**Title**
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**Journal**
Nature Energy, 2(9)

**ISSN**
2058-7546

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**Publication Date**
2017

**DOI**
10.1038/nenergy.2017.125

Peer reviewed

nature energy

ARTICLES

PUBLISHED: 31 JULY 2017 | VOLUME: 2 | ARTICLE NUMBER: 17125

# Energy storage deployment and innovation for the clean energy transition

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**The clean energy transition requires a co-evolution of innovation, investment, and deployment strategies for emerging energy storage technologies. A deeply decarbonized energy system research platform needs materials science advances in battery technology to overcome the intermittency challenges of wind and solar electricity. Simultaneously, policies designed to build market growth and innovation in battery storage may complement cost reductions across a suite of clean energy technologies. Further integration of R&D and deployment of new storage technologies paves a clear route toward cost-effective low-carbon electricity. Here we analyse deployment and innovation using a two-factor model that integrates the value of investment in materials innovation and technology deployment over time from an empirical dataset covering battery storage technology. Complementary advances in battery storage are of utmost importance to decarbonization alongside improvements in renewable electricity sources. We find and chart a viable path to dispatchable US\$1 $W^{-1}$ solar with US\$100 $kWh^{-1}$ battery storage that enables combinations of solar, wind, and storage to compete directly with fossil-based electricity options.**

In the face of the Paris climate agreement[1], a combined transition to clean energy and acceleration of decarbonization goals will require the refocusing of US and international research and deployment schemes to promote energy R&D[2–4]. Dramatic cost declines in solar and wind technologies, and now energy storage, open the door to a reconceptualization of the roles of research and deployment of electricity production, transmission, and consumption that enable a clean energy transition[5,6]. While basic research remains a vital element to address a clean energy transition, increasingly an interdisciplinary approach is needed. Deeper integration with policies that build market growth[7] and cutting-edge business models will enable far faster uptake of critical research programme outputs.

The majority of technological learning studies to date attribute deployment and innovation as isolated policies to expand and plan for future cost reductions[8–10]. However, we also know there are synergies between deployment and innovation where we can capitalize and strategically target public spending to benefit society[11]. This evolution has been demonstrated for clean energy technologies by analysing s-curve trajectories and identifying missed opportunities for increased investment in wind and geothermal power R&D[12]. Previous frameworks investigated the interaction of technology-push and demand-pull policies to guide public programmes that support clean energy through solar and wind deployment (learning by doing)[13–15]. The two-factor approach, established previously for wind turbines and solar photovoltaics[6,16], demonstrates a theoretical framework to apply to clean energy technologies to develop price trajectories and build technological roadmaps for dramatic energy transitions.

In this article, we develop a two-factor learning curve model to analyse the impact of innovation and deployment policies on the cost of energy storage technologies. We use patent activity, production output capacity (kWh), and historical global average prices to track learning rates of battery energy storage technologies. This allows us to investigate whether lithium-ion batteries can achieve necessary cost targets to push intermittent renewable systems with storage past conventional fossil-fuel-based generators. We also track US and global R&D spending on the energy sector and derive implications for policymakers. With increased investment and strategic research, development, and deployment initiatives, the cost reductions of lithium-ion batteries enable cost-competitive and dispatchable renewable photovoltaic (PV) and wind systems. Using an empirical global dataset of lithium-ion patent activity, production volumes, and average prices from 1991 to 2015, we find that innovation has a significant impact on prices of high-tech energy products and services, especially energy storage. This finding is in accordance with recent research on photovoltaics[6] and on wind turbines[16]. Therefore, we estimate two-factor models with a high prediction capability as an advanced conceptual approach and argue for further application in research compared to traditional one-factor learning curves.

## Applying a framework to innovation in battery storage

Learning rates typically relate the cost reduction of new technologies to key factors such as cumulative installed capacity or units of output produced, and are widely employed to predict future trends[9]. Traditional one-factor models explain the decreased cost with increases in production volume (economies of scale, experience curve approach) only. Although the conventional one-factor model for innovation retains a good explanation value (adj. $R^2 = 0.9861$), the past four years of data overestimate the prices. Figure 1 shows the conventional one-factor learning rates of 17.31% for economies of scale and 15.47% using the experience curve approach. We explore three one-factor models representing annual production, cumulative production, and patent activity as a proxy for innovation.

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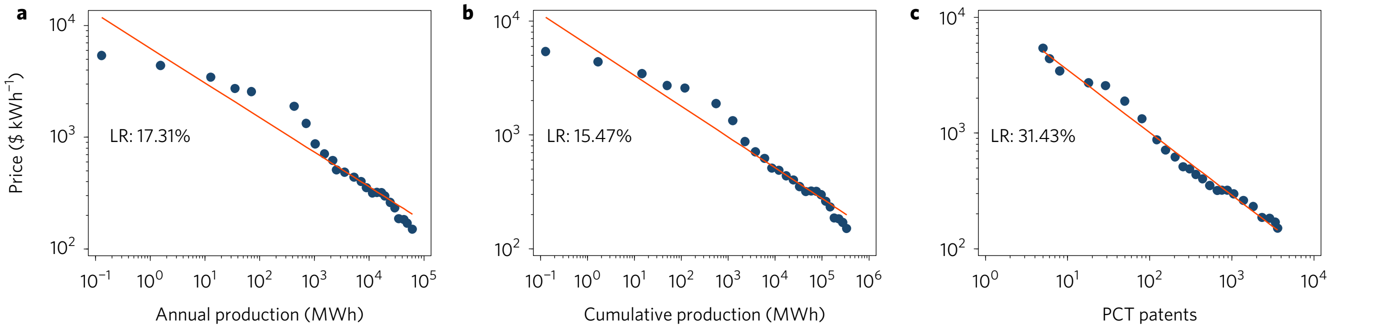


**Figure 1 | Learning rates using the traditional one-factor learning curve model for lithium-ion battery storage. a**, Learning rate of economies of scale at 17.31%. **b**, Experience curve approach with a learning rate of 15.47% for cumulative production. **c**, Learning rates for cumulative patents, amounting to 31.43%. Prices are adjusted to 2015 US dollars. PCT is Patent Cooperation Treaty, an international patent treaty to protect inventions across nations.

The one-factor models under consideration here are as follows:

$$P_t = \delta_0 + \delta_1 Q_t + \epsilon_t \quad (1)$$

$$P_t = \zeta_0 + \zeta_1 CQ_t + \epsilon_t \quad (2)$$

$$P_t = \vartheta_0 + \vartheta_1 I_t + \epsilon_t \quad (3)$$

where $P_t$ is the logarithmized price (US\$ kWh$^{-1}$) (adjusted to 2015 US dollars), $Q_t$ is the logarithmized production volumes (MWh), $CQ_t$ is the logarithmized cumulative production volumes until year t (MWh), and $I_t$ is the innovation activity (cumulative patents until year t). The $\delta$, $\zeta$, and $\vartheta$ represent coefficients, and $\epsilon_t$ represents the error term.

## Modelling economies of scale and innovation

In comparison, our two-factor learning curve model incorporates logarithmized production volumes ($Q_i$), and innovation activity ($I_i$) represented by cumulative international Patent Cooperation Treaty (PCT) patents during each year with $P_i$ (logarithmized price) as the dependent variable. As both independent variables increased during our time series, statistics show a correlation of 0.9644, which introduces multicollinearity[17,18]. Information on the correlation and the variance inflation factor, analysing the degree of multicollinearity can be found in Supplementary Tables 4–7. To resolve this issue, a two-step regression approach using a residual variable ($\eta_i$), as proposed by Qiu and Anadon, as well as Zheng and Kammen, was implemented[6,16]. Detailed information on the regression procedure is shown in Methods.

The final two-factor model (equation (4)) is as follows:

$$P_i = \gamma_0 + \gamma_1 Q_i + \gamma_2 I_i + \epsilon_i \quad (4)$$

$$\text{Forecasted price} = \left(\frac{10^{\gamma_0}}{Q_i^{-\gamma_1}}\right)(10^{\gamma_2})^{I_i} \quad (5)$$

The two-factor learning curve model (Fig. 2, equation (4)) shows a learning rate of 16.9% for economies of scale (doubling annual production) and a decrease in prices of 2.0% per 100 PCT patents. Notably, the two-factor model explains the recent plunge of battery prices better than both conventional models using economies of scale or a classic experience curve approach. As Fig. 2 shows, the two-factor model captures the past five years fairly well (with $P < 0.001$, adj. $R^2 = 0.9465$), while economies of scale and the experience curve approach systematically overestimate prices. The learning rates for lithium-ion batteries fall quicker than literature shows for c-Si PV modules (15.2%) and wind turbines (4.1–4.3%) (refs 6,16). We note that multi-factor models may

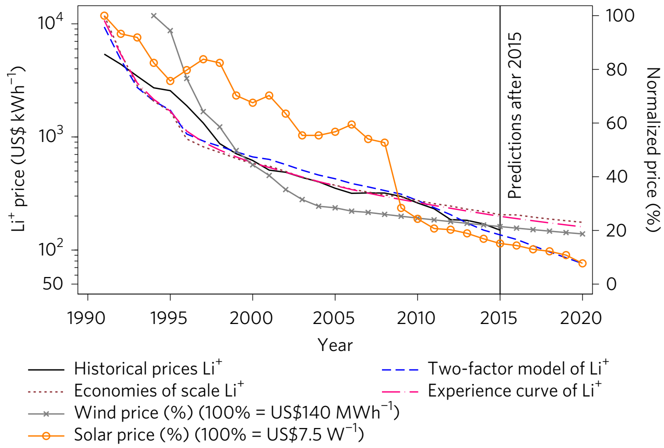


**Figure 2 | Comparing traditional one-factor models and the two-factor model to historical prices.** Lithium-ion (Li$^+$) forecasts are based on projects for production output, and patent activity on the average of the past five years. Prices for wind display averages of data from Qiu & Anadon until 2007 (ref. 16). From 2008 to 2019, prices are interpolated using the 2020 forecast[47]. Prices for solar are taken from Zheng & Kammen and extrapolated using their two-factor model forecast for 2014 and 2015 (ref. 6). Price reductions for wind and solar are normalized in percentage (%) terms and should be read off the right-hand axis. All prices are adjusted to 2015 US dollars.

achieve greater statistical significance (see Supplementary Note 1). To address omitted variable bias, we investigate a 'four-factor' model (Supplementary Table 3), which incorporates raw material prices. We find that it does not maintain a *P* value at the same level of significance as one- or two-factor models. In contrast, although one-factor models describe the price declines at a similar level of statistical significance, they overestimate prices during the 2010–2015 period and perform worse in terms of forecast error.

The two-factor model attributes part of the cost reduction to innovation, which is considered an important component for technological learning. Although costs are highly correlated with the production volume, according to the International Energy Agency (IEA) the share of responsibility of production volume and technological advancements on the cost reductions remain unclear[19]. Our framework supports prevailing technological learning literature that describes innovation as a more critical component of cost reductions compared to deployment[9]. For instance, if scientists increase battery energy densities by 20% through extensive R&D in materials science, yet continue to use materials and production lines at their current cost, the price per kWh of storage could drop by 16.7% before increasing any production volumes. This is also exhibited through advances in net energy performance

**Table 1 | Forecasted prices by using two-factor learning curve model.**

| Year | Forecast: consumer cells | EV/ES cells | EV/ES battery pack |
|---|---|---|---|
| 2016 | 124.15 | 155.00 | 202.88 |
| 2017 | 109.18 | 136.31 | 178.41 |
| 2018 | 96.38 | 120.33 | 157.50 |
| 2019 | 85.55 | 106.81 | 139.80 |
| 2020 | 76.03 | 94.92 | 124.24 |
| Sensitivity range | (66.17–88.32) | (82.61–110.27) | (108.13–144.33) |

Second column represents the forecasted values. Third and fourth columns show estimations for EV/ES (electric vehicle/electric energy storage) cells (+24.85%) and for battery packs (+30.89%), respectively. Cell prices for electric vehicles and energy storage are higher due to different standards and chemistry. This model assumes the same learning across cells and battery packs. Prices are in 2015 US dollars and shown per kWh.

(characteristics including cycle life and energy capacity) measured by energy stored on energy invested[20].

## Forecasting future storage prices

Applying the two-factor model to recent production forecasts of leading industry experts[21] and assuming that patent activity stays on the high level of the five-year average (2011–2015), provides optimistic results with consumer cell prices falling below US\$100 kWh$^{-1}$ by 2018. Figure 2 and Table 1 highlight their respective price trajectories. The forecast is based on 25 annual observations, and although the sample is small, it represents the best available information in a nascent market. We include a detailed sensitivity matrix in Supplementary Note 2 varying future patent activity and production levels since patent counts historically follow random Poisson processes[22]. We incorporate the effect of time lags on patents and knowledge stock depreciation, where patents in the past have less effect on prices than recent patents (Supplementary Note 3). We find lower cost reductions than existing forecasts in the literature, which in the past has found a systematic underestimation of falling electric vehicle battery costs[23]. We account for raw material prices in a 'four-factor' model controlling for the impact of raw lithium and cobalt prices, which we find to lower the learning rate slightly (14.82%), and attributes greater reductions to innovation rather than deployment. However, raw material prices may not be as critical to battery cost reductions as the experience of wind generation to steel prices. Diverse material components comprise lithium-ion batteries, although lithium and cobalt represent important parts of the cathode[24]. Controlling for raw material prices in a 'four-factor' model is not as statistically significant ($P < 0.16$) as the two-factor model ($P < 0.001$). However, sustainability criteria could guide future development as new material innovations become viable[25]. One potential bias in the two-factor model may be the exclusion of subsidies that are typically proprietary and difficult to track. Further research in this area would greatly address a gap in technology and policy innovation studies.

Advances in lithium-ion batteries will probably spur the adoption of EVs. Studies show that EVs will become cost-competitive to internal combustion engine vehicles with prices for battery packs reaching US\$125–165 per kWh assuming 2015 average US gasoline prices[26,27]. According to our model, this critical threshold is reached in 2017 as an upper bound and by 2020 in the low case. Besides battery prices, gasoline prices, electricity rates, and yearly mileage significantly impact when EVs reach cost competitiveness. These forecasts are lower than previously reported literature values[23].

We also investigate the cost of learning by searching compared with the cost of deployment initiatives through the two-factor model results. Learning by searching represents the impact of research, development, and demonstration (RD&D) on the cost of an energy technology[16]. To estimate this, we scaled back patent activity by 33% from the current trajectory in the two-factor model and found an additional 307 GWh of global deployment is required through learning by doing alone to achieve a US\$100 kWh$^{-1}$ battery storage threshold by 2020 (Supplementary Note 2). For perspective, the Tesla Gigafactory plans to deploy 35 GWh per year. Patent activity critically drives the two-factor model. A lack of patent activity would drastically increase costs to reach cell level prices of US\$76 kWh$^{-1}$. At the most extreme case of no new innovation, the opportunity cost of meeting cost reduction targets through deployment alone would be extremely high, in exceedance of 140 billion US dollars through 2020. This is not likely or feasible, but highlights the importance of innovation to achieve cost reductions through the two-factor framework. The vast majority of recent solar PV and wind cost reductions, however, stem from process improvements and corporate R&D that use profits from deployment to further drive innovation[28]. If true for storage, this feedback between innovation and deployment limits our ability to completely decouple the effects of both R&D and deployment targets. This warrants further research and underscores the importance of developing both learning-by-searching and learning-by-doing policies, forming the development of a learning-by-researching and doing approach.

Further, energy storage at the utility and residential scale is on the verge of reaching grid and socket parity. We find that at current targets, if the US reaches the 'SunShot' target pricing for solar electricity at US\$1 W$^{-1}$, the price trajectories estimated here would make residential solar and electric battery storage cost-competitive with grid electricity by 2020, achieving a levelized cost of electricity (LCOE) of around US\$0.11 kWh$^{-1}$ as detailed in the Methods.

Currently, lithium-ion battery-based energy storage remains a niche market for protection against blackouts, but our analysis shows that this could change entirely, providing flexibility and reliability for future power systems. This finding contrasts with recent studies, postulating the value of energy storage for decarbonizing electricity to be low, given high costs of storage technologies[29,30]. According to our forecasts, both studies forecast pessimistic future prices for energy storage that do not consider the complementary effects of innovation and deployment and the value of flexibility for power and/or energy dense storage options in future power systems. Gigawatt-scale grid storage would improve the transmission and distribution system, resulting in lower future investments necessary to ensure grid stability and improve customer reliability[31]. Although total project costs, such as labour and balance-of-system components are included in the capital costs, the modelling highlights the close proximity of this target for lithium- and non-lithium-based electrochemical storage options.

## Implications of R&D spending on price decreases

To enable a storage-driven transition, further research is necessary to maintain patent activity levels. Public R&D spending and private research projects directly trigger innovation by stimulating research and facilitating a high level of experimentation, yet US-federal R&D spending continues to decline. Photovoltaic research remains a prime example of the ability for R&D programmes to drive growth and cost reductions[32]. During the past decade, however, public R&D spending in energy did not keep pace with rising revenues of the energy sector. Figure 3 shows the US-federal R&D expenditures between 1976 and 2015. During this period, total US-federal R&D spending plunged from 1.2% to 0.8% of the US GDP[33,34]. Spending of energy R&D plunged from 0.3% to 0.013% respectively. Global share of energy to total R&D spending declined on average from over 10% to 3.9% as of 2013. The share of energy to total R&D amounted to 2.1% in the US in 2015[33,34]. The current share of energy R&D spending does not reflect the importance of clean energy technology deployment and its role in meeting global climate objectives. With

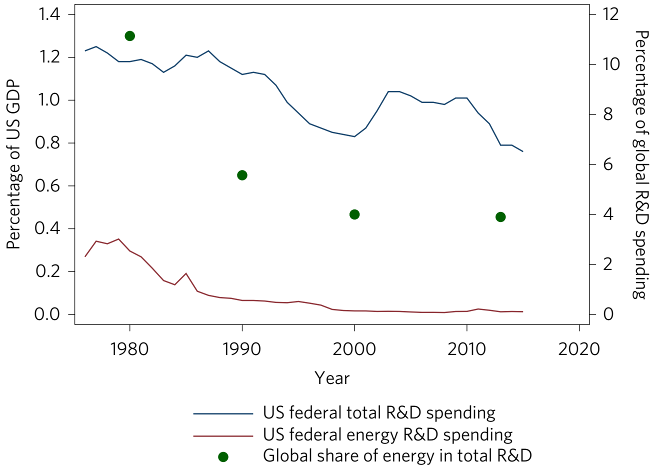


**Figure 3 | US-federal R&D spending from 1976–2016.** US-federal R&D spending declined over the past four decades from about 1.2% to 0.8% of the US GDP. In the same time frame, federal R&D spending of energy-related topics plunged from over 0.3% to 0.013%. The dark green dots show a similar development for the share of energy-related R&D to total R&D spending. In the late 1970s, energy R&D accounted for over 10% of total R&D, of which more than 50% was allocated to nuclear energy globally. By comparison, the international community allocated 3.9% of R&D funds to energy-related activities in 2013. Data are from AAAS[33,34].

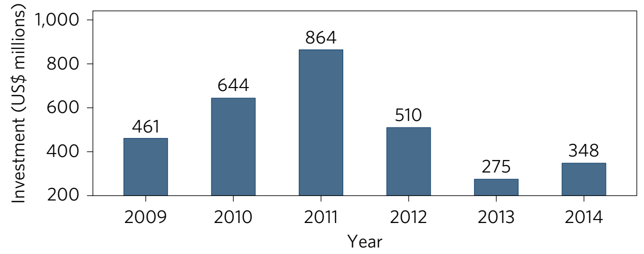


**Figure 4 | Global corporate and VC investment in the energy storage sector.** Following post-financial crisis years 2009, 2010 and 2011, investment levels dramatically decreased by 2014. Data from ref. 48.

regard to battery technology, an urgent call for action to increase public R&D spending and therefore push innovation forward and prices for storage down becomes apparent to create cost-competitive dispatchable solar, wind, and storage electricity.

Further advances in materials science may foster an increase in battery energy density, which remains crucial to increase the driving range of EVs to a competitive level with conventional vehicles and to reduce the cost of grid-scale storage applications. Current patent activity for lithium-ion batteries is on a high level, although it has plateaued within the past five years. This model highlights the importance for policymakers to stabilize declining public R&D spending and fuel innovation activity through systematic funding of clean-tech R&D projects to meet decarbonization goals in a cost-effective manner, affirming results from previous studies and extending not just to electricity generation sources, but also storage[32]. Additionally, policymakers should initiate a standardized framework favouring private venture capital investing in clean technology. Venture capital (VC) is seen as vital to the clean-tech industry[35,36], and research indicates that VC investments are more effective than (public) R&D with regard to patenting, and thus could be applied to target emerging electrochemical and mechanical storage systems[37]. Figure 4 shows the global corporate and VC investment in the energy storage sector between 2009 and 2014. Although large loan guarantees to VC-backed firms have lacked prior cost-effectiveness, government initiatives such as the Small Business Innovation Research Program (SBIR), university R&D programmes, and large-scale demonstration projects have seen more success[38].

## Discussion

According to our two-factor model, adoption policies that incentivize total deployment of EVs or energy storage systems are expensive measures. We calculate that achieving a lower boundary of US\$125 $kWh^{-1}$ for EVs by 2018, at the current five-year patent average, would require a more than twofold increase of yearly production output than currently forecasted. This equals a production of about 300 GWh of additional manufactured capacity. In particular, lithium batteries for consumer devices comprise a significant market share of total production, and it is likely energy applications will continue to lag. Learning by searching, or innovation (learning by 'researching'), very likely plays a larger role than deployment incentives alone by achieving more rapid cost reductions in a shorter time frame. Adoption policies could yield cost improvements at the manufacturing or systems-level value chain for EVs and grid-scale storage. However, incentivizing deployment through capacity targets may create significant windfalls where customers receive incentives for what they would have bought regardless. Deployment targets for energy storage may not prove as effective as research-based, innovation-driven activities.

We propose a strategy that allocates funds toward more cost-effective research and development measures. Governments can play a critical role for promoting research advances and innovations that drive down cost further. Outlining future research and legal frameworks to enable distributed energy systems and vehicle-to-grid interactions is one emergent research area. Another research focus is to understand conditions when grid storage is valuable, operational frameworks to provide spinning reserves or ancillary services, demand response, and opportunities for emission reductions. For vehicle storage applications, incentivizing and designing a tight-meshed charging infrastructure alleviates range limits. All of these outcomes could contribute to innovation-driven cost reductions through not only materials research, but also deployment.

Developing research programmes with an emphasis not only on electrochemical storage for materials science advances, but also emerging mechanical storage applications would provide increased flexibility in power system planning. Some claim that mechanical storage applications could undercut electrochemical storage in terms of price; however, there may be a role for both. Long-duration bulk storage capacity and short bursts from high-power devices that can provide frequency regulation, ancillary services, or simply inject power to the grid during times of intermittency. Finding complementarity between increasing storage performance through energy density and lowering cost will be necessary for both vehicle and grid-scale applications. Storage technologies can learn from asset complementarity driving PV market growth and find niche applications across the clean-tech ecosystem, not just for pure kWh of energy storage capacity[39]. It is likely that multi-utility storage applications may surface as a result of innovation and deployment-driven cost reductions.

Based on the two-factor model, we recommend policymakers to adopt balanced innovation and deployment policies. A portfolio of policies is more likely to successfully drive environmental change than a single policy[40]. We note that the relative decline in public R&D spending could forestall critical cost reduction and advances toward achieving a deep decarbonization in the electricity sector and bringing new material advances from the lab to the market. We find significant value associated with investing in increased patents through research, and one way to drive this research is through government spending that could achieve drastic cost reductions for energy storage systems. The diversity of materials for current lithium-based batteries suggest that, unlike solar photovoltaics or wind turbines, it is likely new material advances in storage technologies are necessary to achieve a US\$100 $kWh^{-1}$ target.

Patent activity and R&D spending continue to drive down the price of electrochemical battery storage technologies. Our two-factor learning curve estimates a turning point in 2019 when forecasted prices cross the threshold of US\$100 kWh$^{-1}$, contradicting current forecasts and studies. The strong relationship in the two-factor learning curve suggests that US R&D could enable further cost reductions through investment in developing new battery materials. Designing a deployment strategy would lower overall costs in decarbonizing the electricity grid and transportation sectors, which account for more than 60% of overall $CO_2$ emissions combined. Therefore, critical to evaluating new technologies remains the material choices to improve safety, energy density, and cost. New research promoting soft-side innovations and business models will expedite integration of electrochemical storage into common markets. Further government support is necessary to promote responsible R&D spending that enables serious cost reductions across solar, wind, and storage, while also decarbonizing electricity and transportation. The US has the opportunity to become a leader, not a laggard, in electric battery storage manufacturing and development. We find that R&D spending is a strong indicator of driving innovation. Therefore, concomitant increases in R&D spending across energy research would promote a diverse suite of storage technologies and materials science advances.

## Methods

**Global battery price and output volume data collection.** We compiled a comprehensive global dataset of average prices and global production output of lithium-ion consumer cells from 1991 to 2015 available at http://rael.berkeley.edu/project/innovation-in-energy-storage. As data within this industry is typically proprietary and not accessible via a transparent platform, we cross-validated data with industry experts and leading international research agencies specializing in the battery market at the Energy Storage North America meeting in October 2015 (http://www.esnaexpo.com).

**Collection of patent data as a proxy for innovation.** Previous research highlights three proxies to measure innovation: private and public R&D expenditures, literature-based innovation output, and number of patents[41].

We consider patents filed according to the Patent Cooperation Treaty (PCT) as a proxy for innovation. Following the work of Griliches[42], others evaluated patenting in the energy sector, and concluded that patents are a valid indicator to measure innovativeness within the energy sector[2,28]. This result has been extended and re-confirmed by a number of authors[43]. PCT patent reviews contain high-quality standards and innovators seeking international protection file for PCT patents, attesting to the high economic value of their patent, which represents a gold standard for patent information[44].

Queries were conducted using Patentscope, a database of the World Intellectual Property Organization (WIPO), retrieving patent information by searching for the keywords 'lithium and ion and (battery or batteries or accumulator or accumulators or cell or cells)' on the patents' front page. We include patents in the manufacturing process and were inclusive of any patent that contained the search terms we determined that we found in Patentscope. Supplementary Fig. 1 highlights the patent activity over time for lithium-ion batteries.

**Multivariable regression analysis to develop a two-factor learning curve model.** For our analysis, we use a two-factor learning curve model. Traditional one-factor models explain the decreased cost with increases in production volume (economies of scale, experience curve approach) only. However, the two-factor model attributes part of the cost reduction to innovation, which is considered an important component for technological learning. Although costs are highly correlated with the production volume, according to the International Energy Agency (IEA) the share of responsibility of production volume and technological advancements on the cost reductions remain unclear[19]. For instance, if scientists increase battery energy densities by 20% through extensive R&D in materials science, yet continue to use materials and production lines at their current cost, the price per kWh of storage could drop by 16.7% before increasing any production volumes. This is an illustrative example demonstrated by the hypothetical situation where a US\$200 kWh$^{-1}$ battery increases in energy density by 20%, which would change the price per kWh to US\$167 kWh$^{-1}$ before changing anything in relation to the bill of materials.

Our two-factor model incorporates logarithmized production volumes ($Q_i$), and innovation activity ($I_i$) represented by cumulative PCT patents during each year with $P_i$ (logarithmized price) as the dependent variable. To resolve the issue of multicollinearity, a two-step regression approach using a residual variable ($\eta_i$), as proposed by Qui and Anadon, as well as Zheng and Kammen, was implemented[6,16].

Developing the two-factor learning curve model follows the subsequent rationale:

$$I_i = \alpha_0 + \alpha_1 Q_i + \eta_i \quad (6)$$

$$\eta_i = I_i - \alpha_0 - \alpha_1 Q_i \quad (7)$$

After introducing the residual variable to remove the correlation, the reformed equation (7) is inserted in equation (6). Further transformation gives the new coefficients $\gamma_0$, $\gamma_2$ and $\gamma_3$. Information on the correlation and variance inflation factor after introducing the residual variable is displayed in Supplementary Tables 4–7.

$$P_i = \beta_0 + \beta_1 Q_i + \beta_2 \eta_i + \epsilon_i \quad (8)$$

$$P_i = \beta_0 + \beta_1 Q_i + \beta_2 I_i - \beta_2 \alpha_0 - \beta_2 \alpha_1 Q_i + \epsilon_i \quad (7) \text{ in } (8)$$

$$P_i = [\beta_0 - \beta_2 \alpha_0] + [\beta_1 - \beta_2 \alpha_1] Q_i + \beta_2 I_i + \epsilon_i \quad (9)$$

$$\gamma_0 = \beta_0 - \beta_2 \alpha_0$$

$$\gamma_1 = \beta_1 - \beta_2 \alpha_1$$

$$\gamma_2 = \beta_2$$

The final model and be found in equations (4) and (5).

$$P_i = \gamma_0 + \gamma_1 Q_i + \gamma_2 I_i + \epsilon_i \quad (4)$$

$$\text{Forecasted price} = \left( \frac{10^{\gamma_0}}{Q_i^{-\gamma_1}} \right) (10^{\gamma_2})^{I_i} \quad (5)$$

**LCOE system cost calculation.** We assume LCOE for residential PV in Germany: 10.7–15.6 US\$-cent + LCOE Powerwall ~15 US\$-cent <36.3 US\$-cent average residential electricity rate in Germany when considering it at 'socket parity.' This is a term referring to the state when cost is equivalent to the retail rate of electricity[45].

We calculate system LCOE costs if SunShot solar goal is achieved by 2020, where LCOE for PV reaches US\$0.05 kWh$^{-1}$ by 2020[46]. We assume a 2-kW residential home solar system represented by average US insolation levels at ~4.8 kWh m$^{-2}$ d$^{-1}$ that could be installed in Kansas City, Missouri (used by NREL to represent average US insolation). We also assume Tesla's lithium-ion-based Powerwall is US\$350 kWh$^{-1}$ for residential customers and US\$250 kWh$^{-1}$ at utility scale and reaches US\$100 kWh$^{-1}$ by 2020. We use a 7 kWp Powerwall with 13.5 kWh energy capacity ratings that charge for six hours during the day with 90% roundtrip efficiency and 100% depth of discharge. The battery discharges at night when electricity is more expensive and net load is higher. This would place residential solar+storage at an estimated US\$0.11–0.12 kWh$^{-1}$ target. Based on a ten-year project lifetime, and in the optimal case assuming a full charge–discharge cycle on a daily basis ignoring losses, LCOE at current prices is US\$0.15 kWh$^{-1}$ at residential scale and US\$0.10 kWh$^{-1}$ at utility scale. Based on current price trajectories and a patent activity level of 444 patents per year using our model, battery prices will fall from 2016 to 2020 by 39%, which puts utility-scale battery storage roughly equivalent to US\$0.06 kWh$^{-1}$ based on current usage rates that model integration of storage into power grids with high penetrations of renewables[5]. Then we find that, although distributed PV and battery storage may not be competitive everywhere by 2020, systems will already hit grid parity in certain locations where electricity prices are higher than average coupled with high solar irradiation. This also occurs before including other use cases including peak shaving, ancillary services, voltage regulation, and the displacement of natural gas peaker plants. In Hawaii and many other states, PV and storage will achieve grid parity[21,45]. This could be achieved at a solar+storage target of US\$0.11–0.12 kWh$^{-1}$.

**Data availability.** The data that support the plots within this paper and other findings of this study are publicly available on the Innovation in Energy Storage database at http://rael.berkeley.edu/project/innovation-in-energy-storage and in the Supplementary Information (Supplementary Data 1).

Received 16 October 2016; accepted 21 June 2017; published 31 July 2017

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## Acknowledgements

We thank the Karsten Family Foundation and the Zaffaroni Family Foundation for generous support. N.K. thanks the NSF-GRFP and Berkeley Center for Green Chemistry (NSF, Grant No. 1144885). F.L. thanks CDTM for ongoing continuous support.


## Author contributions

N.K. conceived and N.K. and F.L. designed the study. N.K., F.L. and D.M.K. collected data. N.K. and F.L. analysed data and wrote the paper. F.L. ran the statistical test. D.M.K. supervised the research, guided the study, and edited the paper.

## Additional information

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**How to cite this article:** Kittner, N., Lill, F. & Kammen, D. M. Energy storage deployment and innovation for the clean energy transition. *Nat. Energy* **2**, 17125 (2017).

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## Competing interests

The authors declare no competing financial interests.