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Evaluating relative benefits of different types of R & D for clean energy technologies☆

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ABSTRACT

Clean energy technologies that cost more than fossil fuel technologies require support through research and development (R & D). Learning-by-doing relates historical cost decreases to accumulation of experience. A learning investment is the amount of subsidy that is required to reach cost parity between a new technology and a conventional technology. We use learning investments to compare the relative impacts of two stylized types of R & D. We define curve-following R & D to be R & D that lowers costs by producing knowledge that would have otherwise been gained through learning-by-doing. We define curve-shifting R & D to be R & D that lowers costs by producing innovations that would not have occurred through learning-by-doing. We show that if an equal investment in curve-following or curve-shifting R & D would produce the same reduction in cost, the curve-shifting R & D would be more effective at reducing the learning investment needed to make the technology competitive. The relative benefit of curve-shifting over curve-following R & D is greater with a high starting cost and low learning rate. Our analysis suggests that, other things equal, investments in curve-shifting R & D have large benefits relative to curve-following R & D. In setting research policy, governments should consider the greater benefits of cost reductions brought about by transformational rather than incremental change.

1. Introduction

Innovation in clean energy technology shapes the future of our energy system and provides solutions for deep decarbonization (Edenhofer et al., 2014; IEA, 2015). Deployment of these technologies at a scale that can significantly reduce greenhouse gas emissions requires them to be cost competitive in energy systems that are currently dominated by conventional fossil fuel technologies. New clean energy technologies can compete with fossil fuel technologies if there is an appropriate policy environment and costs are sufficiently low (Yang et al., 2015).

Studies across many sectors and industries relate historically observed decreases in the cost of a technology to key factors related to diffusion, such as cumulative quantity or experience. In these analyses, a learning rate (R) is used as a metric to express the percentage reduction in the cost of a technology as a result of every doubling of its cumulative quantity. Incremental additions of new technologies achieve cost reduction more quickly than similar additions of mature technologies. However, new technologies have a higher starting cost that impedes their further deployment. Learning-by-doing, where cost reductions are achieved through increased experience, was originally observed in empirical studies in manufacturing (Wright, 1936; Alchian, 1963; Arrow, 1971; Hirsch, 1952) where learning curves (also known as experience curves) are used to estimate the cost reduction as a function of experience gained from increased cumulative quantity.

A very common functional representation of learning-by-doing is a single-factor learning curve, where cost of a technology is a power law of its cumulative quantity (Nagy et al., 2013). Fig. 1 demonstrates empirical learning curves for several clean energy technologies, adopting a power law to represent the relationship between cost and cumulative quantity. As a technology's quantity increases from the starting quantity Q_0 to the critical quantity Q^*, its cost drops from the starting value C_0 to the same cost as the conventional energy technology $\overline{C}$ (Nemet, 2009). We use data from this figure for subsequent analysis of the impact of different types of R & D.

Although the simple relationship between cost and cumulative quantity is useful to represent and project learning, it faces limitations (Nordhaus, 2009). One key shortcoming is that this representation does not distinguish among the various factors that may have

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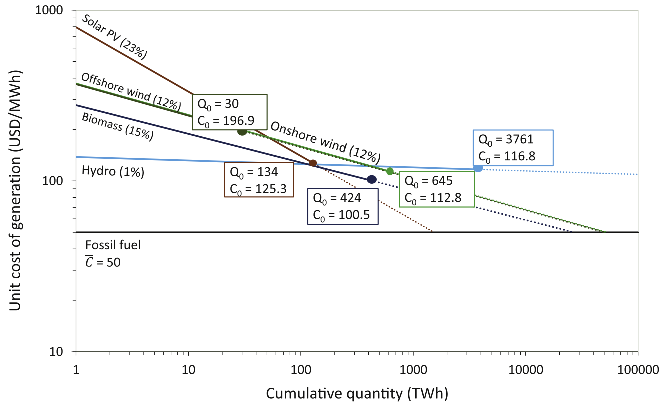

Fig. 1. Learning curves for clean and conventional energy technologies. The horizontal axis represents cumulative quantity of electricity generation and the vertical axis represents the unit cost of electricity generation. Both scales are logarithmic. Learning rates (R) are shown in parentheses. Q_0 indicates starting quantity and C_0 is starting cost. With this axis scaling, straight lines represent power laws (Eq. (1)). We use data from this figure for subsequent analysis of the impact of different types of R & D (EIA, 2015, Wene, 2000; Rubin et al., 2015).

contributed to learning. Some of these reductions in cost may be a consequence of other factors, including economies of scale. Several analyses have indicated that some of the reduction is due to true learning (Lundvall and Johnson, 1994; Gaynor et al., 2005). Here, we use the term learning-by-doing broadly to encompass the many sources of cost reduction as cumulative quantity increases.

The area between the learning curve and cost of the conventional technology represents the total subsidy necessary to reduce the cost of new technology to that of the conventional technology. This "learning investment" is required for any new technology with higher starting cost to achieve cost parity with the conventional energy technology, should all government support come in the form of deployment incentives (Foxon, 2010). In practice, subsidies may be larger than the required learning investment due to inefficient policy design.

Research and development (R & D) can potentially reduce the learning investment in very different ways (Kahouli-Brahmi, 2008). Some R & D could generate knowledge that would have been gained through increased deployment. This type of R & D reduces the cost by following a path along the same learning curve. Therefore, the effective starting cost and quantity will be somewhere down the learning curve from the original starting point. For example, research into incremental improvements in manufacturing processes might generate information that would have been gained as deployment of the technology increased. This resembles many R & D investments in corporate sector where business entities try to maximize their profit by modification to existing products or services. As a convention, we call this type of incremental R & D 'curve-following' R & D. This kind of R & D is often, though not exclusively, undertaken by the corporate sector. For example, Gallagher describes improvements in photovoltaic (PV) wafer efficiency and costs sought by private manufacturers in China (Gallagher, 2014):

> Early shortages of silicon also inspired Chinese firms to use it more efficiently. One firm noted that it focused heavily on how to make the wafer thinner so as to use less silicon. During a tour of one manufacturing plant, I paused to watch a camera flash over each finished wafer to determine its efficiency, and the cell efficiency of most cells was about 16.5%, with approximately 10% of the wafers higher than 17% efficiency. I murmured compliments, which were immediately and forcefully rebuffed as my host declared that the efficiency still wasn't good enough and the goal was to achieve at least 20% efficiency within a few years.

Similarly, several manufacturing innovations have decreased solar module costs and increased efficiency. They include adoption of fluidized-bed reactors for silicon production, diamond wire saws, stencil printing, and anti-reflective coatings, as well as increasing the number of busbars within a cell (McCrone et al., 2016).

In contrast, R & D could also potentially produce transformational knowledge, such as use of a different substrate for PV devices that would not occur in the course of manufacturing scale up. This type of R & D reduces the cost by shifting the learning curve to a lower level with the same slope. Therefore, the new starting cost will be lower than the original cost while the starting quantity remains the same. This transformational learning results from fundamental R & D that aims to transform manufacturing processes. It is often funded by government entities, and undertaken by academics, government-sponsored laboratories, and private industry. The U.S. Department of Energy, for example, is funding research on PV technologies that are far from commercialization, but whose development could have a large impact on the costs and performance of solar energy systems. These include hybrid PV-thermal solar energy systems, and advanced materials for PV, including perovskites (Kim et al., 2015; Branz et al., 2015). As a convention, we call this type of transformational R & D 'curve-shifting' R & D.

There are many reasons why the government and corporate sectors underinvest in transformational R & D. Profit-maximizing firms undertake R & D to maximize their expected returns: as such, they target incremental improvements in existing processes to reduce costs or gain a larger market share. Transformational R & D, in contrast, is often too speculative for corporate actors, or requires a long time to produce successful outcomes (Taylor, 2012). A recent survey of the U.S. corporate sector found that private firms are overwhelmingly focused on short-term returns in their energy innovation investments, with two-thirds of those who measure economic impacts of their investments expecting to recoup expenditures in only two to three years (Diaz Anadon et al., 2011). Additionally, knowledge generated from transformational R & D may not be fully appropriable by private firms, leading to underinvestment (Jaffe et al., 2005). For governments, underinvestment in transformational R & D is instead related to budgetary constraints and the lack of an entrepreneurial culture that accepts risk and encourages competition (Diaz Anadon et al., 2011).

Some studies use a two-factor learning curve in order to account for the role of R & D in reducing costs. Unfortunately, these models face several limitations. Typical two-factor learning curves represent learning-by-researching as a function of R & D spending, which amplifies learning-by-doing through a similar power law (Jamasb and Kohler, 2007; Barreto and Kypreos, 2004; Berglund and Söderholm, 2006). However it is not clear what is a quantifiable measure of cumulative research, or knowledge stock, in these models. Some models use the cumulative R & D spending for a specific technology (Jamasb, 2007; Söderholm and Klaassen, 2006; Barreto and Kypreos, 2004). However, investment data are not easily accessible, especially for non-OECD countries and the corporate sector. Another candidate is the number of patents related to a specific technology. Patents, however, are an imperfect measure of innovation (Johnstone et al., 2010). In any case, finding reliable and robust data points remains a main challenge for calibrating these models (Lohwasser and Madlener, 2013). Moreover, two-factor learning models typically assume that R & D investment and deployment are uncorrelated, which is unlikely (Söderholm and Sundqvist, 2007).

Here, we compare the impacts of two stylized types of R & D, curve-following and curve-shifting, in the context of a single-factor learning curve. Curve-following R & D lowers costs by producing incremental knowledge that would have otherwise been gained through learning-by-doing, increasing effective cumulative quantity. Curve-shifting R & D produces transformational innovations and improvements that would not have occurred through learning-by-doing, reducing costs by a fixed percentage. These curve-shifting R & D investments reduce costs while preserving the original learning rate, R. We consider the potential impact of these two types of R & D spending in reducing the

Table 1
Variables and parameters used in this paper.

Name	Description	Units
Variables		
C	Cost	USD
$\overline{C}$	Conventional energy technology's cost	USD
C_0	Starting cost	USD
r_C	Cost ratio ($=\overline{C}/C_0$)	–
$\hat{C}$	Reduced cost	USD
Q	Cumulative quantity	TWh
Q_0	Starting quantity	TWh
ΔQ	Change in starting quantity	TWh
Q^*	Critical quantity	TWh
Q'^*	New critical quantity	TWh
B_{follow}	Curve-following learning investment	USD
B_{shift}	Curve-shifting learning investment	USD
r_B	Learning investment ratio ($=B_{shift}/B_{follow}$)	–
e_{follow}	Curve-following benefit	–
e_{shift}	Curve-shifting benefit	–
r_e	Shifting-to-following benefit ratio ($=e_{shift}/e_{follow}$)	–
Parameters		
a	Coefficient of learning curve	USD
b	Exponent of learning curve	–
R	Learning rate	–

learning investment, the total investment needed to make a new technology cost competitive.

2. Analytical framework

In this section, we introduce several equations to describe the impact of R & D on cost and learning investment. First, we compare cost reduction in a new technology due to learning-by-doing with the constant cost of a conventional technology. Using a learning curve framework, we define the learning investment. Then, we introduce analytical expressions for the cost reductions resulting from curve-following and curve-shifting R & D. Finally, we compare the learning investment associated with each type of R & D. Additional equations and derivations are shown in the Supporting Information. Table 1 defines all variables and parameters in this paper.

2.1. Learning curves

As discussed in Section 1, typical functional representations of learning curves relate cost reduction to cumulative quantity. Like others, we assume a power law relates cumulative quantity (Q) to cost (C):

$$C = aQ^b, \tag{1}$$

where $a > 0$ and $b < 0$ are learning parameters. Parameter a can be calculated from $C_0 = aQ_0^b$ where C_0 and Q_0 are the starting cost and cumulative quantity. Parameter b defines the learning rate (R), which is the fractional improvement per doubling of cumulative quantity:

$$R = 1 - 2^b. \tag{2}$$

Throughout our analysis, we assume that the cost of a conventional energy technology remains unchanged as cumulative quantity increases (i.e. b=0). New technology, on the other hand, exhibits learning, where cost declines as total installed quantity increases. Fig. 2(a) shows how cost changes as a function of cumulative quantity, using solar PV as an example. The starting cost of the new energy technology is higher than of the cost of the conventional energy technology ($C_0 > \overline{C}$) but as the cumulative quantity increases the cost of new technology reaches cost parity. The critical quantity for cost parity is denoted Q^*, and can be found by equating both cost functions and solving:

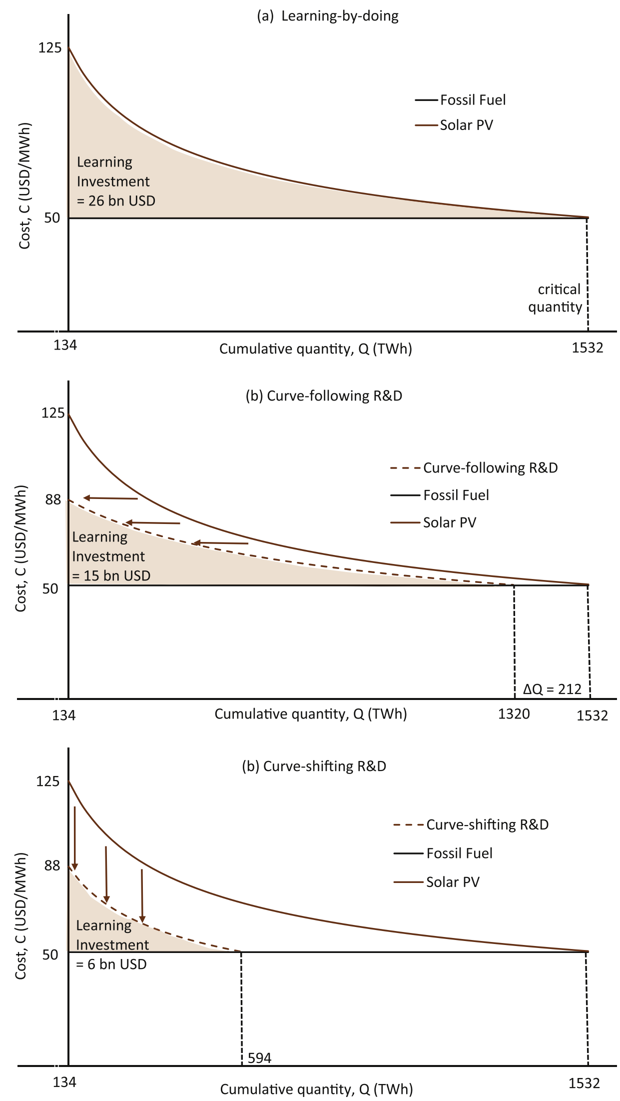

Fig. 2. Illustration of two stylized types of R & D for solar PV, a clean energy technology. (a) Learning-by-doing reduces the cost of the clean energy technology as the cumulative quantity of electricity generation increases. (b) Curve-following R & D reduces cost by producing the same knowledge as learning-by-doing, with an effect equivalent to increased cumulative quantity. (c) Curve-shifting R & D reduces cost by producing knowledge that would not have been gained by learning-by-doing, scaling the learning curve downward by a fixed percentage. The learning investment is the total subsidy necessary to reach cost parity with fossil fuels. For the same initial reduction in cost, curve-shifting R & D reduces the learning investment more than curve-following R & D. Note that horizontal and vertical scales are linear. The learning curves would be straight lines if both scales were logarithmic as in Fig. 1.

$$\begin{aligned} Q^* &= Q_0\left(\frac{\overline{C}}{C_0}\right)^{\frac{1}{b}} \\ &= Q_0 r_C^{\frac{1}{b}} \end{aligned} \tag{3}$$

2.2. Learning investment

The learning investment is the amount of subsidy needed to reach cost parity for a clean energy technology. The area between the learning curves of a conventional and a new energy technology represents the total learning investment (B) needed to reduce the cost until reaching a critical quantity, Q^* (Ferioli et al., 2009). The learning investment is shown in Fig. 2(a) as the shaded area between the solar PV learning curve and cost of fossil fuels. The equation for total learning investment (B) is derived in Eq. (S1) in the Supporting information.

2.3. Two types of R & D

R & D spending reduces the learning investment by reducing the starting cost of deployment, C_0. We consider two stylized possibilities for cost reduction. We use the term 'curve-following R & D' to refer to R & D investments that achieve learning in the same way as increased quantity installation, effectively by increasing starting quantity Q_0 and reducing starting cost. We use the term 'curve-shifting R & D′ to refer to R & D investments that directly reduce the starting cost of deployment without an effective increase in starting quantity. We consider 'incremental' and 'transformational' to be analogous to 'curve-following' and 'curve-shifting' R & D. In both cases, R & D spending can help reduce the potential learning investment by adjusting the cost curve while preserving the original learning rate, R.

These pathways represent two caricatures of R & D. Curve-following R & D resembles learning-by-doing, treating R & D spending as a substitute for production. It provides the developer of the technology with resources to move along the learning curve to a new starting point. As discussed earlier, R & D funded by the corporate sector often targets incremental improvements in the manufacturing process that would have been learned during deployment. Curve-shifting R & D targets new materials or innovative technologies to facilitate potential breakthroughs. As mentioned previously, R & D funded by government entities often aims to produce transformational changes in design that would not occur in the course of manufacturing scale up. We do not claim that these are the only impacts of government and corporate R & D on learning, nor that government funded R & D cannot achieve curve-following R & D outcomes, or vice versa. Instead, these representations are used to probe the relative impacts of different R & D processes.

We make further simplifications. For example, we treat the learning rate as constant in our analysis. In reality, R & D may affect learning rates in addition to costs. In addition, we have not accounted for R & D spillover effects (Bednyagin and Gnansounou, 2012; Cohen and Levinthal, 1989) in this analysis. Real R & D investments, including those both by the government and corporate sectors, result in a combination of curve-following and curve-shifting research.

In Sections 2.4 and 2.5, we show how each type of R & D reduces the cost from its starting value of C_0 to a lower value of $\widehat{C}$, reducing learning investment.

2.4. Curve-following R & D

For curve-following R & D, where the cost reduction is achieved by increasing the effective starting quantity from Q_0 to $\widehat{Q}$, learning proceeds along the original learning curve. Panel (b) in Fig. 2 demonstrates curve-following R & D for a 30% reduction in starting cost for solar PV. In this case, the starting cost reduces to the new cost $\widehat{C}$ as it would if the starting quantity would have increased by ΔQ. The new learning curve can be defined as:

$$C = C_0\left(\frac{Q + \Delta Q}{Q_0}\right)^b. \tag{4}$$

where $\Delta Q = Q_0\left(\frac{\widehat{C}}{C_0}\right)^{\frac{1}{b}} - Q_0$.

Thus, the curve-following R & D is equivalent to having produced another ΔQ units. The effective critical quantity, $\widehat{Q}^*$, (i.e., the cumulative quantity that would result in price equivalence with the conventional energy technology) is:

$$\widehat{Q}^* = Q^* - \Delta Q. \tag{5}$$

We derive the learning investment from curve-following R & D in Equation S2 in the Supporting Information.

2.5. Curve-shifting R & D

In the case of curve-shifting R & D, where R & D targets the starting cost without increasing effective cumulative quantity, learning will follow a new trajectory that will intersect with the conventional energy technology's cost at an earlier critical quantity (Panel (c) in Fig. 2). The new learning curve can be defined as:

$$C = \widehat{C}\left(\frac{Q}{Q_0}\right)^b \tag{6}$$

The new critical quantity will be:

$$\widehat{Q}^* = Q_0\left(\frac{\overline{C}}{\widehat{C}}\right)^{\frac{1}{b}} \tag{7}$$

Similarly, we derive the learning investment from curve-shifting R & D in Eq. (S3) in the Supporting information.

3. Learning investment comparison for R & D

We now compare the impacts of our two R & D pathways on learning investment. First, we compare the effect of curve-following and curve-shifting R & D should they be able to achieve the same cost reduction. *Ceteris paribus*, does curve-following or curve-shifting R & D generate a greater reduction in remaining learning investment? Eq. (8) shows the ratio of learning investment remaining after a specified cost reduction brought about by either a curve-shifting or a curve-following R & D investment. We introduce r_B as the ratio of learning investment under curve-shifting R & D (B_{shift}) to learning investment under curve-following R & D (B_{follow}):

$$r_B = \frac{B_{shift}}{B_{follow}} = \left(\frac{\widehat{C}}{C_0}\right)^{-\frac{1}{b}} < 1. \tag{8}$$

Since $\widehat{C} < C_0$ and $b < 0$ when learning-by-doing reduces cost, the ratio r_B is less than one and therefore, $B_{shift} < B_{follow}$. Thus, for every dollar reduction in the starting cost of new technology, curve-shifting R & D is more efficient in reducing the future learning investment. Put differently, curve-shifting R & D reduces learning investment faster than curve-following R & D, when reducing the starting cost to the same level. Using data for solar PV, which has a learning rate of 23% (i.e., $b = -0.377$), a curve-shifting R & D investment that reduces costs by 30% from $C_0 = 125USD/MWh$ to $\widehat{C} = 88USD/MWh$ would have a $B_{shift} = 6bnUSD$ learning investment. This is 60% less than $B_{follow} = 15bnUSD$ that would result from curve-following R & D investment (i.e., r_B=0.4). The effect of these two stylized types of R & D on learning for solar PV is shown in Panels (b) and (c) of Fig. 2.

Another way of comparing these two stylized types of R & D investment is to calculate the cost elasticity of learning investment, which measures how responsive each type of R & D investment is with regard to a small change in starting cost. We name these cost elasticities curve-following benefit (e_{follow}) and curve-shifting benefit (e_{shift}), for their respective R & D type. We derive expressions for these variables in the Supporting Information. Similar to Eq. (8), we can form a shifting-to-following benefit ratio (r_e):

$$r_e = \frac{e_{shift}}{e_{follow}} = \frac{b}{b+1} . \frac{r_C}{1 - r_C} . (r_C^{-\frac{b+1}{b}} - 1) \tag{9}$$

For observed values of b and $r_C = \frac{C_0}{\overline{C}}$, we expect to have $r_e > 1$ or $e_{shift} > e_{follow}$. That is, for every percentage reduction in the cost ($\partial C_0/C_0$), there will be a larger percentage reduction in the learning investment ($\partial B/B$) under curve-shifting R & D than curve-following R & D. Again using data for solar PV, which has cost ratio r_C=2.5, a curve-following R & D investment has $e_{follow} = 1.0$ while curve-shifting R & D has $e_{shift} = 3.6$. Therefore, r_e=3.6. This means that a cost reduction in solar PV brought about by curve-shifting R & D would reduce the learning

Table 2
Clean energy technologies and their learning parameters. The cost ratio is the ratio of the starting cost C_0 to the cost of fossil fuel electricity generation. Shifting-to-following benefit ratios vary between 3.6 for technologies with high learning rates and extremely large numbers for technologies with low learning rates. This means that a cost reduction in solar PV brought about by curve-shifting R & D would reduce the learning investment 3.6 times more than an equivalent cost reduction brought about by curve-following R & D.

Technology	Learning rate (R)	Cost ratio (r_C)	Shifting-to-following benefit ratio (r_e)
Solar PV	23%	2.50	3.6
Biomass	15%	2.010	12.3
Onshore Wind	12%	2.256	14.4
Offshore Wind	12%	3.938	129.7
Hydro	1%	2.336	approaching ∞

investment 3.6 times more than an equivalent cost reduction brought about by curve-following R & D.

4. Learning in energy technologies

Here, we compare the effects of learning and R & D for several energy technologies. We use a conventional fossil fuel technology as a baseline for calculating learning investments (Berglund and Söderholm, 2006). We base our analysis on 2015 data provided by Energy Information Administration (EIA), International Energy Agency (IEA), and recent academic studies (EIA, 2015; Wene, 2000; Rubin et al., 2015). We display these data in Fig. 1 for several clean energy technologies. Table 2 summarizes the learning rate, cost ratio, and shifting-to-following benefit ratio for renewable technologies compared to a conventional fossil fuel technology.

4.1. Impact of R & D

The government and corporate sector both fund and undertake R & D. For instance, the U.S. Department of Energy has an extensive R & D program that aims to ensure American security and prosperity through science and technology. Corporate technology developers also invest in R & D in order to increase efficiency and reduce costs. As discussed in Sections 1 and 2.3, these kinds of R & D often target, and achieve, different ends.

For instance, innovation in the energy sector has been advanced by government R & D programs such as ARPA-E, the Advanced Research Projects Agency-Energy, which aims to advance high-potential, high-impact energy technologies that are too early for corporate sector investment (Bonvillian and Van Atta, 2011). Other programs at the Department of Energy, such as the Basic Energy Sciences program, fund research that is often too early-stage for private actors to undertake (DOE, 2016). Much of this research supports basic science advances that provide a basis for future energy technology breakthroughs. Therefore, government R & D spending often aims to be curve-shifting R & D that has transformational characteristics. Curve-following R & D, on the other hand, is often characteristic of corporate spending that aims to further develop innovations into new commercial products in an incremental fashion (Wang et al., 2013).

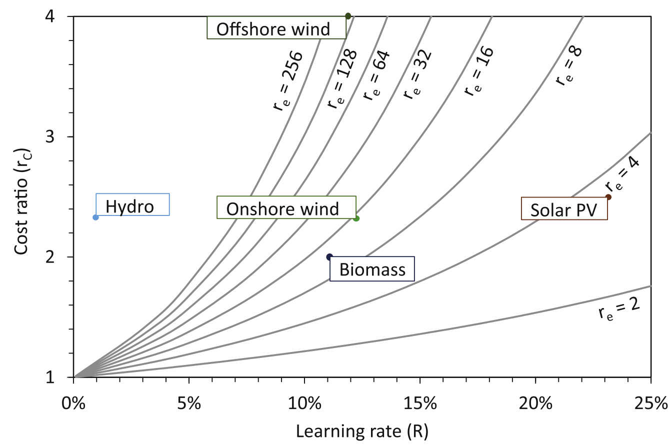

Fig. 3. Shifting-to-following benefit ratio for clean energy technologies. The shifting-to-following benefit ratio is the relative benefit of cost reductions brought about by curve-shifting vs. curve-following R & D. The relative benefit of curve-shifting R & D is greatest for technologies with low learning rates (R) and high costs relative to incumbent technologies (r_C).

Table 3 reports 2015 estimates of global clean energy R & D across several electricity technologies, based on a report by the Frankfurt School, UNEP and Bloomberg New Energy Finance (McCrone et al., 2016). Between 2004 and 2015, global government R & D investment was approximately 33 billion dollars (2015 USD) across selected clean technologies, while corporate R & D was roughly 48 billion. These estimates should be treated with some caution: government R & D in non-OECD countries is not reliably tracked or reported, nor is corporate R & D. However, we can observe several important trends, both in 2015 and cumulative data from 2004 to 2015. First, recent corporate R & D expenditures are commensurate with, and often exceed government R & D. Corporate R & D expenditures are strongest for technologies with the highest amount of recent deployment, including solar and wind technologies. Second, neither total nor corporate R & D investment is necessarily dependent on cumulative quantity (REN21, 2016). In 2015, cumulative wind quantity was roughly twice as large as solar PV, but wind had one third total R & D. Finally, the ratio of government to corporate R & D varies between ~0.5 and 1.8 for the technologies we examine, and are thus relatively balanced between the two sectors.

Fig. 3 shows the shifting-to-following benefit ratio, r_e, for several clean energy technologies using data from Table 2. The ratio r_e is a function of the current cost of a clean energy technology, the cost of a conventional energy technology, and the learning rate (Eq. (9)). We find a large range of shifting-to-following benefit ratios: however, all are greater than 3.6. Technologies with higher cost ratios and lower learning rates have larger shifting-to-following benefit ratios, as the relative benefits of curve-shifting R & D are magnified by the relatively large learning investment necessary to reach cost parity.

In 2015 there was little correspondence between the ratio of government-to-corporate R & D and the shifting-to-following benefit ratio calculated from Eq. (9). As discussed in Sections 1 and 2.3, the government-to-corporate R & D ratio enables a rough comparison of

Table 3
There is little correspondence between the ratio of government-to-corporate R & D and the relative benefit of cost reductions brought about by curve-shifting vs. curve-following R & D (i.e., the shifting-to-following benefit ratio). Investment estimates by Bloomberg New Energy Finance (McCrone et al., 2016). All values reported for 2015.

Technology	Government R & D investment (bn USD)	Corporate R & D (bn USD) investment	Government-to-corporate R & D ratio	Shifting-to-following benefit ratio
Solar PV	1.9	2.6	0.8	3.6
Biomass	0.2	0.3	0.7	12.3
Wind (onshore, offshore)	0.6	1.2	0.5	14.4, 129.7
Small hydro	0.3	0.1	1.8	approaching ∞

relative investment in curve-shifting and curve-following research. r_e, to the contrary, measures how responsive each type of R & D investment is with regard to small change in the starting cost. r_e varies between 3.6 and something approaching ∞ for technologies shown in Table 3 and Fig. 3. For the clean technologies studied here, r_e values suggest a high relative benefit of curve-shifting over curve-following R & D. This result contrasts with actual R & D ratios (~0.5 − 1.8), which suggest that recent portfolios have been more balanced between curve-shifting and curve-following R & D. Taken together, this may indicate relative underinvestment in curve-shifting R & D by the government and corporate sectors.

There are several limitations to this comparison. First, we are unable to determine the actual balance of curve-following and curve-shifting R & D within government and corporate portfolios. Actual R & D investments are directed towards a combination of curve-following and curve-shifting research. Second, given government and corporate incentives to underinvest in transformational R & D, the ratio of government-to-corporate R & D may overestimate the amount of investment in curve-shifting research. Finally, a consistent comparison of curve-shifting and curve-following R & D impacts requires an understanding of the relation between the size of the R & D investment and the cost reductions achieved (e.g. cost reduction per dollar invested) (Baker et al., 2015). Nevertheless, the lack of correspondence between the ratio of government-to-corporate R & D and the relative benefit of cost reductions brought about by curve-shifting vs. curve-following R & D indicates an imbalance in government and corporate R & D portfolios.

5. Conclusions and policy implications

Learning-by-doing and R & D are two drivers of technological change that help facilitate a transition towards a sustainable energy system (Sagar and Van der Zwaan, 2006). R & D investment by both government and corporate sectors impacts costs of new clean energy technologies. Some of what is learned through R & D investment may have been learned later through learning-by-doing, whereas other knowledge would not have been obtained. Curve-following R & D investments reduce the deployment cost in the same way as increased quantity installation. Curve-shifting R & D investments reduce the deployment cost through learning that is not related to cumulative quantity. In either case, R & D investment is a tool to achieve a goal of making clean energy technologies competitive with conventional energy technologies. Curve-shifting and curve-following R & D represent two stylized end-points in the R & D spectrum; real research would generate some knowledge that would be gained through learning-by-doing and some that would not.

In this paper, we demonstrate how these two types of R & D investment diverge in achieving cost-effective decarbonization. We show that if curve-following and curve-shifting R & D investments were able to produce the same cost reduction, the curve-shifting investment would reduce the learning investment to a greater degree than would the curve-following investment. The relative benefit of the curve-shifting R & D is greater for technologies with a higher starting costs and lower learning rates. We find that cost reductions brought about by curve-shifting R & D in solar PV reduce the need for subsidies (i.e., the learning investment) 3.6 times more than the same reduction in cost brought about by curve-following R & D. Relative benefits of curve-shifting R & D are even greater for the other clean energy technologies considered here. The benefits of cost-reductions brought about by curve-shifting R & D investments, relative to those brought about by curve-following R & D investments, are greatest for technologies with low learning rates and with current costs that are high relative to incumbent technologies. The lack of correspondence between recent government-to-corporate R & D ratios and shifting-to-following benefit ratios suggest that society may be underinvesting in transformational change.

Our analysis sheds light on the effectiveness of innovation policies in reducing deployment subsidies and achieving long term climate change mitigation. It highlights the fact that both R & D and learning-by-doing can reduce costs, as part of a portfolio to support diffusion of clean energy technologies. Our analysis also strongly suggests that, for R & D producing the same change in cost, curve-shifting R & D has large benefits relative to curve-following R & D. Of course, the size of the R & D investments needed to produce those cost reductions may differ dramatically and be difficult to predict. Nevertheless, in setting research policy, governments should consider the greater benefits of cost reductions brought about by transformational rather than incremental change.

Appendix A. Supplementary data

Supplementary data associated with this article can be found in the online version at http://dx.doi.org.10.1016/j.enpol.2017.05.029.

References

Alchian, A., 1963. Reliability of progress curves in airframe production. Econ.: J. Econ. Soc., 679–693.

Arrow, Kenneth J., 1971. The economic implications of learning by doing. Rev. Econ. Stud. 29 (3), 155–173.

Baker, E., Bosetti, V., Anadon, L.D., 2015. Special issue on defining robust energy r & d portfolios. Energy Policy, 215–218.

Barreto, L., Kypreos, S., 2004. Endogenizing R & D and market experience in the bottom-up energy-systems ERIS model. Technovation 24, 615–629. http://dx.doi.org/10.1016/S0166-4972(02)00124-4, (URL ⟨http://www.sciencedirect.com/science/article/pii/S0166497202001244⟩).

Bednyagin, D., Gnansounou, E., 2012. Estimating spillover benefits of large r & d projects: application of real options modelling approach to the case of thermonuclear fusion r & d programme. Energy Policy 41, 269–279.

Berglund, C., Söderholm, P., 2006. Modeling technical change in energy system analysis: analyzing the introduction of learning-by-doing in bottom-up energy models. Energy Policy 34, 1344–1356. http://dx.doi.org/10.1016/j.enpol.2004.09.002, (URL ⟨http://www.sciencedirect.com/science/article/pii/S0301421504002927⟩).

Bonvillian, W.B., Van Atta, R., 2011. Arpa-e and Darpa: applying the Darpa model to energy innovation. J. Technol. Transf. 36, 469.

Branz, H.M., Regan, W., Gerst, K.J., Borak, J.B., Santori, E.A., 2015. Hybrid solar converters for maximum exergy and inexpensive dispatchable electricity. Energy Environ. Sci. 8, 3083–3091.

Cohen, W.M., Levinthal, D.A., 1989. Innovation and learning: the two faces of r & d. Econ. J. 99, 569–596.

Diaz Anadon, L., Bunn, M.G., Chan, M., Jones, C.A., Kempener, R., Chan, G.A., Lee, A., Logar, N.J., Narayanamurti, V., 2011. Transforming US Energy Innovation.

DOE, 2016. Basic Energy Sciences (BES) Homepage | u.s. DOE office of science (SC). URL ⟨https://science.energy.gov/bes/⟩.

Edenhofer, O., Pichs-Madruga, R., Sokona, Y., Farahani, E., Kadner, S., Seyboth, K., Minx, J., 2014. Ipcc Climate Change 2014: Mitigation of Climate Change (Contribution of Working Group iii to the Intergovernmental Panel on Climate Change).

EIA, 2016. International energy outlook 2016. URL: ⟨https://www.eia.gov/outlooks/ieo⟩.

Ferioli, F., Schoots, K., van der Zwaan, B.C.C., 2009. Use and limitations of learning curves for energy technology policy: a component-learning hypothesis. Energy Policy 37, 2525–2535. http://dx.doi.org/10.1016/j.enpol.2008.10.043, (URL ⟨http://www.sciencedirect.com/science/article/pii/S0301421508006101⟩).

Foxon, T.J., 2010. Stimulating investment in energy materials and technologies to combat climate change: an overview of learning curve analysis and niche market support. Philos. Trans. R. Soc. Lond. A: Math. Phys. Eng. Sci. 368, 3469–3483.

Gallagher, K.S., 2014. The Globalization of Clean Energy Technology: Lessons from China. MIT Press, Cambridge, Massachusetts, USA.

Gaynor, M., Seider, H., Vogt, W.B., 2005. The volume-outcome effect, scale economies, and learning-by-doing. Am. Econ. Rev., 243–247.

Hirsch, W.Z., 1952. Manufacturing progress functions. Rev. Econ. Stat., 143–155.

IEA, 2015. Energy Technology Perspectives 2015: Mobilising Innovation to Accelerate Climate Action.

Jaffe, A.B., Newell, R.G., Stavins, R.N., 2005. A tale of two market failures: technology and environmental policy. Ecol. Econ. 54, 164–174. http://dx.doi.org/10.1016/j.ecolecon.2004.12.027, (URL ⟨http://www.sciencedirect.com/science/article/pii/S0921800905000303⟩).

Jamasb, T., 2007. Technical change theory and learning curves: patterns of progress in electricity generation technologies. Energy J., 51–71, (URL ⟨http://www.jstor.org/stable/41323109⟩).

Jamasb, T., Kohler, J., 2007. Learning Curves for Energy Technology: A Critical Assessment. URL ⟨https://www.repository.cam.ac.uk/handle/1810/194736⟩.

Johnstone, N., Haščič, I., Popp, D., 2010. Renewable energy policies and technological innovation: evidence based on patent counts. Environ. Resour. Econ. 45, 133–155.

Kahouli-Brahmi, S., 2008. Technological learning in energy-environment-economy modelling: a survey. Energy Policy 36, 138–162. http://dx.doi.org/10.1016/j.enpol.2007.09.001, (URL ⟨http://www.sciencedirect.com/science/article/pii/

S0301421507003813⟩).
Kim, J.H., Liang, P.W., Williams, S.T., Cho, N., Chueh, C.C., Glaz, M.S., Ginger, D.S., Jen, A.K.Y., 2015. High-performance and environmentally stable planar heterojunction perovskite solar cells based on a solution-processed copper-doped nickel oxide hole-transporting layer. Adv. Mater. 27, 695–701.
Lohwasser, R., Madlener, R., 2013. Relating R & D and investment policies to CCS market diffusion through two-factor learning. Energy Policy 52, 439–452. http://dx.doi.org/10.1016/j.enpol.2012.09.061, (URL ⟨http://www.sciencedirect.com/science/article/pii/S0301421512008439⟩).
Lundvall, B.Ä., Johnson, B., 1994. The learning economy. J. Ind. Stud. 1, 23–42.
McCrone, A., Moslener, U., Usher, E., Grüning, C., 2016. Global Trends in Renewable Energy Investment 2016. URL ⟨http://fs-unep-centre.org/publications/global-trends-renewable-energy-investment-2016⟩.
Nagy, B., Farmer, J.D., Bui, Q.M., Trancik, J.E., 2013. Statistical basis for predicting technological progress. PLoS One 8, e52669.
Nemet, G.F., 2009. Interim monitoring of cost dynamics for publicly supported energy technologies. Energy Policy 37, 825–835.
Nordhaus, W.D., 2009. The perils of the learning model for modeling endogenous technological change. Technical Report. National Bureau of Economic Research.
REN21, 2016. Global Status Report. Technical Report. URL ⟨http://www.ren21.net/status-of-renewables/global-status-report/⟩.
Rubin, E.S., Azevedo, I.M., Jaramillo, P., Yeh, S., 2015. A review of learning rates for electricity supply technologies. Energy Policy 86, 198–218, (URL ⟨http://www.sciencedirect.com/science/article/pii/S0301421515002293⟩).
Sagar, A.D., Van der Zwaan, B., 2006. Technological innovation in the energy sector: R & D, deployment, and learning-by-doing. Energy Policy 34, 2601–2608.
Söderholm, P., Klaassen, G., 2006. Wind power in Europe: a simultaneous innovation-diffusion model. Environ. Resour. Econ. 36, 163–190. http://dx.doi.org/10.1007/s10640-006-9025-z, (URL ⟨http://link.springer.com/article/10.1007/s10640-006-9025-z⟩).
Söderholm, P., Sundqvist, T., 2007. Empirical challenges in the use of learning curves for assessing the economic prospects of renewable energy technologies. Renew. Energy 32, 2559–2578.
Taylor, M.R., 2012. Innovation under cap-and-trade programs. Proc. Natl. Acad. Sci. 109, 4804–4809.
Wang, S.L., Heisey, P.W., Huffman, W.E., Fuglie, K.O., 2013. Public r & d, private r & d, and us agricultural productivity growth: dynamic and long-run relationships. Am. J. Agric. Econ., (aat032).
Wene, C., 2000. Experience Curves for Energy Technology Policy. IEA, Paris, France.
Wright, T.P., 1936. Factors affecting the cost of airplanes. J. Aeronaut. Sci. 3, 122–128.
Yang, C., Yeh, S., Zakerinia, S., Ramea, K., McCollum, D., 2015. Achieving california's 80% greenhouse gas reduction target in 2050: technology, policy and scenario analysis using ca-times energy economic systems model. Energy Policy 77, 118–130.