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Commentary

Evaluating the Role of Unit Size in Learning-by-Doing of Energy Technologies

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Learning curves can be employed to study changes in productivity as a result of "learning-by-doing" in a wide range of applications, from investment cost reductions in technology to output volume increases and error occurrence improvements in professional services.[1,2] Here, we focus on the role of learning in energy technology development. In the learning curve literature, the empirically observed historical experience with a technology, for instance, in terms of costs, is typically plotted against a metric of diffusion, often cumulative installed capacity (CIC).[3–5] The learning rate (LR) expresses the steepness of the slope of a learning curve and is usually defined as the percentage change in costs for each doubling in CIC of a technology. Once a learning curve has been determined on the basis of data from the past, it can be used to project the costs of a technology into the future, as it continues to diffuse at a certain pace.[6,7] The value of the LR has a large effect on the achievable reduction in costs. To illustrate this, consider an energy technology that grows from 1 MW to 1 TW of CIC (i.e., approximately 20 doublings), an expansion common for successful technologies in the energy sector. At 1 TW of CIC, the (so-called marginal) cost to install an additional MW of capacity for a technology "learning" with an LR of 4% is 38 times higher than for one with an LR of 20%. The total cumulative level of investments required to deploy the first TW of installations differs 25-fold between these two cases.

Applying the Learning Curve Methodology to Nascent Technologies

An adequately constructed and statistically meaningful learning curve of a technology should be based on empirical data that span at least multiple doublings of CIC and ideally cover a couple orders of magnitude of increase in CIC.[8] It is therefore difficult to apply traditional learning curve analysis to nascent technologies: their dataset for costs and capacities remains insufficient since these technologies are in an early stage of deployment. Particularly these innovative technologies, however, draw the attention of the energy transition and climate change research community. Multiple drivers may exist for technology cost reductions.[9] The extent to which varying combinations and contributions of various cost reduction drivers explain observed differences in LRs between existing technologies is not fully understood.[10,11] These constitute additional reasons for why it is not trivial to use learning curve analysis for new technologies. This raises the question whether certain known physical characteristics of an innovative technology may nevertheless be indicative for the possible level of its future LR. Ex ante inferences on the potential value of the LR could provide insights into the prospective learning process and thus be used for decision making in early-stage technology development.

Learning and Unit Size

Dahlgren et al., for example, review the traditional focus on economies of scale of individual power generation facilities by distinguishing between cost reductions achieved by scaling up in unit-size versus those achieved by scaling up in numbers.[12] Technology that is mass-produced at a smaller unit size has a higher technology turnover in the sense that inventions, modernizations, novelties, and optimizations can more easily be introduced. Such technology also more readily allows for premature scrapping of unfavorable designs. Hence, mass-production allows for quick implementation of innovation

Table 1. Overview of LR Statistics for Three Energy Technology Categories

Technology Category	No. of Technologies	Min/Max	Mean (95% CL)	Median
Energy Demand	18	6%/39%	20% (±5%)	20%
Energy Storage	11	−2%/30%	14% (±5%)	15%
Energy Supply	12	3%/23%	10% (±4%)	12%
Total	41	−2%/39%	16% (±3%)	14%

and thereby faster learning. Dahlgren et al. propose that capital cost reductions realized through faster learning of mass-produced small-size technology generally match those achieved by scaling up in size of individual units.[12] Moreover, smaller unit size technologies can still benefit from economies of scale, for example, associated with the magnitude of the factories in which they are manufactured (for instance, for batteries, fuel cells, or PV modules) and with the size of combined functional units like that of entire solar or wind energy parks. In addition, Dahlgren et al. argue that labor cost reductions, the largest contributor to cost decreases arising from scaling up in unit size, have recently become less important as a result of the availability of low-cost automation technologies.[12] They also point out that the higher locational, operational, and financial flexibility of smaller unit-size technologies can further reduce investment and operating costs. In all, and quite against common wisdom, in order to reduce technology costs, it may be profitable to go small rather than to go big. Do empirical observations reveal a trend that small technologies have a larger capacity to learn than large technologies, and thereby achieve deeper and faster cost reductions?

Energy Technology Learning Rate Inventory

We revisit the work by Dahlgren et al. by analyzing data from the peer-reviewed literature on LRs reported for a broad set of different energy technologies. A full list of LRs, including confidence intervals where available, as well as references to the original sources, is provided in Data S1. We disaggregate the resulting LR inventory into three distinct technology categories: energy demand, energy storage, and energy supply. Energy demand technologies include a wide range of home appliances, vehicles for transport, and heating mechanisms. Energy storage options consist of different types of batteries, electrolysers, fuel cells, and pumped hydro-electric systems. Our energy supply category exists of several renewable energy technologies, nuclear electricity generation facilities, and fossil-fuel-based power plants. For some technologies, multiple LRs are found in the literature. In such cases, we take either the mean LR or use the LR that was computed using the longest time period (see Supplemental Information). Table 1 summarizes the statistical properties of our LR inventory. Each LR is expressed as a range, that is, a mean (and median) specified with min and max values as well as a confidence interval. LRs range between a low (negative) value of −2% for pumped hydro-electric storage and a high value of 39% for central air conditioners. Table 1 shows that, on average, energy demand technologies exhibit the highest LR followed by, respectively, energy storage and supply technologies (see Figure S1 for the distribution of LRs within the three categories). All technology categories show large differences between the lowest and highest LR.

Higher Observed Learning Rates for Smaller Unit Size

We estimate the individual unit size in MW for 41 technologies. For technologies where multiple units generally form a larger single functional facility, like coal-fired power plants, we take the capacity of a typical individual generation chain or entity instead of the sum of several of them. To simplify our analysis, we henceforth only plot the mean value of the LR for each technology and do not consider its corresponding confidence interval, as demonstrated in Figure 1. Our meta-analysis enables us to plot the LR of each of the 41 technologies versus their unit size. The relationship is fitted to a logarithmic function plotted on lin-log axes and indicates a downward trend, where each order of magnitude decrease in unit size corresponds to an increase of the LR by 1.5%. According to the fit, technologies with small unit size (<10 kW) on average seem to learn faster (LR > 17%) than those with medium size (10 kW to 100 MW; 11% < LR < 17%) and large size (>100 MW; LR < 11%). Energy demand technologies are characterized by the highest LR and smallest unit size, accounting for 8 out of 10 technologies with an LR higher than 20%. The other two technologies with LRs exceeding 20% are lithium-ion batteries used in electronic devices (LR of 30%) and solar photovoltaic panels (LR of 23%), which have substantially smaller unit sizes than other energy storage and supply technologies, respectively. The two technologies that display the lowest LR—hydro-electric electricity generation (1%) and pumped hydro-electric storage (−2%)—are characterized by the largest unit size.

By analyzing the LRs of 41 energy technologies, we find that the LR correlates negatively with unit size. The statistical accuracy of the fit, however, is relatively low (indicated by an R^2 of 0.22). Smaller mass-produced technologies indeed may learn faster than their larger custom-built counterparts. The difference in LR of at least 6% points between technologies with either a small or large unit size would—over the course of the deployment phase—exert a major effect on their respective costs. For instance, the final cost of a technology growing from 1 MW to 1 TW learning at LR = 11% would be more than 4 times higher than a technology learning at LR = 17% would be, and the cumulative

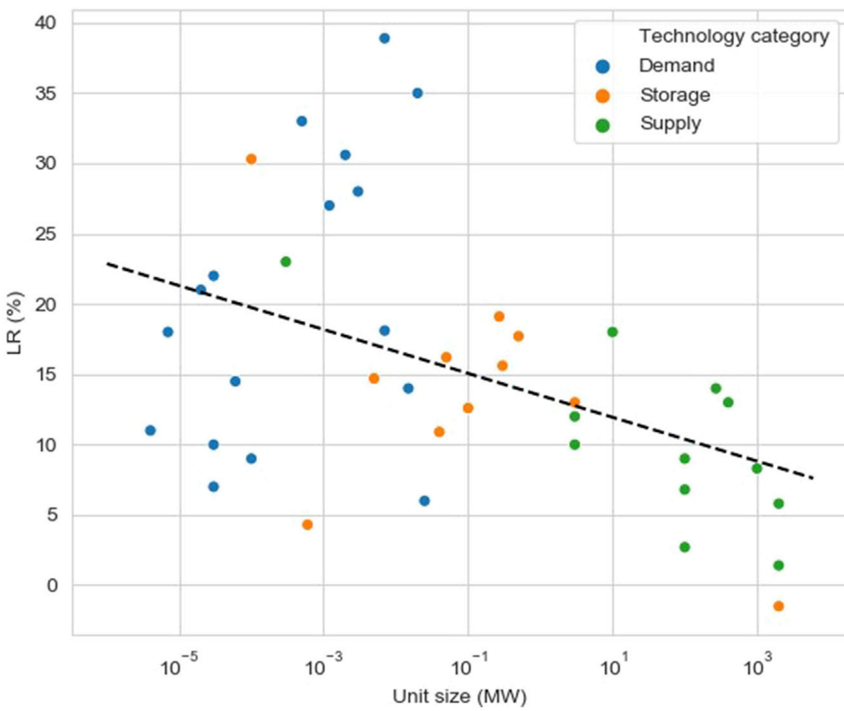

Figure 1. LRs for 41 Energy Technologies

The logarithmic fit shows a negative relation between unit size and observed LR. The logarithmic parameter (a = −0.68, R^2 = 0.22) translates into a 1.5% decrease in LR for each order of magnitude increase in unit size.

investment required to reach 1 TW would be more than 3 times larger. We find little or no relation between CIC (in GW) and LR (see Figure S2 as well as Figure S3). These findings support the view that increased attention must be paid to the factors that influence the potential for cost reductions of emerging technologies. Scaling up by numbers (by down-scaling unit size) may lead to significant cost benefits over scaling up by unit size thanks to faster learning. The development of small unit sizes can also result in earlier adoption because of lower investment risks, for instance, in decentralized applications.

Discussion

Figure 1 shows that a relation might exist between the unit size of energy technologies and their observed LR. Several sources of possible objections, however, can be made against this conjecture, which deserve detailed scrutiny. We here list a number of factors that may complicate the drawing of robust conclusions from comparative LR value analysis, which we discuss in more detail and put in the context of the literature on this subject matter in the Supplementary Information available online as addendum to this Commentary. First, substantial variation exists across the methodologies and assumptions used to calculate LRs, as a result of which it may difficult to directly compare LRs determined for different technologies. Second, one may question the pertinence of analyzing the effect of unit size on LRs across different technology categories for other reasons, as demonstrated when logarithmic curves are fitted to unit size and LR data of distinct technology categories separately (see Figures S4–S6). Third, it remains sometimes unclear what underlying factors contribute to the overall reduction in technology costs upon which most LRs reported in the literature are based. Finally, the potential for learning-by-doing as captured by reductions in costs differs substantially across technologies at different stages of maturity.

Conclusions

In our analysis, we show that for energy-related technologies, unit size might be related to the magnitude of empirically observed cost reductions, as expressed by learning curves. We thus argue that technology developers may need to pay attention up front to the size of energy production units in the design phase if mankind wants to accelerate the energy transition for climate change control purposes. In our discussion, we point to a variety of issues that raise the question of whether a comparison of learning rates between technologies can be rightfully made. These issues must be resolved by future research and detailed desk studies before reliable conclusions can be made with regards to attempts to use physical characteristics of technologies to make an inference on their observed—or, in the case of nascent technologies, expected—learning rate. Follow-up work could also involve regression analysis for individual technologies to test the effects of unit size and economies of scale, as other publications have reported on.[10,12,13] Improving our understanding of the possible relation between the unit size of a technology and its learning rate may have a large impact on the feasibility and affordability of stringent climate change mitigation. With the necessity to achieve the goals of the Paris Agreement and the ensuing imminence of a fundamental transformation of our global energy system, there is ample reason to take learning curve analysis out of its recent lull and revisit the possible relevance of unit size in choosing and designing existing respectively new low-carbon energy technologies.

SUPPLEMENTAL INFORMATION

Supplemental Information can be found online at https://doi.org/10.1016/j.joule.2020.03.010.

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AUTHOR CONTRIBUTIONS

B.S. and B.v.d.Z. designed the study; B.S., R.J.D., and B.v.d.Z. drafted the article; B.S. gathered the data and generated the figures; B.S., R.J.D., and B.v.d.Z. analyzed the data and discussed the results; B.S. and B.v.d.Z. produced the final manuscript.

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Commentary

Assessing the Regulatory Requirements of Lead-Based Perovskite Photovoltaics

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Metal halide perovskite photovoltaic (PV) devices offer promising performance and unique applications, with demonstrated power conversion efficiencies that exceed 20%, stable operation over thousands of hours, and compatibility with flexible substrates.[1] However, the highest-performing perovskite materials for PV applications contain lead, which is regulated worldwide as a hazardous material.[2–4]

As several companies and research labs are considering the possibility of large-scale deployment of lead-based perovskite PV modules,[1] the topic of regulatory compliance is now critical but has been largely overlooked. Here, we present a preliminary evaluation of lead halide perovskite (LHP) PVs according to the European Union (EU) Restriction of Hazardous Substances (RoHS) Directive[2] and United States Resource Conservation and Recovery Act (RCRA) lead regulations.[3] The RoHS Directive and RCRA both aim to reduce the risk of harm caused by hazardous materials and are legal regulatory frameworks that all commercial PVs are subject to (i.e., Si and CdTe). By characterizing the lead concentration and lead leaching behavior of perovskite films on glass and flexible substrates using RoHS Directive and RCRA mandated protocols, we find that some of the key advantages of lead-based perovskites as a solar technology, specifically their potential for high specific power (W g^{-1}) as well as lightweight and portable applications, are at odds with the regulatory frameworks currently in place due to international processing of waste on a

