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Separating Economies of Scale and Learning Effects in Technology Cost Improvements

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Abstract

A contributing factor to the range of results of energy-economy models on feasibility and costs for obtaining specified policy goals such as GHG reductions is the mechanism that translates technological progress into cost reductions per technology. In many models this mechanism is represented via a simple learning curve model, where costs decline as a function of experience, usually represented by cumulative capacity. However, many other factors influence technology-specific cost dynamics, with one major confounding variable being unit level economies of scale- declines in average unit costs arising from the building of larger capacity plants or units. Thus, this paper considers 'de-scaled' learning rates as an alternative to the conventional representation of learning phenomena. De-scaling involves removing unit scale's influence on cost for a given technology, thereby creating a variable that is the residual of cost's remaining determining factors, which then is estimated and interpreted as a more appropriate variable to capture learning effects proper. The influence of scale economies and remaining learning effects on technology costs are estimated econometrically with the analysis complemented by simpler analytical methods as well as incorporating results from the engineering literature to represent uncertainties. This paper finds de-scaling substantially reduces the learning rate for a number of energy supply technologies. De-scaled learning rates expressed over cumulative units installed is concluded to be a superior measure of learning effects over traditional formulations of specific costs versus cumulative capacity that confound economies of scale with learning effects, potentially misguiding policies via its resulting overestimation of the potential cost lowering impacts of demand-pull technology deployment incentives.

Keywords: learning rate; learning-by-doing; economies of scale; unit level economies of scale; scale factors, de-scaling

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Separating Economies of Scale and Learning Effects in Technology Cost Improvements

Stephen Healey

1 Introduction

A key aspect contributing to the range of results of energy-economy models on feasibility and costs for obtaining specified policy goals such as GHG reductions is how policy models represent technological progress, and how this progress translates into cost reductions per technology. Nemet (2007), for instance, notes how a relatively modest change in the learning rate[1] -a common method of an aggregate representation of endogenous technical progress- for Solar PV, from 0.26 to 0.17, results in a large change in the timing of its breakeven point with conventional technologies. The quicker low-GHG technologies can become competitive with conventional technologies, the lower the overall system cost of achieving a given climate target.

Learning rates are an appealing tool for use in energy-economy models due to their simplicity and the explicit link of technological progress to investments, compared to the traditional exogenous representation of technological change, typically as time trend, unaffected by policies and market conditions. Technological change becomes manifest through one dimension, cost, which changes as a function of cumulative experience- represented usually as cumulative capacity for energy technologies. The significance of learning rates is not limited to the energy-modelling community, as there is pressure in policy circles for public-led initiatives to deploy new energy technologies on the assumption that learning will cause their costs to decline more rapidly than otherwise (Rivers and Jaccard, 2006), frequently referred to as policy-led “cost buy down”. Thus, an accurate interpretation and estimation of learning phenomena and derived learning rates is essential.

Of course, many other factors influence cost dynamics, and these are conflated with experience when simple learning rates are used. One major confounding variable is unit level economies of scale- declines in average unit costs arising from building larger capacity plants. This is especially the case since unit economies of scale and learning when represented by cumulative installed capacity are both measured by a common unit, Megawatts (MW). While costing analysis using econometrics can isolate these effects, difficulties may still arise as unit scale and cumulative capacity are highly correlated in most samples. Decomposition analysis could overcome the correlation problem; however

[1] The rate of cost decline for a doubling of cumulative capacity (McDonald and Schrattenholzer 2001). In the above example the unit cost reductions ($/W) assumed range from 26 to 17 percent per a doubling of cumulative installed capacity.

these costing models are complex and difficult to incorporate in energy-modelling frameworks.

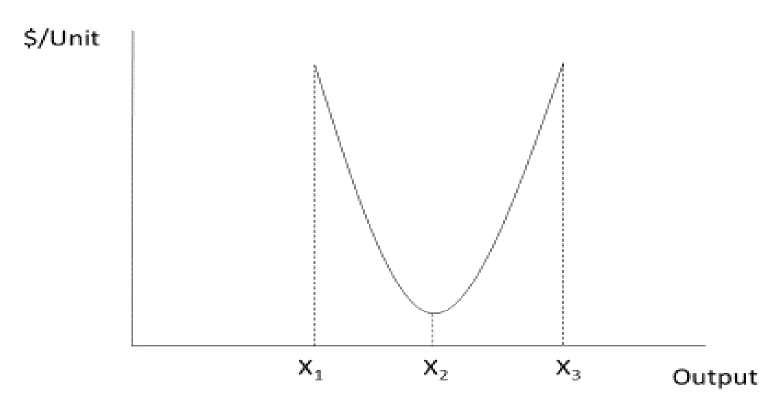
As a possible alternative, costs can be de-scaled before re-estimating the learning rate. De-scaling involves using unit scale factors found in the literature to remove unit scale's influence on cost for a given technology, thereby creating a variable that is the residual of cost's remaining determining factors. Four learning curves can then be calculated- i) original unit costs vs. cumulative installed capacity , ii) original unit costs vs. cumulative units, iii) de-scaled unit costs vs. cumulative installed capacity, and iv) de-scaled unit costs vs. cumulative units. This fourth learning curve, where de-scaled costs and cumulative units are used as an alternative measure of experience, aims to fully separate the confounding effects of experience and unit scale, and is thus suggested for use in energy models as a more accurate representation of learning phenomena. This paper finds de-scaling substantially reduces the value of the learning rate when compared to conventionally estimated learning rates. Furthermore, the magnitude of this de-scaling effect, as well as the magnitude of the learning rate prior to de-scaling, differs according to the underlying unit scale dynamics for a given technology.

The paper is organized as follows. Section two provides background of the concepts of economies of scale and learning-by-doing. Section three outlines the de-scaling method, while section four provides a description of the data. Section five then discusses the results, while section six concludes.

2 Background

Economies of scale are defined as reductions in average unit costs as output increases. These cost declines occur in the long run after all inputs are free to vary. Figure 1 below illustrates this concept graphically. The range X_1 to X_2 shows economies of scale, where unit costs decline with increasing levels of output. X_2 represents the level of output where unit costs are lowest, referred to as minimum efficient scale. Finally, the range X_2 to X_3 shows diseconomies of scale- increasing unit costs with increasing production (Mankiw et al., 2002).

Figure 1: Graphic Depiction-Economies of Scale



There are two main sources of economies of scale. Firstly, lower average production costs can arise through specialization and the division of labour that occurs with larger plant sizes and capital investment. For example, expanding plant size allows the firm to spread fixed costs over higher output volumes thus reducing specific unit costs. Large plants also allow workers to specialize in a specific task, allowing the firm to increase labour productivity as output is standardized and workers improve their proficiency via repetition (Mankiw et al., 2002). Secondly, economies of scale may also arise due to idiosyncratic engineering properties of the technologies in question. For instance, for a given wind speed, wind turbines produce more energy in proportion to the swept area of the turbine blade. Thus, larger turbine blades will produce more energy per swept area, generally resulting in lower unit costs (Danish Wind Industry Association, 2000).

A similar phenomenon in economics is known as learning-by-doing, whereby firms get better at producing a given technology via improved plant management, improved worker productivity via repetition, and improved design- all of which drive down costs (Grubler et al., 1999). Learning curves relate declines in unit costs to increases in either the total cumulative production of that technology, in units, or – more typically- its cumulative installed capacity. The learning rate, derived from the linear estimation of the aforementioned learning curve, is the rate in which unit costs decline for every doubling of cumulative production/capacity (McDonald and Schrattenholzer 2001).

The initial learning curve studies tended to represent learning as a function of cumulative units, and tended to measure productivity directly in labour-hours.[2] Applying this framework to the energy literature, however, involved a shift away from using cumulative units to the use of cumulative capacity[3] as the independent variable instead. As mentioned briefly in the introduction this is problematic, as both economies and scale and learning-by-doing are now measured using a common unit, Megawatts, making it difficult to isolate their individual effects.

3 Methods

3.1 De-scaling

The process of de-scaling involves using scale factors found in the literature to remove scale's influence on cost, thereby creating a resulting cost variable whose dynamics over the specified timeframe become explained by determining factors other than scale, in particular learning-by-doing effects. This process is described step-by-step as follows:

Firstly, the ratio of the scale factor for each technology ($SF_{(t)}$), for each year in the sample, was calculated using the formula

$$SF_{(t)} = k_{(t)}^{\alpha} / k_{(t-1)}^{\alpha} \quad (1)$$

where:

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[2] See e.g. Wright, 1936, that analyzed the specific labor-hour requirements per airframe manufactured versus cumulative output of airframe units. Another early example of such a study is provided by Rapping, 1965, who analyzed productivity gains in the production of US Liberty ships during WWII.

[3] This transition appears to have occurred in the late 1970s in publications performed at the US Solar Energy Research Institute (Krawiec et al., 1980) and originally was largely inconsequential considering that unit size of PV panels and their conversion were mostly static at that time.

$SF_{(t)}$ = scale ratio for the current period
$k_{(t)}$= Average annual unit size for the current period (MW)
$k_{(t-1)}$= Average annual unit size for the preceding period (MW)

and
α = the specific scaling factor taken from the literature

This formula provides the factor by which unit costs would have changed between any two years in the dataset due to unit capacity changes between them- all else equal (See McNearney 2011 for an example of its use in this manner). The α parameter in formula (1) refers to the percent decrease in unit costs arising from a one percent increase in scale- an elasticity. This parameter is negative and is estimated econometrically with the more negative the number representing greater economies of scale. This is not to be confused with the more traditional economies of scale coefficient used in engineering assessments of various energy technologies. A more detailed account of this distinction in scale coefficients is found in section 3.3.

Using the factor (SF_t), the dollar amount by which scale contributed to the cost change between any two years (call this the scale impact-$SI_{(t)}$) was obtained by multiplying the scale factor by the preceding year's cost and then subtracting the resulting product from the preceding year value as per the following formula:

$$SI_{(t)}= C_{(t-1)} - [SF_{(t)}*C_{(t-1)}] \quad (2)$$

Where:

$SI_{(t)}$ = Scale Impact
$SF_{(t)}$ = scale ratio for the current period
$C_{(t-1)}$ = previous year's average investment cost

Assuming there are economies of scale (negative alpha coefficient), positive values for this scale impact term indicate an increase in unit scale between the two periods and, if not for the scale effect, current year costs would otherwise be higher. Conversely, if average scale decreased between the two periods, then this value will be negative indicating that present costs would be lower if scale effects were omitted.

This value is then used to calculate the residual cost change- the year-on-year cost change after scale is factored out of the dataset. However, one must first calculate the actual cost change occurring between the periods:

$$\Delta C_{(t)}= C_{(t)} - C_{(t-1)} \quad (3)$$

Where:

$\Delta C_{(t)}$= Actual change in cost for a given period
$C_{(t)}$= current year's average investment cost
$C_{(t-1)}$= previous year's average investment cost

Subtracting (2) from (3) then gives the residual- the change in cost due to all factors other than scale. By subtracting this value from the previous year's cost, the first point of the de-scaled dataset is obtained. Repeating the process for each year generates a dataset where scale has been removed as a source of cost decline/increase. Figure 2a below provides an example of the original costs, prior to descaling, and the de-scaled costs for coal, while Figure 2b does the same for heat pumps as an opposing example where unit scale has actually been decreasing over time. Average annual unit scale values for coal increases from 14.5 MW in 1913 to 467 MW by 2000. Unit costs decrease by about 24% over this period. Conversely, average annual unit scale values for heat pumps decrease from 18.82kw in 1983 to 9.35kw in 2008, with costs decreasing by 49% over the timeframe.

Figure 2a: Actual vs. De-scaled (Coal)

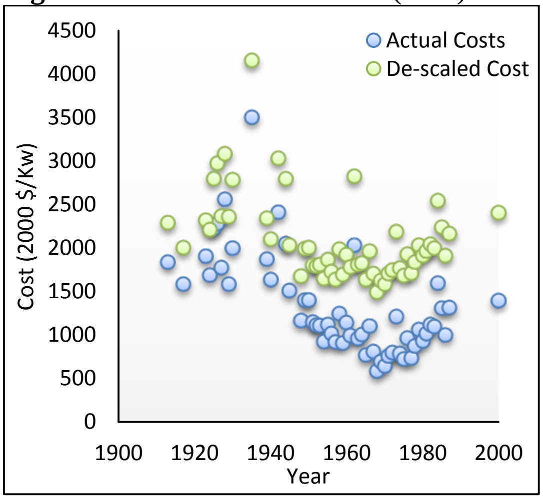
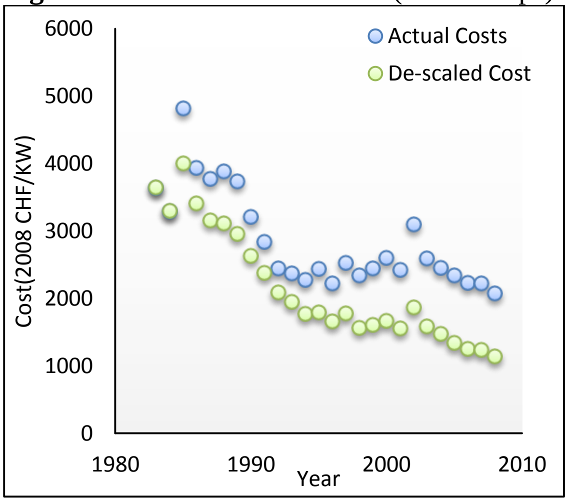


Figure 2b: Actual vs. De-scaled (Heat Pumps)



For the base case, the median of the range of scale estimates obtained from the literature is used to de-scale the data. However, a sensitivity analysis was also performed by taking other values from this range of estimates for de-scaling.

3.2 Learning Curve Calculation

Once the de-scaled datasets have been calculated, 4 learning effects were calculated- i) original unit costs vs. cumulative installed capacity , ii) original unit costs vs. cumulative units, iii) de-scaled unit costs vs. cumulative installed capacity, and iv) de-scaled unit costs vs. cumulative units. As mentioned in the introduction, two measures of experience, capacity and units, were used. However, only the latter measure (cumulative units) provides a better means of separating the confounding effects of unit scale and cumulative capacity. To calculate the learning rate under each specification, the relationship between experience and unit cost were plotted on logarithmic scale and a linear curve was then fitted to the data, obtaining the elasticity of cost with respect to experience. Using this coefficient, the learning rate is then calculated as follows:

$$\textit{Learning Rate} = [(1 - 2^{\wedge \textit{Coefficient}})]*100 \quad (4)$$

3.3 Scale Parameter Calculation

Scaling parameter estimates for the various technologies were predominantly obtained from econometric studies, where a log-log specification of a typical costing equation explained average unit costs as a function of multiple variables influencing costs. In this context, the scale parameter corresponds to the α term in equation (1) above.

However, for several technologies, econometric estimates were unavailable and instead more traditional economies of scale estimates, given by the below formula, were used.

$$Cost_2 = Cost_1 * (Size_2/Size_1)^{Scale} \quad (5)$$

Where:
Cost = total cost (rather than unit cost)
Size = size of the plant/unit in MW

Unlike the negative values for the α coefficient, the scale coefficient here is positive, and usually between 0 and 1. The closer the value is to zero, the greater the economies of scale effect. Rooted in the engineering literature, these estimates were simply given by the authors in most studies to reflect the standard working engineering estimate for scale for that technology. I then converted these to the econometric estimate described above (obtaining an α parameter) using the formula:

$$\alpha = -1 + scale \quad (6)$$

In addition to the econometrically and engineering provided scale estimates, two other sources of estimates were obtained from the literature. Firstly, the unit scale and cost for two data points which represented the range of possible unit scale values for a given technology were provided. With these values, the scale and α parameters were calculated using the formulae above. The second approach involved estimating α parameters from a graphic depiction relating unit costs with unit scale. Reading the co-ordinates from the graph provided a set of unit cost values and a corresponding set of unit scale values. Taking the natural logarithms of these values allowed the fitting of a curve and the estimation of a scale factor for this technology. An implicit assumption in this is that the scale-cost relationship depicted with the curve controls for all other sources of cost decline, and thus actually is an isolated scale effect. While some of the studies using this approach looked at multiple sources of cost decline, others likely did not. The results of this latter method of estimating scaling coefficients are thus deemed less reliable than those obtained from the econometric estimation technique. Table A-1 in appendix A provides the method for which the respective sources obtained their scale estimate and, irrespective of how they were calculated, the equivalent scale exponent as per equation 4. This methodological pluralism in obtaining estimates of economies of scale effects was used in order to more appropriately capture uncertainties compared to the more restricted data sample available for econometric estimation.

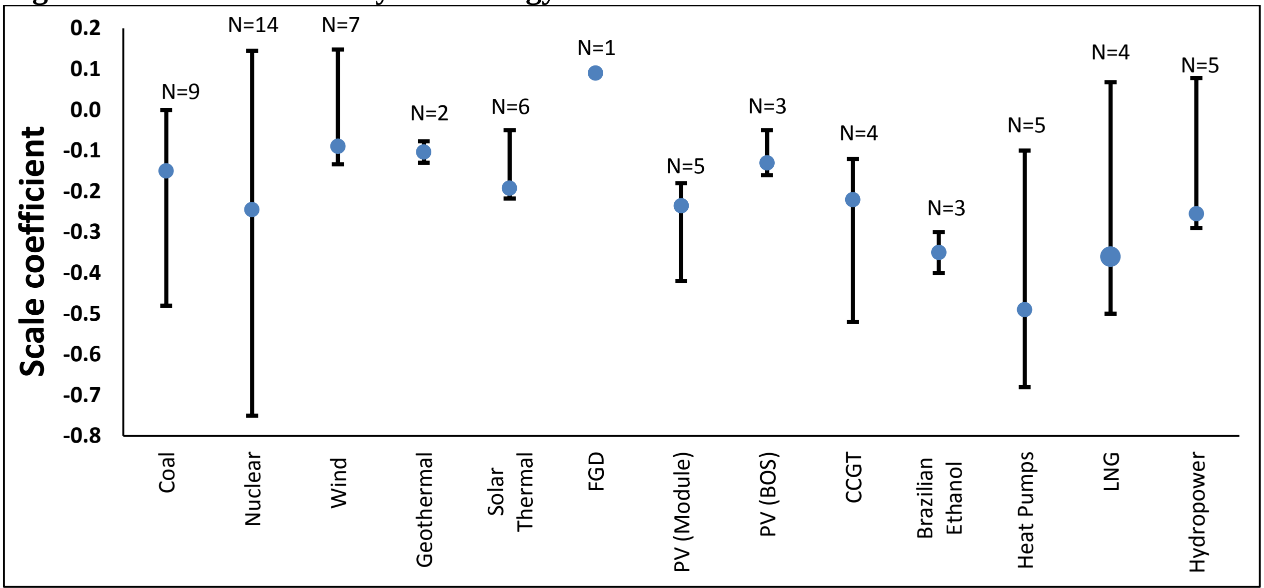
Finally, Table 1 below provides the scale factor used for each technology at the median, upper bound, and lower bound of the range of estimates derived from the literature. Figure 3 then depicts this range graphically for the technologies in the study.

Table 1: Scale Estimate by Technology

Technology	Scale Factor-Midpoint	Scale Factor-Upper Bound	Scale Factor-Lower Bound
Coal	-0.15	-0.48	0
FGD	0.09	0.09	0.09
Geothermal	-0.104	-0.134	-0.077
Solar Thermal- Dataset1	-0.192	-0.218	-0.050
Solar Thermal-Dataset2	-0.192	-0.218	-0.050
Wind-Dataset1	-0.089	-0.134	0.148

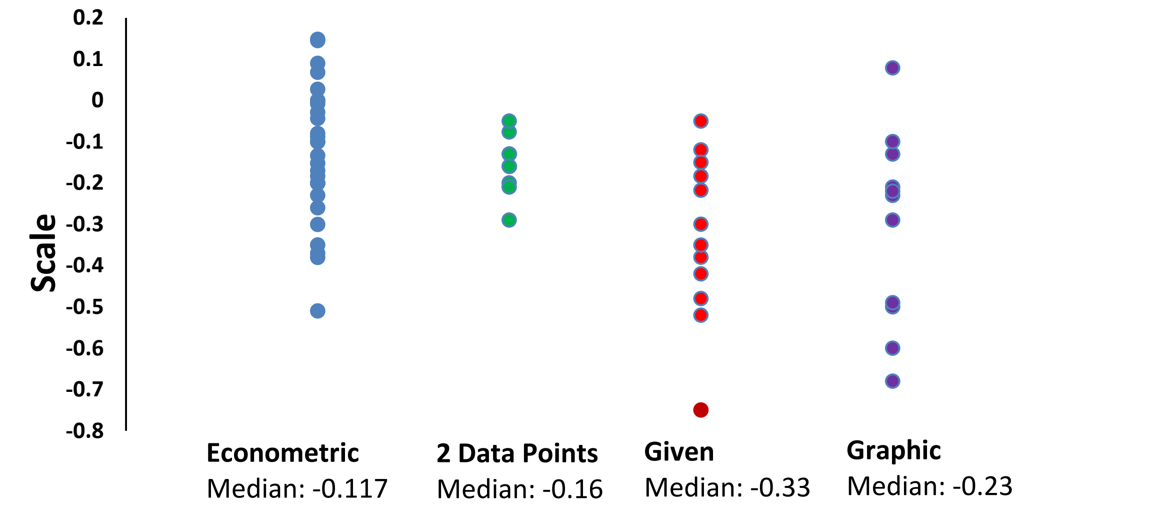
Wind-Dataset2	-0.089	-0.134	0.148
CCGT-Dataset1	-0.220	-0.520	-0.120
CCGT-Dataset2	-0.220	-0.520	-0.120
Nuclear-Dataset1	-0.245	0.145	-0.75
Nuclear-Dataset2	-0.245	0.145	-0.75
Nuclear-Dataset3	-0.245	0.145	-0.75
PV System	-0.235	-0.420	-0.180
PV Module	-0.130	-0.160	-0.050
Hydro	-0.255	-0.290	0.078
Brazilian Ethanol- Dataset1	-0.350	-0.400	-0.300
Brazilian Ethanol- Dataset2	-0.350	-0.400	-0.300
LNG	-0.36	-0.50	0.07
Heat Pumps	-0.490	-0.680	-0.100

Figure 3: Scale Estimates by Technology



Evident from Table 1 is the wide range of scale estimates found for some of the technologies. For instance, unit scale coefficients for nuclear range from 0.15 to -0.75 across 14 observations. Wide ranges are also found for coal and heat pumps. While some of this variance is due to different samples from which the estimates are drawn, another key factor is the methodology used to calculate the scale coefficient. Figure 4 below demonstrates the range of estimated coefficients after grouping them by methodology. Clearly there are some substantial differences, with scale coefficients estimated from 2 data points having the lowest range, while econometrically driven and graphically derived estimates show a wider range of estimates.

Figure 4: Scale Estimates by Source



4 Data

4.1 Sources

Most of the raw data for costs and cumulative capacity were obtained from the Santa Fe Performance Curve Database, http://pcdb.santafe.edu/team.php , a repository of uploaded cost and cumulative capacity data for public use. Unit size data, as well as cumulative unit data, were obtained from a variety of sources. The largest of these was the database compiled by Wilson (Wilson, 2009) and the 2011 Platts Powerplant database. Unit size was measured in MW, MWh, or an equivalency. Table 2 below provides the data source for the various technologies, the years and jurisdiction covered, and the number of observations per dataset. For some technologies there are multiple datasets.

Table 2: Cost and cumulative capacity/output Data Sources

Technologies Included	*Source*	*Years*	*Jurisdiction*	*N*
PV System (Residential/Commercial)	Barbose et al., 2012-Tracking the Sun V (cost data compiled by author from reading off graph)	1998-2011	US	14
Wind Turbines US-Cost/Cumulative Capacity	Wiser and Bollinger, 2013	1985-2011	US	27
Wind Turbines US-Cumuative Units/Unit Size	Compiled by author using data from: American Wind Association	1985-2011	US	27
Wind Turbines DEN-Cost/Cumulative Capacity	Santa Fe performance curve data-Taken from Neji, L. and Andersen, P. D. and Durstewitz, M. and Helby, P. and Hoppe Kilpper, M. and Morthorst, P. E. (2003)	1981-2000	Denmark	21
Wind Turbines DEN-Cumuative Units/Unit Size	Wilson, 2009	1981-2000	Denmark	21
Heat pumps	Kiss et al, 2012	1982-2008	Switzerland	26

Hypropower plants Cost/Cumulative Capacity	POLES database	1971-1997	OECD	27
Hypropower plants Cumulative Units/Unit Size	Compiled by author using data from: Platts 2011 (Large Hydro-Plants>30MW)	1971-1997	Global	27
Nuclear reactors OECD-Cost/Cumulative Capacity	Santa Fe Performance Curve Data: Kouvankis et. al in McDonald, A., and Schrattenholzer, L. (2001)	1975-1993	OECD	19
Nuclear reactors US-Cost/Cumulative Capacity	Santa Fe Performance Curve Data: Nemet 2009	1970-1996	US	25
Nuclear reactors France-Cost/Cumulative Capacity	Grubler, 2010	1972-1990	France	19
Nuclear reactors OECD-Cumulative Units/Unit Size	Wilson, 2009	1975-1993	OECD	19
Nuclear reactors US/France- Cumulative Units/Unit Size	Compiled by author from Platts, 2011	1970-1996; 1972-1990	US, France	19
Ethanol-Cost	Grubler et al., (2013)	1998-2011	Brazil	14
Ethanol-Cumulative Units	Statistic Yearbook of Agrienergy 2012. Brazilian Ministry of Agriculture (MAPA), 2013	1998-2011	Brazil	14
Ethanol-Cumulative Capacity, Unit Size	Different sources. Historical data mostly from Ramos, Pedro; "Agroindustria Canavieira e Propriedade Fundiaria no Brasil". Book, Editora Hucitec, Sao Paulo, Brasil, 1999. Recent data mostly from CONAB	1998-2011	Brazil	14
Coal power plants-Cost/Cumulative Capacity/Cumulative Units	McNearney et al., 2011	1910-2000	Global	58
Coal power plants- Unit Size	Wilson, 2009	1910-2000	OECD	58
Gas combined cycle-Cost/Cumulative Capacity	Santa Fe performance curve data-Taken from The Economics of the Combined Cycle Gas Turbine: An Experience Curve Analysis by Colpier, U., and Cornland, D. (2002)	1981-1996	Global	16
Gas combined cycle-Cumulative Units/Unit Size	Compiled by author using data from: Platts 2011	1981-1996	Global	16
LNG Production-Cost/Cumulative Capacity	Greaker and Sagen, 2004	1964-2007	Global	40
LNG Production-Cumulative Units/Unit Size	Greaker and Sagen, 2004	1964-2007	Global	40
Geothermal-Cost/Cumulative Capacity	Santa Fe performance curve data-Taken from Schilling & Esmundo, 2009	1980-2005	US	26

Geothermal- Cumulative Units/Unit Size	Compiled by author using data from: Geothermal Energy Association- http://geo-energy.org/plants.aspx	1980-2005	US	26
FGD	Healey, 2013	1969-2010	US	41
Solar Thermal Price/Cumulative Capacity	Santa Fe performance curve data- Taken from Hayward, 2009	1984-1990	US	7
Solar Thernal 1,2 Cumulative Units/Unit Size	SEGS Plants- My calculation from graph in Nemet, G. (2012). Technological Improvements of Solar Thermal Electricity in the US, and the Role of Public Policy. Historical Case Studies of Energy Technology Innovation in: Chapter 24, The Global Energy Assessment. Grubler A., Aguayo, F., Gallagher, K.S., Hekkert, M., Jiang, K., Mytelka, L., Neij, L., Nemet, G. & C. Wilson. Cambridge University Press: Cambridge, UK.4	1984-1991	US	8
Solar PV (Module)*	Nemet, 2006	1975-2001	Global	26

* Unit Size was estimated given annual cell area, assumed solar energy input per cell area, and average conversion efficiency of the stock of solar cells per year. Cumulative Units were calculated by then backing out units from annual unit size and annual changes in total capacity (in MW).

4.2 Description

Tables 3 and 4 below summarize some key aspects of the costing and diffusion data respectively including the initial and final cost value for both the original and de-scaled time series, the cost improvement factor for both, the number of cumulative doublings for both cumulative capacity and units, as well as the initial and final cumulative capacity and unit values. The de-scaled data shown here were estimated using the median of the compiled range of scale estimates. The cost values shown in the table were prior to taking the natural logarithm of cost, the latter being a necessary a transformation when calculating learning rates. Appendix B provides a graphic depiction of the learning curves (original and de-scaled) for each technology.

Table 3: Data Description-cost

Technology	Initial/Final Cost Value-Original Data		Initial/Final Cost Value-De-scaled		Cost Improvement Factor	
	1st	Last	1st	Last	Original	De-scaled
Coal (2000US$/kW)	1835	1,394.4	2,291	2,407	1.32	1.17
FGD (1982US $/kW)	25,921	158,351	25,921	130,187	0.165	0.2
Geotherm ($/kwh)	11.7	3.6	11.74	2.28	3.24	5.14
Sthrm (2006US/kW)	5,989.5	4,360.4	6,633	5,842	1.37	1.14
Wind (2010 US/Kw)	3,554.6	2,024	3,555	2,315	1.76	1.54
Wind (DKK/Kw)	11,075	5,563	11,271	7,840	1.99	1.44

CCGT (1990US c/kwh)[4]	4.28	3.41	4.29	3.96	1.26	1.08
CCGT (1990US $/kW)	515	432.6	515.8	513.5	1.21	1
Nuke OECD (1990US $/kW)	3200	2,768	3,248.5	2,973.5	1.16	1.09
NukeUS (2004US$/kW)	401.5	3,243.8	405.6	3,359	0.12	0.12
NukeFrance (2004US $/MW)	1472.3	5538.1	1292.08	5727.70	0.265	0.23
PV System (2011US $/W)	61.1	6	59.14	7.95	13.53	7.44
PV Module (2004US $/W)	61.1	3.85	62.33	13.47	15.84	4.63
Hydro (1990US$/kW)	3,680	3,325.9	3,859	3,513	1.11	1.1
Brazilian Ethanol (R2010/GJ)	28.71	53.58	28.05	54.31	0.54	0.52
LNG ($/Mty)	0.219	0.213	0.25	0.38	1.02	0.66
Heat Pumps (CH2008$/kW)	3,642.5	2,074.7	3,644	1,140	1.7	3.2

Table 4: Data Description- Market Diffusion (in MW unless otherwise noted)

Technology	# of Cumulative doublings		Initial/Final Cumulative Capacity		Initial/Final Cumulative Units	
	Cap	**Unit**	**1st**	**Last**	**1st**	**Last**
Coal	7.2	3.1	2,826	310,197	2,134	3,334
FGD	10.4	7.3	104	152,037	2	330
Geothermal	3.6	3.2	31,672,312 Kwh	334,775,957 kwh	6	59
Sthrm	4.2	3.1	30	287	2	9
WindUS	8.5	4.8	108	42,255	1,119	31,747
WindDen	9.5	3.8	10	7,710	509	5,997
CCGTkwh	3.5	3.67	247 Twh	2,580 Twh	178	1,060
CCGTKW	2.7	3.67	15,269	105,127	178	1,060
Nuke1-OECD	2.1	1.4	75 GW	332 GW	151	376
Nuke-US	3.2	2.4	13,784	114,440	31	133
Nuke-France	5.12	4.17	3.73 (GW)	65.88 (GW)	3	56
PV System	13.3	11.9	1	2,224.4	226	152,311
PV Module	9.35	9.03	1.1	1,373	5703,792	1,092,793,087
Hydro	1.27	1.03	290393	716,469	3,088	5,797
Brazilian Ethanol	1.01	1.04	14.8	29.26	225,036	439,650
LNG	8.1	5.25	64.4	18965	2	40
Heat Pumps	5.7	6.5	0.03 (GW)	1.75 (GW)	3,514	166,695

[4] Additional time series data on CCGT costs/kWh were used to estimate a second set of LRs as a comparison point. LRs expressed over output include the cost impacts of fuel prices, efficiency and capacity factors, and so are not directly comparable with LRs expressed over capacity. Consequently, this data point is included for illustrative purposes, and is not included in the meta-analysis.

As expected, the cost improvement factor is generally higher for the original cost variable relative to the de-scaled cost variable- and so removing the effects of scale on cost in the de-scaled sample reduces the cost variation. Likewise, units see fewer cumulative doublings than capacity, meaning that for technologies with a given cost improvement factor, we should see higher learning rates for units over capacity.

Table 5 below provides similar information pertaining to unit scale by technology. Please note that while there is quite a large variation is the unit scale improvement factor across technologies, there is similarly high variation in the timeframe examined by technology. Hence coal, with the largest unit scale improvement factor, also has the largest time series of data, 90 years, in which to achieve those increases. A technology with such a large time series will likely also cover the full technology life cycle, from the early formative phase to maturity. For other technologies, the dataset likely does not have comparable early estimates, and hence the ultimately realized scale increase might be underestimated.

Table 5: Data Description-Scale

Technology	*Initial Value*	*Final Value*	*Improvement Factor*	*Period*
Coal	14.5	467	32.2	1913-2000
FGD	52.1	460.7	8.84	1970-2010
Geothermal	49.5	23.4	0.47	1981-2005
Solar Thermal	22.5	45	2.0	1985-1990
Wind-US	0.15	1.79	12.2	1986-2011
Wind-Den	0.04	0.79	18.2	1981-2000
CCGT-All Datasets	56.33	123.1	2.19	1982-1996
Nuclear-OECD	815	1,030.5	1.26	1976-1993
Nuclear-US	721.1	1,210	1.68	1971-1996
Nuclear-France	945	1,560	1.65	1978-1999
PV System	0.004	0.02	5.1	1999-2011
Hydro	116.2	125.6	1.08	1972-1997
Brazilian Ethanol	123.1	128	1.04	1999-2011
LNG	64.4	818.15	12.7	1965-2007
Heat Pumps	18.81(KW)	9.34(KW)	0.5	1983-2008
PV Module[5]	31.2(W)	126.8(W)	4.0	1976-2001

5 Results

5.1 Base Results

Table 6 below provides the results for the base case, where median values from the range of scale estimates were used to de-scale the learning rates. The technologies here are ordered by their respective absolute changes in unit scale from high (increases in scale) to low (decreases in scale). As expected, the learning rate across all technologies for the de-scaled data is considerably lower, by more than half, than the original learning

[5] Unit Scale for PV Module data were provided in Nemet, 2006, but were in cm^2. These were converted to capacity units by linking Solar PV's unit size in cm^2 for 2000 to its average capacity in watts for the same year, also provided by Nemet, 2006. Using this reference point, I adjusted annual capacity based off of the proportionate difference of each year's unit size in cm^2 from the 2000 value.

rate, suggesting that the traditional method of estimating learning rates overstates actual learning as it conflates learning and economies of scale. These decreases in the learning rate after de-scaling can be considerable, such as the decline seen for coal-fired boilers. By contrast, some learning rates end up higher after de-scaling. In these cases, the technologies in question have either a positive scale coefficient representing negative economies of scale, as with FGD units, or witness decreasing average unit scale[6] over the time series, as with heat pumps and geothermal power.

The final two columns in Table 6 highlight the percentage point change between the original and de-scaled learning rates as a proportion of the size of the original learning rate. This measure seeks to capture the proportionate change in the learning rate from de-scaling. Using this metric, we see a large relative de-scaling effect for Combined-Cycle Gas Turbines, Solar Thermal, LNG, Ethanol, and Heat Pumps, and to a lesser extent coal and nuclear. Formally, the relative impact is calculated as follows:

Relative Impact = [abs(de-scaled learning rate – original learning rate)/original learning rate] (6)

Table 6: De-scaled vs. Non-de-scaled Learning Rates (medians)

	Non De-scaled-Capacity	Non De-scaled-Units	De-scaled-Capacity	De-scaled-Units	Relative impact-Capacity	Relative impact-Units
FGD	-18.92%	-23.11%	-18.10%	-22.18%	4.34%	4.05%
Coal	13.43%	34.33%	4.74%	13.55%	64.72%	60.54%
NukeUS	-75.69%	-147.94%	-76.79%	-117.50%	0.48%	1.16%
NukeOECD	5.53%	9.37%	1.79%	3.07%	65.21%	65.09%
NukeFr	-28%	-32%	-30%	-34.7%	6.32%	8.68%
CCGTKW	4.47%	4.54%	-1.33%	-1.61%	129.65%	135.41%
Solar Thermal	8.04%	9.19%	2.73%	2.26%	66.01%	75.38%
Hydro	6.96%	9.87%	3.61%	5.13%	48.14%	48.03%
LNG	4.41%	8.49%	-4.61%	-3.81%	204.61%	144.92%
WindUS	4.15%	6.57%	1.79%	2.46%	56.93%	62.47%
WindDen	7.92%	18.38%	4.54%	10.56%	42.68%	42.55%
Solar PV-System	17.75%	20.83%	15.62%	18.38%	12.03%	11.77%
Solar PV-Module	22.62%	30.26%	12.34%	16.49%	45.45%	45.51%
Ethanol	6.05%	-7.18%	1.38%	-13.29%	77.24%	85.14%
Heat Pumps	13.79%	11.67%	24.79%	21.38%	79.82%	83.21%
Geoth	28.60%	26.24%	35.38%	32.64%	23.72%	24.41%
Medians	**6.5%**	**9.3%**	**2.4%**	**2.9%**	**64%**	**68%**

It should be noted that some of the calculated learning rates experienced very poor fits in some cases where an outlier has a very strong effect on an otherwise clear pattern. The learning rates, in other words, were calculated "blind" as a first-order assumption-whereby the learning rate estimated from the corresponding best-fit line was taken at

[6] While this entails a cost penalty (increases in unit cost), such declines in unit scales can widen market applications significantly. For instance, originally heat pumps were so large as to preclude their application in residential buildings limiting their market potential to office buildings largely.

face value and added to the meta-analysis, rather than using a minimum R^2 as a cutoff for inclusion. The implication is that the learning rates are sensitive to the time period, data selection, and outliers.

5.2 Sensitivity Analysis

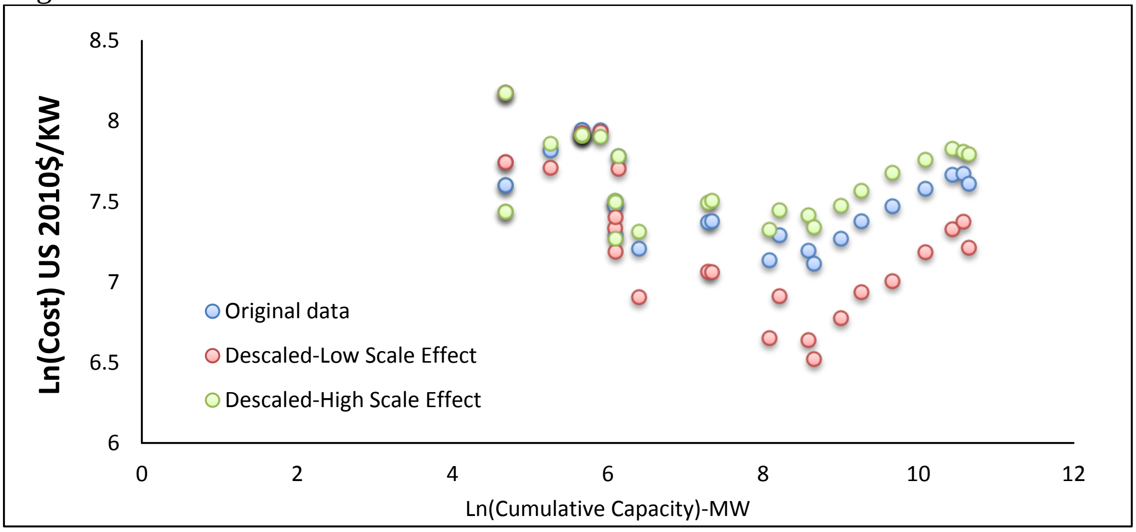
This section tests the robustness of the results in the previous section under different specifications of de-scaling. Firstly, Table 7 below repeats the de-scaling exercise using the lower and upper bound of the range of scale factors found in the literature. Taking the lower bound of this range (the scale factor representing the highest economies of scale effect), the difference between the original and de-scaled learning estimates becomes visibly greater- with median values for learning across the technologies of 0.86% and 1% for capacity and units respectively. Clearly, de-scaling using this scale factor leaves very little residual cost decline that can be attributable to other factors, such as learning-by-doing.

Conversely, de-scaling with the upper bound of the range of scale factors has the opposite effect-actually increasing the learning rate relative to the original cost data. This is due to the upper bound of the range of scale factors for many technologies being positive, representing diseconomies of scale. The combination of diseconomies of scale with a trend of increasing scale for these technologies results lower de-scaled costs relative to the original data and, consequently, a higher learning rate. Figure 5 below provides a visualization of this phenomenon for US Wind, whose upper bound is a positive scale value of 0.148.

Table 7: De-scaled vs. Non-de-scaled Learning Rates (Upper and Lower Bounds)

Technology	De-scaled-Capacity (UBound)	De-scaled-Units (UBound)	De-scaled-Capacity (LBound)	De-scaled-Units (LBound)
FGD	NA	NA	NA	NA
Coal	10.87%	28.55%	1.03%	3.41%
NukeUS	-60.21%	-146.23%	-70.53%	-137.84%
NukeOECD	8.04%	13.55%	-2.81%	-5.34%
NukeFR	-26%	-30%	35%	40%
CCGTKW	1.24%	1.10%	-6.81%	-7.62%
Solar Thermal	6.44%	7.15%	2.06%	1.45%
Hydro	8.81%	12.34%	3.47%	4.87%
LNG	7.79%	12.94%	-6.14%	-6.00%
WindUS	10.00%	16.26%	0.69%	0.55%
WindDen	17.98%	39.50%	3.14%	7.34%
Solar PV-System	16.90%	19.84%	15.21%	17.93%
Solar PV-Module	14.14%	18.77%	8.62%	12.34%
Ethanol	2.06%	-12.43%	0.69%	-14.08%
Heat Pumps	15.33%	12.94%	33.10%	28.70%
Geoth	33.10%	30.74%	39.71%	36.27%
Median	**8.81%**	**12.94%**	**1.03%**	**1.45%**

Figure 5: Three learning curves for WindUS - Original, De-scaled Low, and De-scaled High[7]



In addition to de-scaling using the upper and lower bound of scale coefficients, Table 8 shows the results after de-scaling costs according to a subjective best estimate of the de-scaling rates found in the literature. The subjective best estimate, as the name indicates, was chosen based on the author's opinion the most reliable estimate from the range of scale estimates. The main criterion of selection was method, with econometric estimates deemed the most reliable. For technologies with multiple scale coefficients estimated from econometric studies, the study that was felt would best apply to the underlying data was chosen. For example, wind had multiple studies with econometric scale estimates, however only one used a dataset of Danish wind turbines, the most significant initial market for this technology. Hence, that econometric estimate was used to de-scale the cost data for Danish wind turbines in the sample of this study.

For cases such as French nuclear, the original midpoint of the range of scale estimates found in the literature was kept as the subjective best estimate. This was because while there were no econometric estimates of scale calculated from French nuclear data, there were a large number of good quality studies that derive scale econometrically with datasets from other jurisdictions. Finally, some technologies did not have any of their estimated scale coefficients coming from econometric studies. In these cases, scale estimates from studies that were deemed to be found in higher quality academic sources were used.

Table 8: Subjective best estimate of scale coefficients and resulting learning rates

	Subjective Best estimate-Scale Value	**Method**	**De-trended Learning Rate-Subjective Best Estimate**		**Original Learning Rate**	
			CCAP	*Units*	*CCAP*	*Units*
FGD	0.09	Econometric	-18.1%	-22.2%	-18.92%	-23.11%
Coal	-0.183	Econometric	4%	11%	13.43%	34.33%
NukeUS	0.145	Econometric	8%	13.5%	-75.69%	-147.94%

[7] Multiple observations for the first data point appear graphically due to there being minute differences in cumulative capacity between the first two years in the sample, yet substantial differences in cost.

NukeOECD	-0.245	Midpoint (mostly econometric studies)	1.79%	3.07%	5.53%	9.37%
NukeFr	-0.245	Midpoint (mostly econometric studies)	-30%	-34.7%	-28%	-32%
CCGTKW	-0.21	Graphic Data	-1%	-1%	4.47%	4.54%
Solar Thermal	-0.2	2 data points	2%	2%	8.04%	9.19%
Hydro	-0.22	Graphic Data	4%	5.5%	6.96%	9.87%
LNG	0.068	Econometric	7.8%	12.9%	4.4%	8.49%
WindUS	-0.008	Econometric	3.9%	6.2%	4.15%	6.57%
WindDen	0.148	Econometric	18%	39.5%	7.92%	18.38%
Solar PV-System	-0.16	Graphic Data	14.3%	17.9%	17.75%	20.83%
Solar PV-Module	-0.18	Cited in Literature	14.1%	18.8%	22.62%	30.26%
Ethanol	-0.35	Cited in Literature	1.38%	-13.3%	6.05%	-7.18%
Heat Pumps	-0.49	Graphic Data	24.8%	21.4%	13.79%	11.67%
Geoth	-10.4	Midpoint	35.38%	32.64%	28.60%	26.24%
Median			4.00%	6.20%	6.05%	9.19%

Overall, while this method reduced the magnitude of the de-scaling compared to when sample midpoints were used, a substantial de-scaling effect is still found. By comparing the median of the de-trended learning rate using subjective best-estimates, columns 4 and 5 of Table 8, to the medians of the original learning rates without de-scaling, we observe an estimated de-scaled learning rate that is 2.05 and 2.99 percentage points lower for cumulative capacity and units respectively. This corresponds to approximately a 34% and 33% decline in the learning rate after de-scaling.[8]

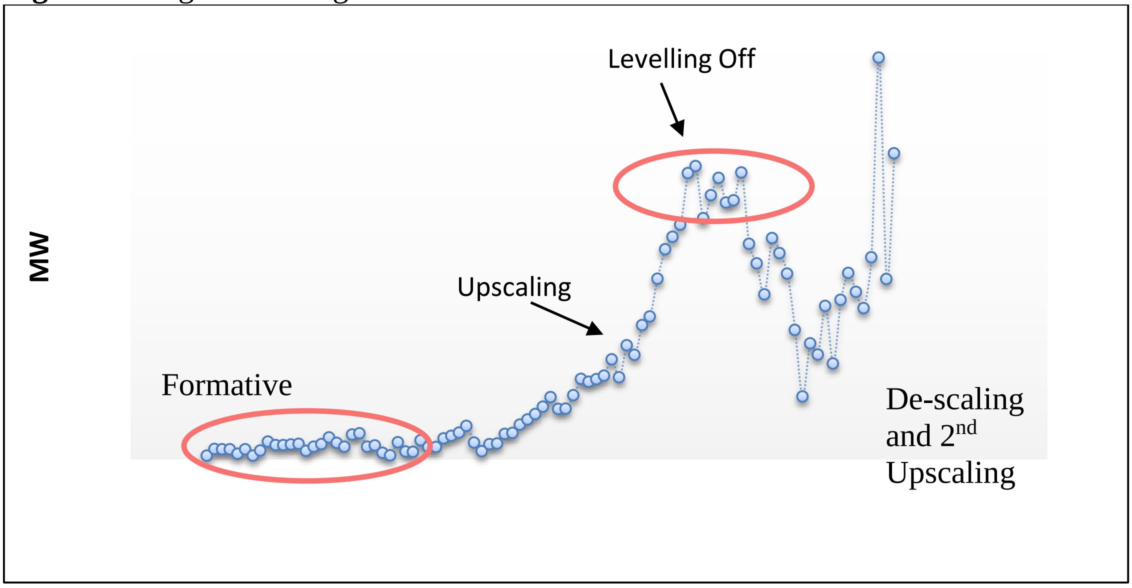
5.3 Non-Linear Learning Effects

An interesting possibility is that there exists a non-linear or kinked learning curve, and a corresponding non-linear impact of de-scaling, due to differences in the rate of change in unit scale for a given technology over time. Wilson (2012) divides a technology's life cycle into a formative or "de-bugging" stage that is then followed by a rapid upscaling stage, where average unit size sees its major increases, and finally a "levelling off" or growth stage where the unit scale frontier is achieved and larger numbers of units are constructed at larger unit capacities. Figure 6 below demonstrates this process for coal whose dataset is long enough to capture all these phases.

[8] In addition, it was suggested by a reviewer to calculate the econometrically estimated learning rate from a multivariate specification where cost is regressed as a function of both cumulative capacity/units and unit scale. This was to control for scale econometrically and test the robustness of the de-scaling methodology. The econometrically estimated learning rate was then compared to the range of de-scaled learning rates calculated using the upper and lower bounds of the scale factors from Table7. If the econometrically derived rate lies within this range, it is deemed to correspond to the de-scaled learning rates. After testing, however, the results were both negative and inconclusive. This is because most of the technologies, especially those where the econometrically estimated learning rate lies outside the de-trended range, also tend to show very high correlation coefficients between unit size and cumulative capacity/units- with many over 0.9. Generally, when one gets multicollinearity of such a magnitude (over +/- 0.7), it becomes very difficult for the statistical package to isolate the effect of each independent variable on the dependent variable, and the estimated coefficients should be viewed suspiciously. Thus, model specification is an issue when trying to isolate the effects of learning from unit scale econometrically.

In addition, we see with coal a descaling and "2nd upscaling" stage following the initial leveling. While this final round of de-scaling is not unique to coal among the technologies examined, it is also not inevitable, with its occurrence likely the result of idiosyncratic features of a given technology. With coal, Yeh and Rubin (2007), noted how lower demand for new capacity in the late 1970s favored smaller plants. The authors also noted the decline of supercritical coal technologies and a return to subcritical units at this time due to performance issues with the former (Yeh and Rubin, 2007). These supercritical units were more cost-effective at larger capacities, and so, as their preponderance in the preceding decade may have driven increases in unit scale, their fall into disfavor could have reversed these trends. Increased pollution control requirements and decreased capacity factors were also observed for coal in the decade preceding the decline in unit scale (McNerney et al., 2011). Both of these trends could have contributed to the desire to build smaller units.

Figure 6: Stages of average unit size-Coal



The general hypothesis explored here is that the magnitude of de-scaling differs for each stage of the above cycle. The formative and "leveling off" stages, for instance, see little absolute change in scale, and so it is likely that the impact of economies of scale on cost would be less pronounced than when compared to the upscaling stage. This implies less conflation of economies of scale with other causes of cost decreases and hence, less of a de-scaling effect during these timescales. Conversely, time series' covering the upscaling phase would witness a greater conflation of scale and learning and thus, should see a greater relative de-scaling effect.

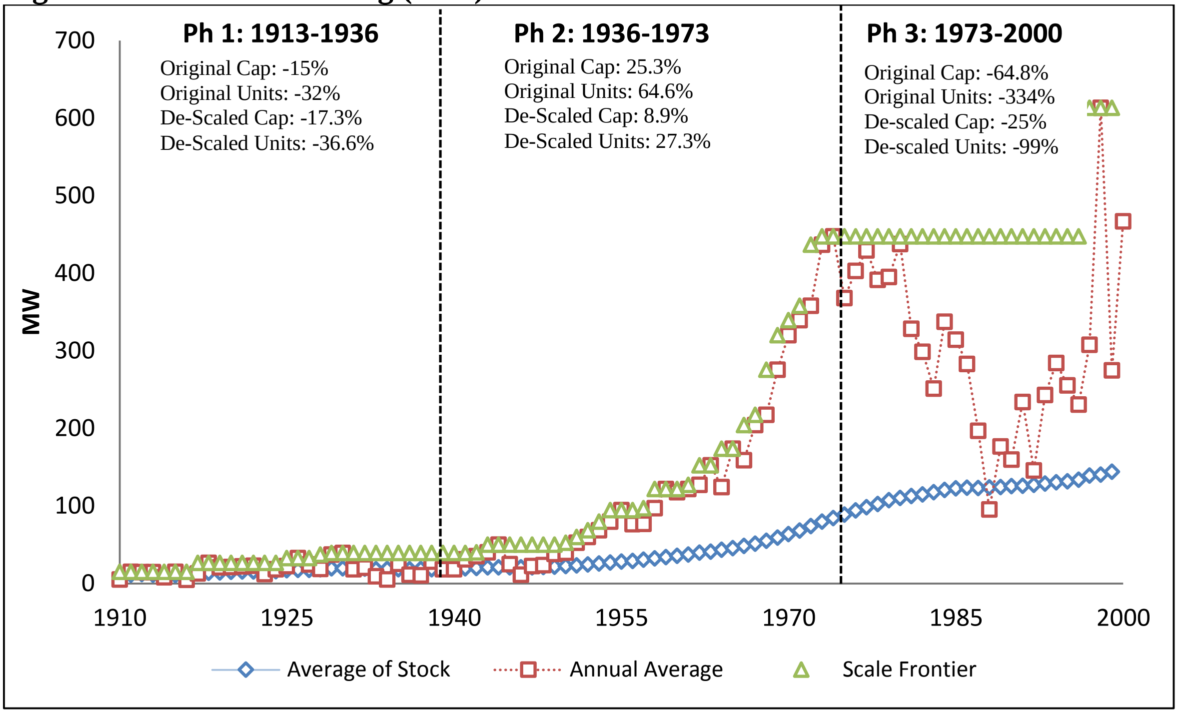
Figures 7a, b, and c below show the scale dynamics of technologies that exemplify three types of scaling patterns witnessed in the analysis:

a) Coal- Mature technology where there is a full cycle of formative, upscaling, de-scaling and second upscaling phases (represents mature technologies)
b) FGD- where the scale frontier is achieved rapidly and there is early negative learning as a result (represents FGD, LNG)

c) Danish Wind- A long formative phase followed by rapid upscaling (represents emerging technologies such as wind and solar)[9]

The different time phases and learning rates corresponding to each phase are clearly delineated on the graph.

Figure 7a: Coal Unit Scaling (MW)



[9] Some of the technologies only had data covering one of the aforementioned phases, and thereby not allowing such a comparison between phases to be made. These include geothermal, heat pumps, solar thermal, ethanol, and hydro.

Figure 7b: FGD Unit Scaling (MW)

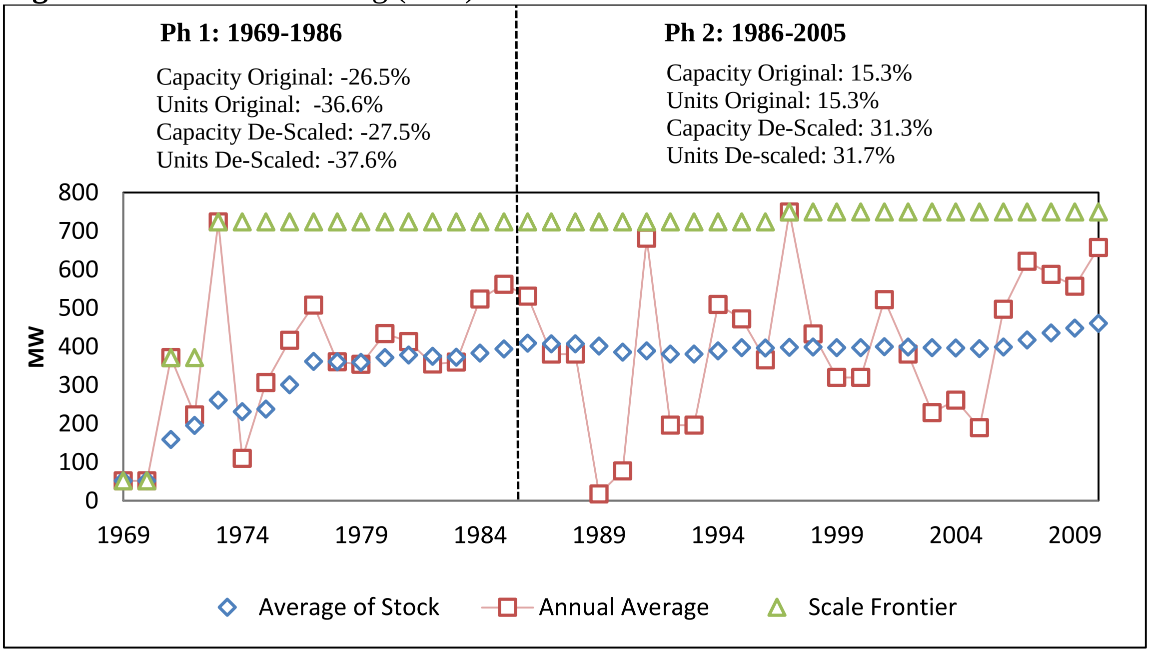
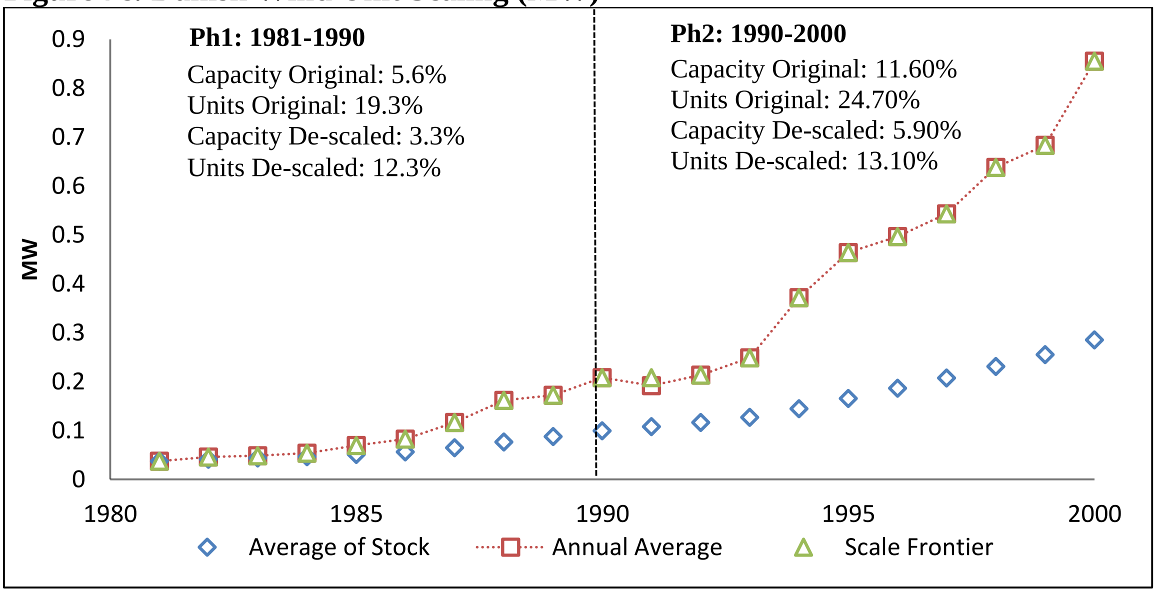


Figure 7c: Danish Wind Unit Scaling (MW)



Some key findings from these figures:

a) As expected, the de-scaling effect on the learning rate was greatest during periods of rapid upscaling compared to periods without. This is intuitive as the former is the phase where most of the conflation with economies of scale occurs. Consequently, after de-scaling, the cost declines attributable to other factors such as learning-by-doing are nowhere near as impressive for this phase in the technology life cycle.

b) Also as expected, the original learning rates (prior to de-scaling) differ according to the period examined for most of the technologies. For coal and solar, the original learning rate appears highest during the upscaling phase due to economies of scale effects occurring simultaneously with other influences on cost. For coal, only the upscaling phase has a positive learning rate, while all other timeframes actually see negative learning. The aggregate learning rate for the entire coal sample, which is positive, masks these important temporal differences.

c) FGD witnesses both negative learning and rapid upscaling almost immediately following its introduction. The rapid upscaling phase for FGD (and also LNG, which follows a similar pattern) coinciding with cost increases shortly following its introduction, is a considerably different dynamic than that seen for most technologies. Yeh and Rubin (2012) noted this phenomenon for both LNG and FGD. This price increase could be interpreted as the economic price to pay for extremely rapid upscaling. With these technologies, the lack of a "formative phase" prior to upscaling could lead to less experimentation and de-bugging of design flaws occurring for these technologies before settling on a dominant design (Wilson, 2012). Instead, for these technologies the de-bugging and upscaling are occurring simultaneously, possibly resulting in costly errors along the way.

6 Implications and Conclusion:

The results of the de-scaling exercise provide some insights into the appropriateness of using conventional learning rates in a forecasting role. Firstly, we see that unit scale effects matter. After de-scaling, we get a residual learning rate that is substantially below the original rate for a number of energy technologies. This indicates that much of the historic cost decline for energy technologies has been due to unit economies of scale and not learning in the traditional sense. This holds true whether cumulative capacity or cumulative units is used as the dependent variable, although this de-scaling effect seems to be slightly higher when cumulative units are used.

In addition, disaggregating the time series according to the technology's stage in its life cycle reveals some substantial differences in the absolute learning rate across periods. This implies that using a single aggregate learning rate in energy models will understate the cost decline in periods of upscaling (where cost declines from learning and unit economies of scale are occurring simultaneously), while overstating cost declines in periods where growth in unit sizes has halted. Likewise, the impact of de-scaling remains higher for technologies during their upscaling phase, where the impact of scale economies on cost is most prominent.

Therefore, the use of simplistic, one-period learning curve models in energy-economy models is highly problematic as confounding classical economies of scale effects and learning effects proper, potentially misguiding policy along trivialized demand-pull "cost buy down" policy concepts. Evidently, both effects can be stimulated by policies, but require different instruments and complementary measures. Consider for instance that a classical demand-pull policy such as subsidies or mandated (high) feed-in tariffs promises limited impact on realization of economies of scales in cases where technological scale frontiers have already been reached, or if complementary innovation incentives (R&D), required for upscaling technologies, are lacking.

Instead, the results of this study suggest that models should separate strictly between economies of scale and learning effects proper. Economies of scale and their economic impacts can be considered via traditional exogenous technology-specific modelling assumptions, whereas learning effects can be treated endogenously by using de-scaled learning rates as estimated here applied to cumulative units installed as measure to approximate cumulative experience gained. The demand-pull effects of policies on technology costs, will necessarily be smaller in such a modeling formulation, but much better founded theoretically as well as in historical experience.

7 Works Cited

Alvarado-Ancieta, C.A. (2009). Estimating E&M powerhouse Costs. *International Water Power and Dam Construction, (2009), 21-25.*

American Wind Energy Association: http://www.awea.org/Resources/Content.aspx?ItemNumber=5728&navItemNumber=5776. Retrieved December 2011.

Barbose, G., & Wiser, R. (2012). Tracking the Sun V: An Historical Summary of the Installed Price of Photovoltaics in the United States from 1998 to 2011. Lawrence Berkley National Laboratory. LBNL-5919E

Berry, D. (2009). Innovation and the price of wind energy in the US. *Energy Policy*, *37*(11), 4493–4499.

Blum, P., Campillo, G., & Kölbel, T. (2011). Techno-economic and spatial analysis of vertical ground source heat pump systems in Germany. *Energy, 36*(5), 3002-3011.

Cantor, R., & Hewlett, J. (1988). The Economics of Nuclear Power: Further Evidence on Learning, Economies of Scale, and Regulatory Effects. *Resources and Energy, 10 (1988)* 315-335.

Chaurey, A., & Kandpal, T. C. (2010). A techno-economic comparison of rural electrification based on solar home systems and PV microgrids. *Energy Policy*, *38*(6), 3118–3129.

Charles, R. P., Davis, K. W., & Smith, J. L. (2005). Assessment of concentrating solar power technology cost and performance forecasts. *Sargent & Lundy LLC, Technical Report*.

Colpier, U. C., & Cornland, D. (2002). The economics of the combined cycle gas turbine: an experience curve analysis. *Energy Policy, 30(2002)*. 309–316.

Companhia Nacional de Abastecimento (CONAB) http://www.conab.gov.br/

Cornot-Gandolphe, S. (2005). LNG cost reductions and flexibility in LNG trade add to security of gas supply. *IEA (2005): Energy Prices and Taxes, Quarterly Statistics. First Quarter*.

Danish Wind Industry Association (2000). Size of Wind Turbines. http://ele.aut.ac.ir/~wind/en/tour/wtrb/size.htm Retrieved Oct 2014.

Ek, K., & Söderholm, P. (2010). Technology learning in the presence of public R&D: The case of European wind power. *Ecological Economics*, *69*(12), 2356–2362.

Feldman, D., Barbose, G., Margolis, R., Wiser, R., Darghouth, N., & Goodrich, A. (2012). Photovoltaic (PV) Pricing Trends, Recent, and Near-Term Projections. US Department of Energy. Technical Report DOE/GO-102012-3839

Goodrich, A., James, T., Woodhouse, M. (2012). Residential, Commercial, and Utility-Scale Photovoltaic (PV) System Prices in the United States: Current Drivers and Cost-Reduction Opportunities. National Renewable Energy Laboratories. Technical Report NREL/TP-6A20-53347

Greaker, M., Sagen, E.L. (2004). Explaining Experience Curves for LNG Liquefaction Costs: Competition matter more than learning. Discussion Papers No. 393, October 2004 Statistics Norway, Research Department

Grubler, A., Nakicenovic, N., & Victor, D. G. (1999). Modeling Technological Change: Implications for the Global Environment. *Annual Review of Energy and the Environment*, *24*(1), 545–569.
Grubler, A. (2010). The costs of the French nuclear scale-up: A case of negative learning by doing. *Energy Policy*, *38*(9), 5174–5188.
Grubler, A., F. Aguayo, K. Gallagher, M. Hekkert, K. Jiang, L. Mytelka, L. Neij, G. Nemet and C. Wilson, (2012): Chapter 24 - Policies for the Energy Technology Innovation System (ETIS). In *Global Energy Assessment - Toward a Sustainable Future*, Cambridge University Press, Cambridge, UK and New York, NY, USA and the International Institute for Applied Systems Analysis, Laxenburg, Austria, pp. 1665-1744.
Healey, S. (2013). Scaling and Cost Dynamics of Pollution Control Technologies: Some Historical Examples. Laxenburg, Austria: Interim Report IR-13-008, International Institute for Applied Systems Analysis.
IRENA (2012). Electricity Storage and Renewables for Island Power. IRENA, Abu Dhabi.
Joskow, P.L., Rose, N.L., (1985). The effects of technological change, experience, and environmental regulation on the construction cost of coal-burning generating units. *Rand Journal of Economics 16*(1).
F Krawiec, J Thornion, M Edesess, 1980. An investigation of learning and experience curves. Report SERI/TR-353-459Solar Energy Research Institute, Golden, CO, USA (1980)
Kelholfer, R., Bachmann, R., Nielsen, H., & Warner, J. (1999). Combined Cycle Gas and Steam Turbine Power Plants Second Edition. Pennwell Publishing Company: Tulsa Oklahoma.
Kiss, B., Neij, L., & Jakob, M. (2012). Heat Pumps: A Comparative Assessment of Innovation and Diffusion Policies in Sweden and Switzerland.
Komanoff, C. (1981). Power plant cost escalation. *Nuclear and coal capital costs, regulation, and economics. New York: Komanoff Energy Associates*.
Kosnik, L. (2010). The potential for small scale hydropower development in the US. *Energy Policy*, *38*(10), 5512–5519.
Krautmann, A. C., & Solow, J. L. (1988). Economies of Scale in Nuclear Power Generation, *Southern Economic Journal 55*(1), 70–85.
Kumar, A., T. Schei, A. Ahenkorah, R. Caceres Rodriguez, J.-M. Devernay, M. Freitas, D. Hall, Å. Killingtveit, Z. Liu, 2011: Hydropower. In IPCC Special Report on Renewable Energy Sources and Climate Change Mitigation [O. Edenhofer, R. Pichs-Madruga, Y. Sokona, K. Seyboth, P. Matschoss, S. Kadner, T. Zwickel, P. Eickemeier, G. Hansen, S. Schlömer, C. von Stechow (eds)], Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA
Lang, M., & Schier, M. (2009). Consider Mid-Scale LNG to Monetize Natural Gas. *Munich: Linde Engineering Division, Linde AG. MARINTEK. Maritime Gas Fuel Logistics-Work Package*, 3519-3525.
Lee, T.H. (1976). The Case for Evolutionary Optimization. Conference Proceedings - Future Strategies for Energy Development.
Locatelli, G., & Mancini, M. (2010). Small–medium sized nuclear coal and gas power plant: A probabilistic analysis of their financial performances and influence of CO_2 cost. *Energy Policy, 38*(10)

Lovekin, J. (2000). The Economics of Sustainable Geothermal Development. Proceedings, World Geothermal Congress 2000. Kyushu- Tohoku, Japan. May 18- June 10, 2000.
Mankiw, N.G., Kneebone, R.D., McKenzie, K.J., Rowe, N (2002). Principles of Microeconomics: Second Canadian Edition. Nelson: Toronto, Canada.
Marshall, J. M., & Navarro, P. (1991). Costs of nuclear power plant construction: theory and new evidence. *The Rand Journal of Economics*, 148-154.
McCabe. M. (1996). Principals, Agents , and the Learning Curve: The Case of Steam-Electric Power Plant Design and Construction. *The Journal of Industrial Economics*, *44*(4), 357–375.
McDonald, A., & Schrattenholzer, L. (2001). Learning rates for energy technologies. *Energy policy*, *29*(4), 255–261.
McNerney, J., Doyne Farmer, J., & Trancik, J. E. (2011). Historical costs of coal-fired electricity and implications for the future. *Energy Policy*, *39*(6), 3042–3054.
Mooz, W. E. (1978). Cost Analysis of light Water Reactors. R-2304-DOE. Rand Corporation: Santa Monica California.
Mooz, W. E. (1979). A Second Cost Analysis of light Water Reactors. R-2504-RC. Rand Corporation: Santa Monica California.
Neij, L., Andersen, P. D., Durstewitz, M., Helby, P., Hoppe-Kilpper, M., & Morthorst, P. E. (2003). *Experience curves: a tool for energy policy assessment*. Environmental and Energy Systems Studies, Univ..
Nemet, G. (2006). Beyond the learning curve: factors influencing cost reductions in photovoltaics. *Energy Policy*, *34*(17), 3218–3232.
Nemet, G. (2009). Interim monitoring of cost dynamics for publicly supported energy technologies. *Energy Policy 37(3)*, 825-835.
Nemet, G. (2012). Technological Improvements of Solar Thermal Electricity in the US, and the Role of Public Policy. Historical Case Studies of Energy Technology Innovation in: Chapter 24, The Global Energy Assessment. Grubler A., Aguayo, F., Gallagher, K.S., Hekkert, M., Jiang, K., Mytelka, L., Neij, L., Nemet, G. & C. Wilson. Cambridge University Press: Cambridge, UK.
Nieves, L. A., Patton, W. P., Harrer, B. J., & Emery, J. C. (1980). Marginal cost of electricity 1980-1995: an approximation based on the cost of new coal and nuclear generating plants (No. *PNL-3458). Battelle Pacific Northwest Labs., Richland, WA (USA).*
Okimi, H. (2003). Comparative economy of LNG and pipelines in gas transmission. In *Paper for world gas conference*.
Perl, L.L., (1982). The Economics of Nuclear Power. Presented at the Annual Conference of the Atomic Industrial Forum, Washington, DC (November 15, 1982).
Platts (2011). World Power Plant Database. Platts, London, UK.
Price, H. W., & Carpenter, S. (1999). The Potential for Low-Cost Concentrating Solar Power Systems. National Renewable Energy Laboratory. NREL/CP-550-26649.
Price, H., & Kearney, D. (1999, January). Parabolic-trough technology roadmap. In *Road Map Workshop Proceedings, USA.*
Prospective Outlook on Long-term Energy Systems (POLES)
Qiu, Y., & Anadon, L. D. (2012). The price of wind power in China during its expansion: Technology adoption, learning-by-doing, economies of scale, and manufacturing localization. *Energy Economics*, *34*(3), 772–785.

Ramos, Pedro; "Agroindustria Canavieira e Propriedade Fundiaria no Brasil". Editora Hucitec, Sao Paulo, Brasil, 1999.
Rapping, L. (1965). Learning and World War II production functions. *The Review of Economics and Statistics*, 81-86.
Rafferty, K. (1995). A capital cost comparison of commercial ground-source heat pump systems. *TRANSACTIONS-AMERICAN SOCIETY OF HEATING REFRIGERATING AND AIR CONDITIONING ENGINEERS*, *101*, 1095-1102.
Rivers, N., & Jaccard, M. (2006). Useful models for simulating policies to induce technological change. *Energy Policy*, *34*(15), 2038-2047.
Rodrigues, M. (2003). Techno-economic analysis of co-fired biomass integrated gasification/combined cycle systems with inclusion of economies of scale. *Energy*, *28*(12), 1229–1258.
Sanyal, S. K. (2004). Cost of geothermal power and factors that affect it. Proceedings, Twenty-Ninth Workshop on Geothermal Reservoir Engineering Stanford University, Stanford, California, January 26-28, 2004 SGP-TR-175
Santa Fe Institute Performance Curve Dataset http://pcdb.santafe.edu/
Schilling, M. a., & Esmundo, M. (2009). Technology S-curves in renewable energy alternatives: Analysis and implications for industry and government. *Energy Policy*, *37*(5), 1767–1781.
Statistic Yearbook of Agrienergy 2012. Brazilian Ministry of Agriculture (MAPA), 2013
Van den Wall Bake, J. D., Junginger, M., Faaij, A., Poot, T., & Walter, A. (2009). Explaining the experience curve: Cost reductions of Brazilian ethanol from sugarcane. *Biomass and Bioenergy*, *33*(4), 644-658.
Stewart, J. F. (1979). Plant size, plant factor, and the shape of the average cost function in electric power generation: A non homogeneous capital approach. *The Bell Journal of Economics*, 549-565.
U.S. Department of Labor (1982). Projections of Cost and Annual on Site Manual Labor Requirements for Constructing Electric Generating Plants 1980-1990. Construction Labor Demand System
Wilson, C. (2009). Meta-analysis of unit and industry level scaling dynamics in energy technologies and climate change mitigation scenarios. Laxenburg, Austria: Interim Report IR-09-029, International Institute for Applied Systems Analysis.
Wilson, C. (2012). Up-scaling, formative phases, and learning in the historical diffusion of energy technologies. *Energy Policy*, 50,81-94
Wiser, R., Bolinger, M., (2013). 2012 Wind Technologies Market Report. US Department of Energy.
Wright, T.P. 1936. Factors affecting the costs of airplanes. *Journal of the Aeronautical Sciences*, 3(February):122–128.
Yeh, S., & Rubin, E.S., (2007). A centurial history of technological change and learning curves for pulverized coal-fired utility boilers. *Energy, (32),* 1996–2005.
Yeh, S., & Rubin, E. S. (2012). A review of uncertainties in technology experience curves. *Energy Economics*, *34*(3), 762-771.
Zimmerman, M.B. (1982). Learning Effects and the Commercialization of New Energy Technologies: The Case of Nuclear Power. *The Bell Journal of Economics 13(2)*, 297-310.

Appendix A: Scale Estimates by Source

Table A1 below provides estimates of the alpha estimated scale elasticity, the data source, the method utilized to estimate the elasticity, and the equivalent exponential scale coefficient (the engineering estimate).

Please note that there are multiple estimates provided for some of the sources. This is due to some of these papers providing multiple econometric estimates from various model specifications, from providing estimates for slightly different technology makes, or for providing estimates of different timeframes.

Table A1: Source and Scale Estimate by Technology

Technology	Estimate	Source	Method	Equivalency
Coal	-0.380	McCabe, 1996	Econometric	0.62
Coal	-0.183	Joskow and Rose, 1985	Econometric	0.817
Coal	-0.044	Komanoff, 1981	Econometric	0.956
Coal	-0.029	Komanoff, 1981	Econometric	0.971
Coal	-0.15	Lee, 1976	Given	0.85
Coal	0	Stewart, 1979	Econometric	1
Coal	-0.48	Nieves et al., 1980	Given	0.52
Coal	-0.2	Perl, 1982	Econometric	0.8
Coal	-0.08	US Department of Labor, 1982	Econometric	0.92
FGD	0.09	Healey, 2013	Econometric	1.09
Geothermal	-0.077	Lovekin, 2000	2 points	0.923
Geothermal	-0.130	Sanyal, 2004	2 points	0.87
Solar Thermal	-0.200	Price & Carpenter, 1999	2 points	0.8
Solar Thermal	-0.210	Price & Carpenter, 1999	2 points	0.79
Solar Thermal	-0.184	Price & Kearney, 1999	Given	0.816
Solar Thermal	-0.218	Encyclopedia of Energy, 2004	Given	0.782
Solar Thermal	-0.050	Charles et al., 2005	2 Points- Forecast Data	0.95
Solar Thermal	-0.160	Charles et al., 2005	2 Points- Forecast Data	0.84
Wind (Turbine)	-0.008	Berry, 2009	Econometric	0.992
Wind (Turbine)	0.027	Berry, 2009	Econometric	1.027
Wind (Farm)	-0.100	Berry, 2009	Econometric	0.9
Wind (Farm)	-0.100	Berry, 2009	Econometric	0.9
Wind (Farm)	-0.089	Qiu and Anadon, 2012	Econometric	0.911
Wind (Farm)	-0.134	Qiu and Anadon, 2012	Econometric	0.866
Wind (Power)	0.148	Ek and Soderholm, 2010	Econometric	0.852
CCGT	-0.52	Locatelli and Mancini, 2010	Given	0.48
CCGT	-0.12	Locatelli and Mancini, 2010	Given	0.88
CCGT	-0.210	Rodrigues, 2003	Graphic Depiction	0.79
CCGT	-0.230	Kehlholfer et al, 1999	Graphic Depiction	0.77
Nuclear	0.145	Cantor and Hewlett, 1988	Econometric	1.145
Nuclear	-0.170	Zimmerman, 1982	Econometric	0.83
Nuclear	-0.260	Zimmerman, 1982	Econometric	0.74

Nuclear	-0.300	McCabe, 1997	Econometric	0.7
Nuclear	-0.200	Komanoff, 1981	Econometric	0.8
Nuclear	-0.152	Komanoff, 1981	Econometric	0.848
Nuclear	-0.38	Locatelli and Mancini, 2010	Given	0.62
Nuclear	-0.350	Mooz, 1978	Econometric	0.65
Nuclear	0.000	Mooz, 1979	Econometric	1
Nuclear	-0.230	Marshall and Navaro, 1991	Econometric	0.77
Nuclear	-0.200	Marshall and Navaro, 1991	Econometric	0.8
Nuclear	-0.750	Nieves et al., 1980	Given	0.25
Nuclear	-0.370	US Department of Labor, 1982	Econometric	0.67
Nuclear	-0.510	Perl, 1982	Econometric	0.49
Solar PV-System	-0.160	Feldman et al., 2012	2 points- From Graph	0.84
Solar PV-System	-0.130	Feldman et al., 2012	2 points- From Graph	0.87
Solar PV-System	-0.050	Chaurey and Kandpal, 2010	Given	0.95
Hydro	0.078	Kumar et al., 2011	Graphic Depiction	1.078
Hydro (Small)	-0.29	Kosnik et al, 2010	2 Points	0.71
Hydro (Small)	-0.220	IRENA, 2012	Graphic Depiction	0.78
Hydro	-0.290	Alverado-Ancieta, 2009	Graphic Depiction	0.71
Ethanol	Range: -0.3 to -0.4	Van den Wall Bake et al., 2009	Given	0.6 to 0.7
LNG	0.068	Greaker and Sagen, 2004	Econometric	1.068
LNG	-0.3	Okimi, 2003	Given	0.7
LNG	-0.42	Cornot-Gandolphe, 2005	Given (adding a second train)	0.58
LNG	-0.5	Lang & Schier 2009	Graphic Depiction	0.5
Heat Pump*	-0.49	Blum et al., 2011-My calculation from Figure4	Graphic Depiction	0.51
Heat Pump	-0.68	Rafferty, 1995	Graphic Depiction	0.32
Heat Pump	-0.6	Rafferty, 1995	Graphic Depiction	0.4
Heat Pump	-0.13	Rafferty, 1995	Graphic Depiction	0.87
Heat Pump	-0.1	Rafferty, 1995	Graphic Depiction	0.9

*All heat pump sale estimates pertain to Ground Source Heat Pumps

Appendix B: Learning Curves

Figure B1: FGD Original Data (Capacity)

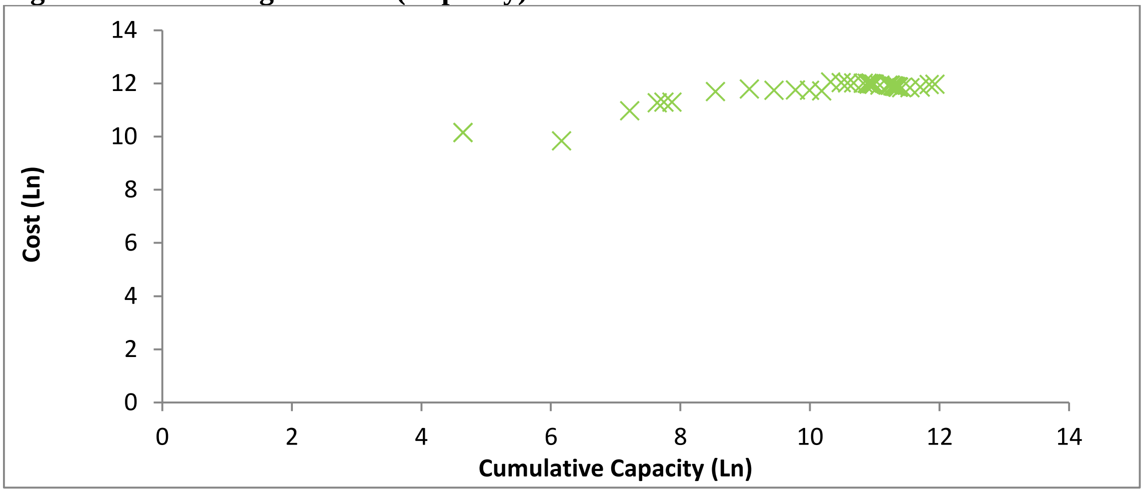


Figure B2: FGD Original Data (Units)

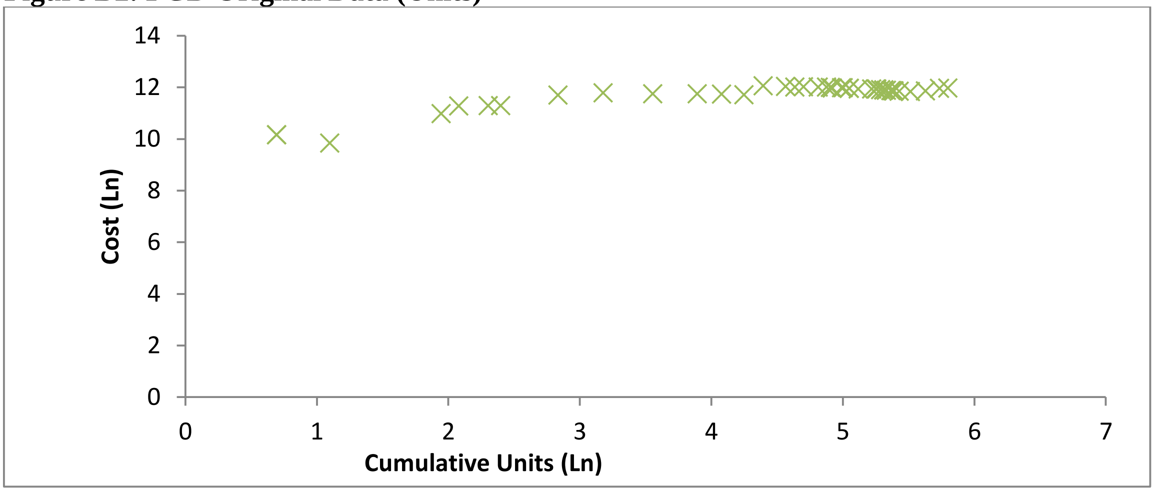


Figure B3: FGD De-scaled (Capacity)

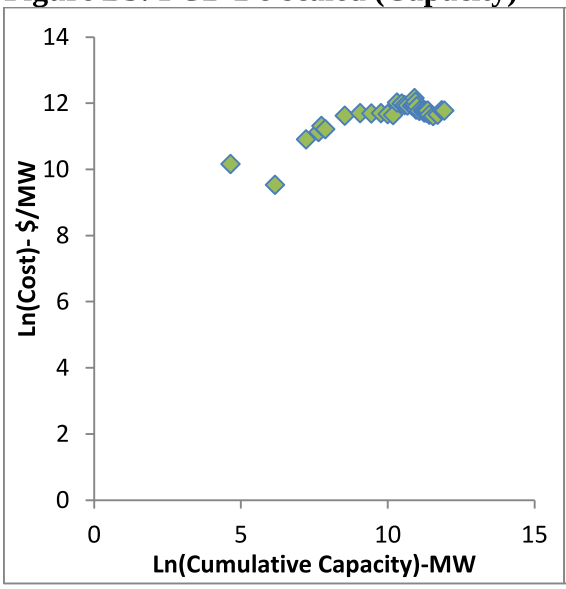


Figure B4: FGD De-scaled (Units)

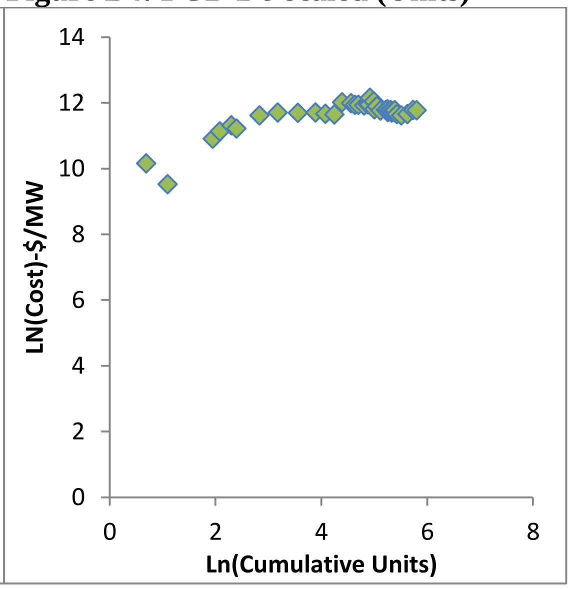


Figure B5: Nuke3 Original Data (Capacity)

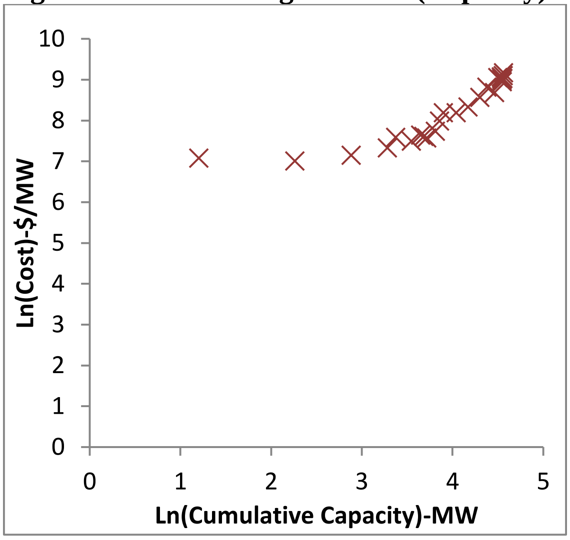


Figure B6: Nuke3 Original Data (Units)

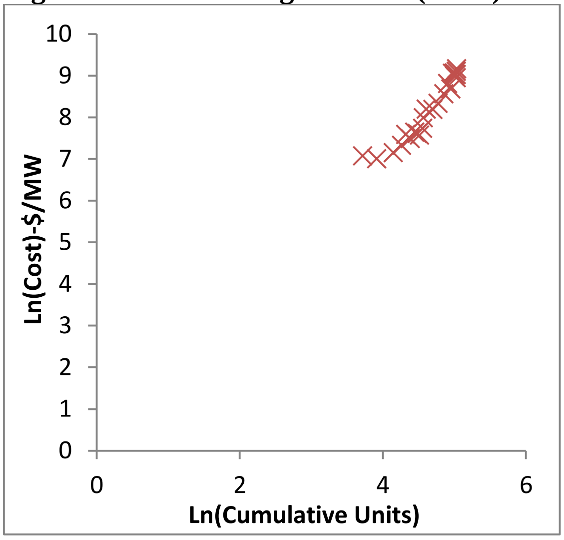


Figure B7: Nuke3 De-scaled (Capacity)

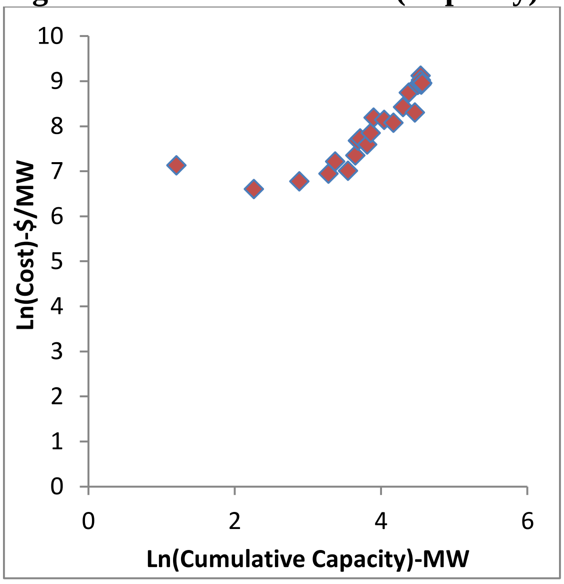


Figure B8: Nuke3 De-scaled (Units)

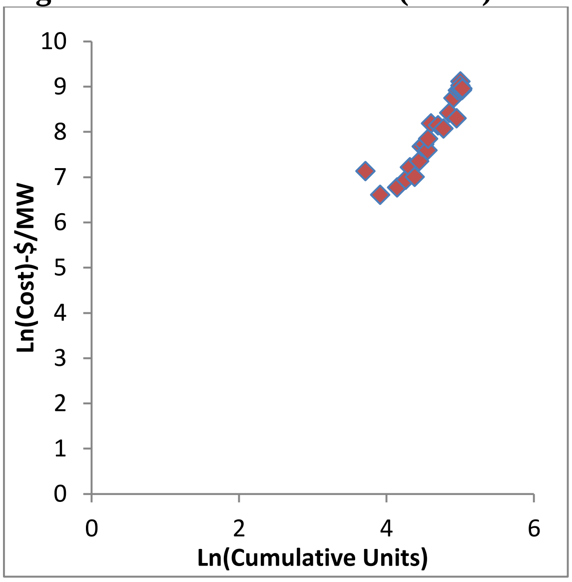


Figure B9: Coal Original Data (Capacity)

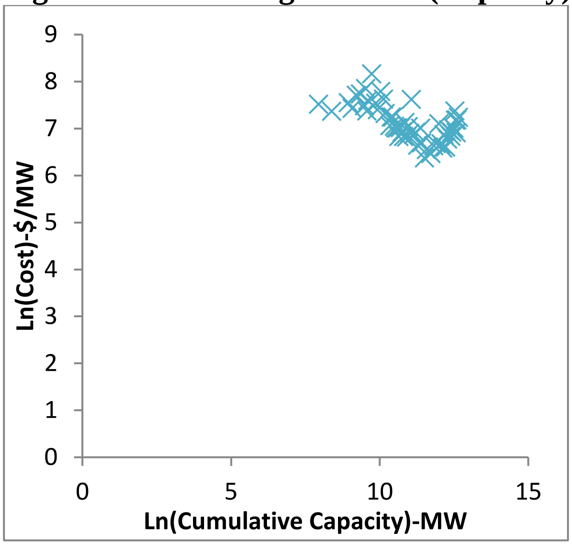


Figure B10: Coal Original Data (Units)

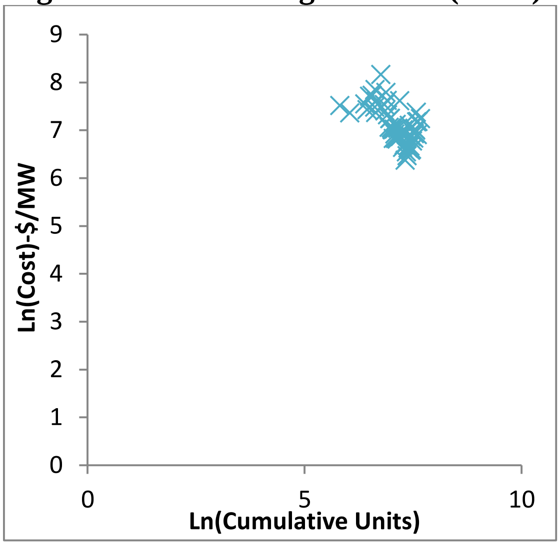


Figure B11: Coal De-scaled (Capacity)

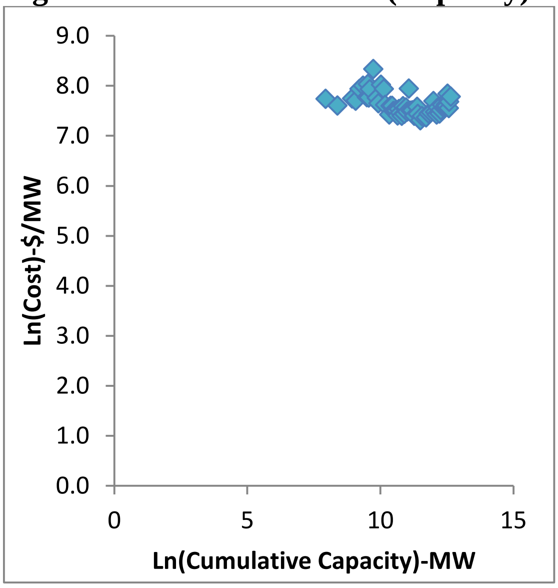


Figure B12: Coal De-scaled (Units)

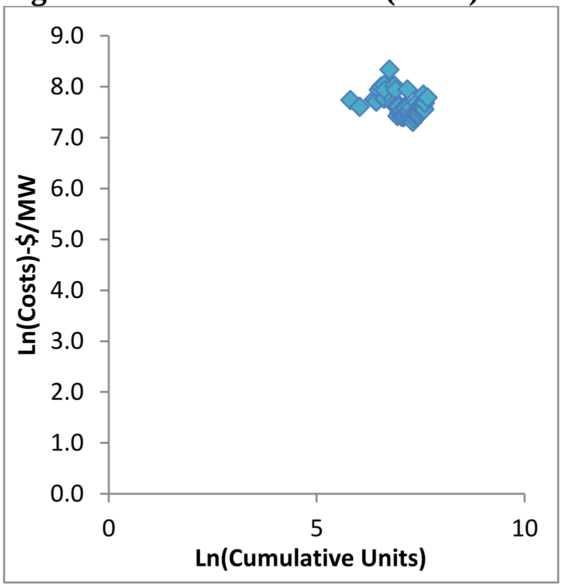


Figure B13: Nuke2 Original Data (Capacity)

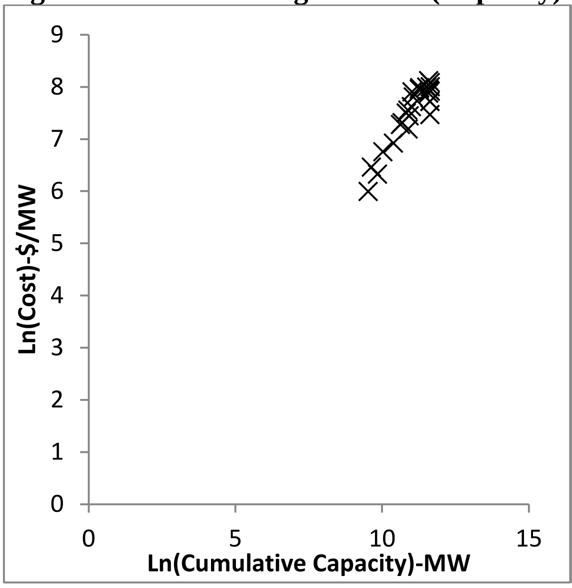


Figure B14: Nuke2 Original Data (Units)

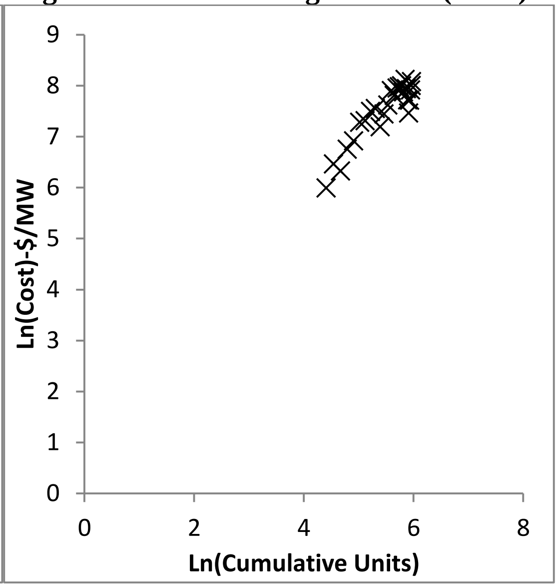


Figure B15: Nuke2 De-Scaled (Capacity)

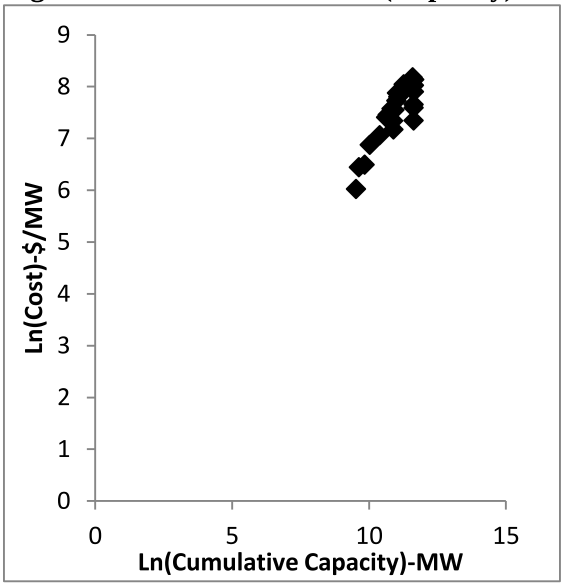


Figure B16: Nuke2 De-Scaled (Capacity)

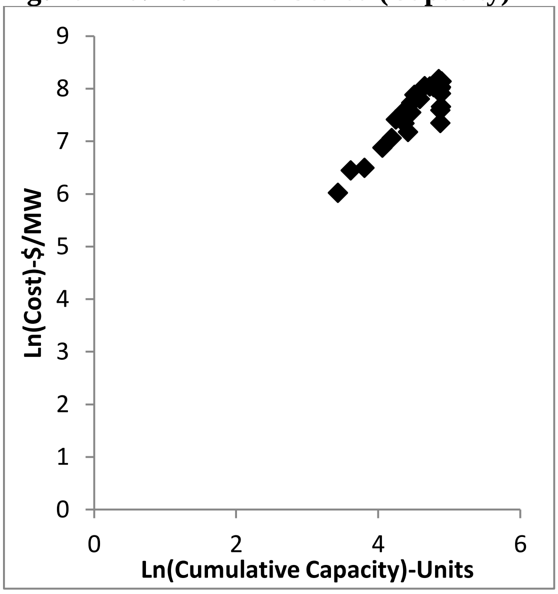


Figure B17: Nuke1 Original Data (Capacity)

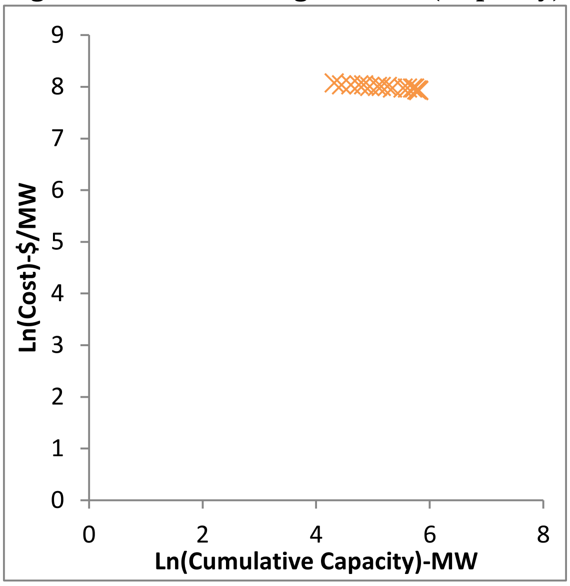


Figure B18: Nuke1 Original Data (Units)

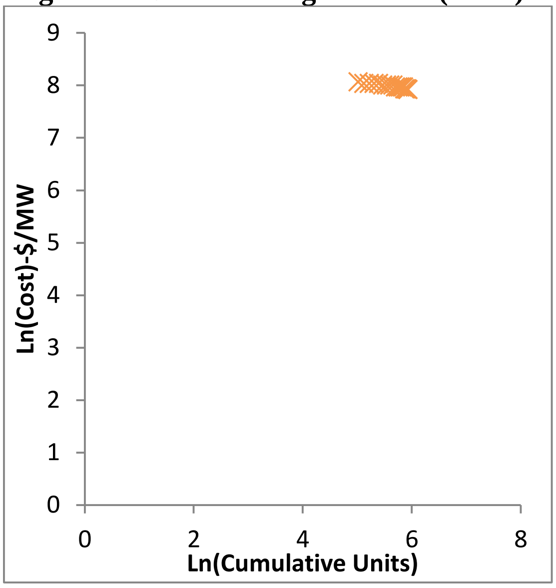


Figure B19: Nuke1 De-scaled (Capacity)

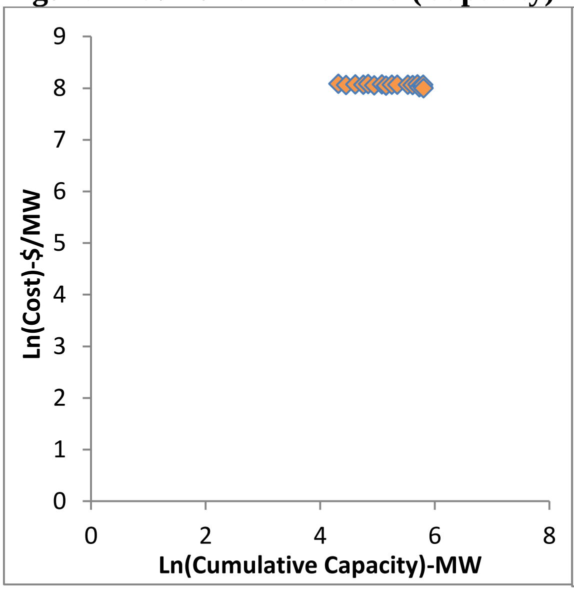


Figure B20: Nuke1 De-scaled (Units)

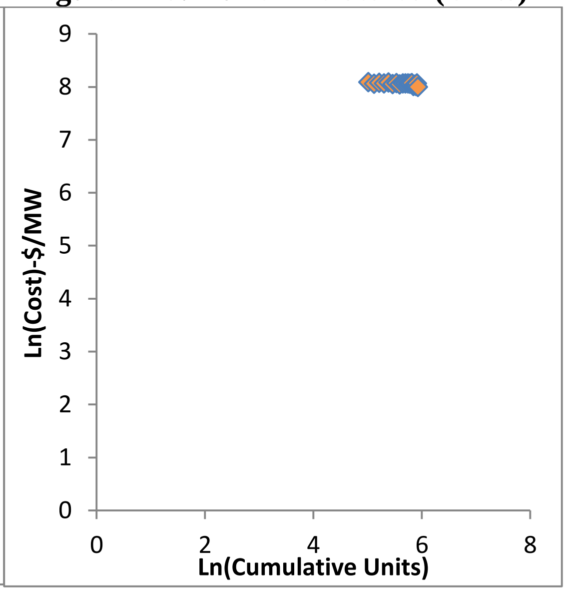


Figure B21: CCGT1 Original Data (Capacity)

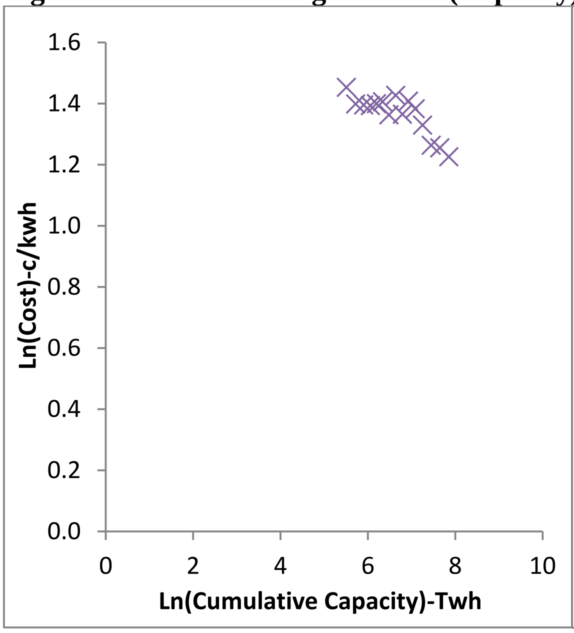


Figure B22: CCGT1 Original Data (Units)

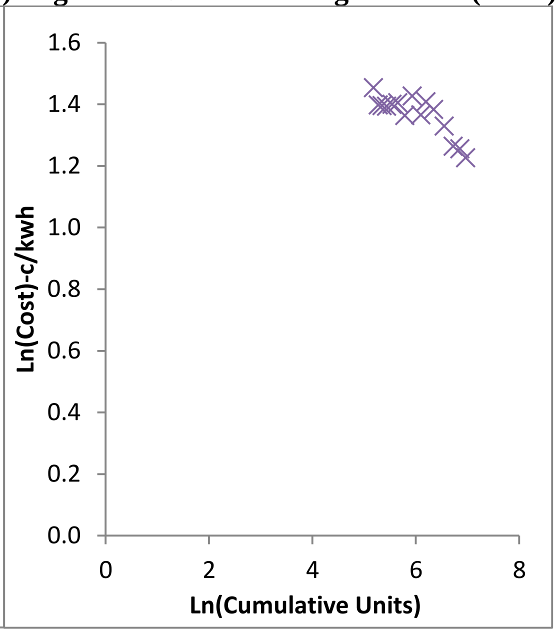


Figure B23: CCGT1 De-scaled (Capacity)

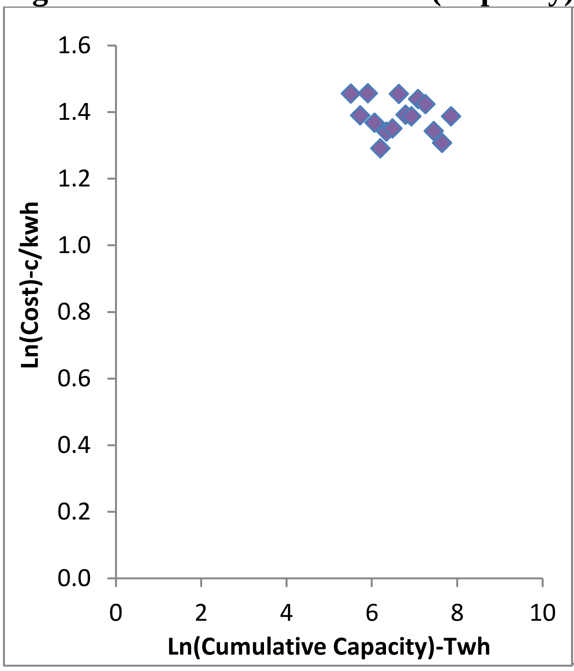


Figure B24: CCGT1 De-scaled (Units)

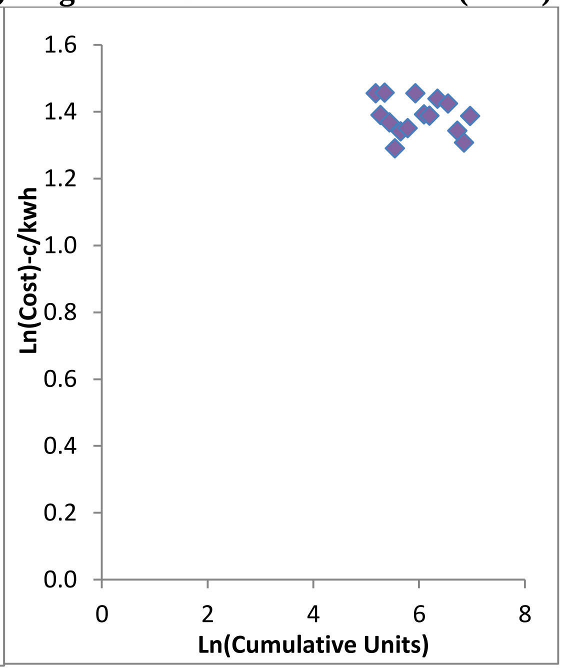


Figure B25: CCGT2 Original Data (Capacity)

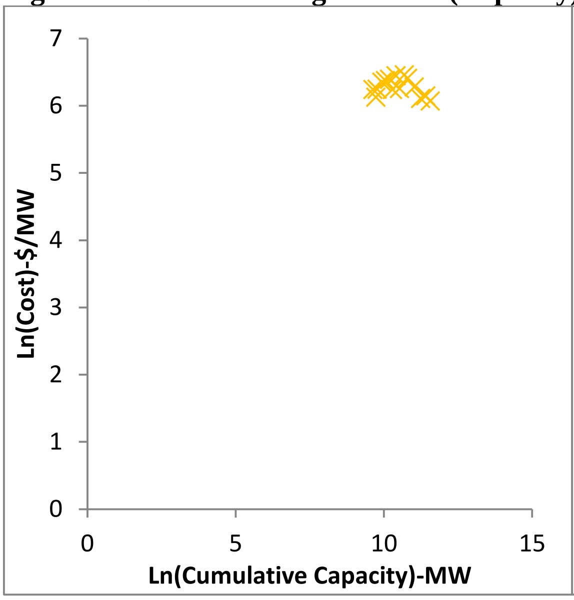


Figure B26: CCGT2 Original Data (Units)

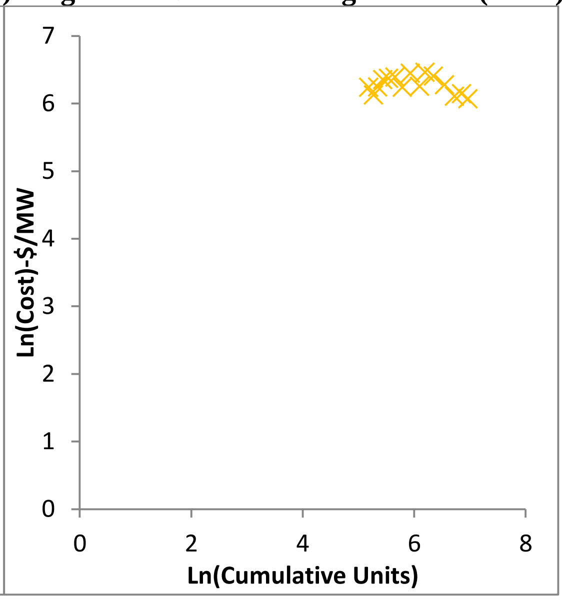


Figure B27: CCGT2 De-scaled (Capacity)

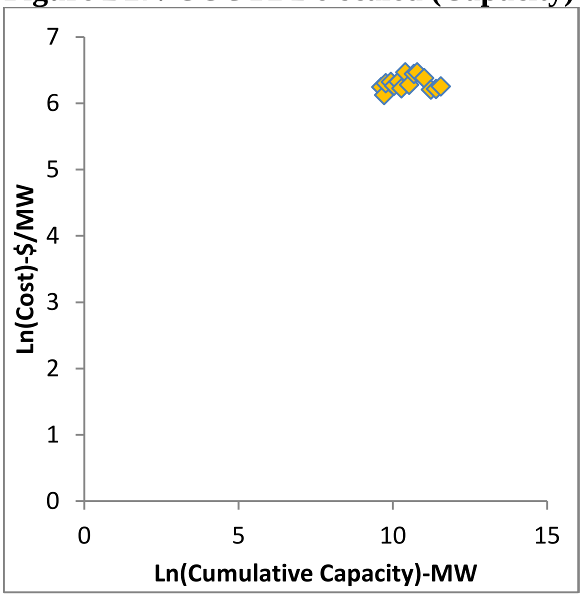


Figure B28: CCGT2 De-scaled (Units)

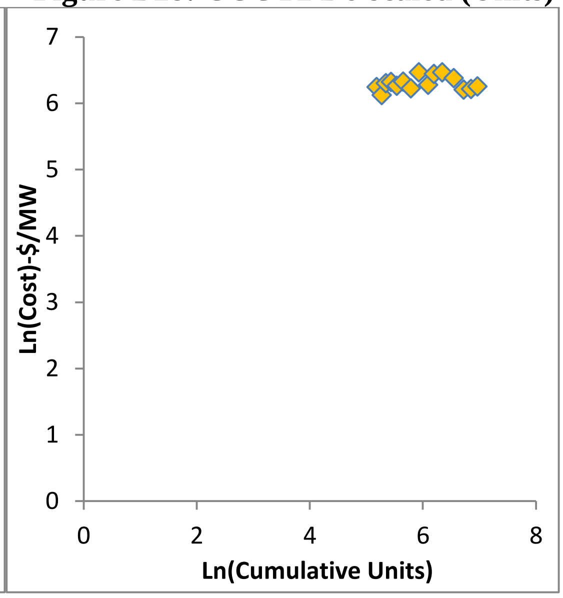


Figure B29: Sthermal-1 Original Data (Capacity)

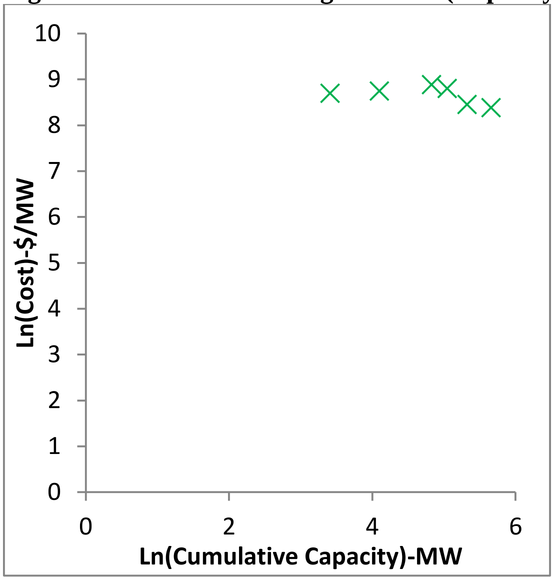


Figure B30: Sthermal-1 Original Data (Units)

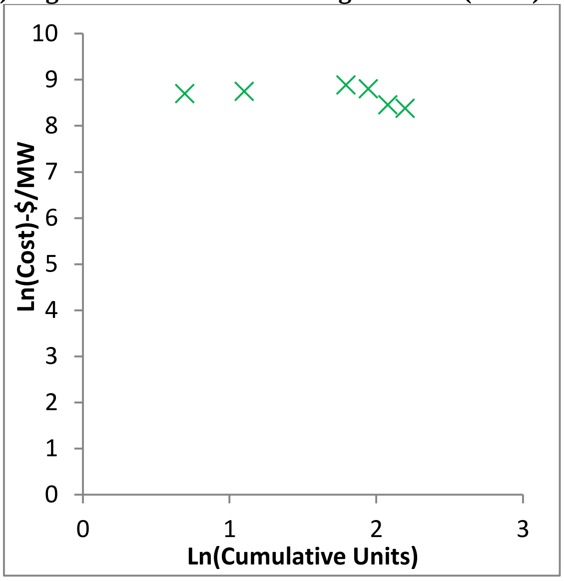


Figure B31: Sthermal-1 De-scaled (Capacity)

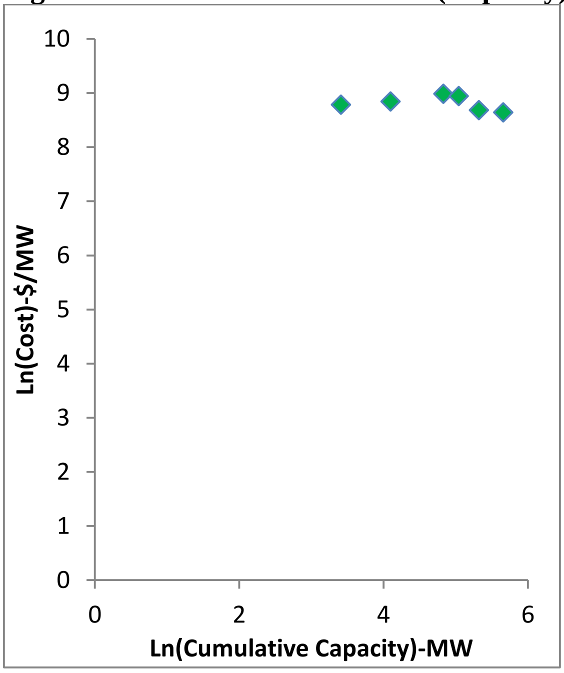


Figure B32: Sthermal-1 De-scaled (Units)

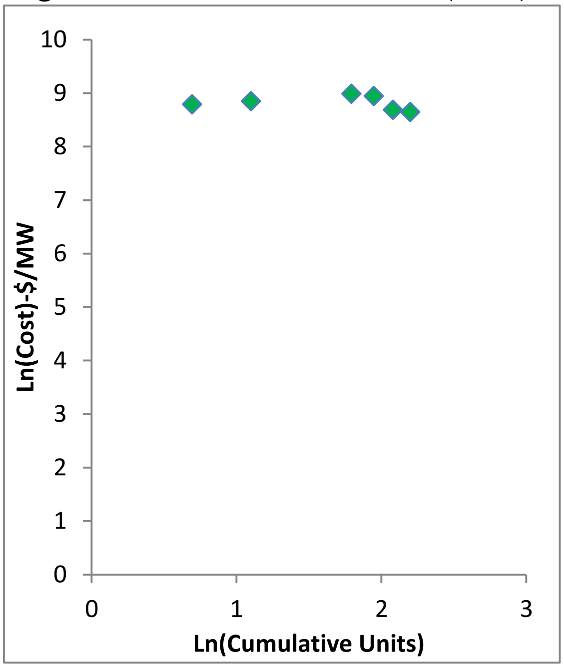


Figure B33: Hydro Original Data (Capacity)

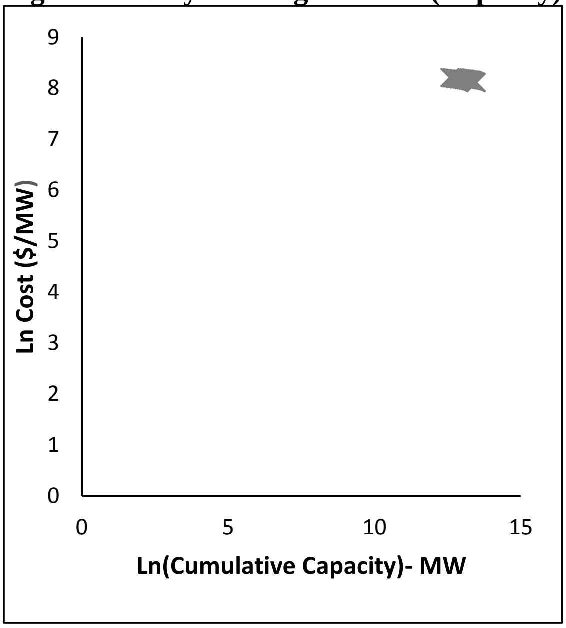


Figure B34: Hydro Original Data (Units)

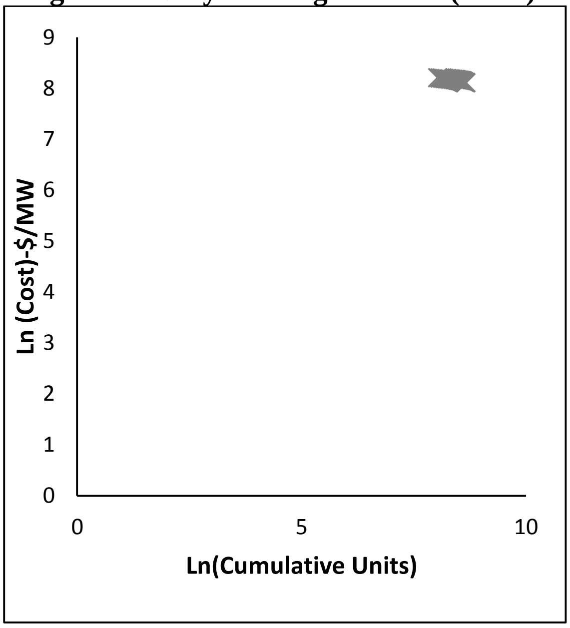


Figure B35: Hydro- De-scaled (Capacity)

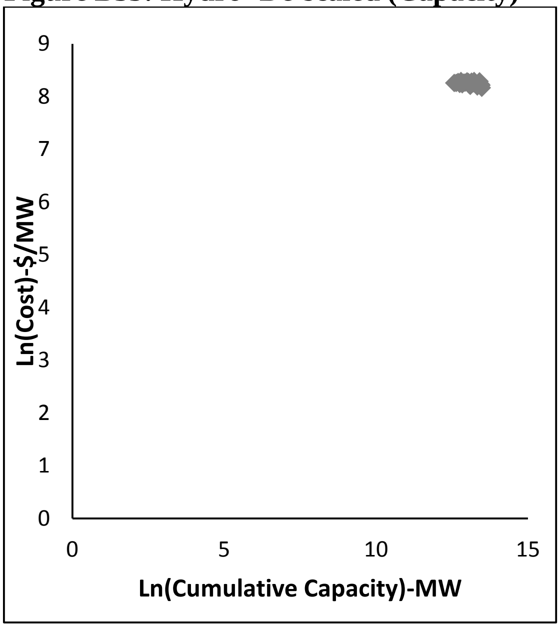


Figure B36: Hydro- De-scaled (Units)

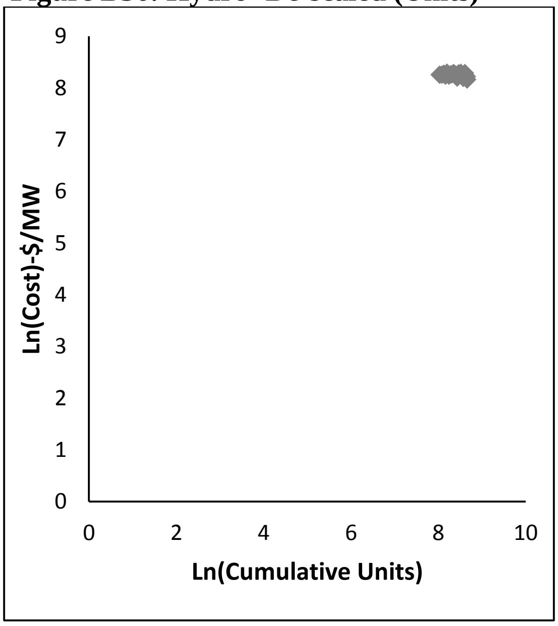


Figure B37: Sthermal 2 Original Data (Capacity)

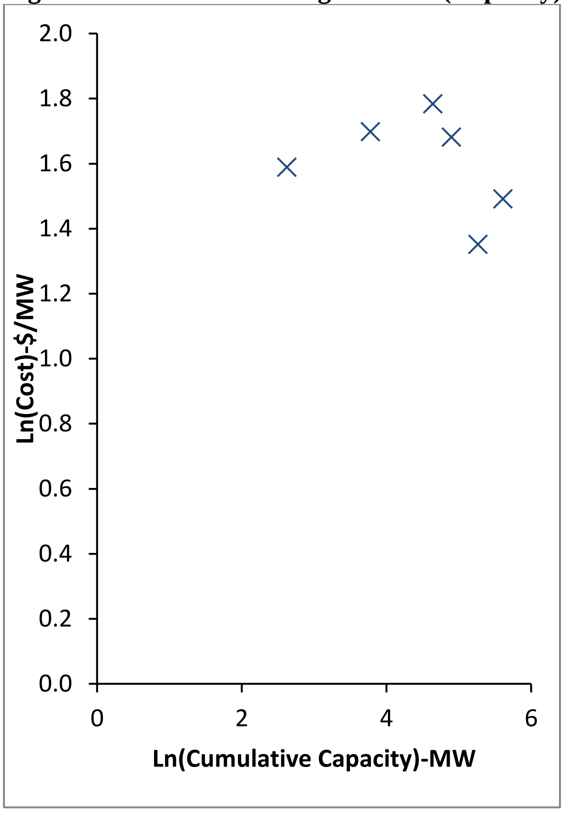


Figure B38: Sthermal 2 Original Data (Units)

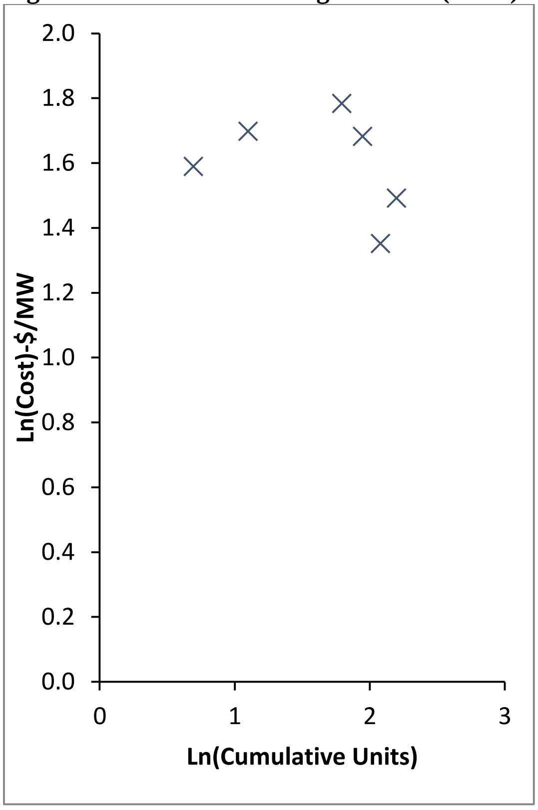


Figure B39: Sthermal 2 De-scaled (Capacity)

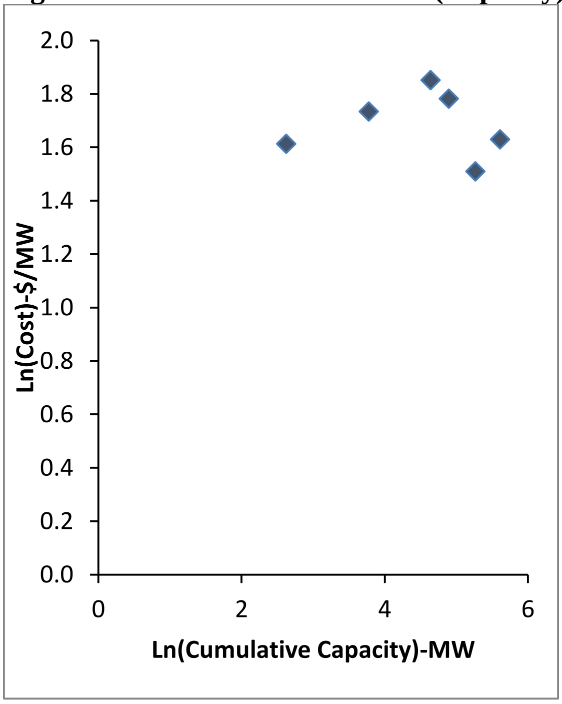
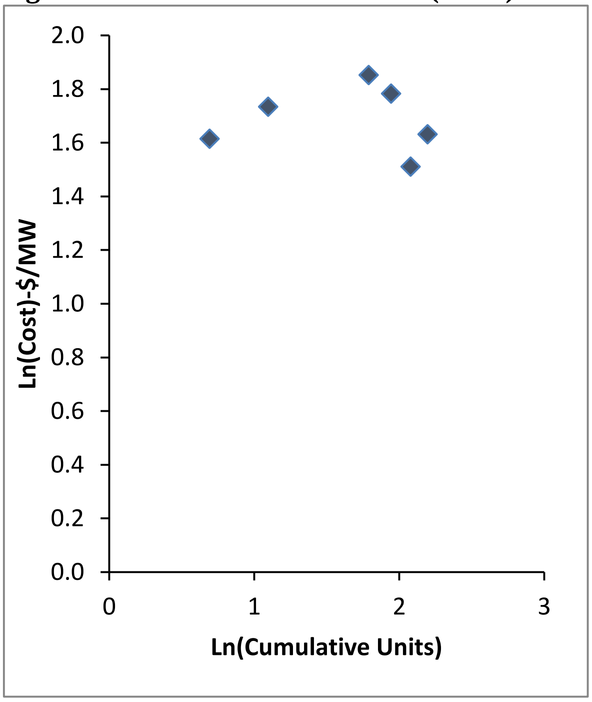
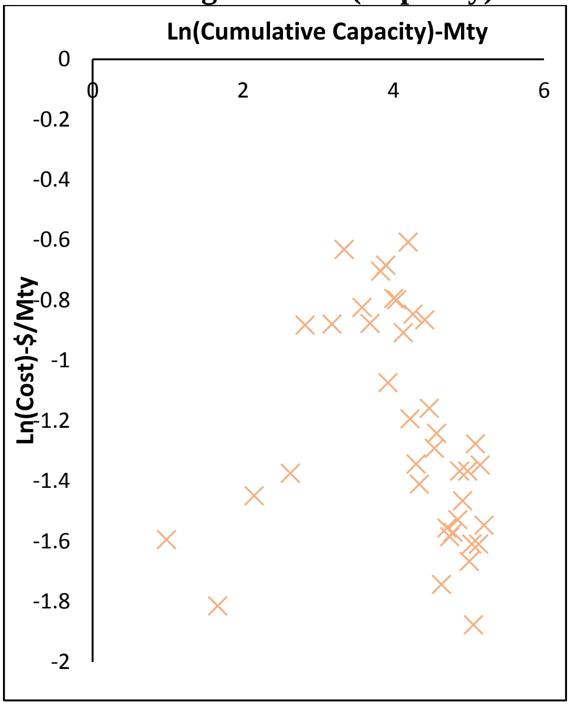


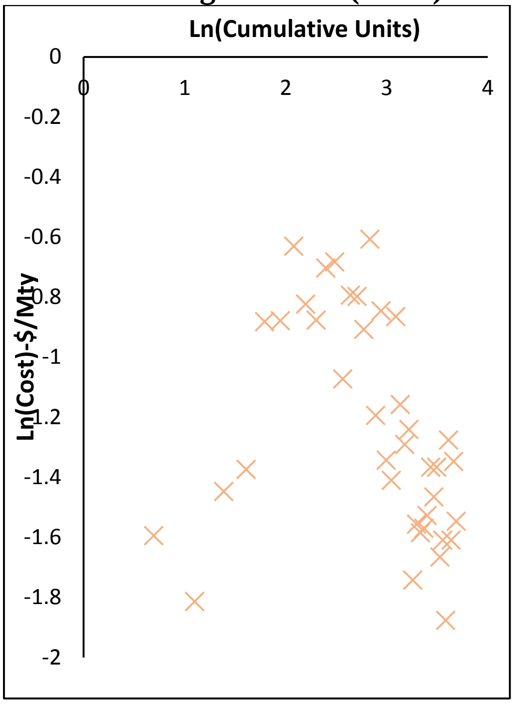
Figure B40: Sthermal 2 De-scaled (Units)



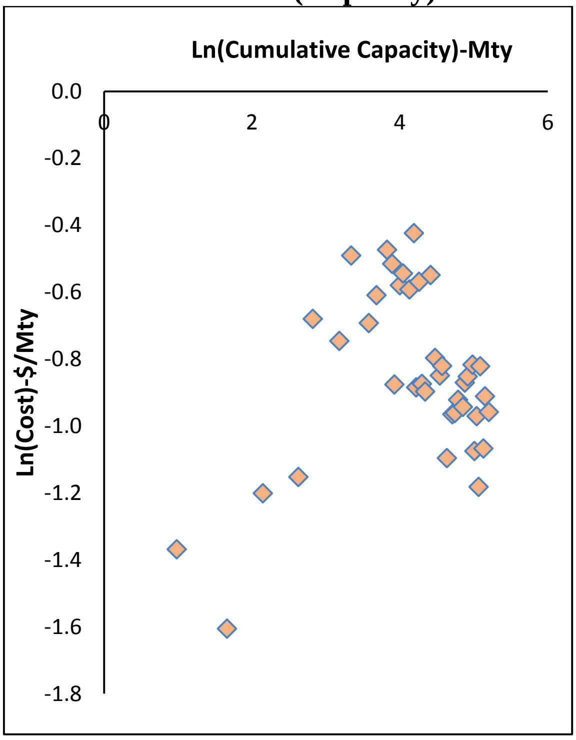
B41: LNG Original Data (Capacity)



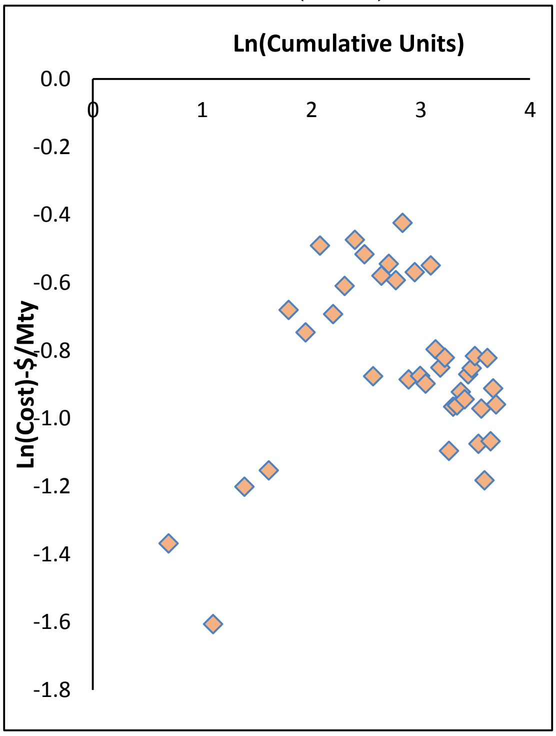
B42: LNG Original Data (Units)



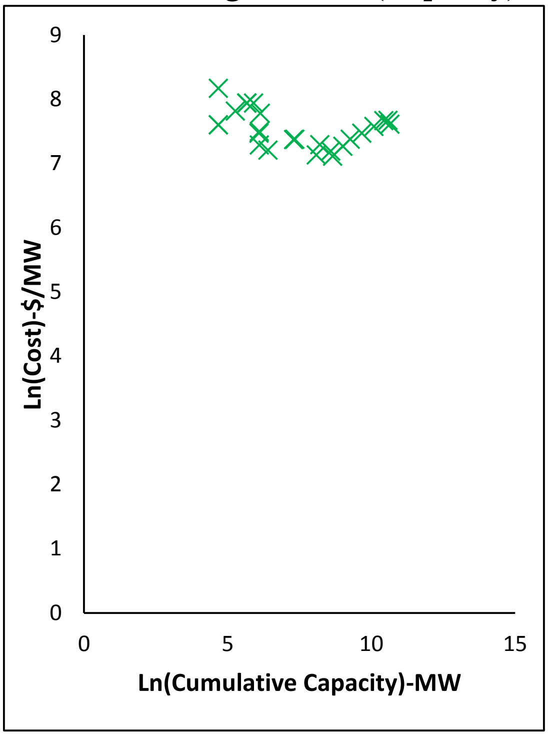
B43: LNG De-scaled (Capacity)



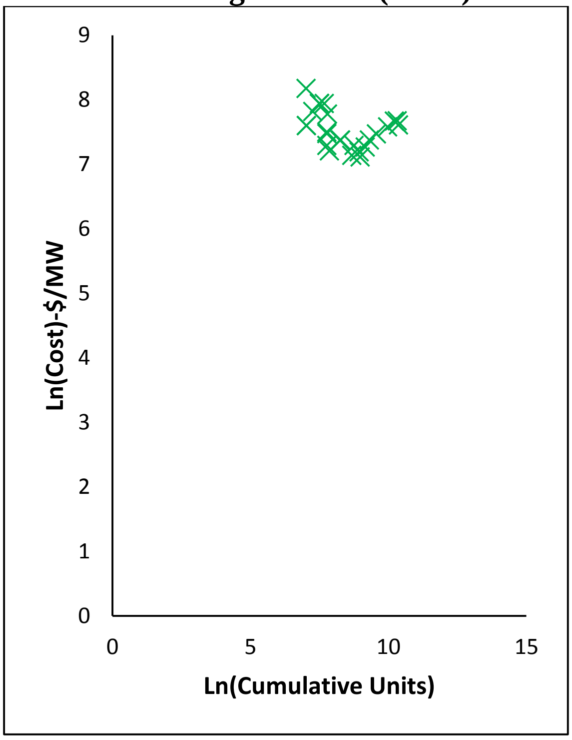
B44: LNG De-scaled (Units)



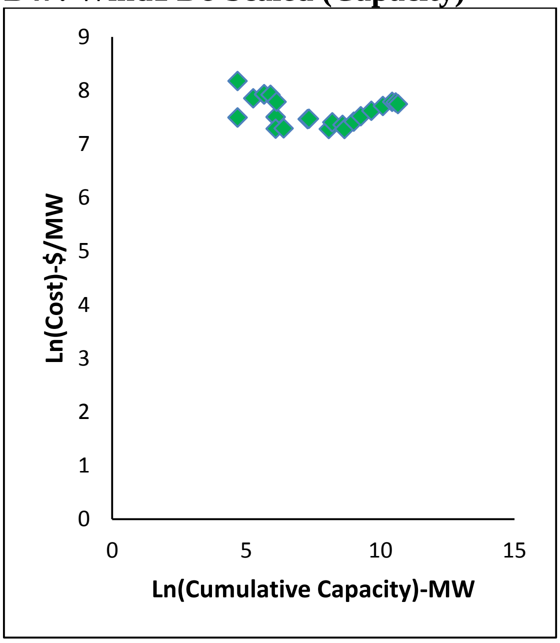
B45: Wind1 Original Data (Capacity)



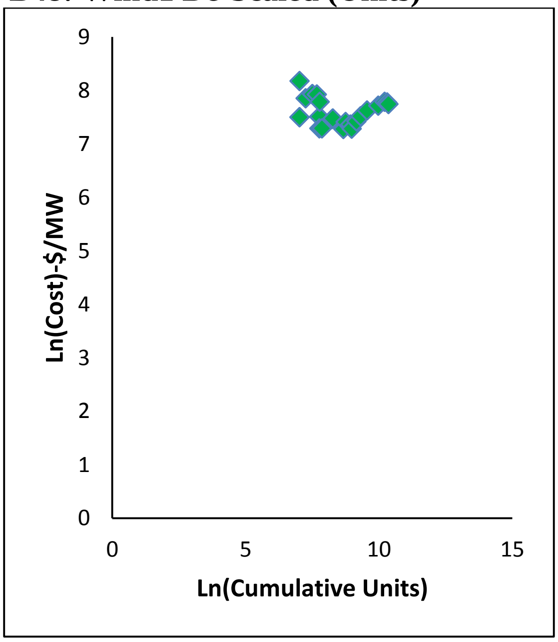
B46: Wind1 Original Data (Units)



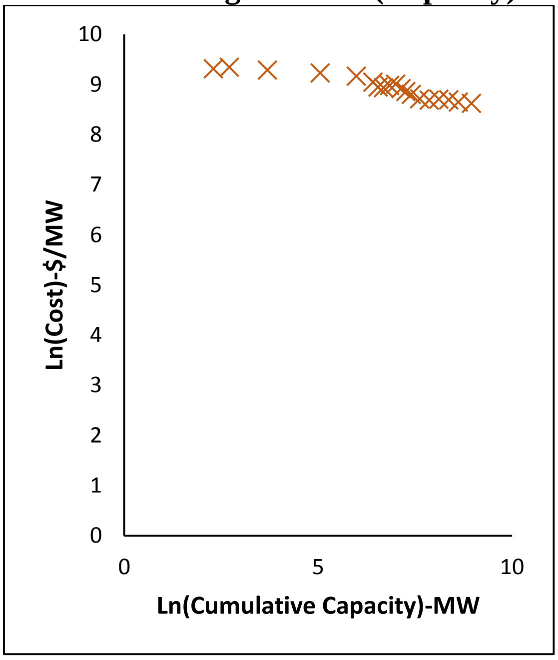
B47: Wind1 De-Scaled (Capacity)



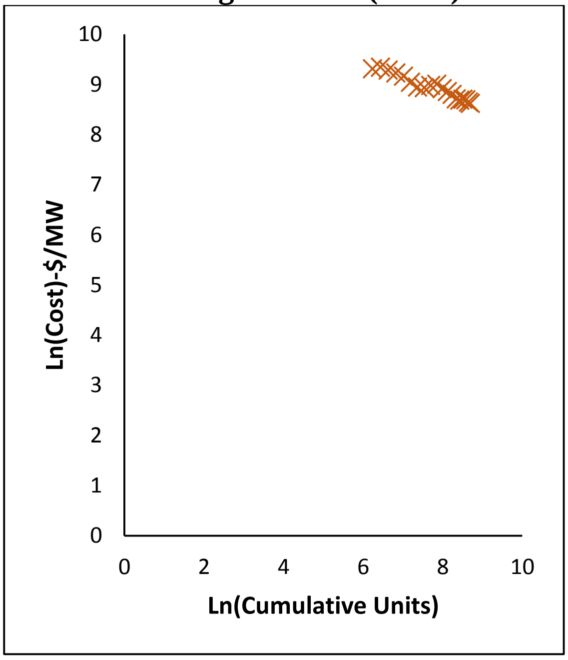
B48: Wind1 De-Scaled (Units)



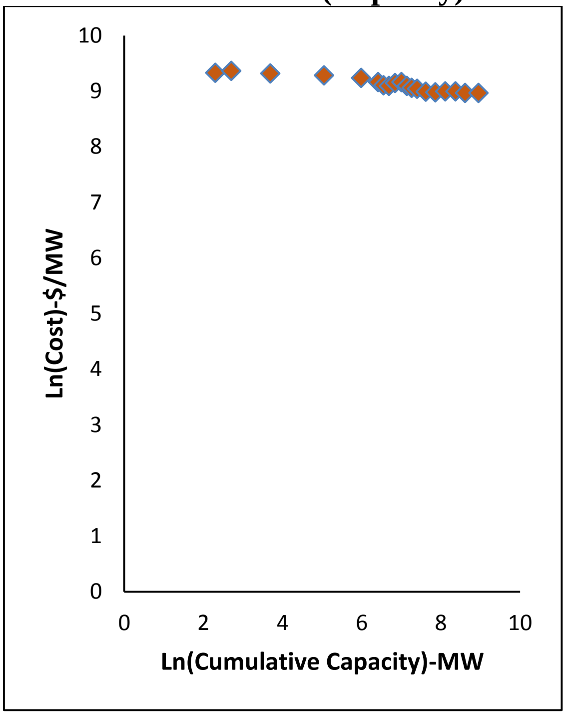
B49: Wind2 Original Data (Capacity)



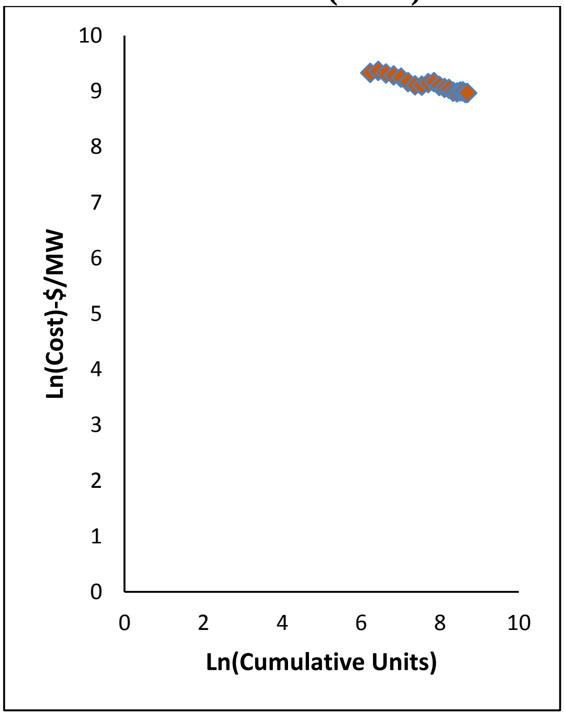
B50: Wind2 Original Data (Units)



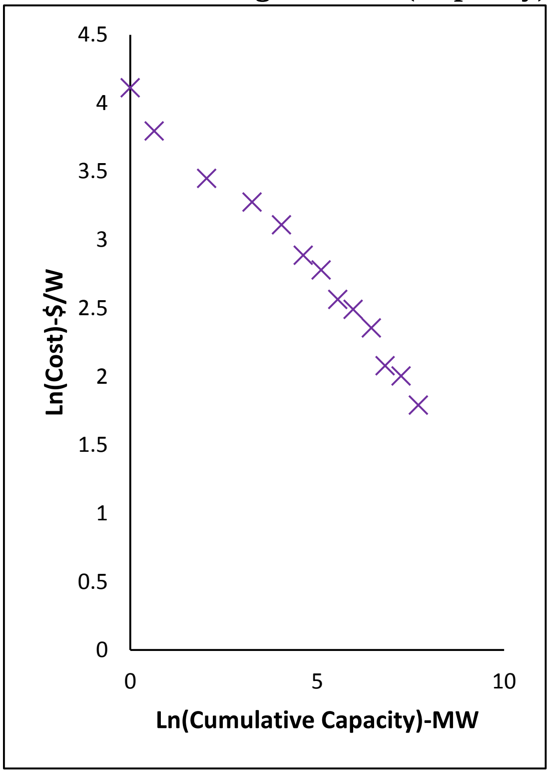
B51: Wind2 De-Scaled (Capacity)



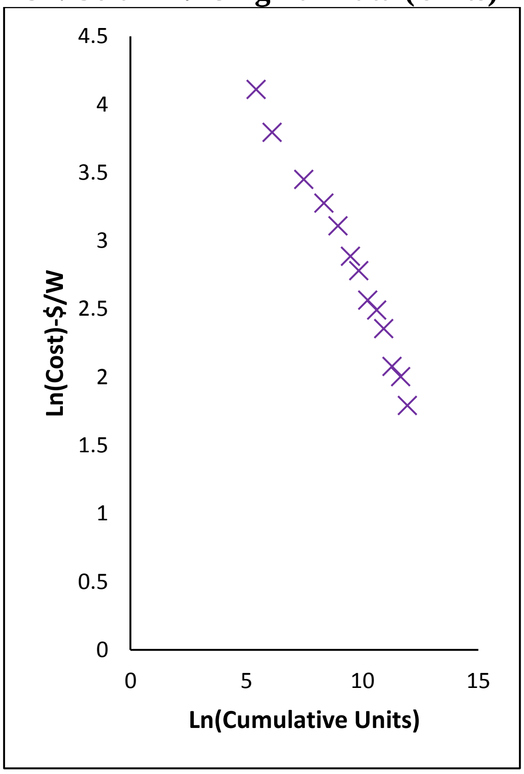
B52: Wind2 De-Scaled (Units)



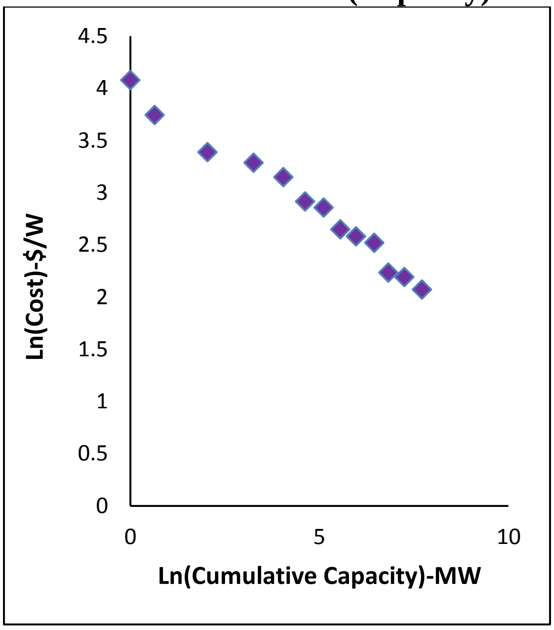
B53: Solar PV Original Data (Capacity)



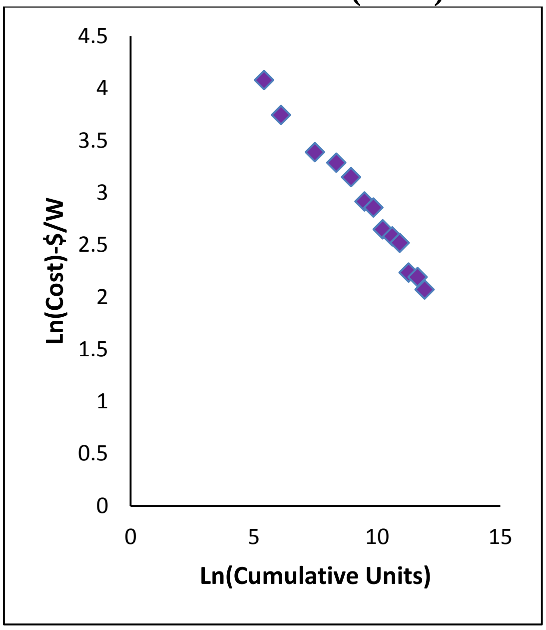
B54: Solar PV Original Data (Units)



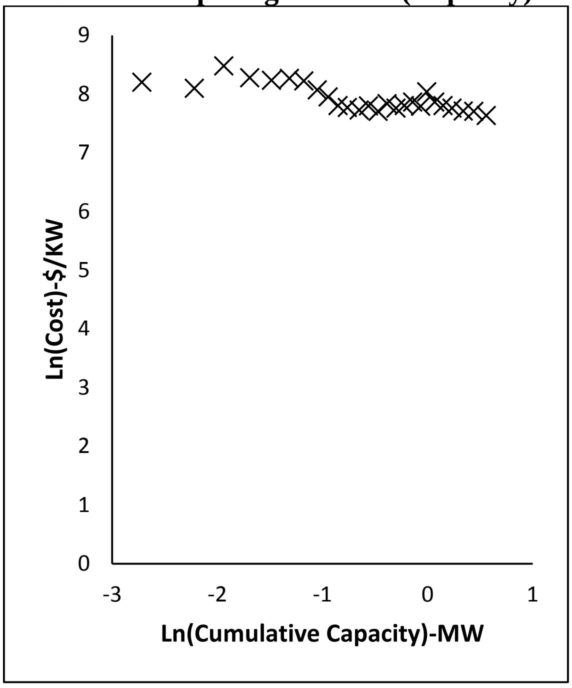
B55: Solar PV De-scaled (Capacity)



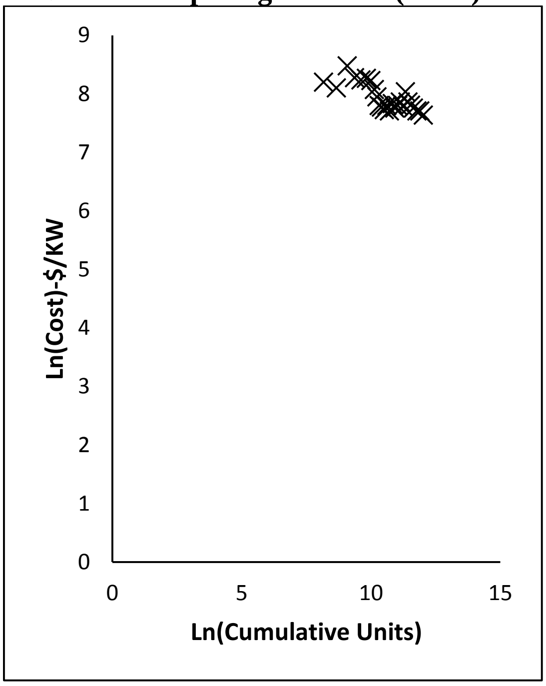
B56: Solar PV De-scaled (Units)



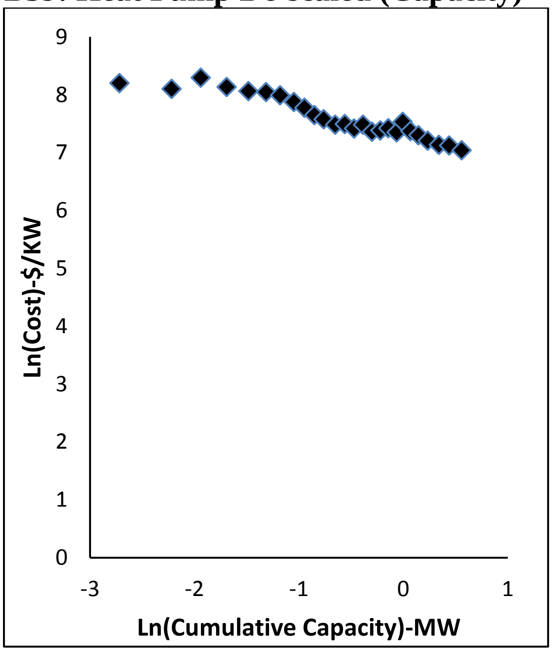
B57: Heat Pump Original Data (Capacity)



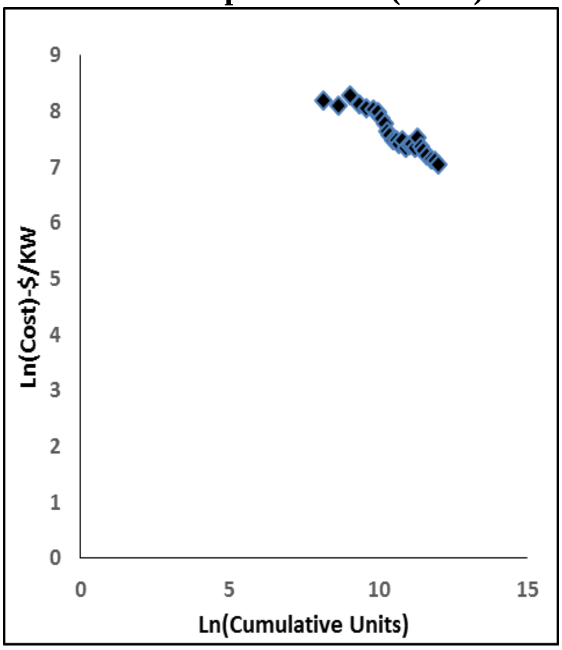
B58: Heat Pump Original Data (Units)



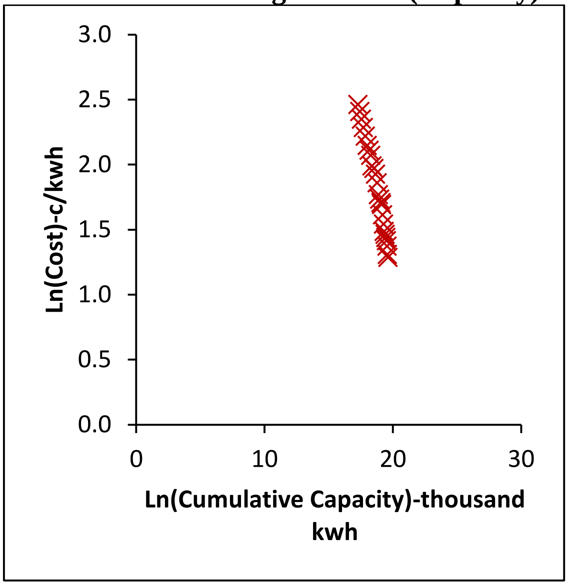
B59: Heat Pump De-scaled (Capacity)



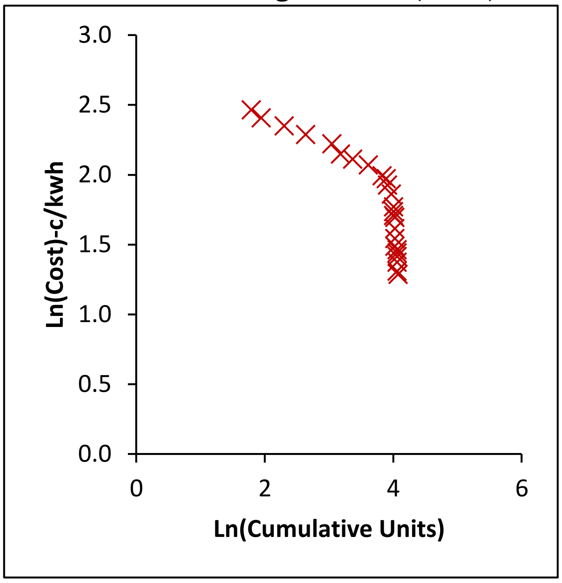
B60: Heat Pump De-scaled (Units)



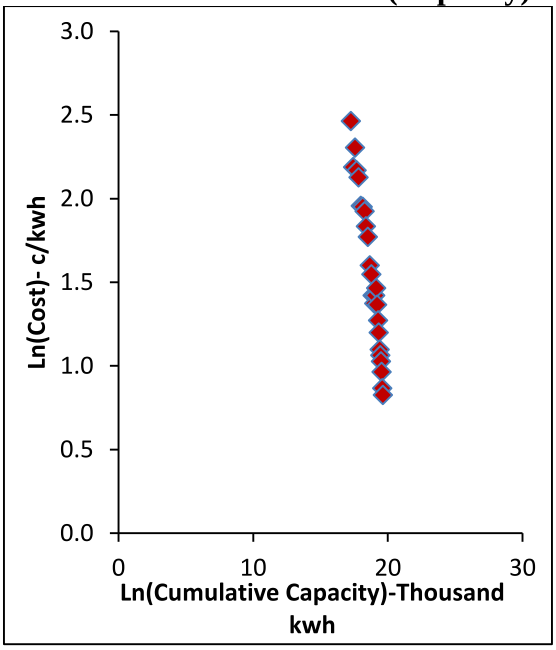
B61: Geothermal Original Data (Capacity)



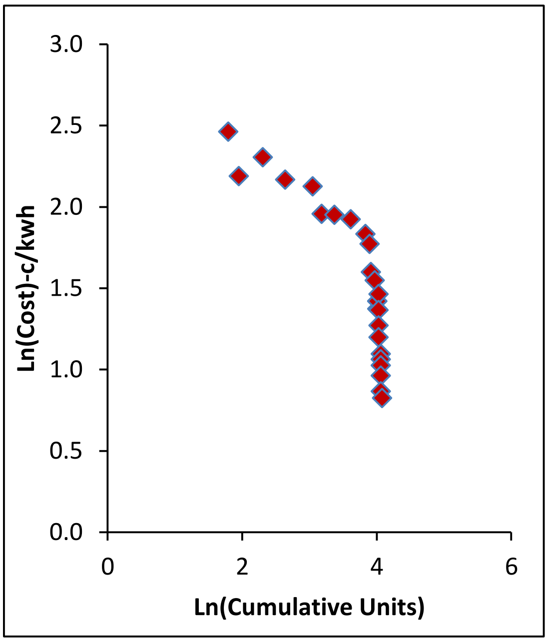
B62: Geothermal Original Data (Units)



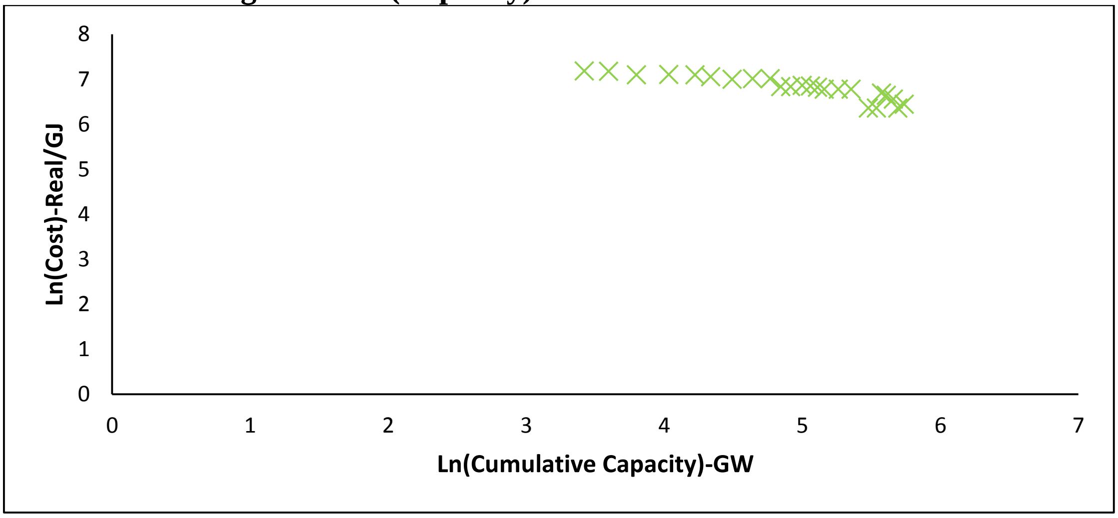
B63: Geothermal De-scaled (Capacity)



B64: Geothermal De-scaled (Units)



B65: Ethanol Original Data (Capacity)



B65: Ethanol De-Scaled Data (Capacity)