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

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Background

- EPRI has developed the REGEN model to assess the technical, economic, and environmental impacts of U.S. energy supply options and policies
- Assumptions about the future cost of energy supply technologies are critical to model projections; at the present time EPRI uses exogenous specifications of technology-specific capital and O&M costs over time.
- Various types of "learning curves" (experience curves) also have been proposed to relate future technology costs to key parameters such as installed power plant capacity and other factors
- However, there has been little systematic study of how alternative cost projection methods and models affect the outcomes of large-scale energy-economic models

Study Objectives

- Conduct a literature review to characterize the current state of technology learning models for different types of electric power plants
- Review selected large-scale computer models that incorporate endogenous technology learning to draw insights about effects on model results
- Suggest preliminary computer experiments in REGEN to study the impacts of alternative cost projections (based on learning models)
- Provide recommendations for future testing and representation of technological change in REGEN

Technologies of Interest

- PC plants
- PC with CCS
- IGCC plants
- IGCC with CCS
- NGCC plants
- NGCC with CCS
- NG turbines
- Biomass plants
- Nuclear
- Hydroelectric
- Geothermal
- On-shore wind
- Off-shore wind
- Solar PV
- Conc. solar thermal

Draft Report Under Review

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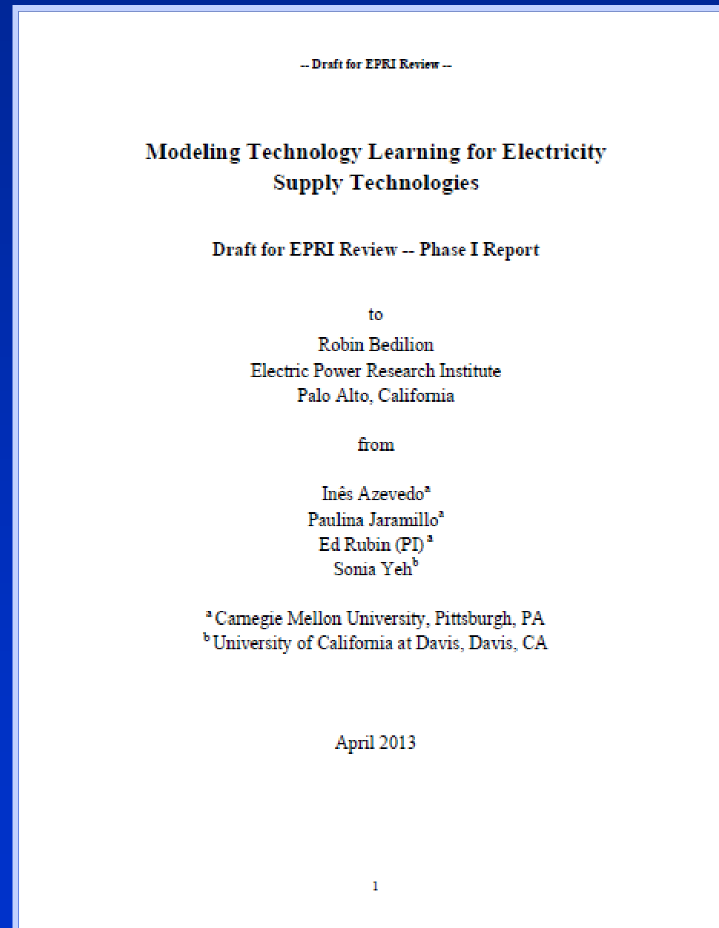

-- Draft for EPRI Review --

Modeling Technology Learning for Electricity Supply Technologies

Draft for EPRI Review -- Phase I Report

to

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I will present a few highlights from our report

Theory of technological change and learning rate results

Theory of Technological Change

Key drivers of cost reduction include:

- Diffusion/adoption of technology
- Research and development (R&D)
- “Cluster” learning
- “Spillover” effects
- Policies that promote the above

Various types of quantitative models have been proposed to account for these effects

One-Factor Learning Curves are the Most Prevalent

General equation:

$$C_i = a\, x_i^{\,-b}$$

where,

C_i = cost to produce the i^{th} unit

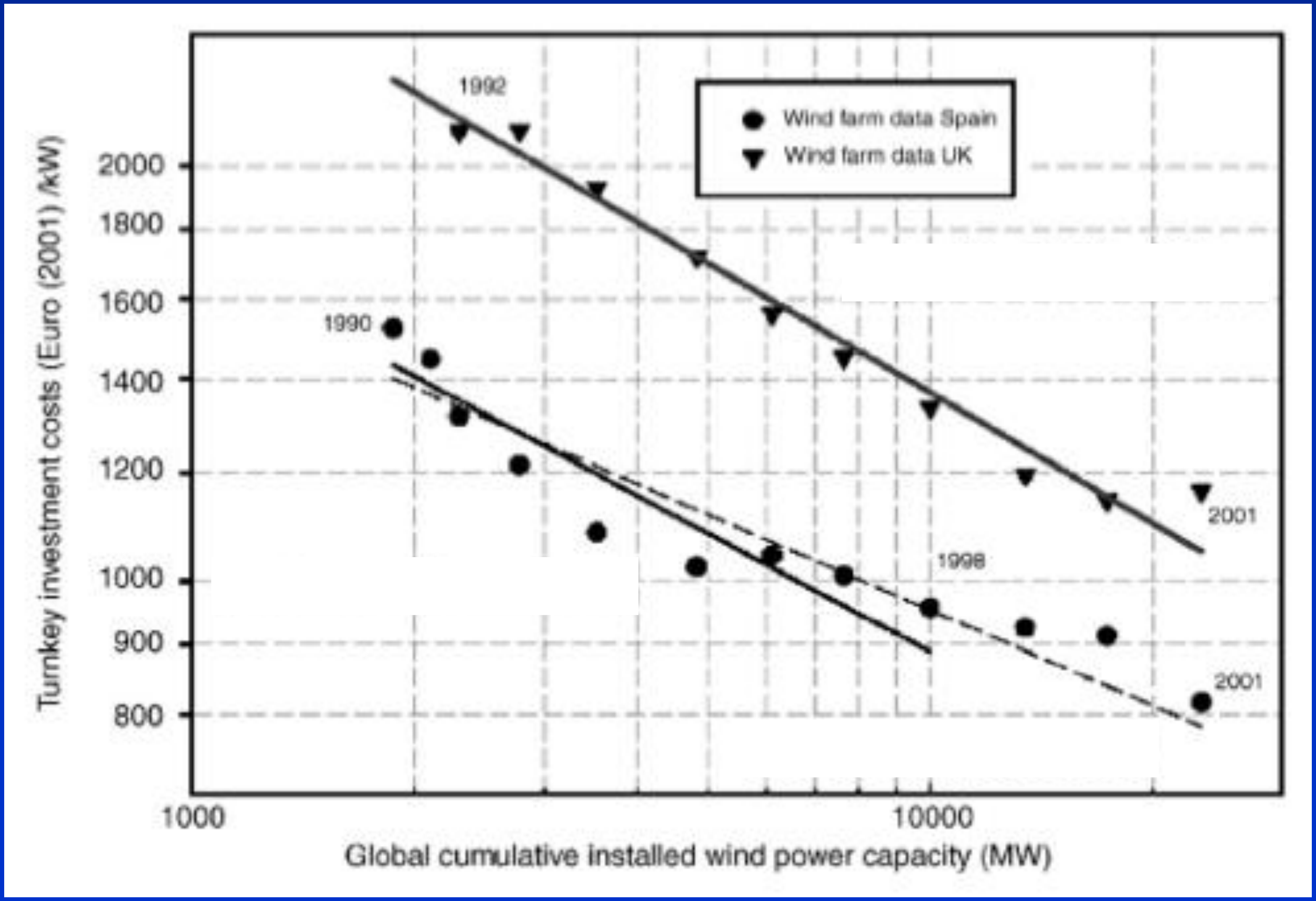
x_i = cumulative production or capacity thru period i

b = learning rate exponent

a = coefficient (constant)

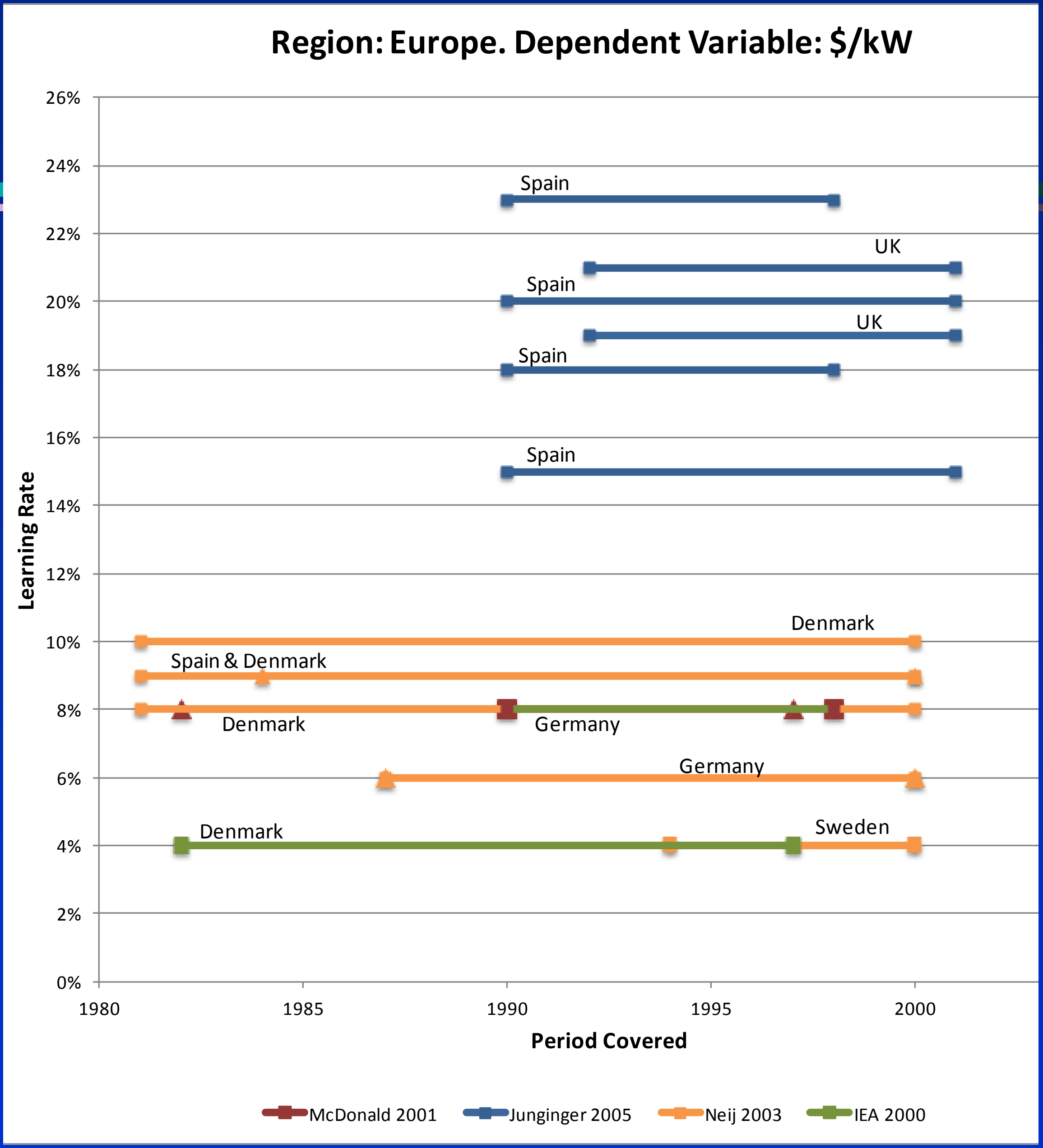
- *Fractional cost reduction for a doubling of cumulative production is defined as the <u>learning rate</u>: $LR = 1 - 2^b$*
- *Some studies report the progress ratio: $PR = 1 - LR$*

Examples of One-Factor Learning (Experience) Curves—Wind Farms



Source: Junginger 2005

Examples of reported learning rates for wind turbines based on $/kW



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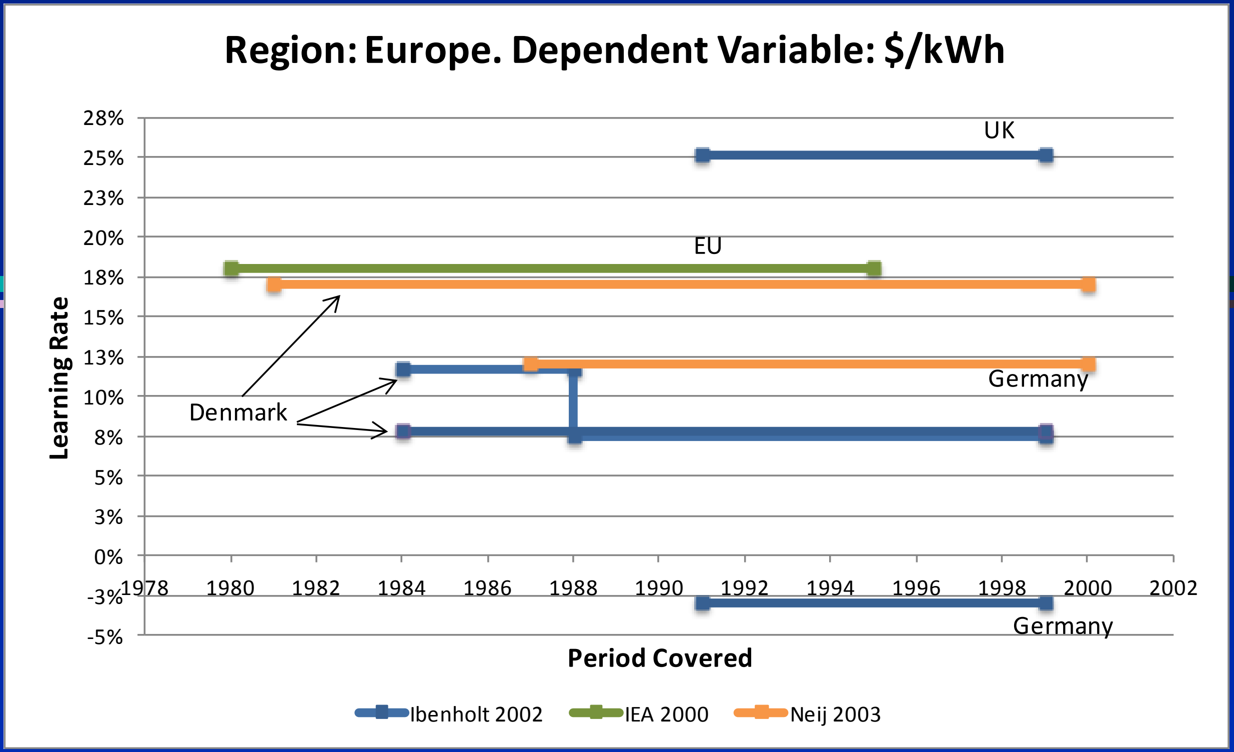
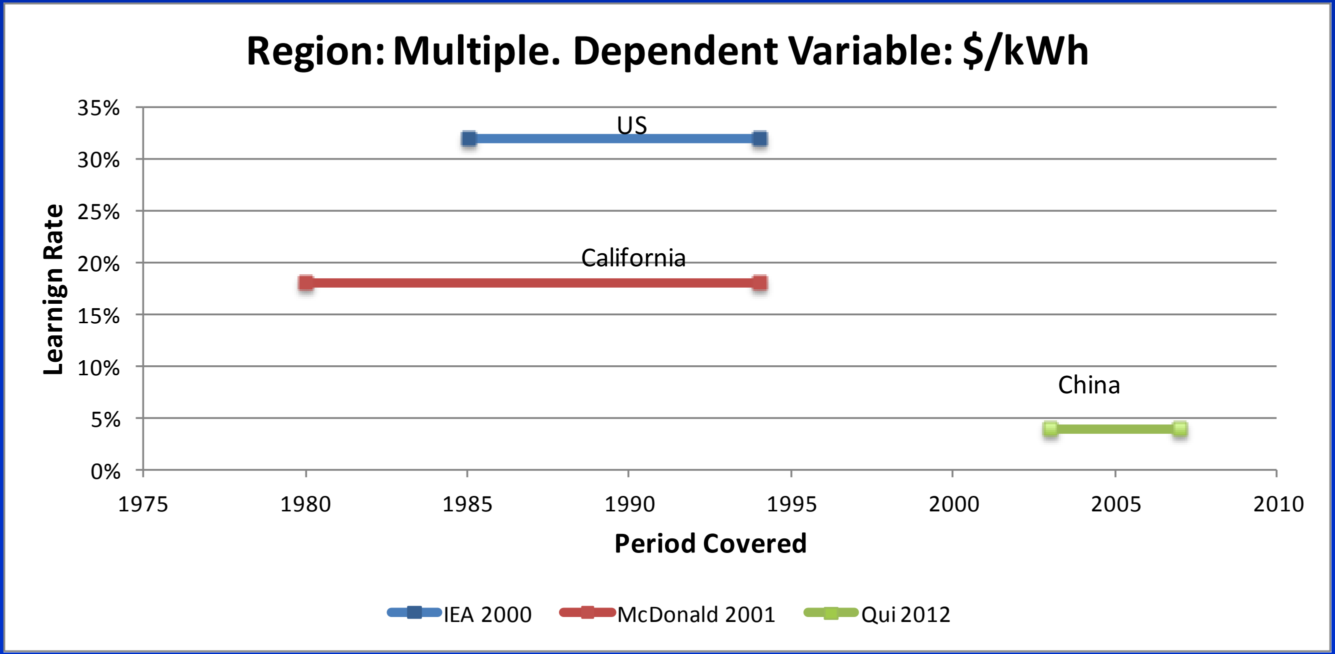
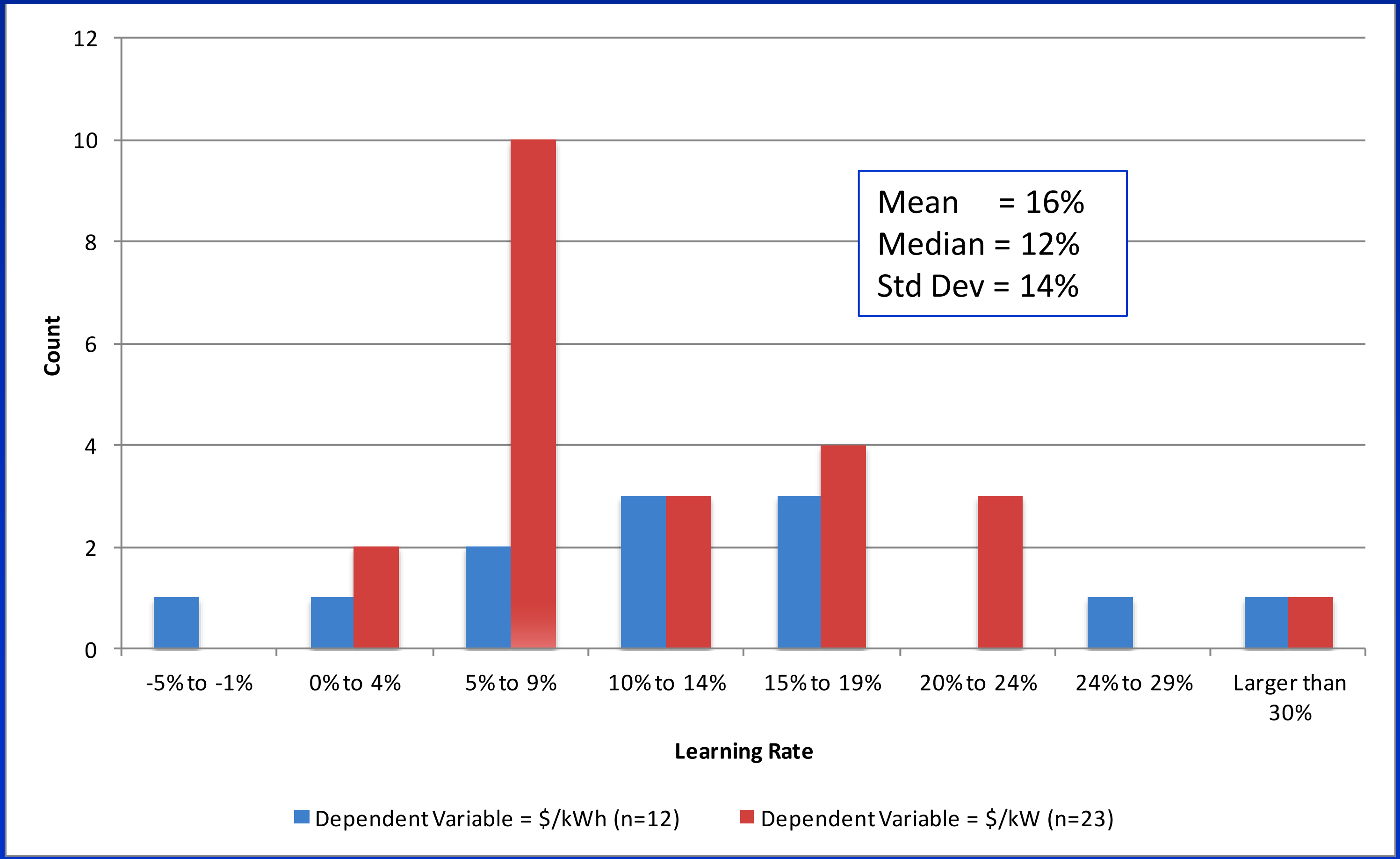
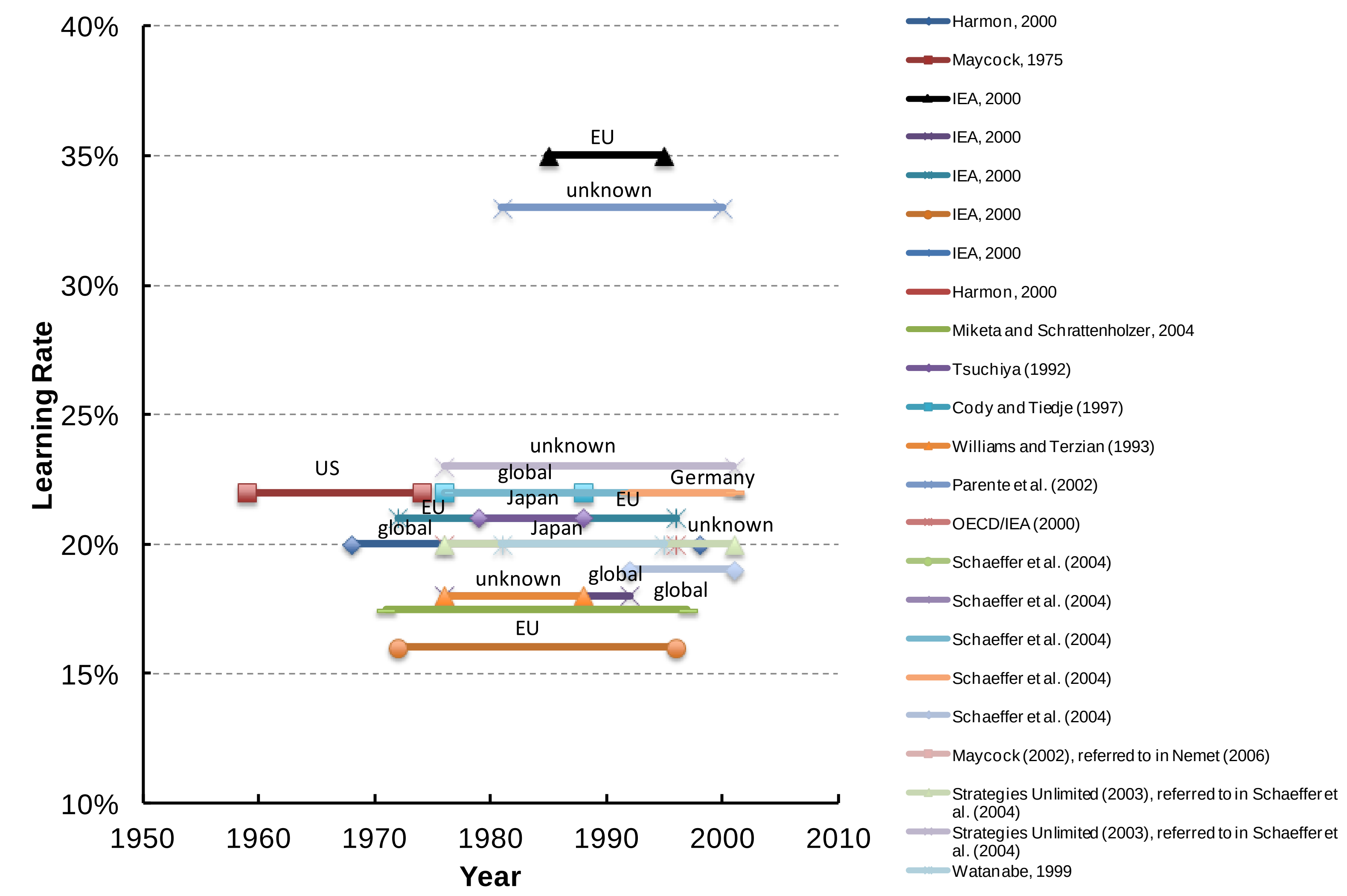




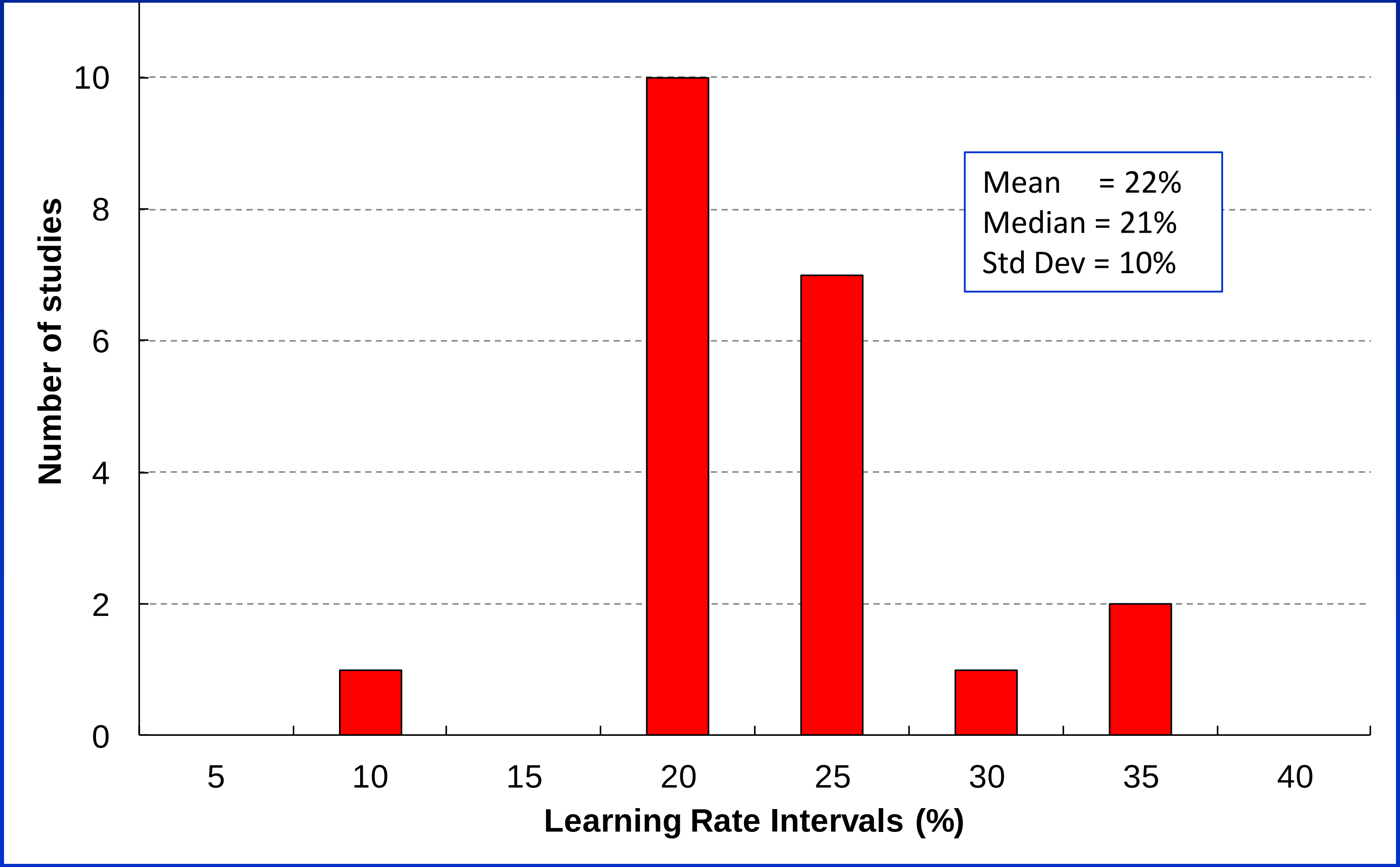
Histogram of Reported Learning Rates for On-Shore Wind Turbines



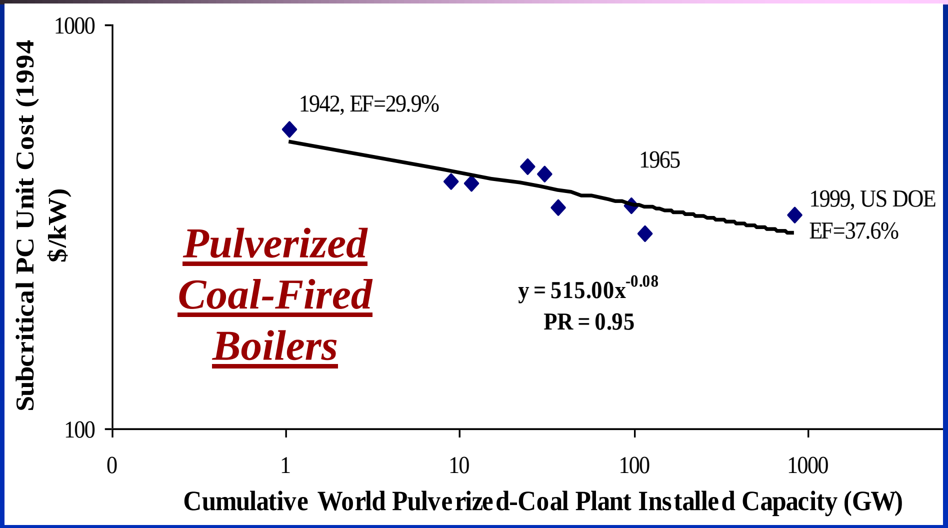
Learning Rates for Solar PV

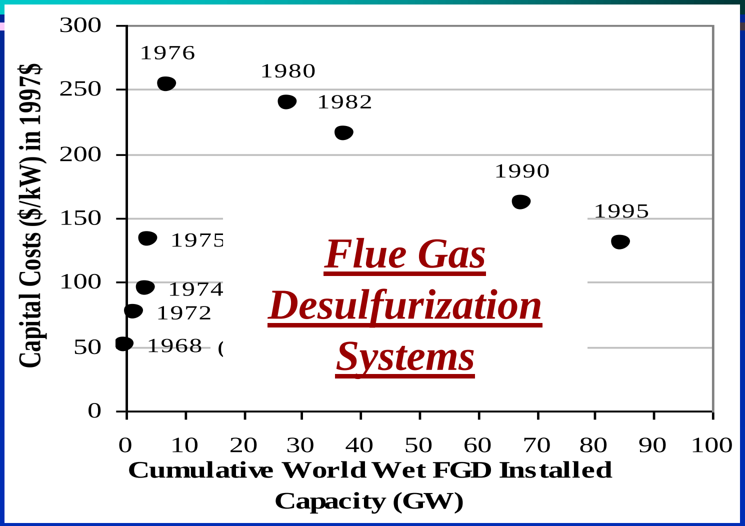


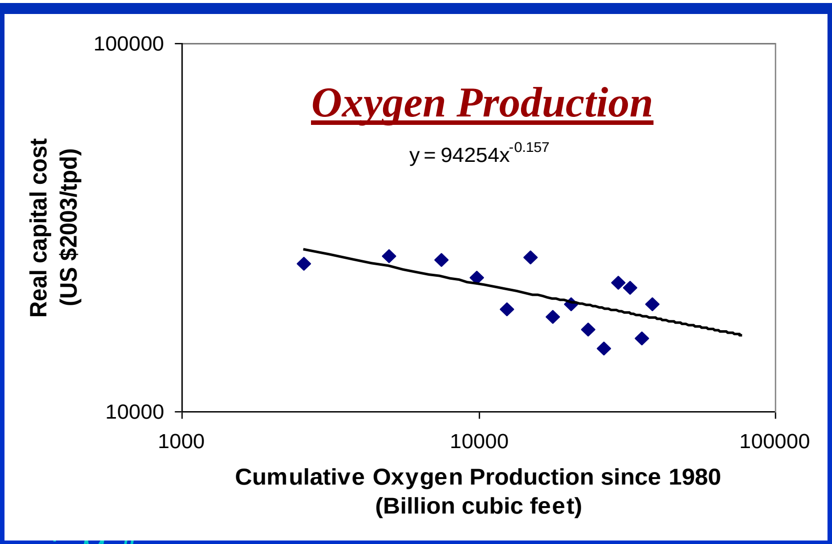
Histogram for Solar PV

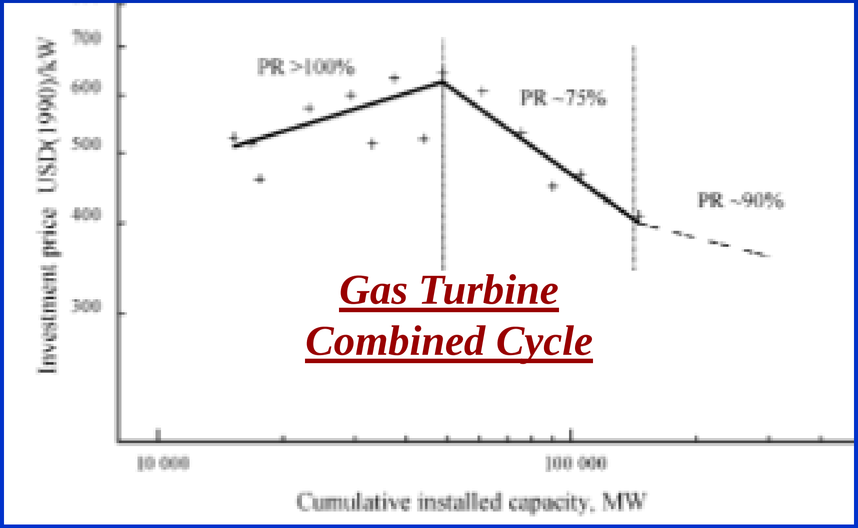


Examples of One-Factor Learning Curves for Power Plant Components



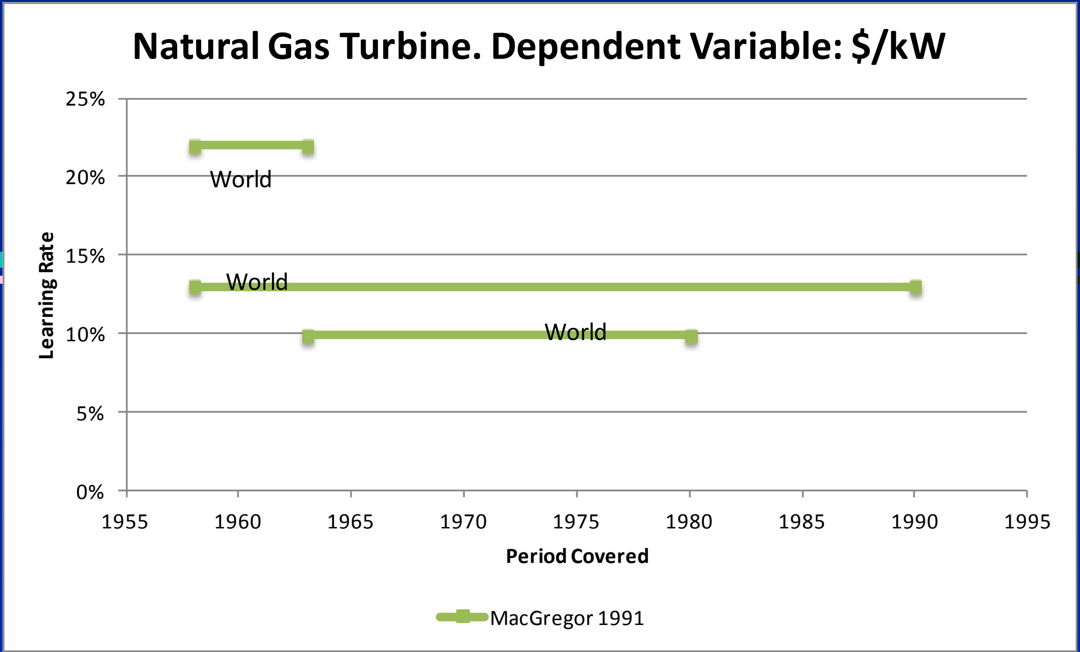


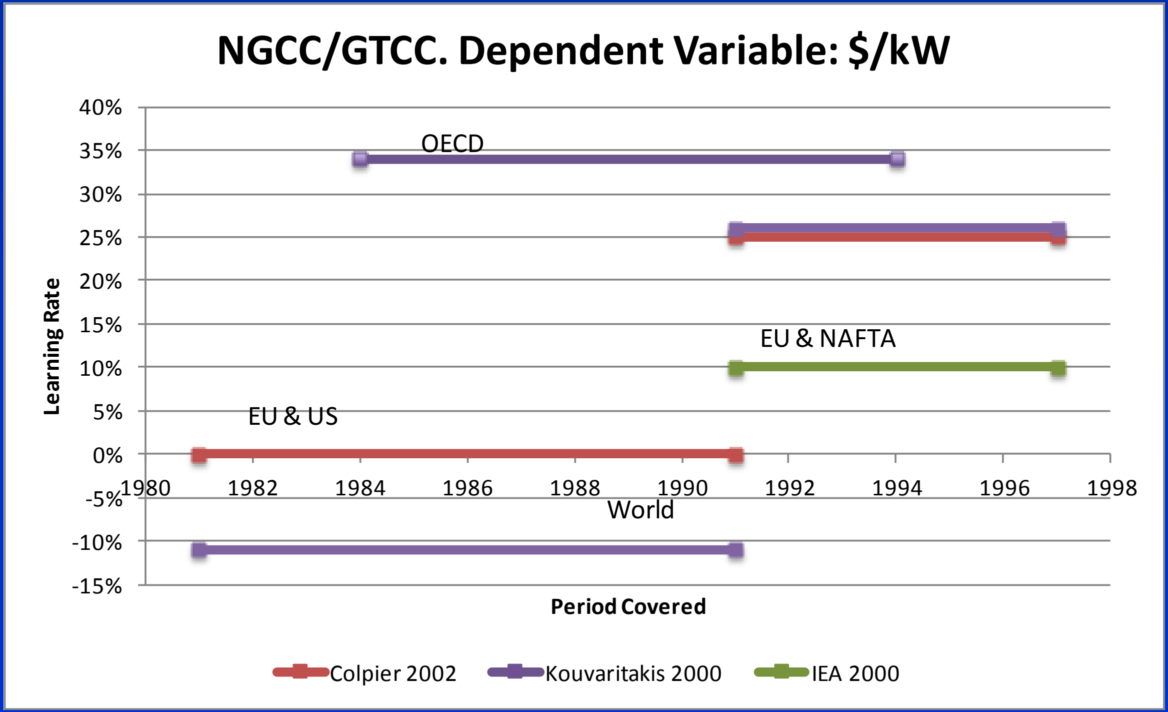




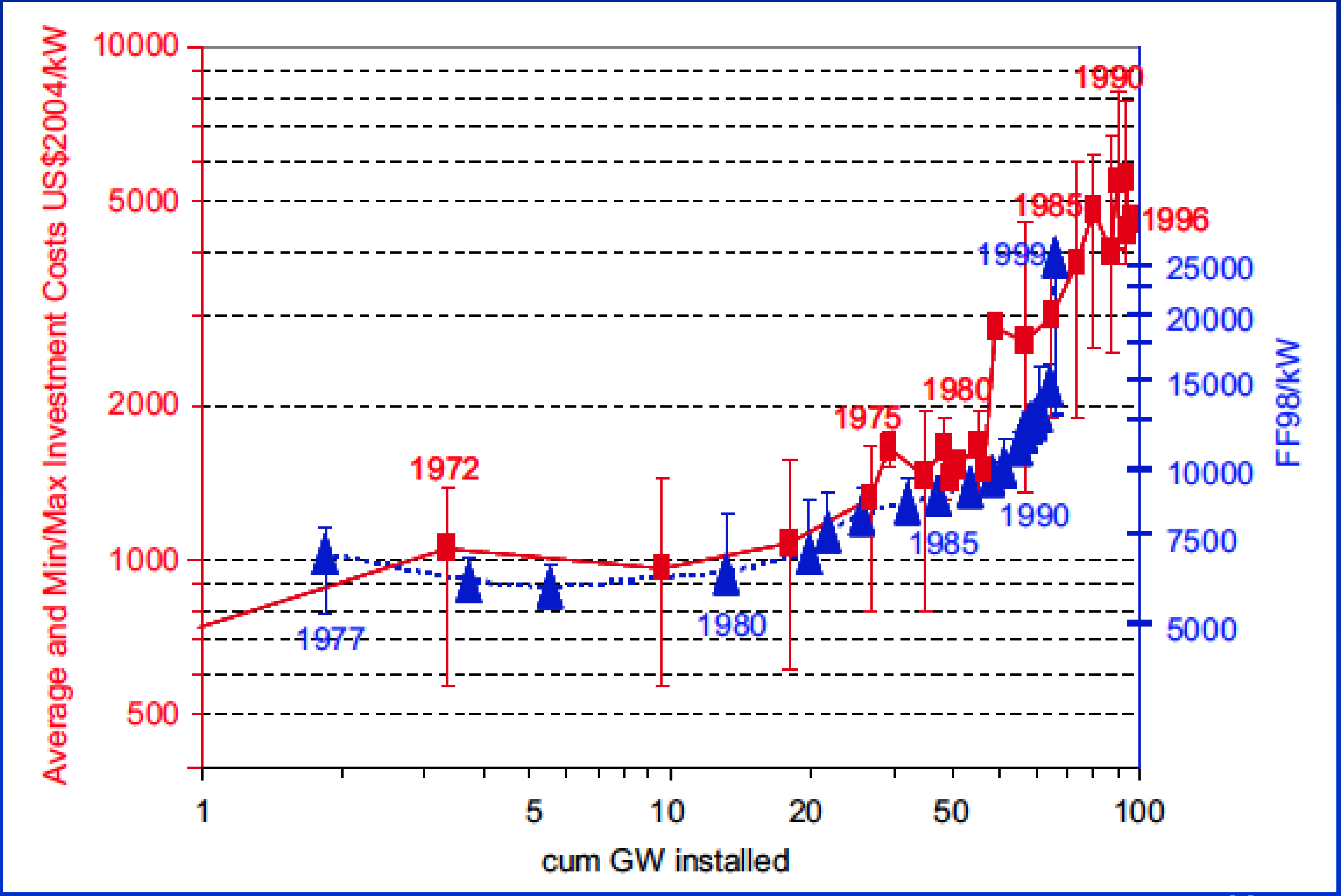
Sources: Rubin et al. 2007; Colpier 2002

Examples of reported capital cost learning rates for natural gas-fired plants





Reported Cost Trends for U.S. and French Nuclear Plants



Source: Grubler, 2010

Two-Factor Learning Curves

Model form: $C_i = a_i \, (x_i^{-b_{LBD}}) \, (RD_i^{-b_{LBR}})$

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 have limited the practical applications of this two-factor model

Range of Technology Learning Rates from the Literature Review

Technology	Number of studies reviewed	Number of studies with one factor	Number of studies with two factors	Range of learning rates for "learning by doing" (LBD)	Range of rates for "learning by researching" (LBR)	Years covered across all studies
Coal						
PC	2	2	0	5.6% to 12%		1902-2006
IGCC	1	1	0	2.5% to 7.6%		(projections)
Natural Gas	8	6	2	0.65% to 5.3%	2.4% to 17.7%	1980-1998
Nuclear	4	4	0	<0% to 6%		1975-1993
Wind (on-shore)	35	29	6	-3% to 32%	10% to 23.8%	1980-2010
Solar PV	23	22	1	10% to 53%	10%	1959-2001
BioPower						
Biomass production	4	4	0	12% to 45%		1971-2006
BioPower generation	7	7	0	0% to 24%		1976-2005
Geothermal power	3	0	0			1980-2005
Hydropower	3	0	2	0.5% to 11.4%	2.6% to 20.6%	1980-2001

Conclusions about Learning Rates

- 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.
- Our literature review reveals 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

Learning Rate Conclusions *(con't.)*

- More complex models also have been proposed to explain the "learning" phenomenon in terms of additional factors, such as expenditures on R&D
- Alternative formulations of one-factor models also have been proposed to more realistically model the "shape" of historical experience for some power plant technologies (e.g., an S-shaped learning curve).
- In general, data limitations severely limit the ability to test and validate alternative models except in limited situations
- Given the large uncertainties, energy-economic models used for planning and policy analysis should explore a wide range of cost projection models to seek robust conclusions

Endogenous learning in large-scale energy models

We Prepared Brief Reviews of Seven Energy-Economic Models

Model	MESSAGE
Modeling Type	Optimization
Geographic Scope	Global
Data Sources	Rao, Keppo, and Riahi (Rao et al. 2006)
Type of learning	Default is exogenous (AEEI). Endogenous learning - single factor and constant learning rate is applied in some studies
Technology representation/details	A total of 18 technologies are assumed to have ETL. Learning rates range from 0-15%. Exogenous learning rates of 3-5% are assumed according to the B2 scenario for the other technologies.
Cluster learning	Spillover across tech. ‘technology clusters’ has been applied in several modeling approaches (Seebregts et al. (Seebregts et al. 2000); Riahi et al. (Riahi et al. 2005)). Technological spillovers can occur within a cluster (for example: carbon capture technologies, centralized and decentralized solar PV) but not from outside the cluster (for example: improvements in the semi-conductor industry).
Spillover	Spillover across regions. The learning process for technology improvements is assumed to take place on a global scale. Although this might not necessarily be consistent with the existence of trade barriers, regional economic blocks or the importance of localized learning
MACRO	MESSAGE and MACRO are linked iteratively to include the impact of policies on energy costs, GDP and on energy demand. MACRO, a top-down macroeconomic equilibrium model captures capital stock, available labor, and energy inputs determine the total output of an economy according to a nested constant elasticity of substitution (CES) production function. The linking of a bottom-up technology-rich model and a top-down macroeconomic model results in a fully consistent evolution of energy demand quantities, prices, and macroeconomic indicators (such as GDP, investments and savings).
Key insights	1. The existence of technological learning while reducing overall energy system costs becomes particularly important in the context of a long-term climate policy. 2. Spillovers across technologies and regions due to learning results in increased upfront investments and hence lower costs of carbon free technologies, thus resulting in technology deployment and emissions reductions, especially in developing countries.3. Learning and spillover effects can lead to technologically advanced cost-effective global energy transition pathways. 4. Earlier studies using the MESSAGE model (Roehrl and Riahi (Roehrl & Riahi 2000); Nakicenovic and Riahi (Nakicenovic & Riahi 2001)) have shown that alternative parameterizations of technological change have significant implications for the technology portfolio as well as associated costs.

… plus a summary of an IPCC review of global top-down models with endogenous learning (17 studies)

Study	Model	ETC channel	Number of production sectors	Number of regions	Major results (impact of ETC)	Comments	Focus of analysis
Bosetti *et al.*, 2006	FEEM-RICE	LBD	1	8	An index of energy technological change increases elasticity of substitution. Learning-by-doing in abatement and R&D investments raise the index. Energy technological change explicitly decreases carbon intensity.		Experimental model exploring high inertia.
Crassous *et al.*, 2006	IMACLIM-R GCE	R&D and LBD	1	5	Cumulative investments drive energy efficiency. Fuel prices drive energy efficiency in transportation and residential sector. Learning curves for energy technologies (electricity generation).	Endogenous labour productivity, capital deepening.	
Edenhofer *et al.*, 2006	MIND Optimal growth	LBD	1	1	R&D investments improve energy efficiency. Factor substitution in a constant-elasticity-of-substitution (CES) production function. Carbon-free energy from backstop technologies (renewables) and CCS. Learning-by-doing for renewable energy. R&D investments in labour productivity. Learning-by-doing in resource extraction		
Gerlagh, 2006	DEMETER-1 CCS	LBD	1	1	Factor substitution in CES production. Carbon-free energy from renewables and CCS. Learning-by-doing for both and for fossil fuels.		
Masui *et al.*, 2006	AIM/Dynamic - Global	R&D	9	6	Factor substitution in CES production. Investments in energy conservation capital increase energy efficiency for coal, oil, gas and electricity. Carbon-free energy from backstop technology (nuclear/renewables).		Focus on energy efficiency with limited supply-side substitution.
Popp, 2006	ENTICE-BR	R&D	1	1	Factor substitution in Cobb-Douglas production. R&D investments in energy efficiency knowledge stock. Carbon-free energy from generic backstop technology	R&D investments lower price of energy from backstop technology.	

Endogenous Learning Rates (%) in Several Bottom-Up Energy Models

Technology	(a) One-factor learning curves				(b) Two-factor learning curves			
	ERIS	MARKAL	MERGE -ETL	MESSAGE	ERIS		MERGE-ETL	
				Learning Mode:	LBD	LBR	LBD	LBR
Advanced coal	5	6	6	7	11	5	6	4
NG combined cycle	10	11	11	15	24	2	11	1
New nuclear	5	4	4	7	4	2	4	2
Fuel cell	18	13	19	-	19	11	19	11
Wind power	8	11	12	15	16	7	12	6
Solar PV	18	19	19	28	25	10	19	10

LBD= learning by doing; LBR= learning by researching

Source: IPCC (2007)

Learning Rates for New Generation Components in NEMS

Technology Component	Period 1 Learning Rate	Period 2 Learning Rate	Period 3 Learning Rate	Period 1 Doublings	Period 2 Doublings	Minimum Total Learning by 2025
Pulverized Coal	-	-	1%	-	-	5%
Combustion Turbine - conventional	-	-	1%	-	-	5%
Combustion Turbine - advanced	-	10%	1%	-	5	10%
HRSG[1]	-	-	1%	-	-	5%
Gasifier	-	10%	1%	-	5	10%
Carbon Capture/Sequestration	20%	10%	1%	3	5	20%
Balance of Plant - IGCC	-	-	1%	-	-	5%
Balance of Plant - Turbine	-	-	1%	-	-	5%
Balance of Plant - Combined Cycle	-	-	1%	-	-	5%
Fuel Cell	20%	10%	1%	3	5	20%
Advanced Nuclear	5%	3%	1%	3	5	10%
Fuel prep - Biomass IGCC	20%	10%	1%	3	5	20%
Distributed Generation - Base	-	5%	1%	-	5	10%
Distributed Generation - Peak	-	5%	1%	-	5	10%
Geothermal	-	8%	1%	-	5	10%
Municipal Solid Waste	-	-	1%	-	-	5%
Hydropower	-	-	1%	-	-	5%
Wind	-	-	1%	-	-	1%
Wind Offshore	20%	10%	1%	3	5	20%
Solar Thermal	20%	10%	1%	3	5	20%
Solar PV	15%	8%	1%	3	5	20%

Source: EIA (2012)

Conclusions from Energy Models with Endogenous Learning

- Endogenous technological learning tends to reduce overall energy system costs and becomes particularly important in the context of a long-term climate policy
- Endogenous learning results in increased upfront investment costs, but lowers the overall costs of carbon-free technologies, resulting in greater technology deployment and emissions reductions, especially in developing countries.
- Spillovers across technologies and regions can lead to more cost-effective global energy transition pathways.
- Alternative parameterizations of technological change can have significant implications for the technology portfolio as well as associated costs.

Remaining tasks

Work in Progress

- Finalize the literature review (Phase I) report
- Analyze sample cost trajectories and overall results from REGEN
- Suggest alternative cost trajectories based on learning models, and assess their impact on key results from REGEN
- Prepare a brief Phase II report including recommendations for future work

Thank You

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