Executive Summary

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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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]

Why Build an Innovation Model: The limitations of Learning by Doing

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 transportation, 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 incorporate new learning into the process. Accelerating the development of an emerging technology

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

[4] Pillai, 2015; Nemet, 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.

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 nine-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 systems 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] During the rapid growth of U.S. wind generation from 2004 to 2009, wind energy costs

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

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

[9] Nemet, 2009.

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 ongoing 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.

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[10] *See* chapter 3, section 3.6 of Full Report.

[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-emissions, 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?

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

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

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.

[15] Diaz Anadon, Appendix B to the Full Report; Diaz Anadon et al., 2017.

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