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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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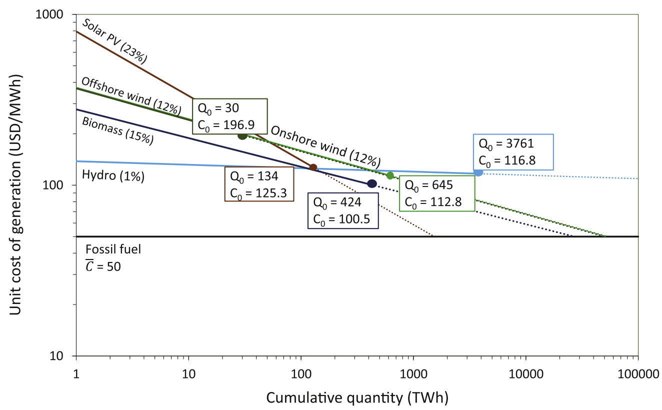

Fig. 1. Learning curves for clean and conventional energy technologies. The horizontal axis represents cumulative quantity of electricity generation and the vertical axis represents the unit cost of electricity generation. Both scales are logarithmic. Learning rates (R) are shown in parentheses. Q_0 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