Title
Careful currency conversion

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Energy economics
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International energy economic analysis frequently involves conversion of all monetary figures to a single currency, typically US dollar. This can cause significant variation in estimation of values that change over time such as learning rates for new energy technologies.

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Since the 1930s, economists, engineers, and scientists have studied how technology costs decrease with continued deployment.[1] The prevailing metric for measuring cost reduction trends is the learning rate, which describes the percent reduction in costs for every doubling of cumulative output. Choices made by the analyst can greatly impact the learning rate of a given technology. While a learning rate based on manufacturing cost captures cost reductions from learning-by-doing and economies of scale, one based on product price, for which data is often more readily available, also includes impacts from profit margins, learning in the financial sector, the broader supply chain, and political factors. Cost and price units may or may not be normalized to service or efficiency metrics[2], the learning rate may be allowed to change over time or be held constant,[2,3] and market data may be aggregated at various geographic scales. Writing in Nature Energy, Johan Lilliestam and colleagues at Institute for Advanced Sustainability Studies in Potsdam, University of Potsdam and ETH Zürich report on the impacts of an additional choice made by analysts: currency used and consideration of currency exchange rates.[4] They demonstrate the impact of this choice using global data of large-scale PV plants, and present a method for correcting for this impact.

Learning rates are at times used not just for observing past trends in technology costs, but for predicting costs in the future. These rates therefore significantly impact policy and investment decisions as well as results from models that incorporate technological development and project future energy and environmental impacts.[5] Therefore, it is crucial to understand what exactly a given learning rate represents and the underlying uncertainty in the estimate. Large variation in published learning rates can cause confusion for researchers who wish to use them in system models. Studies like the one by Lilliestam and colleagues provide useful frameworks for understanding the variation in published learning rates and finding the consensus values most relevant for any given energy system model or policy analysis. This work is in particular significant because it allows modellers to more accurately account for future technology costs in global models where technologies are developing in multiple currency regions but entering a global market.

In this work, the researchers analyse a database of costs for 1,990 large-scale solar PV projects commissioned from 2006-2016 in six different countries with different currencies. They demonstrate that using a typical method for converting costs to a base currency, the learning rate varies between 27-33% for the full 11-year period -depending on the base currency chosen- and 17-28% and 21-37% for the 2006-2011 and 2011-2016 sub-periods. They then remove the exchange rate-based variation by using the base year's exchange rate as opposed to a time-varying one. The difference is presented as an "adjustment factor" to the learning curve's weighted cost, which removes the impact of exchange rate fluctuations from the learning rate, presenting a narrower range that should better represent technological cost reductions. The authors warn, however, that the learning rate is still impacted by the inflation rate of the base currency chosen, as well as the price (and exchange rate) of imported technology components.

The scale of learning rate variations described here can have significant impacts on forecasted costs, particularly for technologies early in development, which are very significant in many long-range energy and climate models. For example, imagine a technology for which the market is 1000 units per year, which has grown and is assumed to continue to grow with an annual growth rate of 30%. The 10-year forecasted cost for a learning rate of 20% will be 1.7 times the cost if a 30% learning rate is assumed, as demonstrated in Figure 1. For a 20-year period, this becomes a 2.8x difference. Therefore, it is not only critical to reduce the uncertainty in past learning rates as much as possible, but to understand the inherent uncertainties in forecasting costs based on learning rates.

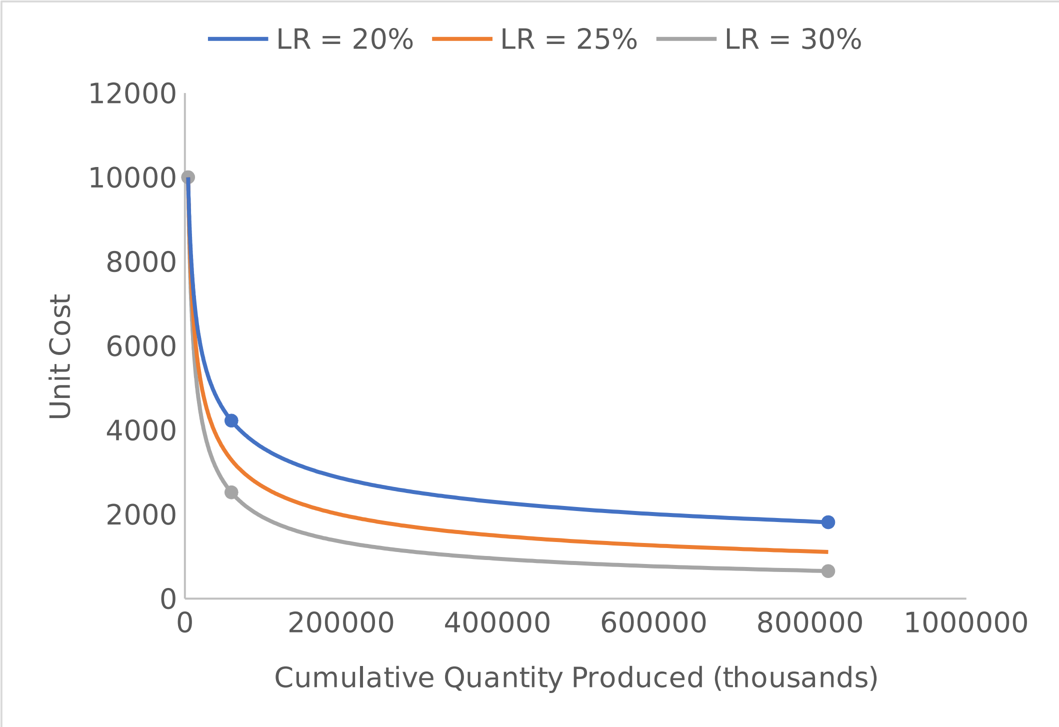

Figure 1: Technology Learning Curve at Three Different Learning Rates. At t=0, the technology has a market size of 1,000 units per year, which grows at a rate of 30% per year. After 10 years, the forecasted cost for a learning rate of 20% is 1.7 times that of a learning rate of 30%, and after 20 years, this ratio is 2.8.

The analysis and discussion from Lilliestam and colleagues' provides a framework for diagnosing and accounting for a previously unconsidered layer of uncertainty. Their work highlights the importance of communicating the methods through which a learning rate is calculated, particularly when multiple currencies are involved. Additionally, it sets the stage for much needed future work regarding the impacts of component import exchange rates, varying labor rates, and inflation on learning rates. With these analyses, researchers can improve estimates for technology learning and more thoughtfully forecast future technology costs in energy and climate models.

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