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Understanding and accounting for the effect of exchange rate fluctuations on global learning rates

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Abstract

Learning rates are a central concept in energy system models and integrated assessment models, as they allow researchers to project the future costs of new technologies and to optimise energy system costs. Here, we argue that exchange rate fluctuations are an important but thus far overlooked determinant of the learning rate variance observed in the literature. We explore how empirically observed global learning rates depend on where technologies are installed and which currency is used to calculate the learning rate. Using global data of large-scale PV (≥5 MW) plants, we show that the currency choice can result in learning rate differences of up to 16 percentage points. We then introduce an adjustment factor to correct for the effect of exchange rate and market focus fluctuations and discuss the implications of our findings for innovation scholars, energy modellers and decision-makers.

When new technologies mature, their costs and performance typically improve due to learning-by-doing and economies of scale in both the manufacturing and use of the technology[1,2]. The typical metric that determines the extent of these effects is the *learning rate*, which describes the relative cost reduction per doubling of the cumulative output[3].

Learning rates are a central concept in energy system models (ESMs) and integrated assessment models (IAMs), as they allow researchers to project the future costs of new technologies, including renewables[4,5]. These models have become standard tools not only in science but also in supporting policymakers in formulating effective and efficient strategies to address climate change – one of the most pressing challenges of our time[6-8]. Over the last two decades, a large amount of learning rate literature has emerged, examining and identifying learning rates for new technologies such as photovoltaics (PV)[9], concentrated solar power[10], wind power[11,12], battery storage[13] and conventional energy conversion[14]. Learning rate studies have become increasingly sophisticated, correcting for technology-exogenous parameters[15], using multi-variate approaches such as two-factor learning – which considers R&D spending as a cost reduction driver[15-18] – and differentiating between global and local learning[19,20].

Learning curve analyses have also been extended to investigate how other parameters develop as a function of cumulative deployment – for example to analyse the development of renewable energy financing costs[21] and energetic performance[22]. While our understanding of technological learning curves and their underlying processes has increased greatly, identified learning rates vary substantially between studies. For example, a meta-analysis by Rubin, et al. [1] found learning rates for PV modules of 10 to 47% (mean: 23%) and for wind power of –11 to +34% (mean: 14%), and note that the ranges are not explainable by systematic variation in key variables. However, learning rates vary across time and geographies as they are influenced by a range of factors: technology develops unevenly at different times, and technology development is influenced by (typically national) policy[23,24]. Learning rates may also change as the economic context develops, for example as wages increase or more or less hidden (industry) subsidies are introduced or abandoned[25]. These large ranges in observed learning rates are an especially grave problem for the modellers who *use* learning rates in their analyses. As IAMs and ESMs typically generate cost-minimised energy futures, the technology with the highest learning rate is likely to become dominant – and a difference of a few percentage points can lead to an entirely different power mix[26,27]. Hence, learning rate figures must be robust and measure as precisely and exclusively as possible what they are supposed to measure (technological learning); otherwise, models may produce 'misleading results for policy'[28-30].

Here, we argue that estimates of global learning rates, based on expansion in several countries and currency areas, are biased because they overlook the effect of currency exchange rate (fx) fluctuations. This effect is important as renewables deployment happens in multiple currency areas simultaneously and as the geographic focus shifts over time. We explore how empirically observed *global* learning rates depend on which currency is used to calculate the learning rate. Using global data of large-scale PV (≥5 MW) plants, we show that the currency choice can result in learning rate differences of up to 16 percentage points. We then introduce an adjustment factor to correct for the effect of exchange rate and market focus fluctuations and discuss the implications of our findings for innovation scholars, energy modellers and decision-makers.

Dynamics in PV markets and exchange rates

As renewables are deployed globally and manufactured in various countries, learning effects cross boundaries and currency areas. To estimate a global learning rate, all cost statements must be converted to one currency – the *base currency*. The common practice for doing this is to convert the average local costs into a base currency with the relevant exchange rate at the time of installation; create an average cost (typically unweighted, based on project counts[10,27,31-33]) of all projects during a time interval (often yearly); and then deflate the nominal into real average costs using a deflator for the base currency. Often, the *US Dollar* (USD) is chosen as base currency, especially in global learning rate analyses[17,34,35]. While this reflects the dominance of USD in global trade and economic analyses, global studies based on the *Euro* (EUR) exist as well[36,37]. For national studies, authors often use the local currency of the investigated region, such as the Chinese *Yuan*[38,39] (CNY), the Korean *Won*[40] or the Danish *Krona*[41]. However, the last decade has seen a shift in the geographical focus of renewables and particularly large-scale PV expansion from Europe (mainly Germany, Italy and Spain) to Asia (primarily China and Japan) and a simultaneous 12-fold increase in global capacity installation pace from 2006 to 2016[42]. This has three implications regarding the relationship between technological learning and fx fluctuations.

First, approximately 90% of the global PV deployment in the 2006-2016 period for which we have detailed project data happened in six currency areas (Figure 1a and b) and especially in EUR, CNY and Japanese *Yen* (JPY). Only 11% of the large (≥5 MW) PV capacity was installed in the US[42]. Second, by far most PV modules were manufactured in China or Taiwan[9]. This implies that while modules have been exported to other markets, often with a national currency or USD 'price sticker', changes of exchange rates to CNY and the New Taiwanese Dollar can affect the cost trajectory of PV systems in markets around the world (and depending on whether module manufacturers depends on imports of components or machinery, second-order fx effect may apply). Third, as the support schemes, such as feed-in tariffs or auctions, in all countries that saw large-scale PV expansion were denominated in their domestic currencies, almost all large PV projects have their revenues in a currency other than USD, most commonly CNY, JPY and EUR. If components were imported, fx fluctuations affected the revenue of PV projects, as the by far largest share of the global PV fleet was remunerated in domestic currencies. The three latter observations imply that almost the entire global PV fleet was exposed to exchange rate fluctuations concerning at least one non-USD currency, even if – which may be the case, especially with the rise of Asian module manufacturers post-2010 – parts of the globally traded components are invoiced in USD.

In the last decade, exchange rates among the six currencies relevant to PV fluctuated considerably (Figure 1c). For example, the USD appreciated strongly against the EUR, from 0.67 in 2008 to 0.95 in 2016, as did the CNY, by about 50% from late 2009 to early 2015[43-45]. Note that the CNY is not free-floating like most industrialised countries' currencies, but is managed as a part of the Chinese government's general economic policy, and many argue that it is kept artificially low to increase international competitiveness of Chinese export-oriented firms[46]. As PV modules (and important balance-of-system (BOS) components, such as inverters) are traded internationally, every estimate of a PV learning rate in all markets, national and global, includes such technology-unrelated fx developments. The USD, as a general trend, has appreciated against other currencies (except CNY) since the financial crisis of 2008, and therefore a global learning rate based on USD will be higher than the actual technological progress.

The mechanism behind this is simple: if, for instance, the CNY depreciates compared to the USD, projects realised in the CNY area become cheaper in USD terms. Global learning rates using USD as the base currency would then overestimate technological learning, as part of the observed 'improvement' is caused by the changing exchange rate. Here, we develop a method to correct the calculated learning rate for the (unwanted) impact of exchange rate fluctuations and make the aggregation across currency areas fx-independent.

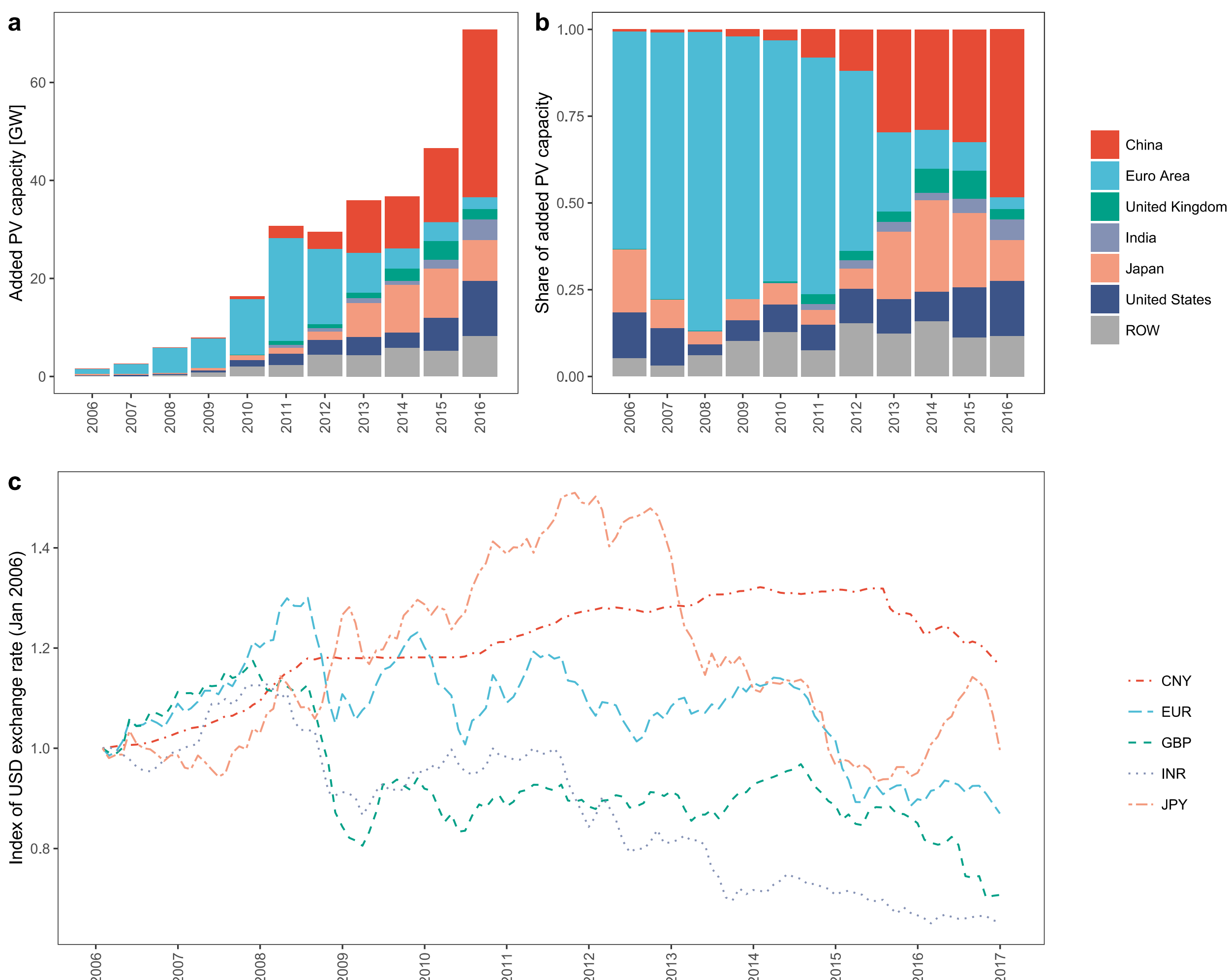

Figure 1: Global large PV deployment by country and exchange rates. Deployment of greater than 5 MW plants as (a) total global capacity, (b) shares of yearly installations and (c) development of the nominal exchange rates of the main markets for large PV 2006-2016, indexed in (CNY|EUR|GBP|INR|JPY)/USD, with January 2006=1; an increase indicates appreciation, a decrease indicates depreciation against the USD (b). Sources: IRENA[42] (a and b) and OFX[43] and OECD[44] (c).

A global PV learning rate and its exchange rate dependence

In this section, we estimate a global learning rate for large-scale PV (≥5 MW) with each of the six large currencies mentioned in Figure 1 as base currency. Our analysis is based on all projects for which the investment costs are available in the Bloomberg New Energy Finance (BNEF) database with commissioning date 2006-2016 (Table 1). This is the most comprehensive global renewable power project database available (see Method for data description and methodological details). We calculate the learning rates for the investment costs of projects, not just for modules, as this is the cost that needs to be remunerated by policy support or consumers. Furthermore, ESMs and IAMs use the learning rate for the full project cost, making this the most relevant scope.

Table 1. Summary of our subsets of the BNEF dataset. All lower rows include the filter criteria from the upper rows.

	Projects	**Share projects**	**Capacity (GW)**	**Share capacity**
Commissioned PV projects	14,250	100%	188.9	1.00
With capacity ≥5 MW	7573	53%	175.3	0.93
With financing date	7363	52%	173.2	0.92
With investment costs reported	2173	15%	62.2	0.33
Without outliers	2164	15%	62.1	0.33
Operated from 2006-2016	**1990**	**14%**	**57.0**	**0.30**

We estimate the learning rates with a global one-factor learning curve model based on average costs per year and cumulative deployment per year[12,47] Note that the majority – for large PV often 2/3-3/4 of the hard costs[48] – of components for large PV is globally traded goods, namely the modules and important parts of the BOS components (inverters and switchgear).We formulate the global learning curve as

$$\textbf{(1)} \qquad P_t^l = P_0^l \left(\frac{\chi_t}{\chi_0}\right)^{-a^l}$$

with P_t^l, P_0^l as market share-weighted (based on yearly capacity additions per currency area) average global cost (per MW) converted to base currency l in years t and 0, χ_t, χ_0 as the global cumulative deployment in years t and 0, and a as the learning-by-doing elasticity (which depends on the choice of base currency l)[12]. We weight by the capacity-based market share, and not by the project count as most other studies do, to better reflect the actual geographical distribution of capacity deployment – the independent variable of learning rate assessments – and use data from IRENA[42] for the global expansion and the national market shares (see Supplementary Note 1). The cost changes are described by the learning rate

$$\textbf{(2)} \qquad LR = 1 - 2^{-a^l}.$$

Depending on the base currency, the observed learning rate varies between 27 and 33% for the whole period (Figure 2; see Supplementary Note 2 for complete numerical results). As exchange rates often move in different directions, the fx effect may be larger in shorter time intervals. For example, the 2011-2016 learning rate based on CNY is 37%, whereas it is 28% in the EUR-based estimate and only 21% in the JPY-based estimate, corresponding to a maximum difference of 16 percentage points compared to a maximum difference of 6 percentage points for the longer 2006-2016 timespan. Hence, for longer time intervals, the differences between learning rates for different base currencies are smaller if exchange rate fluctuations level out over time (e.g. EUR-USD). However, systematic depreciations (e.g. INR-USD) or appreciations (e.g. CNY-USD) can persist over long periods (Figure 1a), biasing the estimated learning rates in a systemic way.

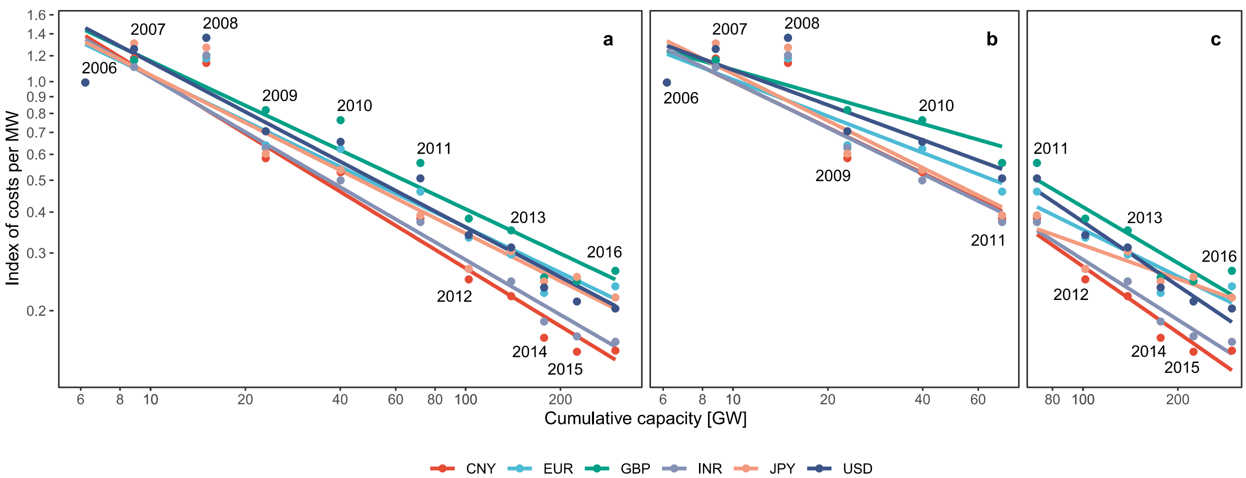

Figure 2: Global learning curves for large PV in different currencies. PV installations ≥5 MW. Results for a) the whole interval 2006-2016, and two subintervals b) 2006-2011 and c) 2011-2016. The lines show the uncorrected, market share-weighted learning curves in different base currencies. The underlying yearly average costs depicted by the coloured points are an index of the 2006 market share-weighted average costs for each currency (real cost, 2017 basis). For numerical results, R^2 values and confidence intervals, see Supplementary Note 2.

For each global learning rate estimate, the analyst must choose a base currency, and several different choices are defendable. For example, the choice may be based on the largest installed capacity (EUR area until 2012; China since 2013) or it may be based on USD as the default currency for global markets. The lack of a strongly compelling reason to choose one base currency over another is problematic in two respects. First, if the learning rate result depends on a choice for which several decisions are defendable, the estimate is not robust; however, given the importance of learning rates in IAMs and ESMs, robust estimates are critical – and a learning rate difference of up to 16% (Figure 2) is likely a dominant uncertainty in model runs. Second, the concept of learning refers to cost reductions through technological advances, but learning rates calculated using the method of simply converting costs into a base currency and aggregating them into a global average evidently hold a large non-technological component: exchange rate development. We thus need an estimation method that is independent of exchange rate fluctuations, i.e., a method that corrects for the confounding factor fx dynamics.

Exchange rate and market focus fluctuation corrections

To make the global learning rate independent of shifting geographic focus of deployment and of the fx effect in order to better reflect technological learning, we modify Eq. (1) and give the market share-weighted (based on nameplate capacity) average global costs $\widetilde{P_t^l}$ in a base currency (see the Method section for details). The new $\widetilde{P_t^l}$ in Eq. (4) differs from the approach used for P_t^l in Eq. (1) as we apply a correction factor for exchange rate changes between the years 0 and *t* (for details, see the Method section). Hence, the result is unaffected by the fx changes relative to the base currency. The correction factor α_t^l is defined as

$$\textbf{(3)} \qquad \boldsymbol{\alpha_t^l = \frac{\sum_i \delta_t^i w_0^{l/i} C_t^i}{\sum_i \delta_t^i w_t^{l/i} C_t^i}}$$

with δ_t^i as the share of deployment (capacity share of global total per currency area) with cost reported in currency *i* in year *t*, $w_0^{l/i}, w_t^{l/i}$ as the exchange rates between currency *i* and the base currency *l* in price notation, and C_t^i as the observed average cost in currency *i* in year *t*. The fx-corrected one-factor learning curve model is then

$$\textbf{(4)} \qquad \boldsymbol{\widetilde{P_t^l} = \alpha_t^l \cdot P_t^l = P_0^l \left(\frac{\chi_t}{\chi_o}\right)^{-b}}$$

with P_t^l, P_0^l as the market share-weighted average global cost converted to the base currency l in years t and 0, χ_t, χ_0 as the global cumulative deployment in years t and 0, and b as the currency-corrected learning-by-doing elasticity. The fx-corrected learning rate is then

$$\textbf{(5)} \qquad \boldsymbol{LR = 1 - 2^{-b}}.$$

Applying this correction factor has profound effects, especially by reducing the difference between estimates in different base currencies due to the elimination of the fx bias factor. The fx-corrected global learning rate for large-scale PV across the whole period 2006-2016 is 29% with USD as base currency (Figure 3). The corrected learning rate estimates in all base currencies (except the high-inflation INR, see Discussion) for the entire time interval are 28-31% (see Supplementary Note 2, esp. Supplementary Figure d-f), compared to 17-33% in the uncorrected estimates (Figure 2). The shorter time spans show a similar picture: for 2006-2011, all base currencies (except INR) are 20-24% (uncorrected 17-27%) and for 2011-2016, they are 34-36% (uncorrected 21-37%).

The fx-corrected estimate is unaffected by fx fluctuations and shifting deployment, and hence measures the technological learning more closely. However, the result is still not entirely independent of the base currency choice, as inflation is different in different currency regions: the JPY-based estimates are lower than the rest due to the lower (and sometimes negative) inflation in Japan. The much higher inflation in India is the reason for INR estimates being very different from the others, suggesting that high-inflation currencies are unsuited base currencies for learning rate estimates (see Discussion). This is the only impact of the base currency choice: in nominal values, the fx corrected learning rates are identical (see Discussion and Supplementary Notes 2 and 3). Eliminating the effects of fx fluctuations also reduces, without removing, the impact of the time interval selection: this still has an impact – as it should, since learning rates vary over time[23,24] (see Introduction) – but as the result is now fx-independent, the bias from shifting global markets in the calculation is lower.

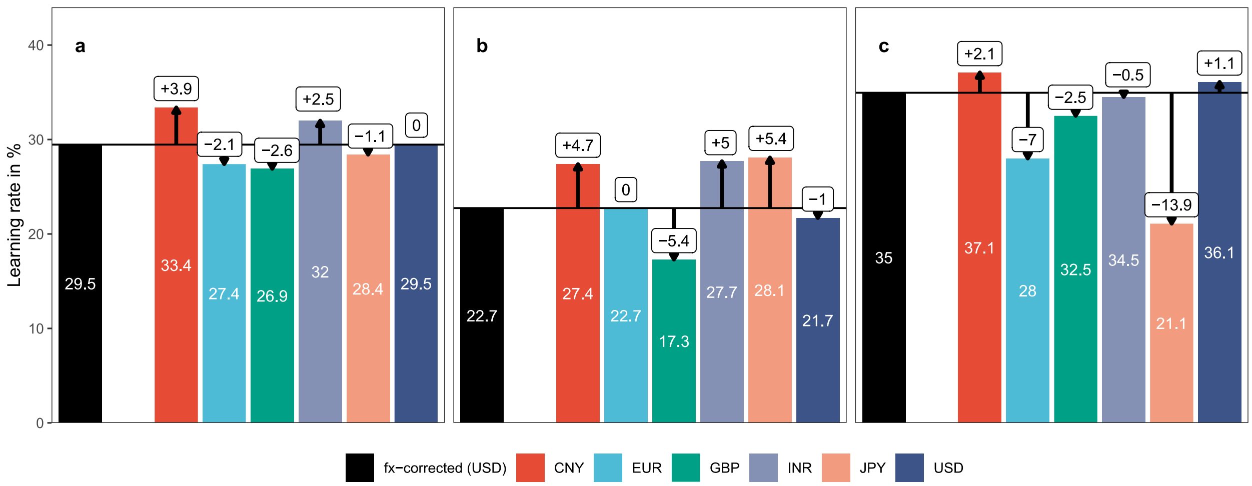

Figure 3: fx-corrected, market share-weighted learning rate. Fx-corrected results with USD as base currency (black bar) and uncorrected learning rates with different base currencies (all other bars) for large (⩾5 MW) PV for different time intervals: (a) 2006-2016, (b) 2006-2011 and (c) 2011-2016. For R^2 values, confidence intervals and all learning rate estimates in all base currencies, in real and nominal values, see Supplementary Note 2.

Discussion

In this article, we quantified the effect of exchange rate fluctuations on global learning rates using large-scale PV as an example and developed a method to correct for it. This method can be adapted for use in all types of learning rate estimation methods, including two-factor learning rates. The commonly used approach of converting project costs into a base currency, deflating the costs and then calculating a learning rate results in strongly diverging learning rates in the range of 17-37%, depending on the chosen base currency and time interval; within one time interval (2011-2016), we observe differences of up to 16 percentage points. To address this problem, we defined and used a correction factor to make the global learning rate estimate fx-independent, which provided a corrected learning rate for large-scale PV of 28-31% for the period of 2006-2016 (except in the high-inflation outlier INR, see below).

As expected, currencies which consistently appreciated (against the USD, or the whole set of currencies) see lower estimated learning rates when we use them as base currency (e.g. CNY, all periods; JPY 2006-2011), whereas the opposite happens for generally depreciating currencies (e.g. EUR, GBP, all periods). Although the identified learning rates are high across all base currencies and periods, currency fluctuations and shifts to new markets have masked or exaggerated the observed cost reduction due to learning for large-scale PV.

In this article, we discuss the impact of fx fluctuations for global learning rate estimates based on project data from different currency areas, and propose a method to correct for it. However, we acknowledge that the issue we investigate – fx fluctuations – may have effects beyond the one we assess.

First, fx changes may affect the import prices of components, which can also bias global learning rates – and even local learning rates within a single currency area, if projects use components imported from other currency areas. In this paper, we do not account for this "component fx effect", but expect that it would – for our specific case of PV ≥5 MW – be small, as the main country of module production has been roughly the same as the focus of deployment (first Euro zone, then moving to China): if large parts of module manufacturing and deployment happen in the same currency area (albeit different regions over time), there are few component imports. Nevertheless, the fx effect for imported components will likely gain importance in the future with Asian manufacturers becoming increasingly dominant and more countries deploying PV, and it could already be more relevant for other technologies than for PV: further research will be needed to explore this issue. Our method for addressing fx fluctuations in global aggregations – i.e. using the correction factor α_t^l to derive adjusted cost data points $\widetilde{P_t^l}$ to be used in learning curve regressions – can be extended to correct for imported components as well, with the factor α_t^l being applied only to the cost share relating to imports in a two-component learning curve. It however requires detailed data on the import shares from the different currency areas for each market and year, and of the cost share of each imported/domestic component – and such data is not consistently available for the global analysis as presented here. This is the reason why we did not do this analysis in the present paper.

Second, the fx effect "artificially" makes internationally traded technology appear cheaper or more expensive without an underlying technological change, biasing the learning rate estimate. This effect may also *affect* learning indirectly: if products are "artificially" more expensive due to persisting appreciation (e.g. CNY 2005-2015), companies cannot easily maintain the same price margin on exported goods[49] – which increases pressure on domestic companies to innovate and push their products down the respective learning curves. We have not assessed this potential source of learning here, but – as the Chinese PV industry outcompeted foreign companies based on cost very rapidly – expect it to be small for our case. In the long term, persisting appreciation or depreciation could also affect domestic costs independently from learning (e.g. monetary expansion relative to other currency areas causing higher wages). Assessing the impact of such economy- or industry-wide effects on global costs for specific goods such as PV modules is an area for further research.

Finally, it should be reiterated that fx effects are only one among several non-technological potential biases in global learning rate estimations, e.g. state support for manufacturing or keeping wage increases below productivity increase – issues often criticised in the context of China and PV manufacturing[25]. Hence, correcting for fx fluctuations will not necessarily lead to entirely unbiased learning rate estimates, but it is an important step to reduce the bias and measure the effect of technological advances more closely.

Implications for analysts and decision-makers

Our analysis of solar PV has a number of implications that can be generalised to all renewables – and other new high-tech components or technologies that are deployed across currency areas.

First, our findings cast doubt on previous learning rate estimates. Often, authors may not even be aware of the fx effect, as many datasets state costs already converted to USD. Although the fx effect *can* be strong (in our case up to 16 percentage points), for other technologies, currencies or time periods, it could be small and undramatic. The fx effect is often not critical for the learning rate studies themselves as their conclusions may be quite general (e.g. 'the observed trend of decreasing costs is strong'[10]) and not dramatically affected by such quantitative variations. Yet, it is a biasing factor that must be corrected – we provide a method for doing so here – and acknowledged in future global learning estimates not only for PV and other renewables but also for any technology for which such quantifications are needed and used. Again, we note that our method is not independent of the base currency; our estimates are still affected by inflation, which is different in different currencies, suggesting that it is important to base studies on hard currencies with low inflation, such as EUR or USD. If analysts do this, the impact of inflation is minor, although not zero (see Supplementary Notes 2 and 3).

We believe that correcting for exchange rate fluctuations and market shifts is particularly important for relatively *new* (globally traded) technologies, such as automotive- or grid-scale batteries. Because they do not yet have a long market history[13], their short track record may be particularly impacted by short-term fx and market shift dynamics, masking or overemphasising technological progress. This finding comes with a caveat: rapid currency appreciation could be an important short-term deployment driver, by directly increasing the profitability of investments under a national support scheme (and vice versa for depreciation). Further, governments can (and do) use currency depreciation to influence the international competitiveness of their domestic industry. Although it is unlikely that governments steer their exchange rate explicitly to push renewable energy technology exports, given the small size of this industry, an "artificially low" exchange rate will nevertheless have this effect. In such cases, it is not only the technological progress measured by the (corrected) learning rate that stimulates expansion, but also the fx movement, which is effectively (from the perspective of the analyst) an unpredictable ad hoc factor. For the learning rate metric itself, however, the fx effect remains an unwanted bias.

Second, and of great importance to energy system and policy research, the dependency of learning rates on technology-external factors such as fx variations cast serious doubt on the robustness of models and forecasts *using* empirically estimated but uncorrected learning rates as central input parameters. As small variations in IAM and ESM input data can lead to great differences in the results, inaccuracies such as those we identify for large-scale PV can tip the energy mix of a scenario in one direction or another and give potentially misleading advice. The assumption of a fixed learning rate decades into the future is already highly debateable and unaffected by our work; however, our method makes the identified historical learning rate figures more robust and closer connected to the technological learning they are supposed to measure by eliminating the impact of one technology-external factor, as indicated by the much smaller range of corrected estimates compared to the uncorrected.

Finally, the fx effect is important for decision-makers who rely on scientific input or advice regarding past and expected cost trends – for example, policymakers deciding whether to introduce a new or continue an existing renewable power support scheme. On the one hand, the cost trajectory in their domestic currency is important: this is the cost they will need to justify to electricity consumers, taxpayers and, ultimately, voters. On the other hand, exchange rate fluctuations are a factor that is typically unrelated to the technology in question and unrelated to the success or failure of policy action: a support scheme may have led to considerably higher or lower cost reductions than those revealed by analyses, with the true rate hidden behind exchange rate fluctuations. Basing new policies and reforms on fx-independent metrics of technology cost trajectories is a further step towards more evidence-based policy action, and the method we developed and applied here can be used to achieve this aim.

Method

Approach

If experience with a new technology accumulates not only within a region but also worldwide (e.g. through deployment in several markets), cost dynamics are best described through global learning curves. PV is an example of such a global commodity[48]. Estimating global learning curves from global cost data thereby requires the aggregation of information expressed in different currencies. Here, we describe the approach of converting all data into a base currency in two steps. The first step results in the fx-dependent learning rates as frequently used in the literature. We use market share-weighted (capacity-based) average yearly costs instead of the more common "unweighted", i.e. based on number of projects, aggregation used in the literature to better reflect actual market developments for non-exhaustive data sources (such as the BNEF project data that we and others use). The second step results in the fx-independent market share-weighted learning rates. We perform these steps for both nominal and real costs. In the last step, the learning rate is fx independent, but still not independent of the base currency choice, as we use real costs, and inflation differs between currency regions. The nominal corrected learning rates are identical in all base currencies (see Supplementary Note 2). We analyse the entire 2006-2016 period and two arbitrarily chosen subintervals (2006-2011, 2011-2016).

For the following calculations, let

- δ_t^i denote the share of capacity deployment (in %) with cost reported in currency *i* in year *t* (i.e. the amount of deployment per currency area relative to all global deployment),
- x_t^i denote the cumulative capacity deployed (in MW) with cost reported in currency *i* in year *t*,
- χ_t denote the global cumulative capacity deployed (in MW) in year *t*,
- C_t^i denote the average cost (per MW) in currency *i* in year *t* (i.e. only projects that were financed in currency *i*),
- P_t^l denote the market share-weighted average global cost (per MW) converted to base currency *l* in year *t*,
- $\widetilde{P_t^l}$ denote the fx-corrected, market share-weighted average global cost (per MW) converted to base currency *l* in year *t* and
- $w_t^{l/i}$ denote the exchange rate between currency *i* and the base currency *l* in year *t* in price notation (i.e. one needs to pay $w_t^{l/i}$ units of the base currency *l* to receive one unit of currency *i*).

Correction for data coverage

Here, we describe how we estimate the uncorrected, fx-dependent learning rate (resulting in Figure 2), using the common practice method of converting cost statements from local currency to a base currency, aggregating costs into yearly averages (we use a market share-weighted average instead of a project number-weighted one), and deflate the costs to real costs for a target year (here: 2017). We weight the average global costs by market shares (capacity-based) of each currency area, not by number of projects listed in the BNEF dataset - which strongly over-represents Chinese projects – to better reflect the actual deployment (see Supplementary Note 1 for a description of the project data focus). We use IRENA data[42] for the actual market shares. First, we aggregate the single project costs to yearly average costs C_t^i. The nominal market share-weighted, average global cost P_t^l is then calculated as

$$\textbf{(6)} \qquad \boldsymbol{P_t^l = \sum_i \delta_t^i w_t^{l/i} C_t^i}, \text{ with } \boldsymbol{\delta_t^i = \frac{x_t^i}{\sum_j x_t^j}} \text{ and } \boldsymbol{\sum_i \delta_t^i \equiv 1}.$$

The global one-factor learning curve is then described as

$$\textbf{(7)} \qquad \boldsymbol{P_t^l = P_0^l \left(\frac{\chi_t}{\chi_0}\right)^{-a^l}}.$$

If P_t^l is deflated (using the deflator of the base currency), we obtain real learning rates; otherwise, we obtain (somewhat unconventional) nominal learning rates. Using Eq. (6), this can be rewritten as

$$\textbf{(8)} \qquad \boldsymbol{\sum_i \delta_t^i w_t^{l/i} C_t^i = \sum_i \delta_0^i w_0^{l/i} C_0^i \left(\frac{\chi_t}{\chi_0}\right)^{-a^l}}.$$

Following Eq. (2) from the main text, we describe the market share-weighted, uncorrected global learning rate LR_a^l (see Figure 3) as

$$\textbf{(9)} \qquad \boldsymbol{LR_a^l = 1 - 2^{-a^l}}.$$

Correction for exchange rate fluctuations

For applications such as long-term ESMs or IAMs, the learning curve should describe technological improvements only, with exchange rate fluctuations (i.e. changes from $w_0^{l/i}$ to $w_t^{l/i}$) filtered out. To this end, in the second part of the paper, we present a corrected learning rate defined as (note: we repeat Eq. (4) and (5) from the main text for clarity)

$$\textbf{(5)} \qquad \boldsymbol{LR = 1 - 2^{-b}},$$

which is estimated from a learning curve

$$\textbf{(4)} \qquad \boldsymbol{\widetilde{P_t^l} = P_0^l \left(\frac{\chi_t}{\chi_0}\right)^{-b}},$$

where $\widetilde{P_t^l}$ are global average prices converted to currency *l* in year *t*; we correct for exchange rate changes between year 0 and year *t* by using w_0 instead of w_t and hence adjust Eq. (6) to

$$\textbf{(10)} \qquad \boldsymbol{\widetilde{P_t^l} = \sum_i \delta_t^i w_0^{l/i} C_t^i}.$$

If $\widetilde{P_t^l}$ is deflated (using the deflator of the base currency), we obtain real learning rates; otherwise, we obtain nominal learning rates.

We define the adjustment factor α_t^l such that

(11) $\alpha_t^l \cdot \boldsymbol{P_t^l} = \widetilde{\boldsymbol{P_t^l}}$

and use Eq. (6) and (10) to arrive at a formulation for the adjustment factor that uses the average costs in each currency, the market shares of different currency areas, and exchange rates:

(12) $\alpha_t^l = \frac{\widetilde{P_t^l}}{P_t^l} = \frac{\sum_i \delta_t^i w_0^{l/i} C_t^i}{\sum_i \delta_t^i w_t^{l/i} C_t^i}.$

For each base currency and year, we calculate the adjustment factor α_t^l, transform the P_t^l to $\widetilde{P_t^l}$ and estimate the learning rates provided in the second part of the paper (see Figure 3 and Supplementary Note 2) using

(13) $\boldsymbol{LR_b^l = 1 - 2^{-b^l}}.$

While Figure 3 shows the corrected global learning rate estimated using the base currency USD, the choice of the base currency still matters, although much less than using the conventional method (see Supplementary Note 2). The learning rate is identical in nominal terms in all base currencies, underlining the appropriateness of the adjustment factor α_t^l based on the empirical data, whereas the learning rates based on real costs are generally similar (for low-inflation currencies) but not identical (see Supplementary Notes 2 and 3).

In addition, a brief discussion further underlines the appropriateness of α_t^l.

Proposition 1: If $w_t^{l/i} = w_0^{l/i}$ for all *i* (i.e. the exchange rates do not change), then $\alpha_t^l = 1$, and $\widetilde{P_t^l} = P_t^l$. The same holds true if some $w_t^{l/i} \neq w_0^{l/i}$, but only for *t* and *I* where $\delta_t^i = 0$ (i.e. the exchange rate changes only for years in which no capacity is added in the respective currency areas).

Proof: In Eq. (12), by replacing $w_t^{l/i}$ by $w_0^{l/i}$ for all *t*, and *i* where $w_t^{l/i} = w_0^{l/i}$ holds, the proposition follows □.

Proposition 2: For any currency *i* with $\delta_t^i \neq 0$, if $w_t^{l/i} < w_0^{l/i}$ (i.e. the base currency appreciates versus currency *i*) while $w_t^{l/j} = w_0^{l/j}$ for all other currencies *j*, then (i) $\alpha_t^l > 1$, and (ii) $\widetilde{P_t^l} > P_t^l$ (i.e. $\widetilde{P_t^l}$ is corrected for the fact that some observed cost reductions down to P_t^l stem from improved foreign exchange rates only). The inverse is the case for $w_t^{l/i} > w_0^{l/i}$.

Proof: Let $D_t = \sum_i \delta_t^j w_t^{l/j} C_t^j$ where *j* denotes all currencies other than *I*, and let $E_{t=} \delta_t^i C_t^i$. Then, Eq. (12) can be rewritten as

$$\alpha_t^l = \frac{D_0 + E_t w_0^{l/i}}{D_t + E_t w_t^{l/i}} = \frac{D_0 + E_t w_0^{l/i}}{D_0 + E_t w_t^{l/i}},$$

and statement (i) follows. Statement (ii) follows from Eq. (11) □.

Regression analysis

We use the ordinary least squares method to fit a log-log linear regression function to the (nominal and real) yearly average costs to estimate all learning rates. We rearrange the single-factor learning curve model in Eq. (1) to infer the log-log regression model as defined in Lindman and Söderholm [12] where

$$\textbf{(14)} \quad \ln\left(P_t^l\right) = \beta_0 + \beta_1 \cdot \ln\left(\frac{\chi_t}{\chi_0}\right) \mid \beta_0 = \ln\left(p_0^l\right); \beta_1 = -a^l$$

with β_0, β_1 as linear regression estimates. The same applies for $\widetilde{P_t^l}$. We then derive the learning rates from β_1 using:

$$\textbf{(15)} \quad LR = 1 - 2 \cdot \beta_1.$$

Data sources

We rely on three different data types to estimate the learning rates: (1) PV project data from the Bloomberg New Energy Finance (BNEF) renewable energy database[50] describing project characteristics and individual project costs; (2) capacity data from the IRENA renewable energy database describing the total global PV (≥5 MW) expansion and market shares per country[42]; (3) historical exchange rates from OFX [43] and OECD.Stat [44] to convert currencies to the various base currencies, as well as price index (CPI) data from OECD.Stat [51] to convert nominal to real values. For each year, we use only one exchange rate and price index, namely the yearly average.

We use the BNEF database for project cost input, as it gives investment costs for individual installations and projects in the original currencies and is the most comprehensive project database available. Our study is based on a subset of 1990 PV projects that were commissioned between 2006 and 2016 and are reported in one of the six currencies in which most PV expansion, by far, happened (see Figure 1). We only consider projects with capacities ≥5 MW because these projects use a high share of globally traded components[9,48]. **Error! Reference source not found.** summarises how we filtered the database (i.e. how many projects and what capacity remain for each filter criterion). The outliers are projects that we deemed have implausible costs that deviate very strongly (by a factor 10 or more) from the average trend. Very likely, these outliers have been entered incorrectly in the database.

For the global PV expansion and the national market shares, we use IRENA data[42], as it is more complete and describes the actual market development more accurately than BNEF, which overemphasises the Chinese market (see Supplementary Note 1). As IRENA reports market development per country and our learning rate calculation is based on currencies rather than countries, we assume that all projects were paid and remunerated in the main currencies of the corresponding countries. This is very likely to be true in most countries, and the support schemes in the six currency areas we investigated here were denominated in the domestic currency.

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Author Contributions

JL designed the study with the support of all the authors and drafted the article, MM carried out the quantitative analyses and produced the figures, BS designed the correction factor, and all authors contributed to the analysis and the final article.

Data Availability Statement

The data that support the findings of this study are available from Bloomberg New Energy Finance (BNEF) but restrictions apply to the availability of these data, which were used under license for the current study, and so are not publicly available. Data are however available from the authors upon reasonable request and with permission of BNEF.

Code Availability

The source code (in R) and supporting documents are available at Zenodo (10.5281/zenodo.3553796) and can be freely used and manipulated by all users, without restriction, under the MIT licence.

Competing Interests Statement

The authors declare no financial or non-financial competing interests.

References

1 Rubin, E., Azevedo, I., Jaramillo, P. & Yeh, S. A review of learning rates for electricity supply technologies. *Energy Policy* **86**, 198-218 (2015).

2 Samadi, S. The experience curve theory and its application in the field of electricity generation technologies - a literature review. *Renewable and Sustainable Energy Reviews* **82**, 2346-2364 (2018).

3 Wright, T. P. Factors affecting the cost of airplanes. *Journal of the aeronautical sciences* **3**, 122-128 (1936).

4 Gallagher, K., Grübler, A., Kuhl, L., Nemet, G. & Wilson, C. The energy technology innovation system. *Annual Review of Environment and Resources* **37**, 137-162 (2012).

5 Grübler, A., Nakicenovic, N. & Victor, D. Dynamics of energy technologies and global change. *Energy Policy* **27**, 247-280 (1999).

6 Ellenbeck, S. & Lilliestam, J. How modelers construct energy costs: discursive elements in energy system and integrated assessment models. *Energy Research & Social Science* **47**, 69-77, doi:https://doi.org/10.1016/j.erss.2018.08.021 (2019).

7 IPCC. *Special Report on Global warming of 1.5°C (SR15)*. (Intergovernmental Panel on Climate Change, 2018).

8 IPCC. *Special report on renewable energy sources and climate change mitigation*. (Cambridge University Press, Cambridge, 2011).

9 Fraunhofer ISE. *Photovoltaics report, update 10 August 2018*. (Fraunhofer ISE, Freiburg, 2018).

10 Lilliestam, J., Labordena, M., Patt, A. & Pfenninger, S. Empirically observed learning rates for concentrating solar power and their responses to regime change. *Nature Energy* **2**, 17094, doi:http://dx.doi.org/10.1038/nenergy.2017.94 (2017).

11 Hayashi, D., Huenteler, J. & Lewis, J. Gone with the wind: a learning curve analysis of China's wind power industry. *Energy Policy* **120**, 38-51 (2018).

12 Lindman, Å. & Söderholm, P. Wind power learning rates: a conceptual review and meta-analysis. *Energy Economics* **34**, 754-761 (2012).

13 Schmidt, O., Hawkes, A., Gambhir, A. & Staffell, I. The future cost of electrical energy storage based on experience rates. *Nature Energy* **2**, 17110 (2017).

14 Weiss, M., Zerfass, A. & Helmers, E. Fully electric and plug-in hybrid cars - An analysis of learning rates, user costs, and costs for mitigating CO2 and air pollutant emissions. *Journal of Cleaner Production* **212**, 1478-1489 (2019).

15 Söderholm, P. & Sundqvist, T. Empirical challenges in the use of learning curves for assessing the economic prospects of renewable energy technologies. *Renewable Energy* **32**, 2559-2578 (2007).

16 Klaasen, G., Miketa, A., Larsen, K. & Sundqvist, T. The impact of R&D on innovation for wind energy in Denmark, Germany and the United Kingdom. *Ecological Economics* **54**, 227-240 (2005).

17 Jamasb, T. Technical change theory and learning curves: patterns of progress in electricity generation technologies. *The Energy Journal* **28**, 51-71 (2007).

18 Kittner, N., Lill, F. & Kammen, D. Energy storage deployment and innovation for the clean energy transition. *Nature Energy* **2**, 17125 (2017).

19 Huenteler, J., Niebuhr, C. & Schmidt, T. The effect of local and global learning on the cost of renewable energy in developing countries. *Journal of Cleaner Production* **128**, 6-21 (2016).

20 Steffen, B., Matsuo, T., Steinemann, D. & Schmidt, T. Opening new markets for clean energy: the role of project developmers in the global diffusion of renewable energy technologies. *Business and Politics* **20**, 553-587 (2018).

21 Egli, F., Steffen, B. & Schmidt, T. A dynamic analysis of financing conditions for renewable energy technologies. *Nature Energy* **3**, 1084-1092, doi:https://doi.org/10.1038/s41560-018-0277-y (2018).

22 Steffen, B., Hirschier, D. & Schmidt, T. Historical and projected improvements in net energy performance of power generation technologies. *Energy & Environmental Science* **11**, 3254-3530 (2018).

23 van Buskirk, R., Kantner, C., Gerke, B. & Chu, S. A retrospective investigation of energy efficiency standards: policies may have accelerated long term declines in appliance costs. *Environmental Research Letters* **9**, 114010 (2014).

24 Wei, M., Smith, S. & Sohn, M. Non-constant learning rates in retrospective experience curve analyses and their correlation to deployment programs. *Energy Policy* **107**, 356-369 (2017).

25 Gang, C. China's Solar PV Manufacturing and Subsidies from the Perspective of State Capitalism. *The Copenhagen Journal of Asian Studies* **33**, 90-106 (2015).

26 Creutzig, F. *et al.* The underestimated potential of solar energy to mitigate climate change. *Nature Energy* **2**, 17140 (2017).

27 van Sark, W., Alsema, E., Junginger, M., de Moor, H. & Schaeffer, G. J. Accuracy of progress ratios determined from experience curves: the case of crystalline silicon photovoltaic module technology development. *Progress in Photovoltaics* **16** (2008).

28 Nordhaus, W. The perils of the learning model for modeling endogenous technological change. *The Energy Journal* **35**, 1-13 (2014).

29 Pindyck, R. The use and misuse of models for climate policy. *Review of Environmental Economics and Policy* **11**, 100-114 (2017).

30 van Sark, W. Introducing errors in progress ratios determined from experience curves. *Technological Forecasting & Social Change* **75**, 405-415 (2008).

31 Gan, P. Y. & Li, Z. Quantitative study on long term global solar photovoltaic market. *Renewable and Sustainable Energy Reviews* **46**, 88-99 (2015).

32 Yu, C., van Sark, W. & Alsema, E. Unraveling the photovoltaic technology learning curve by incorporation of input price changes and scale effects. *Renewable and Sustainable Energy Reviews* **15**, 324-337 (2011).

33 Nemet, G. Interrim monitoring of cost dynamics for publicly supported energy technologies. *Energy Policy* **37**, 825-835 (2009).

34 IRENA. *Renewable power generation costs in 2017*. (International Renewable Energy Agency, Abu Dhabi, 2018).

35 Mauleón, I. & Hamoudi, H. Photovoltaic and wind cost decrease estimation: implications for investment analysis. *Energy* **137**, 1054-1065 (2017).

36 Junginger, M., Faaij, A. & Turkenburg, W. Global experience curves for wind farms. *Energy Policy* **33**, 133-150 (2005).

37 Fraunhofer ISE. *Current and future cost of photovoltaics*. (Agora Energiewende, Berlin, 2015).

38 Zou, H. *et al.* China's future energy mix and emissions reduction potential: a scenario analysis incorporating technological learning curves. *Journal of Cleaner Production* **112**, 1475-1485 (2016).

39 Lin, B. & He, J. Learning curves for harnessing biomass power - what could explain the reduction of its cost during the expansion in China? *Renewable Energy* **99**, 280-288 (2016).

40 Hong, S., Chung, Y. & Woo, C. Scenario analysis for estimating the learning rate of photovoltaic power generation based on learning curve theory in South Korea. *Energy* **79** (2015).

41 Drud Hansen, J., Jensen, C. & Strøjer Madsen, E. The establishment of the Danish windmill industry - was it worthwhile? *Review of World Economics* **139**, 324-347 (2003).

42 IRENA. *Renewable capacity statistics 2018*. (International Renewable Energy Agency (IRENA), Abu Dhabi, 2018).

43 OFX. *Monthly average rates*, <https://www.ofx.com/en-au/forex-news/historical-exchange-rates/monthly-average-rates/> (2019).

44 OECD.Stat. *Monthly monetary and financial statistics: Exchange rates (USD monthly averages)*, <https://stats.oecd.org/index.aspx?queryid=169#> (2018).

45 Reuters. *Currencies*, <https://uk.reuters.com/business/currencies> (2019).

46 Schnabl, G. China's overinvestment and international trade conflicts. *China & World Economy*, doi:https://doi.org/10.1111/cwe.12293 (2019).

47 Junginger, M., van Sark, W. & Faaij, A. *Technological learning in the energy sector: lessons for policy, industry and science*. (Edward Elgar, Cheltenham, 2010).

48 Fu, R., Feldman, D., Margolis, R., Woodhouse, M. & Ardani, K. *U.S. Solar Photovoltaic System Cost Benchmark: Q1 2017*. (National Renewable Energy Laboratory (NREL), Golden, 2017).

49 Marston, R. Pricing to market in Japanese manufacturing. *Journal of International Economics* **29**, 217-236 (1990).

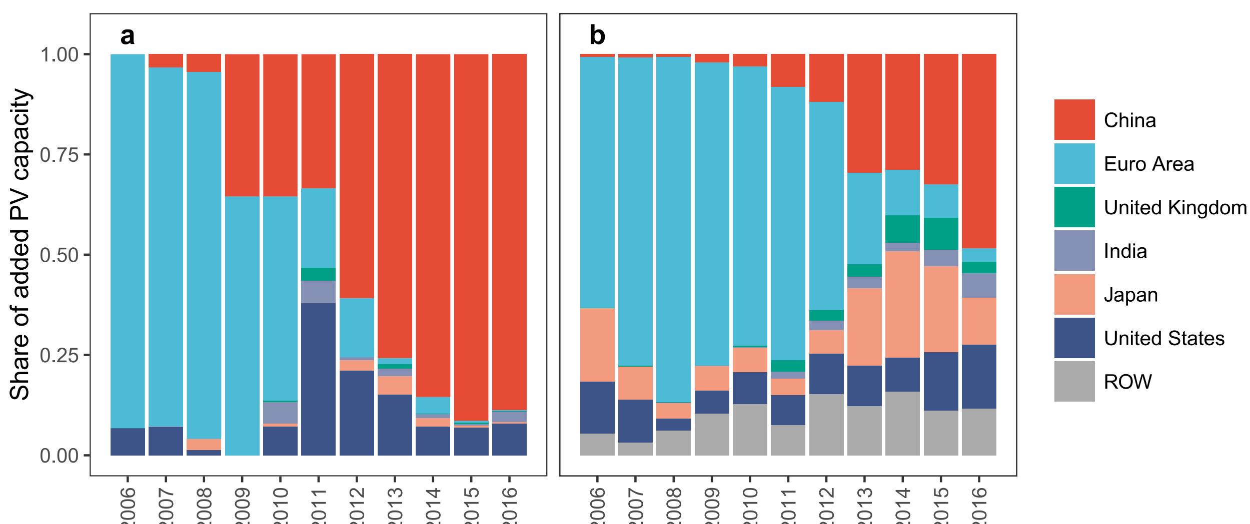
50 BNEF. *Bloomberg New Energy Finance database: renewable energy projects. Retreived in September 2017*. (Bloomberg New Energy Finance (BNEF), London, 2017).

51 OECD.Stat. *Monthly monetary and financial statistics: Relative consumer price indices*, <https://stats.oecd.org/index.aspx?queryid=168> (2018).

Supplementary Information

Supplementary Note 1: Overemphasis of Chinese projects in BNEF project data

In this paper, we presented how to improve learning rate calculation and make it independent of exchange rate fluctuations. For this, we rely on global project data from Bloomberg New Energy Finance (BNEF). As the BNEF data, like all project datasets, has imperfect coverage, the data does not perfectly reflect the actual global expansion of large (≥5 MW) PV deployment. The comparison between the BNEF project data we use (Supplementary Figure 1a) and the most comprehensive description of the global PV deployment per country from IRENA (Supplementary Figure 1b) shows that BNEF strongly overemphasises the Chinese PV deployment: for example, almost 90% of projects in BNEF for 2016 were Chinese compared to just below 50% in actual deployment as described by IRENA. BNEF also consistently underrepresents the Japanese PV deployment, whereas it overrepresents the US deployment share in the years around 2012. As BNEF does not claim to be a complete dataset, we do not criticise it for its incompleteness; nevertheless, it is clear that a learning rate based directly on BNEF data, with the common method of “unweighted” (i.e. based on number of projects) cost averages will be biased and overly based on developments in the Chinese deployment market. To avoid this problem, we base our estimates on yearly market share-weighted (capacity share deployed per currency area, relative to global deployment) costs. This effectively gives the single Chinese projects with costs in BNEF less weight and projects in most other (underrepresented) currency areas more weight in our learning rate estimate.



Supplementary Figure 1: Comparison of global large (⩾5 MW) PV expansion by country as shares of yearly installations 2006-2016. Number of projects of BNEF with costs = 1990 (IRENA is not project-based). Sources: BNEF[50] and IRENA[42].

Supplementary Note 2: Numerical results (nominal and real)

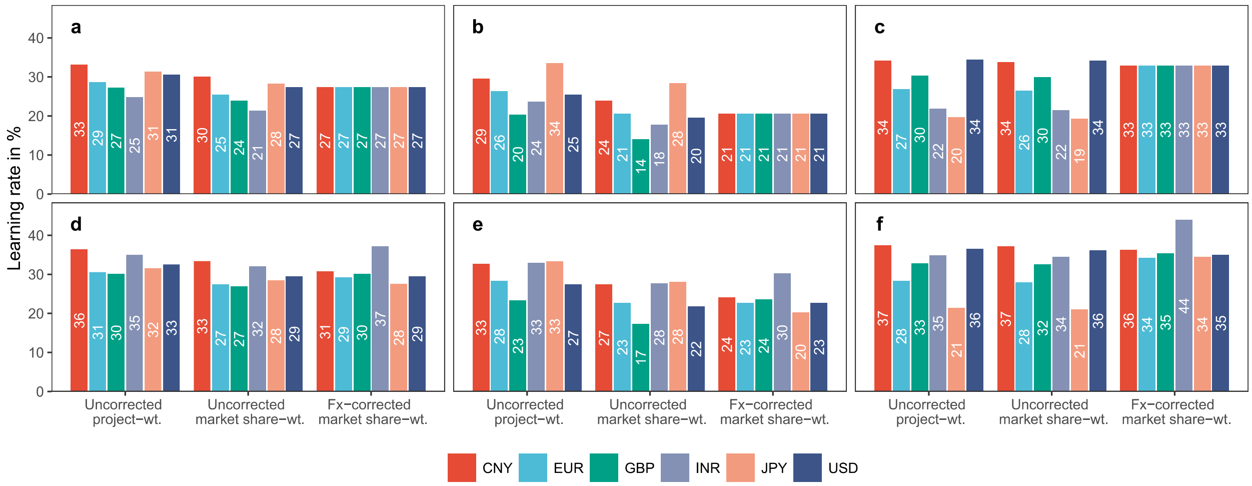
Here, we present the numerical results, expressed in real terms (used in the Figures in the main article) and in nominal terms (emphasising the impact of inflation for our fx-corrected estimates), as well as the confidence intervals and R^2s of the learning rate estimates (Supplementary Table 1 and Supplementary Table 2). For an easier overview and comparison, we also present all results, nominal and real, for the uncorrected and fx-corrected estimates depicted in other format in the Figures in the main article in Supplementary Figure 2.

Supplementary Table 1: Numerical results including estimate, 95% confidence interval and R^2 values for the uncorrected market share-weighted leaning rates. Global learning rates for PV (⩾5 MW) 2006-2016 for three different time intervals and different base currencies, both in nominal and real 2017 values, using project-specific costs for all PV projects (⩾5 MW) with an investment cost statement in BNEF [50] and global deployment figures from IRENA [42].

	Fx-dependent (uncorrected), market share-weighted learning rates								
	10-year interval (2006-2016), N=11			5-year interval (2006-2011), N=6			5-year interval (2011-2016), N=6		
Base currency	Estimate	CI 95%	R^2	Estimate	CI 95%	R^2	Estimate	CI 95%	R^2
nominal									
CNY	30.09	[24.94;34.89]	0.94	23.93	[5.33;38.88]	0.75	33.83	[19.78;45.41]	0.9
EUR	25.41	[20.57;29.95]	0.93	20.58	[3.56;34.61]	0.73	26.45	[11.06;39.17]	0.83
GBP	23.91	[17.73;29.63]	0.87	14.09	[-4.95;29.67]	0.53	29.92	[11.98;44.2]	0.82
INR	21.36	[16.53;25.91]	0.9	17.7	[-0.91;32.87]	0.64	21.51	[11.16;30.66]	0.88
JPY	28.22	[22.58;33.45]	0.92	28.35	[7.83;44.31]	0.77	19.23	[3.35;32.5]	0.73
USD	27.33	[21.52;32.71]	0.91	19.53	[-1.93;36.48]	0.62	34.13	[23.6;43.2]	0.94
real									
CNY	33.41	[28.7;37.81]	0.95	27.36	[11;40.71]	0.83	37.14	[23.66;48.24]	0.92
EUR	27.37	[22.71;31.76]	0.94	22.66	[6.66;35.92]	0.78	27.96	[11.93;41.08]	0.84
GBP	26.87	[20.9;32.39]	0.9	17.32	[-0.76;32.15]	0.64	32.48	[14.49;46.69]	0.84
INR	32.03	[27.55;36.24]	0.95	27.66	[10.57;41.49]	0.82	34.46	[25.12;42.64]	0.95
JPY	28.44	[23.01;33.49]	0.92	28.11	[8;43.82]	0.78	21.05	[5.79;33.83]	0.78
USD	29.46	[23.95;34.58]	0.92	21.74	[1.87;37.59]	0.69	36.15	[25.58;45.23]	0.94

Supplementary Table 2: Numerical results including estimate, 95% confidence interval and R^2 values for the fx-corrected market share-weighted leaning rates. Global learning rates for PV (⩾ 5 MW) 2006-2016 for three different time intervals and different base currencies, both in nominal and real 2017 values, using project-specific costs for all PV projects (⩾5 MW) with an investment cost statement in BNEF [50] and global deployment figures from IRENA [42].

	Fx-corrected market share-weighted learning rates								
	10-year interval (2006-2016) , N=11			5-year interval (2006-2011), N=6			5-year interval (2011-2016), N=6		
Base currency	Estimate	CI 95%	R^2	Estimate	CI 95%	R^2	Estimate	CI 95%	R^2
nominal									
CNY	27.33	[22.42;31.93]	0.93	20.56	[3.36;34.7]	0.73	32.89	[21.91;42.32]	0.93
EUR	27.33	[22.42;31.93]	0.93	20.56	[3.36;34.7]	0.73	32.89	[21.91;42.32]	0.93
GBP	27.33	[22.42;31.93]	0.93	20.56	[3.36;34.7]	0.73	32.89	[21.91;42.32]	0.93
INR	27.33	[22.42;31.93]	0.93	20.56	[3.36;34.7]	0.73	32.89	[21.91;42.32]	0.93
JPY	27.33	[22.42;31.93]	0.93	20.56	[3.36;34.7]	0.73	32.89	[21.91;42.32]	0.93
USD	27.33	[22.42;31.93]	0.93	20.56	[3.36;34.7]	0.73	32.89	[21.91;42.32]	0.93
real									
CNY	30.78	[26.28;35]	0.95	24.14	[9.13;36.67]	0.82	36.25	[25.65;45.34]	0.94
EUR	29.25	[24.54;33.66]	0.94	22.64	[6.48;36.01]	0.78	34.27	[22.64;44.16]	0.93
GBP	30.15	[25.43;34.58]	0.94	23.55	[7.21;37.01]	0.79	35.34	[24.05;44.96]	0.93
INR	37.19	[32.54;41.52]	0.96	30.18	[14.4;43.05]	0.86	43.96	[33.78;52.57]	0.96
JPY	27.55	[22.6;32.19]	0.93	20.29	[3.55;34.14]	0.73	34.4	[23.56;43.69]	0.94
USD	29.46	[24.79;33.84]	0.94	22.74	[6.92;35.88]	0.79	34.95	[23.81;44.47]	0.93



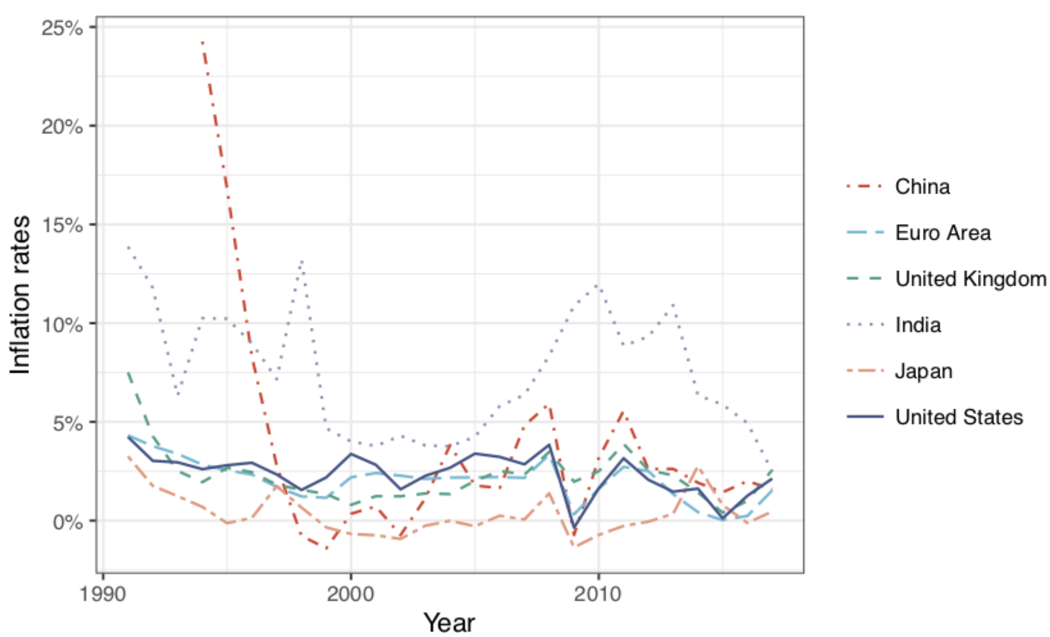
Supplementary Figure 2: Global learning rates for large (⩾5 MW) PV using the fx-dependent (uncorrected) fx-independent (corrected) method for different base currencies and 3 time intervals 2006-2016 (a, b, c in nominal values; d, e, f in real values). All values are based on market-share weighted average costs. Displayed numbers correspond to those in Supplementary Table 1 and Supplementary Table 2.

Supplementary Note 3: Inflation and choosing the base currency

The method we develop and apply in the main paper removes the impact of fx fluctuations. It does not lead to an entirely currency-independent learning rate, as we must still choose a base currency – and each currency has a different inflation rate (Supplementary Figure 3). In nominal terms, all fx-corrected learning rates are identical (see Supplementary Note 2).

Some countries, especially developing countries, have high inflation, leading to decreasing purchasing power of their currency. Economically stronger regions often have lower inflation rates. Among the currencies we analyse here, all but the INR have generally low inflation, especially in the period after 2000. Hence, a learning rate estimate based on INR will have a strong component of inflation in it, also when applying our fx correction factor, and this will in most cases be an undesired bias; consequently, whereas we report INR-based corrected learning rates, we do not draw any conclusions based on them.

The two currencies used for the by far largest part of the learning rate literature – USD and EUR – have very similar inflation rates that follow each other closely, over the entire 27-year time span displayed in Supplementary Figure 3. Hence, with our method the difference between USD- and EUR-based learning rate studies will be minor. For learning rate assessments, therefore, we recommend that analysts use our fx correction method and use either USD or EUR as base currencies, to minimise the dependency of the results on the base currency choice.



Supplementary Figure 3: Inflation rates for the investigated six currencies, 1990-2017. Source: OECD.Stat [51].