Technology Learning Curves and the Future Cost of Electric Power Generation Technology

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While uncertainties remain about the science of climate change, and its impacts, there is no uncertainty about one thing:

**We need to reduce emissions of GHG by roughly an order of magnitude**
That means there will have to be a massive transformation in the way we use and produce energy.

US fleet is old and dirty.

Data from eGRID (2012); Figure from Catherine Izard, 2013.
There is need to understand how technologies are likely to evolve.
To inform policy makers on target feasibility.
How can we learn about how technologies evolved and are likely to evolve?

Look at the past.

Ask experts.

Use scenarios or forecasting models.
We have summarized the learning for the following technologies:

- Wind
- Solar PV
- Nuclear
- Hydroelectric
- Geothermal
- PC plants
- IGCC plants
- NGCC plants
- NG turbines
- Biomass plants
Theory

• Macroeconomic growth theory
  – Neoclassical growth models such as Solow’s (1956) originally treated technical change exogenously, that is, independent of other factors or variables.
  – This assumption leaves a large component of observed growth unexplained. An alternative formulation proposed by Romer (1986), and since followed by much of the technological change literature, suggests that technological change needs to be modeled endogenously, namely as a function of policy choices.
Theory

• A parallel discussion emerged in recent years in the energy modeling literature:
  – Energy technologies we use today have evolved over time: improvements in manufacturing and in efficiency led to a decline in production costs (Junginger et al. 2010).

• Exogenous technological change occurs as an autonomous process?
  – I.e., technological change do not being depend upon other policy or economic variables. (Cohen 1995; Clarke et al. 2006; Klepper & Simons 2000).
  – How do policies influence the pace of technological change? (R&D, feed-in tariffs, green certificates, and other mechanisms)
  – Technological change is not an exogenous process - it occurs as a result of identifiable processes, such as government research and development, corporate technology investment, and economy-of-scale effects. (Grubb & Köhler 2002)
Processes Leading to Technological Change

Targeting directly the technology/component under study:

- **NO POLICY**
  - Technology diffusion with no policies
  - “Learning by doing” (LBD)

- **DEMAND-PULL**
  - Feed-in tariffs, green certificates, etc.
  - Policy effect
  - “Learning by researching” (LBR)

- **SUPPLY-PUSH**
  - (Public and Private) R&D funding

Targeting directly the other technology/component than the one under study:

- **NO POLICY**
  - Technology diffusion with no policies
  - “Learning by doing” (LBD)

- **DEMAND-PULL**
  - Feed-in tariffs, green certificates, etc.
  - Policy effect
  - “Learning by researching” (LBR)

- **SUPPLY-PUSH**
  - (Public and Private) R&D funding

Changes in technology production costs

Direct spillover effects

Changes in other technology production costs
One-Factor Learning Curves

There is a large literature that has empirically observed a relationship between unit costs of production and cumulative production across numerous technologies and products. The relationship has been referred to as an “experience curve” or “learning curve” and, in its simplest form, it can be expresses as (Arrow 1962):

\[ C_i = a x_i^{-b} \]

Where,
- \( C_i \) = cost to produce the \( i^{th} \) unit
- \( x_i \) = cumulative production or capacity thru period \( i \)
- \( b \) = learning rate exponent
- \( a \) = coefficient (constant)

- Fractional cost reduction for a doubling of cumulative production is defined as the learning rate: \( LR = 1 - 2^b \)
- Some studies report the progress ratio: \( PR = 1 - LR \)
Example of One-Factor Learning:

Source: IIASA, 1997

Source: Junginger 2005
Two-Factor or Multiple Factor Learning Curves

\[ C_i = a_i \left( x_i^{-b_{LBD}} \right) \left( RD_i^{-b_{LBR}} \right) \]

where:
- \( C_i \) = unit cost of technology
- \( x_i \) = cumulative adoption of technology \( i \)
- \( RD_i \) = cumulative R&D investment or knowledge stock for \( i \)
- \( b_{LBD} \) = learning-by-doing parameter
- \( b_{LBR} \) = learning-by-researching parameter
- \( a_i \) = unit cost at unit cumulative capacity and knowledge stock for \( i \)

- These models suggest that R&D expenditures contribute significantly to cost reductions; but …
- Data limitations which lead to limited the practical applications of this two-factor model
**Key Findings:**

<table>
<thead>
<tr>
<th>Technology</th>
<th>Number of studies reviewed</th>
<th>Number of studies with one factor</th>
<th>Number of studies with two factors</th>
<th>Range of learning rates for “learning by doing” (LBD)</th>
<th>Range of rates for “learning by researching” (LBR)</th>
<th>Years covered across all studies</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Coal</strong></td>
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<td>PC</td>
<td>2</td>
<td>2</td>
<td>0</td>
<td>6% to 12%</td>
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<td>1902-2006</td>
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<td>IGCC</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>2% to 8%</td>
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<td>Projections</td>
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<td><strong>Natural Gas</strong></td>
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<td></td>
<td>8</td>
<td>6</td>
<td>2</td>
<td>-11% to 34%</td>
<td>2% to 18%</td>
<td>1980-1998</td>
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<td><strong>Nuclear</strong></td>
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<td></td>
<td>4</td>
<td>4</td>
<td>0</td>
<td>&lt;0 to 6%</td>
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<td>1975-1993</td>
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<td><strong>Wind (on-shore)</strong></td>
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<td></td>
<td>35</td>
<td>29</td>
<td>6</td>
<td>-3% to 32%</td>
<td>10% to 27%</td>
<td>1980-2010</td>
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<td><strong>Solar PV</strong></td>
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<td></td>
<td>24</td>
<td>22</td>
<td>2</td>
<td>10% to 53%</td>
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<td>1959-2001</td>
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<td><strong>BioPower</strong></td>
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<td><strong>Biomass production</strong></td>
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<td></td>
<td>4</td>
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<td>0</td>
<td>12% to 45%</td>
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<td>1971-2006</td>
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<td><strong>Power generation</strong></td>
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<td></td>
<td>7</td>
<td>7</td>
<td>0</td>
<td>0% to 24%</td>
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<td>1976-2005</td>
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<td><strong>Geothermal power</strong></td>
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<td></td>
<td>3</td>
<td>0</td>
<td>0</td>
<td>0% to 24%</td>
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<td>1980-2005</td>
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<td><strong>Hydropower</strong></td>
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<td></td>
<td>3</td>
<td>0</td>
<td>2</td>
<td>&lt;1% to 11%</td>
<td>3% to 21%</td>
<td>1980-2001</td>
</tr>
</tbody>
</table>

*Does not include plants with CCS.  **Includes combined heat and power (CHP) and biodigesters.
Wind
Example for Wind (on-shore)

Histogram of Learning Rates in the Literature

- Count:
  - Learning Rate:
    - -5% to -1%
    - 0% to 4%
    - 5% to 9%
    - 10% to 14%
    - 15% to 19%
    - 20% to 24%
    - 24% to 29%
    - Larger than 30%

- Dependent Variable = $/kWh (n=12)
- Dependent Variable = $/kW (n=23)

- Mean = 16%
- Median = 12%
- Std Dev = 14%
Wind ($/kW) by region and time period covered

Global and OECD studies

Region: Europe. Dependent Variable: $/kW

- Spain
- UK
- Spain
- Spain
- Spain

- Spain & Denmark
- Denmark
- Germany
- Denmark
- Sweden

Period Covered

- 0% 5% 10% 15% 20% 25% 30% 35%

Learning Rate

- Global
- OECD
- Global
- Global

Period Covered

- 0% 2% 4% 6% 8% 10% 12% 14% 16% 18% 20% 22% 24% 26%

- McDonald 2001
- Neij 2008
- Nemet 2009
- Wiser 2012

- McDonald 2001
- Junginger 2005
- Neij 2003
- IEA 2000
Wind ($/kWh) by region and time period covered

Region: Europe. Dependent Variable: $/kWh

- UK
- EU
- Denmark
- Germany

Period Covered
- Ibenholt 2002
- IEA 2000
- Neij 2003

Region: Multiple. Dependent Variable: $/kWh

- US
- California
- China

Period Covered
- IEA 2000
- McDonald 2001
- Qui 2012
Solar PV
Solar PV

![Bar chart showing learning rate intervals with mean, median, and standard deviation]

- Mean = 22%
- Median = 21%
- Std Dev = 10%
Learning Rates for Solar PV

Year


Learning Rate

10% 15% 20% 25% 30% 35% 40%

US, EU, Japan, Germany, unknown, global, EU

Harmon, 2000
Maycock, 1975
IEA, 2000
OECD/IEA, 2000
Schaeffer et al., 2004
Miketa and Schrattenholzer, 2004
Tsuchiya, 1993
Cody and Tiedje, 1997
Williams and Terzian, 1993
Parente et al., 2002
OECD/IEA, 2000
Schaeffer et al., 2004
Schaeffer et al., 2004
Schaeffer et al., 2004
Schaeffer et al., 2004
Schaeffer et al., 2004
Maycock, 2002, referred to in Nemet, 2006
Strategies Unlimited, 2003, referred to in Schaeffer et al., 2004
Strategies Unlimited, 2003, referred to in Schaeffer et al., 2004
Watanabe, 1999
Negative Learning? Reported Cost Trends for U.S. and French Nuclear Plants

Source: Grubler, 2010
Conclusions & Discussion

• Historical experience indicates that the real cost of most power generation technologies has declined over time.
• Most analytical models of such “learning” relate changes in the unit capital cost of a technology to cumulative installed capacity in a region (accounting for assumed “spillover” effects). Some models relate the unit cost of generation to cumulative electricity production.
• There is a wide range in the learning rates from these “one-factor” models. In general we found:
  – Largest rates are for renewable energy sources (esp. wind and PV)
  – Smaller learning rates for fossil fuel plant types
  – Mostly negative rates for existing nuclear plants
Conclusions & Discussion

• This type of modeling exercises is needed, and simple models are laudable, but they can only tell you so much.
  – Learning curves may be reasonable at explaining the past, but the use for forecasting or modeling future cost trends is likely to be inadequate.
  – The application of historical learning curves for certain technologies to new or different technologies being developed is arguably even more uncertain.

• Uncertainties:
  – What other factors will lead to cost changes besides installed capacity, and what are the implications of not including those factors explicitly in these models?
  – What is the appropriate measure of capacity or experience?
  – How to account for “spillover” effects, e.g., to what extent is learning shared across a range of technologies or applications?
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Natural Gas

Natural Gas Turbine. Dependent Variable: $/kW

- World

NGCC/GTCC. Dependent Variable: $/kW

- OECD
- EU & NAFTA
- EU & US

Colpier 2002
Kouvarakis 2000
IEA 2000

Learning Rate

4%
2%
14%
1%

Frequency

Mean = 14%
Median = 13%
Std Dev = 13%

Dependent Variable = $/kW (n=9)
Dependent Variable = $/kWh (n=2)
Examples of One-Factor Learning Curves for Power Plant Components

- **Pulverized Coal-Fired Boilers**
  
  \[ y = 515.00x^{-0.08} \]
  
  PR = 0.95
  
  1942, EF=29.9%
  
  1965
  
  1999, US DOE EF=37.6%

- **Flue Gas Desulfurization Systems**

- **Oxygen Production**
  
  \[ y = 94254x^{0.157} \]

- **Gas Turbine Combined Cycle**

Sources: Rubin et al. 2007; Colpier 2002
Examples of reported capital cost learning rates for natural gas-fired plants