Experience Curves for Electrolysis Technologies

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Saheed Bello and David M Reiner

Abstract

Given the rapid increase in green hydrogen research funding and the hopes that this will help drive cost reductions, it is important to incorporate the latest RD&D spending into the estimation of the learning rate for electrolysis technologies. Thus, we develop a two-factor experience curve model with spillovers and economies of scale that allows us to estimate learning rates for both alkaline and PEM electrolysis technologies using both global- and country-level data from OECD countries. Our research strategy allows us to mitigate estimation or omitted variable bias from ignoring technology-push measures, unobserved country-specific characteristics, and knowledge spillovers. Using an OECD cross-country dataset over 2000-2022, we estimate global learning-by-doing rates of 17.5 %-46.8% and global learning-by-researching rate of 9%-42.3% for electrolysis technologies after incorporating learning parameter estimates into the progress equation. When we allow for spillovers, we find a linear relationship between PEM technology and alkaline technology improvements. Based on our OECD panel dataset, which incorporate more observations, we estimate learning-by-doing rates of 0.6%-9.4% and learning-by-researching rates of 4.0%-19.9%. In addition, country-level electrolysis cost is reduced by about 28% for the sample period 2000-2022 because of global experience spillover effects. Therefore, our empirical findings suggest that the role of technology-push measures remains critical for promoting and achieving cost improvements of electrolysis technologies. Furthermore, the absorptive capacity of a country should be improved to maximise the benefits of spillovers from global learning.

Keywords: Green hydrogen technology; experience curves; RD&D spending; Global and OECD; cost reductions

JEL Classification: *O30, C50, Q42, Q55*

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1. Introduction

To meet Paris Agreement targets of keeping global temperatures well below 2°C, more ambitious efforts are required to decarbonise the hard-to-abate sectors such as energy-intensive industries. Achieving this target is complex and extremely challenging and although we will need vast amounts of existing technologies such as solar and wind, we will also require large-scale deployment of novel technologies. In this future decarbonised system, low-carbon hydrogen is seen as having an important role in supporting the future green energy transition (Van de Graaf et al. 2020; Pingkuo and Xue, 2022; Mac Dowell, Haszeldine and Reiner 2022), boosting the integration of renewables into the power system by providing long-duration energy storage to ensure higher grid flexibility (Cheng and Lee, 2022). For some countries like Germany, hydrogen has been put forward both to reduce wind electricity curtailments and residual peak demand (Michalski et al., 2017) as well as to strengthen national energy security to mitigate concerns over natural gas supply (Belova et al., 2023). Given these crucial roles, whether these low-carbon technologies ultimately attain their aspired goals, will depend on the evolution of their costs.

Currently, low-carbon technologies such as green hydrogen are far more expensive than fossil-based hydrogen at the point of market commercialisation. In addition, the current investment in these novel technologies remains unprofitable due to high demand uncertainty and inadequate carbon pricing imposed on the incumbent fossil-based technologies. Thus, as electrolyser technology develops, it is expected to be more cost-effective, which incentivises more green hydrogen demand. Green hydrogen technology shows significant potential for cost reductions as more units can be installed and learned from (Wilson et al., 2020; Trancik, 2014). The future costs of technologies have attracted more attention from academic research and practitioners (Choi and Kim, 2023). Their potential cost reductions and improved performance can be predicted through a better understanding of their cost determinants (Huenteler et al., 2016).

Energy system models account for improvements in technology costs by incorporating endogenous technological change into their projecting future energy transitions (Jiang et al., 2023; Rubin et al., 2015). Particularly, these models approximate technological change with learning rates, that relate technology cost reductions to an increase in experience, often measured as cumulative installed capacity (Glenk et al., 2023; Way et al., 2022). The low-carbon technologies are expected to become cheaper because of technological learning i.e., exploring a variety of mechanisms such as learning-by-doing, learning-by-researching, economies of scale, technological innovation, or factor substitution in manufacturing. Technology learning (defined as the driver of cost reduction for both energy supply and demand technologies) is considered the single most important factor for shaping the future global energy system (Berglund and Söderholm 2006).

In the context of renewable energy technologies, numerous experience curve analyses have been conducted, including establishing their consistency with the outcomes of bottom-up technology assessments (Kavlak et al., 2018; Neij, 2008). However, similar efforts for electrolysis technologies are largely missing. Experience curves for electrolysis technologies are scarce due to data availability and quality concerns. To the extent to which there have been past efforts, they have focused on a single-factor experience curve at the global level.

Existing studies have found learning rates for electrolysis technologies ranging between 10% and 34% (e.g., Glenk et al., 2023; Way et al., 2022). Their estimated learning rates vary in terms of the specific electrolysis technologies (Alkaline, Proton Exchange Membrane (PEM)), sample periods, levels of analysis, and geographical scope (Schauf and Schwenen, 2021). These empirical variations in learning rate estimates might potentially result in large bias when modelling equilibrium outcomes and projections of energy system models. This potential biased estimate can be due to the omission of important drivers such as research and development spending, and failure to account for the role of global development of clean technologies in stimulating local technologies learning, as observed in China's solar Photovoltaic (PV) manufacturing driven by global markets (Nemet, 2019).

Given the existing research gap, our paper derives both learning-by-doing and learning-by-researching rates for electrolysis technologies at both global and cross-country levels. Therefore, we contribute to the related literature through the following channels. First, we develop a single-factor experience curve model for the two most mature electrolysis technologies - Alkaline and Proton Oxide Membrane (PEM), using the most recent reliable and comprehensive empirical databases. Second, we extend the baseline experience curves to include the learning-by-researching effect, in order to correct potential learning rate bias. We then allow for more control variables by including both technology and global spillovers that were not considered in previous electrolysis studies. This allows us to implement the modified learning curve model suggested in the work of Nordhaus (2014). Third, we apply both fixed effect and system generalised method of moments (GMM) approaches to a panel dataset of 30 OECD countries over the sample period 2004-2021 in order to control for unobserved country-specific heterogeneity and address the potential sources of endogeneity. Based on our empirical strategy, we provide reliable and consistent electrolysis learning rates that can provide additional insights into the relevance of the experience curve for energy policy and energy modelling. In addition, as a learning rate is critical to technological development analysis (Grafstrom and Poudineh, 2021), we mitigate the uncertainty in estimated learning rates for electrolysis technologies, by suggesting appropriate ways of incorporating electrolysis technological progress into the energy system transition.

The remainder of our paper is organised as follows. Section 2 reviews the literature on experience curves and applications in non-energy and energy technologies with a special focus on electrolysis technology. Section 3 provides our baseline and extended econometric models and describes our empirical data. Section 4 presents our estimation results and discusses our findings in the context of the related literature. Finally, Section 5 concludes with our summarised findings, policy implications, and the limitations of our study.

2. Literature review

In this section, we first review experience curve models and their application in both non-energy and energy sectors. Then, we specifically provide detailed studies on electrolysis technology learning rates.

2.1. Experience Curves

The commonly used method to quantify the cost dynamics of technologies is the experience curve model. Experience curves also known as learning curves, is an empirical concept developed by Wright (1936) to link the historically observed technology cost reduction to learning arising from the number of units produced or the capacity cumulatively installed.

Wright's original illustration, drawn from the outcome of cost developments in airframe manufacturing, is now termed a learning curve (which implies the effect of learning by doing i.e., a fall in labour cost due to a reduction of working time requirements for manufacturing) Boston Consulting Group extended the learning curve concept by developing a black-box model of total production costs as a function of cumulative production generally termed as experience curve approach (BCG, 1970). This approach empirically models the costs of technologies as a power-law function of cumulative experience i.e., cumulative production. Then, it derives an estimate for learning rates, which describes the rate of cost decline with each doubling of cumulative experience. The concept of learning effect in relation to technical change is termed "learning-by-doing" (Wright, 1936; Arrow 1962).

Experience curve theory was pioneered to explain the relationship between technology improvement and experience accumulation (Wright, 1936). This relationship has been extensively explored using a one-factor experience curve (Rubin et al., 2007; Yeh and Rubin, 2007). The one-factor experience curve estimates a single parameter to capture the cost reduction effect of experience accumulated from the production process (learning-by-doing), technology usage (learning-by-using), and interactions with stakeholders (learning-by-interacting) (Choi and Kim, 2023).

In addition, the experience curve approach is widely applied to forecast technology costs due to its reliable and easy-to-use methodology that provides a very useful first-order approximation of cost reductions based on a simple linear regression analysis. It allows the analyst to assess the impact of policies on technology costs more precisely than in a simple time series analysis. The experience curve approach also permits more realistic cost projections unlike the conventional bottom-up engineering analysis (Alberth, 2008), because it explicitly accounts for technological learning rather than statistically assuming technology costs (Dale et al., 2009).

For almost a century since Wright, this learning concept has been empirically applied across different sectors, entities, and technologies over different sample periods (Argote and Epple, 1990; Dutton and Thomas, 1984). An increasingly urgent need to decarbonise the global economy in order to mitigate the adverse effects of climate change calls for a robust understanding of the evolution of climate mitigation and adaptation technologies. This need extends to how a rapid fall in the cost of renewable energy will influence the deployment of these low-carbon electricity sources (Nordhaus, 2014; Grafstrom and Poudineh, 2021).

The simplicity of experience curves encourages allows energy system modellers to incorporate the learning rate into their energy transition models. However, the one-factor experience curve fails to account for the complex dynamics of technology cost reduction, thus potentially leading to omitted variable bias, and overestimated learning-by-doing rates. This bias is due to the omission of key factors such as research and development (R&D) spending (Jamasb, 2007; Clarke et al., 2006).

Many additional drivers have been considered in the literature, but the well-established extension is also known as a two-factor learning curve which includes a knowledge stock, which is usually proxied by learning-by-searching (LBS) (Jamasb, 2007; Soderholm and Klaassen et al., 2007). This two-factor model combines separate approaches to implementing endogenous technical change into energy system models (Gillingham et al., 2008). The two-factor experience curve addresses this overestimated learning rate issue by separating contributions of R&D and experience (Klaassen et al., 2005; Soderholm and Sundqvist, 2007). In the two-factor experience curve, cost reductions are associated with both cumulative capacity (learning-by-doing) and R&D (learning-by-researching), thus providing useful insights into the value of R&D investment and innovation activity.

This method has been extended to develop multi-factor models in bottom-up cost settings (Kavlak et al., 2018; Nemet, 2006), and to control for more factors that can influence cost reductions in the innovation system dynamics (Kim and Wilson, 2019). The extended two-factor model can account for other learning types such as learning-by-using, learning-by-interacting, or relationship-specific LBD (Kellogg, 2011; Tang, 2018), and learning from spillovers (Irwin and Klenow, 1994; Anderson et al., 2019; Bollinger and Gillingham, 2019; Nemet et al., 2020). Learning-by-interacting, which describes knowledge development by interactions among stakeholders, and learning from spillovers, which describes knowledge development by exploitation of technology (Rout et al., 2009), are considered to be mechanisms that operate through externalities i.e., firms learn from actions taken by other market actors (Malerba, 1992). Non-learning technology cost drivers also considered in the literature are input prices, scale economies, location-specific, market structure, regulatory and macroeconomic factors. However, this leads to model challenges such as the identification of appropriate variables, the dangers of overfitting, and potential causality issues (Choi and Kim, 2023).

2.2. Applications of experience curves

The early applications of experience curves (or progress functions which are based on progress ratio that raises 2 to power of learning parameter) between the 1930s and 1960s focused on product manufacturing (Wright, 1936; Alchian, 1963; Arrow, 1962) and shipbuilding (Rapping, 1965). In the 1970s and 1980s, it was extended to business management, strategy, and organisation studies (BCG, 1970; Dutton and Thomas, 1984; Hall and Howell, 1985; Lieberman, 1987; Spence, 1986; Argote and Epple, 1990). The learning curves have been applied to energy technologies including renewable energy since the 1990s, due to the pressing need for their economic and policy analysis (Bhandari and Stadler, 2009; Lindman and Soderholm, 2012; Papineau, 2006; McDonald and Schrattenholzer, 2001; Criqui et al., 2000). Most of these studies focus on how costs change over time (e.g., Neij, 1997).

In the renewable energy sector, the learning curve is specified by relating the historical cost of the renewable energy technology to its cumulative installed capacity (expressed in megawatts [MW]) or generation (expressed in megawatt hours [MWh]) (Junginger et al., 2010). Using the log-log model, the learning-by-doing elasticity reflects the percentage change in cost due to a one percentage point increase in cumulative capacity. The elasticity coefficient is then used to derive the learning-by-doing rate, which shows the percentage reduction in cost for each doubling of cumulative capacity. For instance, Wright's rule of thumb assumes that a learning-by-doing rate of 0.20 implies that a doubling of the cumulative capacity will lead to a cost reduction of 20% (Wright 1936). This concept has been applied to analyse wind power technology (Klassen et al., 2005; Cory et al., 1999), and to support bottom-up optimisation models of energy technologies (Miketa and Schratenholzer, 2004; Kypreos, 2004).

Some meta-analyses in the energy literature find learning rates which echo the rule of thumb of 20% for solar power such as 15-25% for solar PV (Choi and Kim, 2023). Other studies find quite different rates such as estimates of between 0.16% and 7.13% for the Spanish PV experience curve (Garzon Sampero and Sanchez Gonzalez, 2016) and 33% for residential solar PV in Germany (Wei et al., 2017). Wind power learning rates also vary widely ranging from 3% to 17% (Choi and Kim, 2023) and from -11.4% to 20% for onshore wind (Schauf and Schwenen, 2021). Partridge (2013) found a learning rate of 17.7% for wind power plants in India, compared to 3.1% established in Europe (Soderholm and Klaassen, 2007) and negative rate of -11.4% for onshore wind in Taiwan (Trappey et al. 2013) see Appendix Table A6 for more details. Substantial variations in estimated learning rate for non-renewable generation technologies are also found in the literature (e.g., Rubin et al., 2015; Samadi, 2018). Power system models proxy advances in technology costs through endogenising technological change when forecasting future market outcomes. This proxy is implemented with learning rates (Gillingham et al., 2008; van der Zwaan et al. 2002). Other studies found an estimated learning rate of 43% for onshore wind technology (Lindman and Soderholm, 2012; Rubin et al., 2015; Williams et al., 2017). Learning rates for renewable energy technologies range from -3% for wind in Germany (1991-1999) to 47% for photovoltaic modules (1984-1987), compared to other technologies such as nuclear power plants (9±8%), coal and lignite power (9±5%), coal boilers (22±8%), PV and biomass production (9±8%). These differences can be attributed to data variability, technology specifics such as the novelty of components, and efficiency improvements. Schauf and Schwenen (2021) contributed to the literature by addressing issues related to cost measurement, omitted variables[1], depreciation rates, economies of scale, and endogeneity in a panel dataset of seven European countries. They find learning rates

[1] This literature also controls for additional variables such as material price indices, wind resource quality, competition, requirements on local value creation, and interest rates. Furthermore, economies of scale are proxied by wind farm size, wind turbine unit size (Berry, 2009; Qui and Anadon, 2012; Wilson, 2015), and firm size of the largest wind turbine manufacturers (Schauf and Schwenen,2021).

of 2.8% for learning by doing (learning as capacity accumulates) and 7.1% for learning by researching (learning as a result of increases in RD&D expenditures).

In the electrolysis technology literature, the only learning curve analyses (e.g., Glenk et al., 2023; Way et al., 2022) focus on one single factor, which overlooks the effect of R&D as an influential factor and policy tool (learning-by-researching). Their estimated learning rates for electrolysis technologies range from 5% to 31% as shown in Table 1.

These few studies compromise with the weakness of the experience curve methodology in the aspect of ignoring the role of R&D in promoting electrolysis technology and the endogeneity of diffusion effect of electrolysis technology costs (Jamasb and Kohler, 2007) while implementing their electrolysis learning curve methodology. In addition, they failed to incorporate any form of spillover in their electrolysis model specification.

Thus, our study fills this research gap by conducting a two-factor learning curve analysis to determine the relative importance of these factors that are the key drivers of change in energy technologies (Criqui et al., 2000) to improve technology policy and innovation (Jamasb, 2007). In addition, we can address potential estimation bias from ignoring the role of R&D activities (e.g. basic research, applied R&D) in the process of technical change.

Table 1
Estimated learning rates for electrolysis technologies in the literature

Electrolyser technology	LR	Reference
Alkaline	18 ± 13%	Schmidt et al. (2017)
Alkaline	8%	Hydrogen Council (2020)
Alkaline	12-12%	Hydrogen Council (2021)
Alkaline	24 ± 6%	George et al. (2022)
Alkaline	15.7±2.69%	Glenk et al. (2023)
PEM	18 ± 2%	Schmidt et al. (2017)
PEM	18 ± 6%	George et al. (2022)
PEM	13.85±1.70%	Glenk et al. (2023)
PEM	13%	Hydrogen Council (2020)
PEM	12-20%	Hydrogen Council (2021)
Water electrolysis	18% [5-12%]	IEA (2023)
Water electrolysis	12.9% ±6.7%	Way et al. (2022)
Water electrolysis	5-13%	Pastore et al. (2022)
Water electrolysis	16-21%	IRENA (2021)

Water electrolysis	10-20%	Rogner (1998)
Water electrolysis	18 ± 13%	Schoots et al (2008)
Water electrolysis	18 ± 6%	Schmidt et al. (2017)
Water electrolysis	8%	Gül et al. (2009)

Given the increasing global interest in using R&D spending and expanding country-level networks to support green hydrogen development, we also extend the existing literature to account for this reality by incorporating RD&D spending and global spillover into the electrolysis experience curve model.[2] This novel contribution allows us to identify the role of both demand-pull and technology-push policies as well as knowledge transfer in reducing the cost of electrolysis technologies.

3. Method and data

3.1. Method

In this study, we utilise both one-factor and two-factor models while allowing for control variables subject to data availability and quality. We first develop a one-factor experience curve model to investigate the technological improvement of electrolysis based on the accumulation of cumulative experience (i.e., learning by doing). The experience curve model uses Wright's (1936) power form, which is specified as:

$$y = ax^b \tag{1}$$

Where x is the independent variable and the proxy for experience, y denotes the dependent variable, and the proxy for technology improvement or cost reduction, b represents the learning parameter used to obtain the learning rate (defined as the ratio of cost reduction by doubling experience), and a denotes the constant and the initial technology cost. Following Rubin et al. (2015), the learning rate is mathematically expressed as:

$$1 - 2^b \tag{2}$$

[2] See appendix A6 for wind and solar technology learning rates

Owing to the exponential decrease in cost as experience increases, we employ a log transformation to describe this relation in a linear form. Thus, our baseline one-factor experience curve model is specified as follows:

$$Log(Cost_{i,t}) = Log\ a + bLog(Capacity_{i,t}) + error_{i,t} \tag{3}$$

Where $Cost_i$ is the inflation-adjusted specific installed cost of each electrolysis technology, $Capacity_i$ is the cumulative installed capacity, i denotes the type of technology (alkaline, PEM) while t and $error$ represent the given year and the disturbance term respectively.

We then extend our baseline model in Eq. (3) to the two-factor experience model by incorporating public RD&D spending as another major determinant of cost reduction into the one-factor experience model as specified in the literature (Jamasb, 2007). Thus, we develop the following two-factor experience model:

$$Log(Cost_{i,t}) = Log\ a + b_{LBD}Log(Capacity_{i,t}) + b_{LBR}Log(RDD_{i,t}) + error_{i,t} \tag{4}$$

Where RDD is the public RD&D expenditure on hydrogen. Then, we allow for control variables such as technology spillovers and economies of scale to develop the extended two-factor experience model as follows:

$$Log(Cost_{i,t}) = Log\ a + b_{LBD}Log(Capacity_{i,t}) + b_{LBR}Log(RDD_{i,t}) + \sum_{k=1}^{n} \omega_k\, Log(Z_{i,t}) error_{i,t} \tag{5}$$

Where $Z_{i,t}$ represents control variables such as electrolysis technology spillover, economies of scale, etc.

We first estimate the above-specified models (Eqs. 3-5) of electrolysis technologies in the global context between 2003 and 2020, and then implement their estimation in a panel dataset of 30 OECD countries over the sample period of 2004-2021. In our single-factor learning model, we use the cumulative installed capacity of each electrolysis technology as the explanatory variable and the specific installed system cost of each technology as the dependent variable. We implement the two-factor experience model by including cumulative public RD&D spending as another explanatory variable to quantify the effect of learning-by-researching. Then, we incorporate the control variables into the two-factor learning model to develop an extended model. Second, we re-estimate all three models in a panel setting to account for unobserved country-specific characteristics such as policy and institutional arrangements using a fixed effect method. Finally, we implement a system generalised method of moments (GMM) as a robustness check to address all potential sources of endogeneity (Choi and Kim, 2023) that would produce biased and inconsistent estimates (Greene, 2003), as well as estimation bias due to the correlation between unobserved country effects and regressors (Baltagi, 2008).

3.2. Data

Table 2 provides a summary of the data used in our analysis, which is confined to alkaline and PEM technologies due to limited data availability on Solid Oxide Electrolysis (SOE) since SOE is still at an early stage of technology readiness. Given the absence of reliable historical electrolysis cost data as well as to enable better comparisons with the relevant literature, our installed system cost data is obtained from Glenk et al. (2023).

Table 2
Variable description and data sources

Variable	Description	Sources
Cost	Installed system cost (2020 U$/kW)	Glenk et al. (2023)
Capacity	Installed capacity (MW)	IEA (2023)
RDD	Public expenditures on hydrogen RD&D (research, development and demonstration) in million USD (2021 prices and purchasing power parity)	UK Data Services 2023

We aggregate installed capacities of each technology's plant in operation for each year to obtain the yearly total installed capacity for each electrolysis technology at the global and country levels using the IEA Hydrogen Project Database. As reported in the IEA database, the first alkaline electrolyser started operation in 1965 in Peru, while the first operating PEM electrolysis technology started in 1992, in Sweden using nuclear as its feedstock. That same year, a renewable-based PEM technology was first operated in the United States and also demonstrated in Spain. More recently, China has opened some of the largest electrolysis plants – exceeding 120 MW in 2021, and 260 MW in 2023.

For the case of alkaline technology in Fig. 1, Germany and the Netherlands have surpassed other OECD countries by reaching a cumulative installed capacity of above 8MW since 2013, while Japan became the second largest deploying country in 2020. In 2021, the highest cumulative installed capacity of alkaline (attributed to Germany) was above 16MW, compared to a total of less than 1MW in 2004. This indicates the future potential of more large-scale projects for electrolysis technologies.

Fig. 1. Country-level Cumulative installed capacity of Alkaline electrolysis technology 2004-2021

As illustrated in Fig. 2, the cumulative installed capacity recorded substantial increases in recent years, from less than 2 MW in 2004 to above 40MW in 2021. However, this huge increase is not uniform across the OECD countries, thus indicating significant country-level heterogeneity in the deployment of electrolysis technologies. In 2021, Germany attained the highest cumulative installed capacity of PEM with over 40 MW, followed by the United States which led the deployment race between 2008 and 2016, and Switzerland, while each of the other OECD countries attained less than 10MW.

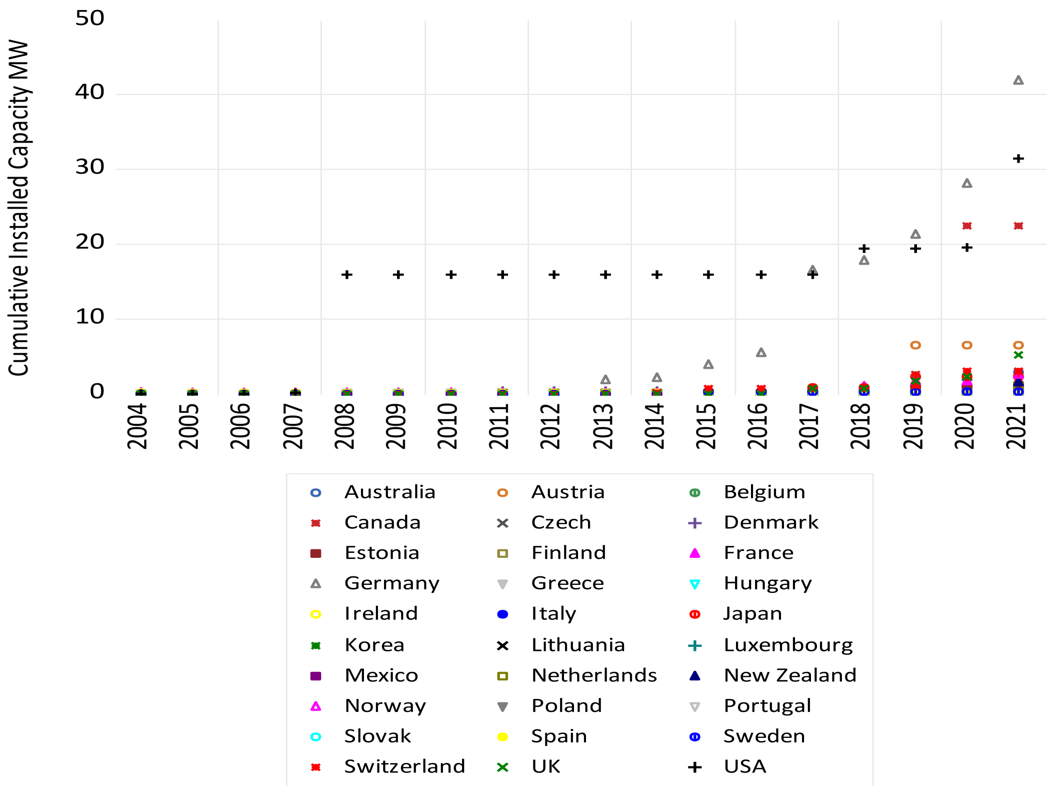

Fig. 2. Country-level Cumulative installed capacity of PEM electrolysis technology 2004-2021

We measure learning-by-researching using the UK Data Services (2023) data on hydrogen R&D and demonstration (RD&D) public spending. We sum this country-level data to obtain the yearly global hydrogen RD&D data. Then, we calculate the cumulative values for both installed capacity and RD&D at the global and country-level landscape.

Fig. 3 depicts the evolution of public RDD investment in hydrogen production over the period 2004-2021 (although some data is missing). There is a clear upward trend in annual public RDD spending in the United States, Japan, and France since 2004. The highest cumulative RDD was above US$ 1,600 million in 2021, compared to about US$200 million in 2004. In 2021, most OECD countries have cumulative RDD spending on hydrogen below US$400 million.

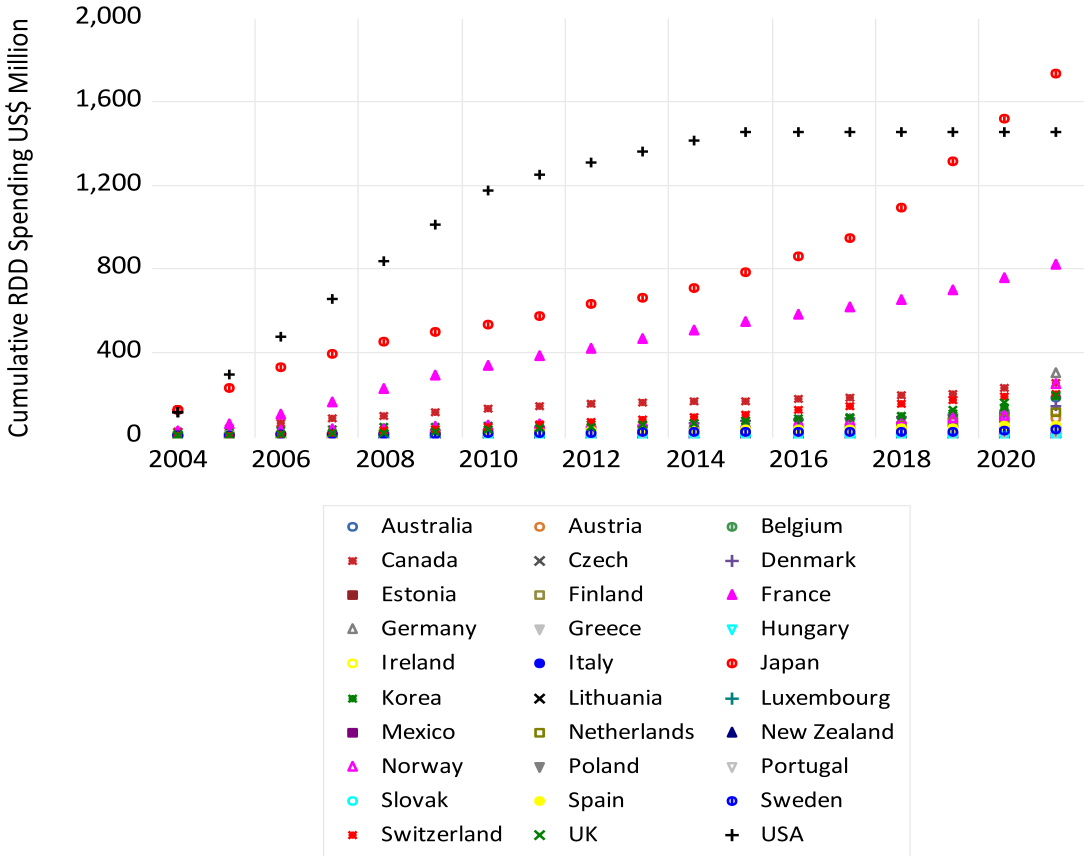

Fig. 3. Country-level cumulative public RDD spending on the entire hydrogen production 2004-2021

To implement our empirical strategy, we first use aggregate global data to have a broader view of technological progress, which allows us to capture any spillover effects that might occur at the national and regional levels (Jamasb, 2007). Then, we employ cross-country panel data to account for unobserved country-specific information (Jamasb, 2007). In Table 3, we provide summarised descriptive statistics of the data we gathered. Owing to the lack of country-level cost data, we assume that each OECD country faces the same installed system costs. This assumption allows us to estimate the experience curve models for electrolysis technologies using a panel dataset. As observed in the table, incorporating RDD spending reduces the number of observations or years for which technologies could be analysed. In addition, the installed system cost of PEM has higher volatility than alkaline electrolysers (as indicated by their standard deviations), which is likely due to the lower level of PEM maturity. Similarly, the standard deviation of cumulative installed PEM capacity at the global level is higher. However, the reverse of this observation is found when considering country-level installed capacity in the OECD panel data.

Table 3

Summary of descriptive statistics

	Alkaline					Proton Exchange Membrane (PEM)				
Global Time-series Data: 2003-2021										
	Mean	Std. Dev.	Min	Max	Obs.	Mean	Std. Dev.	Min	Max	Obs.
Cost	1,445.6	517.32	658.4	3,159.5	106	2,407.35	1,954.55	570.96	9,886.52	79
Capacity	56.29	16.92	25.8	94.06	106	42.86	23.44	8.93	99.62	79
RDD	771.15	243.25	68.1	1,100.4	106	801.02	231.02	68.06	1,100.41	79
OECD Panel Data: 30 OECD (2004-2021)										
Cost	1,723.4	625.9	883.3	3,159.5	480	2,551.44	1,247.08	1,064.00	6,360.0	540
Capacity	2.16	3.6	0.0	17.5	146	2.51	6.35	0.00	41.89	206
RDD	129.57	302.0	0.0	1,734.2	414	130.2	302.64	0.00	1,734.26	412

To address the issue of multicollinearity, our correlation results for electrolysis technologies are presented in Tables 4 and 5. For alkaline technology in Table 4, we find a strong positive relationship between *Capacity* and *RDD* with a correlation coefficient of 0.83, using the global-level data. Therefore, we mitigate the influence of collinearity on our results when using cross-country data. As observed in the table, the highest correlation among independent variables in a panel data set is reduced to 0.20.

Table 4

Correlation matrix: Alkaline

	Log *Cost*	Log *Capacity*	Log RDD
<u>**Global Time series**</u>			
Log Cost	1.00		
Log Capacity	-0.74***	1.00	
Log RDD	-0.70***	0.83***	1.00
<u>**OECD Panel**</u>			
Log Cost	1.00		
Log Capacity	-0.47***	1.00	
Log RDD	-0.34***	0.20*	1.00

Note: ***, **, and * denote significance levels at 1%, 5% and 10% respectively.

Our results reveal coefficients among the explanatory variables in both global and cross-country correlation tests, as shown in Table 5. The highest correlation coefficient is 0.59 for the panel setting compared to 0.85 for the time series setting.

Table 5

Correlation matrix: PEM

	Log Cost	Log Capacity	Log RDD
<u>**Global Time series**</u>			
Log Cost	1.00		
Log Capacity	-0.85***	1.00	
Log RDD	-0.80***	0.82***	1.00
<u>**OECD Panel**</u>			
Log Cost	1.00		
Log Capacity	-0.59***	1.00	
Log RDD	-0.31***	0.29***	1.00

Note: ***, **, and * denote significance levels at 1%, 5% and 10% respectively.

4. Results and discussion

Implementing the global-level model, Table 6[3] shows the results of estimating Eqs. (2-5) for alkaline and PEM respectively on a log-log scale. We estimate a single-factor learning model twice, first using *Capacity* (Column 1 for alkaline; Column 5 for PEM), then using *RDD* as the policy variable (Column 2 for alkaline; Column 6 for PEM) in order to mitigate the effect of the high correlation between *Capacity* and *RDD*. Column 3 (Column 7) contains the results of the two-factor learning curve model for alkaline (PEM). Then, we estimate an extended two-factor model that allows for technology spillover in Column 4 (alkaline) and Column 8 (PEM). In the table, we report our estimated elasticities and the corresponding learning rates for the alkaline electrolysis technology (Columns 1-4) and the PEM electrolysis technology (Columns 5-8).

As shown in Column 1, we estimate a learning-by-doing (LBD) rate of 39.0%, which is statistically significant at the 1% level. Hence, every doubling of cumulative capacity is linked to an installed alkaline system cost reduction of 39%. When we re-estimate the single factor model using the RD&D spending in Column 2, we find a statistically significant learning-by-researching (LBR) rate of 23.7%. However, both the learning effect and explanatory power (0.485) are lower, compared to Column 1 (0.55).

Column 3 estimates the well-established two-factor model that incorporates RD&D spending into Wright's (1936) single-factor experience model. As can be observed, extending the model to include *RDD* reduces LBD to 29.5% (significant at 1%). However, the explanatory power (indicated by adjusted R^2) slightly increases to 0.567, implying that about 57% of the variation in alkaline technology cost is explained by the two-factor model. While allowing for PEM technology spillover[4] in Column 4, we find a significant learning-through-spillover effect, with rate of 14.1%. However, the significant explanatory power of learning-by doing is reduced, and that of learning-

[3] Our results in Table 6 show estimation results in line with the well-established experience curves in the literature, after estimating different model specifications related to Moore's and Nordhaus' theories (see Tables A1 and A2 in the appendix).

[4] We also implement unrelated technology (wind and solar) spillovers (see Tables A3 and A4 in the appendix) but their results reduce the explanatory power with lower adjusted R^2.

by researching turns out to be insignificant. This specification slightly improves the overall goodness of fit. Therefore, we consider Column 4 our preferred model for alkaline and use its results for our discussion and policy recommendations in the global context.

A similar empirical strategy is implemented for PEM electrolysers (Column 5 to Column 8 in Table 6). As shown in Column 5 of the table, the estimated elasticity of cumulative capacity is negative and statistically significant at a 1% level, with a LBD rate of 46.8%, i.e., PEM cost is reduced by about 47% for each doubling of its cumulative capacity. When re-estimating with RDD spending in Column 6, we find lower model performance with a slight fall in the rate. Then, with the estimation of the two-factor learning model in Column 7, the LBD rate substantially reduces but the model performance slightly improves thus indicating overestimated LBD bias in the one-factor PEM experience curve. Allowing the influence of alkaline spillover in Column 8, we find lower learning rates with no improvement in the explanatory power. In addition, the LBR rate turns out to have less significant influence on PEM cost. Our estimated rate variances are higher in Column 8, suggesting less efficiency compared to Column 7. Thus, the experience curve model specification in Column 7 of the table is our preferred model for PEM electrolysis technology cost.

Table 6
OLS results using global-level data

	Alkaline				PEM			
	1	2	3	4	5	6	7	8
Constant	10.059***	9.777***	10.183***	9.568***	10.876***	12.966***	11.982***	12.589***
	(0.251)	(0.257)	(0.252)	(0.342)	(0.232)	(0.454)	(0.411)	(0.598)
Capacity	-0.713***		-0.504***	-0.278**	-0.911***		-0.634***	0.504***
	(0.063)		(0.111)	(0.139)	(0.063)		(0.106)	(0.140)
RDD		-0.391***	-0.146**	-0.071		-0.817***	-0.320***	-0.258**
		(0.039)	(0.065)	(0.069)		(0.069)	(0.312)	(0.110)
PEM Spillover				-0.220**				
				(0.085)				
				14.1%				
ALK spillover								-0.369
								(0.265)
								22.6%
LBD	39.0%***		29.5%***	17.5%**	46.8%***		35.6%***	29.5%***
LBR		23.7%***	9.6%**	4.8%		43.2%***	19.9%***	16.4%**
Adj. R^2	0.55	0.485	0.567	0.589	0.725	0.643	0.754	0.757
N	106	106	106	106	79	79	79	79
Variance estimates:								
Capacity	0.00394		0.01239	0.01941	0.00401		0.01121	
RDD		0.00153	0.00420	0.00482		0.00472	0.01015	0.01970
								0.01206
95%CI [low, high]								
Capacity	[-0.838, -0.589]		[-0.725, -0.283]	[-0.554, -0.001]	[-1.016, -0.806]		[-0.844, -0.423]	[-0.784, -0.225]
RDD		[-0.469, -0.313]	[-0.275, -0.018]	[-0.209, 0.066]		[-0.954, -0.681]	[-0.520, -0.119]	[-0.476, -0.039]

Note: Standard errors are in parentheses while values in the square brackets represent the low and upper boundary of the estimated coefficients at 95% confidence intervals. ***, ** and * denote significance level at 1%, 5% and 10% respectively. Red colour indicates a learning-through-spillover rates.

To account for unobserved country-specific heterogeneity indicated in our gathered data, we implement the panel-fixed effect methods, whose results are reported in Tables 7 and 8 for both alkaline and PEM electrolysis technologies respectively. Table 7 shows different panel model specifications (Columns 1-4) for the estimation of alkaline experience curves. In Column 1, we find that the estimated elasticity of experience is -0.130 with a learning-by-doing rate of 8.6%. An extension to a two-factor specification in Column 2, the estimated coefficient for RDD is statistically significant and negative but the magnitude effect of experience significantly drops, implying an overestimated learning-by-doing rate reduces to 2.8%. In addition, the explanatory power significantly improves to 0.684. We re-estimate the two-factor model with a 2-year lag of RDD (*RDD (-2)*) spending (due to our limited observations) in Column 3 as it takes some time to see the RDD spending impact, to capture the influence of previous RDD spending on the current technology cost as suggested in the literature (Schauf and Schwenen, 2021). In so doing, we find an insignificant LBD rate and lower explanatory power of 0.619. Then, global alkaline capacity is incorporated into Column 4, which allows for the calculation of the effect of technology spillovers. As can be observed in Column 4, both LBR and learning-through-spillover rates are statistically significant at a 1% level with theoretically expected signs. In addition, the country-level alkaline cost reduces by 22.4% for every doubling of global cumulative installed capacity, holding other factors constant. The overall goodness of model fit significantly improves to 0.767, implying that about 77% of variations in alkaline technology cost are explained by the model. Thus, our preferred model is Column 4 for the cross-country experience curve of alkaline electrolysis technology.

Table 7

Panel fixed effect results: Alkaline

	1	2	3	4
Constant	7.148***	8.162***	8.286***	9.007***
	(0.024)	(0.110)	(0.142)	(0.062)
Capacity	-0.130***	-0.041**	-0.009	
	(0.018)	(0.016)	(0.019)	
RDD		-0.267***		-0.084***
		(0.028)		(0.010)
RDD (-2)			-0.321***	
			(0.039)	
Global ALK Cap				-0.366***
				(0.020)
				22.4%
LBD	8.6%	2.8%	0.6%	
LBR		16.9%	19.9%	5.6%
Adj. R^2	0.414	0.684	0.619	0.767
N	127	119	112	365
Country effect	Y	Y	Y	Y
Variance				
estimates:	0.00032	0.00027	0.00037	0.00010
Capacity		0.00080	0.00150	
RDD				
95% CI [low, high]				
Capacity	[-0.165, -0.094]	[-0.073, -0.008]	[-0.047, 0.029]	
RDD		[-0.323, -0.211]	[-0.397, -0.244]	[-0.104, -0.064]

Note: Standard errors are in parentheses while values in the square brackets represent the low and upper boundary of the estimated coefficients at 95% confidence intervals. ***, ** and * denote significance level at 1%, 5% and 10% respectively. The rate in red indicates the learning-through-spillover effect. *Global ALK Cap* denotes the sum of cumulative installed alkaline capacity in all available countries in the IEA Hydrogen Database

Table 8 reports different panel model specifications (Columns 1-4) for the estimation of PEM experience curves. In Column 1, the estimated elasticity of *Capacity* is -0.143 which implies a cost reduction of 9.4% for each doubling. Extending to a two-factor specification in Column 2, the estimated coefficient for *RDD* is statistically significant and negative but the magnitude effect of *Capacity* significantly reduces, implying LBD is reduced to 4.5%. In addition, the model explanatory power significantly improves to 0.628. Column 3 re-estimates the two-factor model using the 2-year lag of *RDD*. As can be observed, this specification increases LBD to 5.3% but reduces LBR to 13.6% (both rates are significant at 1%). Although the overall goodness of model fit slightly reduces to 0.594, it remains robust to using the current RDD as a policy measure.

Several different models were investigated to incorporate technology spillovers into the two-factor model (see Table A5 in the appendix for their results), before obtaining the primary model, which can be found in Column 4 of Table 8. As can be seen, the PEM technology cost reduction is significantly associated with its global cumulative capacity (*Global PEM cap*) and the *RDD* spending, at a 1% significance level. Including global technology spillovers, we find that the RDD elasticity substantially reduces to -0.059, which implies a cost decrease of 4% for each doubling of RDD spending, while learning-through spillover (*Global PEM cap*) reduces the cost by 27.5% for every doubling of the global capacity. Furthermore, the model explanatory power considerably improves to 0.793 with the higher efficiency (indicated by the lowest variance of 0.00016 for *RDD* elasticity). Our preferred model is Column 4 for the cross-country experience curve of PEM electrolysis technology.

Table 8
Panel Fixed Effect Results: PEM

	1	**2**	**3**	**4**
Constant	7.201***	8.394***	8.187***	9.409***
	(0.036)	(0.170)	(0.153)	(0.053)
Capacity	-0.143***	-0.067***	-0.078***	
	(0.012)	(0.015)	(0.014)	
RDD		-0.244***		-0.059***
		(0.035)		(0.013)
RDD (-2)			-0.211***	
			(0.034)	
Global PEM Cap				-0.463***
				(0.021)
				27.5%
LBD	9.4%	4.5%	5.3%	
LBR		15.6%	13.6%	4.0%
Adj. R^2	0.514	0.628	0.594	0.793
N	203	183	173	412
Country effect	Y	Y	Y	Y
Variance estimates:				
Capacity	0.00035			
RDD		0.00022	0.00020	
		0.00126	0.00113	0.00016
95% CI [Low, High]				
Capacity	[-0.167, -0.119]	[-0.096, -0.037]	[-0.106, -0.049]	
RDD		[-0.314, -0.174]	[-0.277, -0.144]	[-0.035, -0.092]

Note: Standard errors are in parentheses while values in the square brackets represent the low and upper boundary of the estimated coefficients at 95% confidence intervals. ***, ** and * denote significance level at 1%, 5% and 10% respectively. The rate in red indicates the learning-through-spillover effect. *Global PEM Cap* denotes the sum of cumulative installed PEM capacity in all available countries in the IEA Hydrogen Database

The cross-country results reported above rely on the fixed-effect method, so we address all potential sources of endogeneity due to reverse causality and omission of relevant variables using the system generalised method of moments (GMM). Table A5 in the appendix reports the system GMM regression results. We find that the learning rates remain robust in terms of significance and magnitude. In general, our system GMM approach validates our fixed effect results that significant learning takes place in explaining the evolution of electrolysis technology cost. Specifically, our system GMM results indicate that country-level learning-by-researching (LBR) is higher than learning-by-doing (LBD). While learning-by-doing has a higher impact on PEM costs than for alkaline, learning-by-researching exhibits the reverse.

We estimate learning-by-doing rates ranging between 17.5% and 39% for the alkaline technology and between 29.5% and 46.8% for PEM. If we compare our global-level results to past studies, our upper LBD rate of 39% is nearly 9% points above previous alkaline learning rates (George et al., 2022; Schoots et al., 2008), while our lower LBD rate is in line with previous research (Glenk et al., 2023). These differences could be attributed to the use of the most recent IEA hydrogen data. For PEM technology, our global learning-by-doing rate is just outside of the range established in the literature (e.g. Glenk et al., 2023; Way et al., 2022) as our lower LBD rate of 29.5% is slightly below their upper LBD rate of 31% (Schoots et al., 2008). Our preferred model's LBD rate of 35.6% is at the higher end and more optimistic.

Based on updated data and better accounting for technology spillovers, our results show that previous studies underestimate learning rates. In addition, the results reveal that less mature green hydrogen technologies (such as PEM) exhibit a higher learning-by-doing rate than more mature technologies (such as alkaline). Our empirical results also are in line with the literature that single-factor learning curves overestimate learning-by-doing by excluding the R&D effect (Jamasb, 2007).

Accounting for unobserved country-specific heterogeneity in a panel dataset, our results reveal LBD ranges of 0.6%-8.6% for alkaline and 4.5%-9.4% for PEM, which are in line with previous studies (e.g. George et al., 2022; Hydrogen Council, 2020; IEA, 2023; Pastore et al., 2022; Schmidt et al., 2017). Furthermore, our estimated learning-by-researching rates for alkaline and PEM technology range between 5.6% and 19.9%, and between 4.0% and 15.6% respectively, while their global spillover effects are 22.4% and 27.5% respectively. These learning-through-spillover rates show that the PEM electrolysis technology gains more from global spillover than alkaline electrolysis technology.

5. Conclusion

Policymakers are being asked to make decisions over the deployment of hydrogen technologies in many countries even though national-level and collective global experience with such technologies is still at relatively early stages. We take advantage of recently updated hydrogen databases and publicly available hydrogen production R&D spending data to fill a gap in the literature on learning rates for electrolysis technologies, that, to date, have mainly focused on single-factor experience curves. In extending the single-learning curves model, we solve key issues with experience curves such as the omission of relevant cost drivers, spillovers, heterogeneity, multicollinearity, and endogeneity.

In line with the previous studies, we find that simple single-factor experience curves can underpin appropriate and robust models for electrolysis technologies at the global level, because an extension of these curves improves the explanatory power of technology cost reductions. Our findings shows that accumulated experience from PEM technology deployment potentially reduces the cost of alkaline technology. In addition, the learning rate for PEM is higher than for alkaline. However, in cross-country level analysis, we find that public R&DD spending and global experiences are the key drivers of electrolysis technology cost improvement. These findings show how electrolysis learning rates can be endogenously incorporated into energy system models as an input to examine electrolysis technology development. In addition, we find evidence for the role played by the global deployment of electrolysis technology in reducing country-level electrolysis technology cost. It is noteworthy that the effect of experience on electrolysis cost differs among electrolysis technologies. Also, most of the reduction in electrolysis technology costs cannot be attributed to country-specific projects. This suggests that policies should also pay more attention to global electrolysis innovation.

Given these findings, we recommend more country-level R&D spending to boost electrolysis technology development. Furthermore, the role of technology push measures remains critical for promoting and achieving cost improvements for electrolysis technologies. The absorptive capacity of a country should be improved in order to maximise the spillover of global learning. This improvement can be achieved through the establishment of global pipelines for the products of local electrolysis technology manufacturers and strengthening the global network ties of local manufacturers. Since reliable estimates of learning rates are necessary for developing trustworthy technology forecasting, we recommend that energy system modellers should consider R&DD spending and technology spillover as essential input parameters in anticipating the evolution of technological change for electrolysis.

Despite data availability considerations limiting our ability to estimate a simultaneous innovation-diffusion mode for electrolysis technology, and include all potential drivers, our electrolysis technology cost model provides a fundamental first step that can be updated as more data becomes available to support more detailed energy system modelling including an assessment of the impact of policy support on electrolyser cost reduction.

Appendix

Table A1

Global Alkaline Learning Curve

Wright regression model results									
	1	2	3	4	5	6	7	8	9
				Estimation method: OLS					
Constant	10.059***	9.777***	10.183***	9.615***	9.568***	9.585***	7.608***	9.513***	9.001***
	(0.251)	(0.257)	(0.252)	(0.407)	(0.342)	(0.402)	(0.046)	(0.413)	(0.297)
Capacity	-0.713***		-0.504***	-0.325**	-0.278**	-0.282*		-0.547***	
	(0.063)		(0.111)	(0.150)	(0.139)	(0.150)		(0.118)	
RDD		-0.391***	-0.146**	-0.150**	-0.071	-0.069			-0.239***
		(0.039)	(0.065)	(0.064)	(0.069)	(0.077)			(0.050)
Trend				-0.002*		0.0001	-0.007***	-0.002	-0.004***
				(0.001)		(0.002)	(0.0008)	(0.001)	(0.001)
PEM Spillover					-0.220**	-0.227*			
					(0.085)	(0.123)			
LBD	39.0%***		29.5%***	20.2%**	17.5%**	17.8%*		31.6%***	
LBR		23.7%***	9.6%**	9.9%**	4.8%	4.7%			15.3%***
Adj. R^2	0.55	0.485	0.567	0.575	0.589	0.585	0.470	0.557	0.560
N	106	106	106	106	106	106	106	106	106

Table A2

Global PEM Learning Curve

Wright regression model results									
	1	2	3	4	5	6	7	8	9
	Estimation method: OLS								
Constant	10.876*** (0.232)	12.966*** (0.454)	11.982*** (0.411)	11.592*** (0.454)	12.589*** (0.598)	12.055*** (0.684)	11.472*** (0.441)	10.851*** (0.442)	8.372*** (0.083)
Capacity	-0.911*** (0.063)		-0.634*** (0.106)	-0.251 (0.227)	-0.504*** (0.140)	-0.218 (0.230)		-0.901*** (0.159)	
RDD		-0.817*** (0.069)	-0.320*** (0.312)	-0.425*** (0.114)	-0.258** (0.110)	-0.368*** (0.130)	-0.521*** (0.073)		
Trend				-0.008* (0.004)		-0.007 (0.004)	-0.011*** (0.002)	-0.0003 (0.004)	-0.020*** (0.002)
ALK Spillover					-0.369 (0.265)	-0.248 (0.274)			
LBD	46.8%***		35.6%***	16.0%	29.5%***	14.0%		46.4%***	
LBR		43.2%***	19.9%***	25.5%***	16.4%**	22.5%***	30.3%***		
Adj. R^2	0.725	0.643	0.754	0.762	0.757	0.762	0.762	0.722	0.609
N	79	79	79	79	79	79	79	79	79

Table A3

Global Alkaline Learning Curve with inclusion of wind and solar technologies

Wright regression model results + wind & solar technology spillover				
	1	2	3	4
Constant	9.783*** (0.466)	11.516*** (1.126)	9.792*** (0.267)	11.136*** (0.488)
Capacity	-0.322 (0.210)	-0.281 (0.215)	-0.325* (0.168)	-0.334** (0.161)
RDD	0.004 (0.161)	0.071 (0.190)		
Solar Spillover	-0.097 (0.095)		-0.094**	
Wind spillover		-0.246 (0.202)		-0.175**
LBD	20.0%	17.7%	20.2%*	20.7%**
LBR	-0.3%	-5.0%		
Adj. R^2	0.567	0.569	0.571	0.572
N	106	106	106	106

Table A4

Global PEM Learning Curve with inclusion of wind and solar technologies

Wright regression model results + wind & solar technology spillover				
	1	2	3	4
	Estimation method: OLS			
Constant	11.842***	16.132***	11.986***	14.836***
	(0.400)	(1.658)	(0.341)	(0.996)
Capacity	-0.427***	-0.392***	-0.448***	-0.441***
	(0.130)	(0.139)	(0.126)	(0.129)
RDD	0.141	0.229		
	(0.203)	(0.234)		
Solar spillover	-0.265**		-0.203***	
	(0.103)		(0.049)	
Wind Spillover		-0.579**		-0.379***
		(0.224)		(0.093)
LBD	25.6%***	23.8%***	26.7%***	26.3%***
LBR	-10.3%	-17.2%		
Adj. R^2	0.771	0.771	0.773	0.771
N	79	79	79	79

Table A5

Panel system GMM results

Experience Curve: Panel System GMM regression model results								
	PEM				ALK			
	1	2	3	4	5	6	7	8
Capacity	-0.067***	-0.010	0.025		-0.041**	-0.023	-0.001	
	(0.015)	(0.010)	(0.024)		(0.016)	(0.017)	(0.660)	
RDD	-0.244***	0.055*	-0.148**	-0.059***	-0.267***	-0.177***	-0.040	-0.084***
	(0.035)	(0.030)	(0.068)	(0.013)	(0.028)	(0.051)	(0.061)	(0.010)
Trend		-0.091***					-0.046***	
		(0.006)					(0.013)	
Spillover			-0.016			0.025	0.005	
			(0.020)			(0.020)	(0.019)	
Global cap			-0.374***	-0.463***		-0.236***	-0.135***	-0.366***
			(0.056)	(0.021)		(0.041)	(0.047)	(0.020)
LBD	4.5%	0.7%	-1.7%		2.8%	1.6%	0.1%	
LBR	15.6%	-3.9%	9.7%	4.0%	16.9%	11.5%	2.7%	5.7%
J-statistic	5.61E-29	9.43E-28	70***	2.39E-27	1.70E-29	6.00E-29	5.59E-28	1.44E-28
N	165	165	74	384	105	60	60	388

Table A6

Experience curve studies for wind and solar technologies

Reference	Technology	LR [%]	Scope & Comments
A. Wind technology			
Revinova et al. (2023)	Wind	7.35 - 9.63	Component-based approach
Junginger et al. (2005)	Onshore wind	19	Global 1990-2001
Wiser et al. (2016)	Onshore wind	16	Global 2014-2030
Williams et al. (2017)	Onshore wind	9.8	Global/USA 1990-2015
Partridge (2013)	Wind	17.7	India
Trappey et al. (2013)	Onshore wind	-11.4	Taiwan 2000-2010
Steffen et al. (2020)	Onshore wind	11	Germany 2000-2017 Project-level
Tu et al. (2019)	Onshore wind	7.5	China 2006-2015 Project level
Schauf and Schwenen (2021)	Onshore wind	2-3	Seven European Countries
Isoard & Soria (2001)	Onshore wind	20	Europe 1981-1995
Kobos (2006)	Onshore wind	14.2	Global 1975-2000
Jamasb (2007)	Onshore wind	13.1/15.7	Global 1990-1998
Jamasb (2007)	Offshore wind	1.0/8.3	Global 1990-1998
Witajewski-Baltvilks et al. (2015)	Onshore wind	3.7	USA 1990-2012
Anderson et al. (2019)	Onshore wind	1.45	USA 2001-2015 Project level
Odam & de Vries (2020)	Onshore wind	2.1- 2.85	1981-2000 Germany, Denmark, Spain, UK
Qiu & Anadon (2012)	Onshore wind	4.2	China 2003-2007
Tang & Popp (2016)	Onshore wind	0.95	China 2002-2009
Schauf and Schwenen (2021)	Onshore wind	2-3	Seven European countries 1998-2018
Ek and Soderholm (2010)	Onshore wind	17	Five European countries 1986-2002
Soderholm and Klaaseen (2007)	Onshore wind	3.1	Europe
Klaassen et al. (2005)	Onshore wind	5.4	Plant-level
B. Solar technology			
Revinova et al. (2023)	Solar	14.28 - 14.44	
Wei et al. (2017)	Residential Solar PV	20 33	The US 2009-2011 Germany 2006-2011
Mauleon (2016)	Solar PV	Above 20	
Garzon Sampedro and Sanchez Gonzalez (2016)	Solar PV	7.13 0.16	Spain 2001-2008 Spain 2009-2012
Gan and Li (2015)	PV module	14.2	1988-2006
Jamasb (2007)	Solar thermal power	2.2/22.5	Global 1990-1998
Parente et al. (2002)	PV Modules	33	1981-2000
Schaeffer et al. (2004)	PV modules PV	10 20-25	Germany & the Netherlands Global

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