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Up-scaling, formative phases, and learning in the historical diffusion of energy technologies

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HIGHLIGHTS

- ► Comparative analysis of energy technology diffusion.
- ► Consistent pattern of sequential formative, up-scaling, and growth phases.
- ► Evidence for conflation of industry level learning effects with unit level up-scaling.
- ► Implications for experience curve analyses and technology policy.

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ABSTRACT

The 20th century has witnessed wholesale transformation in the energy system marked by the pervasive diffusion of both energy supply and end-use technologies. Just as whole industries have grown, so too have unit sizes or capacities. Analysed in combination, these unit level and industry level growth patterns reveal some consistencies across very different energy technologies. First, the up-scaling or increase in unit size of an energy technology comes after an often prolonged period of experimentation with many smaller-scale units. Second, the peak growth phase of an industry can lag these increases in unit size by up to 20 years. Third, the rate and timing of up-scaling at the unit level is subject to countervailing influences of scale economies and heterogeneous market demand. These observed patterns have important implications for experience curve analyses based on time series data covering the up-scaling phases of energy technologies, as these are likely to conflate industry level learning effects with unit level scale effects. The historical diffusion of energy technologies also suggests that low carbon technology policies pushing for significant jumps in unit size before a 'formative phase' of experimentation with smaller-scale units are risky.

1. Introduction

Energy systems have witnessed transformative growth over the last 100 years. Global primary energy consumption increased 16-fold in the 20th century, as did GDP, compared to a 4-fold increase in population (Smil, 2000). Nested within this centennial trend are periods of rapid and pervasive technological diffusion. In the 1960s, roughly one coal-fired steam turbine unit averaging 125 MW in capacity was installed every other day, and around 3 in 4 of these were in OECD countries alone. In the 1990s, Boeing and Airbus' combined production was about three commercial jet aircraft every other day carrying the equivalent of around 150 MW of power plant. The ever-expanding capacity of the energy system to convert primary energy into energy carriers into useful services (and on into human welfare) is the result of increasing numbers of energy technologies, but also increasing sizes: more coal power plants and jet aircraft; larger capacity coal power plants and jet aircraft.

Technological change in the energy system is typically characterised at the industry level. As a current example, frequent reference is made to the double digit growth rates of the wind or solar photovoltaic industries (IEA, 2008). This industry level growth is characterised by falling units costs associated with increasing experience, a relationship described by learning phenomena.

Alongside learning, scaling is another widespread characteristics of technological diffusion in the energy system. Many energy technologies have increased in size and energy conversion capacity over the past 100 years (see Smil (2008) for many examples and graphics). In the early 20th century, the first mass produced car, Ransom Old's Curved Dash, carried around 10 horsepower, and the model-T Ford double that. Over the next 50 years, this increased seven-fold: by 1975, the average new

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vehicle in the US packed close to 140 horsepower. More commonly associated with energy supply technologies, a salient current example of 'up-scaling' is the steady march of wind turbine rated capacities and tower heights from the tens of kilowatts with 20–30 m towers in the early 1980s up to 2–5 MW with hub heights well over 100 m today. The urgency of decarbonisation objectives mean near-term policy and engineering expectations are for rapid up-scaling or increases in the capacities of other low carbon technologies including carbon capture and storage (Haszeldine, 2009) and concentrating solar power (Shinnar and Citro, 2008).

By capturing available scale economies, up-scaling can also lead to reductions in average unit costs. If these are concurrent with increasing production, then scale effects at the unit level may be conflated with learning effects at the industry level. So: what role does the up-scaling of energy technologies play in industry level growth? And by extension, how likely are the potential confounding effects of up-scaling on cost reductions attributed to learning from cumulative experience?

To address these questions, we investigate how rapidly and how pervasively energy technologies have diffused historically, distinguishing the timing of different phases within this overall diffusion process and the 'up-scaling' phase in particular. We also assess the factors that have enabled (or constrained) up-scaling at the unit level within the overall industry level growth. We find consistent evidence for a sequence of formative, up-scaling, and growth phases in our sample of energy technologies, and a trade-off between unit scale economies and heterogeneous market demand in determining the rate and timing of up-scaling. We conclude that up-scaling is likely to be conflated with learning effects in particular for centralised energy supply technologies. We also draw some general implications for technology policy.

2. Energy technology diffusion: learning and up-scaling

2.1. The lifecycle and diffusion of energy technologies

The pattern of diffusion over time for energy technologies has been characterised by logistic substitution models (Marchetti and Nakicenovic, 1979). Logistic growth describes an initial period of gradual diffusion as a technology is introduced as a new commercial application, moving then through a rapid, exponential growth phase, before slowing and eventually saturating (Grubler et al., 1999). The substitution of incumbent technologies by new competitors leads to subsequent decline and eventual obsolescence.

Early on in their lifecycle, new technologies are crude, imperfect, and expensive (Rosenberg, 1994). New energy technologies are attractive for their ability to perform a particular task or deliver a new or improved energy service (Fouquet, 2010). This is often circumscribed by a particular set of needs in a particular context: a market 'niche'. End-users in niche markets are generally less sensitive to the effective price of the energy service provided or have a higher willingness to pay for its performance advantages (Fouquet, 2010). Thus initially, performance dominates cost competitiveness (Wilson and Grubler, 2011). Market niches afford some protection from competitive pressures, allowing technologies to be tested and improved in applied settings, reducing uncertainties with performance or market demand (Kemp et al., 1998). Costs may only fall substantively after an extended period of commercial experimentation, concurrent with the establishment of an industrial base and characteristic moves towards standardisation and mass production (Grubler, 1998). The influence of accumulating production experience on costs is captured by the concept of learning.

2.2. Learning, and experience curves

Learning is a descriptive label for a multi-faceted process of knowledge generation, application and exchange. Learning may lead to product design improvements, material efficiencies, labour productivity, process refinements, lower contingencies or conservatism as perceived risks are reduced, better system integration, and so on (Argote and Epple, 1990). Originally associated with the experience of 'doing' (Arrow, 1962), learning effects have also been attributed to using, operating, implementing, copying, searching and building (Sagar and van der Zwaan, 2006).

Cost reductions associated with learning processes are described by industry-level experience curves which express unit costs as a function of cumulative production experience (Yeh and Rubin, 2012).[1] The learning rate measures the cost reduction for each successive doubling of cumulative production. Historical learning rates have been extensively characterised for energy technologies. Weiss et al., 2010a compiled data on over 200 learning rates for both energy supply and energy end-use technologies, finding means of $16 \pm 9\%$ and $18 \pm 9\%$ respectively.

Expectations of future learning rates, particularly for low carbon energy technologies, are widely used to inform or rationalise technology policies (Wene, 2000; Nemet, 2009) and to model the diffusion of technologies under different scenario assumptions (Clarke et al., 2008). Although preferable to forecasting either constant costs or declining costs over time (Alberth, 2008), the use of prospective learning rates is contentious.

First, learning rates even for the same technologies are subject to considerable uncertainties (Weiss et al., 2010a). Both data and learning processes are sensitive to the context of analysis, including the temporal and geographic system boundaries (Nemet, 2009) and other social and political factors (Yeh and Rubin, 2012). The price of production inputs, as well as profit margins (if price is used in lieu of cost as the performance measure) may change over time (Ferioli et al., 2009). Changes in product designs and the qualitative characteristics of the energy service provided need to be accounted for in standardising the cumulative production data (Coulomb and Neuhoff, 2006; Weiss et al., 2010b).

Second, learning is not a deterministic outcome of increasing production, but rather is contingent on a host of firm and industry-level innovation processes and efforts (Grubler, 2010). Two-factor experience curves, for example, explicitly represent the influence of cumulative R&D expenditure and the resulting R&D-based knowledge stock on unit cost reductions (Söderholm and Klaassen, 2007; Ek and Soderholm, 2010). But other omitted variables may still introduce biases. Examples include autonomous technological improvement, input price volatility, and knowledge spillovers (Nemet, 2006; Nordhaus, 2009).

Scale effects at the industry level realised through manufacturing and other scale economies are recognised as important drivers of the cost reductions described by experience curves (Argote and Epple, 1990). In their early synthesis, Dutton and Thomas (1984) find that "sometimes much of what is attributed to experience is due to scale". In the case of solar photovoltaic modules in the US, manufacturing scale economies explained 43% of observed cost reductions ($/Wpeak) between 1980 and 2001 (Nemet, 2006). Qiu and Anadon (2012) found economies of scale at the wind farm level in China explained roughly twice as much of the observed cost reductions as learning-by-doing, though the effects of both were dwarfed by the domestication of wind turbine manufacturing to exploit lower labour and material costs. Differing potentials for manufacturing scale economies in the

[1] Learning curves are a similar concept but apply to specific manufacturing plants or processes and focus on labour productivity (Dutton and Thomas, 1984).