CLEAN ENERGY TECHNOLOGIES:
LEARNING BY DOING AND LEARNING BY WAITING

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Energy Policy Research Seminar

September 29, 2014

The scale of the climate problem is enormous. Obtaining cooperation across sectors and countries will require transforming the energy system. The costs of this change present a first-order issue in developing the policy. One argument implies that the costs will be minimal.

> "In remarks on Twitter, Obama said: "This study ["Better Growth, Better Climate"] concludes that no one has to choose between fighting climate change and growing the economy." (Barak Obama, September 16, 2014.)

> "This report ["Better Growth, Better Climate"] argues for a new model where economic growth and climate action are mutually reinforcing – and it shows how we can build it. There is no time to lose." (Ban Ki Moon, September 16, 2014.)

> "It doesn't cost more to deal with climate change; it costs more to ignore it ... and we need to make that clear to people in this country," Kerry told reporters. (John Kerry, New York, September 23, 2014.)

(Global Commission on the Economy and Climate. (2014). "Better Growth, Better Climate." Retrieved from http://newclimateeconomy.report/)

An alternative argument is that the costs will be significant but worth it.

"I am very well aware that these are not easy choices for any country to make – I know that. I've been in politics for a while. I know the pull and different powerful political forces. Coal and oil are currently cheap ways to power a society, at least in the near term." (John Kerry, Jakarata, February 16, 2014.)

"Doing what is necessary to achieve the United Nations' target for reducing emissions would reduce economic growth by about 0.06 percent annually from now through 2100, according to the I.P.C.C. That sounds trivial, but by the end of the century it means a 5 percent loss of worldwide economic activity per year.

"And this cost projection assumes optimal conditions — the immediate implementation of a common global price or tax on carbon dioxide emissions, a significant expansion of nuclear power and the advent and wide use of new, low-cost technologies to control emissions and provide cleaner sources of energy.

"If the new technologies we hope will be available aren't, like one that would enable the capture and storage of carbon emissions from power plants, the cost estimates more than double." (Robert Stavins, NYT, Sep. 20, 2014.)

A central debate focuses on policies to deploy clean renewable energy technologies. The German *Enrgiewende* is the poster child for this discussion.

" … proponents [of Germany's *Energiewende*] highlight the dynamic success of the policy in spurring an increase in renewable energy from 6 percent of total electricity supply in 2000 to 23 percent in 2012.5 This increase in renewable energy in electricity generation has created additional environmental, economic, and security benefits. Renewable energy in the electricity sector is estimated to have saved Germany €11 billion from 2009 to 2012 in fossil fuel imports and avoided 101 million tonnes of GHG emissions in 2012 alone.

… Moreover, the government and other supporters view the *Energiewende* as a model for other countries, even suggesting that the fate of the global battle to combat climate change hinges on Germany's success." (Ebinger, C., Banks, J. P., & Schackmann, A. (2014). *Transforming the Electricity Portfolio: Lessons from Germany and Japan in Deploying Renewable Energy*. Energy Security Initiative, Brookings Institution.)

"In Germany, a system of subsidies has supported and encouraged the rapid expansion of renewable energy production. On the whole, these well-intentioned laws have proved to be an extraordinarily wasteful means of supporting improvements in environmental quality and reducing greenhouse gas emissions." (Morey, M., & Kirsch, L. (2014). Germany's Renewable Energy Experiment: A Made-to-Order Catastrophe. *The Electricity Journal*, 27(5), 6–20.)

The case for the success of the German *Enrgiewende* emphasizes the reduction in costs for future deployment rather than the immediate environmental benefits.

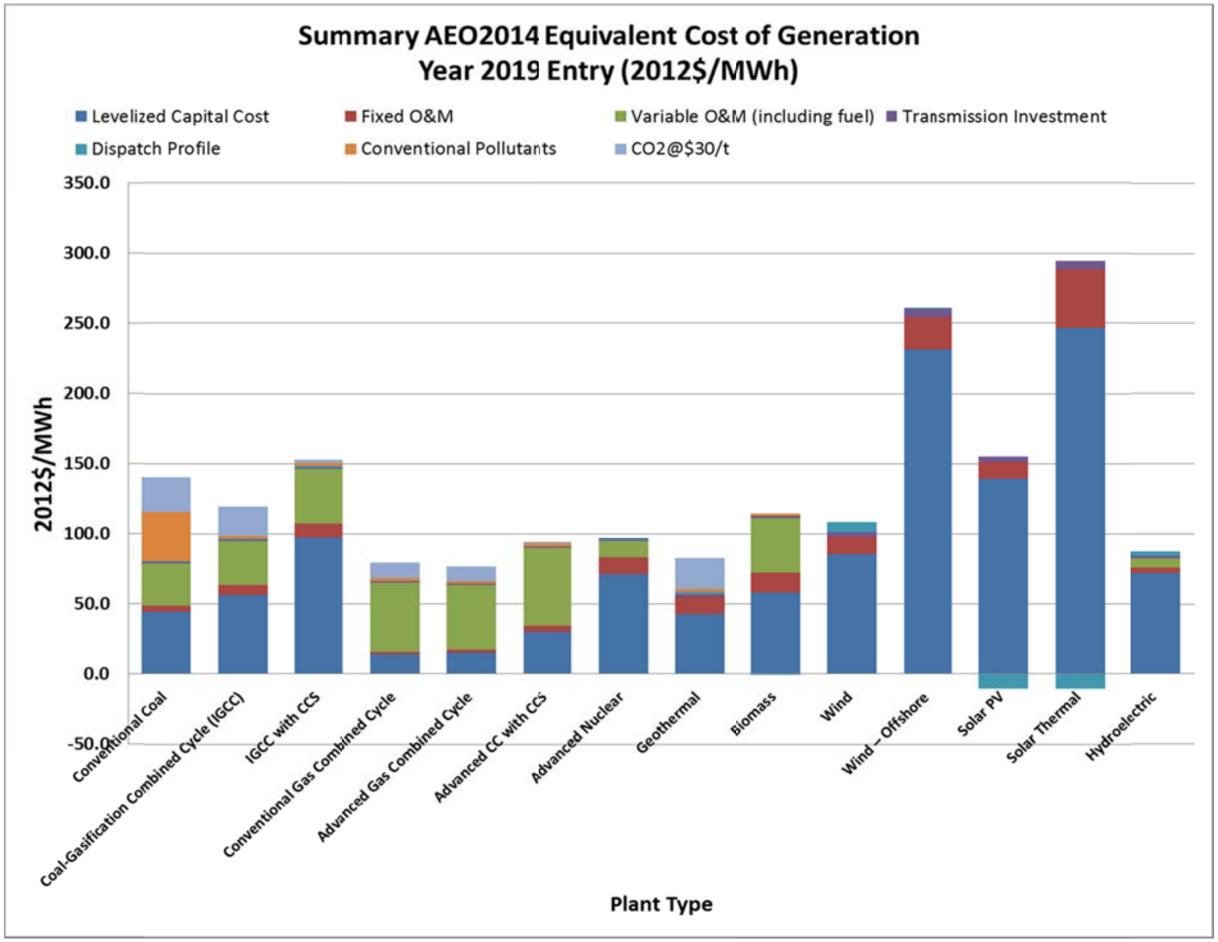
> "The German (and Spanish, and several U.S. states) commitments to solar in the early, expensive years were not simply to purchase zero-carbon energy: **Their main point was to drive down the price, so that there would be vast amounts of clean energy available at a reasonable price in the future.** Looking back at the Energiewende, the proper question is not whether the initial tranche of renewable energy was cost-competitive with other technologies, but whether the investment drove the price down enough to give the world new, affordable, clean technology options." (emphasis in original) (Hal Harvey. (2013)."A Tale of Two Countries: Renewable Energy in Germany." Energy Innovation LLC.)

The costs of clean technologies are high, but declining. Success stimulating the development of less expensive will be crucial in achieving the climate goals.

- **RE<C.** The earlier mantra from Google, where renewable energy (RE) is cheaper than coal (C). This would make adoption of renewables an easy choice even without considering the environmental benefits.
- **RE<C+Carbon Price.** The economic welfare outcome that internalizes the carbon externality. Renewable energy is expensive, but it is worth it. Climate policy includes a mix of mitigation and adaptation.
- **RE>C+Carbon Price.** Renewable energy is too expensive, and climate policy leans heavily towards adaptation.

It is important to know where we are and where we are going. The policy prescription depends on the diagnosis. How and how much should we be supporting the development of clean energy technologies?

A starting point is an assessment of the current costs of competing energy supply technologies. The levelized cost of energy (LCOE) provides one benchmark. This is an apples-to-apples comparison based on the assumptions and input data for the United States as developed by the Energy Information Administration.



The details of the EIA LCOE components appear in the table.

Summary 2019 Levelized Cost of Generation: Year 2019 Entry (2012$/MWh)

Plant Type	Levelized Capital Cost	Fixed O&M	Variable O&M (including fuel)	Transmission Investment	Dispatch Profile	Conventional Pollutants	CO2@$30/t	Total System LCOE
Conventional Coal	44.4	4.2	30.3	1.2	0.7	35	24.6	140.6
Coal-Gasification Combined Cycle (IGCC)	56.3	6.9	31.7	1.2	0.7	2	20.9	119.8
IGCC with CCS	97.8	9.8	38.6	1.2	0.9	2	2.3	152.7
Conventional Gas Combined Cycle	14.3	1.7	49.1	1.2	0	2	10.8	79.2
Advanced Gas Combined Cycle	15.7	2	45.5	1.2	0	2	10.1	76.6
Advanced CC with CCS	30.3	4.2	55.6	1.2	0	2	1.2	94.6
Advanced Nuclear	71.4	11.8	11.8	1.1	1.2	0	0.0	97.3
Geothermal	43.1	12.2	0	1.4	2	2	22.1	82.9
Biomass	57.7	14.5	39.5	1.2	-0.4	2	0.0	114.6
Wind	85.4	13	0	3.2	7.2	0	0.0	108.8
Wind – Offshore	231.7	22.8	0	5.8	0.6	0	0.0	260.9
Solar PV	139.6	11.4	0	4.1	-10.5	0	0.0	144.6
Solar Thermal	246.5	42.1	0	6	-10.4	0	0.0	284.2
Hydroelectric	72.0	4.1	6.4	2	3	0	0.0	87.5

Author's analysis based pn Energy Information Administration. (2014c). *Levelized Cost and Levelized Avoided Cost of New Generation Resources in the Annual Energy Outlook 2014* (pp. 1–12). Retrieved from http://www.eia.gov/forecasts/aeo/pdf/electricity_generation.pdf

A classification of major opportunities for cost reduction pathways focuses on "learning" broadly conceived. The terminology is not fully settled, but the basic ideas have been widely discussed. (Junginger, Sark, & Faaij, 2010)

- **Learning by searching (LBS):** This is R&D broadly writ. The most important features include an intentional and costly effort to develop innovations. Typically the R&D is risky and there are large spillover effects. The goal is to develop the innovation until it is at or near the stage of large scale deployment.
- **Learning by doing (LBD):** Early production produces new information which reduces the cost of future production. Critical characteristics include that LBD learning is passive (Thompson, 2010) and is treated as a free by-product of deployment. There can be significant spillover effects.
- **Learning by using (LBU):** The demand side counterpart for learning by doing. Often not treated separately from learning by doing.
- **Learning by waiting (LBW):** The spillover effects from other industries, technologies or countries are essentially exogenous from the perspective of the firm in the present industry. (Thompson, 2010) The resulting benefits from the innovative technology will appear over time and can be exploited by waiting.

Another pathway often mentioned is important but has different policy implications.

- **Economies of scale:** The standard argument about decreasing unit production costs as production plant reaches an efficient size. In the energy market this is unlikely to be a market-wide phenomenon, i.e. the case of natural monopoly, but may be relevant at the firm level. (Gillingham & Sweeney, 2010) However, "significant economies of scale in any industry, short of creating a natural monopoly, are not generally seen as a basis for government intervention." (Borenstein, 2012) (p. 83)

The case of learning by doing emphasizes the spillover benefits of deployment.

Nordhaus offers a representative learning curve model (Nordhaus, 2014). New production in period *t* is Q_t. The associated cost of production is simplified to a constant marginal cost C_t. Cumulative production is Y_t , where $Y_t = \int_{v=-\infty}^{t} Q_v dv$. Nordhaus includes the effect of all learning that does not require deployment as represented in an exogenous trend where costs decrease at rate h. The learning effect appears as the elasticity b that captures the percentage reduction in costs associated with an increase in experience measured as cumulative production. The stylized model of LBD represents marginal cost of new production as:

$$C_t = C_0 Y_0^b e^{-ht} Y_t^{-b}.$$

The model is linear in logarithms of cost, a trend, and cumulative experience.

$$\ln C_t = \ln C_0 + b \ln Y_0 - ht - b \ln Y_t \ .$$

The description of learning can be summarized by the progress ratio (PR) which is the amount that costs reduce to after a doubling of cumulative production.

$$PR = 2^{-b}.$$

The related learning rate (LR) is one minus the progress ratio.

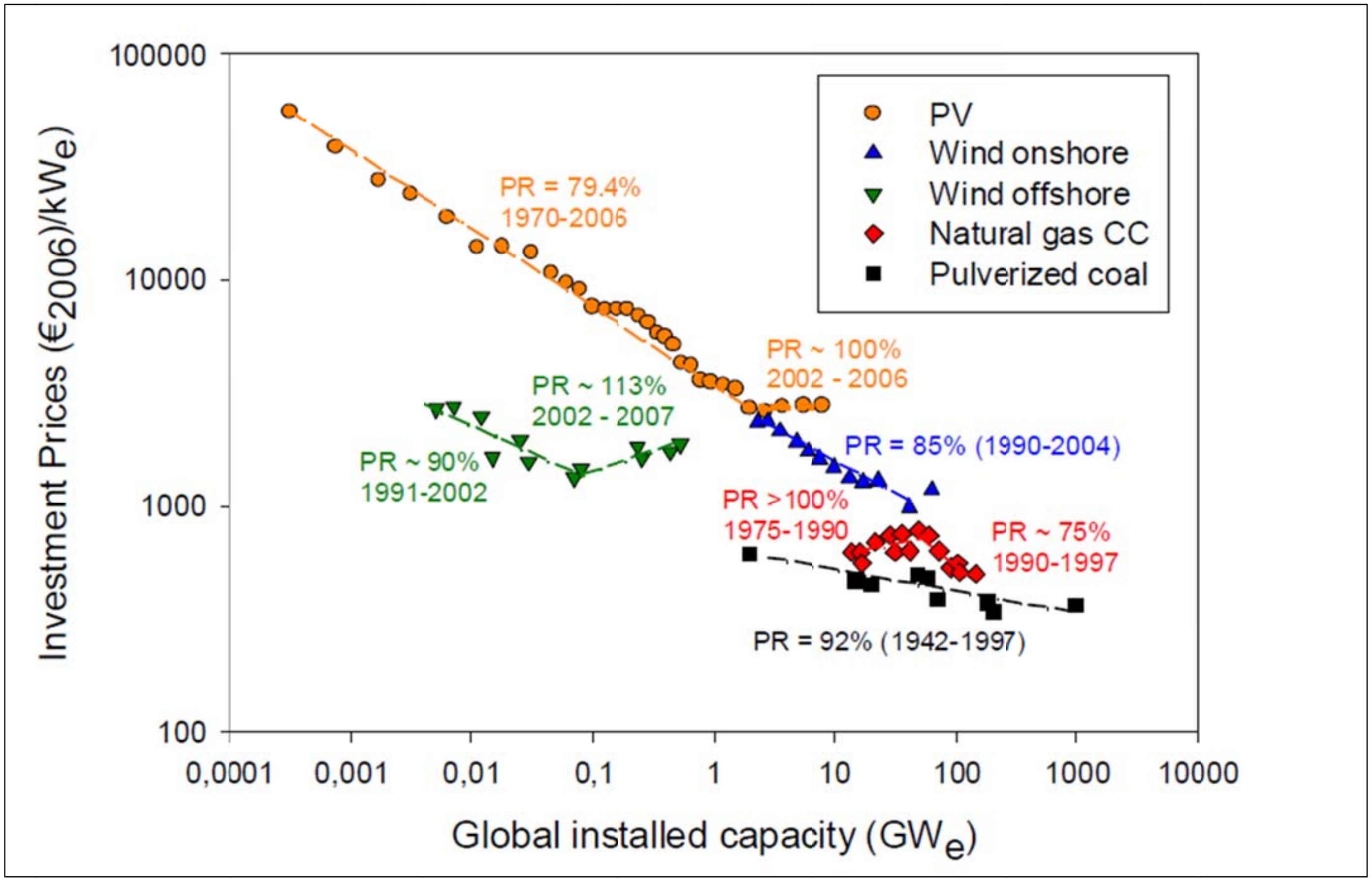
$$LR = 1 - PR = 1 - 2^{-b}.$$

The Nordhaus model connects learning rates and progress ratios.

Learning Curve Rates		
LR	**PR**	**b**
5%	95%	0.07
10%	90%	0.15
15%	85%	0.23
20%	80%	0.32
25%	75%	0.42
30%	70%	0.51
35%	65%	0.62
40%	60%	0.74
45%	55%	0.86
50%	50%	1.00

Single factor models across a range of industries yield learning rates dispersed around 20%. (Thompson, 2010) However, the dispersion of learning rates across industries is wide, and within industries and technologies the learning rate can vary over time and be quite different for technologies of different types and stages of development.

The picture illustrates the variations in learning rates for a range of energy technologies including the prominent sources of clean energy.



Comparison of historic experience curves and progress ratios (PR=1-Learning Rate) of energy supply technologies. (Junginger, Lako, Lensink, Sark, & Weiss, 2008) (p. 10)

The empirical results for learning rates have important implications for deployment policy.

Nordhaus describes the problems of separating out the effect of accumulating experience from other factors that change over time. (Nordhaus, 2014) In an important and oft cited paper, (Nemet, 2006) provides a disaggregated study of the development of photovoltaic (PV) technology. Nemet separated PV costs into several components and addressed the evidence for cost reduction in each of the components. “The evidence presented here indicates that a much broader set of influences than experience alone contributed to the rapid cost reductions in the past.” (Nemet, 2006) (p. 3230) A similar result for Chinese experience in producing wind generators appears in (Qiu & Anadon, 2012), where there were large cost reductions over time but the learning rate estimate is only 4%.

As usual with effects of compound growth, extrapolations of learning benefits are sensitive to small initial rate errors. “However, especially for long-term forecasts, small variations in PRs can lead to significantly deviating cost reductions in scenarios or completely different model outcomes in energy and climate models.” (Junginger et al., 2008) (p.13) Nordhaus builds on related observations to make the point that small errors in the estimated learning rate can produce large biases in the forecast of future costs and the associated premium that might be the target of a deployment subsidy motivated by LBD. Furthermore, Nordhaus finds that reasonable learning rates imply relatively small learning premiums.

The Nordhaus model illustrates calculation of the premium for learning by doing (LBD).

Given exogenous forecast of future clean technology production, Q_t, with discount rate (r), the present value of the cost of future clean production is given by:

$$V_0 = \int_{t=0}^{\infty} Q_t C_t e^{-rt} dt = \int_{t=0}^{\infty} Q_t \left[C_0 Y_0^b e^{-ht} Y_t^{-b} \right] e^{-rt} dt.$$

With an immediate production increment of θ , we have

$$V_0(\theta) = (Q_0 + \theta) C_o + \int_{t=0}^{\infty} Q_t \left[C_0 Y_0^b e^{-ht} (Y_t + \theta)^{-b} \right] e^{-rt} dt.$$

With exogenous Q_t, the resulting marginal cost of the incremental production is:

$$V_0'(\theta) = C_0 - b \int_{t=0}^{\infty} Q_t C_t Y_t^{-1} e^{-rt} dt.$$

The resulting difference between the current marginal cost (C_0) and the total marginal cost is the learning premium:

$$\pi_I = b \int_{t=0}^{\infty} Q_t C_t Y_t^{-1} e^{-rt} dt .$$

This result shows that the premium is declining in cumulative production and increasing in the volume of future production. Using a further simplification by assuming a constant growth in the rate of deployment, the model yields a convenient closed-form solution. See (Nordhaus, 2014) for details.

The Nordhaus solution provides a learning premium summarized here as a per cent of marginal cost of clean production, C_0.

Learning By Doing (LBD) Premium			
	Discount Rate		
LR	**3%**	**5%**	**10%**
0%	0%	0%	0%
10%	13%	8%	4%
20%	24%	16%	9%
30%	34%	24%	13%

The table illustrates that the LBD premium is sensitive to the assumptions and is relatively low. Clean energy subsidies justified as necessary to jump start deployment and bring the cost down have often been higher. Subsidies set high enough to make clean technologies competitive with dirty technologies that cost half as much or less imply a premium of more than 50% of the clean technology cost.

A minimal extension of the Nordhaus model can incorporate important additional tradeoffs.

The premium calculations can be done with a non-zero assumption about the rate of exogenous technological change. This is straightforward but has an important interaction with the analysis of the rate of clean technology diffusion. In particular, with a non-zero rate of exogenous technological change (or investments in LBS), the best policy might be to learn by waiting; wait until the costs have declined enough to make the other premiums justify large scale deployment. (Montgomery & Smith, 2007) (Santen, Webster, Popp, & Pérez-Arriaga, 2013)

The simple learning model implies that with enough cumulative production the unit cost of new production will be driven to zero. Although going this far would be extreme, as we shall see it is not an innocuous assumption. Clearly there is some positive lower bound on the cost. This could be included as a simplified version of a component model where the total cost is divided into two parts, one of which is amenable to technological change and learning, and the other which is the long-run lower bound on the total cost, $C_{\min}$. (Manne & Richels, 2004) (Neuhoff, 2008)

The treatment of the benefits of substitution for dirty technologies could be incorporated by assuming an exogenous growth rate for the total new technologies and allowing introduction of the clean technology when it is competitive, including accounting for the effect of the negative dirty technology externality and the positive clean technology learning externality. This could be seen as a cost-effectiveness analysis for the electricity sector, without accounting for any impacts of higher electricity prices and reduced electricity consumption.

Some of the benefits of learning can be captured. The capture of learning benefits can be set as a parameter ρ. The component that is a spillover is $1-\rho$, following (Fischer & Newell, 2008).

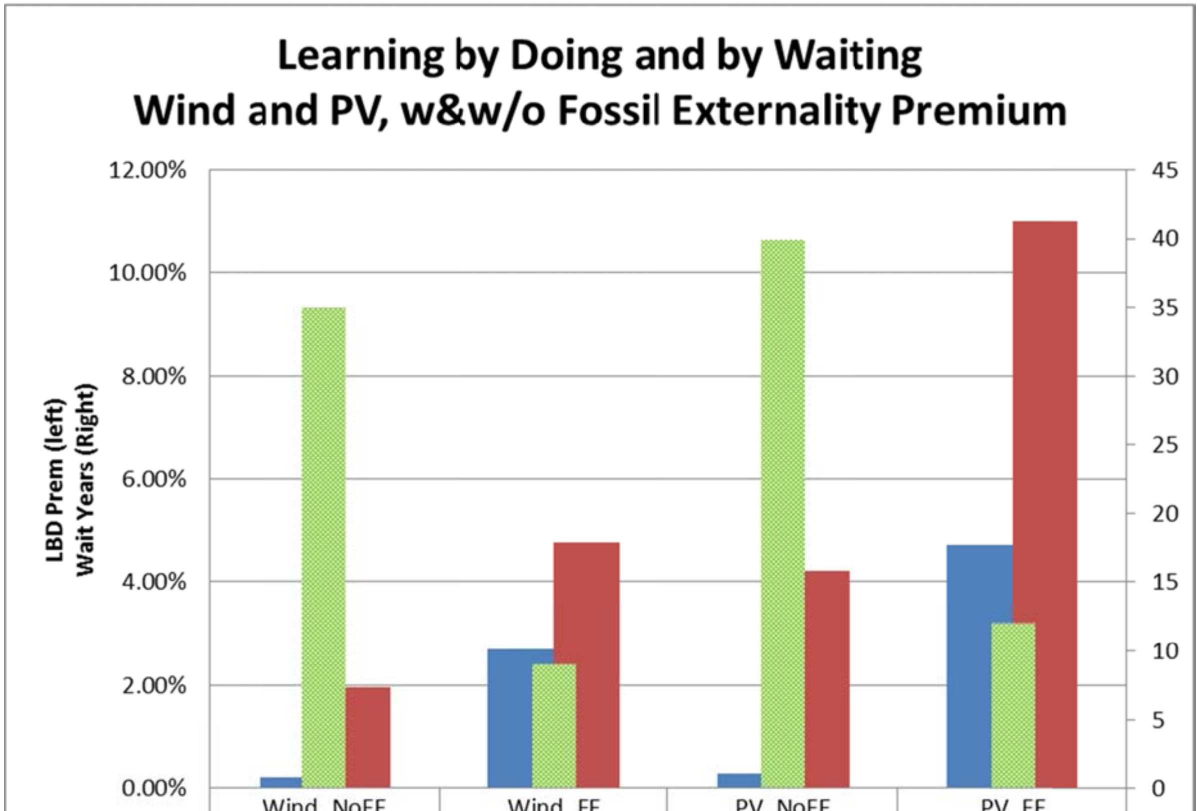
The expanded Nordhaus model used here employs a number of assumptions.

Parameter	Benchmark Values	Sources
Discount rate (r)	5%	
Learning Rate (LR)	10%, 20%	
Exogenous technological change (h)	5%	
Learning capture rate (ρ)	50%	(Fischer & Newell, 2008)
Electricity growth rate	2%	
Clean Cost (C_0)	Wind=1.75, PV=2.4	(Greenstone & Looney, 2012)
Minimum Clean Cost ($C_{\min}$)	0.9	
Dirty Price (P_t)	1.0	
Dirty Externality (E_0)	0.2	New CC Gas. (Greenstone & Looney, 2012)
Dirty Externality Growth Rate	5%	(Nordhaus, 2013)
Base Electricity Demand (GWh)	3724	AEO2013 Reference Case (Department of Energy, 2014)
Renewable Energy Generation (GWh) (Y_0)	476	AEO2013 Reference Case (Department of Energy, 2014)
Starting Additions Rate	Ret+Growth=7%	

The alternative cases illustrate the tradeoff between "LBS-LBW", and LBD. The LBD premium is relatively small, especially when compared with the impact of the assumed fossil externalities.

Without a fossil externality price, an assumed 5% rate of exogenous technological change takes a very long time to make the clean technologies competitive. The wait is essentially forever. Hence, the LBD premium is essentially zero. The premium becomes larger in the distant future and reaches its maximum when deployment begins, but the maximum learning premium is still relatively small.

With a fossil externality, it is still optimal to wait. The immediate premium is larger and the optimal waiting period is shorter for the wind type technology. The learning premium is small compared to the benefits of reducing the dirty externality.



	Wind_NoFE	Wind_FE	PV_NoFE	PV_FE
LBDNow	0.21%	2.70%	0.28%	4.71%
LBDMax	1.96%	4.76%	4.22%	11.01%
Wait	35	9	40	12

The analysis implicitly assumes that there is one-for-one substitution between green energy and fossil fuels. This is not true.

> "Subsidies pose a more general problem in this context. They attempt to discourage carbon-intensive activities by making other activities more attractive. One difficulty with subsidies is identifying the eligible low-carbon activities. Why subsidize hybrid cars (which we do) and not biking (which we do not)? Is the answer to subsidize all low carbon activities? Of course, that is impossible because there are just too many low-carbon activities, and it would prove astronomically expensive. Another problem is that subsidies are so uneven in their impact. A recent study by the National Academy of Sciences looked at the impact of several subsidies on GHG emissions. It found a vast difference in their effectiveness in terms of CO_2 removed per dollar of subsidy. None of the subsidies were efficient; some were horribly inefficient; and others such as the ethanol subsidy were perverse and actually increased GHG emissions. The net effect of all the subsidies taken together was effectively zero!
>
> So in the end, it is much more effective to penalize carbon emissions than to subsidize everything else." (Nordhaus, 2013) (p. 266)

The sensitivity analysis and literature review reinforce lessons for policy modeling.

- **Multifactor Models.** "Multi-factor models of this type offer improved explanations of the processes that contribute to cost reductions for the technology under study, and thus arguably provide more accurate assessment about the magnitude of investments or subsidies needed to bring down the cost of technology." (Yeh & Rubin, 2012) (p. 768) The EIA uses multi-factor models with different learning rates for different technology components and declining learning rates with increased deployment. (Energy Information Administration, 2014)

- **Alternative Learning Types.** The importance of active research (LBS), rather than passive learning (LBD), is intuitively plausible. Other things being equal, direct is better than indirect learning. Both can be valuable and both types of investment face diminishing marginal returns. There is a consistent conclusion with two factor models that represent LBS and LBD, and that "…examine the relative importance of R&D and capacity deployment for different technology categories. The results generally show higher learning by research than learning by doing rates. We do not find any technological development stage where learning by doing is the dominant driver of technical change." (Jamasb, 2007) (p. 52)

- **Multiple Periods.** A model with many periods would be necessary to track vintages of technologies and the tradeoffs of waiting for costs to decline or externality benefits to grow.

- **Uncertainty.** "Results show that under a carbon constraint, the optimal investment strategy includes lower solar PV RD&D spending upfront but more RD&D spending later—with potentially higher spending overall—when compared to a strategy under perfect foresight about RD&D outcomes or based on single-shot decision-making under uncertainty without learning." (Santen & Anadon, 2013)

The sensitivity analysis illustrates the basic tradeoffs for policy development for clean energy innovation and deployment.

- **Upstream Investment for Innovation is a High Priority.** Reducing the cost of clean technology sets the stage for later large scale deployment. Learning by (re)searching, overcoming the many obstacles that precede large scale deployment, and waiting for costs to fall, are critical elements of the analysis.

- **Fossil Externality Costs Dominate Learning Premiums.** Pricing carbon and other fossil externalities produces many benefits and facilitates the introduction of clean technology.

- **Learning by Doing is Important as a Complement to Other Policies.** The best estimates of learning benefits and the premium that creates a market externality imply that the optimal learning by doing subsidy is relatively small.

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