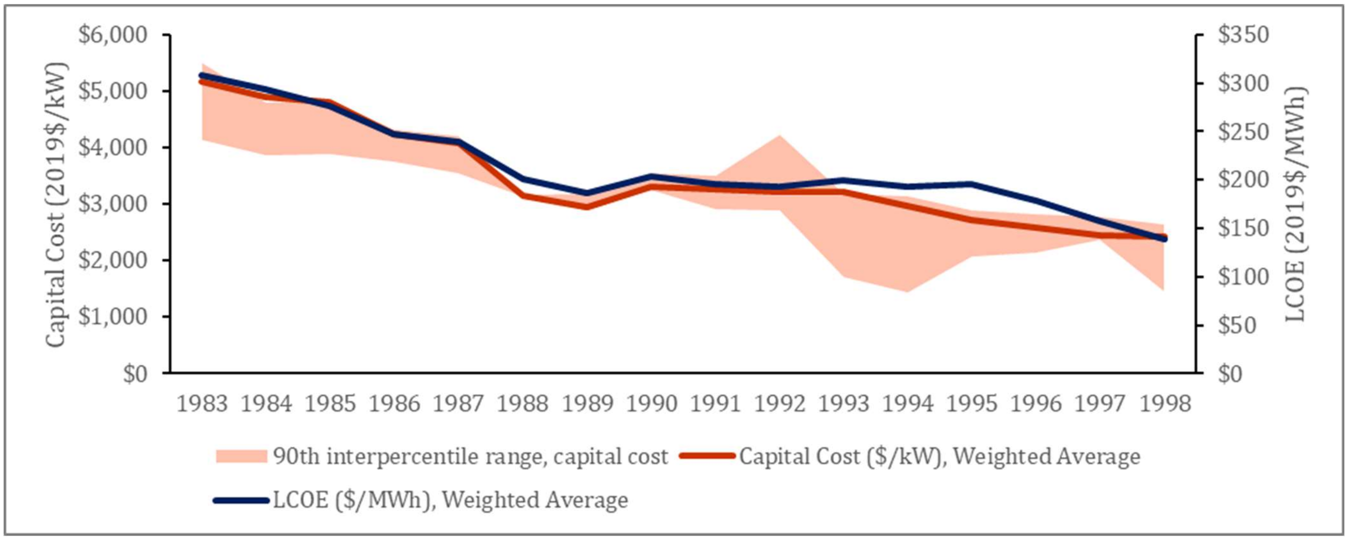

Figure 12: Global Wind Capital Cost Trends, 1983-1998

Around 2005, the nexus of wind capacity growth shifted from Europe to the U.S. – from 2005-2011, the U.S. would add almost as much wind capacity as all of Europe. This period of rapid deployment was associated with a large increase in the cost of wind energy, in a reversal of two decades of decline. Rising wholesale electricity prices made wind an attractive investment – however, foreign currency movement, increased prices for construction materials and labor, and higher profits for wind companies all contributed to a 50% increase in the capital cost of on-shore wind between 2005 and 2009. This period of rising costs was also a period of low technological progress in wind turbine design and performance. Turbine size and capacity factors, after rising rapidly from 1998-2005, stagnated or declined. It seems that at a time of constrained supply chains and high profits, wind manufacturers focused on manufacturing and producing supply rather than on R&D. When prices started to decline again in the 2010s, a new era of technological progress took hold.

The year 2012 saw the beginning of a multi-year increase in capacity factor driven by a resurgence in technological improvement as well as a reversal in the trend of declining wind site quality, as shown in Figure . Newer models of wind turbines were taller and had much wider rotors, resulting in high capacity factors and low specific power.[171] In 2011 no installed wind turbines in the U.S. had a rotor diameter greater than 115 m. In 2018, more than half did, and the average had increased from 89 m to 116 m, while average hub height only increased from 81 m to 88 m. Constraints on interconnection and economic incentives in electricity markets incentivized the installation of these larger, higher

[171] Low specific power, in W/m^2 (nameplate capacity divided by swept area), is a measure of a turbine's level of trade-off between maximum power output at high wind speeds and power output at low wind speeds. Increasing rotor length increases swept area more than nameplate capacity.

capacity factor turbines. In addition, transmission initiatives such as the Competitive Renewable Energy Zones (CREZ) in Electric Reliability Council of Texas (ERCOT) unlocked new high-quality wind sites for development, and reduced curtailment from 17% in 2009 to 0.5% in 2013.

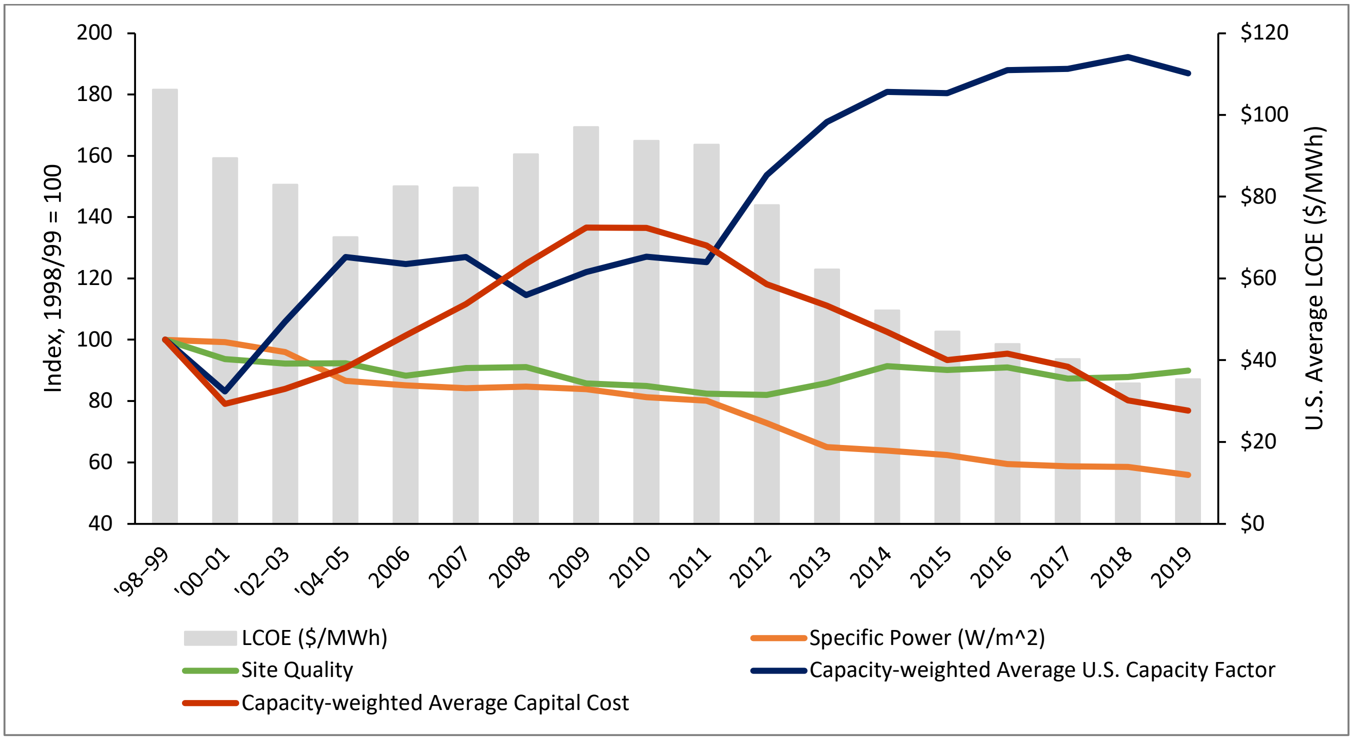

Figure 13: LCOE ($/MWh) plotted against four factors that influence LCOE

Indexed to 100 in 1999: Site quality, specific power, capital cost, and capacity factor

Despite the increase in turbine size, capital costs declined significantly during the 2012-2018 period. Some of this decline was the reversal of exogenous trends that increased prices in the last half of the 2000s, such as currency movements and construction material cost declines. Besides external forces, though, we would generally expect increased turbine size to increase cost, since bigger turbines require more materials and higher transportation and installation costs. But so far, manufacturers have been able to stay ahead of these natural cost curves through more sophisticated control systems and improvements in manufacturing productivity.

The Clean Energy Buyer's Alliance (CEBA) recorded its first announced renewable energy deal in 2008, but announcements and virtual PPAs for renewable energy did not reach significant levels until around 2015, when new Scope 2 guidance from the World Resources Institute and the World Business Council for Sustainable Development allowed corporations to use renewable energy PPAs to offset their carbon emissions. As Figure shows, this procurement largely follows the decline in wind costs, and it still represents a small fraction of annual installed wind capacity.

In the past couple of years, the trend of increasing rotor diameter and decreasing specific power has been stalling in favor of a growth in nameplate capacity. Average U.S. nameplate capacity averaged 3 MW in 2021, up from 2 MW in 2015, and half of that increase has occurred since 2019. All major manufacturers have announced next-generation 5 MW on-shore wind turbines, and expert elicitation predicts that the average on-shore wind turbine in 2035 will have a nameplate capacity of 5.5 MW, but the same specific power as today's turbines. This new trend will change the current paradigm of declining costs – indeed, average LCOE has not declined since 2018. It remains to be seen whether the cost declines of the past decade can continue with the next generation of wind turbines.

3.2: Early Development (pre-1980)

In the early days of electrification in northern Europe, there was some experimentation on wind turbine design and many of the key concepts were discovered. Innovation continued through the 1930s in northern Europe and the U.S. and wind turbines were useful in some niche applications like rural electrification.[172]

Post-WWII, there was some funding and development in government labs in Germany, Denmark, and France. Researchers experimented with key design parameters such as number of blades, turbine direction (upwind/downwind), nacelle rotation, and braking. The true revival in interest was due to the 1970s oil shock/energy crisis. NASA worked with the aerospace industry to design and build wind turbines bigger than any that came before, resulting in the 2-blade, downwind Mod-1 (2 MW) and Mod-2 (3.2 MW), which were plagued by mechanical failures and never reached their expected potential. Germany's R&D program had similar issues. In Denmark, on the other hand, more decentralized R&D resulted in smaller (30-60 kW), more reliable 3-blade upwind turbines. By the late 1970s, companies in Denmark and the US were manufacturing these types of turbines, just in time for the second oil embargo of 1979.

3.3: Technology Improvements and Early Deployment (1980-1998)

After the oil embargo, Denmark launched a wind incentive program, and the U.S. launched federal tax credits.[173] The major opportunity was in California. California measured wind speed across the state and released that data publicly, instituted their own 25% tax credit on top of the federal credit, and ordered the utilities to provide grid connections and fixed-price contracts to independent power producers.[174] PURPA required that public utilities buy the output of renewable generators at "avoided cost" but left it up to state regulators to calculate avoided cost.[175] Starting in 1983, the CPUC defined a "standard offer" contract (SO4 contract) at generous rates due to the high price of energy, which was expected to continue to rise. 15 GW of development signed up for the contract, and by 1984 California had 75% of the world's wind power capacity, with 17,000 turbines installed by 1985.[176] In 1985, it became clear that the Standard Offer 4 contracts were too expensive and the CPUC terminated the

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[172] Gape & Möllerström, An overview of the history of wind turbine development: Part I - The early turbines until the 1960s, 2022.

[173] *The wind rush in California*, 2022.

[174] Gape & Möllerström, An overview of the history of wind turbine development: Part II–The 1970s onward, 2022.

[175] Hirsh, 1999.

[176] Gipe, 1991.

program.[177] The federal tax credits also expired in 1985, and California ended its tax credit in 1987. Focus shifted to Denmark, and the U.S. market would not pick up again until the late 1990s. Despite this, the California wind rush kicked off a decade and a half of innovation that led to large cost declines and the prominence of the MW-scale, 3-blade, upwind “modern” turbine that has dominated the 21st century.

From 1983 to 1998, global capacity-weighted average capital cost for wind turbines decreased from ~$5,200/kW in 1983 to ~$2,400/kW, with 10 GW of wind capacity installed globally by 1998, as shown in Figure .[178] Growth in the size of turbines played a major role. In the 1980s, though much larger turbines did exist, most installed turbines in the U.S. were much smaller, such as the U.S. Windpower 56-60 (50 kW) and the Bonus Danregn turbine (55 kW), which had rotor diameters of 16-17 meters.[179] These types of small turbines dominated installations during the California wind rush period. By 1998, typical turbine capacity was approaching 1 MW with rotor diameters around 50 m, a 20x increase in rated capacity and a 10x increase in swept area in 15 years.[180] This growth in size and capacity led to higher capacity factors and reduced fixed costs. At the same time, increased productivity in manufacturing led to lower labor costs – one major manufacturer employed seven people per delivered megawatt in 1992, but only two people per megawatt in 2001.[181]

Significant manufacturing and design improvements contributed to reduced cost and greater performance. The history of Vestas, a major wind turbine manufacturer, bears this out.[182] In 1980, Vestas had just begun mass production of wind turbines when a manufacturing defect in the blade caused catastrophic failure. By 1981, Vestas had identified the issue and started producing its own more reliable components – just in time for the California wind rush, where they sold hundreds of turbines. In 1985, Vestas introduces OptiTip, which provides pitch regulation for turbine blades, increasing efficiency and decreasing mechanical stress. By 1990, they had reduced turbine blade weight from an initial 3800 kg to 1100 kg. In 1994, they introduced the V44 model, which had a rated capacity of 600 kW. In 1997, they introduced the V66, with a rated capacity of 1.65 MW – an almost threefold increase in three years. Two years later, they introduced the V80-2.0, with 2.0 MW rated capacity.

This early deployment and technological development period were clearly critical in making on-shore wind a reliable, cost-competitive technology that would be deployed on a large scale over the next two decades. Investments in manufacturing and materials improvements and lessons learned from

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[177] Hirsh, 1999.

[178] BP, 2022.

[179] Gape & Möllerström, An overview of the history of wind turbine development: Part II–The 1970s onward, 2022.

[180] Ibid.

[181] Milborrow, 2022.

[182] Vestas, 2022.

deployment in the 1980s and 1990s in the U.S., Germany, and Denmark led to cost declines and technological development that positioned wind power for a boom in the 21st century.

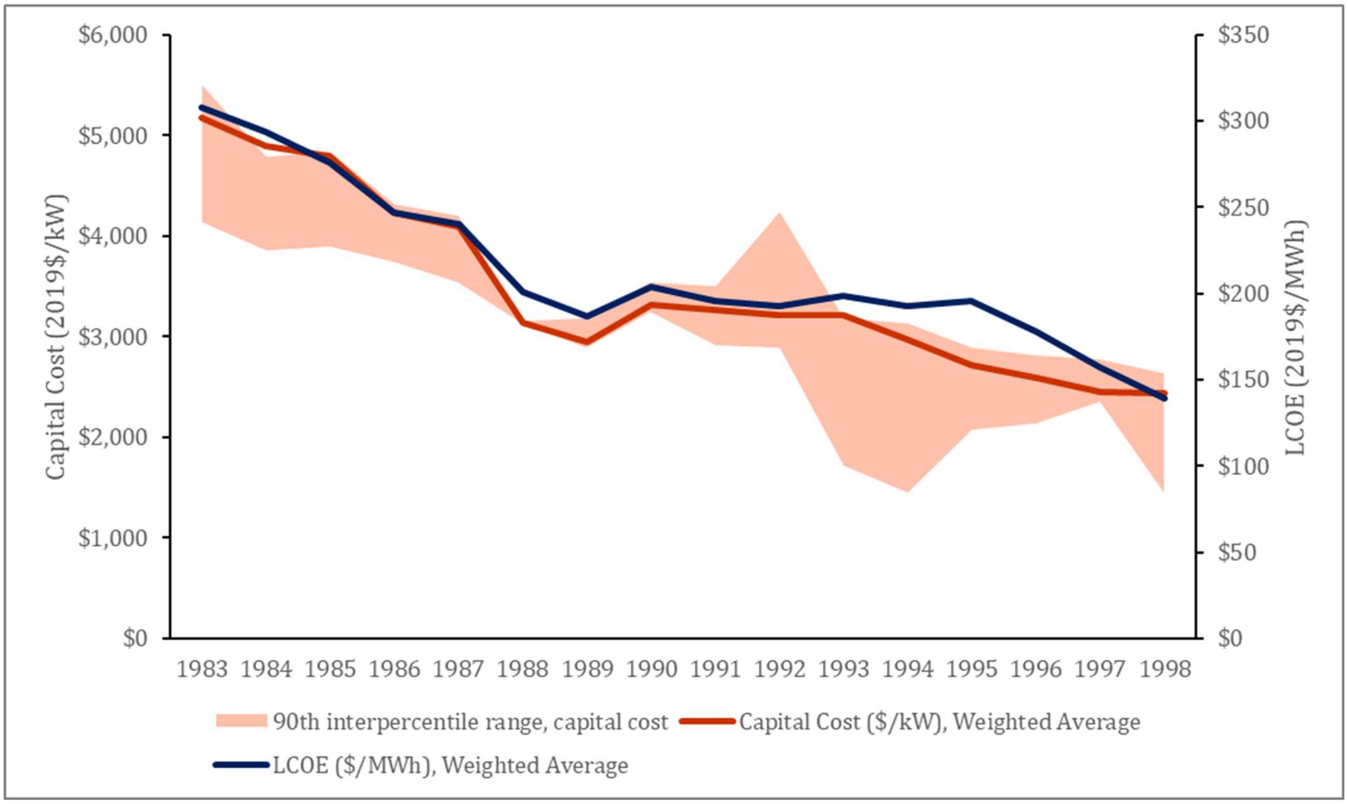

Figure 14: Global Wind Capital Cost Trends, 1983-1998

3.4: Policy Spurs Rapid Deployment (1998-2005)

In the U.S., the Energy Policy Act of 1992 included a PTC (inflation-adjusted $15/MWh) for wind energy that was originally set to expire in 1999, but was then extended multiple times. The continued impending expiration and extension of the PTC created a boom-and-bust cycle in the U.S. during this period, as can be seen in Figure . Despite the uncertainty around the PTC, the U.S. saw a 3.5x increase in wind capacity during this period, from 2.4 GW to 8.7 GW.

The introduction of state RPS programs, which often accompanied the restructuring of electricity markets in the late 1990s and early 2000s, incentivized new renewable generation such as solar and wind. Through 2007, RPS programs drove non-hydro renewable energy build-out, including in the fastest-growing wind markets in Texas and the Midwest. Post-2007, we see that growth in non-hydro renewable energy generation greatly outpaces RPS requirements. In Texas, RPS requirements were completely fulfilled in 2008 (seven years ahead of schedule), yet wind development continued due to the PTC, declining capital costs and excellent wind resources. In the Midwest region, RPS requirements remained, but growth in wind generation was much greater than required for compliance.[183]

[183] Barbose, 2021.

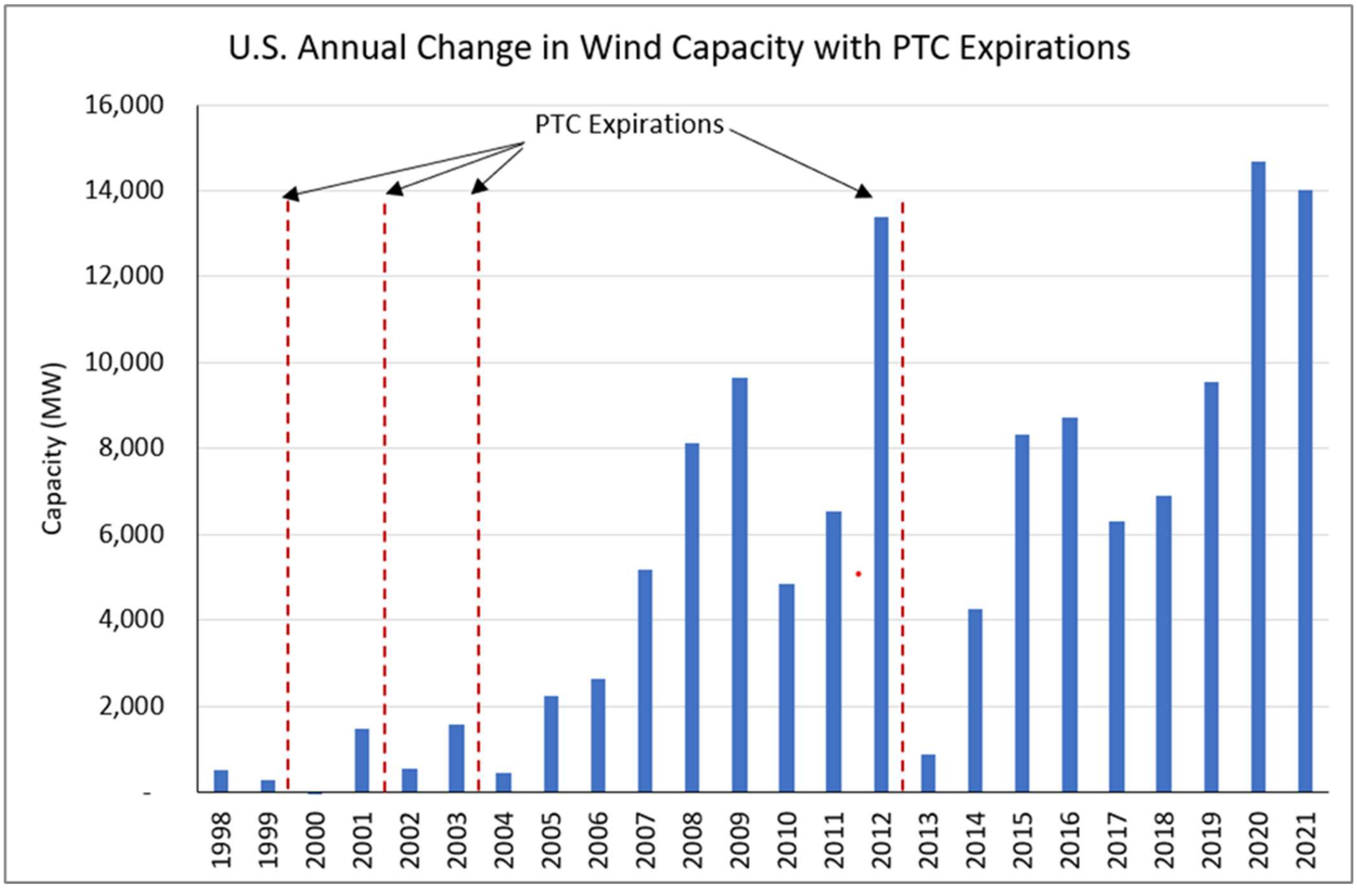

Figure 15: Annual Change in U.S. Wind Capacity, with PTC Expiration Years Noted

In Europe, FiTs were the policy of choice for renewable energy incentivization. Often paired with guarantees of interconnection and long-term contracts with utilities, they provided strong and stable subsidies, and development in wind power took off around the turn of the century, especially in Germany, Spain, and Denmark. These subsidies meant steadier, faster development in Europe than in the U.S in this period. The effect of these subsidies was substantial. Figure 16 shows annual capacity additions in five European countries before and after a change in FiT or other renewables-focused policy, indexed to the year before the policy change. When Denmark's FiT was eliminated, additions went to almost zero. In Germany, Italy, Portugal, and the UK, implementation of policy is linked with large increases in the growth of on-shore wind capacity.

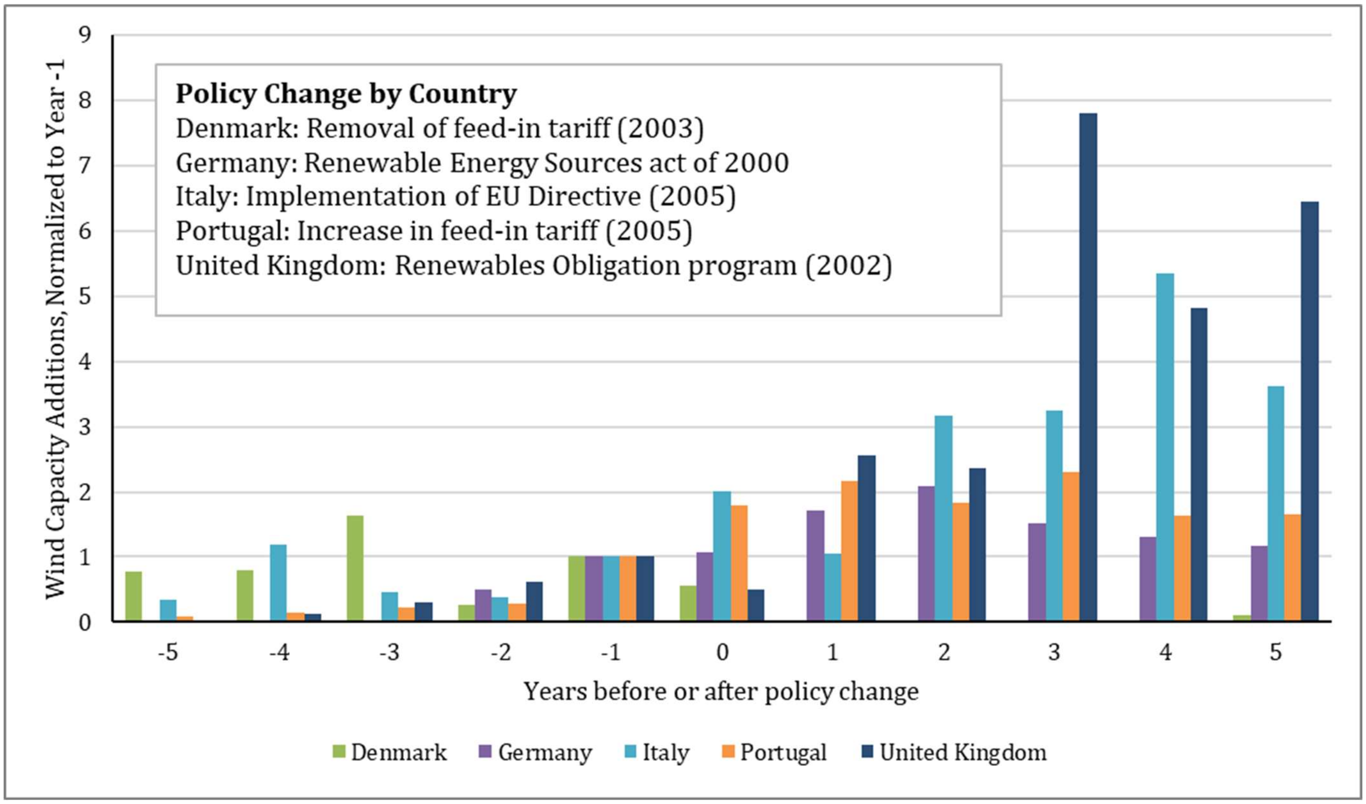

Figure 16: Annual on-shore wind capacity change in 5 European countries

Changes indexed to the year before a significant policy change. Policy changes and year are noted in text box.

Germany's Electricity Feed-in Act in 1991 provided guaranteed interconnection and a FiT for wind energy, leading to over 6 GW of installed capacity by 2000, more than the U.S. and Denmark combined, and representing about half of all wind capacity in Europe. The Renewable Energy Sources Act of 2000 created a 20-year FiT for wind energy with an obligation to purchase on the utility side.[184]

In Denmark, a fixed FiT for wind power was introduced in 1993, along with tax benefits. This resulted in a 6x growth in wind capacity (500 MW to 3 GW), keeping Denmark at the forefront of wind energy worldwide. In 2003, however, Denmark replaced its FiT program with an RPS-type scheme that did not guarantee interconnection. Over the next 5 years, only 129 MW were installed.[185]

In Spain, the Electric Power Act of 1997 and Royal Decree 2818 on renewable energy gave renewable energy producers rights to sell power to the grid at a premium to wholesale market prices. Other countries such as Italy, Portugal, and Greece also implemented FiTs and other wind-friendly policies.[186]

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[184] International Renewable Energy Agency, 2013.

[185] Ibid.

[186] Ibid.

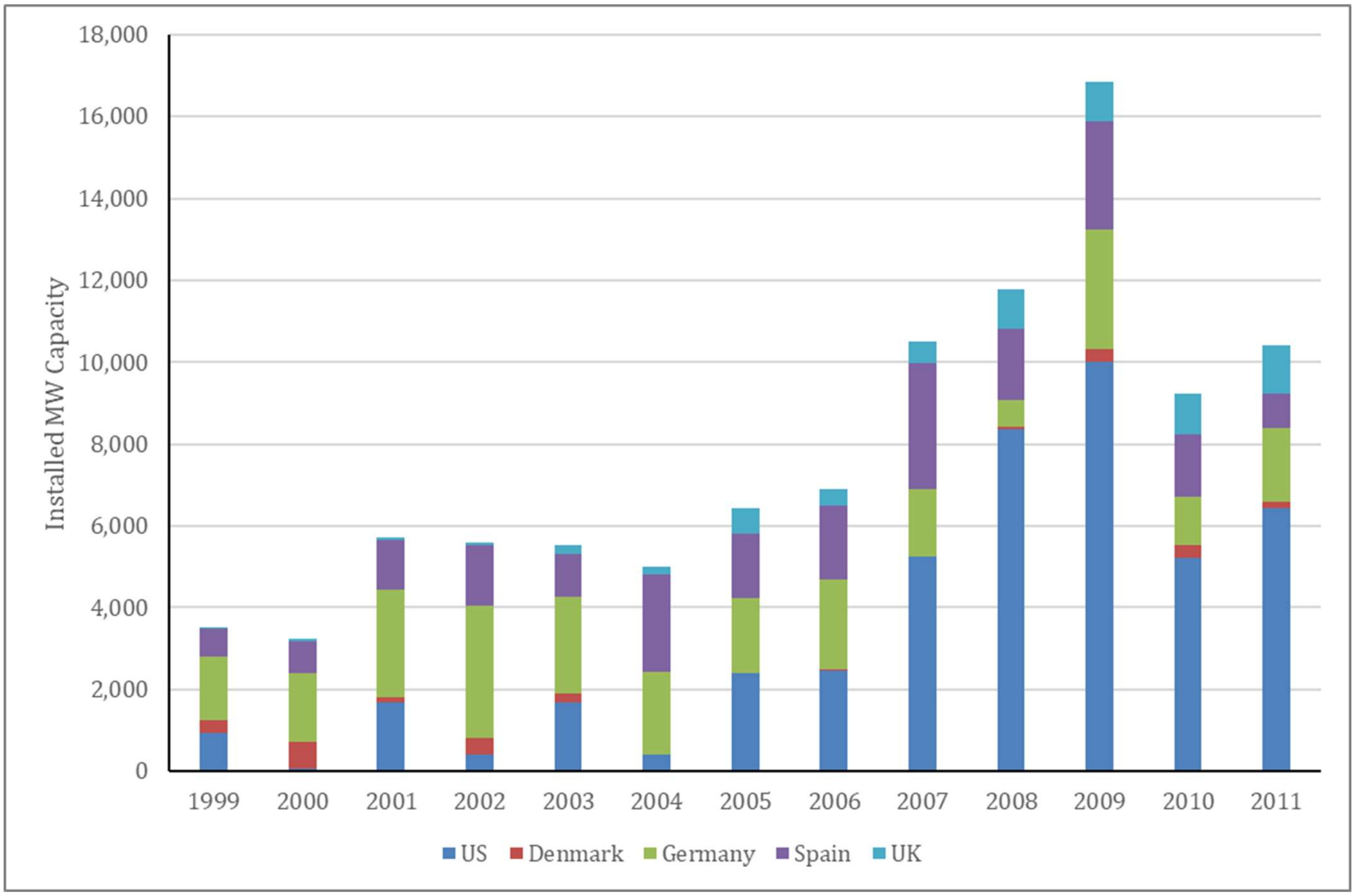

Figure 17: Annual on-shore wind installation in the U.S. and selected European countries, 1999-2011

This increase in deployment was accompanied by significant changes in technology and cost. Between 1998 and 2005, U.S. average turbine nameplate capacity doubled from 0.72 MW to 1.46 MW, hub height rose from 56.6 m to 74.1 m, and average rotor diameter grew from 48.2 m to 73.6 m.[187] If the period before 1998 saw the development of the modern turbine design, the period from 1998-2005 saw the development of modern turbine size. Not since this period has nameplate capacity or hub height increased so quickly.

Despite rapid size scaling, capital costs declined slightly in this period both globally and in the U.S. In the U.S. average capital cost declined from $1,790/kW in 1998-9 to $1,630/kW in 2004-5, while globally it declined even more, from $2,350/kW to $1,910/kW.[188, 189] Increased rotor diameters increased capacity factors in the U.S. from ~20% to ~25%, even as average site quality decreased. Both factors led to a 30% decline in levelized cost of energy for wind projects in the U.S.

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[187] Lawrence Berkeley National Laboratory, 2022.

[188] Ibid.

[189] IRENA, 2022.

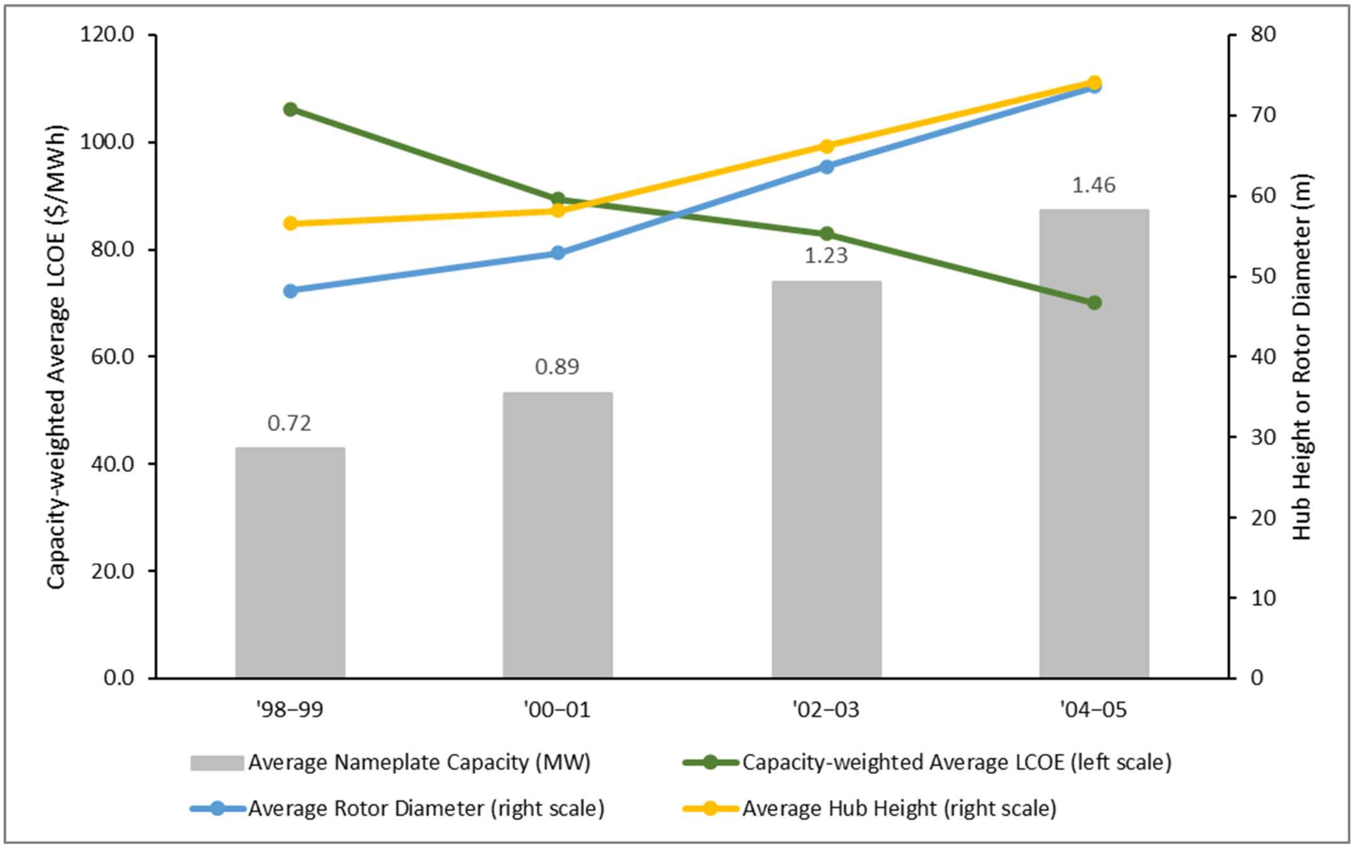

Figure 18: Average U.S. on-shore wind nameplate capacity, LCOE, rotor diameter, and hub height from 1998-2005

Credit: *LBNL Land-Based Wind Market Report. Data aggregated across two years due to annual variation in installation.*

Altogether, early policy implementation made Europe the center of growth for the wind industry in the mid-2000s. Improvements in manufacturing, materials, and supply chain efficiency allowed capital costs to fall somewhat even as turbines doubled in size, meaning that on a levelized basis costs fell dramatically. In the U.S., RPS programs may have driven early growth in wind capacity, but the PTC provided the largest incentive, as shown by what happened after the times that it expired.

3.5: Rapid U.S. Growth and Price Increase (2006-2011)

After hitting a low point of $1,630/kW in 2004-5, average U.S. turbine prices and capital costs rose until 2009, when average installed project cost was $2,643/kW. A 2017 NREL analysis[190] quantified the drivers of the price increase in this period (and subsequent decrease), which is shown in Table . They found that exogenous factors such as increases in commodity prices and foreign currency movements were the main factors. Some endogenous factors also contributed – labor costs rose, and profit margins for manufacturers rose as a quick rise in demand outpaced overwhelmed existing suppliers. In contrast to an earlier study,[191] they did not find that turbine scaling (growth in turbine size) played a role in increased costs. Despite larger turbines requiring more material (power scales by the square

[190] Mone et al., 2017.

[191] Bolinger & Wiser, 2011.

of rotor diameter and turbine tower height, while material volume scales by the cube), manufacturers were able to improve turbine design enough that kg/W values remained constant in this period.[192]

Table 3: Cost drivers of turbine price trends 2001-2015.

	2001-2008 (2015 $/kW)	2008 - 2015 (2015$/kW)
Endogenous Drivers	**+171**	**-36**
Labor costs	+79	-4
Warranty Provisions	+37	-34
Profit Margins	+60	+24
Turbine Scaling	-4	-24
Exogenous Drivers	**+258 to +425**	**-171 to -272**
Materials Prices	+77	-60
Energy Prices	+13	-11
Currency Movements	+168 to +335	-101 to -202
Total Impact	**+429 to +597**	**-207 to -308**

Source: Reproduced from Mone et al., 2015 (revised 2017)

Post-2011, staffing costs reversed trend and fell back to 2004/5 levels by 2015. Additionally, efforts to improve product quality cut warranty provision costs by more than half, though the absolute magnitude of this change is only ~$50/kW. They show that profitability increased from 2005-2008, declined until 2012, then increased again through 2015. So, while increased profitability played a role in increasing costs through 2009, costs decline from 2012-2015 occurred despite increased profitability. The conclusion is that exogenous factors were the driving force behind the rise and fall of prices from 2001-2015. Among endogenous factors, labor costs and profit margins were the main drivers, both of which may have been driven by the broader macroeconomic situation as well as changes in manufacturing or technology.

In this period, demand for wind turbines grew more quickly than suppliers could handle, causing high prices and increased profit margins. Though U.S. on-shore wind installations accelerated (see Figure), average installed capacity factor and turbine nameplate capacity did not continue to increase but stalled for several years. At a time of high demand and high profits, with constrained supply chains, wind turbine manufacturers may have focused on manufacturing rather than R&D. Another factor may have been a change in tax incentives. In the wake of the financial crisis, wind projects were allowed to take a 30% investment cash grant in lieu of the PTC. This led to developers completing less energetic projects in their pipeline, dragging down average capacity factor and LCOE.[193]

[192] Mone et al., 2017.

[193] Bolinger et al., 2022.

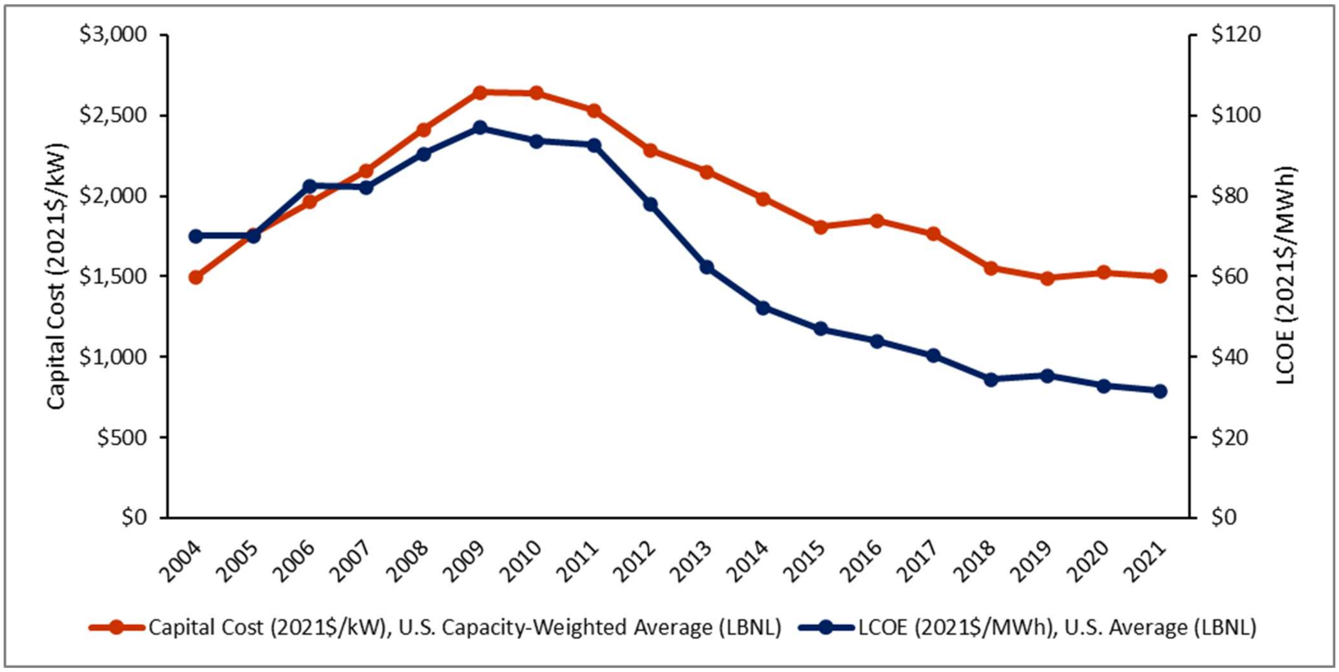

Figure 19: U.S. average capital cost and LCOE for on-shore wind, 2004-2021

Credit: *LBNL Land-Based Wind Market Report*

3.6: Turbine Scaling and Price Reduction (2012-2018)

Declining capital costs and increased capacity factors over the 2012-2018 time period resulted in record low LCOEs for new on-shore wind turbines, averaging less than $40/MWh in both 2018 and 2019. The increase in capacity factors was driven by turbine scaling, particularly increases in rotor diameter, and new transmission lines opening more high-quality wind sites for development. Capital costs declined despite increases in turbine size, due to reverses in exogenous trends in the previous decade and more sophisticated control technologies. Production of wind turbines increased rapidly during this period, which may have reduced capital costs through economies of scale and improvements in manufacturing and installation logistics.

2012 saw the beginning of a multi-year increase in capacity factor driven by a resurgence in technological improvement as well as a reversal in the trend of declining wind site quality. Newer models of wind turbines are taller, but also much wider in terms of rotor diameter, and total swept area is outpacing rated turbine capacity, meaning that newer turbines are geared towards "filling in" their power curve and achieving higher capacity factors than producing higher peak power.

We can see this as a decline in average specific power (W/m2), which divides rated turbine capacity by total swept area. These turbines have higher capacity factors and are also more well-suited to moderate or low wind speed regimes. Even so, we are seeing these types of turbines deployed across high-value wind sites.[194] This may be for economic reasons – wholesale market prices in markets like ERCOT, MISO, and SPP are likely to be lowest when wind speed is highest, so it is more profitable to

[194] Wiser et al., 2021.

produce power at lower wind speeds than at higher wind speeds.[195] In addition, in the U.S. and other land-rich countries, project capacity is constrained by contractual, interconnection, and transmission limits, which means that optimizing for high capacity factors is better than building the highest-capacity turbine.[196]

In addition to turbine scaling and lower specific power, transmission expansion opened better sites for wind development and reduced curtailment. In Texas, the public utilities commission identified CREZ and developed a plan to increase transmission capacity to these zones, which was completed by 2013.[197] This reduced wind curtailment in ERCOT from 17% in 2009 to less than 0.5% in 2013. In addition, it unlocked new sites with strong wind potential for development. Figure below from LBNL shows that wind site quality in the U.S. had been declining for years before making a major reversal in 2013.

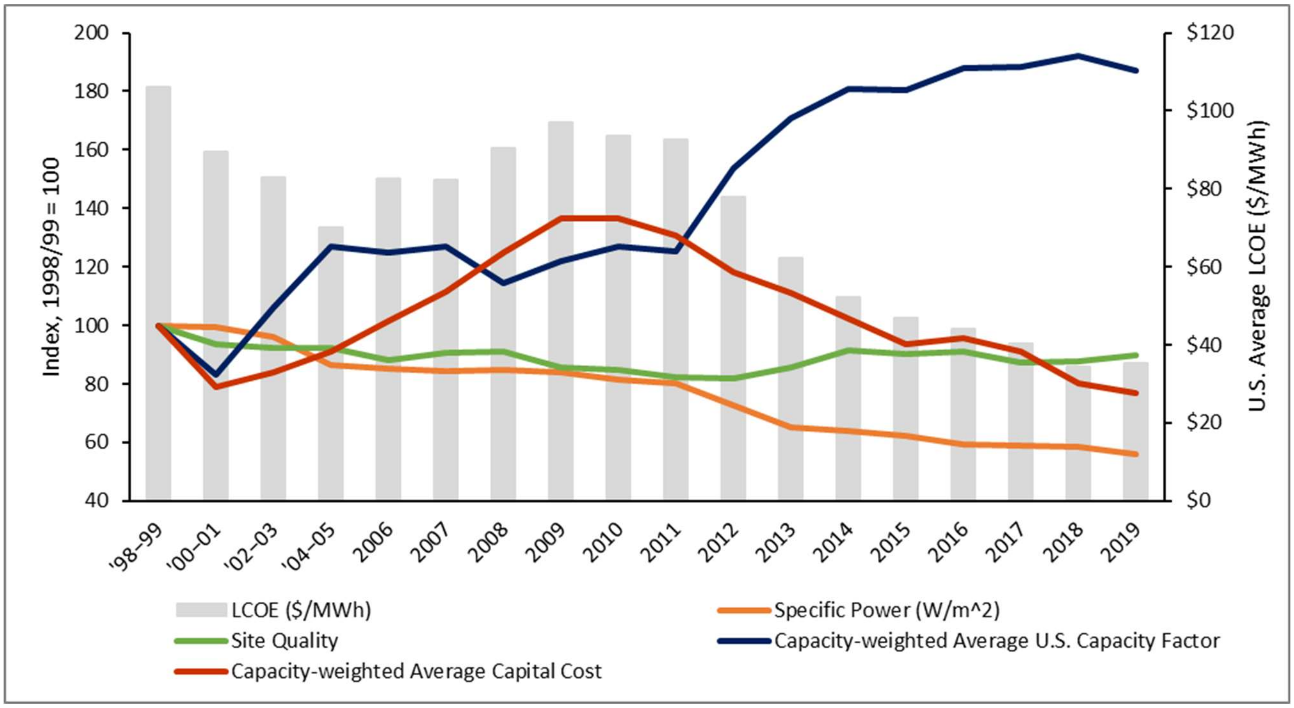

Figure 20: Average LCOE along with four contributing factors to LCOE

LCOE indexed to 100 in 1998/99

Credit: *Lawrence Berkeley National Laboratory, 2022*

Despite increased turbine size, especially rotor diameter, capital costs fell significantly during the 2012-2018 period (from $2,285/kW in 2012 to $1,553/kW in 2018, according to LBNL. With sophisticated control systems in modern turbines, extending blade length was achieved with relatively

[195] Bolinger et al., 2020.

[196] Ibid.

[197] Dorsey-Palmateer, 2020.

limited impact to the rest of the turbine system (nacelle, tower, foundation).[198] However, as mentioned earlier, there are natural scaling curves for increasing length, and while manufacturers have been able to stay ahead of these mass and cost curves so far, the extent to which that will work going forward is uncertain. In addition, larger rotor diameters impose increasing costs in transportation and installation, and larger turbines increase the chance of running afoul of regulatory agencies or local government. Besides capital costs, operation and maintenance have also seen declines, due to improved data analytics and autonomous inspection, improved practices, and greater competition in the market for O&M services.[199]

During this period, China became the dominant market for wind installation. Wind capacity in China sextupled from 2011-2020, and at present China is adding as much wind capacity every year as the rest of the world combined.[200] However, the Chinese wind market is highly segregated, with demand being almost entirely met by Chinese suppliers, and Chinese suppliers not having much success selling to Europe and the U.S.[201] Goldwind, the largest Chinese manufacturer, claims to have installed more than 92 GW of wind capacity, but according to S&P Global, only 452 MW of this is outside of China. Though Chinese turbine prices have undercut the global average since 2008, they have struggled to compete with established vendors in Europe and the U.S. for contracts. One reason for this is that Chinese models have typically been a generation behind models from European and U.S. vendors. So, despite rapid growth, it doesn't appear that Chinese deployment of wind turbines has had much effect on price or technological improvement elsewhere.

Announcements of corporate procurement of renewable energy are tracked by CEBA, while signed power purchase agreements for installed wind and solar capacity are tracked by S&P Global. These data sources are not directly comparable – the CEBA Deal Tracker tracks announcements and includes some non-PPA deals, while the data from S&P Global only includes executed PPAs for installed wind and solar capacity.

However, both these data sources show that voluntary corporate procurement did not begin in earnest until 2014/2015, as shown in Figure 21, broadly coincident with the World Resource Institute's and World Business Council for Sustainable Development's 2015 update to Scope 2 reporting guidelines allowing corporations to use renewable energy purchases to offset emissions.[202] This follows the steepest decline in wind LCOE in the first half of the 2010s, as LCOE decrease slows after 2015, and stops declining at all in 2019.

The available evidence does not suggest that corporate purchasing of wind power was a significant factor in bringing down the costs of wind energy. Corporate purchasing occurs after the largest cost declines, and rate of cost decline has slowed since corporate purchasing became a significant factor in

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[198] Ibid.

[199] IRENA, 2022.

[200] Ibid.

[201] Blackburne, 2022.

[202] Greenhouse Gas Protocol, 2015.

the renewable energy market. In addition, the cost declines that have occurred in the era of corporate purchasing are the result of a continuation of trends that began earlier, such as the trend towards declining specific power due to increased rotor diameter.

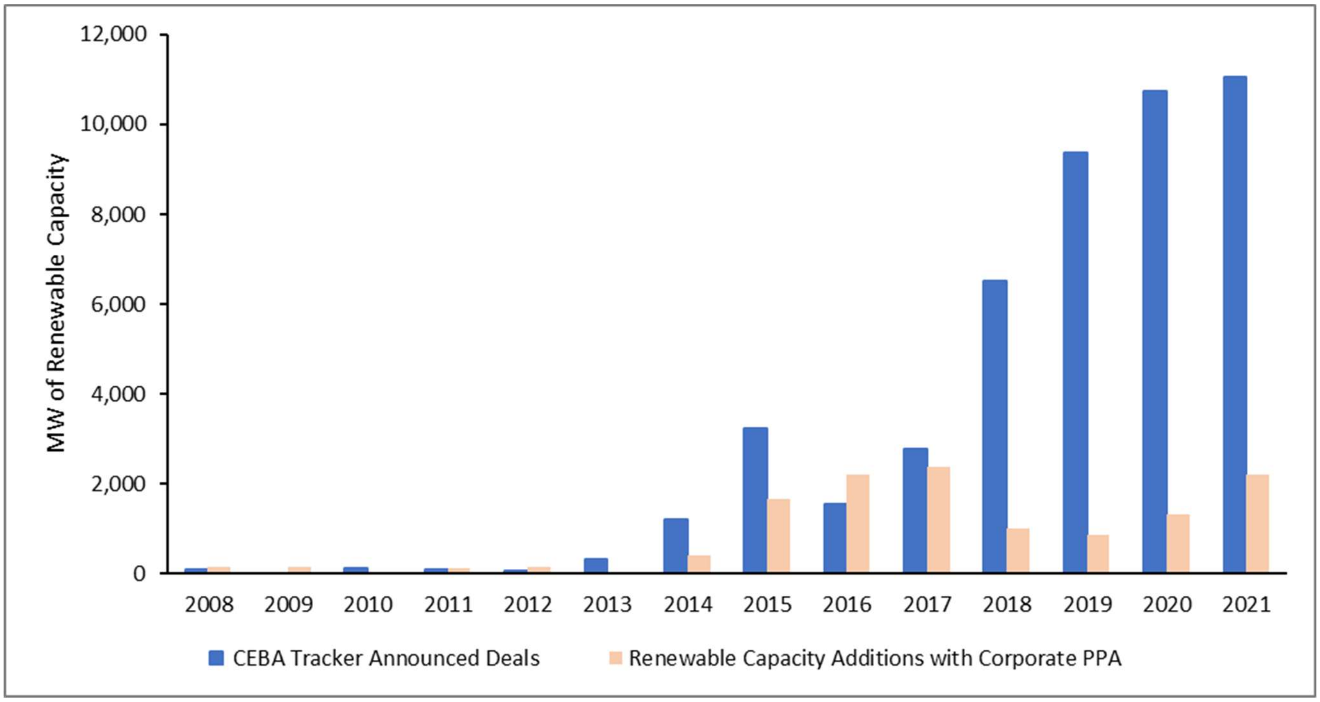

Figure 21: CEBA Tracker announced deals and actual renewable capacity additions with corporate PPA

Renewable capacity additions with an actually executed corporate PPA, per S&P Global data.

Credit: *CEBA, 2022, S&P Global Capital IQ, 2022*

3.7: Next Generation of On-shore Wind Turbines (2018-present)

After several years of steady decline, U.S. average on-shore wind LCOE has not decreased since 2018, remaining around $34/MWh.[203] This stagnation is a combination of two factors – U.S. average capacity factor flattening out at about 40% (see Figure), and capital costs ceasing to decline around 2018.

This cost stagnation coincides with the stalling of trends of increasing rotor diameter and decreasing specific power in favor of more rapid growth in nameplate capacity, as shown in Figure . In 2021 average installed nameplate turbine capacity in the U.S. reached 3.0 MW (up from 2 MW in 2015), and nameplate capacity increases have accelerated every year since 2017, while specific power decline has stalled completely since 2018.

[203] Lawrence Berkeley National Laboratory, 2022.

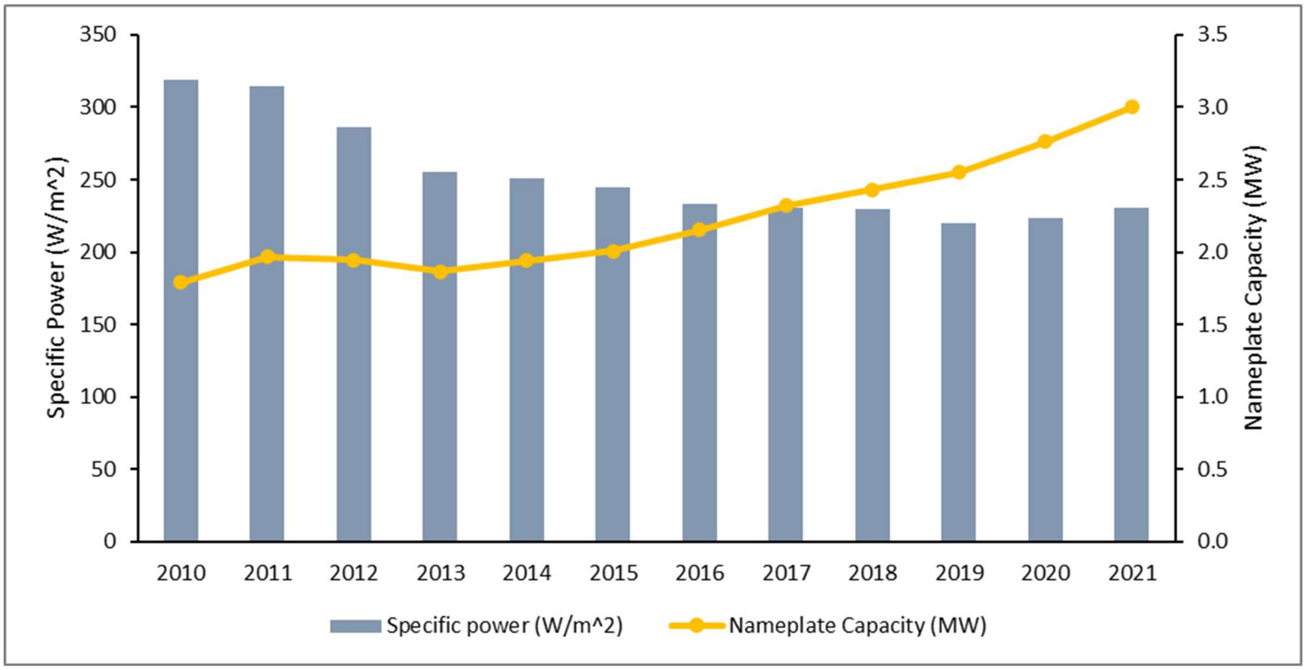

Figure 22: U.S. Nameplate capacity and specific power trends, 2010-2021

Credit: *Lawrence Berkeley National Laboratory, 2022*

This trend can be expected to continue. All major manufacturers have announced next-generation 5 MW on-shore wind turbines, and expert elicitation predicts that the average on-shore wind turbine in 2035 will have a nameplate capacity of 5.5 MW, but the same specific power as today's turbines, marking a serious departure from the design trends of the previous 10 years.

Chinese wind turbine manufacturers may also be able to enter the global market, creating more competition and lower prices. Turbine prices in China have been somewhat lower than the global average at least since 2008, but that gap is widening, as Chinese prices seem unaffected by global commodity price increases. Though Chinese manufacturers have struggled to establish themselves in Europe and the U.S., there may be other opportunities in emerging markets for wind power in Asia, South America, and Australia. In addition, Chinese manufacturers, which for a long time lagged U.S. and European manufacturers in turbine size and technology, are moving to the forefront of technological innovation. Mingyang, one of the big three Chinese manufacturers, recently announced development of a 16 MW offshore wind turbine, which would be the largest offshore wind turbine in the world.[204] They also plan to build a blade manufacturing facility in the U.K., a sign that the global turbine marketplace may become more integrated.

It remains to be seen whether the cost declines of the past decade can continue with the next generation of wind turbines. Global LCOE has continued to decline, reaching \$33/MWh in 2021 – approximate cost parity with the U.S. average.[205] Whether global LCOE will also stall around this value

[204] Durakovic, 2021.

[205] IRENA, 2022.

or continue to drop is uncertain. Integration of Chinese manufacturers into the global market may be able to drive down turbine capital costs, like Chinese supply chains have done for solar panels.

It seems both possible that the next generation of wind technology will drive costs down even further, or that wind technology has reached a mature stage in which trade-offs between size and cost become well-established. The next generation of turbines will be much larger than today's turbines, and as was mentioned in the previous section, there is no guarantee that manufacturing, transportation, and installation costs can continue to decline as size increases. Expert elicitation for the U.S. wind turbine industry predicts a further 12% decrease in LCOE by 2025, and a 27% decrease by 2035, but they also note that there is considerable uncertainty about future costs.[206]

[206] Wiser et al., 2021.

CHAPTER 4: Case Study 3: Nuclear

4.1: Executive Summary

Compared to some of the other clean energy technologies, nuclear power is characterized by the complex nature of the technology and the complicated safety and regulatory environment governing its deployment and operation, which is poorly suited to rapid innovation. Studies analyzing historical cost data indicate that the cost of nuclear power has varied across countries and time periods and has generally *increased* over the years as more reactors have been deployed, rather than decreased, as one might expect. Differences in country-specific costs reflect various regional economic, regulatory, and historical factors. In the United States, construction costs for nuclear power plants decreased during the very early years of R&D and deployment and then increased dramatically beginning around the mid- to late-1960s. However, the rapid cost escalation that occurred in the United States is an outlier in the global history of nuclear power development. Most other early-adopting countries, including France and Canada, also experienced cost decreases during the earliest years of deployment followed by moderate increases in overnight capital costs. Japan has achieved a record of stable overnight capital costs and construction durations over the past 40 years. Perhaps the most successful example of a nuclear reactor program is in South Korea, which began developing nuclear power plants much later than the other countries with large nuclear reactor fleets. However, even under very favorable conditions (e.g., a single utility building a series of standardized reactors), South Korea has achieved only modest cost declines over the course of its pressurized water reactor program. In recent years, the Koreans adopted a new pressurized heavy-water reactor design and construction duration for their two newest reactors has increased to 10 years, likely resulting in increased costs compared to historical levels. Studies indicate that the factors leading to the cost increases seen in many countries can be grouped into two broad categories: the inherent difficulty of executing an extremely complex infrastructure project and the requirements imposed to ensure safe operation of the plant.[207] The first category includes, but is not limited to, factors such as poor project management, a fragmented industry, and a lack of reactor design standardization. The second category includes factors such as the regulatory approval and licensing process, back-fit requirements necessary to meet changing safety standards, and increased design complexity including increases in the number of plant components, new control systems, redundancy in equipment, and added safety features.[208] However, some best practices for deploying highly complex technologies can be learned from the experience deploying nuclear power in the United States and other countries, including the importance of having a finished design at the start of construction, design standardization, operating in an environment with regulatory certainty, and continuity in the project teams such that learning can be achieved.

4.2: Background

[207] Eash-Gates et al., 2020.

[208] Ibid.

4.2.1: Prevalence, Location, and Timeline of Nuclear Reactor Development

The first commercial nuclear power station in the United States, the Shippingport Atomic Power Station located near Pittsburgh, began producing power in 1957.[209] Three years earlier, the first ever nuclear power station to power the electric grid began operations in Obninsk, in what was then the Soviet Union. By 2022, 439 nuclear reactors were in operation across 32 countries, according to the International Atomic Energy Agency (IAEA), accounting for approximately one-third of global low-carbon electricity generation. Within the United States, in 2022, 92 nuclear reactors were operating at 54 nuclear power plants across 28 states, accounting for approximately one-fifth of the nation's total annual electricity generation and roughly half of low-carbon electricity.[210] Globally, construction starts on new capacity additions peaked in 1976, as shown in Figure . From 1977 to 1993, approximately 78 GW of new capacity additions were suspended or cancelled in the wake of accidents at Three Mile Island and Chernobyl, as shown in Figure . Since 1986, approximately 96 GW of nuclear power capacity has permanently retired, much of which was at the end of its useful life, while approximately 227 GW of new capacity has come online.

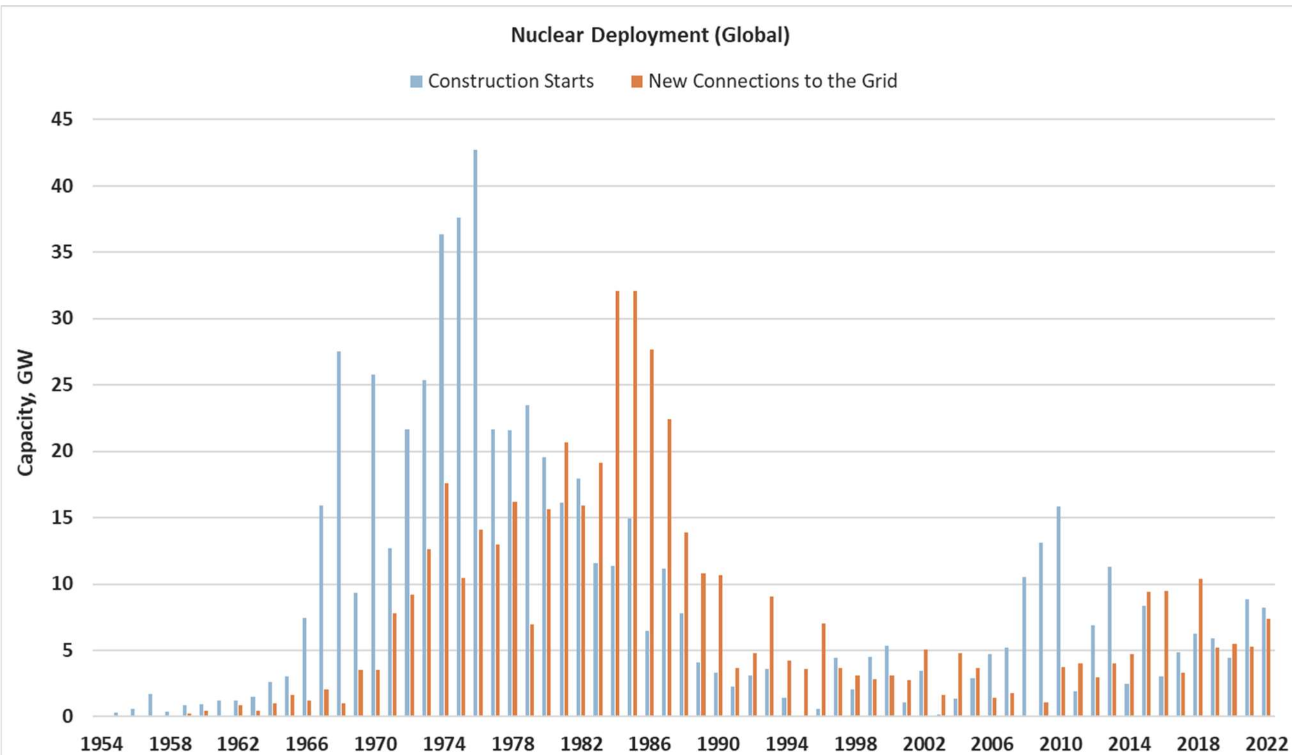

Figure 23: Nuclear Deployment (Global)

Credit: *Data from IAEA's Power Reactor Information System (PRIS)*

[209] U.S. Energy Information Administration, "Nuclear explained: U.S. nuclear industry."

[210] U.S. Energy Information Administration, "Nuclear explained: Nuclear power plants."

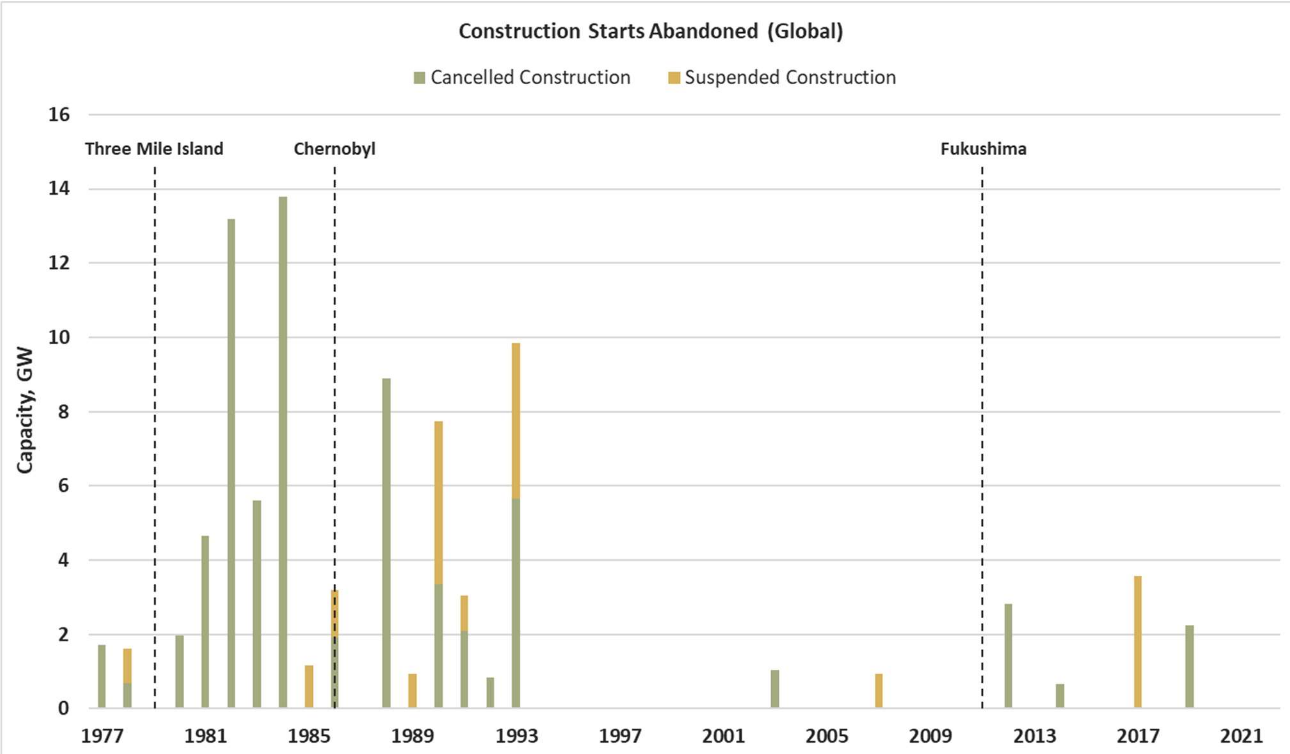

Figure 24: Construction Starts Abandoned (Global)

Credit: *Data from IAEA's PRIS*

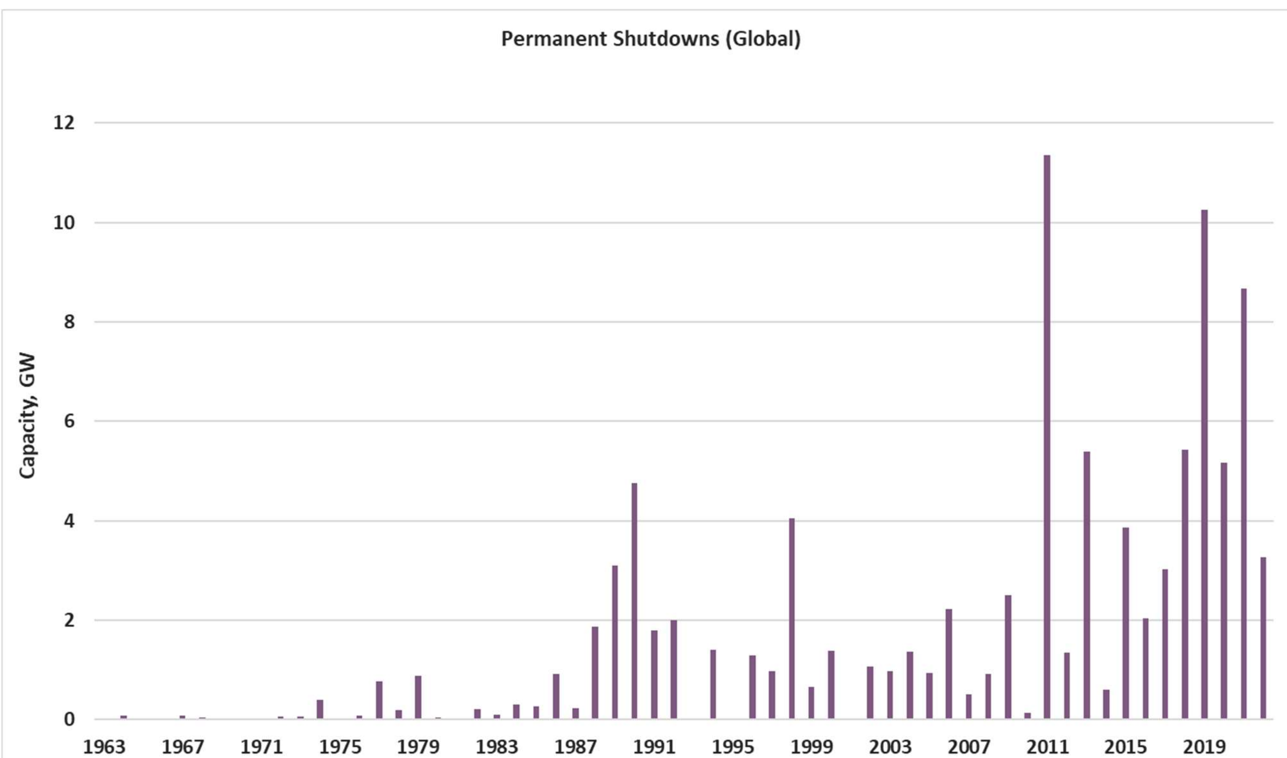

Figure 25: Permanent Shutdowns (Global)

Credit: *Data from IAEA's PRIS*

As of 2022, the largest operating nuclear power fleets are in the United States (92.2 GW), France (60.5 GW), China (50.5 GW), Japan (31.7 GW), Russia (27. 8 GW), and South Korea (24.4 GW).[211] The United States, Russia, France, Canada, Germany, and the United Kingdom were early adopters of nuclear power technology. Over the past decade, countries in East and South Asia and Eastern Europe, including China, Russia, the United Arab Emirates (UAE), South Korea, Turkey, and India have been most active in the development of new nuclear power reactors, while the development of new reactors has largely slowed in Western countries, except for a few recent projects in the United States and France. Since 2012, sixty-four out of the sixty-eight new operating reactors were in China (39), Russia (9), South Korea (6), Pakistan (4), India (3), and UAE (3).[212]

4.2.2: Characteristics of Nuclear Power Plants

In contrast to commercial wind- and solar-powered electric generation facilities, which are typically developed and operated by independent power producers, nuclear power plants have generally been built by governmental entities (in most countries) and private, regulated utilities (in the United States and other Western countries).[213]

Nuclear power stations are primarily operated as baseload units; that is, they continually run at or near full capacity to meet base system demand. This style of operation reflects the fact that most of the cost of nuclear power is derived from capital costs, with a much smaller proportion coming from fuel costs as compared to coal- or gas-fired power plants. As a result, there is rarely a cost saving achieved by running a nuclear power plant at less than full capacity.

Nuclear power plants have several key characteristics that make them an attractive power source and could give them a competitive advantage in the marketplace. First, like wind- and solar-powered generating facilities, nuclear power plants provide a carbon-free source of electricity. Second, unlike variable renewable resources, nuclear power plants can operate around the clock to provide a reliable source of electricity. Third, in contrast to other dispatchable technologies such as coal- and gas-fired power plants, the price of electricity produced by nuclear power plants experiences low volatility because fuel costs are more stable and comprise a smaller proportion of overall costs.

However, despite these advantages, nuclear power plants have proven to be particularly expensive to build relative to other electric generation technologies, especially in developed countries. The high cost, in combination with several high-profile accidents at nuclear power plants around the world, has significantly slowed deployment over the past three decades. Further, lower wholesale market prices in recent years, in part due to the increasing penetration of renewable resources and low natural gas prices, have put as many as 15-20 plants at-risk of premature retirement by 2030. However, this risk has been mitigated by state support, by the Infrastructure Investment and Jobs Act of 2021 (also known as the Bipartisan Infrastructure Bill), the Inflation Reduction Act of 2022, and by recent

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[211] IAEA, PRIS.

[212] Ibid.

[213] Ramana, 2015.

increases in the price of natural gas since 2020 and the corresponding effect on wholesale energy prices.

4.2.3: Overview of Costs of Building a Nuclear Power Plant

Although they have relatively low variable costs, nuclear power plants are expensive and time-consuming to build, usually taking between five to ten years, but sometimes more. Capital costs – which includes site preparation, licensing, design/engineering, manufacture/procurement, construction, and financing – have historically dominated the LCOE for nuclear power.[214, 215, 216] One study found that labor accounts for two-thirds of the capital expenditure of nuclear power stations,[217] however, due to the long construction period, the cost to finance the project is also a key component of the overall capital cost.[218] Table 3 illustrates how financing costs contribute to the total construction cost under various cost of capital and construction duration assumptions.[219]

Table 4: The Impact of Financing Costs on Total Construction Cost

Financing Costs as a Fraction of Total Construction Costs

	Construction Period		
	One Year	Five Years	Ten Years
5% Cost of Capital	2%	12%	22%
10% Cost of Capital	4%	22%	40%
15% Cost of Capital	6%	30%	54%

Source: *Reprinted from Davis, 2011*

Operating costs include fuel, operations and maintenance (O&M), treatment and storage of spent fuel, and decommissioning of the plant.[220] Unlike wind- and solar-powered electric generation facilities, the costs associated with decommissioning are included into the cost of electricity from a nuclear power

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[214] World Nuclear Association, "Economics of Nuclear Power."

[215] Stein et al., 2022.

[216] Lovering et al., 2016.

[217] Mott MacDonald, 2011.

[218] World Nuclear Association, "Economics of Nuclear Power."

[219] The calculations assume that expenditures are uniformly distributed across months during the construction period and that financing charges accrue monthly at the cost of capital. *See* Davis, 2011.

[220] World Nuclear Association, "Economics of Nuclear Power."

plant. Nuclear power plants require large staffs, meaning fixed O&M costs are high relative to most other types of electric generation technologies.

Nuclear power plants have historically had very high capacity factors, operating at 90% – 95% over the past decade, according to the U.S. EIA.[221] This high capacity factor works to attenuate the high capital expenditures and fixed O&M costs and bring down the LCOE of nuclear power. Because capital cost is the primary driver of the total cost of generating electricity from a nuclear power plant, we will primarily focus our discussion on capital costs throughout the remainder of this report.

4.3: Observed Cost Trends

We begin by noting that data on nuclear reactor costs is not as widely available as other data related to nuclear reactors such as reactor capacity, construction start date, and construction duration, for which comprehensive data is publicly available through the IAEA's Power Reactor Information System (PRIS) database. Nevertheless, several studies have investigated nuclear reactor costs, primarily focusing on reactors constructed in the United States and France. For example, Koomey and Hultman's reactor-level assessment of levelized costs for 99 nuclear reactors in the United States[222] and Grubler's review of the history and economics of the French Pressurized Water Reactor program[223] are two such examples among others. In this report, we primarily focus on Lovering et al.'s analysis of Overnight Capital Costs (OCC) for nuclear reactors constructed through 2016 in seven countries (the United States, France, Japan, South Korea, Germany, Canada, and India) because it provides a consistent dataset that spans multiple countries and goes back to the start of nuclear reactor development during the 1950s.[224] The OCC metric – which is designed to reflect the cost of the project if it was constructed "overnight" – includes costs related to design/engineering, licensing, procurement, and construction but does not include Interest During Construction. Nevertheless, OCC might still reflect some duration-related expenses such as inflation of material and labor costs during the duration of the construction project, additional labor and equipment fees incurred as a result of project delays, and back-fit costs caused by regulatory changes during construction. The final, all-in cost of constructing a nuclear reactor depends on the OCC, the construction duration, and the financing terms (e.g., the interest rate). As illustrated in Table , when construction duration is high, interest can add a significant amount to the total cost of the project. In addition to Lovering et al.'s OCC data, the following sections also include information on construction durations, which was sourced from IAEA's PRIS database. Interest rates will, of course, vary across countries and time periods and are not discussed further in this report. While the OCC data does not reflect final, all-in costs, when OCC are combined with data on construction durations the combination of the two factors provides a useful

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[221] U.S. Energy Information Administration, "U.S. nuclear electricity generation."

[222] Koomey & Hultman, 2007.

[223] Grubler, 2010.

[224] Jessica Lovering is an Executive Director at the Good Energy Collective, a policy research organization that states it is building the progressive case for advanced nuclear energy as part of the broader climate change agenda.

metric for assessing whether there is any evidence of progress associated with the cost of construction of nuclear reactors.

Lovering et al. gathered their OCC data from several sources.[225] For reactors constructed in the United States, sources include existing literature (for reactors built between 1967-1978), cost estimates prepared by United Engineers and Constructors and appearing in an Atomic Energy Commission report from 1974 (for reactors built from 1962-1968), and from literature citing USAEC reports (for reactors built between 1954-1963). For reactors constructed in France, construction cost data was sourced from existing literature. For reactors constructed in Canada, cost data was acquired from representatives from the Atomic Energy of Canada Ltd. For reactors constructed in Germany, cost data was obtained from plant operators, the IAEA, and existing literature. For reactors constructed in Japan, cost data was primarily sourced from the Institute for Energy Economics, Japan and corroborated with data from IAEA and the literature. For reactors constructed in India, cost data was provided by representatives from the Nuclear Power Company of India Ltd. and from literature citing data found in Indian Department of Atomic Energy reports. For reactors constructed in South Korea, cost data was provided directly by the Korea Hydro and Nuclear Power utility company.[226] Figure shows the time period during which nuclear reactor development occurred in each of these seven countries.

[225] Complete citations to the various sources can be found in Lovering et al., 2016.

[226] Lovering et al. state that they corroborated the national utility-provided data against figures from two independent bodies: the National Assembly Budget Office and the Korean Power Exchange. *See* Lovering et al., 2017.

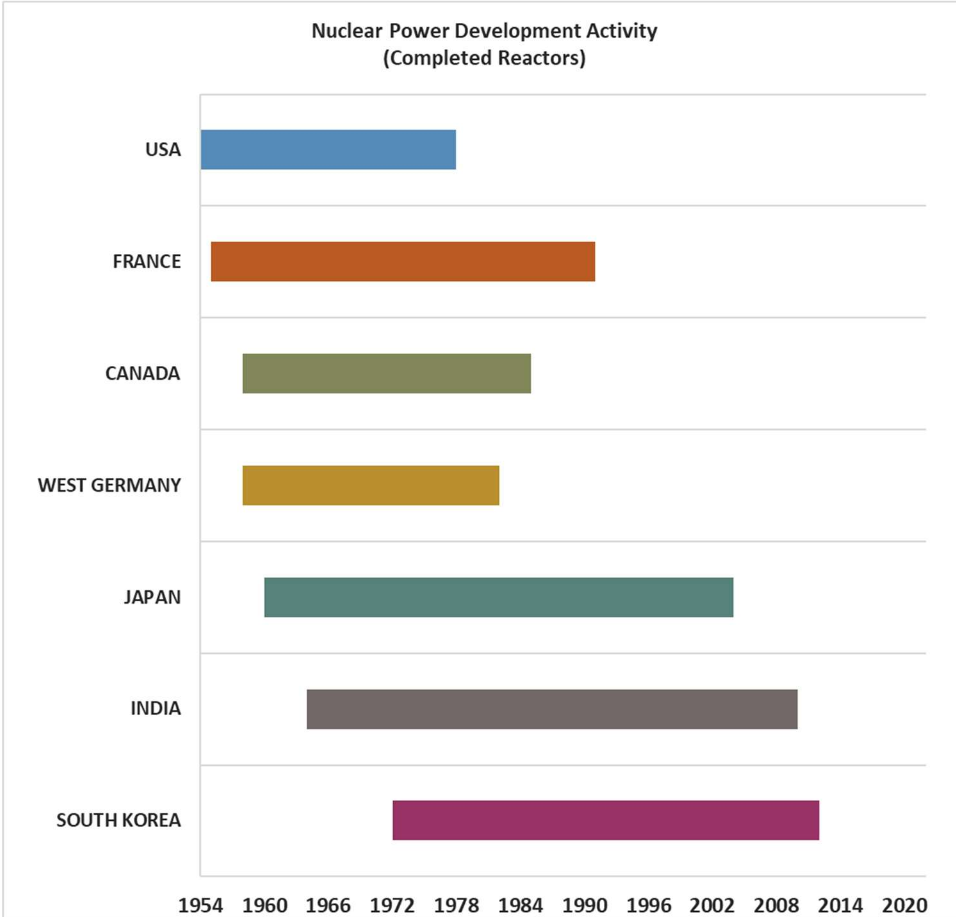

Figure 26: Nuclear Power Development Activity (Completed Reactors)

Credit: *Data from IAEA's PRIS*

4.3.1: Early Adopters (1950s – 1980s)

4.3.1.1: United States

In the United States, construction starts on new reactors peaked in 1968, with construction starting on 27 new reactors totaling approximately 23.3 GW of generating capacity, as shown in Figure . Construction of new reactors halted abruptly following the accident at Three Mile Island in 1979.

During the early years of development and deployment, roughly 1954 to 1963, reactor sizes were relatively small, averaging less than 200 MW with all but three out of 17 reactors having a capacity less than 100 MW. OCC for reactors beginning construction during this period ranged from approximately $2,000-$6,800/kW (2010USD), exhibiting an overall decreasing trend. In 1964, average reactor size jumped to approximately 537 MW and continued to increase to a maximum of approximately 1,240 MW in 1976 before decreasing slightly, as shown in Figure . The increasing trend in average reactor size is correlated with an increasing trend in average construction duration, which peaked in 1974 at approximately 12.2 years, when Watts Bar Nuclear Plant (an extreme outlier) is excluded from the data. OCC remained relatively constant for reactors beginning construction from about 1964 to 1967, hovering between approximately $1,000-$1,500/kW. For reactors beginning construction from approximately 1968 through 1978, OCC exhibited a sharply increasing trend, as shown in Figure , reaching a maximum of approximately $11,000/kW (2010USD) for reactors beginning construction in

1973. The increase in both OCC and construction duration during this period is almost certainly due, in part, to additional regulatory requirements stemming from the Calvert Cliffs court decision in 1971, which required application of National Environmental Policy Act environmental reviews to nuclear permitting and licensing, and the accident at Three Mile Island in 1979. According to Lovering et al., reactors that were under construction when the Three Mile Island accident occurred had median costs 2.8 times higher than reactors that received their operating licenses before the accident occurred and median construction durations 2.2 times higher than pre-Three Mile Island durations.[227]

In 2013, four new reactors – both two-reactor expansions of existing power plants (the V.C. Summer Nuclear Station in South Carolina and the Vogtle Electric Generating Plant in Georgia) – began construction, the first new reactors to begin construction in the United States in over 30 years.[228] The new Summer units were abandoned in 2017, reportedly after sunk costs of $9 billion (equating to about $4,000/kW), while Vogtle-3 and Vogtle-4 are expected to come online in 2023 after a decade of construction and an estimated cost of about $30 billion ($13,429/kW, all-in).[229]

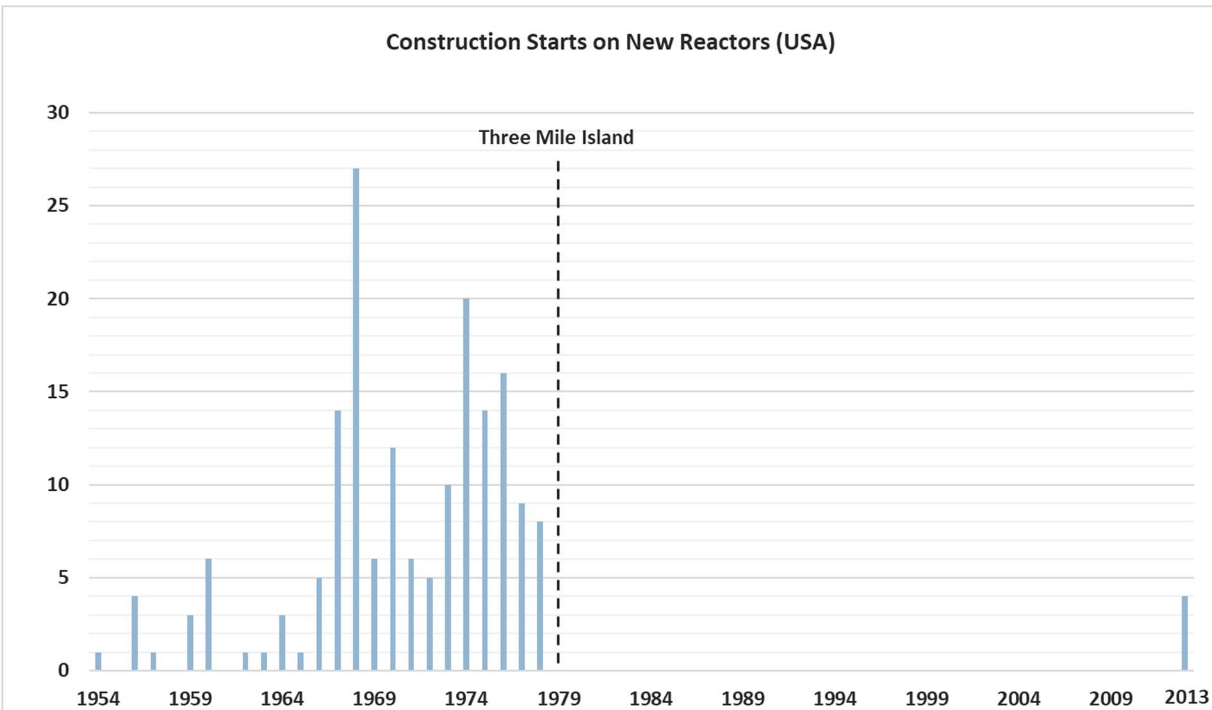

Figure 27: Construction Starts on New Reactors (USA)

Credit: *Data from IAEA's PRIS*

[227] Lovering et al., 2016.

[228] In addition to concerns about reactor safety and nuclear proliferation, sustained low natural gas prices continuing into the early 2000s contributed to the lull in nuclear reactor development in the United States.

[229] Kann, 2022.

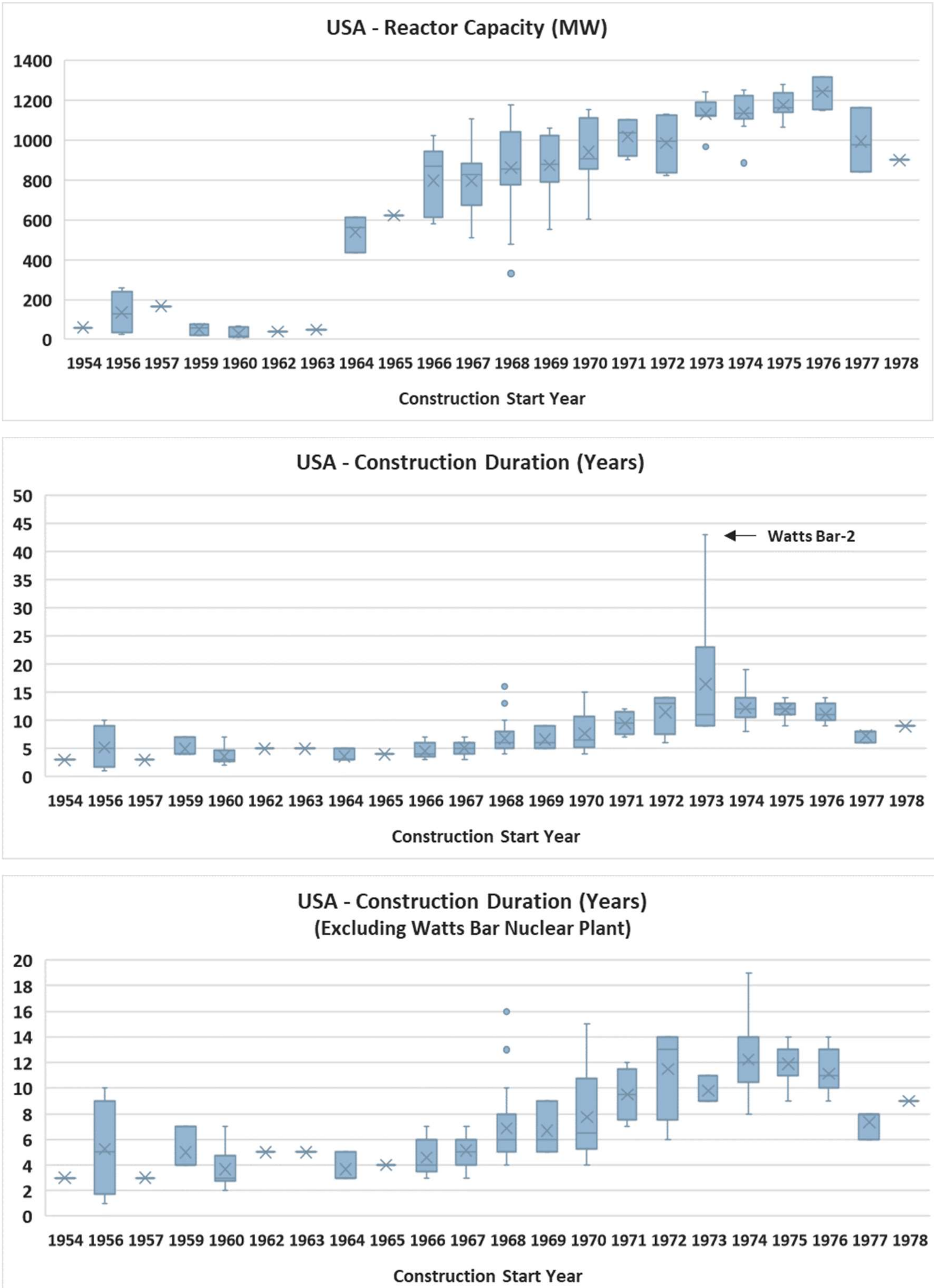

Figure 28: Reactor Capacity and Construction Duration (USA)

Reactor capacity and construction duration for nuclear reactors constructed in the United States, by Construction Start Year.

Credit: *Data from IAEA's PRIS*

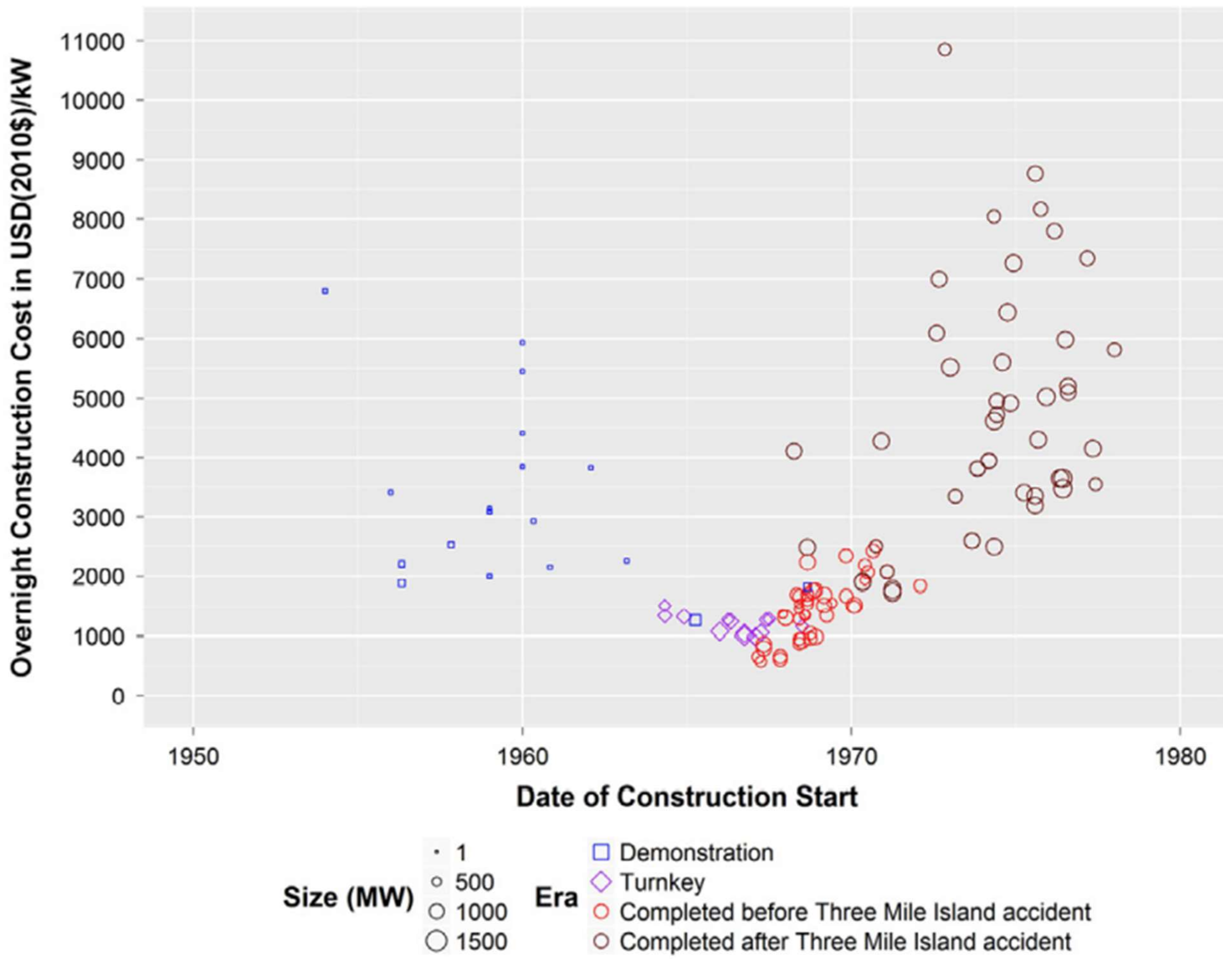

Figure 29: Capacity-Weighted Overnight Construction Cost (USA)

Capacity-Weighted overnight construction cost of reactors constructed in the United States by construction start year.

Credit: *Reprinted from Lovering et al., 2016*

4.3.1.2: France, Canada, Germany

France has the second largest nuclear power generation fleet, behind the United States. From 1955 to 1991, France built 70 nuclear reactors. From 1955 to 1968, France built a series of small, mostly gas-cooled reactors, progressively increasing in size from approximately 39 MW to 540 MW. OCC for these reactors decreased from €6,500/kW to €1,200/kW (2010EUR). This mimics the decreasing trend observed during the early years of development and deployment in the United States and tracks conventional wisdom, since costs should decline as plant size increases, all else being equal. Beginning in 1971 with the Fessenheim-1 unit, France adopted a larger pressurized water reactor design and began to successively scale up reactor size, as shown in Figure . Despite the increase in reactor size, construction duration remained relatively constant for reactors beginning construction through 1981, averaging approximately 5.8 years. However, for reactors beginning construction from 1981 to 1985, average construction duration increased each year, reaching a maximum of 12 years for reactors beginning construction in 1985. Of particular note during this time period are the new additions at the Chooz Nuclear Power Plant in Ardennes, with both units Chooz B-1 and Chooz B-2, beginning construction in 1984 and 1985, respectively, each taking 12 years each to complete construction. From

1971 to 1991, OCC for French reactors ranged from approximately €1,070-€2,060/kW, as shown in Figure 31. In 2007, France began construction on the Flamanville 3 reactor, which is based on a different reactor design than previous French projects. Flamanville 3 is expected to start producing electricity at the end of 2023 at an estimated cost of 12.7 billion euros (equating to roughly €7,938/kW), significantly over budget and a decade behind schedule. The plant was originally expected to cost 3.3 billion euros (equating to roughly €2,063/kW) and start operations in 2012.[230] According to reports, the construction delays are partly the result of having to fix faulty welding work.[231]

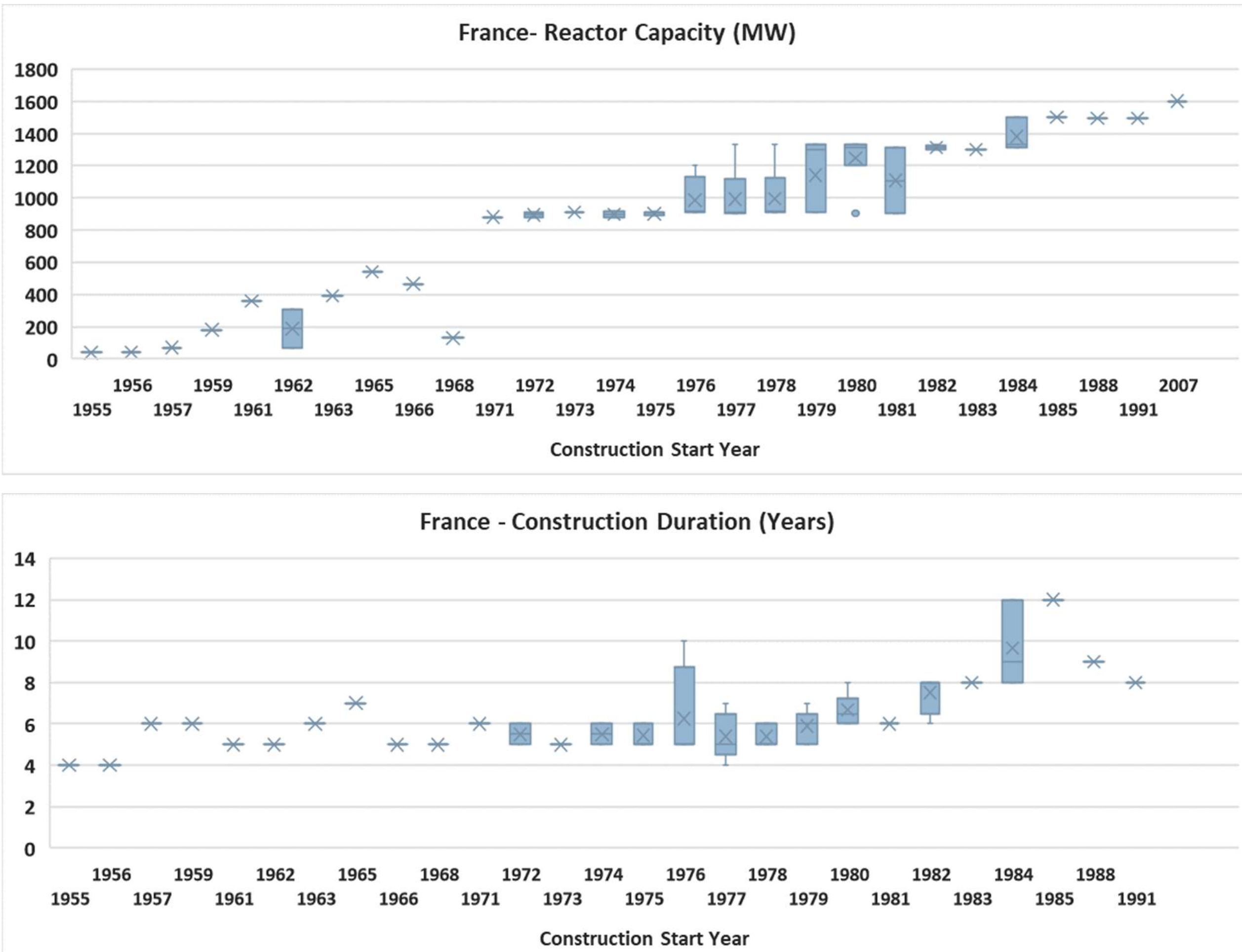

Figure 30: Reactor Capacity and Construction Duration (France)

Reactor capacity and construction duration for nuclear reactors constructed in France, by Construction Start Year.

Credit: *Data from IAEA's PRIS*

[230] Mallet, 2022.

[231] Ibid.

Figure 31: Capacity-Weighted Overnight Construction Cost (France)

Capacity-Weighted overnight construction cost of reactors constructed in France by construction start year.

Credit: *Reprinted from Lovering et al., 2016*

From 1958 to 1985, Canada built 25 reactors located at seven plants, utilizing a standardized, domestic Deuterium Uranium (CANDU) reactor design. Beginning in 1966, Canada began constructing larger plants consisting of four or eight reactors. Like France, Canada experienced relatively stable costs over time, with OCC for reactors beginning construction after 1960 ranging from approximately $2,000-$4,000/kW (2010CAD) (See Appendix, Figure).

Germany built 42 reactors from 1958 to 1984. Its first reactor, constructed in 1958, reportedly cost approximately €2,700/kW (2010EUR). Over the next 10 years, OCC decreased to below €1,000/kW. From the late 1960s through 1984. OCC trended upward, reaching approximately €3,000/kW by 1984 (See Appendix, Figure).

4.3.2: Recent Builders (1980s – 2020s)

South Korea has the sixth largest nuclear power fleet, building all its reactors after 1971. As shown in Figure , until about 2008 South Korea demonstrated remarkable consistency in both reactor sizing and construction duration. South Korea's first reactor was a 576-MW Westinghouse design that cost approximately ₩4,000,000/kW (2010KRW). From 1972 to 1994, South Korea imported an additional 11 reactors from American, French, and Canadian companies. Beginning with Hanbit-3 in 1989, South

Korea constructed (or has begun construction) on an additional 18 reactors based on domestic designs. South Korea's first domestic reactor cost ₩2,600,000/kW, with subsequent costs declining steadily to approximately ₩2,000,000/kW for reactors beginning construction in 2008, as shown in Figure . Beginning in 2008, South Korea began constructing larger, 1340-MW reactor designs. As of 2022, three such reactors have completed construction. The first of the larger reactors took eight years to build, at a cost of approximately ₩2,000,000/kW, while the latter two reactors took 10 years to complete construction; cost data for these reactors does not appear in Figure , which was published prior to their completion. A fourth is expected begin commercial operation in 2023, also having taken more than 10 years complete.

Figure 32: Reactor Capacity and Construction Duration (South Korea)

Reactor capacity and construction duration for nuclear reactors constructed in the South Korea, by Construction Start Year.

Credit: *Data from IAEA's PRIS*

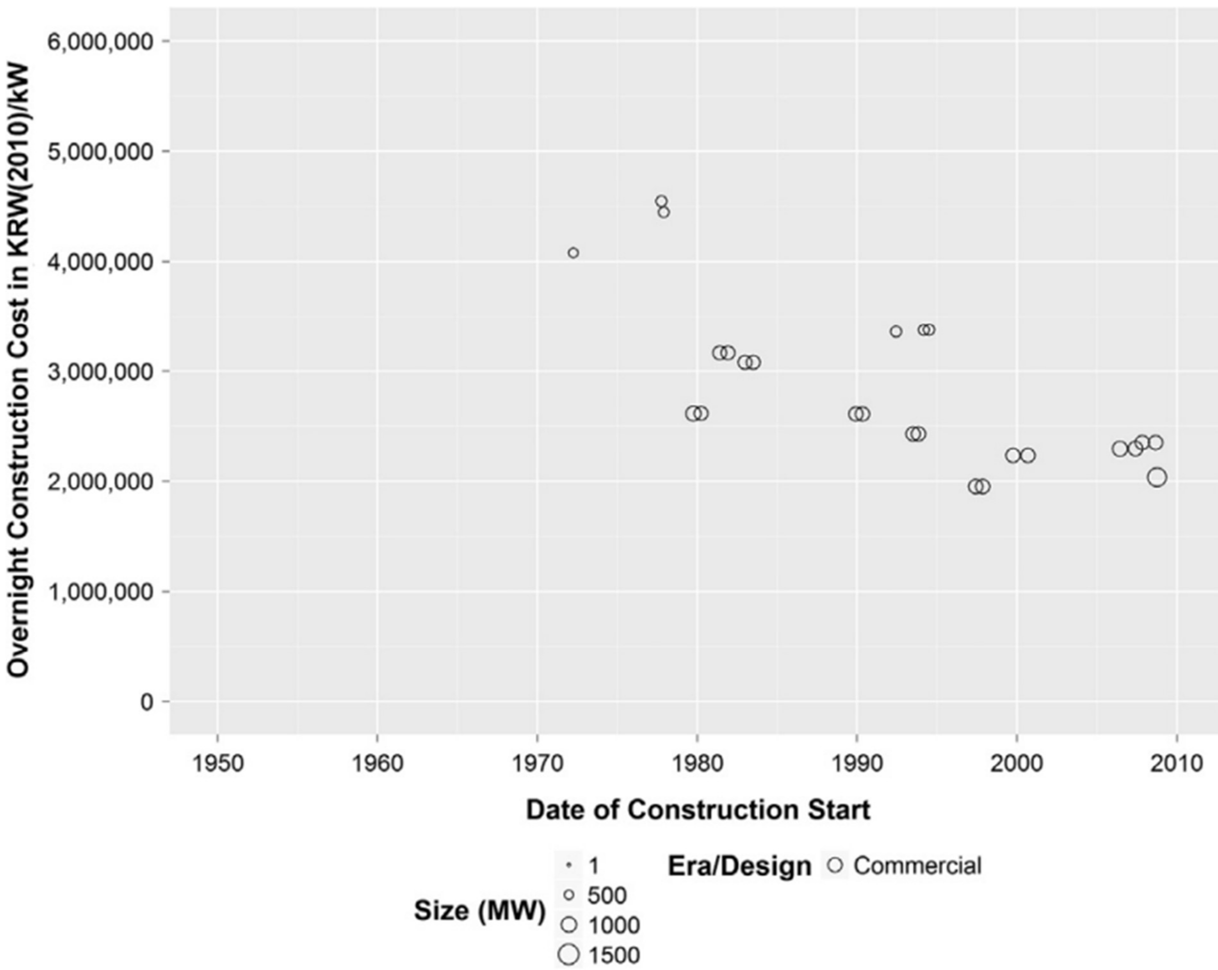

Figure 33: Capacity-Weighted Overnight Construction Cost (South Korea)

Capacity-Weighted overnight construction cost of reactors constructed in South Korea by construction start year.

Credit: *Reprinted from Lovering et al., 2016*

Japan has completed 60 reactors that began construction from 1960 to 2010, while two additional reactors that began construction in 2006 and 2010, respectively, remain under construction. Its first two reactors, both small reactors with capacities of 10 MW and 159 MW, were imported from American and British companies at a cost of approximately ¥1,100,000/kW (2010JPY) and ¥600,000/kW, respectively. Through 1969, reactor sizes successively increased (but remained small relative to modern reactors) and OCC fell to approximately ¥150,000/kW in for reactors beginning construction in 1971. Beginning around 1970, Japanese companies began manufacturing and constructing nuclear reactors domestically.[232] From 1970 to 1980, OCC rose from approximately ¥100,000/kW to ¥300,000/kW, presumably as Japanese industry gained experience in the construction of nuclear reactors. Beginning in 1980, OCC began to stabilize and remained relatively constant through the early 2000s, ranging from approximately ¥200,000-¥500,000/kW (See Appendix, Figure).

[232] Lovering et al., 2016.

India has completed 23 reactors that began construction from 1964 to 2010, while an additional 8 reactors that began construction in 2004 or later remain under construction. India's first two reactors were imported American and Canadian designs, costing ₹45,000/kW (2010INR) and ₹65,000/kW, respectively. Beginning in 1971, India began developing a domestic reactor design and produced two reactors at a cost between ₹35,000-₹45,000/kW. However, OCC subsequently increased to a range of approximately ₹90,000-₹110,000/kW for reactors beginning construction after 1974, which coincided with year India began testing nuclear weapons (See Appendix, Figure).

Figure summarizes the capacity-weighted OCC data, shown in 2010$ USD equivalents.

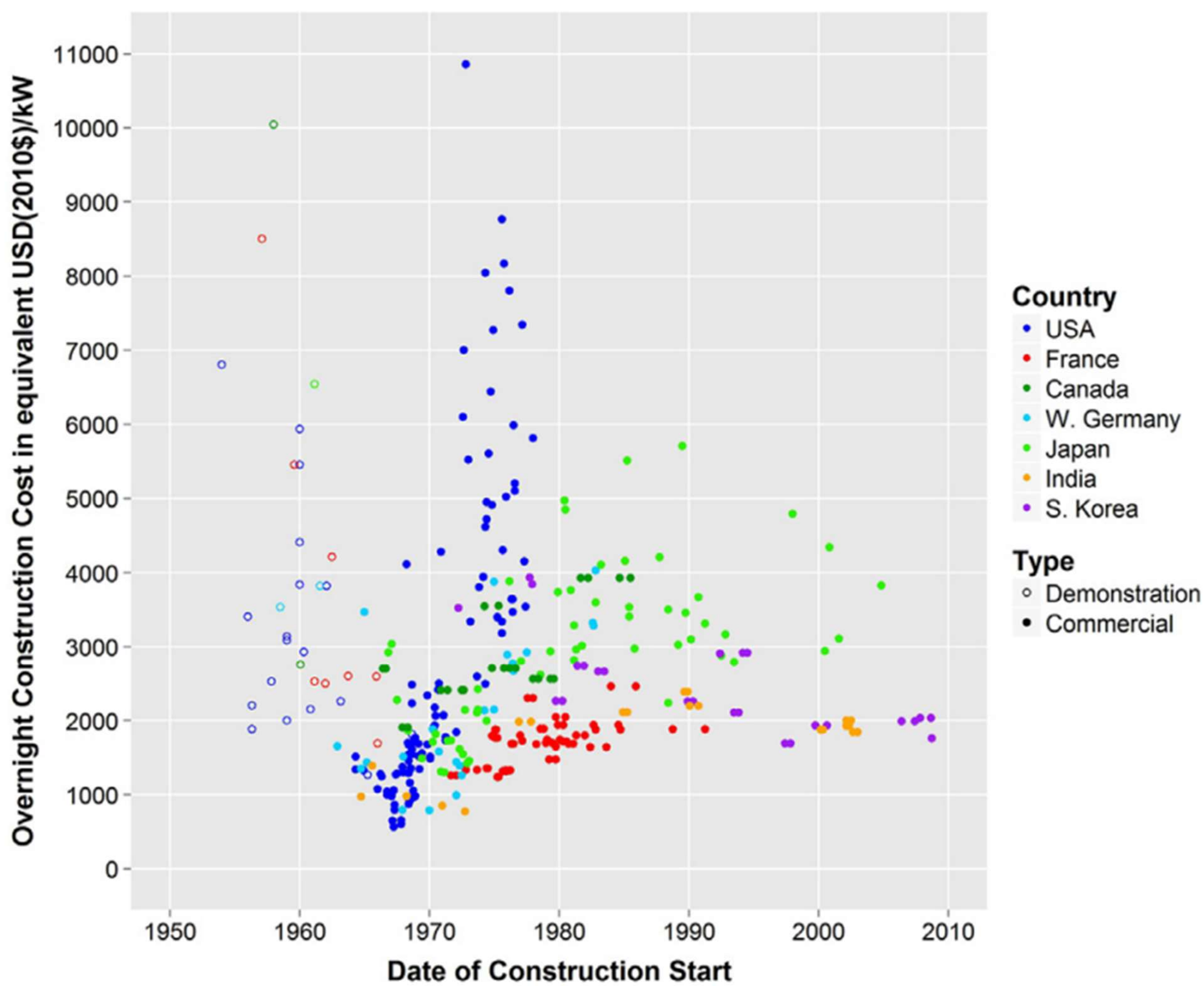

Figure 34: Capacity-Weighted Overnight Construction Cost

Capacity-Weighted overnight construction cost of reactors constructed in seven countries by construction start year shown in USD2010.

Credit: *Reprinted from Lovering et al., 2016*

4.4: Understanding the Factors Driving Costs

One thing that is evident from Figure is that experiences deploying nuclear power technology vary significantly across countries, indicating that there are many factors at play. However, one common trend observable in the data is that costs for early reactors in many countries, including the United States, France, Canada, Germany, and Japan, experienced steep declines in the earliest years of commercialization. Indeed, except for South Korea, most countries reached their lowest capacity-weighted overnight capital cost shortly after beginning deployment, only to see costs rise over time.

We begin by noting that nuclear power plants are a much different type of product than wind- or solar-powered electric generation facilities. Two aspects of nuclear power plants differentiate them from other types of clean energy technologies and make them more susceptible to construction delays and cost overruns.

First, for obvious reasons, nuclear power plants are subject to more stringent safety and regulatory scrutiny than are other types of electric generation facilities. Prior to beginning construction in the United States, a nuclear power plant must secure licensing from the U.S. Nuclear Regulatory Commission and – for first-of-a-kind designs – design certification. The amount of time and effort required to complete this process makes iteration and innovation impractical. In addition, safety concerns can directly impact costs to build due to the need for sophisticated safety features, redundant control systems, design changes that require plants to be backfitted with modified equipment, and the necessity to re-do work that has failed safety standards.[233]

Second, nuclear power plants are *constructed* rather than *assembled* in a manufacturing facility. Building a nuclear power plant is a massive infrastructure project that requires thousands of workers, huge amounts of material, and detailed project schedules and a range of factors contribute to the final project cost. Like other large-scale construction projects, costs and implementation challenges are often underestimated and the success of the project is highly sensitive to effective project management.[234] Poor project management has historically been a major source of construction delays, which drives up costs. Construction delays directly contribute to cost overruns by extending the period over which equipment must be rented, salaries must be paid, and interest on initial capital costs accumulates.[235]

Eash-Gates et al. found that "soft" factors (as opposed to direct costs associated with materials, construction labor, and equipment), including engineering/design services ("home office services" in Figure), construction site supervision, and temporary housing facilities, accounted for 72 percent of the cost increases between 1976-1987 for nuclear reactors constructed in the United States, as shown in Figure .[236] Although the trend of increasing capital costs appears to be primarily driven by indirect costs, Eash-Gates et al. also found that costs of the reactor containment building more than doubled

[233] World Nuclear Association, "Economics of Nuclear Power."

[234] Ibid.

[235] Stein et al., 2022.

[236] Eash-Gates et al., 2020.

from 1976 to 2017 due, in part, to increased commodity use (i.e. the use of more steel and concrete in the construction process.)[237]

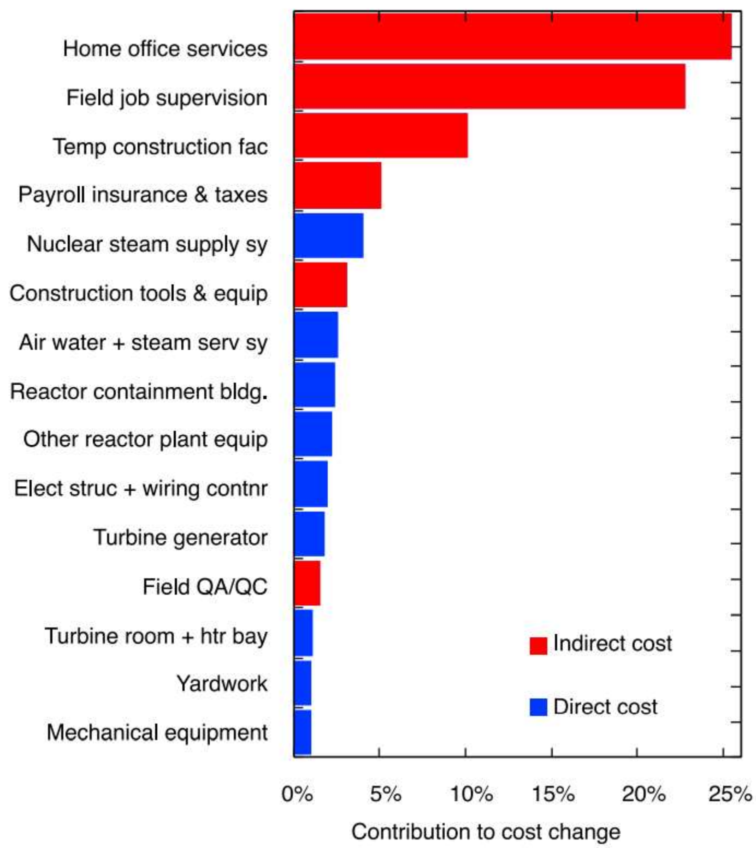

Figure 35: Sources of Cost Increases in Nuclear Plant Construction in the United States, 1976-1987

Credit: *Reprinted from Eash-Gates et al.*

Although it is difficult to empirically link these cost increases to a key driver, it stands to reason that increased costs related to engineering/design services, field site supervision, and materials for the reactor containment building are all, to some extent, a function of extended construction durations driven, in part, by safety and regulatory concerns stemming from the accident at Three Mile Island.

4.5: Lessons Learned

In general, the most expensive nuclear power plants share the following characteristics: they began construction before achieving a completed design; they utilized a first-of-a-kind design; and they had long construction durations and high labor hours.[238] These observations point to some best practices

[237] Ibid.

[238] Stein et al., 2022.

for deploying a technology, like nuclear power, that is characterized by technological and regulatory complexity.

First, despite long construction times, it is often counterproductive to begin construction without achieving a completed design. Projects that begin construction prematurely often incur additional time and expense associated with having to repeat work or with having to pause construction while awaiting regulatory approval.[239]

Second, countries that adopted a standardized design, such as Canada, India, and South Korea, show lower and more stable costs.[240] This could indicate that for technologies like nuclear fission (i.e., complex technologies subject to strict regulatory regimes) challenges stemming from design iterations – including loss of construction knowledge and delays and additional costs associated with the regulatory approval process – likely outweigh any technological advances of new reactor designs. A prototypical example of this is France's experience with the Flamanville 3 reactor, which offered incremental advances in reactor technology but has experienced significant construction delays and cost overruns.

A standardized design provides the opportunity for learning, which can be achieved through effective planning and project management. For example, South Korea staggered builds, limited the number of reactors under construction at any one time, and built reactors in pairs at the same site. Moreover, all the reactors in South Korea were built by the same utility. This approach created opportunities for learning and construction synergies. In contrast, most nuclear reactors in the United States were constructed during a relatively short time period (relative to construction duration) by different utilities, using different designs, and working simultaneously; conditions which do not facilitate learning.[241]

A final lesson to takeaway is the importance of public perception to the adoption of new technologies. Nuclear power plants have suffered from public disapproval in the United States, largely stemming from the accident at Three Mile Island in 1979. As of 2022, twelve states restrict or ban the construction of new nuclear generating stations.[242] Public perception influences politicians and regulators. When the public is skeptical about a new technology, regulators will respond with increased scrutiny, which drives up costs and makes widespread adoption of the technology less likely.

4.6: Next Generation of Nuclear Reactors

Recently, the urgency to decarbonize the electric system has renewed interest in Advanced Nuclear Reactors (ANRs) and SMRs, which are nuclear reactors that have a power capacity of up to 300 MW per

[239] Vlahoplus & Lawrie, 2021.

[240] Lovering et al., 2016.

[241] Vlahoplus & Lawrie, 2021.

[242] Stein et al., 2022.

unit.[243] Proponents of ANRs and SMRs argue that they offer increased safety, reduced costs, and more market opportunities.[244]

For example, smaller reactor designs may offer inherent safety benefits as a result of smaller fuel loads and more efficient, passive cooling characteristics, as well as reduced costs associated with additional materials and construction work.[245, 246] In addition, advocates argue that SMRs also facilitate reduced costs because the smaller, simpler designs offer the potential to be manufactured and assembled in a factory and then transported to the project site for installation.[247] Furthermore, by reducing the total labor hours required, SMRs may have a lower risk of the construction delays and cost overruns that have been associated nuclear power projects. Finally, proponents of the technology believe there will be additional market opportunities for SMRs, such as siting in remote areas with limited demand and industrial applications such as desalination, among others.[248]

However, it should be noted that these purported advantages are, as of yet, only theoretical. There are no SMRs currently in operation. Moreover, small reactors were explored during the early days of nuclear power. Early prototypes *were* small reactors and capacities increased to achieve economies of scale because the small reactors were not cost effective. The U.S. Air Force and Army – two organizations with deep budgets – both abandoned small reactor programs because of the high costs.[249] Recently, an SMR design developed by NuScale Power, LLC (NuScale) received a design certification from the U.S. Nuclear Regulatory Commission, the first SMR design to do so. NuScale, in a partnership with Utah Associated Municipal Power Systems (UAMPS), is developing an SMR plant based on the design at the Carbon Free Power Project located in Idaho. Construction of the project is scheduled to begin in 2026. In November 2022, it was reported that higher steel prices and interest rates are driving up the projected costs of electricity from the project. Previous estimates priced power from the 6-unit, 462-MW plant at $58/MWh but the project developers have reportedly told UAMPS that prices could be as high as $90/MWh to $100/MWh after taking into account approximately 30% in savings through the Inflation Reduction Act.[250]

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[243] Advanced Nuclear is a broad term that refers to the cutting edge of nuclear technology. Such reactors are purported to offer advantages such as improved safety features inherent to new reactor designs and faster load-following abilities to better supplement variable renewable resources.

[244] Cooper, 2014.

[245] Stein et al., 2022.

[246] Vlahoplus & Lawrie, 2021.

[247] Stein et al., 2022.

[248] Ibid.

[249] Ramana, 2015.

[250] Walton, 2022; Schlissel & Wamsted, 2022.

It is also unclear whether the market for SMRs will develop as some suggest considering the significant changes the electric grid is experiencing, particularly in the Western United States. Nuclear power's role as baseload capacity may no longer be available given the increasing penetration of renewable resources, which already overproduce in certain hours. While SMRs have the operational ability to follow load, potentially reduced capacity factors due to curtailments when there is excess wind and/or solar will make the electricity they generate even more expensive.

GLOSSARY

Term	Definition
a-Si	Amorphous Silicon
AI	Artificial Intelligence
Al-BSF	Aluminum Back Surface Field
ANR	Advanced Nuclear Reactor
BOS	Balance of System
CEBA	Clean Energy Buyer's Alliance
CPUC	California Public Utilities Commission
CREZ	Competitive Renewable Energy Zones
EIA	U.S. Energy Information Administration
ERCOT	Electric Reliability Council of Texas
FiT	Feed-in Tariff
GW	Gigawatt
IAEA	International Atomic Energy Agency
ISO	Independent System Operator
ITC	Investment Tax Credit
kW	Kilowatt
LCOE	Levelized Cost of Energy
LMP	Locational Marginal Pricing
MISO	Midcontinent System Operator
MIT	Massachusetts Institute of Technology
MITI	Ministry of International Trade and Industry (Japan)
MW	Megawatt
O&M	Operations and Maintenance
OCC	Overnight Capital Cost
OPEC	Organization of the Petroleum Exporting Countries
PERC	Passivated Emitter and Rear Contact

PRIS	Power Reactor Information System
PTC	Production Tax Credit
PURPA	Public Utility Regulatory Policies Act of 1978
PV	Photovoltaic
QF	Qualifying Facility (a designation under PURPA)
R&D	Research and Development
RD&D	Research, Development, and Demonstration
RPS	Renewable Portfolio Standards
RTO	Regional Transmission Organization
SEC	U.S. Securities and Exchange Commission
SMR	Small Modular Reactor
SPP	Southwest Power Pool
UAE	United Arab Emirates
UAMPS	Utah Associated Municipal Power Systems
UNSW	University of New South Wales

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APPENDIX A: Nuclear – Additional Charts

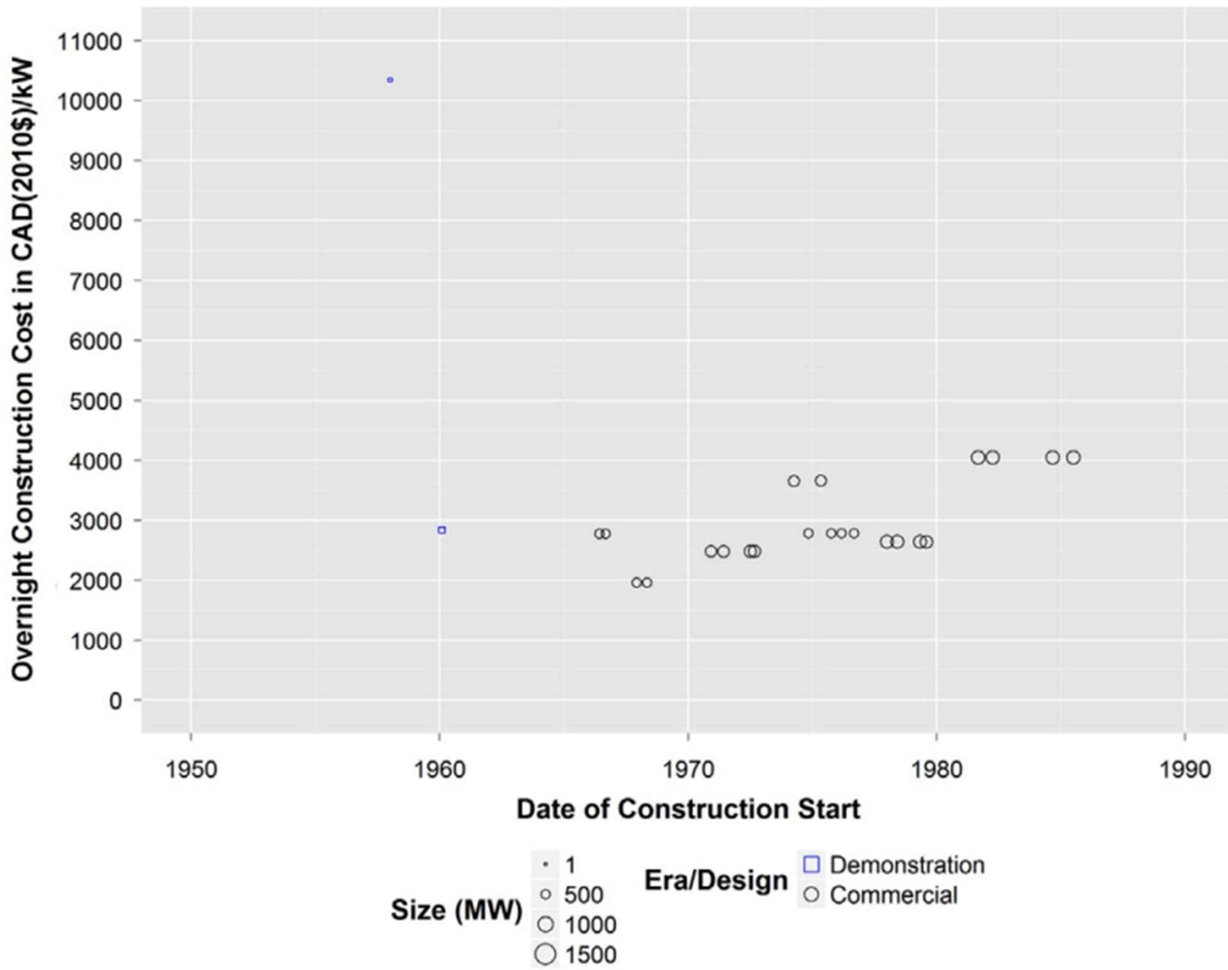


Figure 36: Capacity-Weighted Overnight Construction Cost (OCC) of reactors constructed in Canada by Construction Start Year

Credit: *Lovering et al., 2016*

Figure 37: Capacity-Weighted Overnight Construction Cost (OCC) of reactors constructed in Germany by Construction Start Year

Credit: *Lovering et al., 2016*

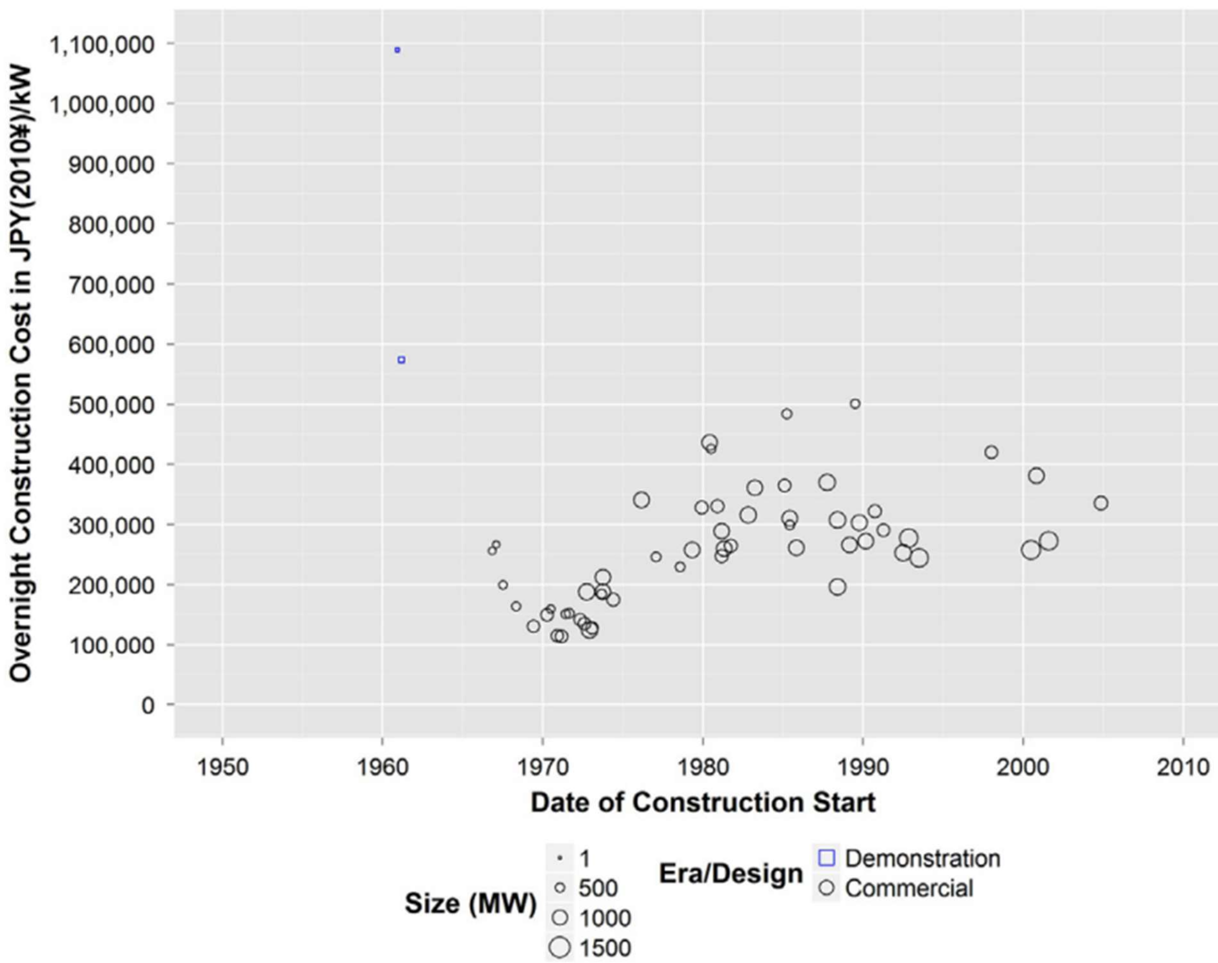


Figure 38: Capacity-Weighted Overnight Construction Cost (OCC) of reactors constructed in Japan by Construction Start Year

Credit: *Lovering et al., 2016*

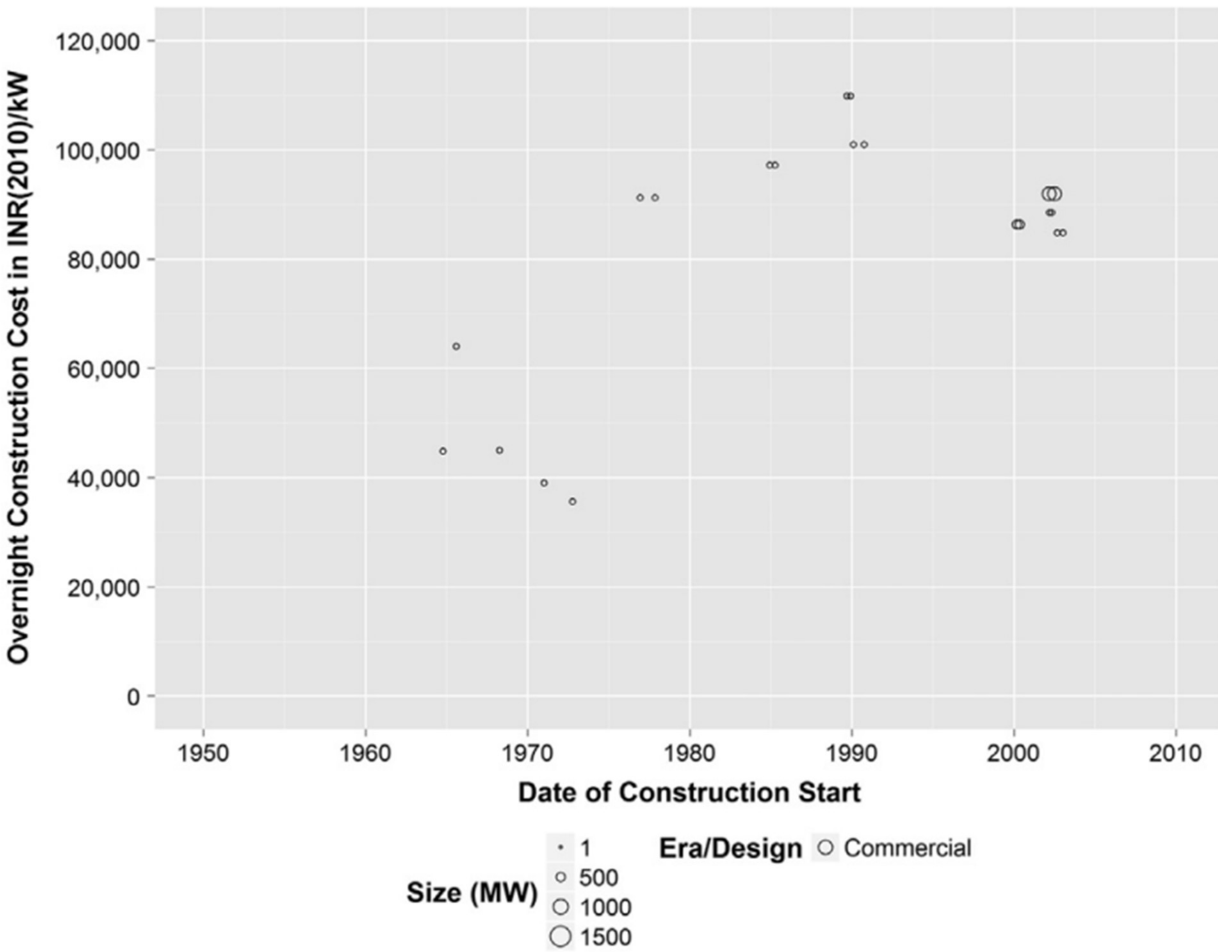


Figure 39: Capacity-Weighted Overnight Construction Cost (OCC) of reactors constructed in India by Construction Start Year

Credit: *Lovering et al., 2016*

APPENDIX B: Independent Report by Prof. Laura Diaz Anadon

(Appendix begins on next page.)

Report

Forecasting the Cost of Clean Energy Technologies

Prof. Laura Diaz Anadon

Chaired Professor of Climate Change Policy

University of Cambridge

January 9, 2023

Executive summary

Greater investments in and deployment of clean energy technologies are necessary to meet net zero emissions goals in the electricity sector and beyond. Over the past 10-20 years a growing amount of research has sought to understand what factors have shaped over time the costs of clean energy technologies involved in energy generation, consumption and storage and how to forecast future costs. This increased understanding can have implications for prioritizing and designing investments in innovation and anticipating how different trends may affect the costs technologies involved in the energy transition.

Most of this research has focussed on understanding the evolution of the costs of energy technologies in terms of their installed cost or levelized cost of generation or storage over time at a global or national level and what cost trajectories may look like in the future. It has uncovered particular patterns regarding the accuracy of different forecasting methods and the possible role of different underlying factors. Among other findings, research at a global or national level has indicated that public policy creating financial and/or regulatory incentives to promote clean technology deployment has played an important role inducing technology improvements and cost reductions.

At the same time, innovation systems studies have revealed that a broad range of actors—including researchers, financiers, corporations, civil society and the public—is involved in and necessary to foster a faster energy transition. Data suggests corporate actors made up a significant percentage of installed renewables capacity as of 2021 through power purchase agreements (PPAs). There is little independent academic research assessing the separate role of corporate purchases by one or multiple entities on the evolution of costs in energy technologies. This could be partly explained by the fact that data on such purchases is hard to come by, that such purchases are themselves partly driven by some of the same policies aiming to incentivize a faster deployment of renewables, and that, until recently, corporate purchases of renewable energy had not reached a sufficiently large size.

Given the scale of the role of corporate buyers and the strategic importance of such decisions for both firms and the energy transition, this report reviews research on forecasting and energy innovation systems and considers what key findings emerge for the design of clean energy technology policy and investments. It considers innovation drivers, empirical evidence on energy forecasts, and patterns in data on energy innovation trajectories and their relationship to technology characteristics.

The key findings of regarding energy innovation drivers and patterns and forecasting methodologies that emerge are as follows:

- It has not been possible to fully separate the contribution of how different innovation policies, such as public R&D and deployment contribute to cost reductions through different innovation mechanism including learning by research, by doing, economies of scale and spillovers, because they are interrelated. However, literature assessing the relationship between different innovation mechanisms and cost reductions and between national level policies and overall cost reductions for different energy technologies has grown over the past few years.
- National level policies including feed-in-tariffs, renewable energy auctions, and renewable standards have contributed to cost reductions through incentivizing deployment by increasing returns and reducing risks. These policies are understood to activate a variety of innovation drivers, including (but not limited to) learning-by-doing. Technology costs are also affected by developments in other areas of the economy (spillovers), which may also be accelerated by market growth.
- Energy technology cost forecasts should be probabilistic or, at the very least, include uncertainty ranges given that there are large uncertainties regarding the future costs of all technologies given the complexity of the innovation system and the uncertainties inherent to innovation.
- When reliable data about observed energy cost and deployment over time globally or in a particular jurisdiction is available over a sufficiently long period of time, model-based forecasts are more accurate than expert-based forecasts. The performance of these forecasts has been tested for large markets (at the global level or at the scale of large countries).
- Model-based forecasts use historical evolution as a function of deployment (Wright's law) or time (Moore's law) as proxy for different innovation drivers, including research, development and demonstration (RD&D), learning by doing, economies of scale, knowledge and technology spillovers, learning in finance, and changes in input prices. These forecasts are sensitive to assumptions about future deployment rates. They should include as much relevant credible data as possible and should strive be updated over time to include the most recent data available to account for possible changes in underlying drivers of costs.
- The evolution of costs in energy technologies over time has differed significantly across technologies. For mass produced and more granular technologies such as solar PV, batteries and LEDs, learning rates (the percentage change in costs as a function of doubling deployment or production) have been greater than for larger scale technologies requiring more customization (such as wind, electrolysis, or biopower). For some technologies in some jurisdictions, such as nuclear, costs have experienced long periods of increases, or negative learning rates. Even for technologies with faster learning rates, it is not uncommon to see short term increases or changes in the rate resulting from higher material prices.
- There is scope for additional development of model-based forecasts to: (a) quantitatively reflect the relationship between different complexity and scale metrics and the rate and uncertainty around cost reductions; (b) model possible structural changes in underlying industries; (c) separately consider the possible dynamics in

material input prices; and (d) determine the extent to which the statistical relationships describing large parts of the market can be adopted to separately describe the evolution of developments in smaller segments.

- Additional development is also necessary to further reduce overconfidence in expert-based forecasts. Such forecasts are particularly important for technologies in the early stages of development, when little to no data on cost and deployment is available. Over the next few additional data will become available to further test the performance of expert-based estimates for emerging technologies.

Overall, we have now a better understanding of various drivers that enable cost reductions and of empirical differences across different energy technologies when considering the full market or large segments thereof. The link between the actions of particular actors (e.g., public policy) and the different innovation drivers, as opposed to a general association with overall cost reductions, remains an area in need of research. The statistical testing of more disaggregated model-based forecasts and of forecasts that consider explicitly technology differences is underway and requires more extensive and granular data over time across technologies.

1. Introduction

Understanding the evolution of the costs of clean energy technologies and their possible drivers is key to designing policies and corporate strategies to mitigate climate change while considering other societal goals.

While the costs of a range of energy technologies such as solar PV, on- and offshore wind, lithium ion batteries and beyond has come down dramatically over the past couple of decades (Shukla *et al.*, 2022), meeting national and international climate targets still relies on many technologies that are only at the prototype or demonstration phase. The International Energy Agency (IEA), for example, estimates that about 60% of needed cumulative emissions reductions to meet the goals of the Paris Agreement depends on technologies that are not yet commercialized (IEA, 2020).

Most research points to a clean energy transition resulting in societal benefits that far outweigh the costs when considering reduced climate damages and co-benefits from climate change mitigation from reduced air pollution and health costs and improved ecosystems, for instance (Shukla *et al.*, 2022). However, the interlinkages between different parts of our economy and the ubiquity of the use of fossil fuels mean that, to meet the goals of the Paris Agreement, the upfront investments by different societal actors in the short- to medium-term are expected to be greater than those under a non-Paris compliant scenario (IEA, 2022b). Under the International Energy Agency's (IEA) Net Zero scenario, by 2030 annual investments in clean energy and energy efficiency globally need to increase by over a factor of three when compared to their baseline scenario. This means that understanding what can be known about the potential for future cost reductions in different technologies can help inform investment and policy priorities.

All public and private organizations have budget constraints. Given that meeting various societal and corporate goals often hinges on developments in energy, it becomes essential to ensure that investments in innovation are made to deliver the greatest returns in terms of cost reductions and climate mitigation, among other goals.

Policymakers are faced with a number of decisions that could affect energy technology cost trajectories including whether and how to set up portfolios of technology R&D investments, performance standards and regulations and financial subsidies or incentives (Anadón, Baker and Bosetti, 2017). In other words, policy decisions include the choice of policy instruments and mixes to meet climate goals and the specific design of such policies. Integrative research using systematic literature review methodologies has concluded that national (and sometimes regional) level government policy in the form of regulation and financial incentives on deployment has played an important role incentivizing deployment and reducing technology costs (Grubb *et al.*, 2021; Peñasco, Anadón and Verdolini, 2021). Research has also considered the relationship between such government policies and a broader set of outcomes, including distributional impacts (Peñasco, Anadón and Verdolini, 2021).

There is much less research on the role of other actors. Corporate buyers of power are starting to account for a significant fraction of annual installed capacity of renewable electricity generation. A recent IEA report using data from Bloomberg New Energy Finance and its own data on global renewable capacity deployment indicated that power purchase agreements (PPAs) globally for renewables accounted for 31 GW of new installations in 2021, which was over 10% of the total capacity additions of renewables of 290 GW in that year (IEA, 2022a). Innovation systems studies have shown that a broad range of actors—including researchers, financiers, corporations, adopters, and civil society—is involved in and necessary to foster a faster energy transition (Shukla *et al.*, 2022 and Blanco *et al.*, 2022, p. 16)).

In spite of the importance of corporate actors, there is seems to be little independent academic research assessing the separate role of corporate purchases of energy technologies by one or multiple entities on cost trajectories. This is something that could be partly explained by the fact that data on such purchases is hard to come by, that such purchases are themselves partly driven by some of the same government policies aiming to incentivize a faster deployment of renewables, and that the role of corporations as buyers role has only become importantly over the past few years. It is also perhaps not surprising given that quantitative research on the relationship between government innovation procurement in energy and cost reductions is itself extremely limited (Peñasco, Anadón and Verdolini, 2021).[1] An additional consideration relevant for thinking about the role of corporate power procurement on innovation trajectories is that some forms of power procurement by corporations may not be directly considered to be additional in terms of leading to additional renewable electricity generation and possible cost reductions within a particular jurisdiction if the renewable electricity being purchased either already exists or is being supported through government mechanisms such as contracts for difference (CCC, 2020).

The objective of the rest of this report is to distil what is known about different methods that have been used to forecast the cost of energy technologies, the various drivers of the evolution of costs and the technology characteristics that may explain historical cost patterns.

The rest of the report is structured as follows: (2) brief overview of the theories and empirical literatures on the drivers of innovation, (3) a survey of technology cost forecasting methods, (4) empirical evidence for energy technologies on the performance different technology cost forecasting methods, (5) a discussion of the evidence regarding technology characteristics that

[1] See here https://dpet.innopaths.eu/#/ for more details on the literature assessing the relationship between government procurement (as well as R&D, carbon prices, portfolio standards, feed in tariffs, auctions, etc) and various policy outcomes, including costs, innovation, and distributional outcomes.

may be associated with different patterns of cost reductions in energy, and (6) a very brief conclusion.

2. The drivers of technology innovation

Technology innovation is the "process by which technology is conceived, developed, codified, and deployed" (Brooks, 1981). The technology innovation process and its determinants are often analysed in the context of countries, sectors and technologies. Research highlights the role of different actors and relationships (Anadon *et al.*, 2016), for example, by considering the role of different actors at a national level (Nelson, 1993), the functions of innovation that contribute to innovation in a particular technology (Hekkert *et al.*, 2007), and the different levels of activity that shape the development of an industry from niche markets onward (Geels, 2002).

At a high level, the process of technology innovation in energy has been understood as consisting of interconnected stages with feedbacks and shaped, at a policy level, by a range of technology push and market pull policies. Figure 1 condenses the stages of the process of technology innovation as described, for example, in (Grubler *et al.*, 2012; Anadon *et al.*, 2016). It also includes the metrics or indicators commonly used to study the evolution or activities along different innovation stages and the types of policies that most directly affect the innovation process. An even more holistic representation of the innovation process would also need to include a wide range of actors and a representation of broader socioeconomic factors and technology developments in other industrial areas. The takeaway is that technology innovation must be understood as a complex, adaptive process (Anadon *et al.*, 2016).

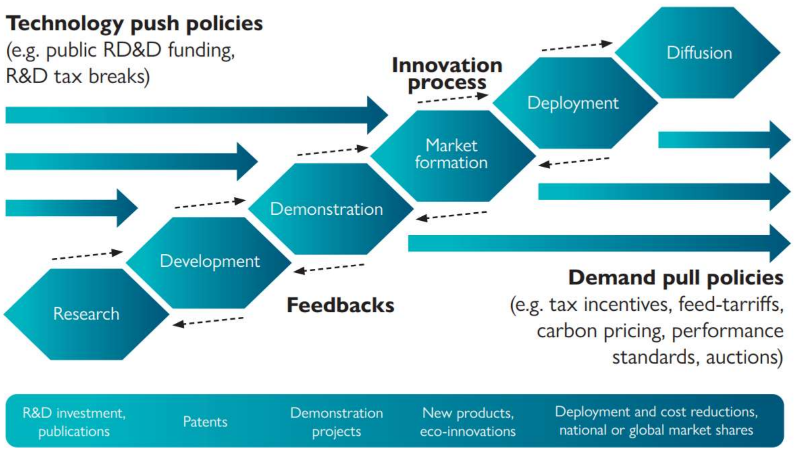


Figure 1. Partial overview of the technology innovation process. The bottom part contains some of the indicators used to understand innovation activity around particular stages (Peñasco, Anadón and Verdolini, 2021). Source: (M. Grubb *et al.*, 2021). Technology obsolescence, the role of a wider set of actors beyond policy, and developments and trends in other parts of the economy also shape the technology innovation process but are not included in this schematic representation.

The literature on the economics of innovation, in turn, has worked on identifying the drivers or mechanisms that are associated with technology innovation and/or productivity increases over time, often at an economy or sectoral level.

Synthetic research on the economics of innovation (e.g., Grubler *et al.*, 2012; Blanco *et al.*, 2022) highlights the role of the following drivers:

- market demand or induced innovation (Nordhaus, 2002),
- knowledge spillovers from other areas of technology (Scherer, 1982; Aghion and Jaravel, 2015) or across different actors and geographies (Audretsch and Feldman, 2004)
- learning-by-doing or by-using (Arrow, 1962; Gruber, 1998),
- research and development (Romer, 1990) and
- economies of scale (Rosegger, 1996).

There is also a growing set of literatures related to complexity economics that focus on the relationships between technology components and materials and agents, enabling considerations of the non-equilibrium nature of innovation (Frenken, 2006).

There is a growing literature trying to disentangle the relative contributions of these different mechanisms by technology area focussing on energy technologies. Quantitative causal attributions linking different innovation drivers and public or private initiatives, however, are very difficult given the interdependencies between the drivers above and the fact that many of the public or private initiatives that shape those drivers overlap (Grubb *et al.*, 2021; Peñasco, Anadón and Verdolini, 2021). In addition, there are limitations related to the availability and consistency of granular cost data (of different technology cost components). This hinders statistical analysis across technologies regarding innovation drivers and the actions by public or private actors that may shape them. We turn to reviewing the energy technology specific literature linking, mostly through correlations, the relationship between the various innovation drivers listed above and energy technology costs.

The two-factor learning curve literature, for instance, attempts to separate the influence of learning-by-doing (which is a basis of Wright's law; see section 3.1) from other factors when explaining the evolution over time of the cost of different energy technologies (Blanco *et al.*, 2022). (Klaassen *et al.*, 2005; Rubin *et al.*, 2015), among others, aim to disentangle the relative contributions of **learning by doing**, using deployment as a proxy, and **research and development (R&D)**, using public R&D investment by technology as a proxy. However, information on public energy R&D investments by technology area for developing countries and emerging economies is not systematically collected (Verdolini *et al.*, 2018), although there has been some progress (Meckling *et al.*, 2022). In addition, it is even harder to obtain consistent and comprehensive data about private R&D investments for different energy technologies globally or nationally (Grubler *et al.*, 2012). A recent study on lithium ion batteries develops estimates trying to separate the contributions of R&D, learning by doing and economies of scale using a detailed cost model (Ziegler, Song and Trancik, 2021). In general, all this research across technologies strongly suggests that all of these factors have all played a role. Separating the contributions of learning-by-doing and R&D, among other factors, with precision is challenging because of issues related to measurement, endogeneity, and collinearity (Qiu and Anadon, 2012; Grubb *et al.*, 2021) and exogenous technological change (Nordhaus, 2014). This means that estimates trying to separate those effects using two-factor learning curves, for instance, should be measured. For example, R&D investments are clearly important, but it may be the case that R&D resulting from targeted investment in a technology is different from the induced R&D resulting from growth in market demand.

Other work has tried to estimate the possible impact of learning by doing on the financing component of technology costs, which they term '**financial learning**' (Egli, Steffen and Schmidt, 2018). All else being equal, as more projects with new technologies get built and financed, investment risk tends to decrease, as do financing costs, including in low-income countries (Probst *et al.*, 2021). The cost of capital of renewable projects does not only change with time and experience, but also across renewable technologies and countries (Egli *et al.*, 2022). Just like in other drivers of innovation, the cost of financing can be affected by developments outside of the energy sector, such as changes in interest rates (Egli, Steffen and Schmidt, 2018).

Some energy technology studies have considered the role of **knowledge or technology spillovers** from other technologies or industries. A significant body of work has considered the extent to which patents in clean energy technology, including solar PV, onshore wind and lithium ion battery technologies, cited patents or publications coded as primarily belonging to other technologies or industries (Nemet, 2012; Battke *et al.*, 2016; Huenteler *et al.*, 2016). These studies, however, do not aim to assess the possible relationship between patent citations to 'external patents' and quantitative technology innovation outcomes or cost reductions. Recent qualitative research has moved more in this direction by considering the extent to which breakthroughs in lithium ion batteries have relied on external knowledge (spillovers) and how the connections to external knowledge were made (Stephan, Anadon and Hoffmann, 2021). But, overall, while there is consensus that knowledge spillovers are important, the magnitude of the contribution of knowledge spillovers from other sectors at the technology level is the subject of ongoing work. Also on the topic of spillovers, a recent paper using solar PV installation data in the US estimated **knowledge spillovers between firms** and their contribution to **reducing the soft costs** (mostly installation costs—e.g., installation labour, supply chain, permits, and marketing). More specifically, (Nemet et al., 2020) identified a positive and significant effect of knowledge spillovers across firms in the US on soft costs. The effect was not robust to all specifications tested and only took place for larger installers of PV, but it provides an interesting example of the possible role of market size or scale when thinking about the reductions in particular component costs and possible drivers (knowledge spillovers).

Some energy technology specific studies have tried to quantify the contribution of **raw materials and fuel costs** to total energy technology costs. (Nemet, 2006; Kavlak, McNerney and Trancik, 2018) tried to isolate the contribution of silicon costs to solar PV prices globally. When considering the factors shaping bids for onshore wind power projects in China, (Qiu and Anadon, 2012) considered the contribution of steel costs. Turning to fossil fuel power generation, (McNerney, Doyne Farmer and Trancik, 2011) considered the role of the cost coal and its role in the relatively flat but volatile inflation-adjusted cost of coal power over time These contributions are in principle easier to measure and separate from the others. Crucially, raw material and fuel costs are often themselves affected by policies in the particular domains, by broader economic and social developments and, in many cases, technology developments outside of the particular industry. Research has also found that energy technology costs do not always decline, particularly when a significant component of raw materials is involved (Way *et al.*, 2022), something that is partly explained by the fact that often the cheaper resources are extracted first. It is worth noting that cost increases in areas like nuclear generation (Grubler, 2010; Rangel and Leveque, 2015; Lovering, Yip and Nordhaus, 2016) are not primarily explained by materials and more likely by issues related to scale, technology complexity, policy design, knowledge depreciation and social acceptance, among others.

Finally, a couple of studies tried to separate the role of **economies of scale** and silicon prices for silicon PV (Nemet, 2006; Yu, van Sark and Alsema, 2011) and of economies of scale in organic PV technologies (Gambhir, Sandwell and Nelson, 2016; Kavlak, McNerney and Trancik, 2018). The role of economies of scale has also been identified as a big driver of the cost reductions in light emitting diodes over the past two decades (Weinold, Kolesnikov and Anadon, 2021) and, as previously mentioned, a study on lithium ion batteries tried to separate the impact of R&D, learning by doing and scale (Ziegler, Song and Trancik, 2021). Just like other innovation drivers in energy, the evolution of the scale of different energy technologies can depend on a range of factors, including technology specific characteristic, support policy design, industrial structure and/or other economic or geographic or socio-political factors (e.g., size of windfarms may also depend on the landscape, etc). There seems to be no systematic effort trying to understand the extent to which different factors shape economies of scale, but there is a growing empirical literature trying to understand the correlation between technology complexity, granularity or modularity and overall cost trajectories (see section 5).

3. Technology forecasting methods and their use in energy technologies

Physicist and Nobel Prize winner Niels Bohr is often quoted as having said "prediction is very difficult, especially if it's about the future!"[2]. As explained in the introduction, however, decisions in the policy, businesses, and communities in the energy transition deal often require making assumptions explicitly or implicitly about future costs. In many cases, assuming costs remain static, for example, would be a really bad assumption. Therefore, in spite of the difficulties with predictions, clean energy technology forecasting is, in practice, done in different ways in a wide range of organizations.

Given the complexity, interdependencies and uncertainties characterizing technology innovation, energy technology cost forecasting should, when at all possible, be conducted in a probabilistic basis (Anadón, Baker and Bosetti, 2017). To date, two main types of forecasting approaches have been developed and used to produce future-looking quantitative and probabilistic estimates of technology costs: **expert-based** and **model-based** approaches.

3.1 Expert-based approaches

As described in more detail in (Meng *et al.*, 2021), **expert-based approaches** include "different ways of obtaining information from knowledgeable individuals who may have differing opinions and/or knowledge about the relative importance of various drivers of innovation and how they may evolve." The value of experts is that, when producing their forecasts, they can in principle take into consideration public information about industry growth, technology diffusion and costs and also information that may not yet be widely available or codified (Verdolini *et al.*, 2018), something that may be particularly valuable for emerging technologies in the early stages of the innovation process (Meng *et al.*, 2021) (i.e., in the early stages of innovation shown in Figure 1). Expert-based approaches make (often implicitly) judgments about the underlying drivers of innovation discussed in section 2. Table 1 includes a brief explanation of the subtypes of expert-based approaches and their known public application (or lack thereof) in the field of energy technologies.

To date, the most widely applied expert-based method to generate probabilistic cost forecasts for energy technologies according to the information publicly available has been, by far, **expert elicitation** (underlined in Table 1). (Meng *et al.*, 2021) include more detail on expert-based approaches.

[2] Most likely he popularized a common Danish saying.

Table 1. Overview of expert-based approaches to forecast technology costs, the different subtypes and applications to energy technologies. Source: Adapted from Supplementary Information of (Meng *et al.*, 2021)

Subtypes	**Rationale**	**Example energy technology references**
Unstructured expert input	Asking experts informally about cost parameters in the future. Simplest and least resource intensive method. Information about the consulted expert(s) is often not provided, leading to a lack of transparency.	Deterministic forecasts: Most IAM scenarios, many examples, e.g. (van Vuuren *et al.*, 2011). Some uses include 'high' and 'low' forecasts (sensitivity analysis or scenarios), but are not probabilistic. Probabilistic forecasts: N/A.
<u>Expert elicitations</u>	Highly-structured formal processes aimed at reducing different psychological biases from individual experts. Interactive and resource intensive. In some cases, multiple expert answers are aggregated (Baker *et al.*, 2015).	Deterministic forecasts: Not applicable, since this approach was designed to elicit probabilistic estimates. Probabilistic forecasts: Many examples, e.g. (Curtright, Morgan and Keith, 2008), see review in (Verdolini *et al.*, 2018)
Group methods – Delphi method	Structured iterative group process aiming to lead to a convergence of opinion, a group response.	Deterministic forecasts: N/A Probabilistic forecasts: Available for some technologies. E.g. (Hussler, Muller and Rondé, 2011; Anadón, Nemet and Verdolini, 2013). Sometimes used to obtain insights about non-cost technology attributes.
Prediction markets	It assumes that trading in futures contracts (or betting) by large groups of people may help predict events better than individuals or smaller groups of experts (Wolfers and Zitzewitz, 2004).	Method could be applied to make deterministic and probabilistic forecasts. No examples related to energy technology costs or availability were found.

It is important to note that a relevant difference across expert elicitations on energy technologies is that some studies only report individual answers and others also aggregate answers across experts. There is a significant literature on the advantages and disadvantages of aggregating or not aggregating individual expert answers and of different ways of doing so (e.g., Morgan, 2014; Baker *et al.*, 2015; Verdolini *et al.*, 2018).

3.2 Model-based approaches

As explained in (Meng *et al.*, 2021) "**model-based approaches** explicitly use one or more variables from available observed data to approximate the impact of the full set of drivers of innovation on technology costs, implicitly assuming that the rate of change in the past will be the best predictor of the rate of change in the future". Model-based methods can be classified according to the functional form they use—i.e., the relationship between the dependent (in this case energy technology costs) and independent variables (other observed data)—and the way in which uncertainty is characterized.

Table 2 includes a brief explanation of the subtypes of expert-based approaches and their known public application (or lack thereof) in the field of energy technologies. The subtypes listed, namely Wright's law, Moore's law, etc, correspond to the **functional form** of the model. Most model-based analysis of the evolution of clean energy technologies has used the Wright's law or Moore's law functional forms (underlined in Table 2). These formulations have a longer history and rely on data that has been historically more widely available. (Nagy *et al.*, 2013) conducted a statistical analysis on cost, deployment and time data on a range of technologies (including some energy technologies as well as a broader set) and found that those two formulations have historically done better at predicting future costs, all when used in a probabilistic manner. (Meng *et al.*, 2021) include more detail on the functional form behind the different model-based approaches.

Table 2. Overview of model-based approaches to forecast technology costs, the different subtypes and applications to energy technologies. Source: Adapted from Supplementary Information of (Meng *et al.*, 2021)

Subtypes	Rationale	Example energy technology references
Wright's law (also known as' experience curves')	Costs as a function of cumulative production or deployment. While the link is made to learning by doing, in practice it is very hard to separate it. Link to induced innovation (Nordhaus, 2002).	Deterministic forecasts: Many instances, e.g. (Lilliestam *et al.*, 2017) Probabilistic forecasts: E.g. (Nemet, 2009; Nagy *et al.*, 2013; Farmer and Lafond, 2016; Meng *et al.*, 2021)
Moore's law	Evolution of costs as a function of time	Deterministic forecasts: E.g. (Goddard, 1982) (Application in circuits, arguing about importance of time) Probabilistic forecasts: (Nagy *et al.*, 2013; Farmer and Lafond, 2016; Meng *et al.*, 2021)
Nordhaus model	Evolution of costs as both a function of time and deployment (combining Moore and Wright)	Deterministic forecast: (Nordhaus, 2014) considers major US industry groups (not energy technologies) Probabilistic forecasts: (Nagy *et al.*, 2013)
Goddard model	Evolution of costs as a function of economies of scale	Deterministic forecasts: N/A Probabilistic forecasts: (Nagy *et al.*, 2013)
SKC model	Evolution of costs as a function of scale (unit costs) and deployment (combining Goddard and Wright).	Deterministic forecasts: (Sinclair, Klepper and Cohen, 2000) (application in chemicals). Probabilistic forecasts: (Nagy *et al.*, 2013)
Two factor learning curve	Evolution technology costs is represented as a function of R&D investments and deployment.	Deterministic forecasts: E.g., (Klaassen *et al.*, 2005; Rubin *et al.*, 2015) Probabilistic forecasts: N/A

A second important characteristic differentiating probabilistic model-based forecasts is the **characterization of uncertainty** and how it is used to project future costs.

The application of deterministic model-based forecasts often involves the use of a simple regression applied to observed data for a given technology. The relevant estimated parameter (or parameters) is then used to project technological change forward in a deterministic manner given particular assumptions about the evolution of deployment at different points in time in the case of Wright's law, for instance. This produces a point forecast for a given technology.

Probabilistic forecasts introduce uncertainty, which can arise from measurement error, the inherent uncertainty in the innovation process (endogenous uncertainty, and because of unforeseeable events in other parts of the economy (exogenous uncertainty). Different probabilistic forecasting methods incorporate these types of uncertainty in different ways. The measurement error and inherent uncertainty has been captured partly assuming that the technological change parameter (e.g., the learning rate) can change over time (Nemet, 2009). The exogenous uncertainty has been captured by uncertainty characterization methods that add extra "noise" terms to the model (e.g., periodic shocks representing unforeseeable fluctuations in the economy, e.g., (Farmer and Lafond, 2016; Meng *et al.*, 2021; Way *et al.*, 2022). Once an uncertainty specification has been selected and estimated, probabilistic forecasts can be produced, for example, by using Monte Carlo methods, which involve generating a large number of deterministic forecasts randomly and aggregating them to produce a probabilistic forecast). A recent analysis (Meng *et al.*, 2021) used what they refer to as the **Stochastic Shock** uncertainty forecasting method, developed by (Farmer and Lafond, 2016; Lafond *et al.*, 2018), and the **Stochastic Exponent** method, which they develop by modifying the work by (Nemet, 2009).

A third dimension of model-based forecasting model development that is used to assess the accuracy of model-based models is the **use of forecast error models**. To develop more accurate model-based methods the literature has focussed on systematically doing in-sample testing of different specifications using historical data. The underlying rationale for this approach is that the evolution of a technology is likely the result of sufficiently similar mechanisms and that, therefore, technologies can be treated as a set of nearly identical independent experiments that can be pooled to generate inferences about the future, as discussed in (Meng *et al.*, 2021). A number of studies have used this approach on energy technologies and beyond (Nagy *et al.*, 2013; Farmer and Lafond, 2016; Lafond *et al.*, 2018; Way *et al.*, 2022). As more data becomes available and a better understanding of technology characteristics and their link to innovation becomes clear, further development of these methods is both possible and desirable to incorporate structural change, materials prices and technology characteristics.

4. Empirical evidence on the performance of different forecasting methods

Since the late 2000s, several studies have tried to collect data and take stock of the evolution of energy technology costs over time. Some of that research has compared the fast rates of improvements in technologies like semiconductors, genetic sequencing and chemicals with that of different energy technologies (Farmer and Lafond, 2016).

Within energy technologies, data shows that rates of change have varied widely. Figure 2 below, from (Way *et al.*, 2022), shows global data on the cost over time of a range of energy technologies. Notably, the cost trajectory of fossil fuel technologies is relatively flat but variable, while that of clean energy supply technologies shows declining and less variable costs over time, with significant differences across clean energy technologies. Work on other technologies also shows improvements. For example, recent work on LED performance and costs (see Figure 3) shows progress along the faster end of the range for the energy technologies shows in Figure 2 (more similar to solar PV and lithium ion batteries).

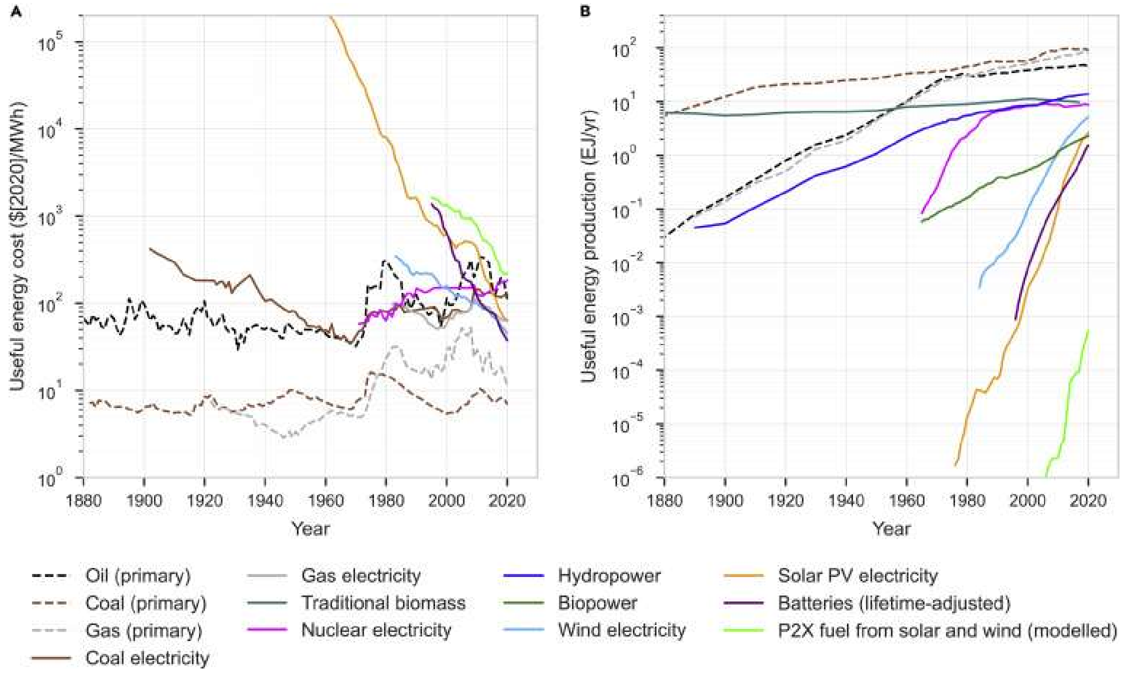


Figure 2. Historical costs (panel A) and production levels (panel B) of key energy supply technologies. Source: (Way et al., 2022)

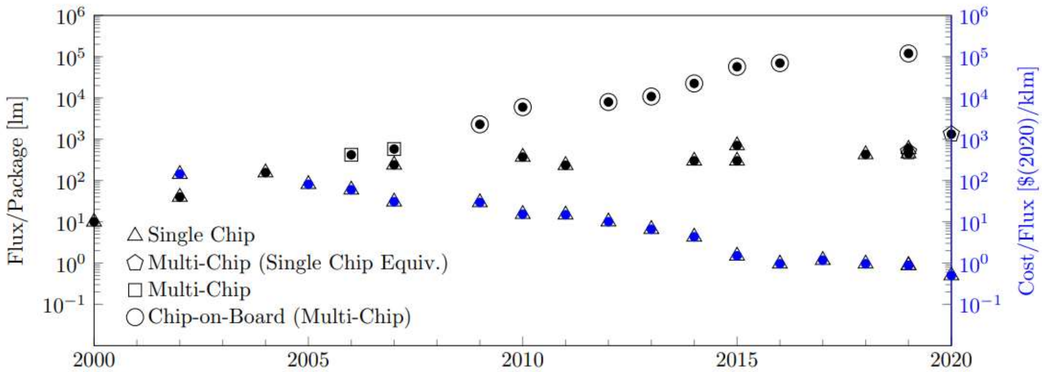


Figure 3. Increase in flux (black) and decrease in cost (blue) for the highest-performing white light-emitting diode (LED) single chips and multi-chip packages. Source: (Weinold, Kolesnikov and Anadon, 2021)

(Meng *et al.*, 2021) systematically compared the performance of subtypes of expert- and model-based methods for which sufficient data on energy technologies is available, namely, expert elicitation forecasting approaches and model-based approaches based on Wright's and Moore's laws. They used the Stochastic Shock and Stochastic Exponent methods of uncertainty propagation, generated probabilistic cost forecasts of energy technologies rooted at various years in the past using such methods and compared them with observed costs in 2019.

As shown in Figure 4, model-based methods using Wright's and Moore's law (based on using deployment and time, respectively, as a proxies for the innovation process) outperformed expert elicitations both in terms of capturing 2019 observed values and producing forecast medians that were closer to the observed values. All methods underestimated technological progress in almost all technologies by producing 50th percentile estimates that where, with the exception of for nuclear, lower than the average observed costs.

Calculating the log of the ratio of the 50th percentile of the cost forecast and the observed cost value, (Meng *et al.*, 2021) generated a dimensionless metric for characterizing the performance of the different methods. Analysing this metric showed that the expert elicitation estimates were overconfident (with uncertainty bounds that did not include actual values) and further emphasized that, all method types, during the time period covered between the late 2000s and early 2010s and 2019, underestimated the path of development in non-nuclear energy technologies.

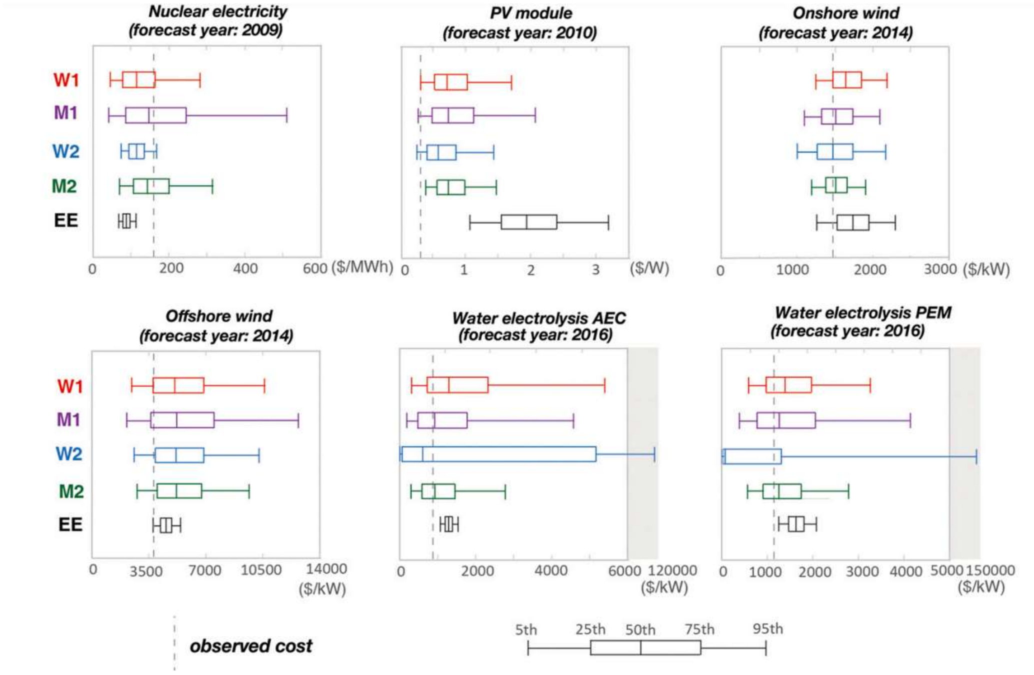


Figure 4. Comparison of the expert elicitation and model-based 2019 forecasts for six energy technologies with the corresponding average 2019 realized values. The year listed in brackets below the name of the technology indicates the year in which the expert elicitation (EE) was conducted and, consequently, the latest observed data included as input to the model-based forecasts. W1 and W2 refer to the use of the Wright's law method using Stochastic Shock and Exponent uncertainty methods, respectively. M1 and M2 refer to the use of the Moore's law method using Stochastic Shock and Exponent uncertainty methods, respectively. The far-right whisker (the 95th percentile) of the W2 distribution for water electrolysis alkaline electrolysis cells (AEC) and proton exchange membrane (PEM) cells is shown inside a grey band, indicating that the x-axis was extended to include said forecast. Source: (Meng *et al.*, 2021)

The reasons for the systematic underestimation of average costs by the median forecasts using the expert- and model-based methods tested may include unforeseen changes in the industry structure and policy compared historical trends and/or an underestimation of the level of deployment. Wright's law forecasts naturally require assumptions about the level of deployment. Deployment trajectories used in Wright's law forecasts often come from different types of extrapolation of observed trends over time or levels of deployment associated different policy or industry evolution scenarios. Moore's law forecasts, in turn, require either different types of extrapolations (e.g., different functional forms) of cost changes over time or (again) deviations of such extrapolations developed based on different qualitative assumptions in scenarios.

It is important to note that the five energy technologies for which forecast medians from experts and models were higher than 2019 costs in (Meng *et al.*, 2021) are likely correlated, in the sense that they are shaped by a partly shared group of drivers related to "decarbonization policies, investor perceptions and preferences, firm expectations, and societal pressures". Therefore, the results of the analysis need to be contextualized given the time period investigated and points to the importance of including the most up-to-date data possible to consider possible changes in underlying factors over time.

(Meng *et al.*, 2021) also generated 2030 cost forecasts for the 10 energy technology areas for which such forecasts were feasible from expert elicitation and Wright's and Moore's models. Figure 5 shows that, consistent with the 2019 performance comparison, elicitations tend to produce narrower 2030 cost uncertainty ranges compared to model-based methods. In addition, for technologies that are typically thought of as being more modular and smaller, the forecasts using model-based forecasts yield lower cost projections when compared to elicitations, i.e., they are more optimistic in terms of future cost reductions. [3]

Like Figure 2, Figure 5 makes clear that patterns of the evolution of costs differ across technologies and that there are instances of cost increases, in some cases due to raw materials prices. In addition to the temporary increases in onshore wind costs due to steel costs, the impact of coal prices and the impact of silicon costs of PV, Figure 5 shows that the cost of bioelectricity has also had periods of increases and of generally flat average costs, likely due to biomass costs to some extent. Electrolysis has also experienced some periods of increased costs.

A few observations that emerge from the research reviewed so far on these methods:

- Using past data, when available, in a probabilistic manner along the lines of the Stochastic Shock method, has outperformed expert elicitation estimates; it been shown to be more likely to include observed costs than expert-based methods.
- In spite of continued work and progress in expert elicitation methodologies, in the periods and technologies considered expert-based methods applied to energy have resulted in overconfident (and in many cases pessimistic) probabilistic estimates. This points to the need to additional work on such methods since there is little alternative when no previous data is available to enable the use of model-based probabilistic approaches.
- The use of model-based approaches does not imply attributing all improvements to learning-by-doing. Depending on the future looking assumptions about deployment over time, for instance, they assume that the underlying drivers of innovation discussed in section 2 continue as in the past or become stronger or weaker.
    - One example of a factor shaping costs (or driver) that is included in model-based analysis using historical deployment data, for instance, is the evolution of financing costs. The data on the cost of solar PV and onshore wind globally shown in Figure 5 includes projects in Germany, for which data is available regarding reductions in the cost of capital over time (see Figure 6). In other words, the fact that solar PV probabilistic models have captured PV costs over

[3] For completeness, it is important to add that for offshore wind, even though the capital cost does not show large cost reductions over time, the levelized cost of electricity (LCOE)—which includes considerations of improvements in capacity factors, for instance—would show a more pronounced cost decline. (For example, (Anadon *et al.*, 2022) show steep reductions in the LCOE for offshore wind in the UK over time). The LCOE of offshore wind was is not included in Figure 5 because the objective was to compare in a fair manner the different forecasting approaches under consideration and that was not possible for offshore wind LCOE using elicitations given data availability

short to medium time periods does not imply that they assume that cost reductions come only from learning-by-doing in manufacturing and operation.

- The more and more up-to-date data, the better the forecasts in terms of an increased likelihood of generating ranges that will capture future trajectories (Nagy *et al.*, 2013; Meng *et al.*, 2021; Way *et al.*, 2022).
- Not all energy technologies evolve in the same way and there are developments typically thought to be part of the broader socioeconomic environments, as opposed to the innovation system of actors and institutions more directly relevant to that technology that can affect costs.
    - Some of the differences in the evolution of costs over time can be attributable to materials costs, such as fossil fuel (e.g.(McNerney, Doyne Farmer and Trancik, 2011) or steel costs (Qiu and Anadon, 2012), which are shaped by extraction and supply chain dynamics, as well as other developments outside the energy sector. It has been suggested that for, technologies with a high fraction of variable and fuel costs, where cheaper resources are extracted first, autoregressive models a natural choice (Way *et al.*, 2022). For technologies that display some cost reductions over time, it is argued, the models in Table 2 (and in particular Wright's and Moore's law) may be more applicable.
    - Some of the differences in the rate of cost reductions over time for technologies that experience improvements may be attributable to factors specific to different technologies, such as their complexity or granularity. Thus, there is also room for improvement in model-based approaches, particularly in terms of adding to the emerging data on technologies and classifying technologies robustly according to metrics related to scale or granularity (Wilson *et al.*, 2020) and/or complexity measured in various ways related to patents or trade (Surana *et al.*, 2020), for instance (see section 5 for an overview of this work).
    - There may be also be differences between cost forecasts of novel and dominant subtechnologies within the same energy technology (Meng *et al.*, 2021). "Novel" subtechnologies (i.e., offshore compared to onshore, newer solar technologies compared to silicon PV, and newer batteries compared to lithium ion) generally have higher 2030 expert forecast medians and larger uncertainty ranges when compared to expert estimates for the dominant subtechnologies. (Meng *et al.*, 2021) were not able to compare novel vs. incumbent subtechnology forecasts for model-based methods because of data limitations. This points to the particular value of elicitations to get an initial understanding—which ought to be revisited over time—of the possible cost trajectories of energy technologies for which cost and deployment data is not available. Time will tell whether or not the experts were right and the comparatively novel technologies for which expert forecast data is available will "catch up" with their dominant technology by 2030.
- While there is work at the firm level on soft costs (e.g. (Nemet *et al.*, 2020; Gao, Rai and Nemet, 2022), most of the data available for forecasting is at a national or global level, suggesting that additional development may be needed when considering the impact on costs of smaller scales of deployment on different technology cost components when compared to national or global markets at a corporate level, for instance.

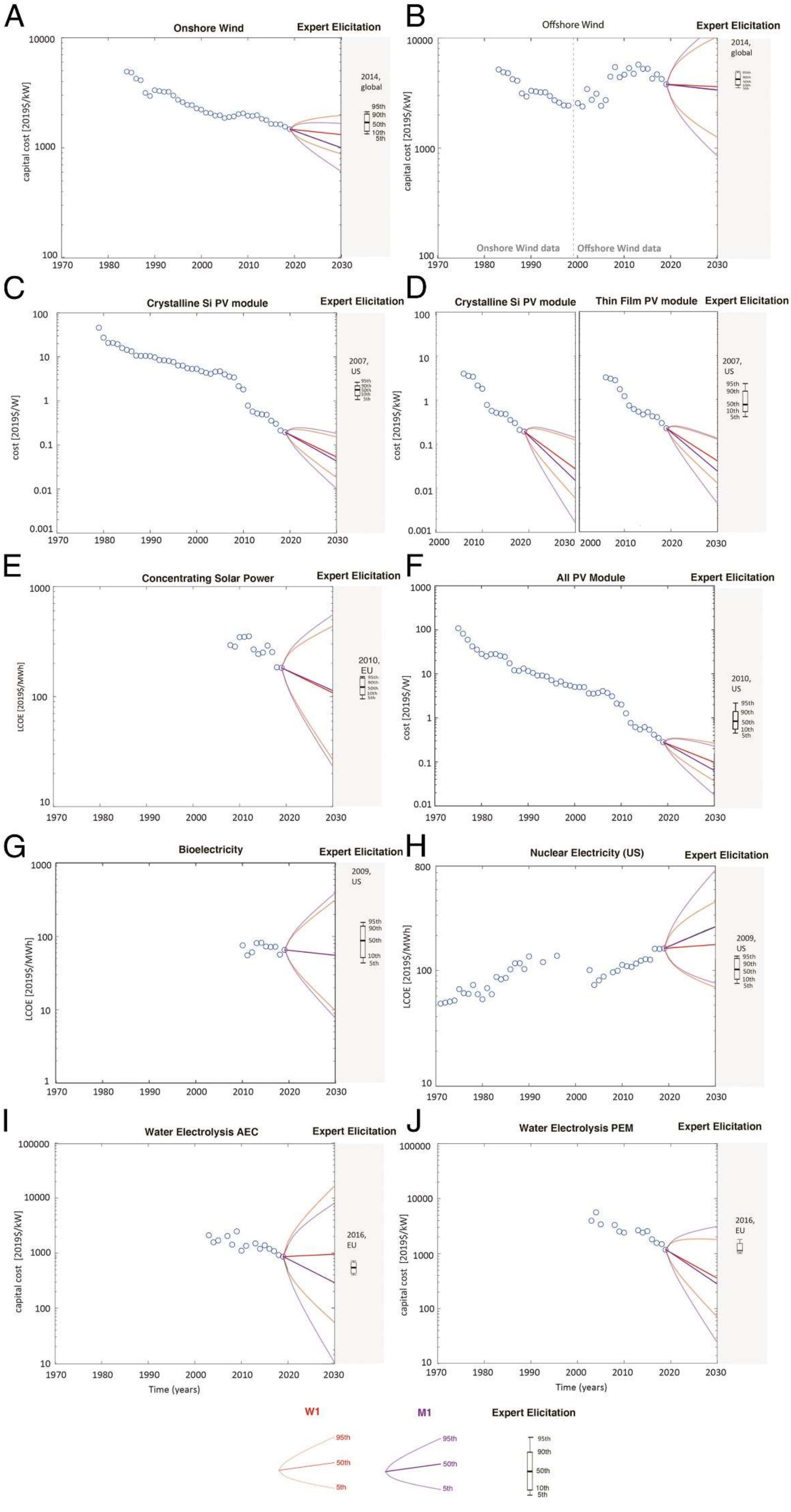

A
Onshore Wind
Expert Elicitation
capital cost [2019$/kW]
2014, global
B
Offshore Wind
Expert Elicitation
capital cost [2019$/kW]
2014, global
Onshore Wind data
Offshore Wind data
C
Crystalline Si PV module
Expert Elicitation
cost [2019$/W]
2007, US
D
Crystalline Si PV module
Thin Film PV module
Expert Elicitation
cost [2019$/W]
2007, US
E
Concentrating Solar Power
Expert Elicitation
LCOE [2019$/MWh]
2010, EU
F
All PV Module
Expert Elicitation
cost [2019$/W]
2010, US
G
Bioelectricity
Expert Elicitation
LCOE [2019$/MWh]
2009, US
H
Nuclear Electricity (US)
Expert Elicitation
LCOE [2019$/MWh]
2009, US
I
Water Electrolysis AEC
Expert Elicitation
capital cost [2019$/kW]
2016, EU
Time (years)
J
Water Electrolysis PEM
Expert Elicitation
capital cost [2019$/kW]
2016, EU
Time (years)
W1
M1
Expert Elicitation
95th
90th
50th
10th
5th

Figure 5. Comparison of probabilistic 2030 cost forecasts using expert elicitations (EE) and model-based methods. For each of the 10 technologies, (A) onshore wind, (B) offshore wind, (C) crystalline Si PV, (D) crystalline Si PV and thin-film PV, (E) concentrating solar power, (F) all PV module, (G) bioelectricity, (H) nuclear electricity, (I) water electrolysis electrolysis alkaline electrolysis cells (AEC), and (J) water electrolysis proton exchange membrane (PEM) cells, the lines from 2019 to 2030 show the 5th, 50th, and 95th percentile forecast using the Wright's law using the Stochastic Shock (SS) method, W1 (the red and orange lines) and the Moore's law using the SS (M1) method (the purple and light purple lines), with the underlying observed data used to make them shown in blue circles. For each of the 10 technologies, the grey band on the right-hand side shows the EE forecast and the year in which the EE was conducted. The box with black borders with whiskers in this grey area indicates the 5th, 10th, 50th, 90th, and 95th percentiles (from the bottom to the top). Source: (Meng *et al.*, 2021)

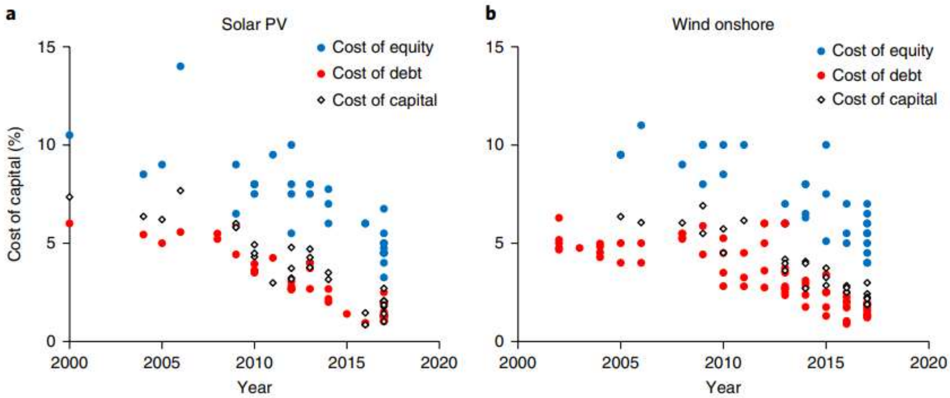


Figure 6. Cost of capital (CoC) over time. Panel a and panel b show the cost of debt, cost of equity and CoC in Germany for 43 solar PV (a) and 78 wind onshore (b) projects between 2000 and 2017 (N= 121). The figure shows numbers only for projects where cost of debt and cost of equity, as well as capital structure (leverage), are known (29 solar PV and 26 wind onshore projects). Source: (Egli, Steffen and Schmidt, 2018).

5. Patterns of the cost evolution of clean technologies and technology characteristics

Beyond the work mentioned in section 4 indicating the importance of using different models for technologies with a greater reliance on variable costs (e.g., (Way *et al.*, 2022), and the observations about different trajectories and forecasts for different technologies (e.g., (Meng *et al.*, 2021)), other work has tried to understand what may explain differences in innovation rates across technologies.

5.1 Technology characteristics: mass production, complexity and standardization

The Abernathy and Utterback model of innovation (Abernathy and Utterback, 1978) suggests that in the early years of an industry the focus is generally on **product innovation**, because during this period firms "try to exploit the performance potential of the discontinuous innovation and compete in the market with many alternative product designs" (Huenteler *et al.*, 2016). This earlier stage, which they refer to as 'era of ferment' then leads to an era of dominant design that emerges as a result of a standardization in components and supply chains. In this second stage, they argue, the focus of innovation tends to be more on **process innovations** and specialized materials. A different model of innovation that focusses on complex products, the Davies model, suggests that for those technologies, the focus of innovative activity moves across components over time (Davies, 1997).

Work specific to the energy sector by (Huenteler *et al.*, 2016) has built on this distinction to point out that two additional dimensions are relevant for energy. The first is the **complexity of the product architecture**, understood as the number of sub-systems and components and the complexity of their interactions in the system. While this complexity can result in opportunities for improvement, the complexity of a technology can make the final product hard to predict (Rosenberg, 1983). The second is the **scale of the production process**, which can be understood as the “modularity of the system as well as the size and homogeneity of user demand” (Huenteler *et al.*, 2016).

(Huenteler *et al.*, 2016) then compare innovation over time in solar PV with wind using patent citation networks. They show that solar PV has a scale of the production process that is higher than that of wind turbines and, conversely, that the complexity of the product architecture is higher for wind than for solar. They consider both phases of the life-cycle (product vs process innovation) and find that solar PV, which has a higher scale of production (it is mass produced) is better described by the A-U model positing a shift over time from product to process innovation. In contrast, the more complex technology (wind) was better characterized by the Davies model in that patents, over time, focussed on different parts or components. In this sense, (Huenteler *et al.*, 2016) suggest that increased scale and deployment led to innovation mainly in process innovation for PV and component innovation for wind.

Research has also considered how differences in **technology characteristics across components** in individual energy technologies may shape innovation. Looking at the global value chain in wind and considering wind turbine components, (Surana *et al.*, 2020) showed that technology complexity of nine different wind turbine components (e.g., blades, gearboxes, towers, bearings, etc), measured using different **patent and export complexity metrics**, was associated with a greater ease of expansion of component manufacturers in wind in a larger number of countries. This could suggest that higher complexity, using these metrics may be associated with higher barriers to innovation and (conversely) greater capabilities.

Subsequent work analyzed the extent to technology characteristics, such as complexity, may be related to experience rates at the technology level across energy technologies. (Malhotra and Schmidt, 2020) classify energy technologies qualitatively based on **design complexity** and the **need for product customization or standardization**, which building on the complexity vs mass (or scale of) production dimensions from the literature.

Figure 7 shows how (Malhotra and Schmidt, 2020) refer to mass-produced products as those with low design complexity and need for customization. They refer to them as Type 1 technologies and include solar PV and LEDs as examples of technologies in that group. Type 2 technologies, they argue, have more intermediate levels of design complexity and customization—they include electric vehicles, wind turbines and rooftop PV in that category (this is linked to the soft PV cost findings related to learning mentioned above). Technologies like combined heat and power, nuclear, and biomass are included in the Type 3 category, and are characterized by high design complexity and customization needs.

(Malhotra and Schmidt, 2020) then aggregate the global data and global and national level data on learning rates (as a function of deployment only) for those three categories and find that the distributions of learning rates decrease from Type 1 technologies, with a median learning rate of around 20%, to 10% for Type 2 technologies, to more around 5% for Type 3 technologies, approximately. Note that some Type 3 technologies display, as previously noted, negative learning rates—i.e., cost increases over time (no Type 1 technologies and only a very small number of data points for Type 2 technologies included in the study display negative learning rates).

To be useful for probabilistic forecasting, average learning rates for technologies slotted into the three types of technology categories need to be complemented by more granular annual data using the methods described in section 3.2. Important next steps in this research include quantifying and better justifying some of the concepts in Figure 2 using metrics such as those used in (Surana *et al.*, 2020), for instance.

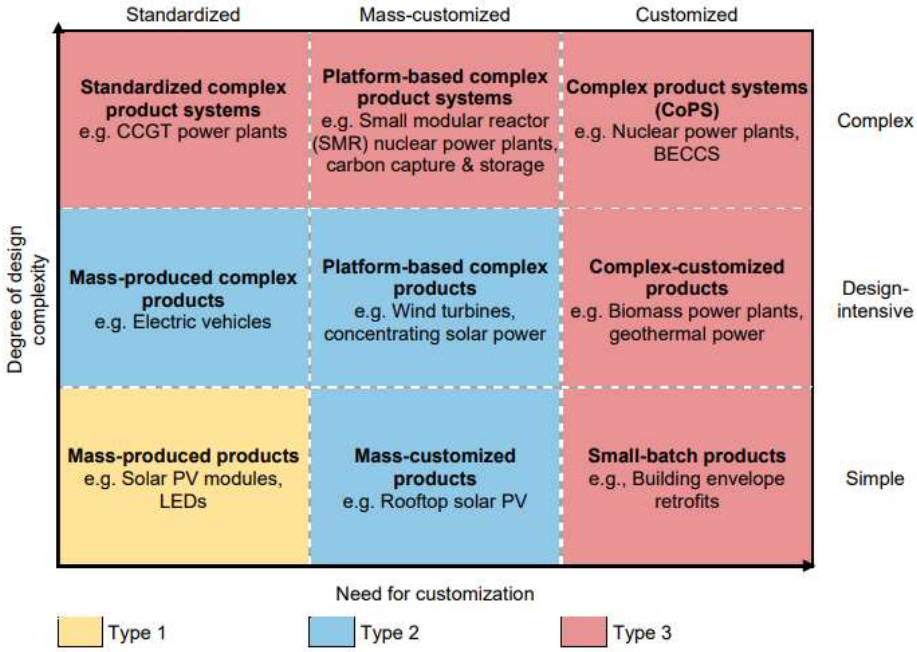


Figure 7. Characterization of energy technologies based on their design complexity and customization need. The axes represent a continuum along each of these two dimensions. The locations of technologies within this framework are relative to each other. Source: (Malhotra and Schmidt, 2020)

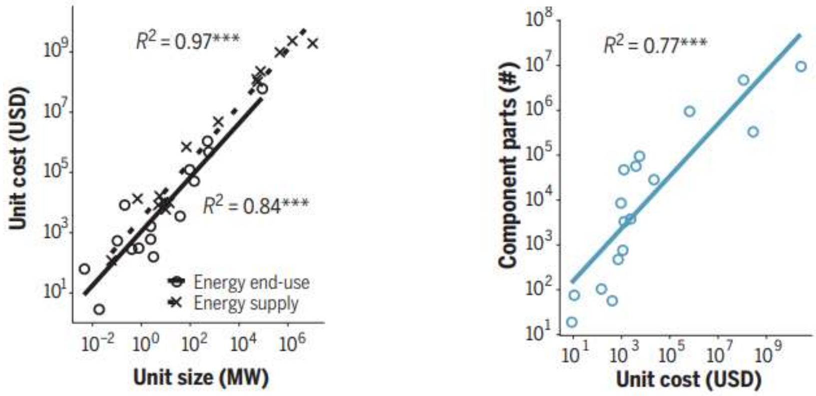
5.2 Technology granularity

Around the same time as (Malhotra and Schmidt, 2020; Surana *et al.*, 2020), work by (Wilson *et al.*, 2020) suggested the importance of technology granularity. They use the term 'granularity' to describe technologies in terms of scale—physical, economic, or both—by which "more-granular energy technologies have smaller and more variable unit sizes (MW/unit) and lower unit investment costs in absolute terms ($/unit), and are more modular or divisible. They posit that such technologies are more likely change at a faster rate and scale through replication.

(Wilson *et al.*, 2020) suggest that unit cost (measured by $/MW) and unit size (measured by MW per unit) are appropriate and interchangeable (or at least highly correlated) metrics for granularity (see panel A in Figure 7 below). They also point to a correlation between such granularity metrics and a proxy for technology complexity, i.e., the number of component parts in a technology (panel B, Figure 7). Furthermore, they indicate possible associations between such granularity metrics and faster innovation progress as measured by faster diffusion times and cost reductions (see panels C, D and E in Figure 7 below). These are preliminary results that should be subject to additional testing and data.

There are a few avenues for further development. First, additional analysis could help determine the extent to which the associations identified by (Wilson *et al.*, 2020) are robust to the beyond those covered; if the technologies on diffusion time scales and other metrics for which the data is available are or not different from that of other technologies of interest in the energy transition at earlier stages of development. Second, the granularity metrics are not necessarily static over time (unit costs and size can change), so there are additional difficulties in applying and interpreting them for forecasting purposes. Third, the number of component parts is one of other possible metrics for complexity involving components. Having noted these areas for further work, the patterns described in 5.1 and 5.2 and the possible rationales discussed are unlikely to be completely unrelated to the empirical findings in the other literatures mentioned in sections 2 and 4.

Panel A - Granularity metrics Panel B – Component parts



Panel C - Diffusion time scales Panel D - Learning rates Panel E - Descaled learning rate

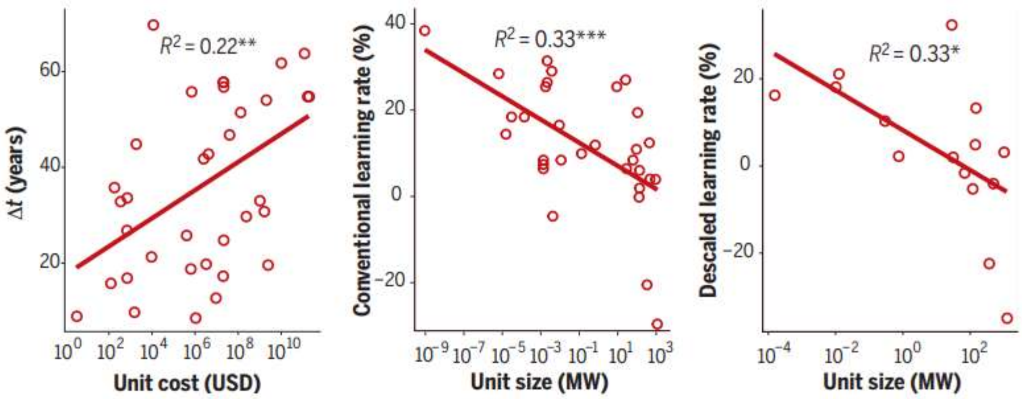


Figure 7. Characteristics of unit scale or cost for different energy technologies and link to different innovation metrics. Each data point represents an energy technology. Panel A shows that unit size and unit cost correlate strongly. They are used interchangeably as measures of granularity on log horizontal axes in the rest. Panel B shows the relationship between the number of parts and unit s. Panel C shows the relationship between Dt (i.e.,, the time period over which a technology diffuses from 1 to 50% market share) and unit cost. Panel D shows the relationship between the learning rate as a function of deployment (% cost reduction per doubling of cumulative numbers of units) and unit size. Panel E shows the relationship between a "descaled" learning rate, % cost reduction per doubling of cumulative numbers of units, stripping out the effects of unit scale economies on cost trends. R^2 and p values denoted by asterisks describe simple bivariate model fits (*p < 0.05, **p < 0.01, ***p < 0.001). Source: very slightly adapted from (Wilson *et al.*, 2020).

These types of characterization and the observations in Figures 2 and 5 are not in conflict with occasional increases in commodity prices that can result from situations in which demand outstrips manufacturing capacity. We may be seeing an example of this in recent increases in lithium ion batteries (BNEF, 2022), although over time one can expect additional decreases that can best be approximated using the model-based probabilistic models described.

6. Concluding remarks

Many policy and investment decisions in the energy and climate space explicitly or implicitly are based on predictions regarding how technology cost or performance will evolve, in some cases partly as a function of such decisions. This report has reviewed research on energy technology innovation and its drivers, energy technology cost forecasting methods and the possible relationship between technology characteristics and patterns of energy technology cost reductions.

Given the particular context of this report it seems important to highlight here a couple of additional themes beyond those included in the executive summary above.

First, the past decade and, more markedly, the past handful of years have seen significant growth in this research, partly driven by the importance of climate in policy and private sector. Not surprisingly, there is ongoing research globally on most of the areas for further development identified.

Second, the majority of the research on clean energy and energy technologies regarding drivers reviewed relies on national or global level data. This is because energy technology cost and performance data over time (among other types of data) is needed to identify patterns across technologies and drivers; such data is available largely at the national and global level. The fact that a lot of the studies cited here rely on national or global level technology data or boundaries may have implications for using some of the methods and insights here to design initiatives that capture smaller segments of the global markets for clean energy technologies.

Third, while difficulties linking specific policy or investment initiatives to specific innovation drivers and then to quantifiable cost improvements in individual energy technologies remain, we now have a better understanding of the fact that different innovation mechanisms all play a role and that specific R&D and market creation policies have been associated in a consistent manner to deployment and different innovation outcomes. We also know that materials costs, financing, and learning by doing in things like soft costs may be worth considering separately.

Fourth, when sufficient, reliable data is available, probabilistic model-based forecasts, which reflect statistical relationships that aggregate the impact of different concurrent drivers, have (at least to date) been tested to a greater extent than other methods and shown to be more accurate.

Fifth, the evolution of costs differs across energy technologies, including costs decreasing with deployment at differing rates, relatively flat costs with volatility and increasing costs. A growing amount of research sought to explain these trends using technology characteristics (e.g., complexity, granularity, mass production, and customization need). While additional work is needed to improve the quantification of such metrics, practitioners could usefully begin reflecting some of the emerging findings in their decision-making processes.

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