Use and Abuse of Learning Curves for Energy Subsidies

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Abstract

In this paper, we review the theory of the learning-by-doing effect, particularly as it relates to energy technology. We observe several important limitations to the learning effect as a tool for modeling an energy transition and forming public policy, including data quality challenges, issues in assessing causality of price decreases, and empirical evidence that learning rates decline with increasing production. We assess that, while learning-by-doing is a real phenomenon, great care is needed to avoid overestimating expected cost declines.

1 Introduction

The world's energy system is dominated by fossil fuels–coal, oil, and natural gas–at 84% of primary energy in 2023 and at a record high in absolute terms [28]. These fuels have been critical in driving world prosperity since the Industrial Revolution, but concerns about negative impacts of fossil fuel combustion, particularly climate change, have motivated efforts to develop new energy sources with lesser negative impact.

As energy is fundamental to the world economy, a transition to a low-carbon energy system will necessarily be an extensive and lengthy process. Most or all of the following elements will be required [127]. World electricity, which is also produced predominately by fossil fuels, must instead be generated from low-carbon sources, such as solar, wind, nuclear, or geothermal [37]. The share of electricity in the broader energy system must increase and become commonplace for applications such as personal cars and home heating [70], and where such direct electrification is infeasible, electrification must occur indirectly, such as in the use of electrolysis to produce jet fuel [116]. Industrial processes with inherent greenhouse gas emissions, such as coke for steelmaking [8] and carbon anodes for aluminum smelting [45], need to be replaced with low-carbon alternatives. Where carbon dioxide emissions remains, those emissions need to be captured [88] and either reused for a beneficial purpose [79] or sequestered permanently [7]. Such capture might derive from the ambient atmosphere [115]. Energy efficiency, or the ability to derive a fixed amount of economically useful output for a given energy input, must be improved [20].

Hopes that an energy transition can occur at a price that is affordable to society rest heavily on the expectation that the prices of relevant low-carbon technologies are lower in the future than today's prices. One mechanism by which prices may be lower is a *learning curve*, a mathematical model that predicts that the price of some manufactured product should decrease with increasing cumulative production of that product [130]. Many energy transition models that show a low-cost or costless transition use learning curves to forecast that key transition technologies will be at a lower price in the future than today [83]. Furthermore, subsidies for certain low-carbon technologies are often predicated, in part, on the expectation that subsidies will stimulate production and thus future cost decreases [58].

Luderer et al. [70] make these expectations explicit by forecasting a dramatic increase in the rate of electrification by 2050, a forecast that is predicated on cost reductions resulting from learning. Lackner and Azarabadi [62] use learning curves to project that "several hundred million dollars" of capital investment will be sufficient to bring direct air capture to an acceptable price for widespread carbon mitigation. The expectation of price declines with deployment of direct air capture motivates Stripe, Inc.'s investment in the technology [114].

As we will discuss in this paper, there are many reasons to doubt that direct estimation and application of learning curves to the price of some product will yield accurate price forecasts. For this reason, models that rely on price reductions modeled from learning curves may produce overly optimistic forecasts, and policies to subsidize production of certain goods may be misguided.

Outline The remainder of this paper is organized as follows. In Section 2, we review the theory of learning curves. In Section 3, we consider the application of learning curves to energy. In Section 4, we consider the rationale of subsidizing energy production, as well as some of the hazards. In Section 5, we consider the challenges of properly measuring learning rates. In Section 6, we review evidence of declining learning rates as production of a technology expands. In Section 7, we answer the question of whether learning-by-doing is an externality to clean energy production, and how the learning effect can be properly subsidized. Finally, Section 8 concludes.

2 The Theory of Learning Curves

A learning curve posits a regular improvement in the cost of manufacturing a given product, whether that cost is measured in terms of labor or financial cost, as the cumulative production volume of that product increases. Learning curves were introduced by Theodore Paul Wright in 1936 to analyze the cost of aircraft manufacturing [130]. Hirsch [50] and Rapping [92] are among the early scholars who developed the theory of learning curves. Kenneth Arrow [3] argues that knowledge, as embodied in cumulative capital investment, is a fundamental input into economic production, suggesting that learning is central to economic growth.

There is a distinction between cost curves based on learning and those based on experience [11]. Learning is more narrowly defined and refers to the direct production of a good, while experience, such as defined by the Boston Consulting Group [39], is broader and includes all costs related to production, including research and development, marketing, and distribution. These concepts are similar and frequently used interchangeably [11].

2.1 Mathematics of Learning Curves

The most common form of the learning curve equation is expressed as follows [118].

$$c(t) = c(0)y(t)^{-\beta} \tag{1}$$

In Equation 1, $c(t)$ is the unit cost of some good at time t, $y(t)$ is the cumulative production at time t, $c(0)$ is the initial cost, and β is the rate of learning, or the *learning rate*. Equation 1 can also be expressed as follows.

$$c_n = c_0 n^{-\beta} \tag{2}$$

Here, n is the cumulative production of a good, c_n is the cost after a production of n units, c_0 is the initial cost, and β is as above. The parameter β is related to the *progress ratio*, which is defined as $2^{-\beta}$ [118]. In words, the progress ratio is the expected unit cost percentage decline if total production is doubled.

The standard learning curve yields a linear relationship between logarithm of price and the logarithm of cumulative production as follows.

$$\log c_n = \log c_0 - \beta \log n \tag{3}$$

The learning rate can thus be estimated as slope of the relationship in the $\log - \log$ plot. Although the learning rate is constant under the basic learning curve formulation above, this need not be the case in general, as we will see below.

A similar formulation was provided a few years later by Crawford [24], as discussed in Brown and Anderson [17], differing from Wright's formulation in that it is the marginal unit cost, rather than cumulative average cost, that is expressed. Unless otherwise noted, we will consider marginal unit cost as per Crawford.

A reliable estimate of β is critical for producing meaningful cost estimates of a product over a production run. Brown and Anderson [17], for instance, consider a hypothetical run of 500 satellites, based on the observed learning rates of Argote and Epple [2] for various industries, ranging from -8% (negative learning, indicating that costs rise with increasing production) to 46%. The resulting cost estimates of the full production run differ by a factor of 45.

2.2 Estimates of Learning Rates

Since Wright's 1936 paper [130], numerous researchers have estimated learning rates for various technologies. Considering labor unit cost as a function of cumulative production, Wright estimated a learning rate of 0.322 for aircraft, corresponding to a progress ratio of 0.8. Wright further estimated that unit cost showed a learning rate of just over 0.2, and he posited that similar learning curves can be derived for material waste and material usage per plane.

The phrase *experience curve* was introduced by Bruce Henderson, founder of the Boston Consulting Group, in 1966 [47]. Henderson later observed a typical learning rate of 0.1 to 0.15 for labor for wartime aircraft production and a typical learning rate of around 0.25 for prices [48].

In 1984, Dutton and Thomas [27] examined many industries and found progress ratios ranging from 55% to 108%. Six years later, Argote and Epple [2] considered manufacturing processes in over 100 industries and similarly found progress ratios ranging from 0.54 to 1.08, with a modal value of 0.81. A progress ratio greater than 1 corresponds to a negative learning rate, meaning that unit costs grow with increasing production volume. This situation, while uncommon, has been observed in some cases.

More recently, Bongers [14] found learning rates of around 9% for the F-35A Lightning II and around 14% for the A/F-18E/F Super Hornet and F-22A Raptor, three significantly different aircraft that are produced simultaneously from the same airframe.

Meisl and Morales [76], using Wright's cumulative average model, find learning rates of 0.05 for satellites with cumulative production between 1 and 10 units; 0.1 when cumulative production is between 11 and 50 units; and 0.15 when cumulative production is above 50 units. Brown and Anderson [17] note that, within the aerospace community, a learning rate of 0.05 is typically used for spacecraft with runs of less than 5 units. The findings of Meisl and Morales are in contrast to the pattern of learning rates that decline with greater production, as further discussed below.

Heng considers 20 industries in Singapore and finds progress ratios between 0.289 and 0.976 [49]. Heng argues that Singapore's learning curves are analogous to those found in Japan and South Korea, with the policy implication that for Singapore, a small country, the most economically advantageous strategy is public investment in a small number of strategically chosen industries. Lieberman examines 37 chemical processes and finds progress ratios ranging from 0.5 to 1.0 [67]. Strategos Inc. [91] considers several industries and finds learning rates as low as $5-7\%$ (raw materials) and as high as $15-25\%$ (machine tools and electrical wiring).

Levitt et al. [65] consider learning at an unspecified automobile plant, and they find that the logarithm of the number of defects at the plant level decreases linearly in terms of the logarithm of cumulative production, demonstrating a learning curve where "cost" is the number of defects rather than financial cost.

2.3 Multifactor Learning

Many variations of the standard learning curve described in Equation 1 are considered. This formulation is sometimes called a one-factor learning curve, with the one factor being cumulative production.

Two-factor learning curves, as described by Kouvaritakis et al. [61] and Wiesenthal et al. [129], incorporate learning from cumulative research and development expenses as well as from cumulative production. The research term is also sometimes called *learning by searching*.

$$c(t) = c(0)y(t)^{-\beta}r(t)^{-\alpha} \tag{4}$$

Here, $c(t)$ is the unit cost at time t, and $y(t)$ and $r(t)$ are, respectively, the cumulative production of the item in question at time t and cumulative R&D expenses at time t. The parameters β and α are, respectively, the elasticity of price with cumulative production and cumulative R&D expenses. As above, $c(0)$ is the baseline cost before any learning from production or R&D is applied. Note that $y(t)$ and $r(t)$ are considered exogenous to the model and may vary independently.

Wiesenthal et al. [129] present the second term of Equation 4 as knowledge stock, for which cumulative R&D spending is a proxy.

Jamasb [52] finds that the learning rate for research and development is generally higher than the learning rate for production at all levels of production, and furthermore, that one-factor learning models will generally overestimate the learning rate, especially if they are applied for an early-stage technology. Likewise, Lindman and Söderholm [68] find that a two-factor model usually yields lower learning rates than a one-factor model. Rivera-Tinoco et al. [94] find a higher learning rate for solid oxide fuel cells for research than for cumulative production at the pilot stage.

Söderholm and Klaassen [107] find a learning-by-doing rate of 3.1% and a learning-by-searching rate of 13.2% for wind turbines. Their observed learning rate is lower than that of many other studies, perhaps because they consider markets in which wind power is more mature.

Studying a PEM fuel stack, Mayer et. al [73] apply a two-factor model and find a learning rate of 13% for a "generalized experience effect", which includes learning-by-doing, economies of scale, and other factors related to volume of production; and a 20% rate for research and development. If a one-factor model is applied based entirely on the generalized experience effect, a learning rate of 22% is found with a lesser R^2 value.

Although less common, a three factor learning model has been proposed, in which the three factors are cumulative production, cumulative research and development, and average scale [136].

$$c(t) = c(0)y(t)^{-\beta}r(t)^{-\alpha}q(t)^{-\gamma} \tag{5}$$

In Equation 5, $c(t)$, $c(0)$, $y(t)$, β, $r(t)$, and α are the unit cost at time t, the initial unit cost, cumulative production at time t, the elasticity of price with respect to cumulative production, cumulative research and development at time t, and the elasticity of price with respect to cumulative research respectively, all as in Equation 4.

Additionally, $q(t)$ is the average scale at time t, and γ is the elasticity of price with respect to scale. Here, "scale" refers to average unit size, such as the typical size of a wind turbine in power capacity, which has tended to increase with time [131].

A four-factor model has also been proposed, which incorporates the same factors as in a three factor model, as well as a term to indicate input prices over time [131]. Learning models with three or more factors suffer from problems of collinearity. For example, if scale and cumulative production both increase with time, it can be difficult to distinguish which factors most contributed to cost changes over time. In other words, it can be difficult to determine the elasticities α, β, and γ with precision or confidence, which limits the models' ability to generate useful price forecasts [84]. For this reason, most learning curve literature does not incorporate more than two factors [131].

2.4 Forgetting

Just as an individual can be expected to forget, which translates to performance degradation over time, forgetting has been incorporated into learning curves. Theory on forgetting tends to be more conceptual than theory on learning [117]. For example, Globerson [34] describes forgetting as a process resulting from employee turnover and limitations in communication and documentation of processes.

Badiru [4] models a forgetting process of exponential decay in performance, analogous to radioactive decay. Under such a model, performance can be expressed as

$$P(t) = P_0 e^{-kt}, \tag{6}$$

where t is time, $P(t)$ is the performance at time t, P_0 is the initial performance, and k is a positive constant that is determined empirically. Under this model, the half-life, or the time it takes for half of performance to be lost, is determined by

$$t_{1/2} = \frac{1}{k} \ln 2.$$

As discussed below, several learning models beyond the log-linear model discussed above incorporate forgetting, including hyperbolic models, the S-curve model, and the Dejong model. In each of these models, the learning rate converges to 0 as cumulative production grows, indicating that learning gains are impossible beyond a certain point, as the loss of performance from forgetting will negate any gain from learning.

3 Learning Curves as Applied to Energy

3.1 Estimates of Energy Learning Rates

Learning curves have been used particularly extensively for energy technology. Rubin et al. [96] review several one-factor and two-factor learning curves for various energy production technologies. Among the studies they review, the strongest learning rates are found among solar photovoltaics (10% to 47%) and biomass production (20% to 45%), whereas the weakest learning rates are found for nuclear power, for which the highest rates are 6% and some show negative learning. Rubin et al. report at least one study with a two-factor model for natural gas combined cycle, onshore and offshore wind, solar PV, and hydroelectricity, and for these technologies, the mean of the learning rate for learning-by-research was higher than that for learning-by-doing for all technologies except solar PV.

Earlier, McDonald and Schrattenholzer [75] performed a similar analysis on 42 energy technologies. Citing various studies, they find learning rates as low as -11%, for investment in gas turbine combined cycle plants [21], to 35% for the production cost of solar PV [128].

Bolinger et al. [12] find learning rates of 15% for wind and 24% for solar PV in the United States. Kim and Lee [59] find modest learning rates for shale oil between 3% and 4% for both one-factor and two-factor models.

Learning curves are also applied to energy efficiency technologies. Karali et al. [57] consider 75 energy efficiency technologies related to iron and steel, an industry that is responsible for 5% of world CO_2 emissions. They find that the learning rate decreases with larger market penetrations of the technologies, with rates of 2% for technologies with 80-100% penetration, 3% for technologies with 60-80% penetration, 3% for technologies with 40-60% penetration, 6% for technologies with 20-40% penetration, and 10% for technologies with less than 20% penetration. Thus Karali et al. find evidence of decreasing learning rates with market maturity.

In 2013, de La Tour et al. [25] found that studies that use only experience to derive a learning rate for solar photovoltaics found an average 20.9% learning rate. In the specific case of solar PV, this phenomenon has been termed *Swanson's Law*. Hansen et al. [43] forecasted in 2015 that if the trend were to continue indefinitely, then solar generation could reach 100% of then-current world electricity consumption by 2028. Partain et al. [87] forecasted in 2016, based on Swanson's Law, that solar PV would match electrical generation at the time by 2032. In 2016, Farmer and Lafond [32] forecasted that solar PV would reach 20% of global primary energy consumption by 2027.

For wind power, Junginger et al. [56] find a global progress ratio between 77% and 85%, with a mean value of 81%. Schauf and Schwenen [99] find more modest learning rates of $2-3\%$ for learning-by-doing (cumulative production) and $7-9\%$ for learning-by-searching (cumulative research). For the National Renewable Energy Laboratory, Shields et al. [105] model, using a combination of learning rates and bottom-up cost estimates, that offshore wind electricity should have a levelized cost of 5.3¢ per kilowatt-hour for fixed-bottom turbines and 6.4¢/kWh for floating turbines by 2035. They review several estimates of learning rates of offshore wind power in the literature and find estimates ranging from 3% to 31%. In 2018, Ratner and Khrustalev [93] surveyed several papers and found learning rates for wind power in Denmark to range from 7.8% to 11.7% and in the UK to range from 3.1% to 13.2%. Across several countries, most studies surveyed in Ratner and Khrustalev found learning rates ranging from 3.5% to 32%, with studies varying across countries, time periods, and the precise cost metric assessed. The exception was Trappey et al. [121], which found a learning rate of -5.6% for wind power capacity costs in Taiwan from 2001 to 2010, meaning that costs rise with deployment.

Schoots et al. [103], considering several hydrogen production technologies, find a learning rate of $11 \pm 6\%$ for steam methane reforming equipment, the dominant hydrogen production technology today; $18 \pm 13\%$ for electrolysis equipment; and no statistically significant learning rate for construction costs for facilities for coal gasification. Schoots et al. note that these learning rates for capital costs for various hydrogen production routes do not translate into discernible learning rates for the complete hydrogen production process, and they question how applicable learning curves are to modeling energy technology costs in general. Schmidt et al. [100] find that production scale-up may reduce capital costs of various hydrogen electrolysis technologies by $17-30\%$, compared to a reduction of $0-24\%$ that is expected from research and development. In later work, Schoots et al. [104] find a learning rate of $18 \pm 9\%$ for alkaline fuel cells and $21 \pm 4\%$ for PEM fuel cells. Wei et al. [126] find an 18% learning rate for fuel cells for Japanese combined heat and power systems, while SOFC fuel cell systems in California were found to have a near-zero learning rate. Staffell and Green [111] find a learning rate of $19.1-24.1\%$ for PEM fuel cells.

Using a learning curve analysis, Schmidt et al. [101] project that several stationary energy storage technologies may reach a per-capacity price of $\$340 \pm 60$ per kilowatt-hour and that battery packs may reach $\$175 \pm 25$/kWh with one terawatt-hour of cumulative storage deployed. Considering per-discharge prices, Schmidt et al. [102] project, extrapolating observed learning rates, that the levelized cost of storage for secondary response may reach about \$300 per megawatt-hour for flywheels in 2050; \$170/MWh for lithium-ion batteries; \$300/MWh for sodium-sulphur batteries; \$1050/MWh for lead-acid batteries; \$180/MWh for vanadium-redox flow batteries; \$800/MWh for hydrogen; and \$700/MWh for supercapacitors; while pumped hydro and compressed air are not expected to show significant cost reductions from learning curves.

Van der Zwaan et al. [124] find that CH_4 (methane) pipelines are a technologically mature technology, and negligible learning-by-doing cost reductions for CH_4, CO_2, and H_2 pipelines should be expected in the future.

3.2 Learning to Model the Energy Transition

In modeling long term economic change, such as the evolution of the energy system, it is necessary to incorporate technological change. Failure to do so may result in overly pessimistic models of resource depletion and environmental damage. The 2006 Stern Review on the economics of climate change

[113], for instance, incorporates cost projections of energy technology that are based on learning curves. In general, endogenous technical change, or change induced by the deployment of a technology, has become widely used in modeling of climate change economics [54].

For example, Grübler et al. [40] in 1999 used learning curves to model the diffusion of energy technology and thus to forecast the pace of decarbonization. Faber et al. [31] apply learning curves to carbon capture and utilization and argue that, in modeling energy transitions, one should be careful about making direct comparisons between those technologies that have had the chance to benefit from learning curve cost reductions and those that have not. Rubin et al. [97] find that the cost of a decarbonization scenario is significantly lower when learning curves of carbon capture and sequestration technology is accounted for than when it is not.

As electricity-generating technologies generally show stronger learning effects than other energy-producing technologies, future energy models that take learning into account suggest that the portion of final energy in the form of electricity will grow over time. Luderer et al. [70] estimate that in a carbon-constrained future, electricity will comprise 66% of the world's final energy consumption. Enerdata reports that the share of electricity in final energy demand rose from 17.6% in 2010 to 20.6% in 2023 [29]. The pace of electrification must therefore increase by more than a factor of 7 from 2023 to 2050 to meet the forecast of Luderer et al.

Some energy transition forecasts based on learning curves have proven to be overly optimistic optimistic. Partain and Fraas [86] forecasted in 2015 that solar PV and wind, firmed by vehicle-to-grid technology, could displace all coal and nuclear power in California by 2022.

Learning-by-doing cost reductions are essential for forecasts that project a cost-effective transition to a low-carbon energy system. Way et al. [125], for instance, apply a one-factor learning curve model to energy technologies to forecast that a transition to a low-carbon energy system will occur with net positive financial impact, even without accounting for environmental benefits such as reduced climate change.

As further discussed below, however, there are many difficulties with measuring and applying learning curves as discussed above, and it is probable that forecasted learning rates for technologies relevant to decarbonization are too high. In that case, the error may cause a severe underestimate of the cost of a transition to a low-carbon energy system, and it may also mislead policymakers of the wisdom of public financing for research, development, and deployment of certain technologies [85].

3.3 Learning to Inform Policy

Bollinger and Gillingham [13] consider learning-by-doing as an explicit justification for the California Solar Initiative, a $2 billion program that subsidized rooftop solar PV in California from 2006 to 2016. Bollinger and Gillingham find that about 12 ¢ per watt of cost decline in the non-hardware costs of solar PV in California from 2002 to 2012 can be attributed to learning-by-doing effects; this is about 15% of total non-hardware cost drops. Over the same period, hardware costs–mainly the PV modules and inverters–declined from over $7.00 per watt to under $3.50 per watt. As hardware is traded internationally, hardware costs are not expected to be greatly affected by deployment in California alone. Previous work [16][18][123] has found that the CSI is unlikely to be a cost-effective program when only environmental externalities are considered.

Learning curves often suffer from data quality problems, and their validity and relevance is not always clear, and therefore Neij et al. [80] do not recommend the use of learning curves to analyze the cost-effectiveness of policy.

Learning curves can be especially hazardous when used to evaluate policy support for technologies that are not yet at a significant commercial level. Although it may be tempting to estimate the cost trajectory of a new technology by applying the learning rate of a similar technology, such an approach may fail because subtle differences may cause large differences in learning rates, and advances in the old technology may translate to the new technology in such a way that the new technology should not be assumed to be starting from scratch when measuring cumulative deployment [11].

4 Subsidizing Energy Production

Economists generally regard carbon pricing–whether that takes the form of a carbon tax, a cap and trade system, or some other policy–as a necessary and perhaps the most important element in any decarbonization strategy [5][6][112]. Carbon pricing has, for instance, been found to be more effective than clean energy subsidies in reducing CO_2 emissions by Gugler, Haxhimusa, and Liebensteiner [41].

Basic theory suggests that subsidizing energy production, including renewable energy production in particular, should undermine energy efficiency. This has been observed in the case with kerosene by Mills [77]. By lowering prices to consumers, Sovacool [110] finds that energy subsidies create a disincentive for energy conservation and investment in more efficient consumption.

The rebound effect is well-known in energy economics. It refers to the tendency for energy consumption to decrease by a lesser amount, in response to improved energy efficiency, than would naively be expected. Three classes of rebound effects are considered by Dimitropoulos [26]:

- Direct rebound: the lower price for a good results in more production of that good,
- Indirect rebound: the lower price of one good leaves households with more money to purchase other goods,
- Economy-wide rebound: lower prices stimulate economic growth, which leads to increased energy demand.

A similar phenomenon has been observed with clean energy deployment. While clean energy subsidies are often justified on the grounds of avoided negative externalities from the less clean energy sources that they displace, York [134] has found that about 25% of non-fossil fuel energy added to the supply displaces fossil fuels, and the remainder either satisfies new demand or displaces other non-fossil energy. While percentages are difficult to ascertain, a similar phenomenon has been observed with the deployment of natural gas, whereby some portion of new gas on the power grid has led to increased overall electricity demand, rather than replacement of coal-fired power [38], [42].

The rebound effect is not necessarily an undesirable outcome, as increased consumption is generally welfare-enhancing [109]. However, understanding of the rebound effect should temper our expectations that energy efficiency or clean energy deployment will, on their own, reduce greenhouse gas emissions.

5 Measurement Challenges with Learning Rates

As straightforward as the learning curve model may seem, determination of reliable learning rates is difficult. Söderholm and Sundqvist [108] document widely diverging learning rates for the same technologies that result from sensitivity to data variations, exogeneity of cost reductions over time, the assumption that installed capacity is an independent variable, and omitted variable bias. Grafström and Poudineh [36] discuss similar problems specifically in the context of wind and solar energy.

Sagar and van der Zwaan [98] observe a survivorship bias in learning rates that are reported in the literature: those technologies that show higher learning rates are more likely to survive to commercial maturity, and their learning rates are more likely to be the subject of academic research. Thus a literature review may show learning rates that are biased high.

Though cost and production data are often readily available, learning rates are often measured with low statistical significance because many confounding factors, such as fluctuating commodity prices, also affect observed costs [11].

5.1 Difficulties in Attribution

As Clancy [22] demonstrates, given data on declining unit cost and increasing cumulative production of some good over time, it is generally very difficult to determine whether cumulative production *causes* costs to decrease. Citing the example of declining solar photovoltaic costs [95], Clancy shows how causality could plausibly be argued in either direction: it may be that solar PV deployment is causing prices to fall via the learning effect; or it may be that prices are falling for some reason that is exogenous to cumulative production, and that falling prices are causing production to increase; or it may be some combination of these two explanations.

Nordhaus [85] observes the same attribution problem and finds that the empirical learning rate, when exogenous costs are not accounted for, will generally be higher than the actual learning rate that does account for exogenous costs.

Lafond [63] considers whether a traditional learning curve model, or whether a model in which unit prices decrease exponentially exogenously, better forecasts prices for 51 products and technologies. Lafond finds that both models fit the data reasonably well, and thus it is difficult to decipher from data how much of observed cost decline can be attributed to learning curves.

Lafond et al. [64] approach the endogeneity problem by considering the costs of producing equipment for the American military during World War

II. Because demand for equipment was clearly exogenous to price and highly variable, World War II military hardware datasets provide a unique opportunity to identify scale, cumulative production, and exogenous time effects on price. Lafond et al. find that about two thirds of the decline in man-hours of labor across types of equipment can be explained by learning curves, while about a third can be explained by exogeneous effects. On a different data set, Lafond et al. find that 60% of the unit cost decrease of military equipment can be explained endogenously, while 40% can be explained by the learning curve.

Nagy et al. [78], in work with the Santa Fe Institute, test six models of the cost trajectory of various products. One is the Wright model–or the standard learning curve model of Equation 1–and another is a Wright model lagged by one year. One is a Moore's Law model, in which costs decrease exogenously with time. One is the Goddard model [35], in which costs are based on economies of scale, and there is no long-term learning based on cumulative production. The Nordhaus model combines the Wright and Moore models [85], while the Sinclair, Klepper, and Cohen [106] model combines the Wright and Goddard models. The models are tested against a dataset of the cost and annual production of 62 technologies. In general, the technologies show approximate exponential growth in production over time, which causes the Moore and Wright models to yield similar results. Nevertheless, the Wright model is found to yield the best forecasts, while the Moore model yields the second best forecasts with accuracy only slightly less than those of the Wright model.

5.2 Economies of Scale

Economies of scale are the tendency for a product to demonstrate lower per-unit production cost for larger volumes of production [72]. Economies of scale in general are driven factors such as specialization and division of labor, and they may further be driven by idiosyncratic factors for particular industries [46]. For example, wind energy is marginally cheaper with larger turbine sizes [30], and economic headwinds from the 1970s may have caused a demand for smaller coal-fired power plants, increasing their per-megawatt cost [132].

Economies of scale are distinct from learning curve effects, as the former is based on current production, and the latter is based on cumulative production. However, when the annual volume of a product grows with time, economies of scale and learning curve effects may look very similar and can be difficult to distinguish based on cost data. Healy [46] attempts to do so by "descaling" several energy technologies based on econometrically-determined economy of scale factors. Considering costs in terms of cumulative installed generation capacity, Healy finds a median learning rate across 16 technologies and regions, without attempting to correct for economies of scale, of 9.3%. If descaling is applied, then the observed learning rate is 2.9%. Thus about two-thirds of the observed learning rates for these technologies can be better explained as economies of scale rather than as learning curve effects.

Nemet [82] considers cost reductions with solar photovoltaics and posits several other explanations in addition to learning curve effects, including economies of scale with a growing PV industry. Qiu and Anadon [90] find that learning curves, economies of scale, and other factors all contributed to falling wind energy prices in China. Yu, van Sark, and Alsema [135] also find that changing input prices and economies of scale, as well as learning curve effects, explain falling prices of solar PV.

6 Models with Declining Learning Rates

There is empirical evidence to suggest that learning rates tend to decline as an industry matures, and that for constant learning rates to hold indefinitely is not to be expected. For this reason, it is reckless to assume that observed learning rates for an emerging technology can be extrapolated to much larger volumes of production. Brown and Anderson [17] note this problem with satellites; the industry's learning models assume production runs of spacecraft that are usually not more than five units, and it is not clear that they can extrapolated to estimate costs for constellations of hundreds of satellites. Sagar and van der Zwaan [98] also observe that learning rates for energy technologies measured in the past cannot necessarily be expected to hold in the future.

Anzanello and Fogliatto [1] and other authors consider several variations of the learning formula, some of which we will review in this section.

6.1 Log Linear Models

The standard Wright learning curve of Equation 1 is called a log linear model because it posits a linear relationship between the logarithm of cost and the logarithm of cumulative production. Here we consider variations of log linear models.

Many researchers have identified a plateau phenomenon, whereby the learning rate approaches zero as production increases [66]. A simple form of a plateau model is as follows.

$$y = C + C_1 x^b \tag{7}$$

Boone [15] considers learning rates in the context of procurement by the United States Air Force and finds that learning rates tend to decrease over time. Boone proposes the following cost formula.

$$Y = aX^{b/\left(1+\frac{X}{c}\right)} \tag{8}$$

In Equation 8, Y is the cumulative average unit cost, X is the cumulative unit production, a is the cost of the first unit, b is the negative of the learning rate, and c is a constant called the Boone decay factor. The values a, b, and c are constants that are determined empirically for a given product. Boone finds that his modified cost formula predicts costs better, as measured by mean squared error, than the standard learning curve formula of Equation 1.

Anzanello and Fogliatto [1] consider several other more complex and less frequently used variations of the log linear model.

6.2 Prior Experience

In practice, a new technology seldom starts from scratch, as new products build upon older, established products. Prior experience is a method of incorporating this phenomenon.

The Stanford B model, such as presented by Malyusz and Pem [71], is the simplest learning curve model that incorporates prior experience and is a close variation of the standard Wright learning curve.

$$\begin{gathered} y = a(x+B)^{-\beta} \\ \ln y = \ln a - \beta \ln(x+B) \end{gathered} \tag{9}$$

In Equation 9, y and x are marginal unit cost and cumulative production respectively, while β is the learning rate and a is a constant to determine empirically. The constant B is the amount of prior experience.

Malyusz and Pem [71] find that, among several mathematical models, Stanford B shows the best performance in forecasting costs. Unlike most models considered here, Stanford B shows an increasing learning rate over time, though one that converges to β.

Nembhard and Uzumeri [81] present the S-curve learning model as follows.

$$y = C_1 \left(M + (1 - M)(x + B)^{-\beta} \right) \tag{10}$$

In Equation 10, C_1, M, β, and B are valued to be determined empirically. It can be shown that for $M > 0$, the learning rate converges to 0. For $M = 0$, the S-curve formula simplifies to the Stanford B formula.

A new technology will incorporate a mixture of novel elements and elements that are common with some established technology. Previsic et al. [89], for instance, estimated a progress ratio for wave power, which was at a pre-commercial state at the time of the report and remains so today, of 85% based on an historically observed progress ratio for wind power [55], which the authors consider to be similar enough to wave power to extrapolate. However, it may be that if wave power is similar enough to wind power, some past experience with wind should be incorporated into a wave power learning model as prior experience.

Component-based learning is discussed in greater depth below, but we suggest a basic functional form to capture the dichotomy between novel and prior components.

$$c_n = c_0 n^{-\beta} + c_0'(n + p)^{-\beta} \tag{11}$$

In Equation 11, c_n, n, β are as in Equation 1. The full initial cost is $c_0 + c_0' p^{-\beta}$. We add a second term, in which $c_0' p^{-\beta}$ is the portion of the initial cost associated with the prior technology, and p is the cumulative production of the prior technology at the start of deployment of the new technology. Under such a model, the observed learning rate may decrease quickly at the start of production, as the term associated with prior production gains in importance relative to novel production, and the learning rate may then increase as n reaches the order of p and learning with the prior technology is observed along with the novel.

6.3 Exponential Models

Anzanello and Fogliatto [1] discuss exponential models, of which several are presented. One model, presented by Knecht [60], incorporates into the log-linear model discussed above an exponential term. Another is a three-parameter model that incorporates prior experience and a learning rate.

$$y = k\left(1 - e^{-(x+p)/r}\right) \tag{12}$$

In Equation 12, y is a measure of worker performance, and larger values of y indicate greater levels of performance, in contrast to the expression of a cost metric in terms of cumulative production; x is cumulative production; p is the workers' prior experience at the beginning of the production run, and r is the learning rate. Mazur and Hastie [74], according to Anzanello and Fogliatto [1], find that the model of Equation 12 works best when $p > 0$; that is, when the process begins with prior experience.

Anzanello and Fogliatto [1] also discuss a Constant Time exponential learning curve model by Towill [120] and several other variants, including variants that incorporate trigonometric functions to account for cyclical performance variations.

6.4 Hyperbolic Models

Finally, Anzanello and Fogliatto [1] discuss hyperbolic models. The simplest such model, proposed by Mazur and Hastie [74], expresses performance as follows.

$$y = k\left(\frac{x}{x+r}\right) \tag{13}$$

In Equation 13, y is performance as in Equation 12. The hyperbolic learning curve distinguishes between performant and defective unit production; x is the cumulative production of performant units, and r is the cumulative production of defective units. As Mazur and Hastie [74] argue, production is best modeled as a process whereby the number of defective units produced remains constant over time, while the number of performant units increases, and so the performance y converges to k with increasing production.

Mazur and Hastie [74] also consider a variant which incorporates prior experience.

$$y = k\left(\frac{x+p}{x+r+p}\right) \tag{14}$$

In Equation 14, p represents prior experience, and all other variables are as above.

6.5 Incompressibility

Johnson [53] also considers declining learning rates in the context of Air Force procurement and discusses the suitability of the Dejong model.

$$c_n = c_0\left(M + (1-M)n^{-\beta}\right) \tag{15}$$

In Equation 15, c_n is the unit cost after a production of n units, c_0 is the theoretical first unit cost, M is the incompressibility factor, and β is the the learning rate. The M and $(1-M)n^{\beta}$ terms refer to, respectively, the automated portion of production and the manual portion. Johnson assesses that the manual portion, but not the automated portion, is subject to cost reductions from learning. It is easily seen that the cost converges to $c_n \to Mc_0$ as $n \to \infty$; that is, the automated portion of the cost becomes dominant. It follows that the learning rate converges to 0 as $n \to \infty$.

Values of M close to 1 indicate a highly automated production process, while values of M close to 0 indicate a highly manual production process. As machines and robots are not expected to show learning with increased production, a highly incompressible process shows a lower learning rate than a compressible process, all else being equal. However, it is not necessarily the case that automated production systems are immune to learning, as such systems can still be tweaked or reprogrammed [17].

6.6 Component-Based Learning

In the context of small modular reactors, Harrison [44] argues that modeling a single learning rate is too simplistic and instead proposes that an SMR is better understood as a complex system with many components, each of which has its own separate learning rate. Harrison posits the following.

$$C_n = \sum_{m=1}^{M} c_{m,0}\, n^{-\beta_m}, \tag{16}$$

where M is the number of components. If $M = 1$, then Equation 16 simplifies to the ordinary learning curve formula of Equation 1. Learning with incompressibility, discussed above, can be viewed as a special case of Equation 16 where $M = 2$ and $\beta_2 = 1$. A component-based model, in which different components have different learning rates, was proposed by Yelle in 1976 [133].

It can be shown that as $n \to \infty$, the learning rate converges to the lowest learning rate among the components. If some component has no learning, then the learning rate converges to 0.

Ferioli et al. [33] consider component-based learning models for solar PV, wind turbines, and carbon capture and sequestration, and argues that the observed learning rate for these technologies is likely to decline over time as the components with lower learning rates come to dominant costs.

Böhm et al. [11] build a four component model for gas-to-power and find it to be at least as effective as a one-component model in forecasting costs. Tsuchiya and Kobayashi [122] apply a component-based analysis to proton-exchange membrane fuel cells and find that PEM fuel cells exhibit a learning profile similar to that of the internal combustion engine.

Wiesenthal et al. [129] note that identifying costs of individual components is generally much more difficult than identifying overall costs that are used in a one-factor learning curve model, and consequently, whatever the theoretical appeal of a component-based model, relatively few analyses employ it.

6.7 Summary of Models

To summarize the various models, Anzanello and Fogliatto [1] observe that the hyperbolic models, the S-curve model, and the Dejong model incorporate forgetting. For each of these models, the learning rate converges to 0 as cumulative production becomes large, which can be considered as a situation in which, for large volumes of production, the loss of performance from forgetting is equal to the gain in performance from additional experience.

Anzanello and Fogliatto [1] also note that the three-parameter hyperbolic model, some exponential models, and the Stanford B models incorporate prior experience. Prior experience may be particularly important when modeling the cost trajectory of a new technology that is very similar to an established technology.

7 Is Learning an Externality?

Learning can be characterized as purely private learning and as knowledge spillovers [9]. The benefits of private learning accrue strictly to the firm that is manufacturing the product, while knowledge spillovers are cost reduction benefits of learning that accrue to firms that are separate from those that are manufacturing.

Knowledge spillovers are a general phenomenon that is not exclusive to learning by doing. For example, Clancy et al. [23] find that over half of patents cited in agricultural research are not themselves considered to be in agriculture, showing substantial spillover from other disciplines into agriculture. Bloom et al. [10], considering productivity in firms in technology areas adjacent to those firms conducting research and development, find a private return to R&D of 21% and a social return of 55%, indicating that over half of the benefits of R&D may be considered knowledge spillovers. In 2019, a similar analysis by Lucking et al. [69] found a private return of 14% and a social return of 58%.

As discussed by Bläsi and Requate [9], specifically in the context of renewable energy deployment, purely private learning, as it accrues to the firm engaging in production, is not an externality and thus not an appropriate basis, in and of itself, to subsidize production. Knowledge spillovers, however, are externalities and justify subsidies. In crafting good policy, therefore, it is critical not just to identify the learning rates associated with production, but also the extent of private learning and knowledge spillovers.

In the context of the dynamic random access memory (DRAM) semiconductors from 1974 to 1992, Irwin and Klenow [51] find that learning rates average 20% and that firms learn three times as much from a unit of their own cumulative production as from a unit of another firm's production. In other words, the effectiveness of private learning was found to be greater than that of learning spillovers. While Irwin and Klenow find high learning rates for DRAM semiconductors, they do not find evidence for intergenerational spillovers for five of seven DRAM generations assessed; in other words, they do not find evidence for learning-by-doing cost reduction benefits in one generation as a result of cumulative production in the previous generation. As a DRAM generation typically lasts three to five years, the benefits of learning therefore appear to be short-lived. Irwin and Klenow also find the same learning spillovers between firms internationally as they do intranationally. These findings cast doubt on the effectiveness of Japan's promotion of semiconductor manufacturing and whether subsidies and export promotion helped Japanese firms over those of other countries and whether these policies had lasting benefits.

In contrast, Castrejon-Campos, Aye, and Hui [19] find that learning curve models for solar photovoltaics are most effective when experience is modeled as a function of global and local experience, indicating a differential role for global and local learning and indicating that domestic firms might capture disproportionate benefits from spillover learning from cumulative production.

Thornton and Thompson [119] considered building of Liberty ships during World War II and found that, while significant spillovers existed, another firm's experience contributed to one firm's cost reductions 6.5% as much as its own experience, suggesting that the external nature of learning spillovers is modest enough that major policy interventions to correct the market failure are not necessary.

8 Conclusion

Learning curves are a real phenomenon, established by Wright [130] and many subsequent researchers. It should be expected that the cost of a manufactured good will decline with cumulative production of that good, and an accurate forecast of the development of the energy system should account for this cost decline.

However, we have also seen that estimating accurate learning rates is difficult, and models that fail to account for the limitations of learning effects are likely to overestimate cost declines and thus underestimate the cost of an energy transition. Söderholm and Sundqvist [108] document several challenges that lead to widely varying learning rate estimates for similar technologies, depending on the time and location of measurement and on modeling choices, while Sagar and van der Zwaan [98] assess that survivorship biases may bias observed learning rates higher.

It is especially difficult to assess the extent to which prices declines are *caused* by cumulative production, as opposed to being caused by economies of scale or exogenous factors. Data to determine causality reliably is very limited, but it is not unreasonable to suppose that in many cases, about half of observed prices declines can be attributed to cumulative production, and about half can be attributed to other factors. Models which fail to consider the causality question are likely to overestimate learning rates.

The most commonly used learning model, posited by Wright [130] and many others, holds that a constant cost percentage decline should be expected for every doubling of cumulative production. However, the theoretical basis for this pattern is weak, and in many cases, learning models that show declining learning rates with increasing cumulative production better fit the data. It is especially reckless to forecast an energy transition on the basis of a constant learning rate holding for orders of magnitude of increase in cumulative production of some product.

For public policy, the hazards of modeling with learning curves are compounded by the need to distinguish the extent to which learning is a private benefit for the firm engaging in production, as opposed to an external benefit to society that may merit production subsidy. Subsidies that fail to distinguish between private learning and knowledge spillovers are likely to be too generous.

For all these reasons, we urge that for modeling and for policy, learning curves be used with full awareness of their limitations.

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