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Meta-analysis of unit and industry level scaling dynamics in energy technologies and climate change mitigation scenarios

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Contents

Abstract

Historical patterns of growth across a range of energy technologies are used to explore 'scaling'. The term scaling is used to describe a particular form of growth that is (i) both rapid and substantive, and (ii) occurs at multiple levels from the technical unit to the industry as a whole (e.g., from a wind turbine to total installed wind capacity). Unit and industry scaling dynamics are assessed in historical time series data on refineries, power plants (nuclear, coal, gas, wind), jet aircraft, cars and light bulbs. In those cases for which S-shaped growth is clearly evidenced, logistic function parameters are used to compare scaling across different technologies.

Three broad findings emerge from the meta-analysis. Firstly, the relationship between the extent and rate of scaling at the industry level, measured in terms of cumulative total capacity, is consistent across both supply-side and end use technologies. Secondly, the relationship between scaling at the unit level and scaling at the industry level is contingent on certain technology and market characteristics. A conceptual framework with six enabling factors is developed to explain different technologies' scaling dynamics. Thirdly, there is little evidence to support a 'leapfrogging' of scaling dynamics as technologies diffuse spatially from initial to subsequent and late markets.

Applications of these findings are discussed. Firstly, the historical relationships between scaling parameters at the industry level are used to validate projections of low carbon technologies in future scenarios. Despite orders of magnitude projected increases in installed capacities of nuclear power, carbon capture and storage, and renewable energy by 2100, scenarios are found to be conservative in comparison with historical scaling relationships. Reasons why are discussed. Secondly, the conceptual framework of enabling factors for industry scaling is used to illustrate policy approaches for scaling low carbon technologies in the future.

Acknowledgments

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About the Author

Charlie Wilson is a visiting Research Scholar in the TNT Program working under the supervision of Arnulf Grubler. The research for this Interim Report was begun during the Young Scientists Summer Program ('YSSP') in 2008, and continued during the spring and summer of 2009. Currently, Charlie is also working as a Teaching Fellow at the London School of Economics in the UK. Prior to joining IIASA, Charlie completed his PhD at the University of British Columbia in Vancouver, Canada. His research focused on the social and behavioural determinants of energy use. This built on a number of years professional experience in the private sector working on renewable energy finance and climate change policy.

Meta-analysis of unit and industry level scaling dynamics in energy technologies and climate change mitigation scenarios

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1 Research Context & Rationale

1.1 Historical & Future Technological Change in the Energy System

Expectations and scenarios of greenhouse gas constrained futures vary widely in their assumptions, storylines, and analytical underpinning. But all share at least one common feature: order of magnitude increases in the extent to which certain energy technologies are deployed. Some emphasize decarbonising supply-side technologies, such as solar photovoltaics, nuclear power, cellulosic ethanol production, or carbon capture and storage. Others focus on end-use technologies that improve energy efficiency or reduce energy service demand in buildings, transportation systems, or industrial facilities.

Historical data on cost, capacity, output, investment, and configuration are all richer and more readily available for supply-side energy technologies compared to their end-use counterparts. This is, in large part, a natural bias of the smaller numbers, larger 'sizes' and so clearer point sources that register on analysts' radar screens. Compiling data on nuclear plants numbering 3 orders of magnitude is a far simpler proposition than the equivalent task for the highly dispersed 8-9 orders of magnitude numbers of fridges or 11-12 orders of magnitude numbers of light bulbs.

An important consequence is that demand-side technological change is modelled with far coarser resolution than the more centralised and larger scale energy supply chains from resource extraction and conversion to end use. For example, exogenously-defined rates of 'autonomous energy efficiency improvement' have been widely used to represent all non-price induced changes in energy intensity (energy per measure of output, e.g., GJ/GDP) (Azar & Dowlatabadi 1999). This single parameter aggregates changes over time in both the efficiency of all end-use technologies and the levels of activity in different sectors of the economy. Underlying such assumptions are a complex of technological and institutional dynamics related ultimately to the demand for energy services, and the technologies used to provide for that demand.

In comparison, changes in carbon intensity (tCO_2/GJ) have been extensively and richly modelled as they are concentrated upstream in the energy system. Myriad technologically explicit projections describe how the energy supply can be decarbonised in order to meet climate stabilisation targets (see, e.g., Fisher et al. 2007; Riahi et al. 2007).

Carbon and energy intensities are widely used indicators of change in the supply- and demand-side of the energy system respectively. Historical trends have been well documented and explored and set the backdrop against which ever-greater rates of change are required as stabilisation constraints for future atmospheric CO_2 concentrations tighten(see, e.g., Grübler 1998; Smil 2000). As the IPCC's Fourth Assessment Report in 2007 concluded:

> "The range of stabilization levels assessed can be achieved by deployment of a portfolio of technologies … [whose contribution] will vary over time, region and stabilization level … Energy efficiency plays a key role across many scenarios for most regions and timescales … For lower stabilization levels, scenarios put more emphasis on the use of low-carbon energy sources ... *In these scenarios improvements of carbon intensity of energy supply and the whole economy need to be much faster than in the past*." (authors italics; p25 of Summary for Policy Makers of Fisher et al. 2007).

'Discontinuity' is therefore a common, albeit implicit framing of the global energy system under carbon constraints. The future will not – can not – resemble the past. Driven by accumulating policy and analytical attention to climate change mitigation, and the ongoing depletion of non-renewable energy resources, this 'discontinuity' framing points to the next cycle of capital stock replacement and institutional changes in the energy sector as a critical juncture (Nakicenovic & Rogner 1996). This in turn links to substantial literatures on the management of systemic transitions (Rotmans et al. 2001; Smith et al. 2005) and the potential for policy to induce technological change (Newell et al. 1999; Gritsevskyi & Nakicenovic 2000; Grubb et al. 2002).

In this brave new carbon constrained world, how relevant are the lessons of history?

The contention of this paper is that the evolution of the energy system through capital stock growth and renewal remains the best guide to understanding how *feasible* will be dramatic technological change over the next 20, 50 or 100 years.[1] At the very least, empirical evidence allows a robust formulation of what we know to be possible, albeit in analogous conditions. After all, the 20th century has witnessed explosive growth in both supply-side and end-use technologies as part of a wholesale transformation of the energy system. Over the past 100 years, global primary energy consumption has increased 16-fold, as has GDP, compared to a 4-fold increase in population (Smil 2000). In the 1960s, roughly one coal-powered steam turbine unit averaging 125 MW in capacity was installed every other day, and around 3 in 4 of these were in OECD countries alone. In the 1990s, Boeing and Airbus' combined production was about 3 commercial jet aircraft every other day carrying the equivalent of around 150 MW of power plant.

Against this backdrop of continual growth and expansion, the effects of World War II and the oil shocks are distinguishable on most 20th century trend lines of energy-related data. During and following these perturbations, technological change was particularly marked. Over the 3 years from 1941 to 1944, the number of B-17s rolling off the production lines at Boeing's Plant No. 2 in Seattle increased from an initial 5 per month to a peak of 362; an over 70-fold increase in 3 years. The workforce doubled to 20,000 in just 6 months (Mishina 1999). The oil shocks led to a dramatic slowdown in refinery output and natural gas supply. At the extreme, US regulations prohibited the use of

[1] Marchetti paraphrases a Chinese saying that past history contains all useful precedents for interpreting the present (Marchetti 1994).

natural gas for electricity generation so the limited remaining resource could be saved for higher value uses (Lee & Loftness 1987). A decade later, the construction of natural gas fired power plants was booming across the OECD. The oil shocks also drove marked efficiency gains in end use technologies, from personal vehicles (Sivak & Tsimhoni 2009)to industrial process (IEA 2004).

In this context, the overall goal of the research described here is two-fold. Firstly, there is a simple exploratory question: *Are there common patterns in the historical growth dynamics of different energy technologies?*

Contingent on this exploration are two secondary, applied questions. The first relates to policy: *Do historical growth dynamics reveal any generalisable implications for energy technology and innovation policy?* The second relates to scenario modelling: *Can historical growth dynamics be used to validate or 'reality check' scenario modelling of low carbon technology diffusion?*

These questions have both quantitative and qualitative components. Quantitatively, the research asks how rapidly and how pervasively energy technologies have grown historically. This emphasis on both rates and extents of growth reflects the importance of both temporal and spatial diffusion, as well as the contribution of specific technologies to historical transformations in the energy system as a whole. Qualitatively, the research is interested in the factors that have enabled (or constrained) this type of rapid and pervasive growth. The two components combine into an overall conceptual framework that can be applied to assess technology policy and low carbon scenarios.

1.2 Scaling of Energy Technologies: Industry & Unit Levels

1.2.1 Industry & Unit Level Growth: Introduction

Investigating the growth dynamics for energy technologies requires a meta-analysis of historical time series data covering a selection of both supply-side and end use technologies. Falling squarely in the tradition of empirical technological change studies, this is well trod ground: for energy efficiency in general (Rosenberg 1993); for commercial aircraft (Mowery & Rosenberg 1982); for steel manufacturing (Rosegger 1984); for manufacturing in general (Utterback 1987); for energy technologies in general (Grübler 1998; Smil 2008).

The distinctive characteristic of the research described here lies in its consideration of growth dynamics at both the industry level *and* the unit level, and the relationship between the two.

Historical growth in the energy system has been driven by the growth of whole industries or technology clusters (Grübler 1995). As a current example, frequent reference is made to the double digit growth rates of the wind or solar photovoltaic industries (IEA 2008b). The headline growth in these industries in turn comprises, or is supported by, growth in related industries of materials, components, control systems, installers, business services, and so on.

For many energy technologies, this growth at the industry level has been complemented by growth in the size or capacity of the technological unit itself.[2] This unit level process has been referred to as up-scaling (Luiten & Blok 2003). The power plant and jet aircraft examples given previously are cases in point. For further examples including many graphical illustrations, see (Smil 1994; Smil 2008). Figure 1 shows the maximum and average capacities of steam turbine units installed in coal, nuclear and natural gas-fired power plants through the 20th century. In 1910, maximum unit sizes were in the 5 – 10 MW range for both coal and natural gas. In 1980, the scale frontier in natural gas fired plants was reached with a 1200 MW steam turbine unit in the Soviet Union's Kostroma plant. For coal fired electricity generation, the 1400 MW unit in Cincinatti's Zimmer plant defined the scale frontier in 1991.[3] The first utility scale nuclear power plant opened in 1956 at the Sellafield complex in the UK with an initial capacity of 50 MW. Within just 20 years, a 1300 MW unit had been brought online in Germany, with the scale frontier reached 8 years later in 1984 with a 1500 MW unit installed in Lithuania at the Ignalina plant.

In the case of passenger jet aircraft, Boeing's defining 707-100 model, certified for commercial flight in September 1958, carried 110 – 140 passengers (depending on seat layout) a range of around 6,700km.[4] Its capacity, measured as the 2 dimensional passenger.kilometres[5] was in the order of 750,000. Twenty five years later, in March 1983, Boeing's 747-300 model was certified with an order of magnitude higher capacity of around 7,000,000 passenger.kms, based on a typical load of 565 – 608 passengers over a range of 12,500 km.[6] The unit scale frontier for jet aircraft as a whole was extended further in 2007 by the Airbus A380 whose capacity of 555 – 822 passengers and range of over 15,000km implied 8,400,000 passenger.kms.[7]

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[2] The definition of a technological unit is somewhat arbitrary, particularly for complex system technologies. Which is the technological unit: the semi-conductor, the chip, or the computer? the airframe, the avionics systems, or the aircraft? This definitional issue is returned to in Section 3.

[3] The Zimmer plant was originally designed to be a nuclear facility but converted to coal in the face of an anticipated $3bn cost overrun.

[4] See Appendix for details on all data sources. Aircraft specifications were taken from FlightGlobal, Airliners.net, and Jane's databases.

[5] Passenger numbers are based on typical seat configurations and measure potential rather than actual capacity taking load factors into account. The alternative term, 'available seat.kilometres' or 'ASK' makes these distinctions clearer. Passenger.kms is preferred here for simplicity.

[6] Compared to the 747-300, Boeing's 747-400 model had a larger maximum passenger capacity (660 compared to 608) and a further maximum payload range (13,450km compared to 12,400km). However, its typical passenger.kms is lower due to the greater allocation of cabin space to first and business class seating with a resulting lower average passenger capacity (416 compared to 565).

[7] A full, if somewhat dated, graphic of aircraft scaling can be found on p 229 of (Gardiner 1983)

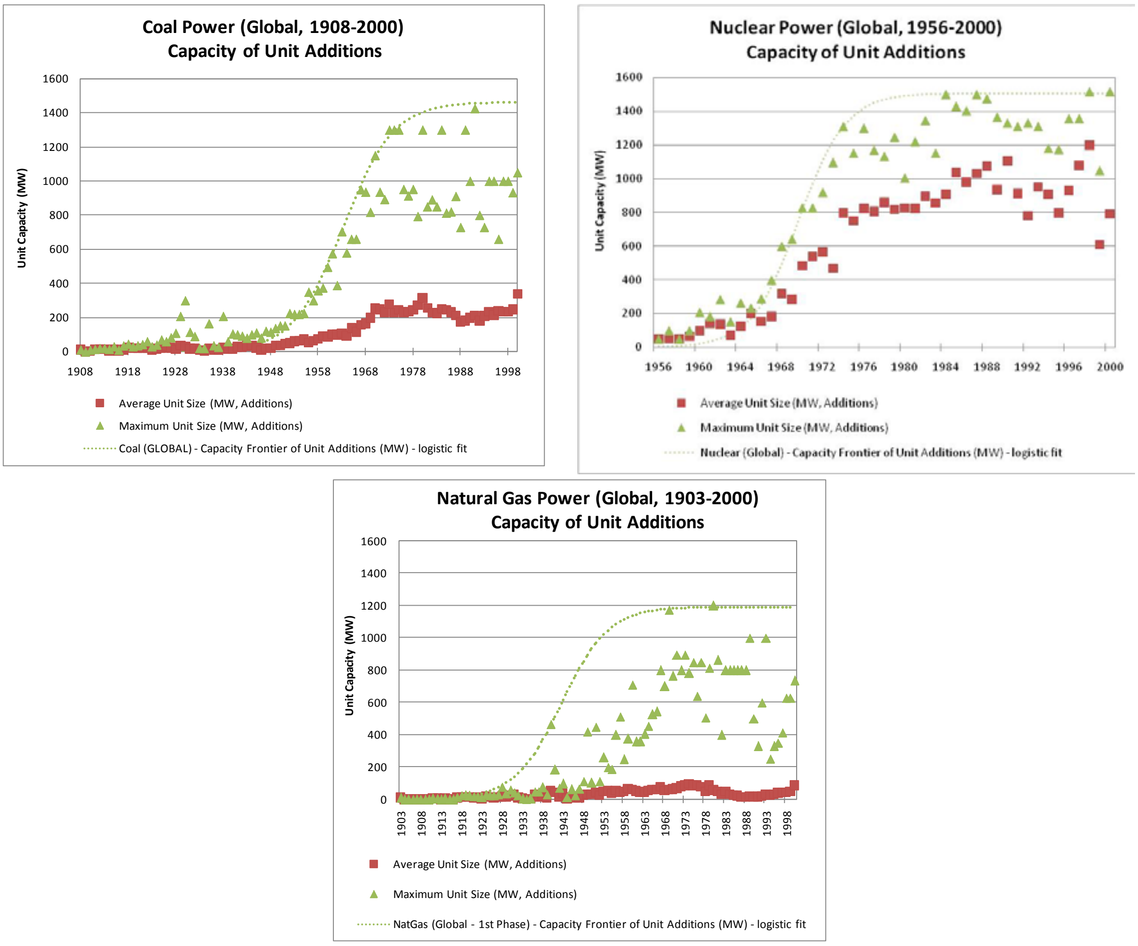

Figure 1: Unit Scaling in Power Plants. Average and maximum capacity (MW) of turbine units added each year (globally) in coal power plants (1908-2000), nuclear power plants (1956-2000), and natural gas power plants (1903-2000). Dotted lines show the logistic fit that traces the scale frontier. Note that individual power plants typically comprise more than one unit. [Data from: (Platts 2005); see Appendix A for details].

1.2.2 Definition of Scaling

The analytical focus on this combination of unit capacity *and* industry growth is described here by the term ‘scaling’. Table 1 provides a simple illustration of scaling using wind power as an example. The plant and system levels are included for the complete picture, and are considered further in the qualitative analysis. The quantitative analysis, however, concerns the unit and industry levels only.

In summary, ‘scaling’ is used here to describe technological growth that is:

i. *both* rapid *and* extensive;
ii. occurs at *both* the industry level *and* the unit level.

Table 1. Scaling at Different Levels: Wind Power.

Level of Scaling	Example	Observed Changes in Capacity over the past 30 years
Unit	wind turbine	Maximum turbine capacities installed each year have increased from the kW range to 3 - 5 MW, with further increases anticipated.
Plant	wind farm	Wind farms combining individual turbines with balance of system electrical components (transformers, grid interconnects, etc.) have increased in maximum capacity from the low MW range to many hundred MW arrays. China has recently announced plans to build several 10-20 GW wind farms.[8]
Industry	wind industry	Wind industry growth, measured as the annual % change in total installed capacity, is consistently double digit. Behind these total capacity data are an increasingly consolidated and globalised sector of turbine manufacturers, coupled to component suppliers (e.g., generators, gearboxes), local assembly operations, service industries (e.g., project developers, wind engineers, finance, etc.), and so on.
System	electricity system	Wind industry growth is ultimately a (small) niche within continually expanding local and regional electricity systems comprising centralised & decentralised generation, transmission and distribution infrastructures, and a proliferation of electrical end use technologies that provide useful services to final consumers. (The electricity system in turn is a subset of the energy system).

1.2.3 Common Other Uses of the Term 'Scale'

In defining 'scaling' thus, it is important to distinguish other uses of the term 'scale' to avoid confusion. Most commonly, 'economies of scale' (or scale economies) describe the falling marginal costs of production as production capacity or output increases. To continue with the example of wind power (see Table 1), the cost per MW of installed wind capacity may fall as turbine manufacturers grow in size. With size comes a greater ability to spread fixed capital costs over larger production volumes, to access lower cost capital, to wield greater market power to reduce input costs, and to improve the productivity of marketing and non-core business activities. Economies of scale may be available at both unit as well as industry levels. (This is discussed further in Section 4, with additional material including literature review in Appendix C).

Technical 'returns to scale' describe increasing technical efficiency as unit size or capacity increases. As the power output of a wind turbine is a function of the swept area of the blades, doubling of blade length quadruples power output. The availability of technical returns to scale defines a scale frontier at which the efficiency of a technology in relation to its size is maximised. Efficiency gains from technical returns to scale may be a source of economies of scale, but not vice versa. (Note that returns to scale are often used to describe economies of scale, though here they are distinguished by the effect of scale on technical efficiency and economic efficiency respectively).

'Scaling' or 'up-scaling' is also used to describe the increase in size of a technological design or unit. Using aircraft design as an example, Frenken & Leydesdorff argue that up-scaling occurs during a period in the technology lifecycle when a radical innovation

[8] Reuters news story (10 Aug, 2009), accessed at http://planetark.org/wen/54140.

becomes embedded as the dominant design.[9] This forms the basis of a sequence of subsequent incremental designs adapted to particular market niches (Frenken & Leydesdorff 2000). These designs vary in scale, but do not fundamentally change the product or service attribute trade-offs that the dominant design implies (e.g., range vs. take-off weight).[10] This argument builds on earlier work on the design evolution of helicopters (Saviotti & Trickett 1992) and also tractors, computers and propeller aircraft (Sahal 1985).[11]

In contrast, the term 'scaling' as used throughout this paper is descriptive rather than analytical. It simply describes an energy technology that grows in size or capacity both rapidly and extensively at both unit and industry levels (referred to hereafter as 'unit scaling' and 'industry scaling'). The underlying explanations for these growth dynamics may undoubtedly concern improving scale economies, technical returns to scale, and incremental changes in size to supply specific market niches. These and other explanatory factors will be discussed in detail below.

2 Research Approach

2.1 Research Objectives

As noted above, the overall goal of this research was to explore the historical growth dynamics of different energy technologies, and to extract lessons for low carbon technology innovation policy and scenario modelling. Specific research objectives pursuant to this goal were:

I. To develop a standard methodology for comparing rates and extents of growth at both unit and industry levels (i.e., 'scaling');
II. To identify a selection of supply-side and end use energy technologies that have 'scaled' historically;
III. To compile historical time series datasets for these technologies on unit capacity, unit numbers, and total industry capacity;
IV. To analyze and compare scaling dynamics within and between technologies (e.g., unit – industry level dynamics for a given technology, and industry – industry dynamics for different technologies);

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[9] For the original formulations of technology lifecycles and trajectories, see (Utterback 1987) and (Nelson & Winter 1977) respectively.

[10] Comparing the 'distance' between sets of product attributes for sequences of designs allows critical transitions to be identified when the design paradigm of a technology shifted. This paradigm subsequently diffuses throughout the industry as succeeding designs become more similar to a single preceding design, but also converges as a single succeeding design becomes more similar to many preceding designs. In the case of aircraft, the convergence process lags the diffusion process by some 15 years (Frenken & Leydesdorff 2000).

[11] Sahal goes further in arguing that the process of learning to overcome structural constraints uncovered by designs of different scales is a major driver of innovation (Sahal 1985). The scaling process leaves constant the ratio of performance or service characteristics to certain technical characteristics. This is shown empirically for propeller aircraft (1928-1957) by strongly linear relationships between take-off weight as a measure of scale, and speed, range, passenger capacity (as service characteristics) or engine horsepower, wing loading (as technical characteristics). Similar relationships are shown for changes in tractors (1920-1968) and computers (1951-1980) with the scale variables being ballasted weight and memory size respectively (Sahal 1985).

V. To develop a conceptual framework that explains observed scaling dynamics;
VI. To apply the conceptual framework and quantitative analysis to assess:
   a. policies to induce low carbon technological change; and,
   b. scenarios of greenhouse gas constrained futures.

The paper is organized according to this sequence of objectives. This section addresses the methodological issues and solutions proposed (Objective I). Section 3 describes the data collection (Objectives II & III), and Section 4 the analysis (Objective IV). Selected figures and data tables are included in the text to illustrate the main findings, with additional data included in the Appendices and online as supporting material.[12] Section 5 links the quantitative analysis to a conceptual framework of the different approaches to scaling, and the technological and system characteristics relevant in different cases. General implications for innovation policy are drawn (Objective V & VI.a). Section 6 applies this framework to scenario modelling (Objective VI.b). Section 7 concludes with a reflection on the strengths and weaknesses of the analysis.

2.2 Research Methods

2.2.1 Methodological Challenges

A meta-analysis of technology scaling presents various methodological challenges. Firstly, growth dynamics change over time, i.e., over the course of a technology's lifecycle. This is most simply captured in the sequential stages of invention, innovation, and diffusion (Schumpeter 1947; Grübler 1996). Over the course of this lifecycle, industry level growth is initially slow as a technology is introduced, moving then through a rapid diffusion phase before slowing and eventually saturating (and subsequently being substituted) (Grübler et al. 1999). A similar pattern is often evidenced at the unit level, though this depends on specific technology characteristics (e.g., the availability of scale economies) that are discussed further in Sections 4 & 5.

This generalized growth dynamic also spreads and varies spatially. In the initial markets or regions where a technology is first commercialized and diffusion begins, industry level growth tends to be slower but more pervasive (Grübler 1996). In subsequent markets, growth tends to be more rapid but saturates at a lesser extent. The spatial diffusion of cars provides a good example of this general pattern, also known as 'Schmidt's Law' (p151, Grübler 1990). Diffusion rates increase and saturation densities decrease as a function of the introduction date or first commercial sale of the car. In the initial US market, car ownership per capita in the 1930s had reached almost the same extent of diffusion as Japan in the 1990s (see Figure 2).

[12] The data collected and analysed through this research is available online through the Transitions to New Technologies program at IIASA. See Appendix A for details.

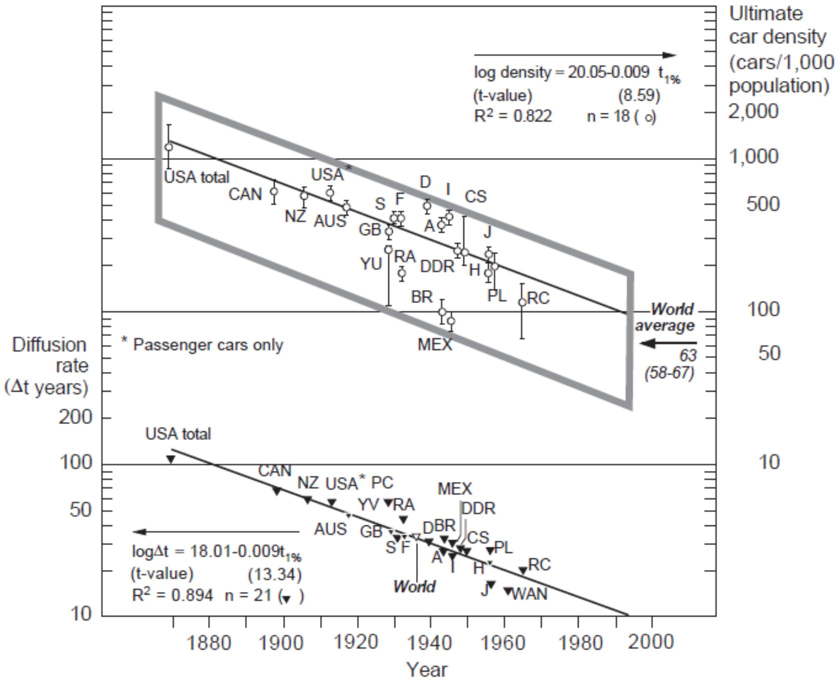


Figure 2. Spatial Diffusion of Cars. Diffusion rate (left-hand axis) and saturation density (right-hand axis) for cars in different countries plotted against their introduction dates. Both rates and extents of diffusion decrease with later introduction dates. Source: (p151, Grübler 1990).

A meaningful comparison of historical trajectories of technology scaling therefore needs to distinguish the stage of a technology's lifecycle in terms of both time and geography. The research goal and definition of 'scaling' also require that the meta-analysis distinguishes both rates and extents of growth at both unit and industry levels.

Given these requirements, two possible methods were tested. Both are described here with a summary of their strengths and weaknesses. The first uses simple growth rates derived from the data; the second uses common growth functions fitted to the data. The growth function approach proved more robust and was used in the analysis. Specifically, logistic growth functions were fitted to spatially-disaggregated time series data on unit and industry level capacity (expressed in MW) so that the Δt and K parameters could be used to compare rates and extents of scaling.

2.2.2 Method 1 (Rejected): Growth Rates

Annual growth rates are widely used to describe changes in the size of an industry, i.e., capacity added over the course of year t as a % of total capacity in year t-1. Through the technology lifecycle, growth rates begin high and rise rapidly (as the denominator is small), before peaking and then decaying towards some equilibrium level of system growth (if the technology sustains a market share) or towards zero (if the technology is substituted).

Whereas annual growth rates describe changes in the *total* capacity of an industry over time, marginal growth rates describe the % change in *additional* capacity from year t-1 to year t. Marginal growth rates are large and positive as the overall industry expands its manufacturing potential and market size early on, but quickly become volatile (swinging between positive and negative) and/or cyclical in line with the broader economy.

As examples, Figure 3 shows the annual and marginal growth rates for refinery capacity in Asia, and global passenger jet aircraft capacity.

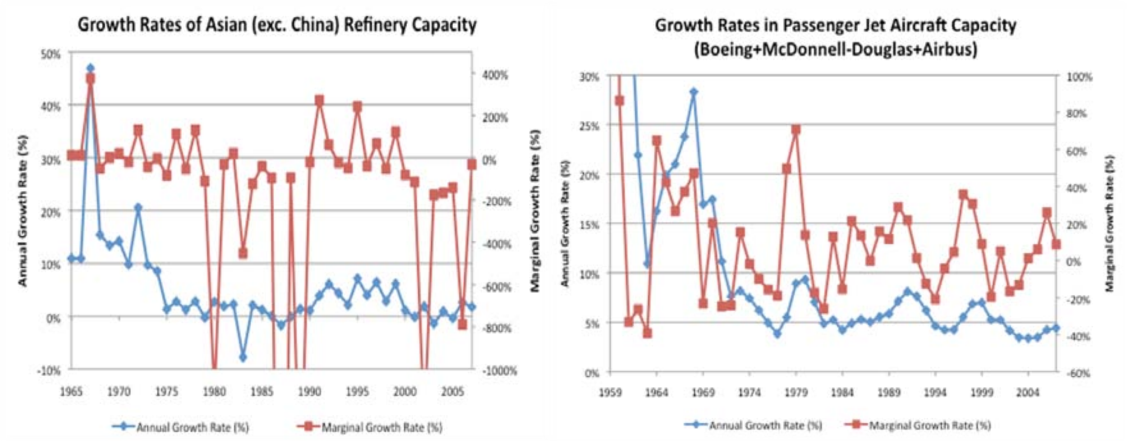


Figure 3. Changes in Growth Rates Over Time. Annual growth rates (% change in total capacity) and marginal growth rates (% change in additional capacity) for refinery output in Asia, excluding China (left-hand graph, 1965-2007) and jet aircraft passenger capacity for Boeing, McDonnell-Douglas & Airbus combined (right-hand graph, 1958-2007). [Data from (BP 2008) and various other sources; see Appendix A for details].

The use of growth rates to compare scaling dynamics across technologies presented various problems related to the methodological challenges described above.

Firstly, and self-evidently, growth rates measure rates not extents of growth. Growth rates can be normalized for growth in the overall energy system, or can be measured cumulatively, but neither approach adequately allowed extents of growth or saturation densities to be compared across technologies. An alternative way to proxy extent is to introduce a time dimension by, for example, integrating under the growth rate curves. However, data quality issues introduced potential biases into this approach, particularly given the often poor availability and reliability of data from the early commercialization phase of technologies. A further approach is to compare the exponents of the annual growth rate decay functions. In this case, exponential best fits were not consistently found across technologies and the same data quality issues applied.

A second problem is that distinguishing the stages of a technology's lifecycle requires growth rates to be analyzed separately in the innovation, diffusion and saturation phases. Defining the transition points between these stages is, however, rather arbitrary, with – as would be expected –incremental changes in growth rates over time rather than marked discontinuities.

A third problem is that comparing growth rates across technologies requires a common unit or denominator (i.e., growth rate of what?). Indices can circumvent this commensuration problem, but indexing introduces biases from the arbitrary selection of base year.[13] Various alternatives were tried including indexing to the year of first commercialization (but with problems of data scarcity), to the year of market saturation (but usually requiring extrapolation), to the year of most rapid growth (but difficult given volatility), or to a fixed time point (e.g., year 2000). Each alternative, however, raised other issues.

Overall, these problems led to the rejection of growth rates as a methodological approach for the meta-analysis.

2.2.3 Method 2 (Accepted): Logistic Growth Functions

Complete historical data series on the growth in number and capacity of different energy technologies are scarce, particularly at a spatially disaggregated level. As noted above, data are particularly poor for the early commercialisation phase of a technology's lifecycle (for those technologies that 'succeed'). Fitting growth functions to available data circumvents this problem, though inevitably introduces uncertainties. This method is only viable if the same growth function (or at least similar growth functions with commensurate parameters) can be fitted to data for different energy technologies at both unit and industry levels.

The technology lifecycle describes a pattern of growth in the adoption of a technology that is typically S-shaped. Growth begins slowly through an often extended introduction phase, before reaching a takeoff point after which diffusion is rapid and accelerating. This phase is not endless, however, and after an inflection point is passed, diffusion starts to slow and then eventually saturate. A wealth of historical evidence supports the use of the simple 3-parameter logistic function[14] to describe this S-shaped growth form (Grübler 1990; Grübler 1998). The logistic function is shown in Box 1. The complete model adds a logistic decline as an incumbent technology is gradually substituted by an innovation with some cost, service or other advantage (Marchetti & Nakicenovic 1979).

There are many explanations as to why diffusion patterns are logistic tends to be logistic, based on information transmission / contagion, risk reduction and familiarity, compatibility with social norms, profitability, and so on. For a detailed discussion, see (Grübler 1998).However, these are not immediately relevant here as logistic functions are used purely descriptively.

To the extent that logistic curves can be reliably fitted to historical data (see Section 3 for further discussion), parameters of the logistic function can be used to compare the

[13] A detailed discussion of issues associated with indices, in this case related to consumer prices and the cost of living, can be found in (Moulton 1996).

[14] Various alternative S-shaped models have been proposed, most of which relax the symmetry of the logistic function around the inflection point. Examples include the Gompertz, Sharif-Kabir and Floyd functions, but despite its simplicity, the logistic function has been consistently found to be the most representative form (Grübler 1990).

scaling of different energy technologies. Given the research objectives, two parameters are of particular relevance:

- K, the saturation level, which can be used as a measure of the *extent* of scaling;
- Δt, the diffusion time from 10% to 90% of K, which can be used as a measure of the *rate* of scaling.[15]

Box 1. The 3-Parameter Logistic Function.

$$y = \frac{K}{1 + e^{-b(t - t_0)}} \quad \text{(and also: } \Delta t = \frac{1}{b}\log 81\text{)}$$

with:

K = asymptote (saturation level);

t_0 = inflection point at K/2 (maximum growth);

b = diffusion rate (steepness);

Δt (delta t) = time period over which y grows from 10% to 90% of K.

Previous empirical studies as well as a preliminary investigation of the datasets compiled for this study confirmed the viability of this approach as both unit and industry level growth are commonly logistic in form. As the logistic function describes the full technology lifecycle and provides parameters for both rates and extents of growth, it solves the methodological challenges posed above. Disaggregating the data into initial (core), subsequent (rim) and late stage markets (periphery) based on the dates of first commercialization also accounts for the spatial dynamics of diffusion.

Using fitted logistic functions to compare scaling dynamics meant, however, that historical data not reliably described by logistic growth had to be omitted from the analysis. The basis for omission in terms of acceptable uncertainties in K values is discussed further in Section 3. The potential for these omissions to have systematically biased the findings is discussed in Section 7.

2.2.4 A Common Metric of Scaling

Comparing scaling across different technologies also requires a common metric of size or capacity. The preferred metric in this analysis was cumulative capacity expressed in MW. The use of MW as the units of cumulative capacity followed logically given the empirical focus on energy technologies. For the technologies analyzed, capacity data were either directly available or readily derivable.

Alternative metrics include output / production, investment cost, or metrics of ‘effort’ including labour requirements, R&D, material inputs, and so on. Capacity was preferred as it best captured the potential or ability - both of a technology unit and of an industry - to contribute to growth and transformation in the energy system. Expressing this

[15] Δt also describes the diffusion time from 1% to 50% of K, and similarly from 50% to 99% of K.

potential in terms of energy capacity rather output or other factor inputs also preserves the highest degree of generality in the findings. Differences between technologies in terms of efficiency (affecting production/output), capital intensiveness (affecting investment cost), labour productivity (affecting labour requirements) are therefore endogenous to the scaling dynamics observed and so can be treated as explanatory variables.

Cumulative total capacity was preferred to additional capacity for two reasons. Firstly, cumulative totals contain the whole history of capacity growth. Secondly, cumulative totals smooth short-term growth volatility. The cumulative total capacity data used does not take into account capital turnover (decommissioning, retirement, substitution, etc.). As with efficiency and productivity gains, this makes the capital stock lifetime and turnover rate of a technology endogenous within the observed scaling dynamics.

3 Data Collection & Analysis

This section describes the historical time series data compiled on unit and industry level growth dynamics for oil refineries, power plants (coal, natural gas, nuclear, wind, solar photovoltaic or 'PV'), passenger jet aircraft, helicopters, passenger cars, compact fluorescent (energy efficient) light bulbs, and mobile phones.

3.1 Historical Data

3.1.1 Technology Selection

Selection of technologies for inclusion in the meta-analysis was guided by three criteria, and the inevitable data availability constraint.

Firstly, technologies should range from the centralised, capital intensive energy supply technologies to the distributed, low cost technologies directly providing useful services to end users. A specific research objective was to compare scaling dynamics between supply and demand-side technologies.

Secondly, the technological 'unit' should comprise the level of complexity for which capacity metrics, scaling dynamics *and* role in the energy system are clearest. Technological artefacts ('hardware') are complexes of inter-related components which are typically installed or operated in combination with control systems and practices ('software'). Components can be broken down into sub-components or aggregated into systems. Which is the appropriate unit for analysis: the jet engine, the jet aircraft, or the airline? the fluid catalytic cracking unit, the refinery, or the oil company? the boiler, the steam turbine, or the coal-fired power plant?

Selection of technological 'units' based on the 'level of complexity' rule is subjective. Typically the preferred unit for analysis comprised the highest level of operational aggregation of the energy technology before inclusion of market and institutional factors. For modular technologies installed with balance of plant components, the less aggregated module was treated as the unit (e.g. one of potentially many steam turbine *units* in a single coal fired power *plant*). Scaling at the plant level, intermediate between unit and industry, comprises a further level of analysis (see Table 1). The potential biasing effect of this selection process of technological 'units' is discussed in Section 7. It is not coincidental that data are typically far more readily available at the unit or plant level than at the component level. This data opportunism is also reflected in the facility level emphasis of industrial activity analyses(see, e.g., Ayres 1989).

The third technology selection criteria is that ‘capacity’ should be meaningful in terms of energy service provision (i.e., role of technology in the energy system) and commensurate with the common MW metric used in the meta-analysis. In most cases this was trivial. The capacity of power generation and electricity end use technologies are naturally expressed in MWs, a metric which relates directly to the size of their *potential* contribution to energy conversion. Refinery capacity in barrels per day is simply converted, as are helicopter and vehicle engine capacity in horsepower. Moreover, engine capacity is one of the major attributes of vehicles that enables service provision (i.e., mobility). This was shown empirically for jet aircraft which show a strong positive correlation between power capacity and passenger.kilometres which is used as the industry measure of service capacity. A first order conversion of jet engine capacity from thrust (kN) to power (MW) was used and is discussed further in Appendix A.

3.1.2 Compiled Data

Table 2 summarises the historical time series data compiled. Sources are given in the table footnote, and further details in Appendix A.

Table 2. Historical Data Series. Compiled time series data on unit and industry capacity.

Technology		**Data Form**	**Unit Level**	**Industry Level**		**Notes**	**Main Sources**[i]
			Capacity	**Number**	**Capacity**		
Supply-Side Technologies	Oil Refineries	Total Capacity (bpd) & Average Plant Capacity (bpd)	1940-2000 (US only, average only)	*not available*	1940-2007	Annual not cumulative capacity; fluid catalytic cracking unit as proxy for plant capacity (see text).	Oil & Gas Journal, BP, Enos
	Power - Coal	Capacity Additions (#, MW)	1908-2000 (max. & average)	1908-2000	1908-2000	Cumulative, i.e., includes all substituted / retired capacity	Platts
	Power - Nuclear	Capacity Additions (#, MW)	1956-2000 (max. & average)	1956-2000	1956-2000	Cumulative, i.e., includes all substituted / retired capacity	Platts
	Power - Natural Gas	Capacity Additions (#, MW)	1903-2000 (max. & average)	1903-2000	1903-2000	Cumulative, i.e., includes all substituted / retired capacity	Platts
	Power – Wind	Capacity Additions (#, MW)	1977-2008 (average only)	1977-2008	1977-2008	Cumulative, i.e., includes all substituted / retired capacity	DEA, BTM Consult
	Power - Solar PV	Cumulative Capacity (MW)	*not available*	*not available*	1975-2007	Cumulative, i.e., includes all substituted / retired capacity	Maycock, EPIA
End Use Technologies	Passenger Jet Aircraft	Aircraft Delivered (#, Model)& Engine Thrust (kN)	1958-2007 (max. & average)	1958-2007	1958-2007	Boeing, McDonnell-Douglas, Airbus only[ii]	Jane’s, aircraft databases
	Helicopters	Helicopters Introduced (Model)	1940-1986	*not available*	*not available*	Different measures of unit capacity (see text)	Saviotti & Trickett
	Passenger Cars	Cars Produced (#) & Engine Capacity (hp)	1910-1960 (US only) & 1960-2005 (various)	1900-2005	calculated (see text)	Cars disaggregated from all motor vehicle production data	AAMA, US NHTSA, ACEA

Technology	Data Form	Unit Level	Industry Level		Notes	Main Sources[i]
		Capacity	Number	Capacity		
Compact Fluorescent Light Bulbs	Light Bulb Sales (#)	estimated (see text)	1990-2003	estimated (see text)	Unit capacity assumed constant	IEA
Mobile Phones	Mobile Phone Subscribers (#)	*not available*	1982-2008	*not available*	Unit capacity data not considered meaningful	OECD, ITU

[i] Sources (described in detail in Appendix A): *Refineries* -(OGJ 1999; OGJ 2000; Enos 2002; BP 2008); *Coal, nuclear, natural gas power* -(Platts 2005); *Wind power* -(BTM_Consult 2002; Danish_Energy_Agency 2008); *Solar photovoltaics* –(Maycock 2002); *Passenger jet aircraft* -(Jane's 1998); supplementary data from online sources including www.airliners.net, www.flightglobal.com, www.boeing.com, www.airbus.com; *Helicopters* –(Saviotti & Trickett 1992); *Passenger Cars* -(AAMA 1980; AAMA 1995; AAMA 1997); supplementary data from online sources including US National Highways Traffic Safety Agency (www.nhtsa.dot.gov) and European Automobile Manufacturers' Association (www.acea.be); *Compact fluorescent light bulbs* –(IEA 2006); Mobile phones –(OECD 2007; OECD 2009); supplementary data from International Telecommunications Union (www.itu.int/ITU-D/ict/statistics/index.html).

[ii] Authors estimate these 3 manufacturers have accounted for over 2/3 of total cumulative sales of large commercial jet aircraft (and currently account for over 90% of annual sales). Historically, the other main manufacturers were FSU-based (e.g., Tupolev, Ilyushin), but data are not considered sufficiently reliable for inclusion. Smaller turboprop aircraft are numerous but generally fly only short, lower volume routes. See Appendix A for further discussion.

The time series data shown in Table 2 were compiled for both supply-side and end use energy technologies. Subject to availability, data begins at or close to first introduction date of technology and is global in scope. Technologies are ordered from high to low unit capacity. Discussion of key points follows in the text.

Spatial Disaggregation

To account for the spatial characteristics of technology diffusion, the global data for each technology was disaggregated into three regions following the core – rim – periphery sequence from the initial market in which a technology was first introduced, through to subsequent and then final markets (Grübler 1998). For each technology, the regional disaggregation was driven purely by the sequence of introduction evidenced by the data and so differs in each case (see Table 3). However, the extent of disaggregation was limited to three regions ('Core', 'Rim2', 'Periphery')[16], plus a fourth ('Rim1') corresponding to the former Soviet Union and Eastern European countries (grouped under 'FSU') for technologies which diffused concurrently during the Cold War in both Eastern and Western blocs (e.g., coal and nuclear power generation). The limit of four regions was used for two reasons: firstly, to keep the meta-analysis manageable; secondly, to aggregate or smooth out the specificity and volatility found in scaling patterns at a higher level of spatial resolution.

One issue is whether the difference in geographic or economic 'size' between the regions impacts the analysis. In some cases, the 'Core' region is a single country, in other cases it is the whole of the OECD. Of interest are the relationships between the K and Δt of the logistic growth functions fitted to the regional data. Generally, the effect of region size on both parameters will be positively correlated. It is possible, however, that larger regions will increase K to a greater extent than Δt, particularly if diffusion

[16] The capitalised 'Core', 'Rim1', 'Rim2', 'Periphery' terms denote the specific regional disaggregations used in the meta-analysis.

proceeds concurrently throughout the region. This potential source of bias is discussed further in Section 7. Table 3shows the regional disaggregation for each technology, together with issues related to fitting logistic growth functions. The extent of shaded cells in Table 3 clearly shows that many of the disaggregated regional technology analyses had to be excluded from the meta-analysis. Exclusions were for two main reasons: insufficient data or insufficient time series. Insufficient data refers either to region-technology combinations with very low extents of diffusion and so ‘lumpy’ cumulative growth dynamics (e.g., nuclear power in Africa), or technologies with insufficient data to estimate industry growth (e.g., helicopters). Insufficient time series refers to region-technology combinations with industry growth dynamics still in a takeoff or exponential growth phase, making the fitting of logistic growth functions unreliable, particularly with respect to the estimation of saturation level (the K parameter). This is discussed further below.

The effect of these region-technology exclusions is two-fold. Firstly, it reduces the number of data points in the meta-analysis, particularly in the Rim and Periphery regions for which – by definition – technologies diffused later than in the Core region and so are less likely to have evidenced saturating industry growth rates (see Table 3 for the number of data points in each region). Secondly, it potentially introduces biases into the meta-analysis if the excluded region-technology combinations differ systematically from those included. This potential bias is discussed further in Section 7.

Table 3. Spatial Disaggregation & Logistic Form of Historical Data Series. Shaded cells indicate logistic functions were *not* used in the meta-analysis. Abbreviations are set out in full in the table footnote.

Technology		**Spatial Disaggregation & Logistic Functions**					**Logistic Form / Issues**
		Global	**Core**	**Rim1**	**Rim2**	**Periphery**	
Data Points (#)		6	8	4	4	3	
Supply-Side Technologies	Oil Refineries	Global	OECD, FSU[i]	*separate FSU not applicable*	Asia (ex. China), MidEast[i], L.America[i]	China, Africa	Logistics fit to ‘1st phase’ only with asymptote following oil shocks in 70s
	Power – Coal	Global	OECD	FSU	Asia - *insufficient time series*	Africa, MidEast, L.America	Industry growth still exponential in Asia (Rim2)
	Power – Nuclear	Global	OECD	FSU	Asia – *insufficient capacity*	Africa, MidEast, L.America - *insufficient capacity*	Insufficient capacity (small n of plants) for Asia (Rim2) & other developing countries (Periphery)
	Power – Natural Gas	Global	OECD	FSU	Asia	Africa, MidEast, L. America	Logistics fit to ‘1st phase’ only with asymptote following oil shocks in 70s
	Power - Wind	Global - *insufficient time series*	Denmark	rest of OECD - *insufficient time series*	E.Europe, Asia – *insufficient time series*	Africa, MidEast, L.America – *insufficient time series*	Industry growth still exponential except onshore wind in Denmark (Core)
	Power – Solar PV	Global - *insufficient time series*	US - *insufficient time series*	Japan, Germany - *insufficient time series*	Rest of OECD – *insufficient time series*	Rest of World – *insufficient time series*	Industry growth still exponential in all regions: solar PV omitted from meta-analysis

Technology		Spatial Disaggregation & Logistic Functions					Logistic Form / Issues
		Global	**Core**	**Rim1**	**Rim2**	**Periphery**	
End Use Technologies	Passenger Jet Aircraft	Boeing + McDonnell-Douglas + Airbus	Boeing	*not available*	Airbus	*not available*	Regions based on manufacturers not sales; no (reliable) data for FSU
End Use Technologies	Heli-copters	Global - *insufficient data*	US - *insufficient data*	FSU - *insufficient data*	W.Europe - *insufficient data*	Rest of World - *insufficient data*	No sales data to estimate industry capacity; helicopters omitted from meta-analysis.
End Use Technologies	Passenger Cars	Global (numbers only, not capacity)	US(industry only, not unit level)	FSU& minor OECD	W.Europe, Canada, Japan	Developing countries – *insufficient time series*	Industry growth still exponential in developing countries
End Use Technologies	Compact Fluor-escent Light Bulbs	Global - *insufficient time series*	N.America, W.Europe	*separate FSU not applicable*	Asia - *insufficient time series*	Rest of World - *insufficient time series*	Industry growth still exponential in all regions except OECD (Core)
End Use Technologies	Mobile Phones	Global - *insufficient time series*	Scandin-avia, Japan	*separate FSU not applicable*	Other OECD - *insufficient time series*	Rest of World - *insufficient time series*	Industry growth still exponential in all regions except Scandinavia + Japan (Core), but #s only not capacity, so excluded.

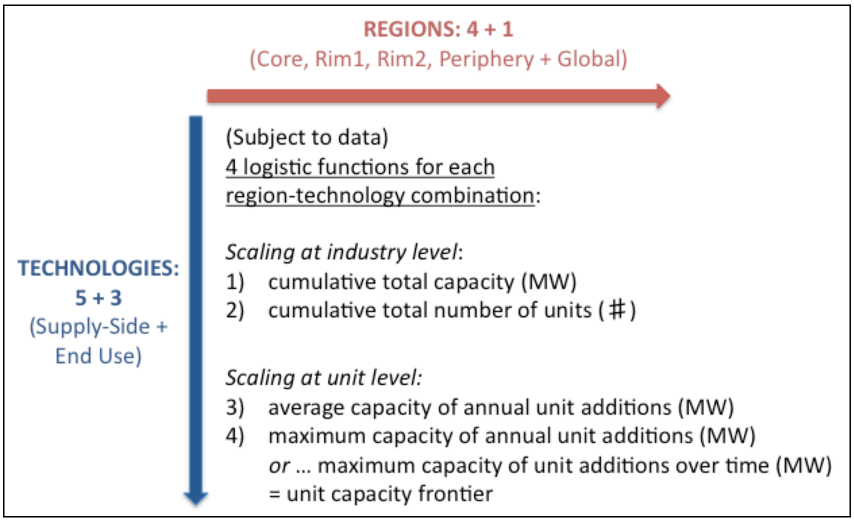
[i] OECD = Organisation of Economic Cooperation and Development corresponding to developed countries; FSU = former Soviet Union corresponding to economies in transition, i.e., including Eastern Europe; L. America = Latin America; MidEast = Middle East.

3.2 Fitting Logistic Functions

For each region-technology combination (i.e., each cell in Table 3), logistic growth functions were fitted to the historical data series to represent scaling dynamics at both industry and unit levels, as shown in Box 2 below. Growth function parameters were estimated using “Logistic Substitution Model II” or ‘LSM2’ software. LSM2 was developed at IIASA and is freely available online.[17]

[17] For further information on LSM2 and for downloads: http://www.iiasa.ac.at/Research/TNT/WEB/Software/LSM2/lsm2-index.html

Box 2. Fitting Logistic Functions.



For unit scaling, logistic growth functions were fitted to the full data period, unless otherwise noted. For scale invariant technologies, variability around average capacities was high so goodness of fit measures were low. For maximum capacity data, logistic functions were fitted *either* to the maximum capacity of unit additions each year *or* to the selection of data points that defined the maximum unit capacity frontier. In some cases these data points were simply the monotonically increasing maximum unit capacities over the data period, but in other cases the data points selected were a sub-set thereof. The selection procedure was guided by maximizing goodness of fit.

For industry scaling, logistic functions were fitted to the full data period available. Exceptions to this rule were for technologies with distinct, sequential phases of growth. In these cases, logistic functions were fitted to the 1st phase of growth only to the extent that it evidenced a clear plateau. This was the case for refineries and natural gas power following the oil shocks (see below for discussion).

The acceptability of estimated logistic models for industry scaling was based on two criteria:

i. *model fits the data:*
   - minimum goodness of fit measure (adjusted R^2) of 0.95;

ii. *sufficient historical data to estimate asymptote:*
   - historical data reaches at least 60% of estimated asymptote parameter (K).

The next two sections discuss the sufficiency of historical data criterion, and the related issue of sequential logistic growth phases.

3.2.1 *Uncertainties in Logistic Model Estimation*

The strict goodness of fit criterion ensured that the estimated logistic models of industry scaling were accurate descriptions of the historical data. However, the reliability of the

K and Δt parameters used in the meta-analysis depends on the length of the historical data series. If historical data extends only through the initial commercialisation and takeoff phases, it is difficult to predict reliably if and when growth will pass an inflection point, slow and then saturate. Indeed, the data are equally well described by an exponential growth curve, so a high goodness of fit for a logistic model risks false precision.

Debecker & Modis used Monte Carlo simulations to generate uncertainties on logistic function parameters depending on historical data errors, the % of fitted K reached by the historical data, and the required confidence interval (Debecker & Modis 1994). As an example, a logistic model fitted to data points with 5% estimation errors covering 1-60% of the asymptote (K) has parameter uncertainties of ±7.9% (K), ±3.2% (b), and ±0.15% (t_0), all with 95% confidence intervals. For a given length of historical data and data estimation error, uncertainties are higher in the asymptote parameter (K) than for the rate parameter (b) and so also Δt. Uncertainties in estimated K increase rapidly for data series that have not passed the inflection point (t_0), i.e., have reached less than 50% of K. This is intuitively obvious as the logistic function at this stage is indistinguishable from an exponential function. A more detailed analysis of logistic model estimation using different minimization techniques for the objective function reached similar conclusions but with higher estimated uncertainties (Grübler 1990).

To ensure that the logistics models used in the meta-analysis were reliable descriptions of the historical data, a rule of thumb was adopted that the data series had to cover at least 1-60% of the full S-curve range. In other words, *actual* industry level capacity (or total number of units) had to have passed its maximum growth rate and reached at least 60% of the estimated asymptote. All the technology-region combinations marked in Table 3 with cross-hatching and 'insufficient time series' failed this criterion and so were not included in the meta-analysis.

As noted, an important consequence of this criterion is that more recent technologies still in an exponential growth phase were excluded. Examples include: wind power (all regions except Core); solar PV (all regions); compact fluorescent light bulbs (all regions except Core); mobile phones (all regions except Core). The potential biasing effect of these exclusions is discussed in Section 7.

3.2.2 Sequential Phases of Logistic Growth

Sequential logistic growth phases for a particular technology are common(Meyer 1994).[18] During or following an initial S-shaped diffusion curve, a technology may move into additional market niches, may substitute for other incumbent technologies, may drive and supply new types of service demand, all within the same geographic region. Electrification in the US is a good example (Ausubel & Marchetti 1996). The initial growth phase, saturating before the Second World War, saw electricity substituting for watermills and gaslight. Demand for newly available services (TVs, air conditioning …) then drove a subsequent growth phase. Future electrification of the transport fleet may underpin a third growth phase, and so on. More generally, the functional development of technologies dynamically expands their potential market and

[18] The "LogLet Lab" software was developed at Rockefeller University to identify sequential but overlapping logistic wavelets (hence: "loglet"). The software is freely available for download at phe.rockefeller.edu/LogletLab/. See also: (Meyer et al. 1999).

so their carrying capacity(Watanabe et al. 2009). Various functions have been tested to describe these sequential asymptotes, including a logistic one(Meyer & Ausubel 1999).

Figure 4 clearly shows the logistic form of nuclear power's cumulative total capacity in the Core region (OECD). The first units were installed in 1956, industry capacity grew rapidly in the 1970s-1980s then slowed dramatically in the 1990s with only a small number of units added annually. By 2000, cumulative installed capacity growth was nearly flat. The logistic model estimated for this data series explains over 99% of the variance and is based on 1-98% of the fitted K. But this *description* of nuclear power's historical growth pattern is *entirely consistent* with a potential second phase of future growth spurred by CO_2 emission constraints or other factors.

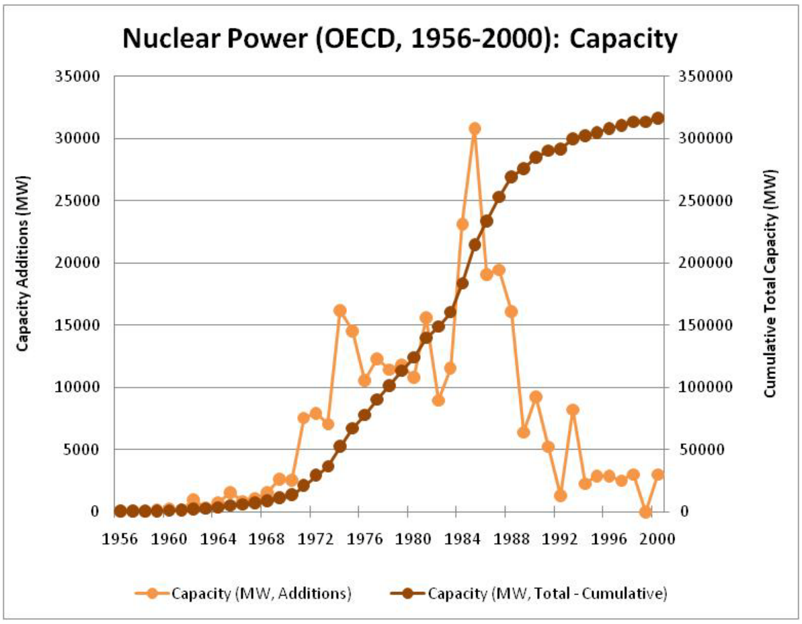


Figure 4. Nuclear Power (OECD): Historical Capacity Data. Capacity additions (left-hand axis) and cumulative total capacity (right-hand axis) of nuclear power in the OECD (1956-2000). [Data from (Platts 2005); see Appendix A for details].

Thus, regardless of any potential future growth – logistic or otherwise – any period of historical growth described accurately (i.e., model is a good fit) and reliably (i.e., empirical data exceeds 60% of fitted K) by a logistic function is considered valid for inclusion in the meta-analysis. These periods may capture a technology's full historical growth up to the present (e.g., nuclear power), or a distinctive logistic growth phase nested within a longer dynamic. As the use of logistic parameters here is purely descriptive, there is no *a priori* constraint that such periods have to span the time from the first introduction of a technology to its final saturation. The consistency of the relationship between K and Δt over a range of Δts is discussed further in Section 7.

The two technologies with historical periods of logistic growth before the present are natural gas power and oil refining (see Figure 5). In the case of natural gas power, capacity growth reached a plateau during the late 1970s, most notably in the US where regulations prohibited the use of natural gas for electricity generation, and elsewhere in the OECD given its perceived scarcity and supply constraints (against a backdrop of falling demand). In the case of refining in the major OECD & FSU markets (Core region), total industry capacity peaked in 1979 before falling through the 1980s as demand for refinery output fell, utilisation rates of existing regional capacity rose, and capacity expansions in Asia and elsewhere gained market share with a concomitant rise in international trade of oil products. The logistic function fitted to Core region data from 1940 to the early 1980s overshoots the actual historical peak by some 15-20% given the rapidity of this transition. However, as the historical refinery capacity data are annual (net) totals rather than cumulative totals, this overshoot is itself likely overstated.

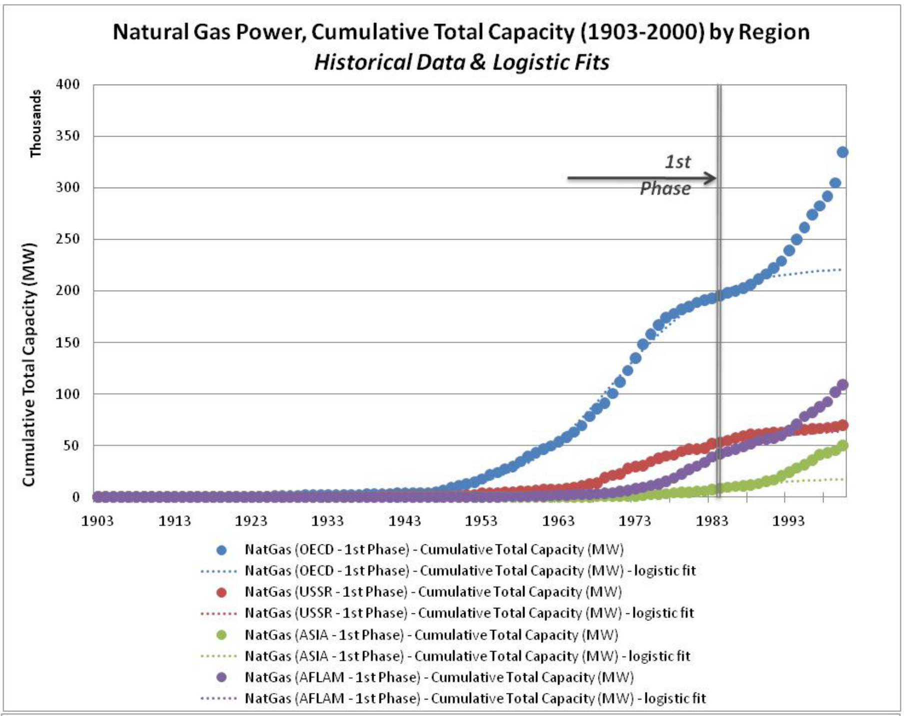
This overshoot of the '1st phase' logistic growth function raises another issue. Mature technologies that have diffused to their maximum extent tend to be substituted by emergent technologies as they gain market share. This logistic substitution process has been a common pattern in the energy system throughout its history (Marchetti & Nakicenovic 1979; Marchetti 1987; Grübler 1998; Fisher et al. 2007).

But the logistic models estimated for the purposes of this meta-analysis are neutral as to the fate of a technology once saturated. This is consistent with the research objectives and methods which exclusively concern scaling and not substitution, contraction or obsolescence dynamics. For both natural gas power and refineries, logistic functions approximate growth in Core region markets up to the capacity peaks of the early 1980s. The validity of these '1st phase' K and Δt parameters is not affected by the subsequent decline of refinery capacity in contrast to the stabilization and then resurgence of natural gas power.

Finally, the selection of the '1st phase' growth period introduces an element of subjectivity into the logistic model estimation. For both natural gas power and refineries, the end of the data period was defined so as to maximize the goodness of fit of the logistic models in the Core region. The same data period was then applied to the Rim and Periphery regions (see Figure 5). Meyer proposes a less subjective parsing of 1st phase and subsequent growth by estimating a single model comprising the sum of two logistic functions(Meyer 1994). The preferred regression technique for this bi-logistic model depends on the error structure of the data and requires initial parameter estimates. Consequently, bi-logistic models do not fully remove subjectivity, so the simpler approach used here is preferred for reasons of transparency.

3.3 Data & Logistic Fits

Detailed explanations and plots of the historical data series used for each technology at both unit and industry levels with their respective fitted logistic functions are included in Appendix A. Salient issues for particular technologies also discussed further in Appendix A include: conversions to MW-equivalents for non-power technologies; data quality and validation; potential sources of bias.



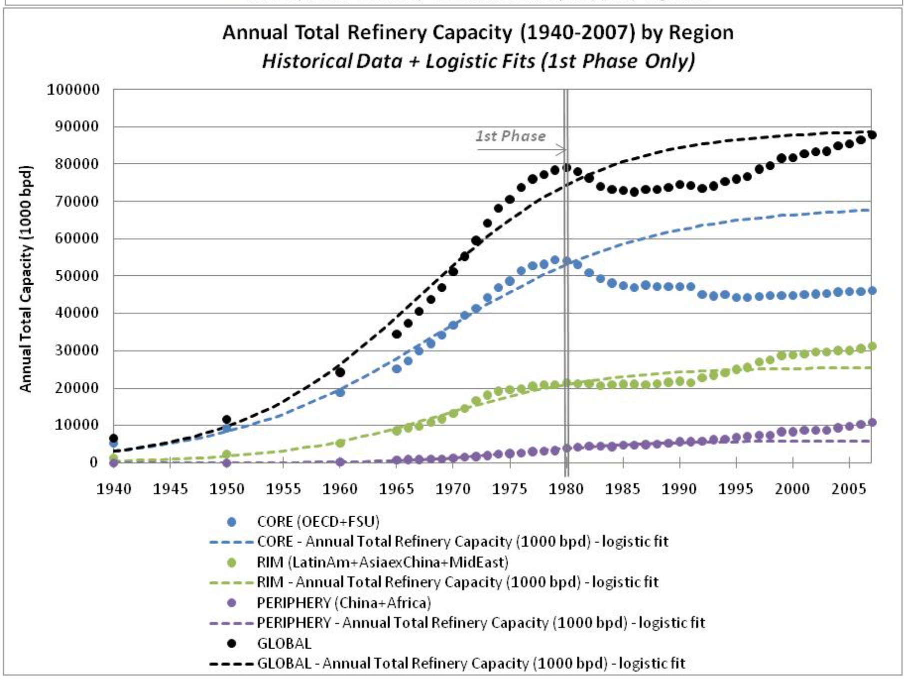


Figure 5. 1st Phase Logistic Growth. Historical data (markers) and logistic fits to 1st phase of growth (dashed lines) for natural gas power (1903-2000, upper graph) and refinery capacity (1940-2007, lower graph) by region. The impact of the oil shocks explain the logistic form of a '1st phase' of industry level growth to the early 1980s. [Data from (Platts 2005) and (BP 2008); see Appendix A for details].

4 Technology Scaling Meta-Analysis

4.1 Introduction

The K and Δt parameters of the logistic functions allow extents and rates of scaling to be compared for different technologies at both industry and unit levels. By normalizing logistic curves by their respective asymptotes (K) and plotting along the same timeline, the relative rates *and timing* of scaling can be easily compared, either at the unit and industry level for the same technology, or at a given level for different technologies.

This section discusses the main findings, organized as follows:

- rates (Δt) of unit scaling (Section 4.2);
- rates (Δt) of industry scaling (Section 4.3);
- relationships between rates (Δt) of unit and industry scaling (Sections 4.4 & 4.5);
- spatial diffusion of rates (Δt) of unit and industry scaling (Section 4.6);
- extents (K) of unit and industry scaling (Section 4.7);
- relationships between extents (K) and rates (Δt) of industry scaling (Section 4.8).

4.2 Measures and Rates of Unit Scaling

Unit scaling was measured in three different ways, depending on the availability of data and the type of technology (see Box 2 in Section 3). As Table 4 shows, the logistic models mainly cover supply side technologies for which unit scaling has been more integral to profitability, performance and efficiency than is the case for end use technologies. This relates to differences in function.

Energy supply and conversion technologies (e.g., refineries, power plants) produce one or a small number of homogeneous energy carriers (e.g., liquid transportation fuels, electricity) that are subsequently distributed to the point of use. Unit scaling has therefore been enabled by the co-evolution of a hub-to-spoke distribution infrastructure (e.g., pipelines, tankers, grids) and attendant markets and institutions.

By comparison, end use technologies (e.g., aircraft, light bulbs) supply a particular energy service (e.g., mobility, illumination) in a wide variety of contexts. Each context, or market niche, determines the appropriate scale of technology. In general, these niches are more heterogeneous for distributed end use technologies than for centralised supply-side technologies. At the two extremes are electricity and light bulbs. Although electricity is ultimately used to provide a wide range of energy services, as an energy carrier it is a homogeneous, standardised product. With transmission networks and reasonable proximity to concentrated load centres, electricity generation has historically been characterised by strong scale economies and unit scaling.[19] By comparison, the illumination services provided directly by light bulbs span myriad niches. As a result, bulbs range in capacity over 5 orders of magnitude, from several watts (LEDs) to over

[19] Distributed generation, close to the point of use, challenges the economic preference for large-scale centralized plant, but is constrained by infrastructures and institutions that have co-evolved with centralized generation. For detailed discussion, see (Lovins et al. 2003).

10,000 W for specialised exterior lighting (metal halide lamps)(IEA 2006).[20] There is no strong unit scaling dynamic, but rather a strong heterogeneity of required unit scales.

Table 4. Measures of Unit Scaling & Logistic Fits. 'Some' means data available or logistic fits appropriate only for some regions. '-' means either data not available or no reliable logistic fits.

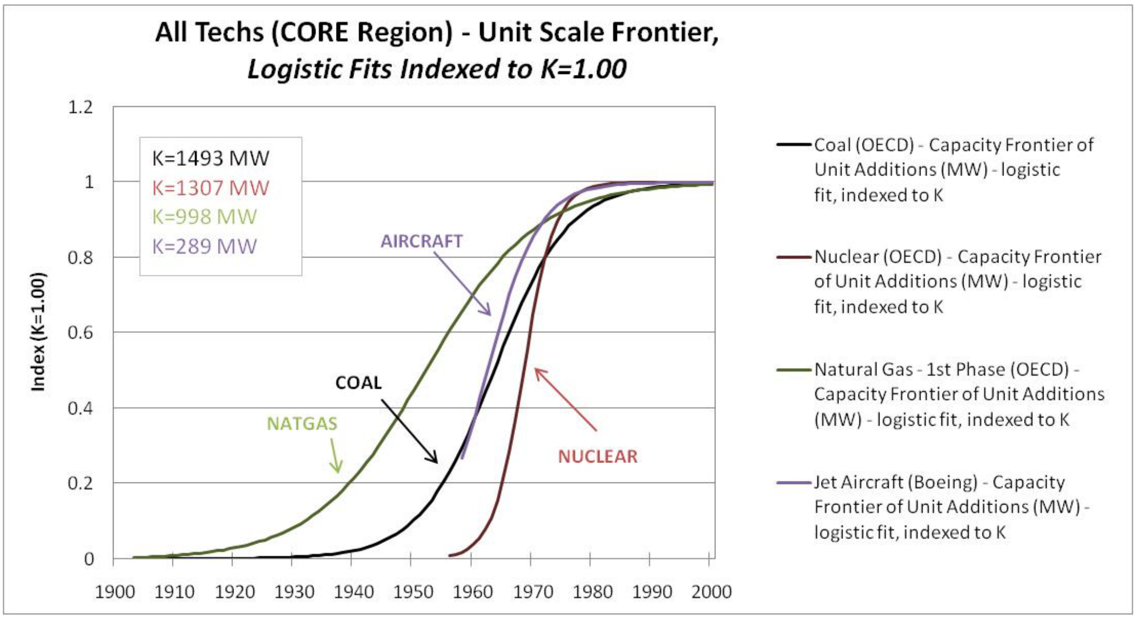
	Refineries	Coal Power	Nuclear Power	Natural Gas Power	Wind Power	Jet Aircraft	Cars	Light Bulbs
Average capacity (annual unit additions)	some	all	some	all	some	some	some	-
Maximum capacity (annual unit additions)	-	all	some	all	-	-	-	-
Maximum capacity frontier (unit additions over time)	-	all	some	all	-	all	-	-

Figure 6 compares the unit scaling dynamics for the technologies for which data was both available *and* described by a logistic function. Data presented is for the Core region which has the most data points (see earlier discussion). As the technologies vary widely in their unit capacity (and so K), each curve is normalized to its own saturation level (i.e., K=1 for each technology). This allows both the rates of scaling (steepness of the curves) and their timing (point of takeoff) to be easily compared. The upper graph shows the unit capacity frontier; the lower graph shows the scaling of average unit capacity. In each case, the absolute values of K are shown in the boxes.

In terms of maximum unit capacity, scaling rates point to the strength of scale economies. At the unit capacity frontier, nuclear power (Δt=11) and jet aircraft (Δt=19) are the technologies that scale most rapidly. By comparison, unit capacities of natural gas power (Δt=41) scale slowly to their eventual maximum.

In terms of average unit capacity, scaling is a proxy for flexibility or scale independence. Technologies with slower average scaling rates, and larger differences between maximum and average scaling rates, are demonstrably viable across a more diverse range of market niches which favour different unit scales. The most marked case is natural gas (Δt=64) which illustrates the trade-offs between demand constraints on the one hand, and technical returns to scale and unit scale economies on the other. Natural gas power spans distributed applications in the kW unit range up to the more familiar centralised combined cycle configuration in the high MW or even GW range. In this case, its ability to supply different niches (defined by demand constraints) and its scale independence in terms of technical efficiency (Lee 1987) outweighs any scale economies.

[20] In a residential context, incandescent bulbs typically range from 30 - 150 W, and compact fluorescent bulbs from 15 - 120 W. In this analysis, the unit scale of compact fluorescent light bulbs is assumed to be a constant 15 W.



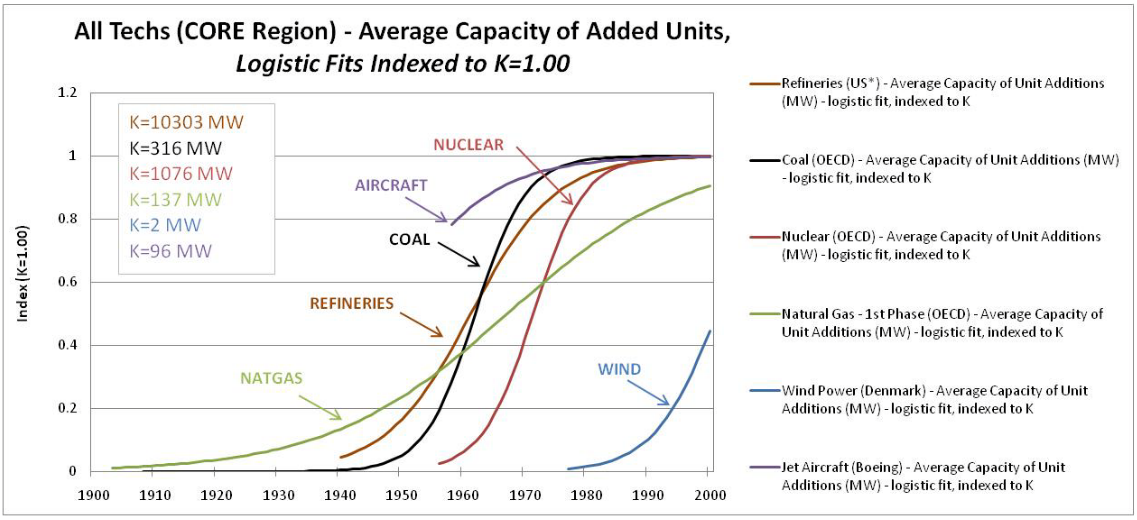


Figure 6. Unit Scaling for Different Technologies. Logistic fits of unit scaling dynamics in the Core region. Dynamics shown at unit capacity frontier (upper graph) and in terms of the average capacity of annual unit additions (lower graph). All logistic curves are indexed to K, with respective K shown in the boxes.

As shown in Figure 6, jet aircraft also scales slowly in terms of average unit capacity (Δt=38) although the portion of the logistic function described by its growth history is limited. Again, this corresponds to the diversity of demand for the energy service it provides. By contrast, the average unit capacity of nuclear power (Δt=18) scales only slightly slower than its capacity frontier (Δt=11). Nuclear power's economies of scale strongly dominate its potential versatility across diverse contexts. (These economies of scale relate to the transaction costs of permitting, building, operating and managing the waste of nuclear facilities as well as the technical efficiencies of larger unit sizes).

Differences between the centralised power technologies are further illustrated by the pattern of unit additions worldwide shown earlier in Figure 1. Differences between maximum and average capacities of nuclear units are much lower than for coal and natural gas. In addition, maximum capacities are less variable around the eventual unit capacity frontier. In contrast, natural gas units show highly variable maxima, and consistently low average capacities.

In sum, unit scaling dynamics capture the tension between technical returns to scale and economies of scale (driving faster scaling at the unit level) and scale flexibility or independence coupled with demand constraints and heterogeneous market niches (driving slower scaling particularly in terms of average unit capacity). As a general rule, demand constraints will be more influential on the scaling of end use technologies for which the technical and economic efficiency of larger scale is less clear.

Isolating the magnitude of unit scale economies is complex given the many potential determinants of cost, and the concurrence of scaling at the unit and manufacturing levels, as well as potentially at the plant, industry and system levels. The relative importance of cost dynamics at the unit and manufacturing levels is technology dependent. Modular end use technologies (e.g., cars) are more likely to be characterised by manufacturing scale economies (holding unit capacity constant).[21] Large capacity supply-side technologies (e.g., power plants) are more likely to be characterized by unit scale economies (holding unit numbers constant). But methodologies to isolate these effects from other sources of cost reduction are complex (see Appendix C for further discussion). In the case of power plants, for example, data in the form of levelised production costs ($/MWh) mask the effect of unit scaling by endogenising efficiency, intermittency, reliability, and other factors.

Energy technology assessments and modelling studies that use a single profile of cost reductions over time further conflate different scale economies with learning effects. Learning effects describe cost reductions associated with cumulative experience as a technology matures commercially (Argote & Epple 1990). The underlying mechanisms for learning-related cost reductions are many and varied. They include design improvements, better system integration, material or other input efficiencies, process refinements, lower contingencies or conservatism as perceived risks are reduced, and so on. Originally associated with 'doing', learning effects have also been attributed to using, operating, implementing, copying, searching and building (Sagar & van der Zwaan 2006).

The relationship between unit costs and unit scale economies in energy technologies is discussed further in Appendix C.

[21] Even in cases with apparently clear manufacturing scale economies, cost drivers must still be identified. For CFLs, the dramatic shift in manufacturing from developed to Asia markets through the 2000s was, at least early on, not associated with scale economies and automation but rather semi-automatic 'compact' production facilities with greater flexibility to retool for different products, lower investment costs, and shorter capital recycling times (Fumin 2002). These characteristics proved advantageous in a still relatively immature industry with diverse and changing product characteristics.

4.3 Measures and Rates of Industry Scaling

Industry scaling can be measured either in terms of cumulative total capacity (in MW) or cumulative total number of units. The underlying data are incomplete, as shown in Table 5, but to a lesser extent than for unit scaling. End use technologies are better covered, as are Rim and Periphery regions allowing analysis of spatial diffusion dynamics.

Table 5. Measures of Industry Scaling & Logistic Fits. 'Some' means data available or logistic fits appropriate only for some regions.'-' means either data not available or no reliable logistic fits.

	Refine-ries	Coal Power	Nuclear Power	Natural Gas Power	Wind Power	Jet Aircraft	Cars	Light Bulbs
Cumulative total capacity	all	some	some	all	some	all	some	some
Cumulative total unit numbers	-	some	some	all	some	all	some	some
Order of magnitude of unit capacity (MW)[i]	10^{4}	10^{2to3}	10^{3}	10^{1to2}	10^{0}	10^{1to2}	10^{-1}	10^{-6}
Order of magnitude of unit numbers (#s)[i]	?	10^{2to3}	10^{3to4}	10^{3to4}	?	10^{4to5}	10^{9to10}	10^{10to11}

[i] Unit capacities are typical values. Unit numbers are approximated by the asymptotes of the logistic functions fitted to global data.

Comparison of these industry scaling dynamics across different technologies shows that:

i. industry scaling *tends* to be faster in terms of capacity than unit numbers;
ii. industry scaling *tends* to be faster for technologies with larger unit capacities or less unit numbers;
iii. both these *tendencies* are robust as a technology diffuses spatially.

Figure 7 shows the rates of industry scaling (Δt) for the Core region. The technologies are ordered from top to bottom by increasing unit capacity or decreasing total unit numbers (see Table 5 for order of magnitude estimates).

Firstly, in all cases for which data are available, industries scale more quickly in terms of cumulative total capacity than cumulative total unit numbers. This is intuitively obvious as industry capacity scaling *contains* the unit scaling dynamics discussed in the previous section. But the difference holds even for technologies without pronounced unit capacity scaling (e.g., natural gas, cars). This points to the often prolonged early commercialisation phase in a technology's lifecycle during which unit numbers are built out before unit capacities are scaled (so extending the Δt of total unit numbers). This argument is developed further below.

Secondly, rates of industry scaling tend to be faster (shorter Δt) as technologies increase in unit capacity and/or decrease in total unit numbers (i.e., from top to bottom of Figure 7, or from right to left in Table 5). Again, this is intuitively obvious as the diffusion of greater numbers of units will require more manufacturing and distribution capability, more end users, more extensive institutional support, more demand niches and so on. Although not necessarily more complex or qualitatively demanding, the observed pattern suggests an increase in the marginal diffusion 'effort' required per MW of energy technology as the number of units increases.

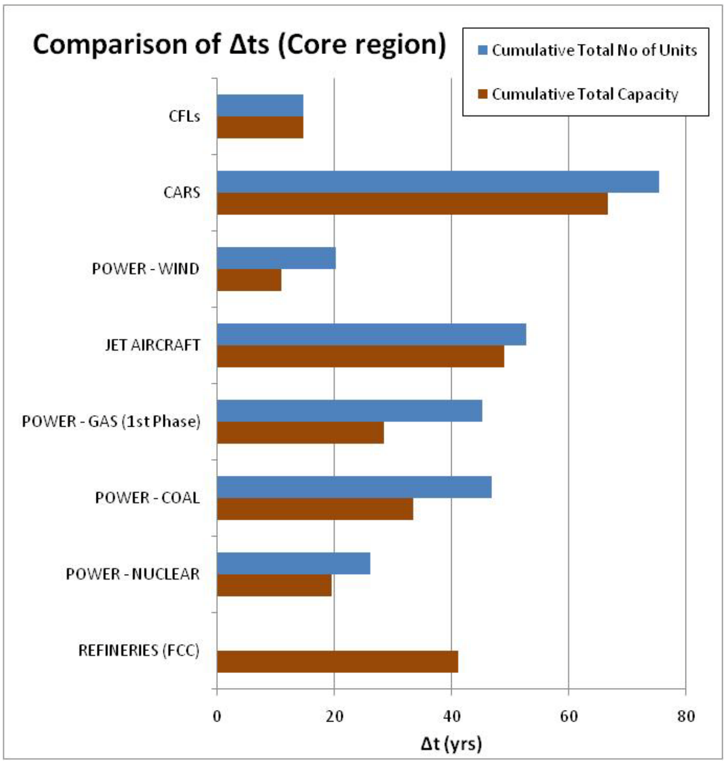


Figure 7. Industry Scaling Rates. Industry scaling rates (Δt) in terms of cumulative total numbers of units (blue bars) and cumulative total capacity (brown bars) for different technologies (Core region). Technologies are ordered from top to bottom (approximately) by increasing unit capacity and/or decreasing total unit numbers.

Compact fluorescent light bulbs and wind power are clear exceptions to this second tendency. Both have relative fast industry scaling rates (short Δt) despite their relatively high numbers of units (and/or small unit size). Why? Compared to the other technologies, compact fluorescent light bulbs and wind power:

- are less capital intensive in $ per unit terms (not $ per MW);
- have more recent introduction dates and have diffused into more globalised markets;
- are more direct substitutes for incumbent technologies, requiring less concurrent change in supporting infrastructures and institutions.

Lower $ per unit costs reduce capital availability constraints in absolute terms, potentially increasing diffusion rates. (This logic should also apply to passenger cars but these have a long Δt). More globalised markets create larger demand for technologies following their successful commercialisation in a Core region, potentially speeding up spatial diffusion and driving a faster increase in manufacturing capacity and market development.

The most likely explanation, however, is also the most systemic. Technologies diffuse more rapidly if they are ready substitutes for existing technologies (Grübler et al. 1999). Compact fluorescent light bulbs may require different or adapted light fixtures, but in general they can be simply purchased and installed in lieu of the dominant incandescent bulb. Although wind power requires new technologies and institutions to manage unpredictably intermittent supply[22], at the utility scale wind power has been commercialised on the back of a century of electrification. Grids, markets, utilities, end use technologies, loads: all already exist. Of course, all are also still co-evolving along with the changes in electricity supply, but this inter-dependency was far more marked for coal and natural gas power during the first half of the 20th century (and later outside the Core region). The exemplar of a technology which created rather than substituted for existing markets and service demands is the motor vehicle. Its initial diffusion in the US and elsewhere required a largely new physical infrastructure which in turn had a profound impact on, and was impacted by, urban form, lifestyle, forms of social organisation, and so on(Rae 1984). Being ready substitute technologies, the wind power and compact fluorescent light bulb industries have scaled rapidly despite the high numbers of units involved.

An additional point specific to wind power is that its Core region (Denmark) is smaller in absolute size than the Core regions for other technologies (e.g., US or OECD). This does not inherently mean that its Δt will be shorter, as the energy system into which it is diffusing is correspondingly smaller. Impacts of region size on K and Δt are discussed further in Sections 4.8 & 7.

Comparison of industry scaling rates between Core, Rim and Periphery regions (subject to data availability) shows that the tendencies described above remain robust as technologies diffuse spatially. In other words, in all regions, industry scaling was faster in terms of capacity than unit numbers, and industry scaling tended to be faster for technologies with larger unit capacities and/or lower unit numbers. This first point is shown in Figure 8 which compares the scaling rates of total capacity and total unit numbers for all available data points in each region.

[22] There are many examples of technologies and institutions that have co-evolved with the diffusion of renewable power. These include: regulatory frameworks to internalise the social benefits of clean, secure electricity generation; market rules to prioritise or require purchase and dispatch by utilities; reform of planning and permitting regimes; and public underwriting of major capital investments in infrastructure.

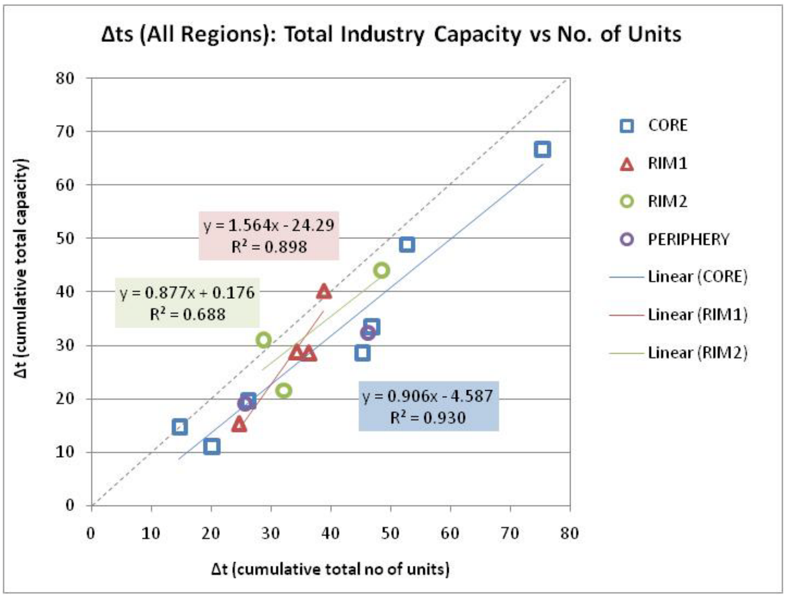


Figure 8. Industry Scaling Rates for Different Regions. Industry scaling rates (Δt) in terms of cumulative total number of units (x-axis) and cumulative total capacity (y-axis) for Core, Rim1, Rim2 and Periphery regions. Data points below the dotted x=y diagonal scale more rapidly in terms of total capacity. Solid lines show linear best fits for each region (excluding Periphery which has insufficient data points).

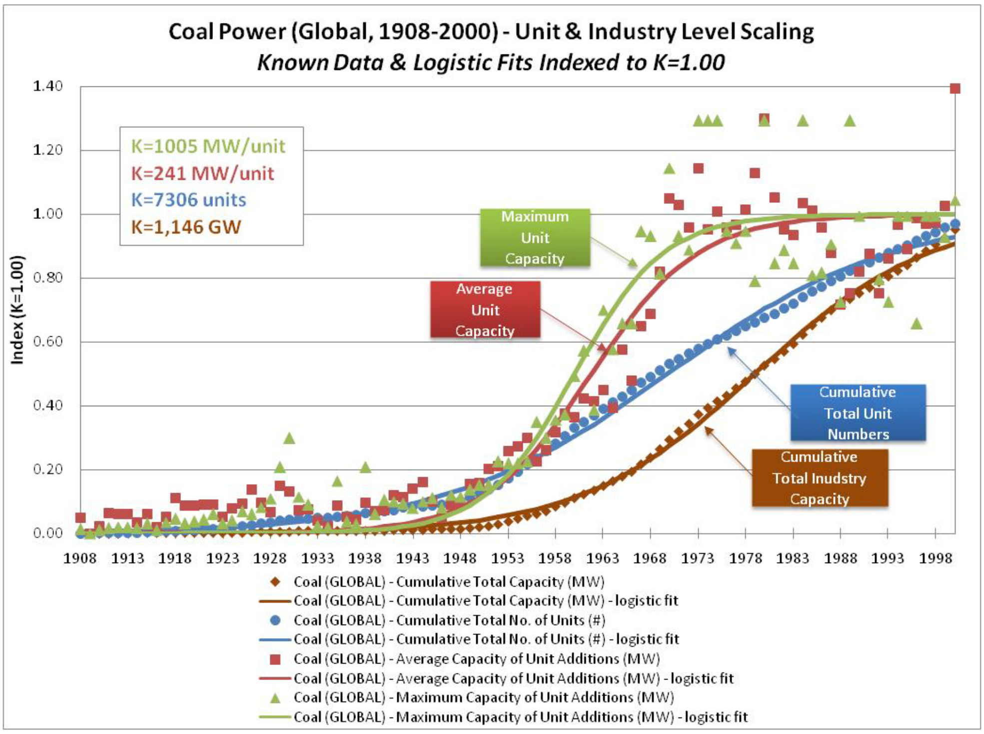


Figure 9. Scaling Dynamics of Coal Power. Known data (markers) and logistic fits (solid lines) of unit and industry scaling for coal power globally. Average unit capacity (red), maximum unit capacity (green), cumulative total unit numbers (blue) and cumulative total industry capacity (brown) are all indexed to the asymptotes of their respective logistic models. Asymptotes or extents of scaling (K) are shown in absolute terms in the box.

Figure 9 represents this sequential pattern of unit and industry scaling using coal power (globally) as an example. Each logistic model is indexed to its respective K (shown in the box) to make timing and rates of scaling easily comparable. In the first 50 years of the industry's lifecycle, the (slow) growth in total capacity is driven by unit numbers.[23] Then unit scaling is concentrated in the 20 year period from 1950 to 1970. By the late 1970s, the unit capacity frontier is reached, and continuing growth in cumulative total capacity is again driven by unit numbers.

This basic sequence of unit numbers, then unit capacity, then unit numbers as the main drivers of total industry capacity is more distinct for those technologies with stronger unit scaling dynamics and lower unit numbers. Unit scaling of nuclear power, for example, occurs near the beginning of the industry's lifecycle. The unique issues associated with managing nuclear fuel cycles coupled with the need to reduce capital costs drove early and rapid unit (and plant) scaling.[24] Natural gas follows a similar pattern to coal, with unit scaling occurring mainly in the 1950s and 1960s. (Average unit capacity scaling is spread throughout the 20th century, but as noted earlier, is to a very limited extent with an asymptote at 59 MW / unit). In jet aircraft, the unit scale frontier (in terms of engine capacity) is defined by the Boeing 707 and DC 8 that pioneered the industry in the late 1950s / early 1960s, and is then largely saturated by the introduction of the Boeing 747-100 in 1969. This is the first 10 years of a 50 year period of continual growth in unit numbers. Larger 747 models introduced in the 1980s, and then the Airbus A-380 introduced in 2007, extended the unit scale frontier (in terms of both engine capacity and passenger.kms) but by diminishing increments (see Appendix A for data and plots).

By comparison, the successful commercialisation of modular end use technologies (e.g., cars, light bulbs) in the 20th century has been associated with mass production (at least since the model T Ford). The initial emphasis on unit numbers is therefore less remarkable than for the higher unit capacity power plants and aircraft.

This general pattern of unit numbers preceding unit scaling emphasizes the importance of the formative phase of a technology's lifecycle following its introduction in the market. The initial build out of unit numbers is a process of testing and experimentation.[25] Experimentation is particularly important for radical technologies

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[23] It is important to note that the indexed logistic functions shown in Figure 9 should only be interpreted relative to each other, particularly with respect to differences in the timing and steepness of the 10% to 90% of K growth phase. The early commercialisation phase may involve unit scaling in an absolute sense, but it is small relative to the scaling dynamic of unit numbers.

[24] This rapid unit scaling early in the industry's lifecycle reinforced the dominance of the light water reactor over potentially superior alternatives as its prior development and adoption by the US submarine fleet meant it was well positioned for diffusing (and scaling) rapidly in the emerging civilian power niche (Cowan 1990). The heavy water reactors developed in Canada first came online at a commercial scale (206 MW) in 1967 by which time there were already 10 commercial light water reactors in operation (excluding the FSU), 4 of which were greater than 100 MW. From this head start, dynamic increasing returns to scale led to the lock-in of the light water design.

[25] Experimentation is one of the key functions of technological innovation systems. These are "a network of agents interacting in a specific technology area under a particular institutional infrastructure to generate, diffuse and utilise technologies" (Carlsson & Stankiewicz 1991). Other functions of technological innovation systems are to develop and diffuse knowledge, to direct the search for technological opportunities, to form markets, to enhance the legitimacy of a technology, and to mobilize resources (Hekkert et al. 2007).

introducing into the market non-incremental changes in design or service provision (Utterback 1994; Suarez 2004). This process of 'learning-by-numbers' generates incremental improvements to the technology and reduces unit costs (learning effects), reduces uncertainties associated with performance or market demand, and drives ancillary changes to complementary technologies and institutions. Building many before building big characterises energy technologies that have successfully scaled historically. For examples, see: (Jacobsson & Bergek 2004; Foxon et al. 2005).

The importance of this early formative phase also emphasizes the demonstration and deployment stages of a technology's lifecycle as a precursor to successful commercialisation. Demonstration projects, for example, help prove the viability of unit capacity scaling from small scale lab applications to commercial prototypes (Sagar & Gallagher 2004). For energy technologies with long payback periods, upside potential limited by regulated markets, and high capital requirements, government support through the formative phase is important (Norberg-Bohm 2000; Harborne & Hendry 2009).

4.4 Effect of Unit Scaling Dynamics on Industry Scaling

The general sequence described in the previous section that relates unit to industry scaling raises the question: to what extent do unit level dynamics drive industry dynamics?

Again, various general tendencies are observed:

i. industry scaling *tends* to be faster when unit scaling is faster, i.e., for technologies with stronger unit scale economies;
ii. industry scaling *tends* to be faster when it is concurrent with unit scaling;

For technologies with earlier unit scaling driven by stronger economies of scale, unit scaling tends to more rapid (shorter Δt) than industry scaling. This is shown in Figure 10 for the Core region. For aircraft, coal power, nuclear power and refineries, industry scaling in cumulative total capacity terms is slower (longer Δts) than unit scaling in terms of both average capacity and at the unit capacity frontier. Natural gas power and wind power are the reverse, with more rapid scaling at the industry level. Unit scaling of cars in the Core region is not logistic (see Appendix A), but in the Rim2 region of non-US developed countries, the equivalent Δt is 102 yrs. Unit scale economies are less relevant for cars (whereas manufacturing scale economies are important), and natural gas power has a high degree of scale flexibility.

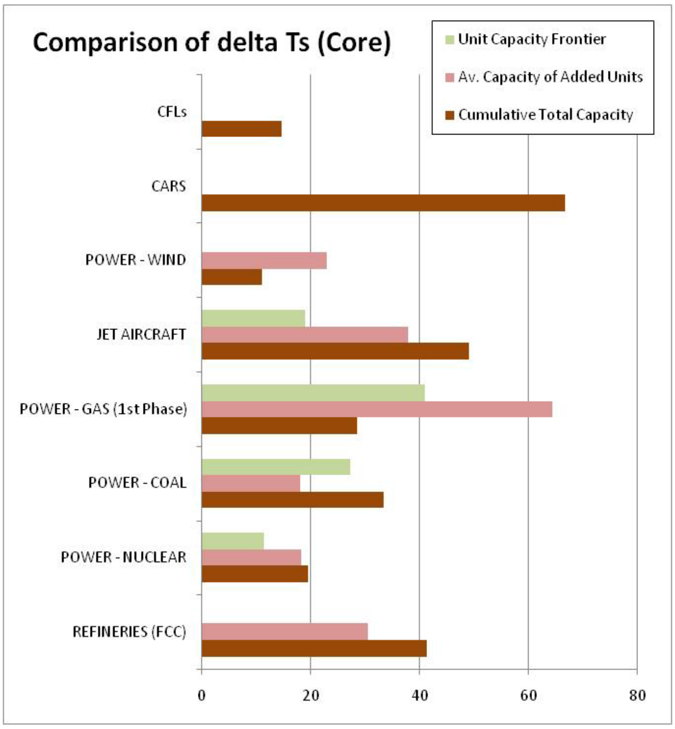

Figure 10. Rates of Scaling at Unit & Industry Levels (Core Region). Unit scaling is more rapid (shorter Δt) than industry scaling for technologies with stronger unit economies of scale.

Wind power is again an anomaly as industry scaling is more rapid despite clear unit scale economies. Figure 11 compares the unit and industry scaling dynamics for wind power in its Core region (Denmark). Complete time series data on maximum unit capacities are not available, but the commercial history of new turbine models developed by Vestas, the leading Danish (and global) manufacturer, is an approximation of the unit scale frontier (see dotted green line in Figure 11). Unit scaling dynamics are still far from saturation, despite the technical returns to scale of capturing stronger wind speeds at higher hub heights and scale economies of spreading fixed plant construction costs over a larger productive capacity.[26] This serves to reinforce the importance of experimenting and learning from the build out of unit numbers in the early phase of an industry's growth. Denmark's success in this regard is contrasted with the early failures in the wind industries of Germany, the UK and to some extent the US. In these countries, early emphasis was placed on unit scaling without the necessary experience of building and operating sufficient unit numbers; see, e.g., (Garud & Karnoe 2003).

[26] This is particularly marked in the emerging offshore market segment with its higher construction costs per MW (barges, cranes, cable laying, substations, etc.). Average unit capacity has scaled relatively slowly given the wide variety of niches in the Danish market from decentralised farm or residential turbines, to utility scale wind farms.

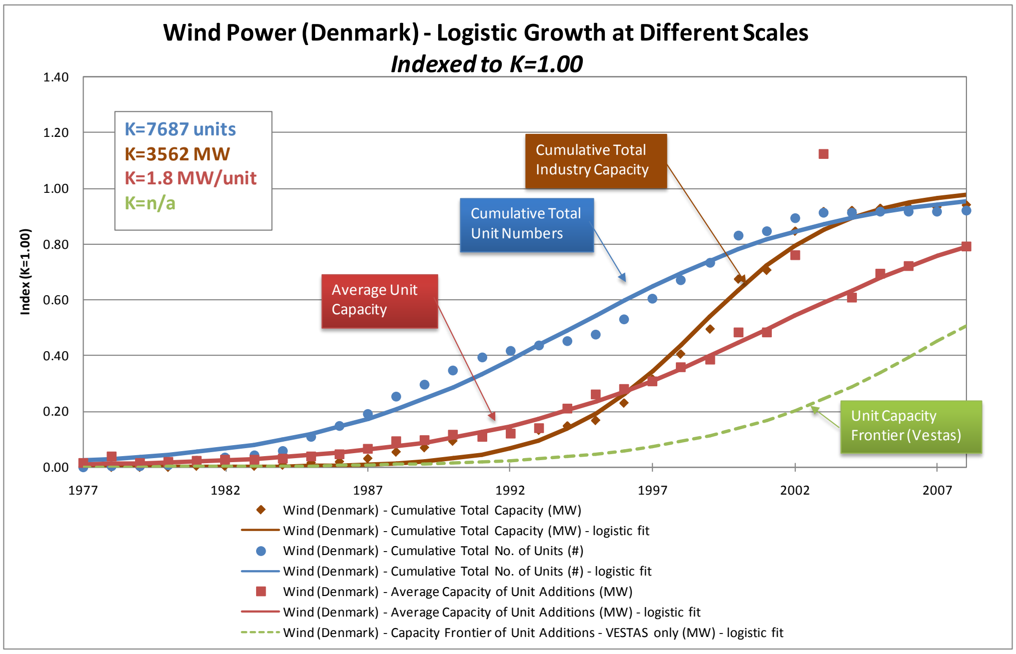

Figure 11. Scaling Dynamics of Wind Power. Known data (markers) and logistic fits (solid lines) of unit and industry scaling for wind power in Denmark. Average unit capacity (red), cumulative total unit numbers (blue) and cumulative total industry capacity (brown) are all indexed to the asymptotes of their respective logistic models. Asymptotes or extents of scaling (K) are shown in absolute terms in the box. An approximation of the unit capacity frontier (dotted green line) is based on the commercial release dates of new Vestas turbine models.

Figure 12 plots the rates of industry scaling against a measure of the relative *timing* of unit scaling (left-hand graph) and a measure of the relative *rate* of unit scaling (right-hand graph).

In terms of timing, more rapid scaling at the industry level (shorter Δt) is associated with concurrent rather than early unit scaling (i.e., data points nearer the left side of the left-hand graph). All the technologies fit this broad pattern, particularly on the supply side. This reinforces the sequence described above: even if strong unit scale economies exist, unit scaling does not precede growth in the overall industry. Industry scaling of aircraft is slower and much delayed in comparison to its unit scaling (measured at t_0, the maximum rate of growth of the fitted logistic functions).

In terms of rates, more rapid scaling at the industry level (shorter Δt) is associated with more rapid unit scaling (positive correlation between Δts on the right-hand graph). Again, all the technologies fit this broad pattern, although it is weaker in the absence of strong scale economies (i.e., natural gas power).

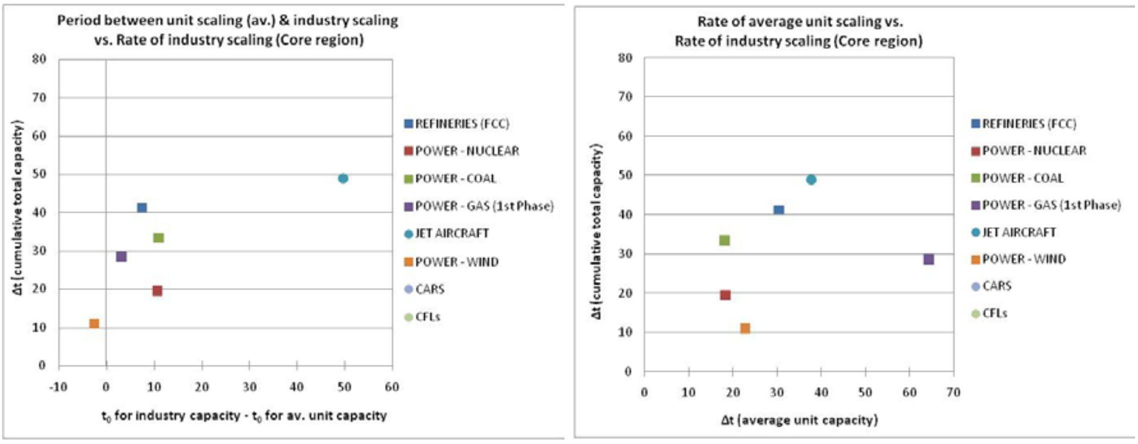

Figure 12. Relative Timing & Rate of Unit Scaling. Δts of industry scaling plotted against the relative timing (left-hand graph) and rate (right-hand graph) of unit scaling for technologies in the Core region. Relative timing is measured as the period between the maximum growth rates of the industry and unit logistic functions: the earlier unit scaling peaks relative to industry scaling, the larger this period and so the further the data points to the right.

To summarise these last two sections, across both supply-side and end use technologies, unit scaling does relate systematically to the overall industry dynamic, in terms of both timing, rate, and sequence. Unit scaling generally occurs after an initial ‘learning by numbers’ phase in which industry scaling is driven by the build out of unit numbers. This is most pronounced for large scale supply-side technologies with clearer unit scale economies. Rapid unit scaling is then associated with rapid industry scaling, particularly when the two dynamics are concurrent.

4.5 Spatial Diffusion of Unit & Industry Scaling

Technologies are introduced commercially in an initial market before diffusing spatially to other markets or countries. In Section 2, the example was given of passenger cars, demonstrating a general pattern known as Schmidt’s Law: as technologies diffuse spatially from initial to subsequent markets, diffusion rates increase but saturation densities tend to decrease (Grübler 1990).

Certain factors aid more rapid spatial diffusion. Consider, for example, a product that is (i) homogeneous, (ii) readily substitutes for an incumbent technology, (iii) is commercialised by transnational companies into (iv) an undifferentiated globalised market[27] that (v) is not constrained by localised intellectual property regimes and (6) is not overly protected by trade barriers. Such products (e.g., CFLs, wind power) would be expected to diffuse more rapidly from Core to Rim than a product with the converse characteristics (e.g., cars, natural gas power).[28]

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[27] i.e., the demand for the service that the product supplies is globalised with little differentiation between markets.

[28] As the limited time series data of CFLs and wind power in Periphery (and also Rim) regions mean logistic functions can not be reliably fitted, this supposition is not testable in the context of this analysis.

In this analysis, data are aggregated into Core, Rim and Periphery regions based on the timing of their industry scaling. According to Schmidt's Law, therefore, rates of industry scaling from Core to Rim to Periphery would be expected to increase (shorter Δt) and extents of industry scaling would be expected to decrease (lower Ks). Although extents of industry scaling can not be directly compared as the regions or markets are of different sizes, the rates of industry scaling do indeed follow this pattern (see Figure 13).[29]

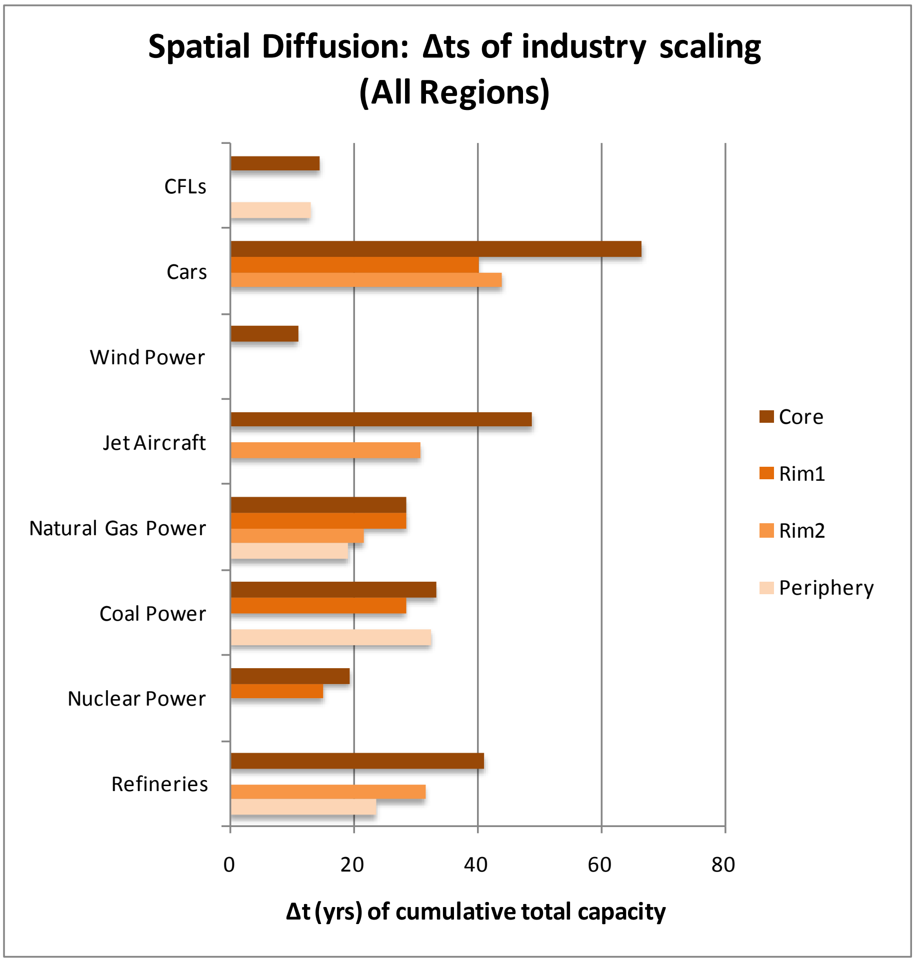


Figure 13. Spatial Diffusion of Industry Scaling Rates. Δts of industry scaling (in terms of cumulative total capacity) for each technology comparing Core, Rim1, Rim2 and Periphery regions (with progressively lighter colours). Omitted bars means data were unavailable.

Initial commercialisation dates in each region are also not known for all technologies. The timing of the industry capacity logistic function's maximum growth rate (t_0) offers a proxy measure that can be compared across technologies. The lag in t_0 between Core and Periphery region is 13 years for coal power, 12 years for natural gas power, 10 years for aircraft (to Rim region), and 7 years for refineries. Data for other technologies are unavailable.

[29] Coal power in the Periphery region is anomalous as it scales more slowly than in the Core or Rim regions, but this is an artefact of South Africa's inclusion as a Periphery country (with the rest of Africa). The restricted access to non-domestic energy resources under the early apartheid regime in South Africa led to an early exploitation of domestic coal for electricity generation.

Schmidt's Law can also be tested at the unit level: do technologies scale with shorter Δts and lower Ks at the unit level as they diffuse spatially from Core to Rim and Periphery markets? This is analogous to the (contested) phenomenon of 'leapfrogging' by which a developing country adopts a less polluting or more efficient technology from a developed country, and in so doing avoids a polluting or inefficient part of the developed country's development pathway(Perkins 2003). In this case 'unit capacity leapfrogging' would see Rim and Periphery markets adopt unit scaling gains from Core markets.

Unit scaling data for all regions is available only for the centralised power generation technologies. For this subset of the meta-analysis, however, there is no clear pattern of 'unit capacity leapfrogging' in terms of scaling rates. Figure 14 plots the logistic functions describing the maximum capacity of unit additions over time. Each function is indexed to its respective K (shown in the boxes). Rates of unit scaling in the Rim or Periphery regions (green and purple lines) are not consistently faster (i.e., steeper) than in the Core region (blue line). In the case of coal power, they are markedly slower.

However, the data do support Schmidt's Law applied to the *extent* of unit scaling. Maximum unit capacities in Rim and Periphery regions are consistently lower than those in the Core region for all three technologies (see boxes in each graph). Note that these observed patterns exclude the Rim1 region representing the former Soviet Union.

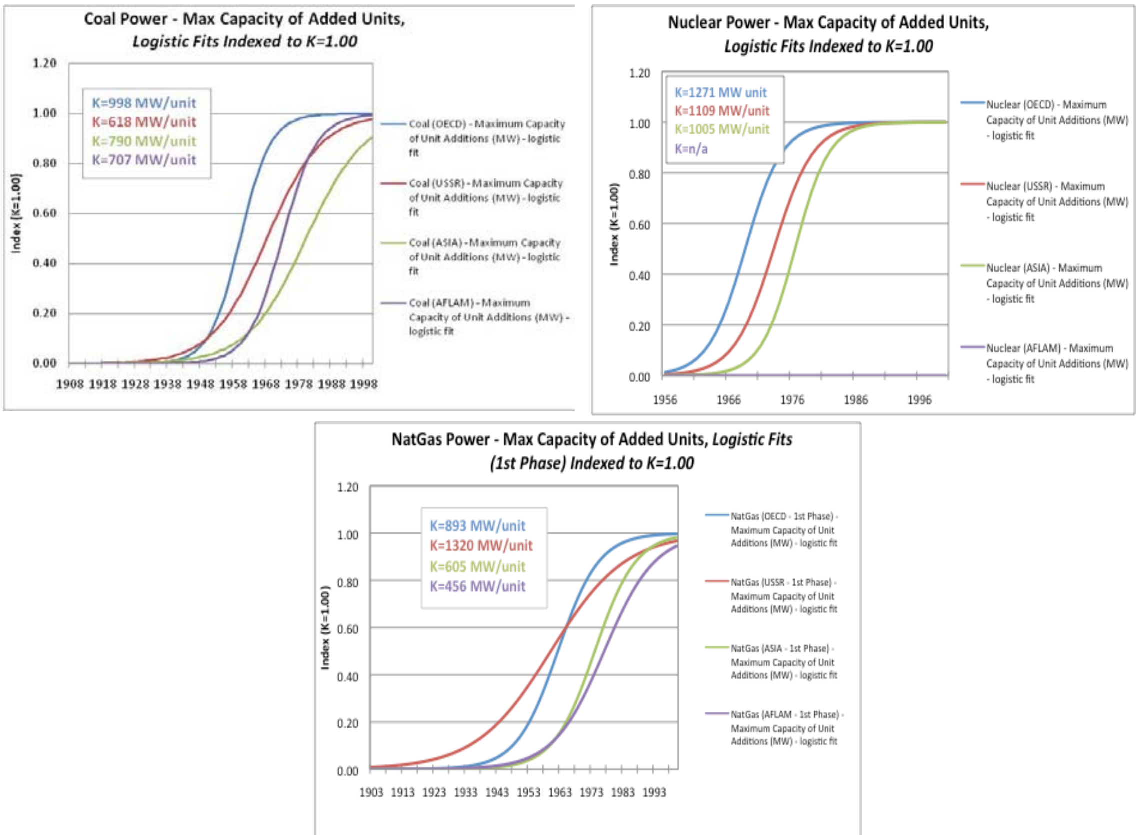


Figure 14. Spatial Diffusion of Unit Scaling: Power Generation. Logistic fits of unit scaling dynamics for Core (blue), Rim1 (red), Rim2 (green) and Periphery (purple) regions for three centralised power generation technologies. Each logistic function is indexed to its respective K (shown in boxes). Scaling is for maximum capacity of added units over time. Note that each x-axis covers a different time period.

The absence of historical evidence for unit capacity leapfrogging of coal, nuclear and natural gas power may partly be explained by the less integrated global markets in the 1960s-1970s during which the unit scaling dynamics were concentrated. Increasingly globalised markets and technology suppliers may facilitate the spatial diffusion of unit scaling. Given the relationship between the rates of unit and industry scaling described in the previous section, unit capacity leapfrogging may help drive more rapid diffusion of energy technologies outside of their initial markets. In a climate change mitigation context, such leapfrogging would be consistent with the technology transfer provisions of the UN Framework Convention on Climate Change, and instruments such as the Clean Development Mechanism (Dechezlepretre et al. 2008).

However, there is also a strong argument why the historical evidence may not simply be outdated. The initial 'learning by numbers' or formative phase of a technology's lifecycle is important for generating the tacit knowledge and institutions needed to design, build and use technologies appropriately. This applies to larger unit capacity technologies too, which is why unit scaling tends to occur after, or towards the backend of this formative phase. The same process and sequence is just as relevant for Rim and Periphery regions. Too rapid, or too early spatial diffusion of unit scaling gains made in Core markets may therefore be inappropriate given the absence of necessary supporting conditions. These are often localised, and not as readily transferred as technological hardware.

4.6 Extents of Unit and Industry Scaling

As the definition of the regions used in this analysis varies depending on the technology and its spatial diffusion pattern, extents of industry scaling can only be meaningfully compared between technologies using global data. The asymptote (K parameter) of the fitted logistic functions can be used as an approximate measure of the extent of scaling at both unit and industry levels (though K becomes less reliable the further saturation occurs in the future).

The left-hand graph in Figure 15 shows the extent of unit scaling in terms of average capacity, also expressed in MW. Data are global unless otherwise noted. A similar ordering of technologies is found for the unit scale frontier.

The right-hand graph in Figure 15 shows the extent of industry scaling in terms of cumulative total capacities. The dominance in the energy system of the conversion chain of crude oil into mobility is remarkable. Cars saturate globally with two orders of magnitude higher cumulative total capacity in MW terms than any other technology except refineries. Moreover, the fitted K for refineries is likely an underestimate as refinery data are in annual rather than cumulative terms, and so are the only technology for which capital stock lifetime and turnover is taken into account (see Section 7 for a discussion of resulting biases). Note also that these measures of the extent of industry scaling should not therefore be interpreted as shares of the energy system at a given point in time, but on a cumulative basis over time.

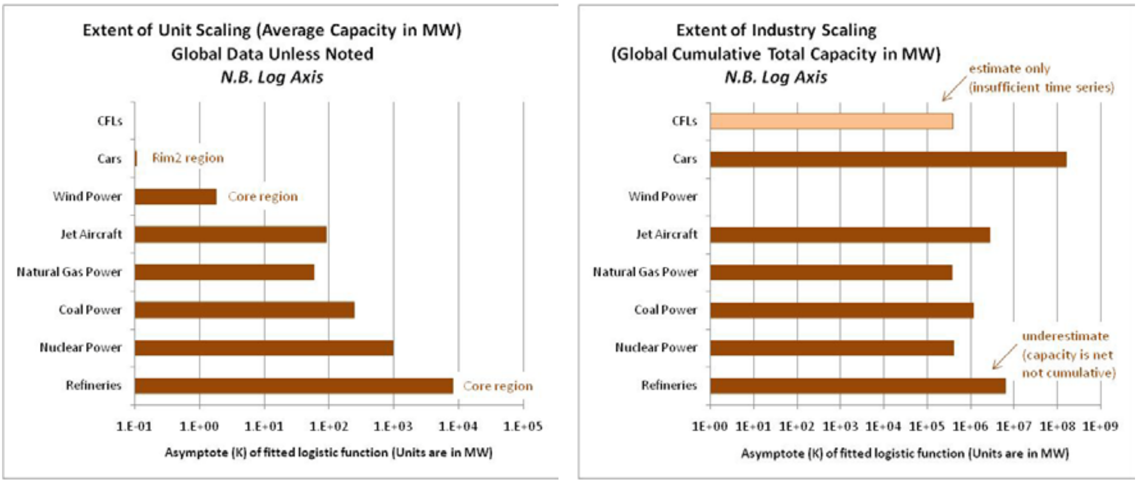


Figure 15. Extents of Scaling. Asymptotes (Ks) of fitted logistic functions to average unit capacity data (left-hand graph) and cumulative total capacity data (right-hand graph) for all technologies, globally. Note log scale x-axis.

A second caveat to interpreting the comparative extents of industry scaling is that they do not account for overall growth in the energy system. This is important as the timing of industry scaling varies for different technologies. Figure 16 plots the growth in cumulative total capacity over the course of the 20th century for each technology. The greater extents of scaling for cars and refineries can be seen in the context of their longer time horizon, although this is similar to coal and natural gas power. (Refinery data are available from 1945 but refineries date back to the 1860s). In addition, the point at which the different technologies' industry scaling starts (or will start) to saturate varies. This is shown more clearly in Figure 17 which indexes to their respective K each of the logistic functions fitted to the data in Figure 16. Here the saturation of nuclear power and refineries in their 1st phases (to the 2000s and to the early 1980s respectively) can be seen, as can the relative youth of the scaling trajectory for all the end use technologies which may be locally saturated in Core markets but have yet to penetrate the Rim and Periphery.

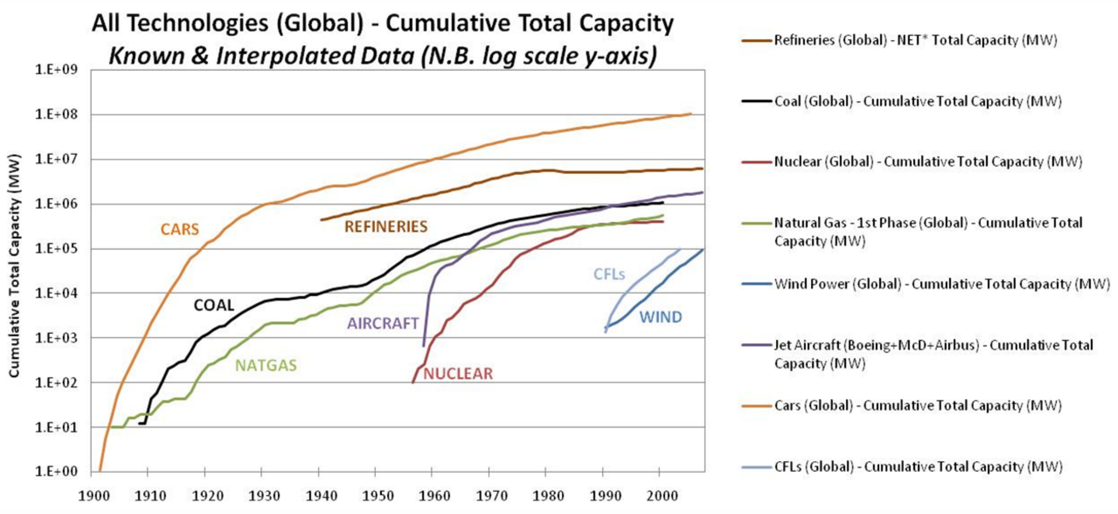


Figure 16. Industry Scaling: Historical Data. Global industry scaling in terms of cumulative total capacity (MW) for all technologies (except refineries which is in terms of annual total capacity). Note log scale y axis.

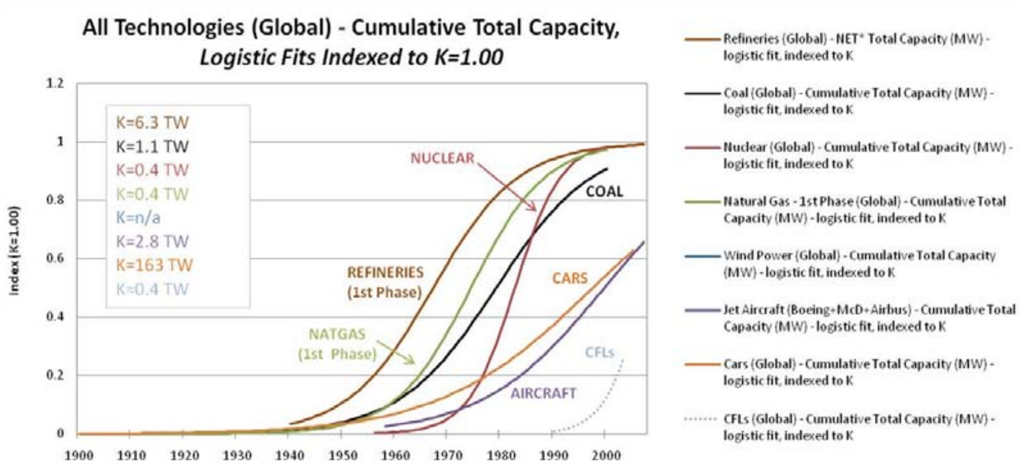


Figure 17. Industry Scaling: Indexed Logistic Fits. Logistic fits of global industry scaling in terms of cumulative total capacity (MW). Each logistic function is indexed to its respective K (shown in the box).

4.7 Comparing Extents of Industry Scaling

As noted above, the extent (K) of industry scaling will be positively influenced by the overall size of 'the system' into which it diffuses. Logically, a technology will diffuse to a greater extent, and so saturate at a higher *absolute* level in a larger system, even though the *relative* share of the particular energy carrier or energy service that it provides may stay the same. The most obvious 'system' in this case is the energy system, which has grown dramatically over the course of the previous century and will continue to do so. Comparing Ks between technologies is meaningful, therefore, only if changes in system size are taken into account. (The other requirement is for the Ks to be expressed in the same units which, here, are MW of cumulative total capacity).

4.7.1 Normalising K for Growth in System Size

In this analysis, extents of scaling are 'normalised' for system growth by dividing by the primary energy consumption (in EJ) at t_0 of the fitted logistic function (see Box 3). T_0 is the inflection point of the logistic function at which growth rates peak and diffusion reaches 50% of its full extent. As the logistic function is symmetrical about t_0 it provides a common time point for cross-technology comparisons.

Primary energy consumption is a useful measure of the overall size of the energy system. Data were taken from (BP 2008) for the period 1965-2007 extrapolated backwards annually to 1900 using decadal data for 1900-1960 from (Smil 2000; Grübler 2008).

Clearly the definition of this overarching system is somewhat arbitrary. Sectorally-defined systems such as electricity production or installed capacity (for power plants) or building floor area (for CFLs) would be relevant for some but not all the technologies. Alternative system metrics applicable to all the technologies include population, GDP (as a measure of the size of the economic system), or total investment (as a measure of the cost of the energy system). However, data on investments are poor, and historically, growth in both GDP and electricity production have been similar to growth in primary energy consumption with the exception of the 1970s global recession clearly visible in Figure 18.

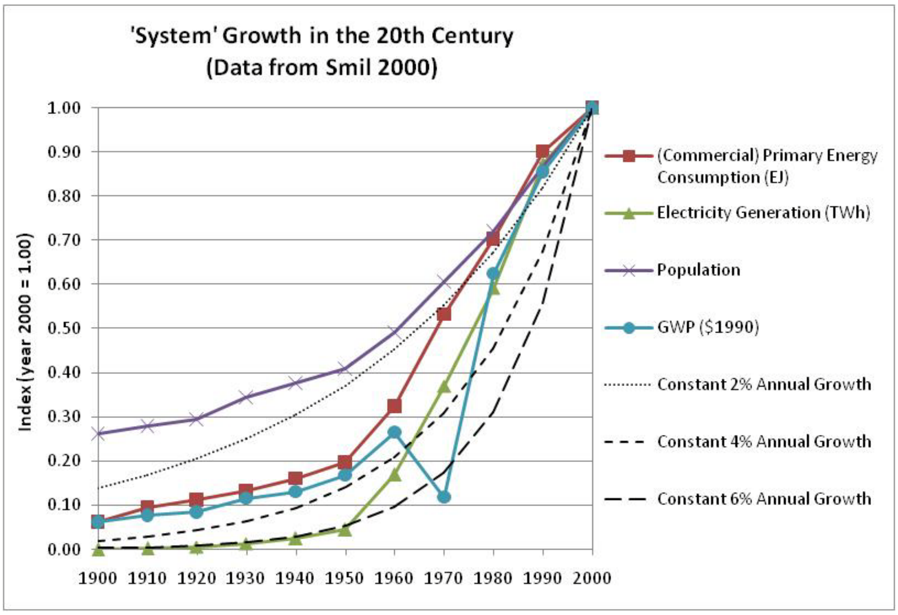


Figure 18. Patterns of 'System' Growth in the 20th Century. Primary energy consumption, electricity production, and gross world product (all global data) from 1900-2000 indexed to 1.00 in the year 2000. Dotted lines show constant 2%, 4%, and 6% growth rates for comparison. [Data from: (Smil 2000)].

As emphasized in Box 3, the normalised Ks should be treated as an index, useful only for comparison against other normalised Ks within the context of this meta-analysis of industry scaling. The absolute values of the normalised Ks (in MW / EJ) are not meaningful.

Box 3. Normalising Extents of Industry Scaling.

$$\text{Normalised K} = \frac{\text{K (in MW)}}{\text{Primary Energy (in EJ) at } t_0},$$

Notes:

- K and $t_0$are taken from the logistic model of industry scaling in terms of cumulative total capacity.
- Normalised K is an index useful only for relative analysis of technologies; it is not meaningful in absolute terms (units are MW / EJ).

Although the normalisation process is important for conceptual consistency, in practice it does not significantly change the relative extents of industry scaling between technologies. Figure 19 compares the extents of industry scaling on a non-normalised (left-hand graph) and normalised basis (right-hand graph) for the technology data points available globally. The relative position of the technologies is very similar in both cases. This is because the t_0 values for all the technologies are clustered in the period from 1970-2000 during which primary energy consumption (globally) roughly doubled but against a 2-3 orders of magnitude difference in the extents of industry scaling between, say, cars (~10^8 MW) and nuclear power (~10^5 MW) as shown in Figure 15.

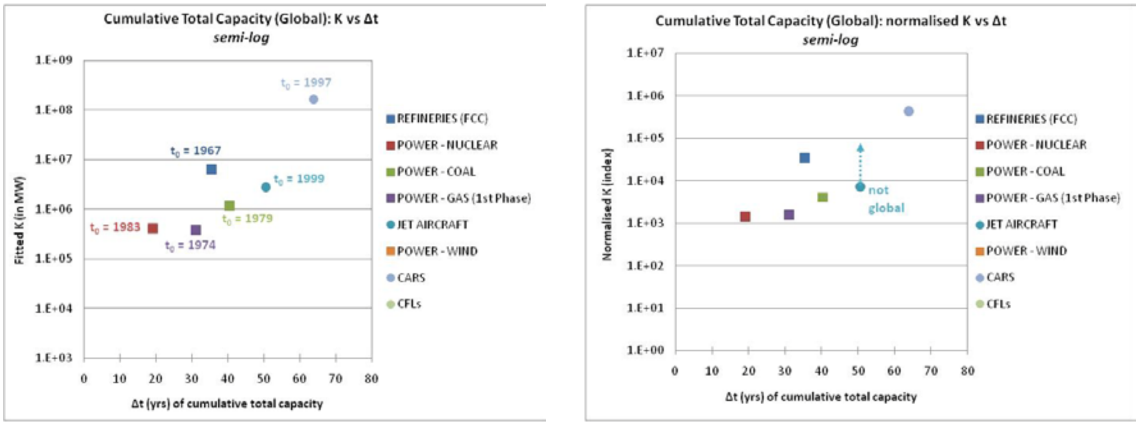


Figure 19. Extent - Rate Relationship of Industry Scaling. Extent (K) vs. rate (Δt) of industry scaling in terms of cumulative total capacity (MW) for all technologies globally. Left-hand graph shows fitted K vs. Δt; data labels show inflection points (t_0) of logistic functions. Right-hand graph shows normalized K vs. Δt. Normalisation is by dividing K by the primary energy at t_0.Note log scale y-axes on both graphs.

One critique of this normalisation method is that it fails to account for changes in system size over the full diffusion lifecycle of a technology. In other words, the normalisation denominator (primary energy in EJ) is the same for 2 technologies with the same t_0 but very different Δts. To take these different scaling dynamics into account, the normalisation denominator could be the change in primary energy over the full diffusion period of a technology (e.g., primary energy at 90% of K / primary energy at 10% K). However, even this more conservative methodology would make a negligible difference to the *relative* extents of industry scaling for the same reason noted above. Changes in primary energy even over the full 20th century are still an order of magnitude lower than the range of fitted Ks (see Table 6).

Table 6. Range of Scaling Extents & Primary Energy Growth.

HISTORICAL	**Fitted K (MW)**	**Primary Energy (EJ)at t_0**	**Primary Energy (EJ) over Full Range**
Min	$4{*}10^5$ (nuclear)	186 (in 1967; t_0 refineries)	25 (in 1900)
Max	$2{*}10^8$ (cars)	379 (in 1999; t_0 jet aircraft)	389 (in 2000)
Max / Min	***500***	***2***	***16***

To match the spatial disaggregation of the technology scaling analysis, global primary energy consumption data were disaggregated into 4 regions: OECD, FSU (inc. Eastern Europe), Asia, and the rest of the world (primarily Africa and Latin America). These 'primary energy regions' were used to normalise the Core, Rim1, Rim2 and Periphery 'technology regions' respectively.

Note that the OECD 'primary energy region' matches the Core region for nuclear, coal, and natural gas power, but is somewhat smaller in energy system terms than the North America + Eurasia region used for refineries. Conversely, it is somewhat larger than the North America + Western Europe region used for CFLs, the US region used for cars, and much larger than the Denmark region used for wind power.[30]These differences in size between the technology regions and the OECD as the primary energy region would be expected to bias upwards the normalised Ks for refineries, but bias downwards the normalised Ks for CFLs, cars, and particularly wind power.

This biasing effect should be relatively small for similar reasons to those discussed above. The variance in Ks greatly exceeds the variance in the size of technology regions in primary energy terms. In addition, the normalised Ks are only meaningful relative to each other at the same level of spatial disaggregation (Core, Rim1, Rim2, Periphery). It is the rates and timing of growth in a particular primary energy region that give rise to *relative* differences in normalised Ks for the corresponding technology region. As long as growth in primary energy regions follows the Core to Rim to Periphery sequence upon which the technology regions are defined, this approach should be valid. As shown in Figure 20, this is clearly the case, at least for the purposes of a first order approximation.

[30] The relative size of Boeing sales (as the Core region for aircraft) to aircraft used in the OECD region on a cumulative basis is not known.

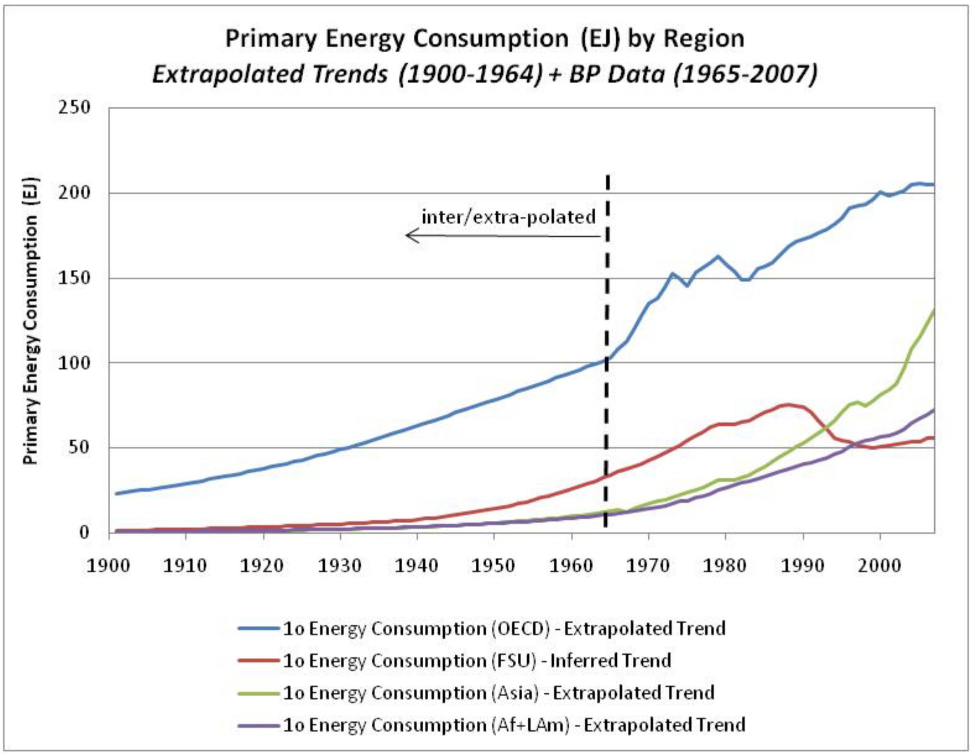


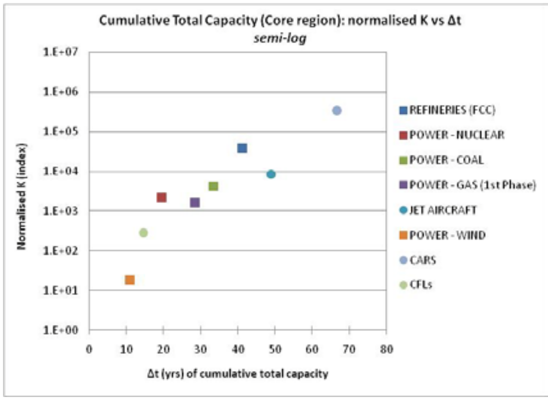
Figure 20. Primary Energy Consumption by Region. Annual primary energy consumption (in EJ) for each of 4 regions used to normalise extents (K) of industry scaling.

To test these biases, adjustments were made to the primary energy data based on the ratio of primary energy consumption in the technology's Core region to primary energy consumption in the OECD measured at t_0. Specifically, primary energy data for normalising refineries was adjusted by 115%, jet aircraft by 75%, wind power by 0.4%, cars by 43%, and CFLs by 83%.[31] The effect of these adjustments is shown on the right-hand graph of Figure 21 (see below). In general, they did not substantively affect the overall pattern of data points, supporting the assumptions made above. Moreover, the adjustments themselves raise another set of issues relating to the equivalence of different technologies (CFLs, cars, nuclear power …) in the context of primary energy consumption. Consequently, normalised Ks are generally presented without this adjustment.

[31] Refineries: t_0 = 1969 when primary energy in North American + Eurasia (technology region) = 158 EJ / primary energy in OECD = 137 EJ; Wind power: t_0 = 1999 when primary energy in Denmark (technology region) = 0.8 EJ / primary energy in OECD = 219 EJ; Cars: t_0 = 1988 when primary energy in US (technology region) = 80 EJ / primary energy in OECD = 187 EJ; CFLs: t_0 = 2000 when primary energy in US (technology region) = 187 EJ / primary energy in OECD = 224 EJ. For jet aircraft, the adjustment was based on a rough estimate of the proportion of aircraft used in the OECD not manufactured by Boeing, less the proportion of aircraft used outside the OECD manufactured by Boeing.

4.7.2 Extent - Rate Relationships for Industry Scaling

The left-hand graph in Figure 21 shows the normalised K parameter on a log scale plotted against its corresponding Δt for each technology in the Core region. A positively correlated extent - rate relationship would be expected. In general, a technology should take longer to diffuse to a greater saturation density (notwithstanding the many factors that affect diffusion rates). Surprising, however, is the consistency of this extent - rate relationship between both end use and supply-side technologies of markedly different characteristics. An exponential best fit explains 85% of the variance between the 8 data points (normalised K = 21.44 $\Delta t^{0.156}$).



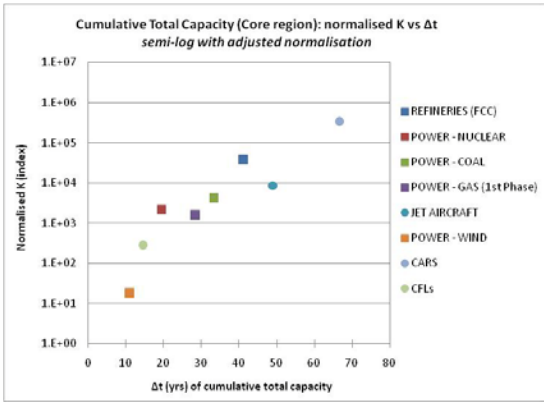


Figure 21. Extent - Rate Relationship for Industry Scaling. Extent (normalised K) vs. rate (Δt) of industry scaling in terms of cumulative total capacity (in MW) for all technologies in the Core region. Note log scale y-axis. Right-hand graph shows alternative normalisation adjusting for differences in primary energy and technology region size (see text for details).

Wind power is the only slight outlier with a lower normalised extent than its Δt might suggest. However, this is explained simply by the mismatch in size between Denmark as the technology region and the OECD as the primary energy region for normalising K (see above). The right-hand graph in Figure 21 re-plots the extent – rate relationships adjusting for this mismatch. The wind power data point duly rises to slightly above the trend, although the relative position of the other technology data points are substantively unaffected, and the general pattern is maintained.

Although the extent - rate relationship for industry scaling measured in terms of cumulative total capacity holds for all regions, the number of data points for Rim and Periphery regions become sparser. Figure 22 shows normalised Ks against Δt for all the data points available, grouped into the 4 regions. The extent - rate relationships are well described by exponential best fit lines in each region, except the Periphery which has only 3 data points.

While consistently exponential, the extent - rate relationships do seem to accelerate from Core to Rim1 to Rim2. In Figure 22, this is observed in the increasingly steep best fit lines. Recall that Schmidt's Law (see Figure 2) holds that as technologies diffuse spatially, the rate of diffusion increases (shorter Δt)but saturation densities decrease (lower normalised K). For a given technology, the Core data point on Figure 22should therefore be further up and to the right of the Rim and then Periphery data points. However, Figure 22 illustrates a different point as a further qualification of Schmidt's Law. As technologies diffuse spatially, the rate of diffusion increases *for a given extent of diffusion*. In other words, the elasticity of K with respect to Δt increases from Core to Rim to Periphery.[32]

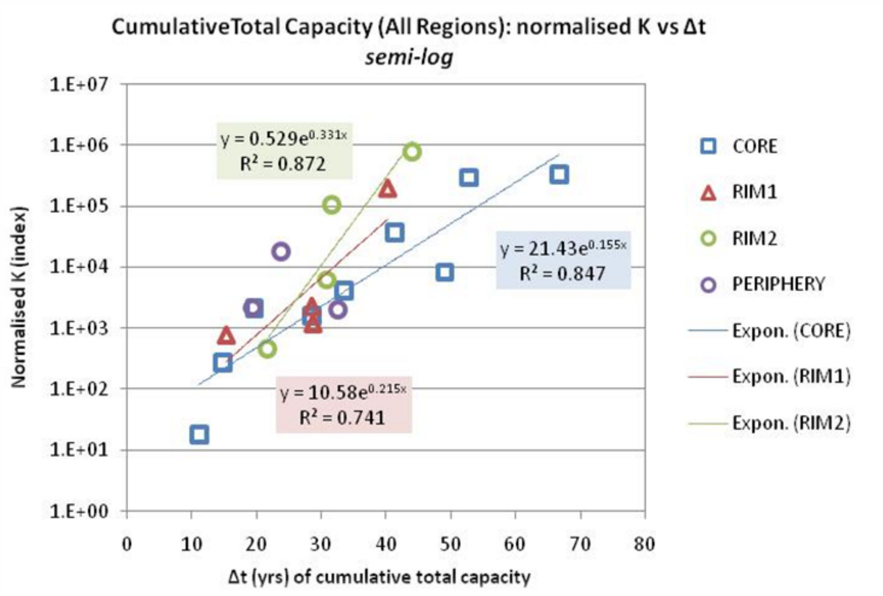


Figure 22. Extent - Rate Relationship for Industry Scaling (All Regions). Extent (normalised K) vs. rate (Δt) of industry scaling in terms of cumulative total capacity (in MW) for all technologies across all regions. Note log scale y-axis.

A further finding is that the extent - rate relationship is not changing systematically over time. This challenges the perception that technological change is accelerating, i.e., that diffusion rates of more recent technologies are increasing for a given diffusion extent. If this were the case, the data points on Figure 23 showing extent / rate plotted against t_0 for each technology should trend from bottom left to top right. This is evidently not the case, and there appears to be no systematic change in extent / rate for energy technologies that diffuse later in the 20th century (at least in terms of cumulative total capacity).

The perception of accelerating technological change, however, is driven in particular by the exponential penetration of information and communication technologies over the last 2 decades. This results from a view of the technology lifecycle biased towards the

[32] Note that K - Δt elasticities are positive as Δt is proportional to the inverse of diffusion 'speed' (the b parameter in the logistic function), i.e., a % increase in Δt (slower rate) is associated with a % increase in extent (larger K). As technologies diffuse spatially, this elasticity increases in magnitude.

highly visible diffusion phase, neglecting the long formative and commercialisation phases of technologies. The exemplars are the internet whose progenitor, ARPANET, dates back to 1969, and the mobile phone, whose commercial use dates back to the early 1970s and significantly earlier if radio telephony is included.[33] These pre-takeoff periods of several decades are the norm not the exception. Their length is determined by a host of factors specific to the technology related to the co-evolution of materials, manufacturing techniques, distribution infrastructures, market institutions, user needs and so on.

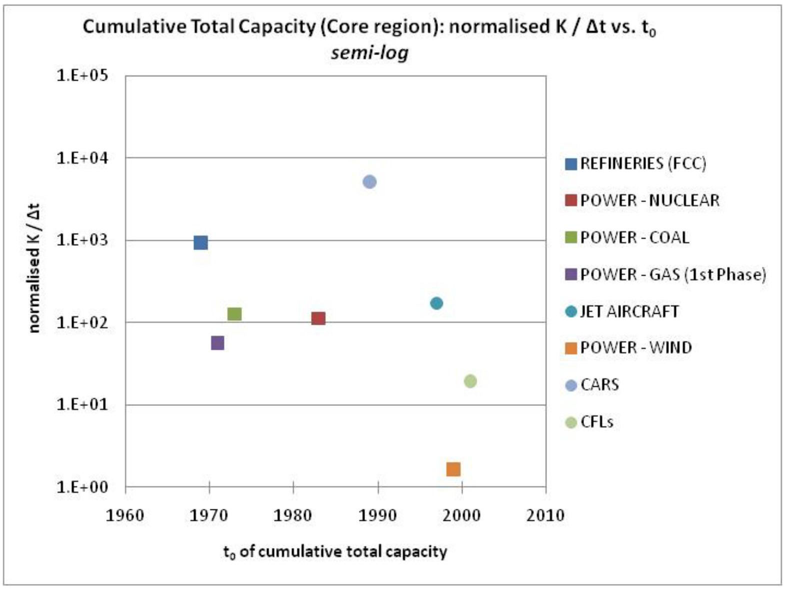


Figure 23. Extent / Rate of Industry Scaling over Time. Normalised K / Δt plotted against the corresponding t_0 or year of maximum growth rate. A systematic pattern would indicate that the extent - rate relationship has changed over time. Note log scale y-axis.

Expressed in terms of cumulative total number of units rather than cumulative total capacity, industry scaling does not show the same consistent extent - rate relationship (see Figure 24). In part this is not surprising as the normalisation of extents uses an approximation of total system capacity (total primary energy consumption). There is no equivalent and meaningful approximation of total system 'numbers'.

More substantively, however, there is a difference between modular end use technologies and large capacity supply-side technologies. The relatively low normalised K of jet aircraft points to the large unit capacity of the technology and so the lower number of units required to reach a given K.[34] More fundamental differences also exist and explain the pattern seen in Figure 24. For large n end use technologies (e.g., CFLs),

[33] Ericsson's "mobile telephone system A" was released in Sweden in 1956 with handsets weighing 40kg!

[34] This is not the only explanation though. A plot of normalised Ks of industry scaling (total unit numbers) against fitted Ks of unit scaling (average capacities) shows a positive correlation but declining exponential rather than linear. However, there are only 5 data points for the Core region, and 4 are closely grouped.

industry scaling in terms of cumulative total numbers of units is driven substantively by scaling of manufacturing and sales capacity. For small n supply-side technologies (e.g., power plants), comparable industry scaling in terms of unit numbers is influenced more by scaling of installations and distribution infrastructures. These underlying differences explain the lack of a consistent extent - rate relationship across technologies for industry scaling in terms of unit numbers. Converting these unit numbers into industry capacity terms (in MW) effectively normalises for differences in unit capacities that in turn affect the magnitude of total unit numbers; only then does a consistent extent – rate relationship emerge (see Figure 21).

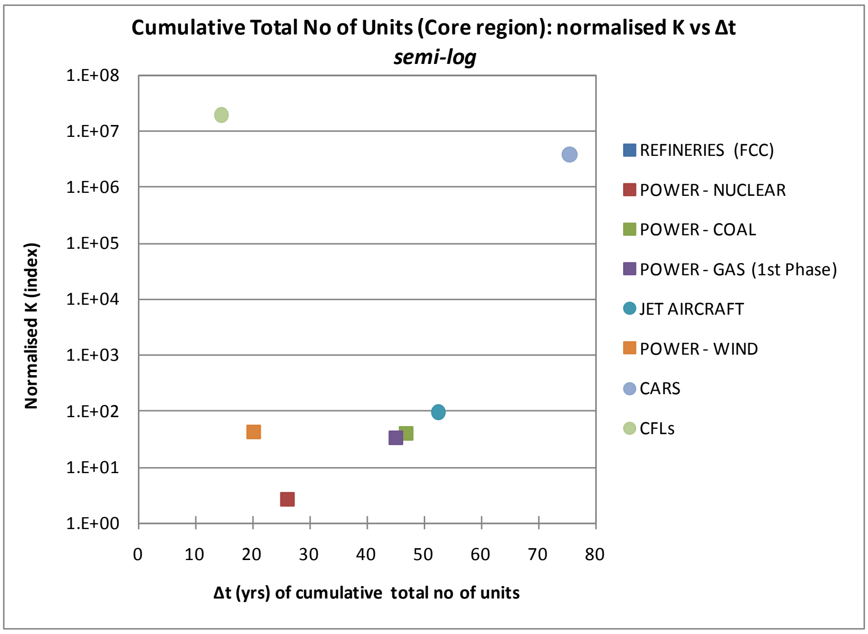


Figure 24. Extent - Rate Relationship of Industry Scaling in Terms of Unit Numbers. Extent (normalised K) vs. rate (Δt) of industry scaling in terms of cumulative total numbers of units for all technologies in the Core region. Note log scale y-axis.

4.8 Summary of Scaling Meta-Analysis: Key Findings

Table 7 summarises the key findings of the scaling meta-analysis. Together these comprise a body of patterns, tendencies, and relationships common to a wide range of energy technologies from 10 GW-eq oil refineries to 15W compact fluorescent light bulbs. These commonalities across energy technologies can be applied in general terms to energy technology policy and modelling. Two such applications are discussed in more detail below. Section 5 draws together and elaborates on the qualitative points raised in preceding sections to develop a conceptual framework for industry scaling. This is then used to illustrate innovation and technology policies (in general terms) to induce scaling of low carbon energy technologies. Section 6 uses the consistent extent – rate relationship for industry scaling as a quantitative validation measure for technologically explicit climate change mitigation scenarios.

Table 7. Summary of Scaling Meta-Analysis.

Category	Finding
Unit Scaling: Rates ***Section 4.2***	Rate of unit scaling in terms of maximum capacity or at the unit capacity frontier is an indication of the importance of technical returns to unit scale or economies of unit scale.
	Rate of unit scaling in terms of average capacity is an indication of the importance of unit scale flexibility or invariance.
	Rate of unit scaling, particularly for end use technologies, is constrained by heterogeneity across market niches and, more broadly, the nature of demand for the energy service provided.
Industry Scaling: Rates ***Section 4.3***	Industry scaling tends to be more rapid in terms of cumulative total capacity than cumulative total unit numbers.
	Industry scaling tends to be more rapid for technologies with larger unit capacities and/or less unit numbers. CFLs and wind power are anomalies, but are substitution not diffusion technologies (and also have diffused into more globalised markets, and have lower $ costs per unit).
	Both these tendencies of industry scaling rates are robust as technologies diffuse spatially.
Unit & Industry Scaling: Sequence & Relationship ***Sections 4.4-4.5***	Industry scaling tends to be driven sequentially by unit numbers, then unit scaling, then unit numbers (cf. formative, growth, and sustaining phases). This sequence is more pronounced for large unit capacity technologies (with stronger scale economies).
	Unit scaling is more rapid than industry scaling if unit scale economies are available.
	Rapid industry scaling is associated with concurrent (rather than early) unit scaling.
	Rapid industry scaling is associated with more rapid unit scaling.
Unit & Industry Scaling: Spatial Diffusion ***Section 4.6***	Industry scaling becomes more rapid as technologies diffuse spatially from Core to Rim to Periphery. (Supports 'Schmidt's Law': faster diffusion (shorter Δt) but to a lesser saturation density (lower K) as technologies diffuse spatially).
	No evidence for 'unit capacity leapfrogging', i.e., more rapid unit scaling as technologies diffuse spatially. (Extent of unit scaling is, however, lower in Rim and Periphery compared to Core).
Unit & Industry Scaling: Extents ***Section 4.7***	Extents of industry scaling in capacity terms vary by up to 3 orders of magnitude, but dynamics occur over different time periods and time horizons.
	Extents of unit scaling in capacity terms vary by over 5 orders of magnitude.
Industry Scaling: Normalising Extents ***Section 4.8.1***	Extent of industry scaling should be normalised for the size of 'the system' during the diffusion / saturation period of a technology. Primary energy consumption is a good proxy for system size.
	Normalisation is conceptually necessary, but does not substantively change the *relative* extents of industry scaling between technologies because the variance between extents for different technologies is far higher than the variance of primary energy within the relevant time period.
Industry Scaling: Extent – Rate Relationship ***Section 4.8.2***	Relationship between extent and rate of industry scaling is consistent (normalised K vs. Δt on a semi-log plot is linear).
	Consistent extent – rate relationship holds only for industry scaling in terms of cumulative total capacity, not cumulative total unit numbers.
	Consistent extent – rate relationship in capacity terms accelerates as technologies diffuse spatially.
	Consistent extent – rate relationship in capacity terms is not accelerating over time.

5 Conceptual Framework of Scaling

5.1 Developing the Conceptual Framework

This section draws together into a conceptual framework of scaling the various factors found to have influenced scaling dynamics. As the technologies selected for the meta-analysis have all demonstrably and successfully scaled, the conceptual framework represents an empirically-founded basis for assessing policies or approaches for inducing scaling in current or future energy technologies.

Figure 25 summarises the main factors that enable or influence industry scaling, either by driving a build out of unit numbers, or by acting on unit capacity. These enabling factors are broadly of two types:

I. characteristics specific to the technology;
II. characteristics specific to the market or system into which the technology diffuses.

It should be emphasized that these characteristics, and so the conceptual framework, are very general. By way of illustration, Figure 25gives examples of technologies to which each enabling factor applies, both historically (in grey) and potentially in carbon constrained future scenarios (in grey italics). The historical examples are covered in the scaling meta-analysis; the scenario examples are suggestive, based on expected technology or market characteristics.

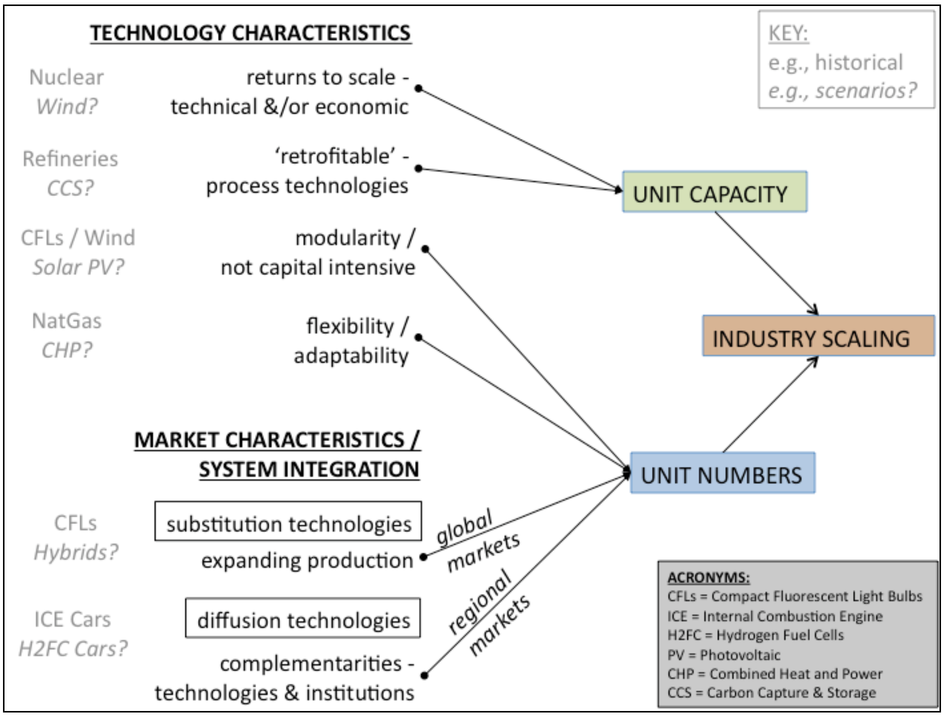


Figure 25. Different Routes to Industry Scaling. A conceptual framework of the factors enabling scaling.

Four technology characteristics shown in the upper half of Figure 25 enable industry scaling:

a. *returns to scale*: technical returns to scale and economies of scale at the unit level are perhaps the most obvious factors enabling unit scaling; these were discussed in the context of nuclear power's rapid unit scaling dynamics at the scale frontier.
b. *'retrofitable':* unit scaling through the retrofitting of existing units rather than the building of new units is a distinctive route to industry scaling characteristic of process technologies; in the sample of technologies analysed, refineries is the only example; capital stock turnover and retirement is potentially less of a constraint for 'retrofitable' technologies.
c. *modularity*: technologies with lower unit capacities, higher unit numbers, and lower capital intensiveness enable more rapid scaling of unit numbers; these characteristics of CFLs and wind power were one potential explanation for their relatively short Δts.
d. *flexibility*: adaptability to heterogeneous market niches, particularly in the absence of strong technical returns to scale or unit scale economies, enables more rapid scaling of unit numbers; natural gas power is a good example historically, particularly when compared to coal and nuclear power which compete as centralised large unit capacity generation plants but lack the scale flexibility of natural gas power; market niches can also be defined by input as well as unit scale; for example, the flexibility of refineries in processing crudes with different compositions and contaminants has supported scaling.

Two market characteristics shown in the lower half of Figure 25 enable industry scaling:

e. *expanding production*: the potential for production or manufacturing capacity to expand is a key enabling factor for scaling of unit numbers, particularly for large n end use technologies; whether this occurs through fewer plants with larger output or more plants with smaller output will depend on product homogeneity and the spatial configuration of demand; as a historical example, the globalised demand for relatively homogeneous CFL products has contributed to its rapid industry scaling.
f. *complementary technologies & institutions*: the potential for complementary developments in supporting technologies, institutions and infrastructures removes a major constraint on both industry and unit scaling; complex technologies may advance through synergistic developments in processes, materials, chemicals, and other components, as well as changes in production techniques, management practices, and market development (see text below for examples).

The importance of these two market characteristics that enable industry scaling is determined by the type of technology and its relationship to the social and technical systems into which it diffuses and integrates. An important distinction is needed between substitution and diffusion technologies (Grübler et al. 1999). This distinction was made earlier in the context of the rapid industry scaling rates of CFLs and wind power compared to, say, cars. Substitution technologies offer ready substitutes to the incumbent, dominant technology. Their relative advantage is typically incremental: for example, a lower cost or greater efficiency per unit of energy service provided. Their diffusion requires little change to existing markets and technological systems. By comparison, diffusion technologies rely on and require significant ancillary changes to other technologies, institutions and infrastructures in order for them to scale. Their relative advantage can be a radical departure from presently available energy services or carriers. The internal combustion engine offered the potential for longer, faster journeys with less frequent refuelling and greater comfort than horse-drawn carriages. But to diffuse, gasoline-powered vehicles also required new technologies (e.g., braking and steering systems, chassis, road building), new infrastructures (e.g., roads, service stations, gasoline distribution), and new institutions (e.g., traffic management rules, road & vehicle maintenance, taxation systems). Diffusion technologies scale through a more complex process of co-evolution between the technology itself, and the markets or systems into which the technology diffuses(Rip & Kemp 1998).

5.2 Using the Conceptual Framework

Interpreted as potential levers for technology and innovation policy to exploit, the enabling factors outlined in Figure 25 comprise different ‘routes’ to industry scaling. Depending on the particular technology in question, policies can target scaling of unit numbers by expanding manufacturing or promoting market niche diversification, or policies can target unit capacity scaling by improving unit scale economies or simplifying the regulations governing retrofits. Table 8provides some examples of these different policy approaches.

Timing, however, is important. As seen earlier, industry scaling tends to follow a sequence of building out unit numbers over an often extended period (the formative or experimentation phase), then quite rapid unit capacity scaling (if returns to scale are available), and then a renewed emphasis on unit numbers as the unit scale frontier is reached. This strikes a cautionary note for policies acting too early in a technology’s commercialisation to support unit capacity scaling; and similarly for policies which presume rather than support the discovery of returns to scale.

Typically, unit capacity scaling occurs earliest in Core markets. Diffusion of any increase in unit scale from Core to Rim and Periphery markets would help drive more rapid industry scaling. However, the historical evidence again suggests caution. Larger unit capacities diffused prematurely into markets without the attendant tacit knowledge and institutional support for successful integration and operation may be inappropriate.

Given the nature of the scaling meta-analysis, this finding is necessarily general. This is not to say, therefore, that rapid unit scaling at the outset of a technology’s diffusion is not feasible. It does, however, raise an important consideration for policymakers. Current emphasis on rapid unit capacity scaling of carbon capture and storage (‘CCS’) technologies (de Coninck et al. 2009) is a good example for which history might suggest a more appropriate initial emphasis on unit numbers not unit capacities. The outcome of unit scaling ‘experiments’ currently underway in China may refute this historical lesson. Rapid and sizeable jumps in unit capacities of both CCS, integrated gasification combined cycle ('IGCC') and other unit and plant-level technologies are expected in the short-term future.

Table 8 illustrates policies that specifically target the two sets of factors that enable industry scaling. Policies are categorised as: technology 'push' or supply-side policies that typically act earlier in the technology lifecycle using R&D to spur innovations towards relative advantages for commercial application; and market 'pull' or demand-side policies that aim to stimulate a market for an innovation, often in protected niches, and so drive the commercialisation process which in turn generates scale economies and learning effects. See, e.g., (Nemet 2009a)for further discussion. Relevant policies for a given technology will depend on its particular characteristics and market environment.

Table 8. Examples of Policies to Enable Industry Scaling.

	Enabling factor for industry scaling	Technology 'push' policies	Market 'pull policies'
I.	***Technology Characteristics***		
I.a	**technical returns to scale / unit scale economies**	conventional late stage R&D investment through first deployment and commercialisation; bridging finance to support early stage venture capital type investment	demonstration projects and field trials at full commercial unit scale
I.b	**retrofitable**	test facilities for assessing retrofits or plug & play modules (e.g., in buildings); extended producer responsibility legislation requiring manufacturers to design reuseable or recyclable products	regulatory shift to support service provision / leasing business models; streamline licensing process for retrofits (versus new builds)
I.c	**modular / low capital intensiveness**	R&D focused on integration of component-based modules (i.e., disaggregation of complex technologies and unit costs); avoid R&D emphasis on rapid unit scaling	regulatory support for small-scale distributed applications (e.g., planning, energy market regulation)
I.d	**flexibility / adaptability**	diversify R&D investments in a technology across multiple sectors and target applications; support R&D for applications in adverse operating environments	create & protect diverse market niches (e.g., multi-sector supply obligations / portfolio standards); use performance or criteria standards rather than technology regulation or standards
II.	***Market Characteristics***		
II.e	**expanding production**	tax credits for investment in manufacturing process scaling	location subsidies or export credit support for concentrated manufacturing & distribution
II.f	**complementary technologies & institutions**	technology roadmapping; open, shared or relaxed intellectual property arrangements within or between research consortia; support cross-sectoral R&D collaborations (e.g., agriculture - energy – chemicals in the case of biofuels)	subsidise early network externalities (especially infrastructure 'seeding')

6 Scenario Analysis

6.1 Scenario Validation

The consistent extent - rate relationship for industry scaling shown in Figure 21can be used as a point of comparison for the technologically explicit scenarios used to assess carbon constrained futures. Specifically: are the growth dynamics of low carbon technologies in future scenarios consistent with historical extent - rate relationships? Comparison of future growth against historical evidence is a means of validating the quantitative modelling assumptions that enrich scenarios' qualitative storylines.

Methodologically, this requires a treatment of technologically explicit scenarios in an identical manner to the historical data sets (see Section 3 for details) comprising the following steps:

i. Compile time series data of cumulative total capacity for different low carbon technologies in future scenarios;
ii. Fit logistic models to time series data and screen for goodness of fit and capacity data exceeding 60% of asymptote (K);
iii. Normalise extent (K) for growth in 'system size' using primary energy consumption data (for the same scenario) measured at t_0 of the logistic function;
iv. Plot extent - rate relationship (normalised K - Δt).

6.2 Scenario & Technology Selection

The technology trajectories assessed in this validation exercise are outputs of the MESSAGE model developed and applied at the International Institute for Applied Systems Analysis (Messner & Strubegger 1995). MESSAGE-generated scenarios have been widely used in the work of the IPCC and others (Nakicenovic et al. 2000; Fisher et al. 2007). The particular set of scenarios used were taken from the recent 'Integrated Assessment Modelling Framework' which encompassed detailed representations of the principal greenhouse gas emitting sectors, including energy, industry, agriculture and forestry, and is described in detail in a special journal issue (Riahi et al. 2007). The global A2r, B1 and B2 scenario families vary across a range of systemic parameters (including economic growth, population growth, rates of technological change, and efficiency gains) and so describe a wide range of greenhouse gas emission profiles and stabilisation scenarios over the period 2000-2100. The A2r family has the highest baseline emissions, and its most constrained stabilisation scenario is 670 ppmv (of atmospheric CO_2-equivalent concentrations measured in parts per million by volume). The B1 family has the lowest baseline emissions and stabilisation scenarios between 480 and 670 ppmv.

Table 9 shows the full range of scenarios; the 8 scenarios selected for this validation exercise are marked in bold / grey cells. Scenarios were selected to examine the widest range of technology trajectories possible. The most constrained scenario in each family describes either the most rapid and/or the most extensive industry scaling for one or more low carbon technology. For example, the constrained B1 scenarios describe strong growth in renewable energy (particularly solar, both centralised and distributed), whereas the constrained A2r scenarios are weighted more towards nuclear, biomass and also carbon capture and storage.

Table 9. Baseline & Carbon Constrained Scenarios. Greyed out cells show the scenarios used in the meta-analysis. Scenarios are taken from IIASA's Integrated Assessment Modelling Framework(Riahi et al. 2007).

Scenario Family	**Stabilisation targets for 2100 (CO_2-equivalent ppmv)**								
A2r				**670**	820	970	1090	1390	**baseline**
B1	**480**	520	590	**670**					**baseline**
B2	**480**			**670**					**baseline**

From each scenario, cumulative installed capacity data were extracted for the period 2000 – 2100 across a range of low carbon technologies that show strong growth in at least one scenario. As the resolution of end use technologies in MESSAGE is highly aggregated (as with most energy sector models), scenario data were limited to supply-side technologies in the electricity generation sector. Technologies analysed included:

- nuclear power;
- natural gas power;
- coal power with carbon capture and storage ('CCS');
- coal + natural gas power with CCS (i.e., all fossil CCS);
- wind power;
- solar PV power (centralised + decentralised).

6.3 Scenario Data & Logistic Fits

For each of the 6*8 technology-scenario combinations, cumulative total capacity data were extracted directly from MESSAGE, and recalibrated to continue from the historical data for 2000.[35] As with the historical data, capital stock lifetime and turnover were not treated explicitly; rather they are implicit within the capacity addition data and help explain scaling dynamics for different technologies. Time series were compiled globally for all technology-scenario combinations, and on a disaggregated 4 region basis for selected combinations. The 4 regions were the same as those used for historical power plant data: OECD (Core); FSU (Rim1); Asia (Rim2); Africa, Middle East, Latin America (Periphery).

Logistic functions were tested for goodness of fit to the cumulative total capacity data describing the full, combined historical + future time series. Logistic models were found to describe industry scaling adequately in all the technology-scenario combinations.[36]

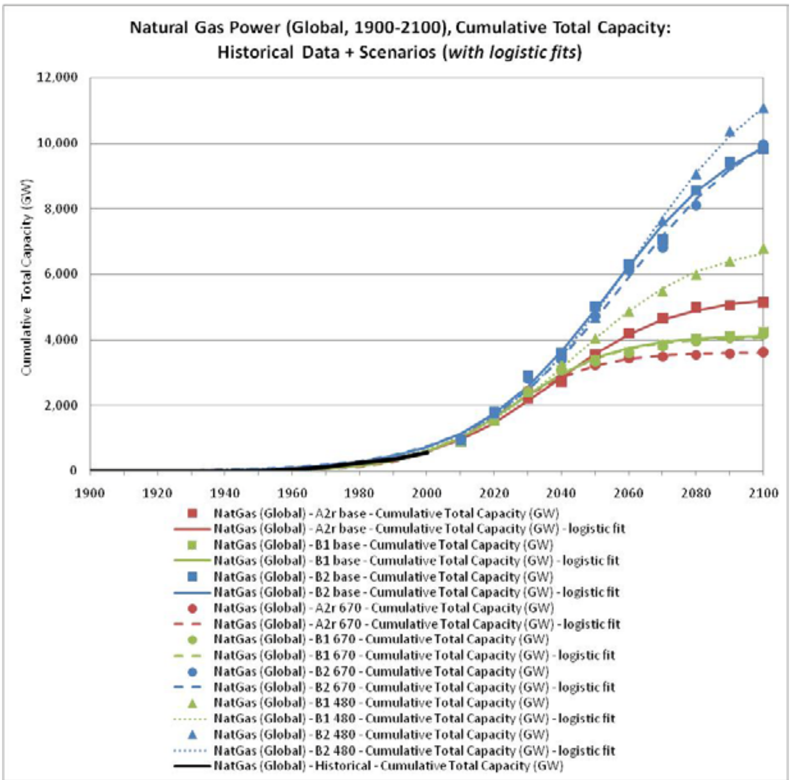
[35] The decadal time steps in MESSAGE start from 1990. Cumulative total capacities are initialized at the net installed capacities for 1990 (i.e., no pre-1990 installed capacity is carried over into the model).
[36] The (trivial) exception are scenarios in which a particular technology showed no diffusion, e.g., CCS in the A2r baseline scenario. As CCS imposes a cost and efficiency penalty on coal power generation, its diffusion is contingent on carbon constraints.

Graphs and further details of both scenario data and logistic fits are included in Appendix B.

Scenario data were not available for unit numbers nor unit capacity scaling. The technological specification of MESSAGE assumes a reference unit (or power plant) of fixed capacity. Exogenously-specified declining capital cost profiles may partly reflect scale economies from larger unit capacities, but this is neither explicit nor disaggregated from other, more commonly modelled learning effects associated with production scaling (see discussion in Section 4.2 and Appendix C).

Figure 26 shows an example of the historical data, scenario data, and logistic fits for the cumulative total capacity of natural gas power and nuclear power globally. Differences between the scenarios in terms of technological change are clear: the A2r family sees more nuclear power, whereas the B2 scenario family relies more on natural gas to meet carbon constraints. Similar differences exist for other technologies depending on the scenario family storyline and the more detailed technological cost, performance, learning and other specifications used to model the scenarios (see (Riahi et al. 2007) for more details). Note that in the case of nuclear power, future growth to a cumulative total capacity of 10 - 25 TW by 2100 renders current levels of cumulative total capacity (0.4 TW in 2000) barely visible on the combined historical + scenario time series.[37]

[37] This is the same for natural gas power, with cumulative installed capacities of 4-11 TW in 2100 compared to 0.6 TW in 2000. This is also the same for CCS, wind power, and solar PV but trivially so because of the very low cumulative total capacity in 2000.



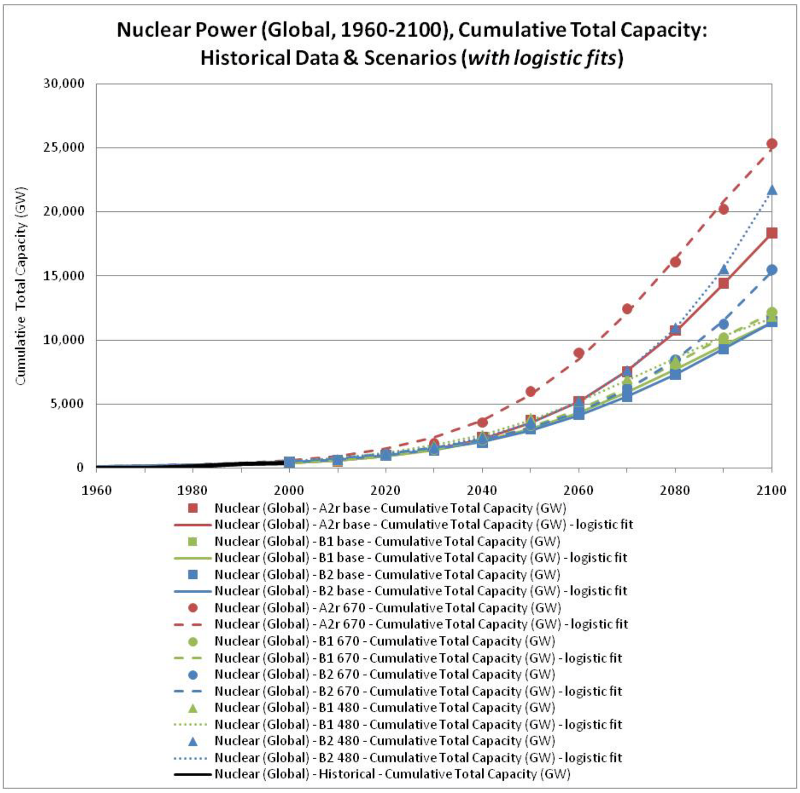


Figure 26. Technology Trajectories in Future Scenarios. Historical data (20th century), scenario data (21st century), and logistic fits (to combined historical + scenario time series) for natural gas power and nuclear power in terms of cumulative total capacity (MW) globally.

6.4 Normalisation of Extents of Scaling in Scenarios

Extents (K) of industry scaling in the 6*8 technology-scenario combinations (measured in terms of cumulative total capacity) were normalised for growth in system size in the same way as historical data. Total primary energy consumption data were taken from the same scenario as the technology data (e.g., B1 baseline primary energy was used to normalise technologies' extent of scaling in B1 baseline scenarios).

As with the historical data, normalisation is necessary for conceptual reasons, but makes little difference to the relative extent - rate relationships between technology-scenario combinations, and also between the historical and scenario data. Figure 27 compares non-normalised extent - rate relationships (left-hand graph) with the normalised extent - rate relationships (right-hand graph) for global data. Data points show all the historical technologies (squares for supply-side, circles for end use) and all the nuclear power scenarios (triangles).

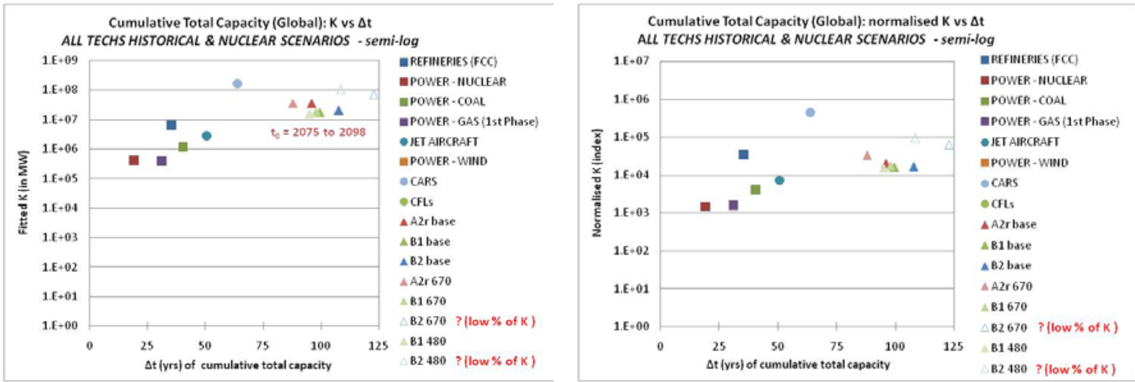


Figure 27. Extent - Rate Relationship of Industry Scaling in Scenarios: Nuclear Power. Extent (K in left-hand graph, normalised K in right-hand graph) vs. rate (Δt) of industry scaling in terms of cumulative total capacity (MW) globally for all historical technologies (squares & circles) and for nuclear power in 8 scenarios (triangles). Unshaded data points for B2 480 & B2 670 scenarios are indicative only as scenario data reached < 60% of fitted K. Note log scale y-axis.

Two scenario data points (B2 480 and B2 670) are shown as unshaded triangles and suffixed with a ? in the key. This denotes that the scenario data (to 2100) reached less than 60% of K in the fitted logistic model. This was the criterion set out in Section 3 to ensure the fitted asymptote was reliable. These two data points are included for indicative purposes only.

The inflection points (t_0) in the nuclear power scenarios fall in the period 2075 - 2098, as shown on the left-hand graph. Total primary energy consumption at each scenario's respective t_0 was used to normalise the fitted K parameters, as shown in the right-hand graph. Although the y-axis changes from fitted K in MW to normalised K as an index, the relative position and ordering of both the historical data points and the scenario data points remains very similar. As with the normalisation of historical data, the range of extents of industry scaling is 2-3 orders of magnitude higher than the maximum change in primary energy, as shown in Table 10.

Table 10. Range of Scaling Extents & Primary Energy Growth: Scenarios.

SCENARIOS	Fitted K (MW)	Primary Energy (EJ) at t_0	Primary Energy (EJ) over Full Range
Min	$4*10^5$ (coal+CCS, B1 baseline)	615 (in 2022; t_0 natgas in A2r 670ppmv)	389 (in 2000)
Max	$1*10^8$ (nuclear, B2 480ppmv)	1747 (in 2099; t_0 nuclear in A2r baseline)	1753 (in 2100, A2r baseline)
Max / Min	***2500***	***3***	***5***

6.5 Comparison of Historical & Scenario Data

The right-hand graph in Figure 27 compares the normalised extent - rate relationships for nuclear power in the 8 scenarios with all the historical data points.[38] Compared to the historical data, cumulative total capacities of nuclear power in future scenarios all have substantially higher Δts (i.e., slower rates of industry scaling). The comparison of Δts is made clearer in Figure 28.

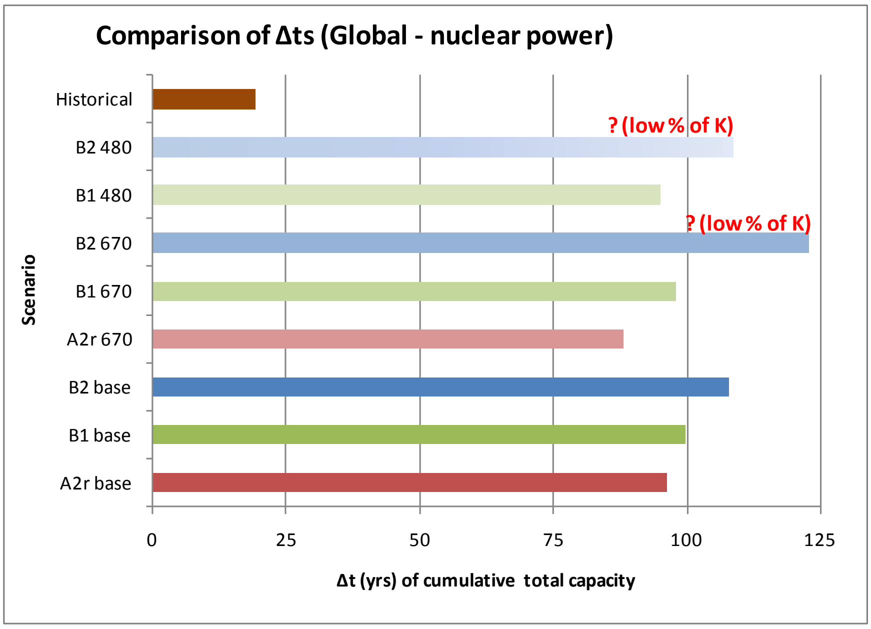


Figure 28. Rates of Industry Scaling for Nuclear Power: Historical & Scenarios. Δts in terms of cumulative total capacity (MW) globally for nuclear power both historically and in 8 scenarios. Bars for B2 480 & B2 670 scenarios are indicative only as scenario data reached < 60% of fitted K.

[38] There are 6 historical data points in total. Global growth of wind power and CFLs is still exponential and so logistic fits are not reliable.

In the scenarios, nuclear power is projected to grow by two orders of magnitude in terms of cumulative total capacity (from ~0.4 TW in 2000 to 11-25 TW in 2100). But once this extent of industry scaling is normalised and assessed against the timescales over which it is reached, *the scenario projections are conservative compared to known historical dynamics of industry scaling for energy technologies.*

Put another way, scenario projections of nuclear power under carbon constraints show similar extents of scaling to those evidenced historically, but at much slower rates. To bring the nuclear scenario data points in line with the consistent historical extent - rate relationships, either normalised Ks would have to increase by another 3 orders of magnitude, or Δts would have to halve. This surprising finding is explained by the scenarios' slow rates of scaling, shown starkly in Figure 28. Reasons for this are discussed in the next section.

The extent - rate relationships for natural gas, wind and solar power in the scenarios relative to the historical data points are similar to those for nuclear power: within the historical range of normalised extents, but with longer Δts. Figure 29 shows the comparison for wind power. The relative position of the scenario data points below and to the right of the upwards sloping historical relationship is similar to that shown in Figure 27for nuclear power.

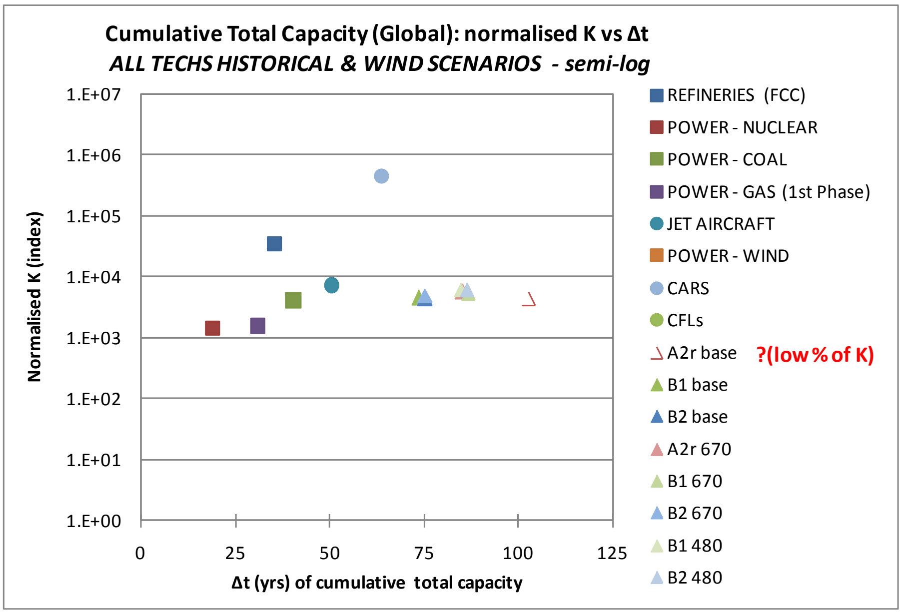


Figure 29. Extent - Rate Relationship of Industry Scaling in Scenarios: Wind Power. Extent (normalised K) vs. rate (Δt) of industry scaling in terms of cumulative total capacity (MW) globally for all historical technologies (squares & circles) and for wind power in 8 scenarios (triangles). Unshaded data point for A2r base scenario is indicative only as scenario data reached < 60% of fitted K. Note log scale y-axis.

Carbon capture & storage ('CCS') is the only technology in the scenarios that approaches the historical extent - rate relationship. Figure 30 shows the comparison for all fossil-based CCS, i.e., coal power and natural gas power combined. The B2 670 data point is indicative only as the scenario data reached less than 60% of the fitted K. Although the cluster of scenario data points still lies to the right of the upward sloping historical relationship, there is some overlap as the Δts are in the range of 24 - 66 years (compared to the historical range across all technologies of 19 - 64 years, with nuclear power and cars as the minimum and maximum respectively). As shown in Figure 31, industry scaling of CCS lies predominantly in the second half of the 21st century in the most carbon constrained scenarios (B1 & B2 480 ppmv). Its delayed scaling relative to other low carbon technologies is a function of modelling cost and performance assumptions which reflect its relative immaturity.

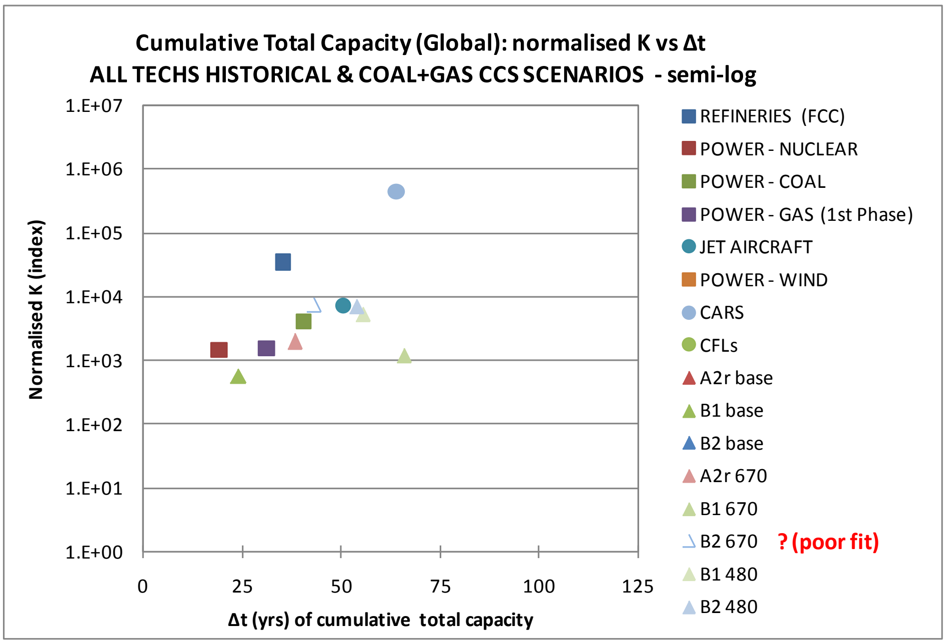


Figure 30. Extent - Rate Relationship of Industry Scaling in Scenarios: Coal+Gas Power with CCS. Extent (normalised K) vs. rate (Δt) of industry scaling in terms of cumulative total capacity (MW) globally for all historical technologies (squares & circles) and for coal+natural gas power with carbon capture and storage ('CCS') in 8 scenarios (triangles). Data point for B2 670 scenario is indicative only as logistic fit was poor. Note log scale y-axis.

That industry scaling of renewables is more conservatively modelled than CCS is also surprising in light of the stronger 'diffusion' characteristics of CCS with its requirements for a whole new distribution and storage infrastructure (Bielicki 2008). Renewables, particularly centralised wind and solar, are clearer substitutes for conventional utility-scale power plants, requiring less ancillary changes to existing institutions and related technologies (Grübler et al. 1999)

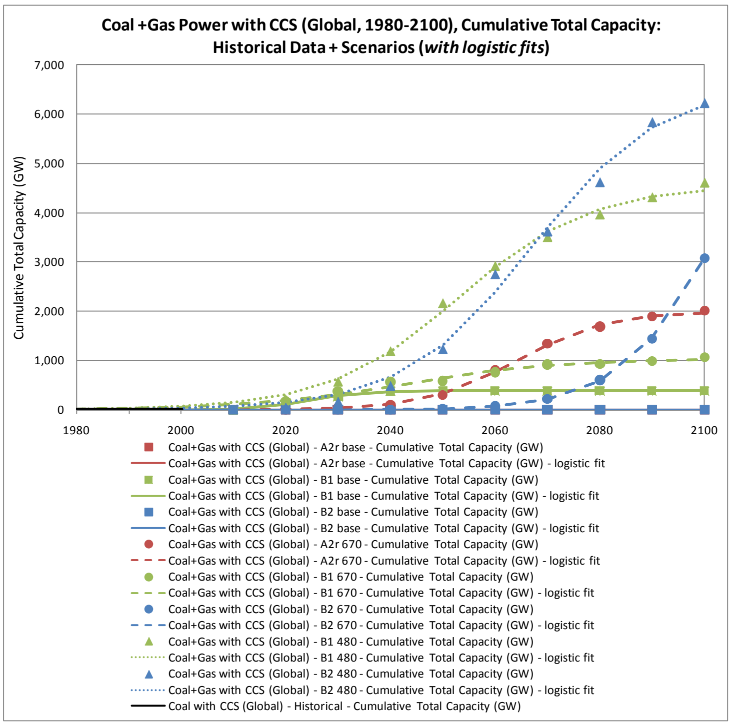


Figure 31. Scaling of CCS in Future Scenarios. Scenario data and logistic fits for coal and natural gas power with carbon capture and storage ('CCS') globally.

Figure 32 brings together the historical and scenario data on industry scaling for all the technologies. The pattern is striking. With the exception of a small number of CCS scenarios (combining both coal and natural gas power), all the scenario data points lie to the right of the empirically-founded historical extent - rate relationship. *Industry scaling of all technologies in all scenarios is therefore more conservative than the historical record indicates is feasible.* This conservatism is attributable to the slow projected rates of industry scaling.

As with the historical data, this observed pattern holds if the global data are disaggregated regionally. Figure 33 shows the same plot as Figure 32 but for the Core region and for a reduced number of scenario data points: nuclear power, all fossil CCS, and solar PV. Note that the historical extent – rate relationship is steeper than for the global data as the K – Δt relationship 'accelerates' or flattens out from Core to Rim (see Section 4.6 & 4.8.2 for discussion).

Two points from Figure 33 are salient. Firstly, the historical data points and scenario data points for each technology have the same relative position regionally as globally. So the discussion above relating to the global data applies equally to the regional data. Secondly, the fossil CCS data points are again the closest to the historical pattern, and in some cases are strongly overlapping. Again, this is for the same reasons as explained above with respect to the global data: concentration of CCS growth in the second half of the 21st century and so shorter Δts.

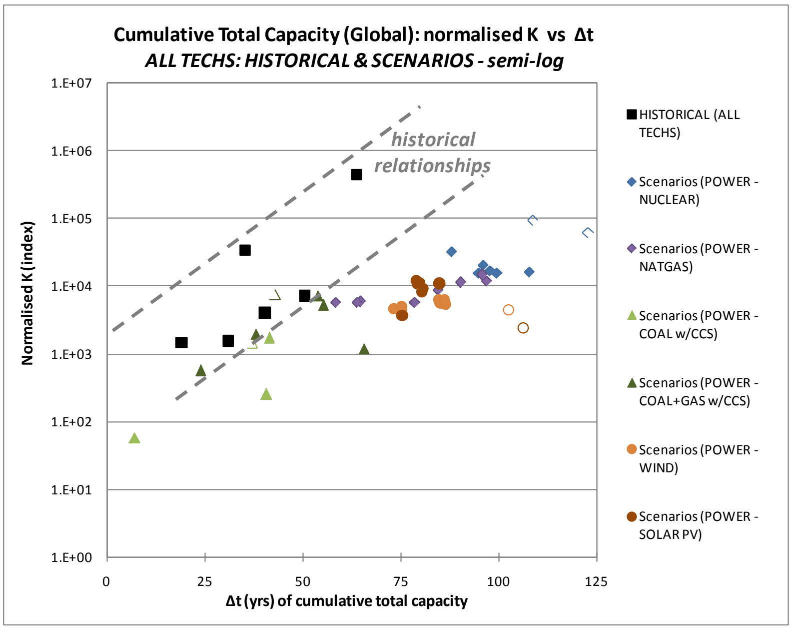


Figure 32. Extent - Rate Relationship of Industry Scaling in Scenarios: All Technologies. Extent (normalised K) vs. rate (Δt) of industry scaling in terms of cumulative total capacity (MW) globally for all historical technologies (black squares) and all technology-scenario combinations (diamonds, triangles, circles). Grey dotted lines show general upward-sloping pattern of historical extent - rate relationships. Unshaded data points are indicative only. Note log scale y-axis.

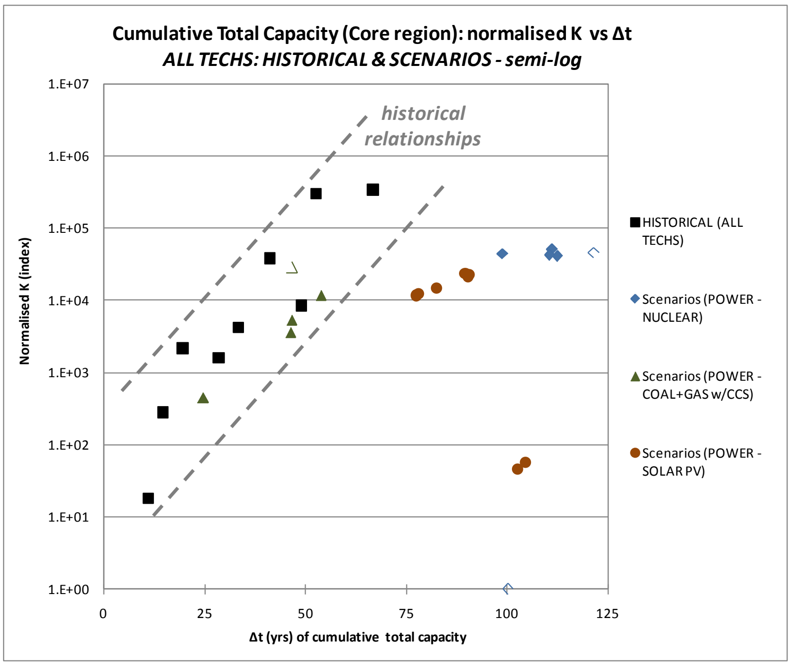


Figure 33. Extent - Rate Relationship of Industry Scaling in Scenarios: All Technologies (Core region). Extent (normalised K) vs. rate (Δt) of industry scaling in terms of cumulative total capacity (MW) in the Core region for all historical technologies (black squares) and all technology-scenario combinations (diamonds, triangles, circles). Grey dotted lines show general pattern of historical extent - rate relationships. Unshaded data points are indicative only. Note log scale y-axis.

6.6 Reasons for Scenario Conservatism

There are various possible reasons why the extent - rate relationships of industry scaling appear conservative in future scenarios relative to observed historical dynamics:

i. the historical data on industry scaling are not directly comparable with the scenario data;
ii. a single time series of cumulative historical + future installed capacity data will inherently describe slow rates of scaling overall, though it may comprise several shorter periods of faster logistic growth including the one for which historical extent - rate relationships were estimated;
iii. MESSAGE specifically, or technologically explicit energy system models in general, are parametrically conservative with respect to industry scaling in terms of market penetration constraints, resource constraints, or learning rates;
iv. MESSAGE specifically, or technologically explicit energy system models in general, are structurally conservative by omitting an explicit representation of unit scaling dynamics.

6.6.1 Discontinuities between Historical Data & Scenarios

Historical extent - rate relationships may not be meaningfully comparable to scenario data if the historical context for scaling is fundamentally different or *discontinuous* from the future context represented in the scenarios. This discontinuity argument was raised in the introduction to this paper. Greenhouse gas constraints, policies for inducing technological change, globalised markets, strong regional growth in Asia are all potential examples of fundamental difference between the 21st and 20th centuries that affect technology scaling.

It is worth noting that all these examples of discontinuity should lead to more aggressive not more conservative extent – rate relationships (i.e., more rapid and/or more extensive scaling). However, the question here is not about discontinuities between the previous and coming centuries, but about discontinuities between the previous century and energy system models' representation of technological change in the coming century. This distinction is important because it reduces arguments about ongoing transformations of the energy system under climate constraints to a simple question of model structure with respect to technological change. At least in theory, models are structured on empirically-founded learning rates, economies of scale, market penetration dynamics, and so on. Similarly, historical evidence on cost and performance trends are used to parameterise models.[39] (See Section 6.6.3 for a discussion of these assumptions). As a result, there is no obvious discontinuity to suggest scaling relationships in the scenarios should not be directly comparable with the historical record.

6.6.2 Nested Scaling Dynamics

The logistic models fitted to scenario data described the scaling of cumulative total capacity over the full course of a technology's (future) history. These single time series

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[39] Note that this does not mean MESSAGE, or any other energy system model, could faithfully reproduce historical dynamics, not least because MESSAGE is an optimisation model implicitly representing the perspective of a cost minimising social planner.

ran from the 1900s in the case of natural gas power, the 1950s (nuclear power), the 1970s (wind power and solar PV), and the 2020s (CCS, depending on the scenario). They ranged in length, therefore, from 80-200 years. For all 6 technologies (across all the scenarios analysed), logistic models were extremely good fits for this 'centurial' time trend. This is clearly shown in Figure 26 for natural gas power and nuclear power, in Figure 31 for CCS, and in Appendix B for the other technologies. (The lowest R^2 as a goodness of fit measure was 98%).

But the historical analysis demonstrated that logistic models also describe industry scaling in the case of natural gas power from 1903 to the late 1970s (the end of the '1st growth phase'), and in the case of nuclear power from 1956 to 2000. The 'centurial' pattern of logistic growth in the combined historical + future time series data for the scenarios therefore incorporates - and conceals - at least one, and potentially more 'episodic' patterns of logistic growth. Using the 'centurial' dynamic rather than any (future) 'episodic' dynamics *inherently* means slower rates or longer timescales (Δts) of industry scaling.

But longer timescales (Δts) should also mean greater extents of industry scaling. If K and Δt are affected proportionately by the step up from an 'episodic' to a 'centurial' timeframe, the extent – rate relationship shown in Figure 32 should still hold. So, again, the scenarios should be directly comparable with the historical record. The assumption that K and Δt are affected proportionately, or that the elasticity of K with respect to Δt is consistent over a range of Δts, is considered in more detail in Section 7.[40]

6.6.3 Model Conservatism

Optimisation models with perfect foresight require technologically-specific constraints to prevent dramatic changes in market shares as parameters vary (Grübler & Messner 1996). An optimal, cost minimised solution for a given set of model conditions may swing from a dominant market position of technology A to a dominant market position of technology B if technology B's relative cost is reduced only marginally. To prevent such unrealistic outcomes, the diffusion rate of specific technologies is limited. In MESSAGE, this takes the form of market penetration constraints (e.g., maximum of *x*% growth in installed capacity over time period *y*) that are based on observed trends and realistic extrapolations. It is possible that these market penetration constraints used in MESSAGE underestimate the rate at which the installed capacity of power technologies may grow. Their calibration is, essentially, conservative.

The same argument could apply to the cost parameters used in MESSAGE for specific technologies. For capital costs, in particular, assumptions are made about future cost reductions through learning or experience as well as scale economies.[41] As with the market penetration constraints, these assumptions are based on empirical trends and realistic extrapolations. These too may be conservative. Moreover, cost assumptions may play out differently depending on other model parameters and constraints. For

[40] Recall from Section 4.8.2 that the elasticity of K with respect to Δt increases as technologies diffuse spatially. Here, the consistent elasticity of K with respect to Δt over a range of Δts applies at a given spatial scale.

[41] Learning can be modelled endogenously, but not in perfect foresight models as technologies are simply selected based on their (known) expected future costs. For further discussion, see (Gritsevskyi & Nakicenovic 2000; Ma & Nakamori 2009).

example, fossil CCS plays a role as a bridging technology to biomass CCS which effectively has negative emissions as it stores biologically sequestered atmospheric CO_2. Even though costly, low stabilisation targets may require its deployment. But as costs through the 21st century are discounted at some positive rate, this deployment will be delayed as much as possible so as to minimise net present costs. Cost assumptions should therefore be sensitised alongside discount rate assumptions.

In general terms, though, the key issue to be tested is whether overly restrictive model parameters for a given technology result in unduly slow rates of industry scaling for a given extent ,i.e., a longer Δt for a given K.

One other way in which MESSAGE could be structurally conservative with respect to industry scaling is in its omission of unit scaling dynamics. As noted above, the cost and performance criteria for technologies are based on a reference unit of fixed capacity. In the case of nuclear power, and CCS for natural gas and coal power, this reference unit is close to the known or anticipated scale frontier (1.5 GW and 1 GW respectively). As the model tracks capital stock in aggregate capacity terms, a unit-by-unit analysis is not required. Declining capital cost profiles (in $/MW) may capture economies of unit scale, but these are not distinguished from more general learning effects associated with cumulative experience (see Appendix C).

It is not clear, however, that modelling reference units with logistic scaling dynamics would substantially increase the rate and/or extent of industry scaling, particularly as existing reference units of constant capacity are near the scale frontier to begin with. Characterising the initial diffusion phase of a technology by many small unit capacities may in fact have the opposite effect in the absence of concurrent adjustments to the model's treatment of industry scaling dynamics. To take one example, the model does not (can not) *explicitly* represent the seeming importance of building out unit numbers before scaling unit capacities (see Section 4.4). Rather, this is all captured *implicitly* by the time profile of technology cost reductions. Testing for the effect of omitting unit scaling is akin therefore to testing for the effect of unduly restrictive cost and market penetration constraints.

6.7 Further Research

The 'model conservatism' explanation for the historical - scenario differences in industry scaling is testable. Incrementally relaxing the market penetration constraints and/or reducing the cost parameters for a particular technology should result in a more rapid and more extensive industry scaling dynamic. The relevant data points in Figure 32and Figure 33should swing up and to the left. At some point, they should shift to within the consistent historical extent - rate relationship bounded by the pair of dotted lines. In effect, this would back-calculate the minimal constraints on technology penetration needed so that future dynamics were consistent with historical dynamics. These minimal constraints (market penetration rates, cost reductions) could then be compared with observed data to revisit their basis and examine whether they are overly restrictive.

Figure 32 suggests that constraints on the expansion of wind power and solar PV power are tighter than those for CCS as they lie further from the historical trend. As noted above, a key difference between CCS and the renewable power technologies is their commercial status. For CCS this remains largely unproven which in turn delays its recruitment into the portfolio of low carbon technologies until later in the 21st century (as required by an additional set of model constraints). This contributes to its compressed scaling and so faster rate. Again, this hypothesis is testable by back-calculating the market penetration rates and cost reduction profiles needed to bring each technology-scenario combination in line with historical dynamics.

7 Discussion & Conclusions

7.1 Critiques

Various issues with the methodology and findings were raised through the text. These are discussed here, in conjunction with several other critiques of the approach taken:

i. the data forms of different technologies are incommensurate;
ii. the spatial disaggregations of different technologies are incommensurate;
iii. the arbitrary selection of technologies & units biases the results;
iv. the exclusion of non-logistic growth forms biases the results;
v. the extent – rate relationship is a trivial artefact of nested sequential logistics.

7.1.1 Incommensurate Data Forms

Industry scaling data were measured in terms of installed capacity (power generation, refineries), production (aircraft, cars) and sales (CFLs). For these measures to be commensurate, an implicit assumption is made that losses from production to sales, and from sales to installation (or use) are negligible. Given the first order nature of the analysis, this is considered robust.

However, these differences also impact the regional disaggregation. The Core region variably describes where technologies are installed but not necessarily manufactured (supply-side technologies) or where they are manufactured but not necessarily used (end use technologies). In the former case, spatial diffusion dynamics relate to the assimilative capacities of energy systems at different stages of development; in the latter case, to the manufacturing capacities of economic systems at different stages of development. It is the latter case, therefore, that introduces confounding factors such as trade relationships, relative manufacturing costs, industrial polices and so on, which extend well beyond the energy system.

It is unclear whether these differences substantively affect comparative scaling dynamics for technologies within a particular region. It seems likely that technologies with a clear distinction between region of manufacture and region of use would be most affected. In the meta-analysis sample, this holds only for CFLs (imported from Rim2 into Core markets). But the CFLs data are not based on manufacturing but rather on sales which should relate strongly to use. Moreover, differences between installation/use data and manufacturing data should not affect the global analysis, and in general, both global and regional scaling dynamics and relationships are consistent.

A third source of potential incommensurability in data forms relates to capital stock turnover. With the exception of refineries, capacity measures of industry scaling were all calculated cumulatively without accounting for capital stock retirements, shutdowns, and so on. As refinery capacities are expressed as annual totals, associated rates and extents of industry scaling should be biased downwards. It is not clear whether both rates and extents will be affected proportionately and so remain consistent in terms of the extent – rate relationship. As a mitigant, refineries are a process technology whose expansion, particularly in mature markets, is driven by retrofits ('revamps'). Scaling by retrofits rather than new additions should reduce the difference between cumulative total and annual total measures of capacity. (See Appendix A for a plot of US refinery capacity expanding markedly over the 30 year period from 1949 to 1979 against a backdrop of falling refinery numbers).

7.1.2 Incommensurate Definition of Regions

The regional disaggregation of technology data was based on the sequence of diffusion. As this differs between technologies, so too do the definition of Core, Rim2 and Periphery regions. (If used, the Rim1 region is consistently the former Soviet Union and Eastern Europe). As an example, the Core region for wind power is Denmark, a single country with a largely integrated electricity network and GDP in the order of $0.3 trillion (in 2008 $). By comparison, the Core region for coal power is the OECD, an aggregation of more than 20 developed countries dispersed globally with distinct electricity networks and a combined GDP two orders of magnitude higher.

Do differences in the geographic or economic 'size' of regions affect the comparison of different technologies' regional scaling dynamics?

Clearly, the potential *extent* of industry scaling is far larger in the OECD compared to Denmark. But of relevance here is whether the potential *rate* of industry scaling is correspondingly slower, as it is the extent – rate relationship that is of interest. Alternatively: is the elasticity of K with respect to Δt consistent over different sizes of region? (A related question raised in Section 6.6.2 was whether the elasticity of K with respect to Δt is consistent over a range of Δts).

If a technology diffuses concurrently in all the distinct markets comprising a region, then it is possible that K will increase proportionately more than Δt for larger regions. Conversely, regional Δts will be longer if diffusion in their constituent markets is sequential, replicating the core to rim to periphery dynamic at a smaller scale. This too is more likely in larger regions.

Within the larger regions used in the meta-analysis, dates of first commercialisation do certainly vary between constituent markets (e.g., coal and natural gas power in different OECD countries). However, the growth phases across these markets are broadly concurrent, and it is these growth phases that define the Δt (covering diffusion from 10 to 90% of K).

Ultimately, this biasing effect can be tested for by further disaggregating regional data into all its constituent markets, and assessing whether the extent - rate relationship holds at different spatial scales. Alternatively, identical regions could be used for all technologies, although this would invalidate the spatial diffusion dynamics if regions no longer corresponded to core, rim and periphery markets for specific technologies.

7.1.3 Arbitrary Selection of Technologies & Units

As noted in Section 2, the selection of technologies for inclusion in the analysis was based on (i) available data (ii) being describable by logistic models (iii) in meaningful MW capacity terms. Each criterion meant the exclusion of certain technologies: helicopters, coal-to-liquids, prime movers, tankers and pipelines in the case of data availability; solar PV and mobile phones in the case of non-logistic growth; mobile phones, semiconductors in the case of MW capacity terms.

Data for each technology that met these criteria were compiled at both unit and industry levels. Whereas the definition of an industry in terms of total capacities installed or produced is generally unambiguous, the definition of a technological 'unit' is more subjective. The working definition of 'unit' used to guide the data selection was the level of complexity for which capacity metrics, scaling dynamics *and* role in the energy system were clearest. This was further specified as the highest level of operational aggregation before inclusion of market and institutional factors: hence car production not car engine manufacture; and conversely, refineries not distillation or cracking units. As steam and gas turbine unit installations are often sequential rather than simultaneous, these comprised the technological unit rather than the full power plant (and likewise for wind turbines).

As these technology and data selection criteria were applied retrospectively, was the meta-analysis biased by the arbitrary inclusion of only those technological units that were known to have evidenced logistic growth in capacity terms and for which data were available?

Firstly, no technologies were excluded *a priori*. The initial net was cast widely, and without prejudice to known logistic growth forms. The 5 supply-side and 3 end use technologies used in the meta-analysis were the subset of technologies that met all the criteria imposed by the methodology.

Secondly, although the meta-analysis is weighted towards power generation, refineries and the 3 end use technologies also all fit within the consistent extent - rate relationship, and share certain similarities in scaling dynamics (see Section 4). It is these commonalities between different technologies in distinct niches of the energy system that mitigates concerns of technology selection bias.

Thirdly, the requirement that each technology's unit capacity should be meaningfully expressed in terms of power rating certainly limits the scope of the meta-analysis to energy technologies, narrowly defined. Investment cost as an alternative cross-technology measure of capacity was considered but rejected both on grounds of data availability and because it introduced many confounding factors especially given the long timescales of the data series. So although the capacity metric limits the potential for generalising the findings, it does not invalidate the methodology *per se*.

7.1.4 Biasing Effects of Excluding Non-Logistic Growth

The exclusion of non-logistic growth forms (at both unit and industry levels) is a specific case of the general critique that data selection criteria and methodology were arbitrary and so bias the findings. Reasons for using the logistic function as a cross-technology model with measures of both growth rate and extent were set out in Section 3. The resulting exclusion of technologies like solar PV that are still diffusing exponentially certainly means the meta-analysis is biased towards mature technologies with slowing or saturating growth rates, at least in a 1st phase of their overall lifecycle (e.g., nuclear power). The meta-analysis is similarly biased towards early adopter or 'technologically mature' regions for the same reason. CFLs and cars may show signs of saturation in the OECD, but not in Asia.

So does the exclusion of non-logistic growth forms, in terms of either technologies or regions, bias the findings?

Firstly, exponential growth is not incommensurate with a logistic model; the post-takeoff phase of a logistic model is exponential in form. Rather, as set out in Section 3, exponential growth simply makes the fitting of a logistic model unreliable, magnifying uncertainties particularly with respect to the asymptote parameter (Debecker & Modis 1994).[42] The pervasiveness and conceptual robustness of S-shaped growth forms suggests technologies with exponential growth are not systematically different from those with logistic growth, they are just being observed at an earlier phase of their lifecycle.

Secondly, as also noted above, this critique certainly limits the potential for generalising findings to mature technologies whose full lifecycle through commercialisation, takeoff, growth, slowdown, and saturation is evidenced in the data. Similarly, the findings are certainly more robust for mature markets.

Thirdly, as with diffusion studies in general, the meta-analysis is biased towards technologies that 'succeeded'. Again, this is a limitation but one that chimes with the application of findings towards policies and scenario projections of low carbon technologies that are normatively expected to succeed.

7.1.5 Extent – Rate Relationships for Nested Sequential Logistics

In the discussion of scenario conservatism in Section 6.6, the question was raised as to whether industry scaling observed over 'centurial' timescales (of combined 20th and 21st century growth) should maintain the same extent - rate relationship as industry scaling observed over 'episodic' timescales (e.g., the 1st phase growths of natural gas power or refineries in the 20th century). Specifically, do longer timescales of analysis lengthen Δt proportionately more than they increase K? If this is so, then the apparent scenario conservatism shown in Figure 32 may simply be an artefact of the logistic function methodology.

This question only applies to the data series of cumulative total capacity to which nested sequential logistic functions are fitted. Each of these nested functions shares the same timing of first introduction of a technology and initial growth dynamic; but each function then differs as to the growth inflection point, saturation dynamic and eventual asymptote. This is important, as it distinguishes the question here from the more commonly addressed problem of identifying sequential growth phases that are summed into an overall, potentially non-logistic growth pattern.[43]

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[42] One alternative considered was to calibrate uncertain estimates of saturation densities using additional assumptions on future market size, market penetration and so on. Ultimately, however, this calibrated measure of extent remains a subjective best guess.

[43] Meyer depicts different decompositions of time series data into overlapping logistic growth curves (Meyer 1994). The sequential logistic is the simplest (and reflects the pre- and post-oil shock growth

An iterative experiment in fitting nested sequential logistics to longer and longer segments of an overall logistic curve offers only a partial answer to the question. Figure 34 shows two different sets of nested sequential logistic curves, both displaying reasonable fits to an overall logistic curve which is analogous to the combined historical + future time series. Figure 35 then shows the extent – rate relationship plot for both sets of curves. As can be seen, the first set of nested sequential logistics clearly show a flattening of the K – Δt relationship, whereas the second set clearly show a linear relationship (on the semi-log plot).

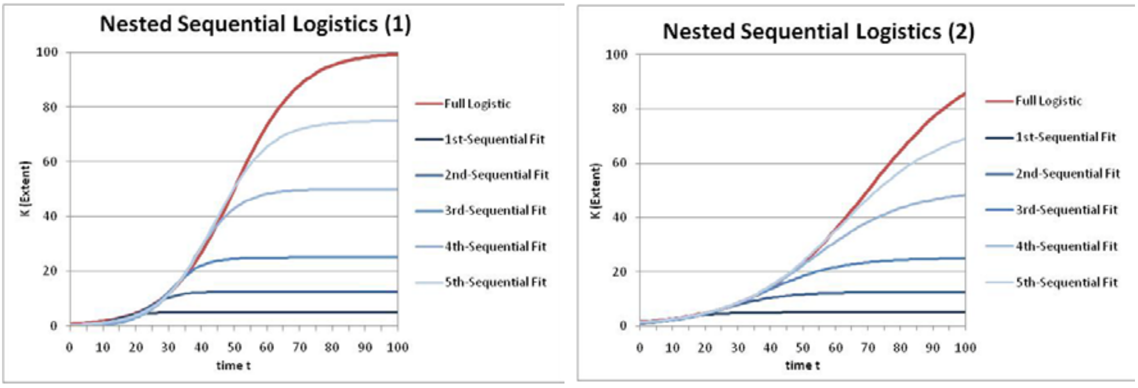

Figure 34. Nested Sequential Logistics. Two sets of nested sequential logistics fitted to different overall or 'full' logistics. Each logistic shares the same initial and early growth, but has different inflection points and asymptotes.

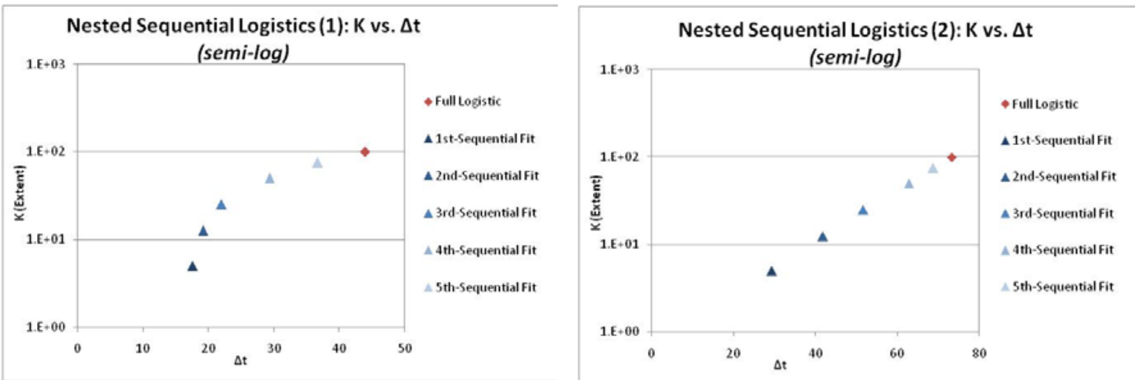

Figure 35. Extent - Rate Relationships for Nested Sequential Logistics. Extent (K) - rate (Δt) relationship for two sets of nested sequential logistics. Note log scale y-axis.

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pattern of natural gas power). But a single *asymmetrical* S-shaped growth pattern can also be decomposed into two concurrent logistic functions with different rates and extents. In either case, the single 'bi-logistic' growth function is the simple sum of the two component logistic functions.

This simple experiment suggests there is no inherent reason or mathematical property of the logistic function which means longer timescales of analysis lengthen Δt proportionately more than they increase K. So the flattening of the extent – rate relationship in the scenarios compared to the historical data is not a simple artefact of the methodology. However, as the first set of nested sequential logistics shows, it can not be ruled out as a partial explanation.

Ultimately, this relates to the subjectivity of model fitting. Figure 36 shows the same graphs as in Figure 34 but with a log y-axis to show the goodness of model fits over short timescales. These are the parts of the overall logistic curve which are most weakly described by the nested sequential models. And for the first of the nested sequential models with the lowest asymptote, these parts also comprise most of the relevant period of the overall logistic curve. It is important to emphasize, therefore, that this corresponds to the historical meta-analysis relative to the combined historical + future time series in the scenarios.

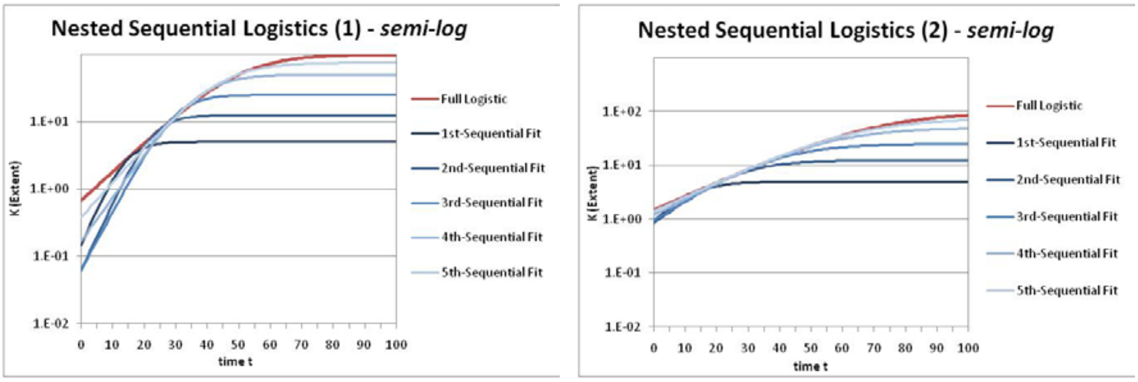

Figure 36. Uncertainties in Nested Sequential Logistics. Two sets of nested sequential logistics fitted to different overall or 'full' logistics but shown on log y-axis to illustrate model fitting uncertainty during the initial period of low t. Note that for the 1st sequential fit in particular, this period corresponds to most of the relevant part of the full logistic.

7.2 Conclusions

Further research is needed in response to these critiques, particularly with respect to the regional disaggregation and extent – rate relationships in nested sequential logistics. But these are refinements to further test the robustness and potential for generalising findings, rather than fundamental methodological problems. In general, therefore, the methodology is considered a valid basis for comparing widely different energy technologies using standardised metrics that encapsulate both rates and extent of growth at both unit and industry level.

Various key findings emerge, not least that unit scaling typically occurs after an initial formative phase of building out unit numbers, and that industry scaling is more rapid but to a lesser extent as technologies diffuse spatially. However, no ‘leapfrogging’ of unit scaling is evidenced. (See Table 7 for a summary of other findings).

These findings are interesting precisely because they are largely robust across different technologies in different regions at different times. The additional finding of a consistent extent – rate relationship for industry scaling across many technologies is perhaps the most surprising, but also the most tentative. More data points covering a wider range of technologies are needed to test the upward-sloping relationship shown in Figure 19 and Figure 21.

The potential to harness these and other patterns found historically provides some general insights for technology and innovation policy seeking to induce low carbon technologies in the future (see Table 8 for examples). The quantitative relationships are also a useful means of validating or ‘reality checking’ scenario projections of low carbon technologies, and exploring their constraints.

As a cautionary note, the meta-analysis is first order. Its inherent generality means it can in no way be used to predict the likely success or scaling rates of any particular low carbon technology. In the same vein, although the general form of the consistent extent – rate relationship shown in Figure 21 is exponential (or linear on a semi-log plot), the elasticity of extent with respect to rate has intentionally not been calculated to avoid any sense of false precision.

The meta-analysis is also predicated on technologies that have ‘succeeded’ and that are ‘mature’ enough to have exhibited signs of saturation. This in turn makes the findings more robust in initial or Core markets compared to later or Periphery markets. Generalisation of findings beyond successful, mature technologies should therefore be more cautious, although the limited number of data points in Rim and Periphery regions confirms the broad trends observed globally and in Core regions.

Thus, the use of logistic functions in the meta-analysis is a strength in that it provides a common growth form with both rate and extent parameters, but also a weakness in that it excludes technologies early in their lifecycle with exponential growth forms. Another common critique of logistic growth models centres on the prediction of saturation densities and/or timings. It should be emphasized again, therefore, that the use of logistic models here is purely to *describe* observed historical data or modelled scenario data.

7.3 Further Research

Many of the areas for further research to extend the scaling meta-analysis and strengthen its methodology have been raised in the text. Most obviously, findings could be interpreted with greater confidence if more data points are found to fit the observed patterns. Further data collection could extend the scope of energy technologies analysed, particularly on the demand-side and also towards older technologies with a saturation and substitution dynamic clearly established. Examples of additional technologies include piston aircraft, steamships, rolling stock, industrial motors, and any number of household appliances (e.g., fridges, microwaves, TVs). On the supply-side, biofuel production (e.g., ethanol, biodiesel) would extend the set of non-power technologies.

Other key issues raised in the critiques include the potential biasing effects of different region sizes, data forms, and technology exclusions. These can all be explored further: by disaggregating regions into constituent markets and comparing scaling dynamics; by compiling regional installation or use data rather than manufacturing data for end use technologies; and by using market studies and estimation techniques to approximate logistic growth forms for technologies still in an exponential phase.

These areas for further research should improve the robustness and potential for generalising findings. In addition, the two applications of these findings can be extended. An important question is whether energy system models like MESSAGE are structurally conservative in their growth projections for low carbon technologies in the future. Such models are widely used and influential tools in policy analysis and planning. The IPCC reports and the ongoing Global Energy Assessment[44] are prime examples in which analysis is structured around scenario storylines with technology scaling dynamics specified by models. A conservatism bias could have important consequences on the perceived feasibility of stabilisation targets and the policy decisions needed to those ends. The sensitivity analysis of market penetration and cost constraints set out in Section 6.6 is an important area for research to which the scaling meta-analysis provides a particular validation method.

The conceptual framework showing the different enabling factors for industry scaling could also enrich this policy debate, drawing on historical experience to generalise approaches for inducing scaling in low carbon technologies such as CCS. The robustness of general policy conclusions would be strengthened by further analysis of key factors endogenous to the scaling dynamics, including capital stock turnover and efficiency improvements. In essence, the finding of consistent dynamics across very different technologies needs to be examined further against the explanatory factors set out in Section 5. This should be integrated with a detailed qualitative analysis of the technologies included in the meta-analysis, particularly during the commercialisation, takeoff, and unit scaling phases of their overall lifecycle. This would help extend the conceptual framework of scaling proposed here, and broaden its applicability.

[44] For further details on the Global Energy Assessment process, see: www.globalenergyassessment.org

Appendix A: Historical Data & Logistic Fits

This Appendix provides detailed information on the source and form of the historical data series used for each technology at both unit and industry levels, MW conversion protocols (where appropriate), the logistic models fitted to these data, and any salient issues that may affect the meta-analysis. The underlying data and logistic models are also available online through the Transitions to New Technologies program on the IIASA website (http://www.iiasa.ac.at/Research/TNT/WEB/Publications/Scaling_Dynamics_of_Energy_Technologies/). Please cite this paper if using or referring to the data.

Oil Refineries

Refinery capacity data was compiled from Oil & Gas Journal Yearbooks for 1940-1960 (OGJ 1999; OGJ 2000), BP's Statistical Review of World Energy(BP 2008), and the US EIA's Annual Energy Review (EIA 2008). The first known refinery dates back to the 1860s (Yergin 2008), so the compiled historical data misses the formative and early growth period which was concentrated in the US.

The standard capacity measure for refineries is barrels per day ('bpd'). These data were converted into MW-equivalents assuming 24 hours per day of operation (i.e., continuous) and boe (barrels of oil equivalent) to Joules to kWh conversion factors (BP 2008).

The historical data, and logistic fits for industry and unit level data are shown in Figures A.1 – A.3.

There are three issues to note:

i. Industry level capacity data are annual (net) totals rather than cumulative totals;
ii. Unit level capacity data are for a typical fluid catalytic cracking unit in a US refinery;
iii. Logistic functions are fitted to the '1st phase' of refinery capacity growth at the industry level.

Unlike the cumulative total capacity data for the other technologies, refinery capacity data were available only on a net basis, i.e., after refurbishments, retirements, and so on. This will bias downwards both the rate and extent of growth, particularly in the Core region with a longer refining history.

The number of refineries operating in the US from 1949-1989 declined steadily with an average of 25 refineries shutdown every year (see Figure A.2). However, total refinery capacity steadily rose during the same period as other refineries were retrofitted with significantly expanded capacity. Scaling of fluid catalytic cracking units for the 1942-1994 period was logistic in form (see Figure A.3). As fluid catalytic cracking is a core throughput process within the refinery complex, it serves as a useful proxy for the scaling or 'swelling' of the refinery as a whole. Unit capacity data are only available for the US (Core region).

Table A.1. Oil Refineries: Summary of Data & Logistic Fits.

OIL REFINERIES		Global	Core	Rim1	Rim2	Periphery
Industry Level	Historical Data	yes	yes	n/a	yes	yes
	Logistic Fit	yes	yes	n/a	no	yes
Unit Level	Historical Data	no	yes	n/a	no	no
	Logistic Fit	no	yes	n/a	no	no

Power Plants (Coal, Natural Gas, Nuclear)

Coal, natural gas, and nuclear power data were compiled from Platts' World Power Plant Database which contains entries for all electricity generating units installed worldwide including details on their location, fuel, start date of operation, and current status (Platts 2005). The first units began operation in 1903 (natural gas), 1908 (coal), and 1956 (nuclear) respectively.

The historical data, and logistic fits for industry and unit level data are shown in Figures A.5 – A.10.

Two issues to note concern data reliability for coal and natural gas power:

i. Entries in the power plant database lacking a start date of operation were excluded;
ii. Entries in the power plant database are incomplete, particularly early in the industry's history.

Although reaching back to the earliest years of electrification, the power plant database is considered more reliable for post World War II data. For coal power, 13% of database entries, corresponding to 6% of total capacity, lacked start dates of operation and so were excluded. For natural gas power, 9% of entries were excluded (11% of total capacity). (All nuclear power plant data were complete).

Selective cross-referencing of these excluded units suggests they were predominantly from the first decades of the 20th century and in the US and FSU regions. It is likely that other units were missing entirely from the database rather than just lacking start years. The extent of missing data was assessed by comparing cumulative total capacities calculated from the power plant database entries against secondary sources:

- EIA data (1980-2005) on total fossil fuel & nuclear power capacity (global + 4 regions) - from Table 11.17 in (EIA 2008);
- IEA data (1974-2006) on total coal, natural gas & nuclear power capacity (OECD only) – from (IEA 2008a);
- US EEI data (1902-1970) on total power capacity (US only) – from Data Series S53-S57 and S74-S85 in (EEI 1995).

None of these secondary sources were directly commensurate because: (i) they were based on net total rather than cumulative total capacities, (ii) they aggregated all fossil fuel plants, (iii) they included or excluded co-generation facilities and/or industrial plants. Despite these commensuration issues, adjusted industry level capacities from the power plant database closely matched the IEA and US EIA data from 1970 for all regions. Pre-1970 secondary source data were only available for the US. Although the power plant database is clearly missing entries in the 1900-1930 period in particular, these discrepancies relative to final saturation levels of each power generation technology are very low (see FigureA.4).

However, the potential biasing effect of omitted or missing units from the scaling dynamics of cumulative total unit numbers (as opposed to cumulative total capacity) may be less trivial. As the omitted or missing units were weighted towards the beginning of the industry's growth, the extent of diffusion (K) of total unit numbers will be lower and the rate of diffusion (Δt) will be likely be faster if the takeoff point of total unit numbers is pushed forward in time. This bias will mostly be relevant for the Core region with its longer electrification history.

Table A.2. Coal Power: Summary of Data & Logistic Fits.

COAL POWER		Global	Core	Rim1	Rim2	Periphery
Industry Level	Historical Data	yes	yes	yes	yes	yes
	Logistic Fit	yes	yes	yes	no	yes
Unit Level	Historical Data	yes	yes	yes	yes	yes
	Logistic Fit	yes	yes	yes	yes	Yes

Table A.3. Nuclear Power: Summary of Data & Logistic Fits.

NUCLEAR POWER		Global	Core	Rim1	Rim2	Periphery
Industry Level	Historical Data	yes	yes	yes	yes	yes
	Logistic Fit	yes	yes	yes	no	no
Unit Level	Historical Data	yes	yes	yes	yes	yes
	Logistic Fit	yes	yes	yes	yes	no

Table A.4. Natural Gas Power: Summary of Data & Logistic Fits.

NATURAL GAS POWER		Global	Core	Rim1	Rim2	Periphery
Industry Level	Historical Data	yes	yes	yes	yes	yes
	Logistic Fit*	yes	yes	yes	yes	yes
Unit Level	Historical Data	yes	yes	yes	yes	yes
	Logistic Fit	yes	yes	yes	yes	yes

*1st phase growth (to early 1980s)

Power Plants (Wind)

Wind power data were compiled from various sources including (BTM_Consult 2002; EWEA 2004; EWEA 2008; GWEC 2008).

At the industry level, total installed capacity data for 6 regions (and the global total) are shown in Figure A.12. At this level of aggregation, all regions show exponential growth rendering logistic fits unreliable (see above). The exception is for Denmark as the Core region with installed capacity data dating back to 1977 and showing a clear asymptote at around 3,500 MW (Danish_Energy_Agency 2008). This does not preclude a sequential growth phase driven by offshore installations (see Figure A.13).

At the unit level, multi-country data were only available for average turbine sizes based on annual capacity additions. A proxy for the unit scale frontier was derived from the introduction of new turbines models by Vestas, the world's leading manufacturer (see

Figure A.11). Currently though, Vestas' largest model is 3MW compared to GE's 3.6MW unit, and Siemens & Repower's 5MW units. Unit scaling is expected to continue to at least 10MW.

Table A.5. Wind Power: Summary of Data & Logistic Fits.

WIND POWER		Global	Core	Rim1	Rim2	Periphery
Industry Level	Historical Data	yes	yes	n/a	yes	no
	Logistic Fit	no	yes	n/a	no	no
Unit Level	Historical Data	no	yes	n/a	no	no
	Logistic Fit	no	yes	n/a	no	no

Power Plants (Solar PV)

Solar photovoltaic ('PV') power data were compiled from: (Maycock 2002; EPIA 2008).

At the industry level, growth in total installed capacity data is exponential, both globally and for the principal markets and regions (US, Japan, Germany, rest of Europe). Aggregated industry level data are shown in Figure A.14; no data were available on unit scaling.

Table A.6. Solar PV: Summary of Data & Logistic Fits.

SOLAR PV		Global	Core	Rim1	Rim2	Periphery
Industry Level	Historical Data	yes	yes	n/a	yes	no
	Logistic Fit	no	no	n/a	no	no
Unit Level	Historical Data	no	no	n/a	no	no
	Logistic Fit	no	no	n/a	no	no

Passenger Jet Aircraft

Passenger jet aircraft data were compiled for the three major OECD-based manufacturers of trunk route, medium-to-long haul aircraft: Boeing, McDonnell-Douglas (which merged with Boeing in 1997 with the final MD-11 aircraft delivered in 2001), and Airbus. In the global market for large commercial jets, the authors estimate that Boeing and Airbus currently account for over 90% of annual sales (by value). Rival OECD-based manufacturers including Lockheed, Convair, Dornier and Fokker no longer compete in the commercial jet market, and production volumes from the major FSU-based manufacturers including Tupolev and Ilyushin have fallen sharply in recent decades. Embraer and Bombardier are the remaining competitors. On a cumulative basis since the beginning of the jet era, the authors estimate that Boeing, McDonnell-Douglas and Airbus have accounted for over 2/3 of total sales. In the period to 1990, the FSU-based manufacturers had larger production volumes, although the data available were not considered reliable for inclusion in the meta-analysis.

Annual data from 1958-2007 on the number of aircraft delivered for each series were based on manufacturers' statistics (www.boeing.com, www.airbus.com). Data on the number of aircraft models produced within each series (e.g., the Boeing 747-400 model within the Boeing 747 series) were compiled from various sources including Jane's All the World's Aircraft databooks (several editions, e.g., Jane's 1998), and online aircraft databases (www.airliners.net, www.flightglobal.com). Discrepancies were resolved by cross-checking between data sources and against manufacturer data. In some cases, manufacturer data were higher as they included freight and convertible (passenger/cargo) variants but these differences were small. Aircraft sales data for each series include some freight aircraft if the passenger and cargo variants are inter-convertible. As the engine capacities of the passenger and convertible variants are similar, this is not considered to bias the scaling meta-analysis.

Data on aircraft model specifications were compiled from the same sources. Specifications used in the analysis included: year of certification or first commercial flight, typical passenger capacity (with standard seat configuration), maximum payload range (km), and engine thrust (kN). As many aircraft models had alternative engine options, the typical engine thrust for a given aircraft model was calculated as a simple average of the most common or standard engine models used. As an example, the engine thrust of an 'average' Boeing 747-100 was 210.3 kN, being the average of 206.8 kN (GE's CF645A2), 208.9 kN & 215.1 kN (Pratt & Whitney's JT9D7A & JT9D7F respectively).

Jet engine thrust is the product of the core power (of the gas turbine) and the propulsive efficiency of the associated low pressure system, and so varies according to the type of engine (e.g., turbojet, bypass turbofan, turboprop) and according to various conditions. The total thrust per aircraft (summed over the number of engines) was converted into rated power using P = F.V (which in SI units is W = N * m/s) based on maximum cruising speeds and maximum engine thrusts. Actual thrust will be a fraction of maximum (static) thrust, and actual power rating will depend on contextual factors including acceleration, altitude, and air pressure.[45] An alternative rule of thumb conversion methodology for a modern turbofan engine is based on an approximate equivalence between the low pressure system output shaft power (in hp) and the takeoff thrust (in lbf). This method gave power capacities around 1/3 lower. The conversion of jet engine thrust (in kN) into rated power (in MW) used in the meta-analysis is therefore a first order approximation only.

Specifications and numbers produced of each aircraft model were used to calculate production-weighted average values (of passenger capacity, engine capacity, etc.) for each aircraft series. These were then combined with the annual deliveries data to calculate total capacities added annually.

The compiled data on unit capacities and numbers of aircraft are shown in Figures A.15 – A.17.

Three issues to note are:

i. The regions used in the scaling meta-analysis are manufacturer-based: Boeing is treated as the Core; Airbus as the Rim2 region, and all 3 manufacturers combined as Global. The 'regions' are therefore not defined spatially but in terms of economic organisation.

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[45] For details, see: Van Sickle, N.D., Welch, J.F., Bjork, L. & Bjork, L. (1999). Van Sickle's Modern Airmanship (8th edition); Soares, C. (2007). Gas Turbines: A Handbook of Air, Land and Sea Applications.

ii. Supply-side technology data describe capacity *installed* within each region. Aircraft data describe capacity *manufactured* within each region, but sold and used globally (cf. cars).

iii. The meaningful measure of passenger jet aircraft capacity is the two dimensional passenger.kms which describes how far an aircraft can carry a given number of passengers. (Available seat.kilometres is a more apt term as it measures the *potential* capacity unaffected by *actual* load factors). As the scaling meta-analysis relies on a common MW metric, the thrust of the aircraft engine was converted into MW as the measure of unit capacity. As engine capacity was found to vary linearly with passenger capacity over the majority of the aircraft considered (see Figure A.16), the use of MWs rather than passenger.kms as a measure of capacity was considered acceptable.

Table A.7. Jet Aircraft: Summary of Data & Logistic Fits.

<table>
<tr><th colspan="2">JET AIRCRAFT</th><th>Global*</th><th>Core*</th><th>Rim1</th><th>Rim2*</th><th>Periphery</th></tr>
<tr><td rowspan="2">Industry Level</td><td>Historical Data</td><td>yes</td><td>yes</td><td>no</td><td>yes</td><td>no</td></tr>
<tr><td>Logistic Fit</td><td>yes</td><td>yes</td><td>no</td><td>yes</td><td>no</td></tr>
<tr><td rowspan="2">Unit Level</td><td>Historical Data</td><td>yes</td><td>yes</td><td>no</td><td>yes</td><td>no</td></tr>
<tr><td>Logistic Fit</td><td>yes</td><td>yes</td><td>no</td><td>yes</td><td>no</td></tr>
</table>

*Global = Boeing, McDonnell-Douglas, Airbus combined; Core = Boeing; Rim2 = Airbus; no data available for FSU (Rim1) manufacturers (e.g., Ilyushin, Tupolev).

Helicopters

Data on helicopter model specifications (engine power, maximum takeoff weight, speed, range, etc.) were available for the period 1940-1986 from a database compiled by Saviotti which is described and analysed in (Saviotti & Trickett 1992). Two Russian MIL models introduced in 1957 and 1981 defined the unit scale frontier (expressed in terms of engine power or some other measure of capacity equivalent to the passenger.kms used for aircraft).

Historical data on helicopter unit capacities are shown in Figure A.18.

No data were available for numbers of helicopters manufactured. As a result, helicopters were not included in the scaling meta-analysis as industry data were unavailable.

Table A.8. Helicopters: Summary of Data & Logistic Fits.

<table>
<tr><th colspan="2">HELICOPTERS</th><th>Global</th><th>Core</th><th>Rim1</th><th>Rim2</th><th>Periphery</th></tr>
<tr><td rowspan="2">Industry Level</td><td>Historical Data</td><td>no</td><td>no</td><td>no</td><td>no</td><td>no</td></tr>
<tr><td>Logistic Fit</td><td>no</td><td>no</td><td>no</td><td>no</td><td>no</td></tr>
<tr><td rowspan="2">Unit Level</td><td>Historical Data</td><td>yes</td><td>yes</td><td>yes</td><td>yes</td><td>yes</td></tr>
<tr><td>Logistic Fit</td><td>no</td><td>no</td><td>no</td><td>no</td><td>no</td></tr>
</table>

Passenger Cars

At the unit level, data on the engine capacity of new cars (i.e., fleet additions) were available for the US (Core region) from 1965 based on statistics of the National Highway Traffic Safety Administration (NHTSA, see www.nhtsa.dot.gov) and

Environmental Protection Agency (EPA, see www.epa.gov). Additional data points for 1910, 1920 and 1949 were added based on various sources including (Rae 1984; Windrum et al. 2009) with the assumption for 1910 that fleet additions were dominated by the Ransom Old's Curved Dash (10 horsepower) and in 1920 by the Model T Ford (20 horsepower). Data for the major Western European manufacturers (Rim2 region) were available from 1968 based on statistics of the European Conference of Ministers of Transport, now the International Transport Forum (www.internationaltransportforum.org/statistics/statistics), and the European Automobile Manufacturers' Association (www.acea.be).

The engine capacity of new cars in other regions was assumed equal to Western Europe, i.e., unit scaling in the Rim1 (FSU) and Periphery (developing world) regions was assumed equal to the Rim2 region. Engine capacities in horsepower were converted using standard horsepower to megawatt conversion factors(BP 2008).

Unit capacity data are shown in Figure A.19.

At the industry level, data on motor vehicle production for 1900-2005 were compiled from various of the data books published by the American Automobile Manufacturers' Association(AAMA 1980; AAMA 1995; AAMA 1997). No production was assumed prior to 1900 (although the first commercial introduction of the car dates back to the late 1880s with Karl Benz's Motorwagen and Siegfrid Marcus' Second Marcus Car).

Additional data on cars as a % of vehicle production (from the same sources) were used to calculate total car production. (Commercial vehicle production, including buses, trucks, trams, were not analysed)). These data were only available for 1950-1993 (globally), and for 1960-1988 (selected countries). Selected country data on cars as a % of vehicle production were applied to the regional production totals as follows: US % used for Core region; FSU % used for Rim1 region; Japan, France, Italy, Germany % (weighted average by share of production) used for Rim2 region; Brazil % used for Periphery region. All data were extrapolated backwards for 1900-1959 at a constant 1960 % share. (This simplification mainly affects just the Core region in which growth pre-1960 was strongest). All data was extrapolated forwards to 2005 at a constant 1988 % share (selected country data) or a constant 1993 % share (global data).

Data for industry scaling in terms of capacity (i.e., cumulative MW of engine capacity added) were calculated simply by combining, in each region, the number of new cars produced each year with the average engine capacity of new cars that year.

The historical data, and logistic fits for industry level data on cumulative total number of units (cars) are shown in Figures A.20 – A.21.

There are three issues to note:

i. Unit scaling in the US has three distinct phases: steady growth from 1900-1970; rapid decline from 1970-1982 (driven by rising oil prices and the CAFE efficiency standards introduced in 1978); then rapid growth from 1970-2005. A logistic model *can* approximate the initial growth phase (cf. refineries), but this is particular to the US so was not included in the regional analysis.
ii. Unit scaling in the EU (assumed equal to the FSU and developing countries) can be described by the post-takeoff phase of a logistic function which extrapolates backwards to describe reasonably the commercialisation phase in the early 20th century.

iii. As with aircraft, industry scaling data describe capacity that is manufactured rather than 'installed' or sold / used within each region.

Table A.9. Cars: Summary of Data & Logistic Fits.

PASSENGER CARS		Global	Core	Rim1	Rim2	Periphery
Industry Level	Historical Data	yes	yes	yes	yes	yes
	Logistic Fit	(yes)*	yes	yes	yes	no
Unit Level	Historical Data	(yes)**	yes	(yes)**	yes	(yes)**
	Logistic Fit	no	no	(yes)**	yes	(yes)**

*Only for total number of units, not total capacity.
** Rim1 & Periphery assumed equal to Rim2; Global based on production-weighted average of all regions.

Compact Fluorescent Light Bulbs

Data on compact fluorescent light bulb ('CFL') sales from 1990-2003 in 8 world regions were compiled from IEA data (IEA 2006)and aggregated into 3 regions for the scaling meta-analysis depending on the timing of sales growth: OECD ex. Japan (Core region); Asia (Rim2 region); Rest of World (Periphery). No Rim1 region was used as diffusion largely post-dated the Soviet Union.

Annual sales data are shown in Figure A.22.

No data were available on the capacity (in W) of the CFLs sold each year in the different markets. A simple assumption was made that the average unit capacity of CFLs has remained constant at 15 W during the period for which sales data are available. A 15 watt CFL has similar luminescence to a standard 75 W incandescent bulb used residentially. CFLs typically fall in the 4 - 120 W range (with an efficacy range of 35 - 80 lumen per W) with larger watt CFLs used in commercial applications. The constant 15 W unit capacity assumption is therefore likely to be conservative.

There are various issues to note with CFLs:

i. Unlike aircraft and cars, the other end use technologies, CFL data are based on sales not manufacturing. The regional disaggregation therefore reflects end use market size rather than the spatial distribution of production.

ii. The assumption of a constant average unit capacity violates the selection criteria for scaling which is required to be at both unit and industry levels (see Section 2.2). The relevant level of scaling for CFLs (as with cars, and to a lesser extent aircraft) is the manufacturing plant rather than the technology unit itself. CFLs were intentionally included in the meta-analysis despite this discrepancy as they were the best example of a very large n end use technology which could be used to test whether industry scaling relationships were consistent across the full range of technology characteristics.

iii. CFLs have a longer lifetime (e.g., 10,000 hours) than the incandescent bulbs for which they typically substitute (e.g., 1,000 hours). Consequently, sales of CFLs would be expected to be an order of magnitude lower than sales of incandescent bulbs, holding market size constant.

Table A.10. Compact Fluorescent Light Bulbs ('CFLs'): Summary of Data & Logistic Fits.

CFLs		Global	Core	Rim1	Rim2	Periphery
Industry Level	Historical Data	yes	yes	yes	yes	yes
	Logistic Fit	no	yes	no	no	no
Unit Level	Historical Data	no	no	no	no	no
	Logistic Fit	no	no	no	no	no

Mobile Phones

Data on the total number of mobile phone subscribers from 1982-2007 as an approximation of mobile phone sales were taken from(OECD 2007; OECD 2009); and International Telecommunications Union online statistical database (www.itu.int/ITU-D/ict/statistics/index.html). Growth in subscriber numbers is still exponential, both globally and for the principal markets and regions (US, Japan, Germany, rest of Europe).

Mobile phone subscriber data are shown in Figure A.23.

Growth in a more narrowly defined Core region comprising Scandinavia and Japan has started to slow and can be reasonably described by a logistic model. However, no data were available on the battery power capacity of mobile phones and how this has changed. Moreover it is unclear whether battery capacity is a meaningful metric of the unit scale of mobile phones (as opposed to say, processing power or some other measure of useful service). As a result, mobile phones were not included in the scaling meta-analysis.

Table A.11. Mobile Phones: Summary of Data & Logistic Fits.

MOBILE PHONES		Global	Core	Rim1	Rim2	Periphery
Industry Level	Historical Data	yes	yes	n/a	yes	yes
	Logistic Fit	no	no	no	no	no
Unit Level	Historical Data	no	no	no	no	no
	Logistic Fit	no	no	no	no	no

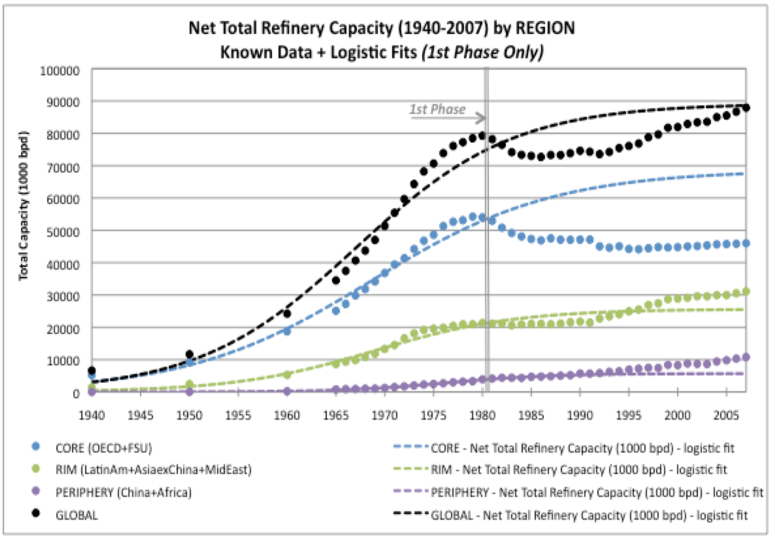


Figure A.1. Industry Level Refinery Capacity. Historical data (markers) and logistic fits (dashed lines) of refinery capacity by region (1940-2007). Logistic fits approximate 1st phase growth peaking in the aftermath of the oil shocks. [Data from (OGJ 1999; OGJ 2000; BP 2008); see text for details].

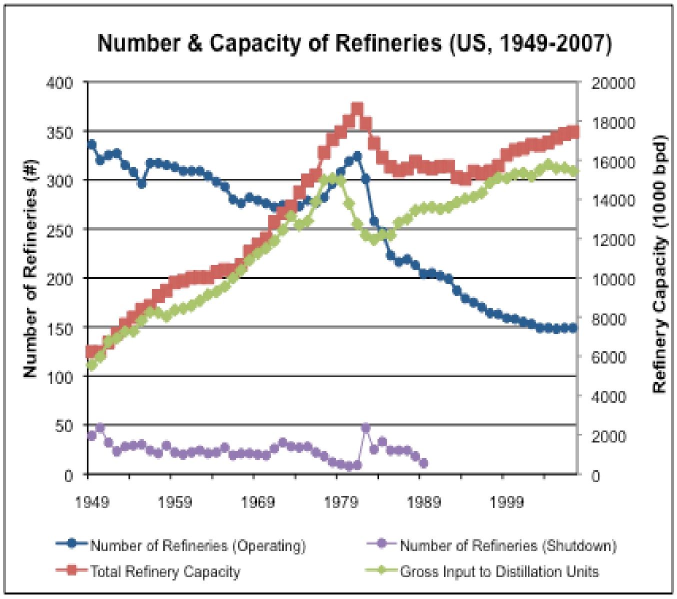


Figure A.2. US Refinery Numbers. Annual total number of operating & shutdown refineries (left-hand axis) and total capacity & throughput (right-hand axis). [Data from (EIA 2008); see text for details].

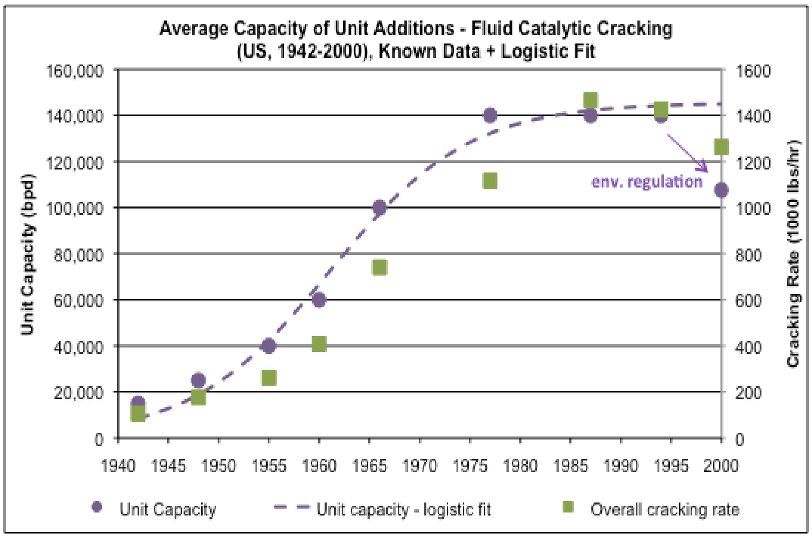


Figure A.3. Unit Level Refinery Capacity. Historical data (markers) and logistic fit (dashed line) of average capacity (bpd) of fluid catalytic cracking units in the US (1942-2000) (left-hand axis). Also shows historical data (markers) of the overall cracking rate (1000 lbs/hr) (right-hand axis). [Data from (Enos 2002); see text for details].

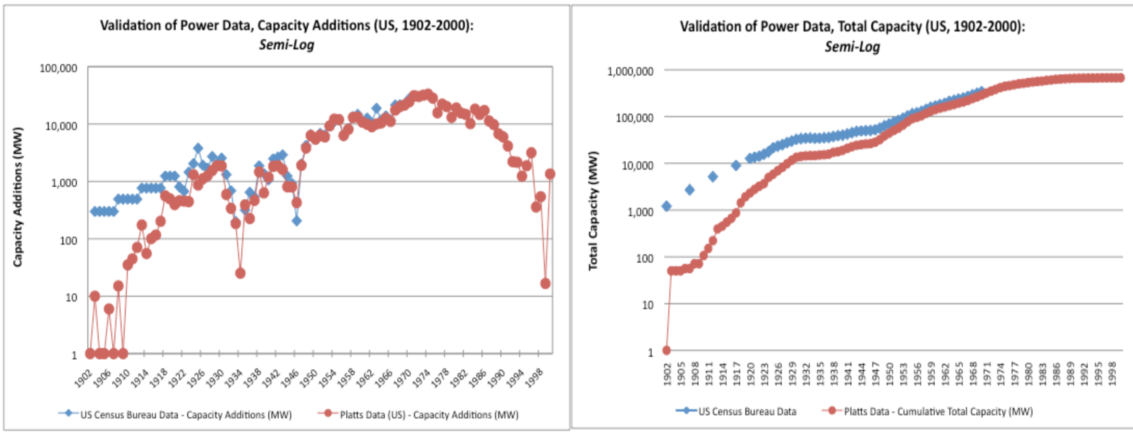


Figure A.4. Power Plant Database Validation. Comparison of power plant database against US Census Bureau data on annual capacity additions (left-hand graph, semi-log) and total capacity (right-hand graph, semi-log). [Data from (EEI 1995; Platts 2005); see text for details].

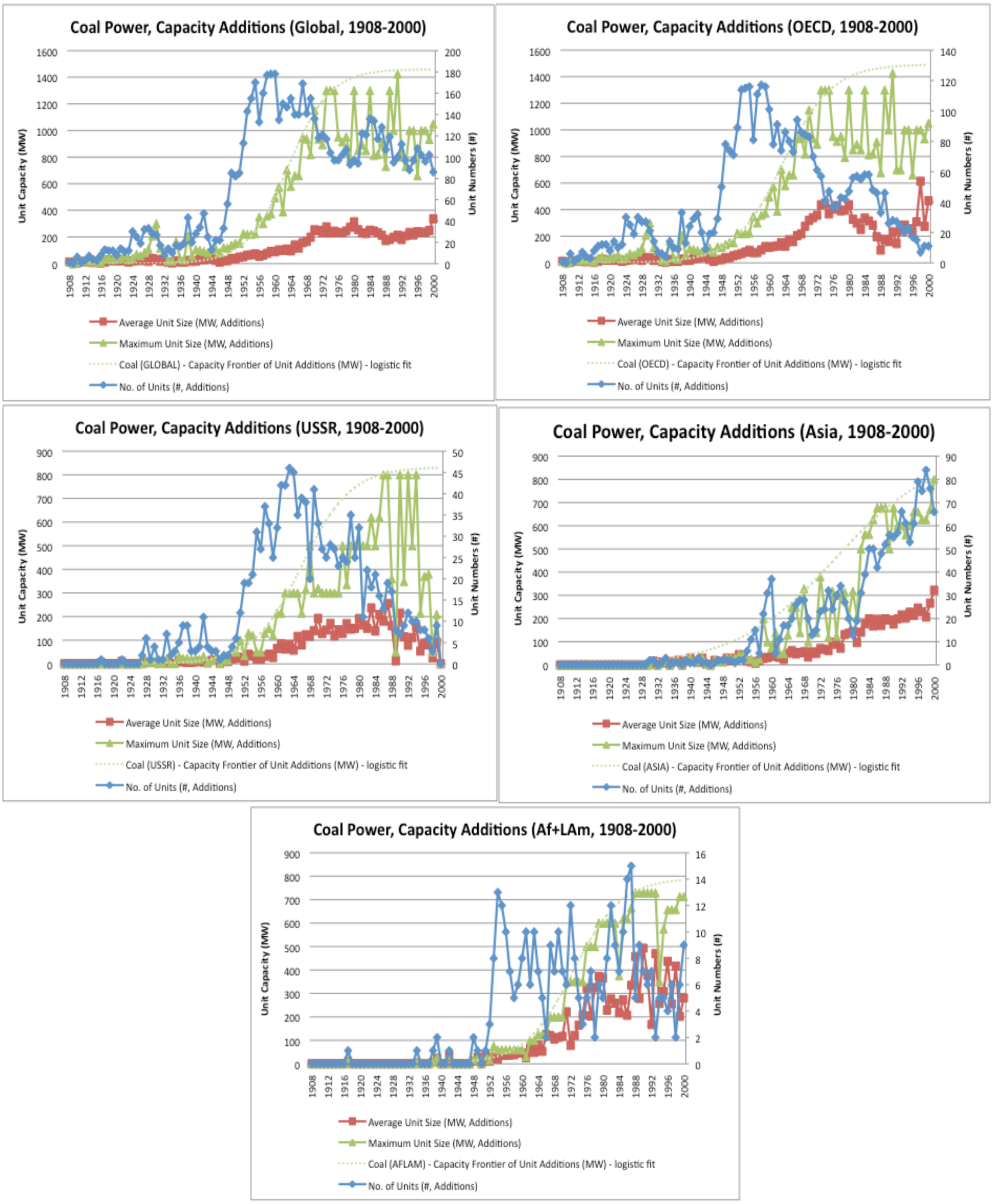


Figure A.5. Coal Power Unit Capacity Additions. Average capacity and maximum capacity of unit additions (left-hand axis), and numbers of unit additions (right-hand axis) in coal power plants, globally and disaggregated into 4 regions. Dotted line shows logistic fit to the unit scale frontier. [Data from (Platts 2005); see text for details].

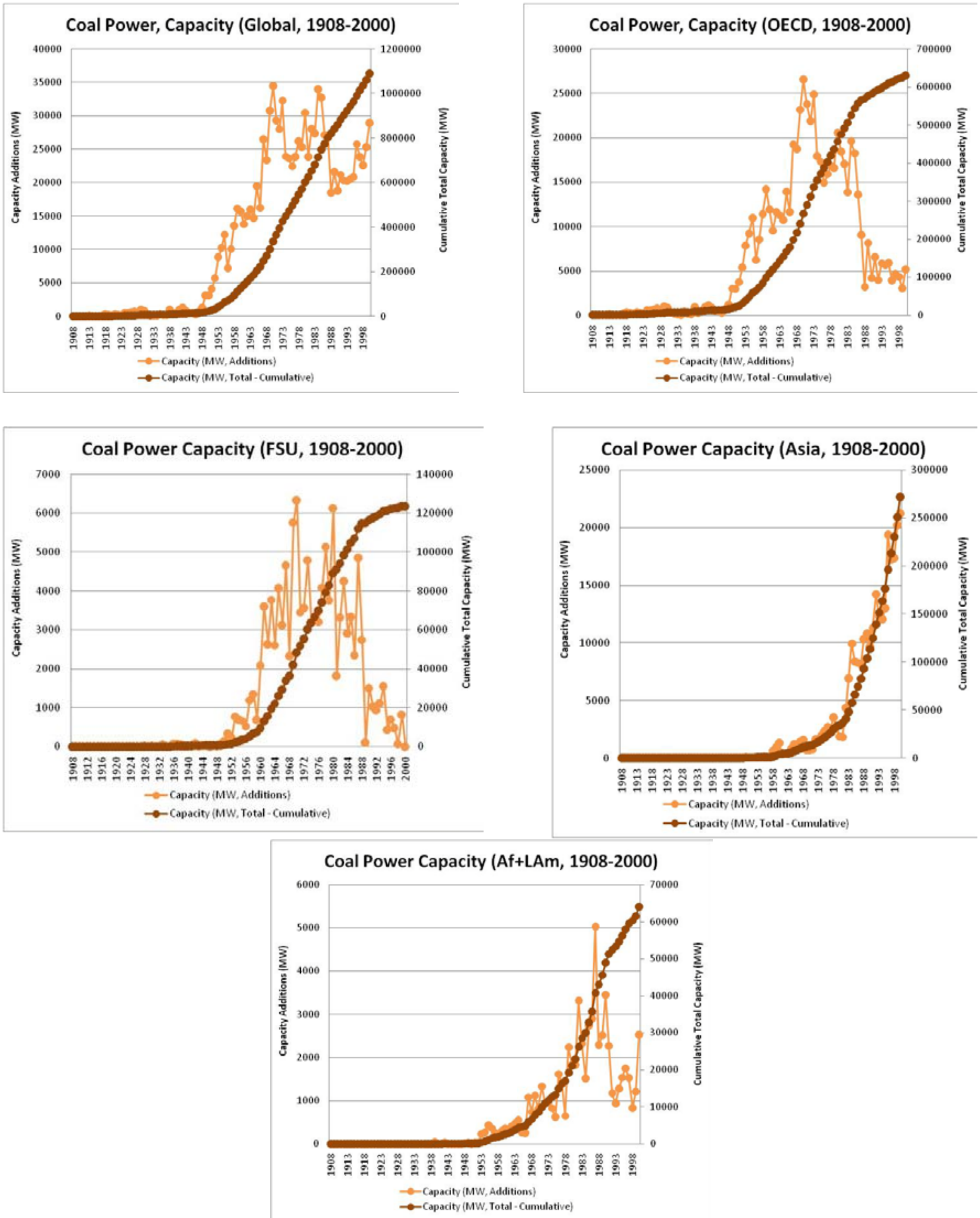


Figure A.6. Coal Power Total Capacity. Total capacity additions (left-hand axis) and cumulative total capacity (right-hand axis) of coal power, globally and disaggregated into 4 regions. [Data from (Platts 2005); see text for details].

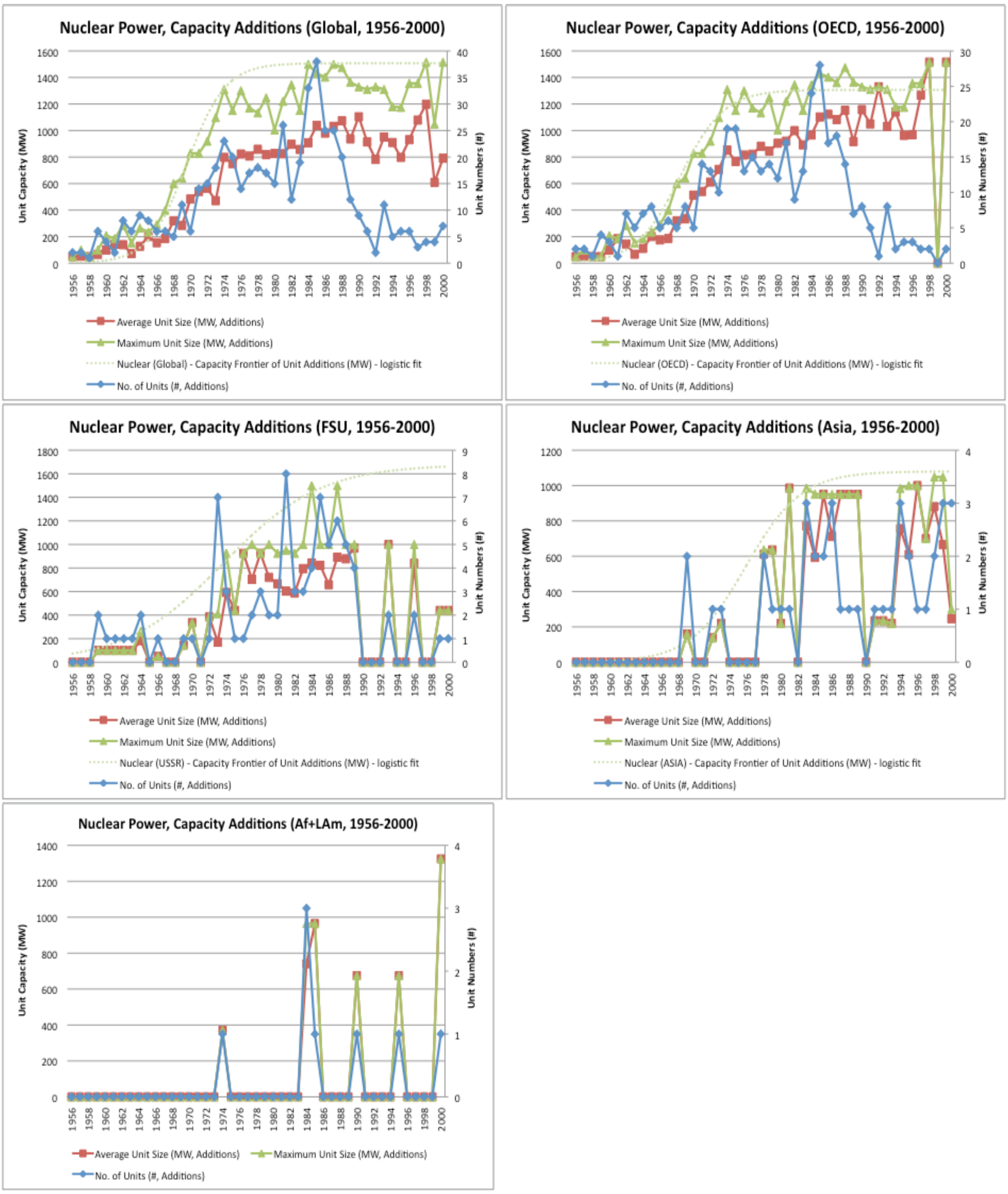


Figure A.7. Nuclear Power Unit Capacity Additions. Average capacity and maximum capacity of unit additions (left-hand axis), and numbers of unit additions (right-hand axis) in nuclear power plants, globally and disaggregated into 4 regions. Dotted line shows logistic fit to the unit scale frontier. [Data from (Platts 2005); see text for details].

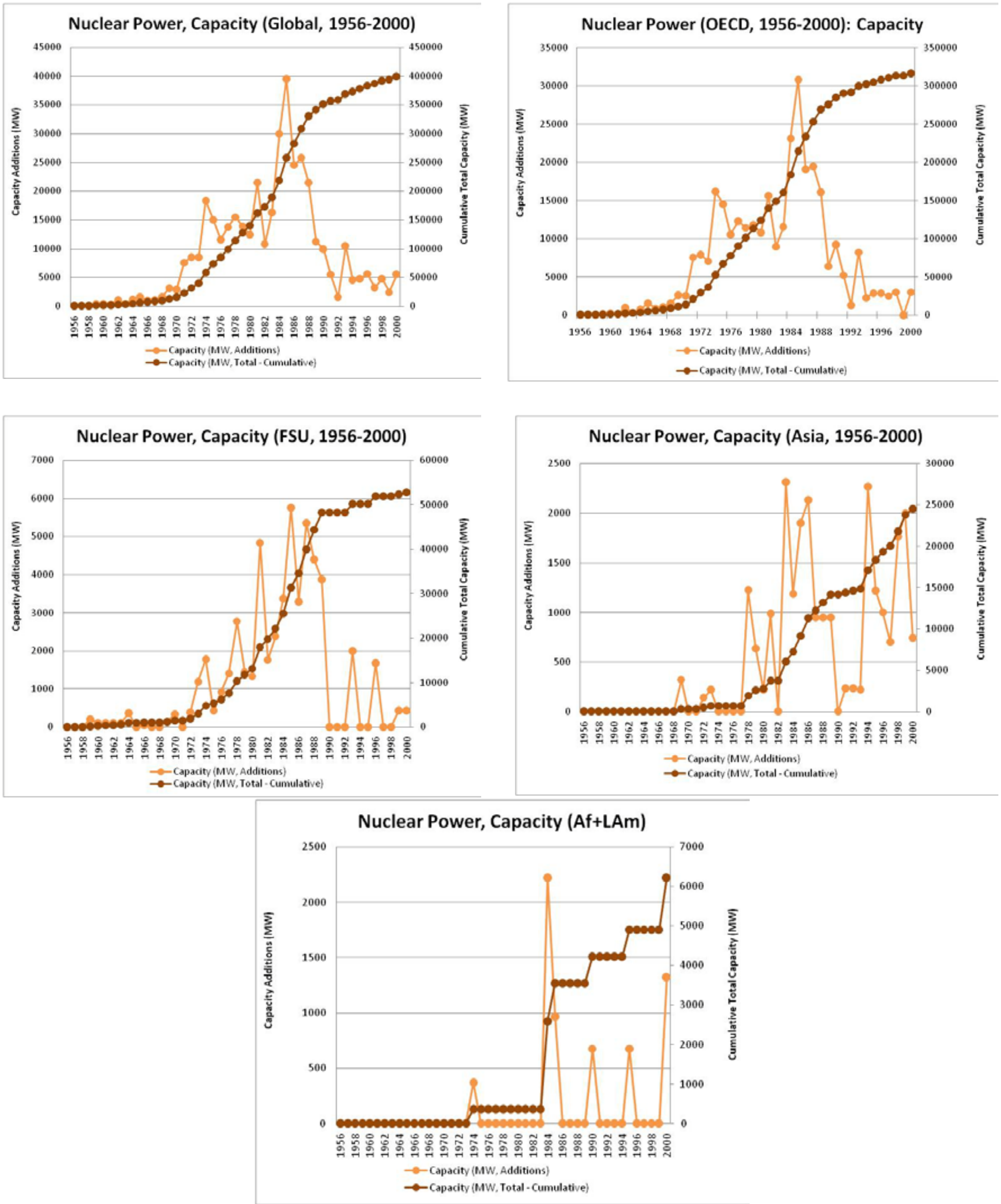


Figure A.8. Nuclear Power Total Capacity. Total capacity additions (left-hand axis) and cumulative total capacity (right-hand axis) of nuclear power, globally and disaggregated into 4 regions. [Data from (Platts 2005); see text for details].

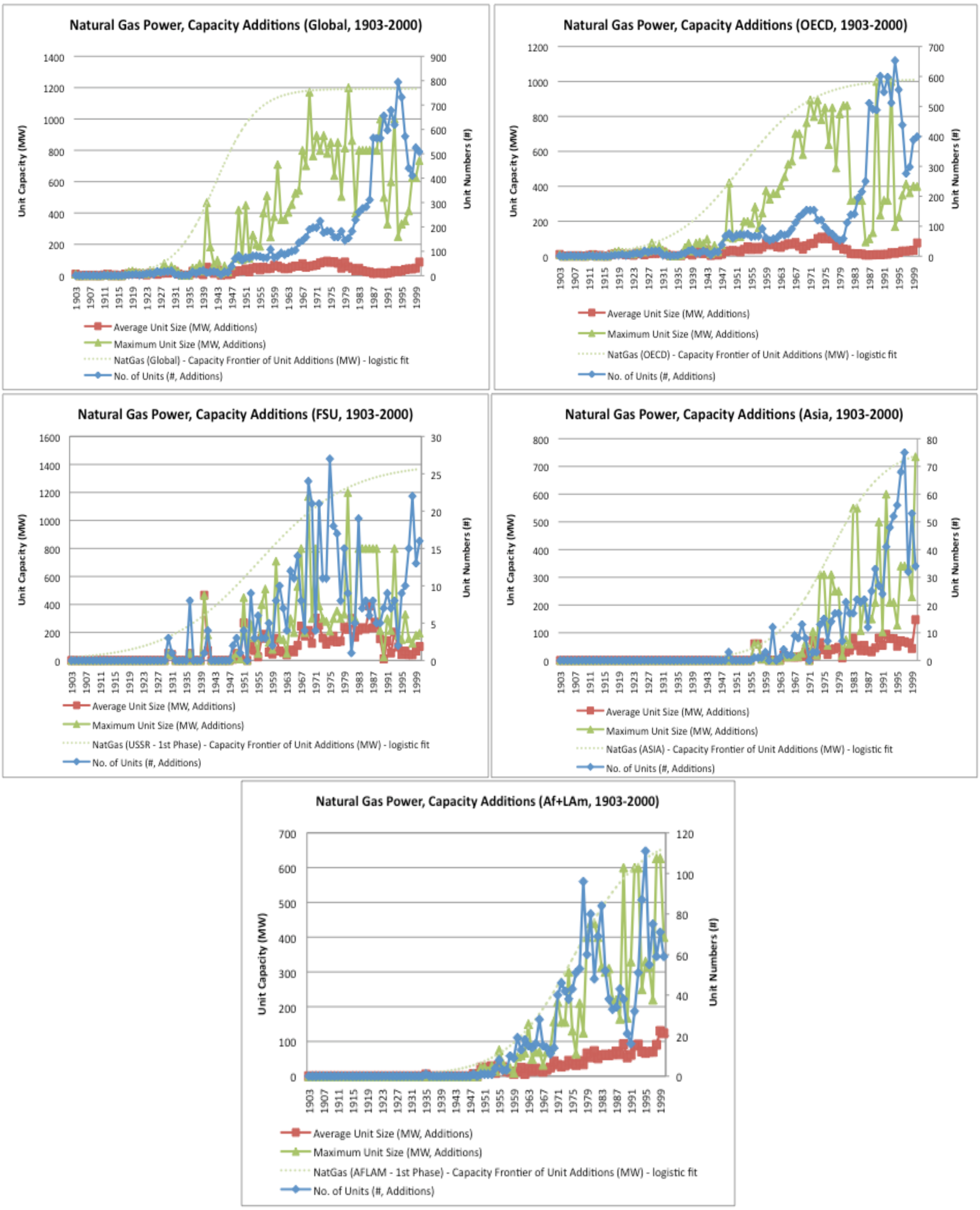


Figure A.9. Natural Gas Power Unit Capacity Additions. Average capacity and maximum capacity of unit additions (left-hand axis), and numbers of unit additions (right-hand axis) in natural gas power plants, globally and disaggregated into 4 regions. Dotted line shows logistic fit to the unit scale frontier. [Data from (Platts 2005); see text for details].

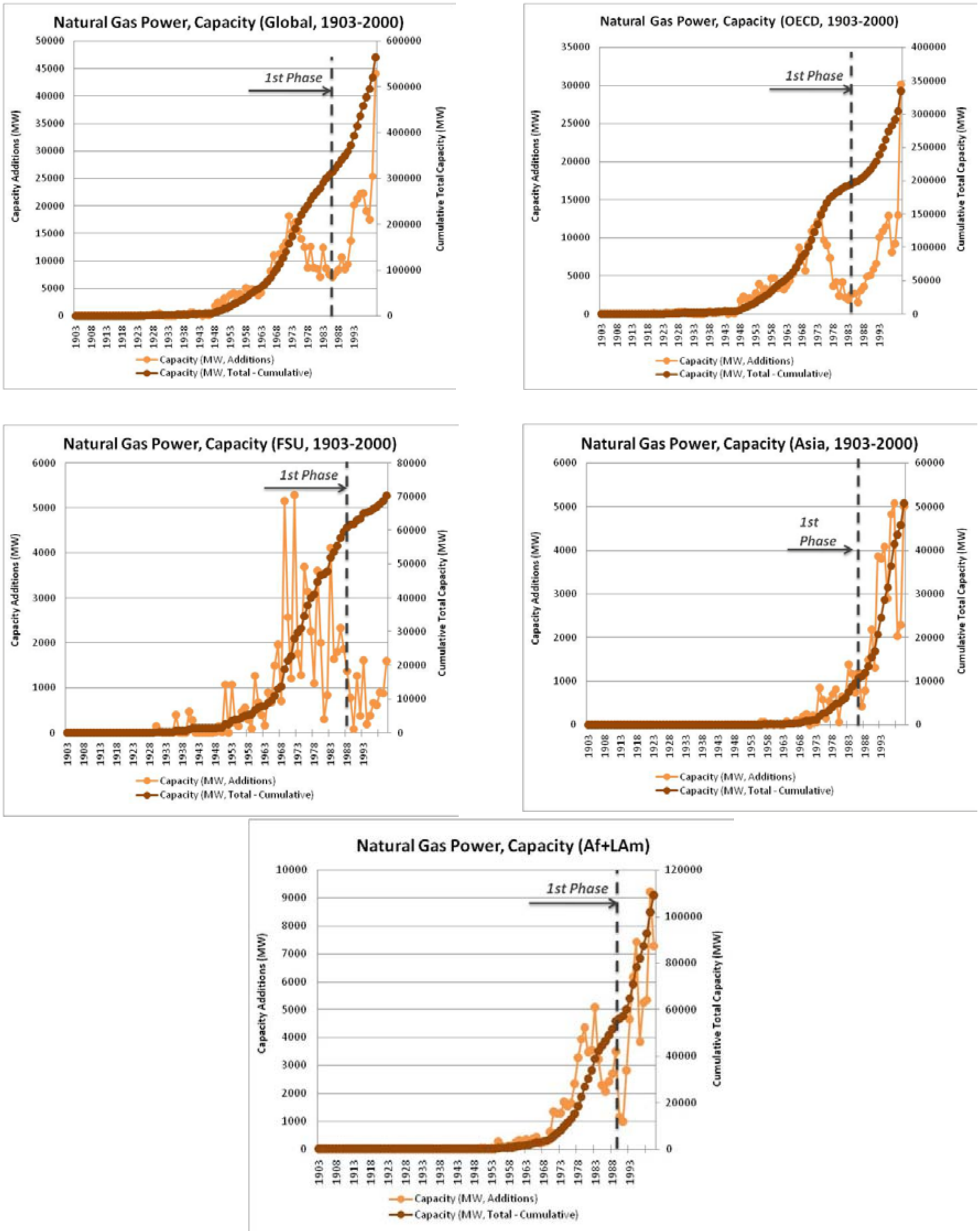


Figure A.10. Natural Gas Power Total Capacity. Total capacity additions (left-hand axis) and cumulative total capacity (right-hand axis) of natural gas power, globally and disaggregated into 4 regions. Vertical dashed line shows approximate end of the '1st phase' following the oil shocks. [Data from (Platts 2005); see text for details].

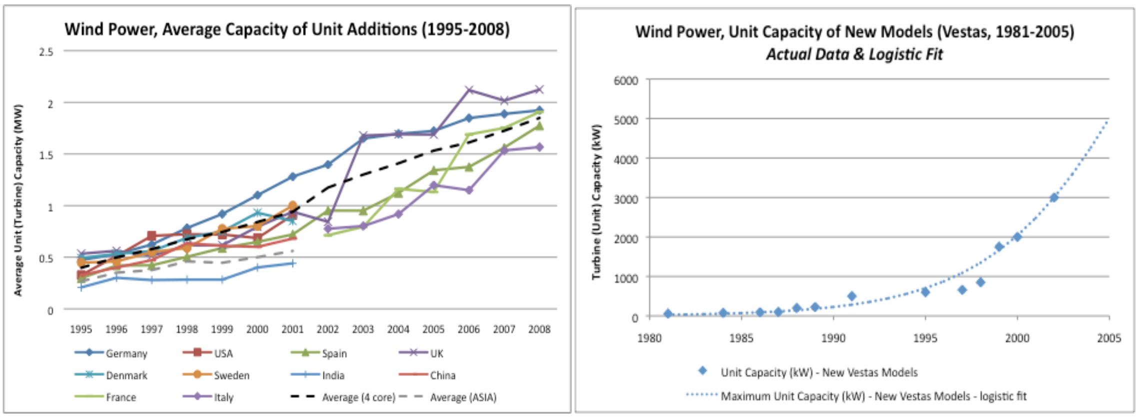


Figure A.11. Wind Power Unit Capacity Additions. Average capacity of wind turbines in 10 countries (left-hand graph) with dashed lines showing average in main 4 markets, and in Asian markets. Maximum capacity of wind turbines introduced by Vestas (right-hand graph), i.e., the major manufacturer's unit scale frontier. [Data from various sources; see text for details].

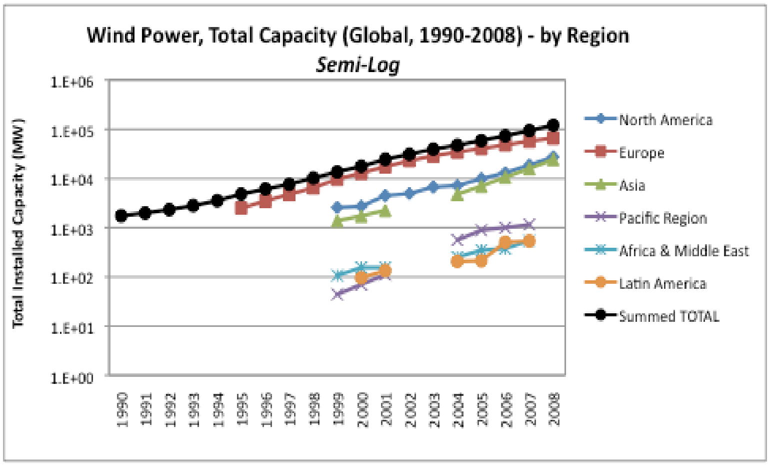
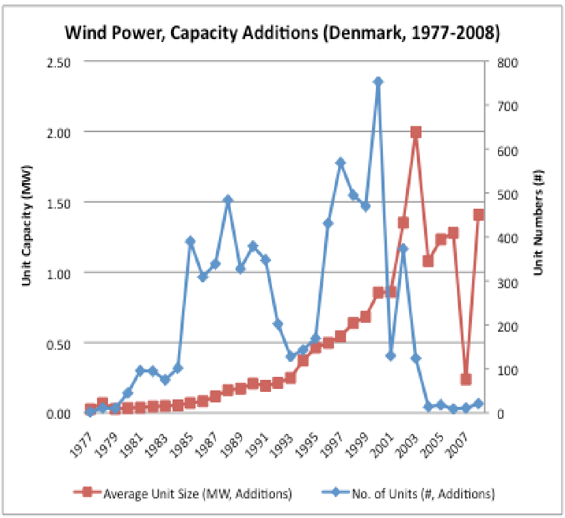


Figure A.12. Wind Power Total Capacity. Cumulative total capacity of wind power, globally and disaggregated into 6 regions (log scale y-axis). Growth at the regional level is still exponential. [Data from various sources; see text for details].



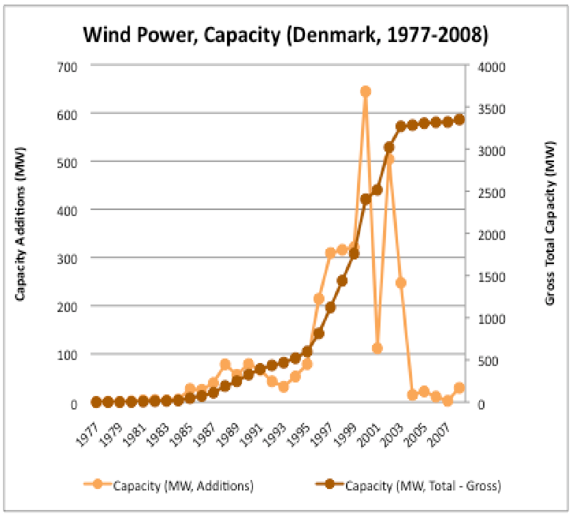


Figure A.13. Wind Power in Denmark (Core region). Number and average capacity of unit additions (left-hand graph); total capacity of unit additions and cumulative total capacity (right-hand graph). Saturation of cumulative installed capacity could move into second growth phase with emerging offshore segment. [Data from (Danish_Energy_Agency 2008); see text for details].

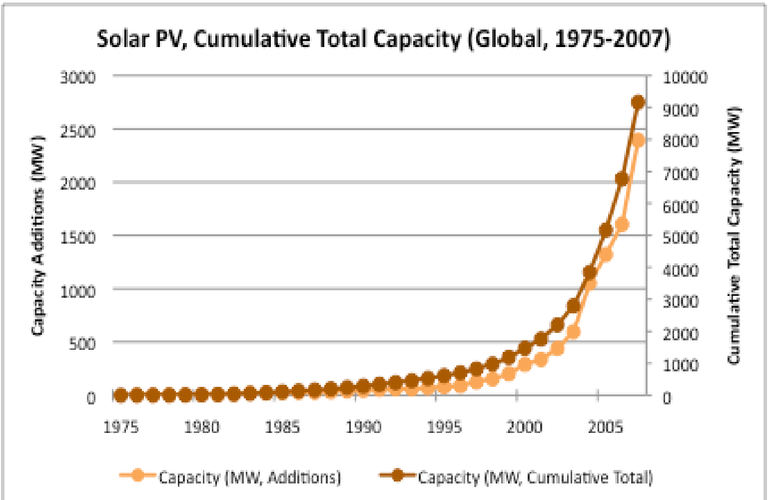


Figure A.14. Solar PV Capacity. Total capacity additions (left-hand axis) and cumulative total capacity (right-hand axis). [Data from (Maycock 2002; EPIA 2008); see text for details].

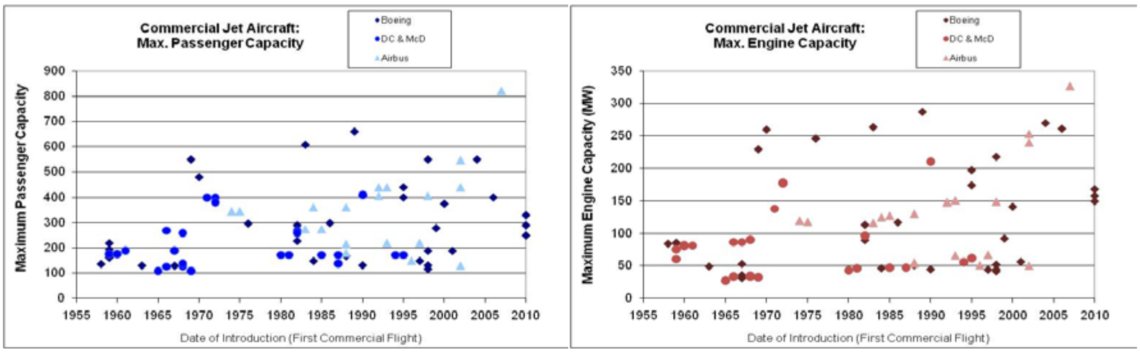


Figure A.15. Passenger Jet Aircraft: Unit Capacity Measures. Maximum passenger capacity (passenger.kms) and approximation of engine capacity (MW) for Boeing, McDonnell-Douglas, and Airbus aircraft models. [Data from various sources; see text for details].

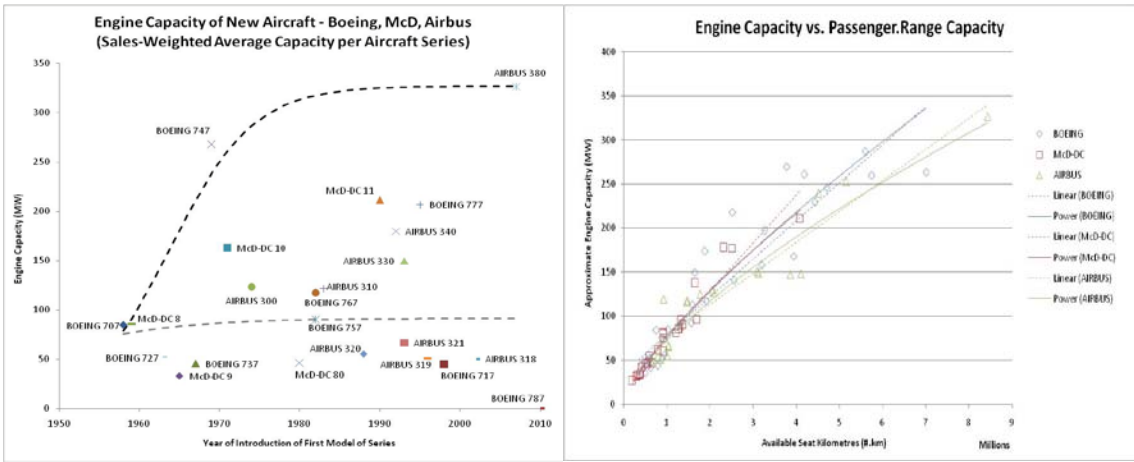


Figure A.16. Passenger Jet Aircraft: Engine Capacities. Left-hand graph shows engine capacity for each aircraft series (using sales-weighted averages for each model in the series). Dotted lines show logistic fits to unit scale frontier and average unit capacities. Right-hand graph shows linear relationship between engine and passenger capacity over most of the range of engine capacities. [Data from various sources; see text for details].

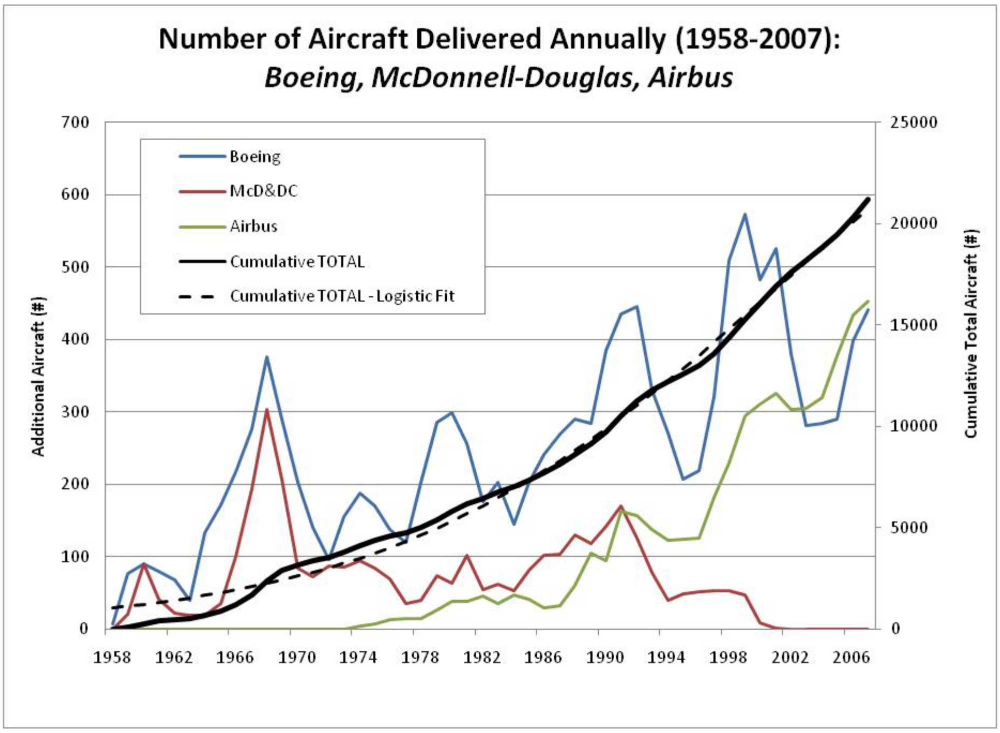


Figure A.17. Passenger Jet Aircraft: Annual and Cumulative Total Deliveries. Numbers of aircraft delivered each year by the 3 major OECD manufacturers. Thick black line on right-hand y axis shows cumulative total; dotted line shows logistic fit. [Data from various sources; see text for details].

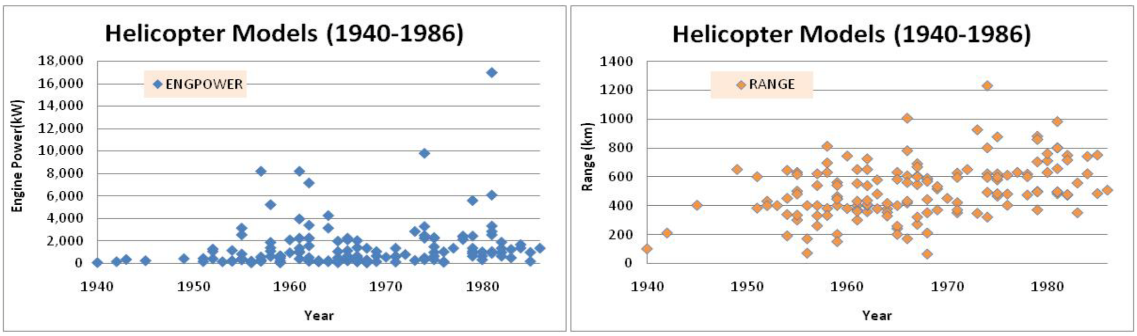


Figure A.18. Helicopters: Unit Specifications. Engine power (left-hand graph) and range (right-hand graph) of helicopter models plotted against year of first flight. [Data from (Saviotti & Trickett 1992); see text for details].

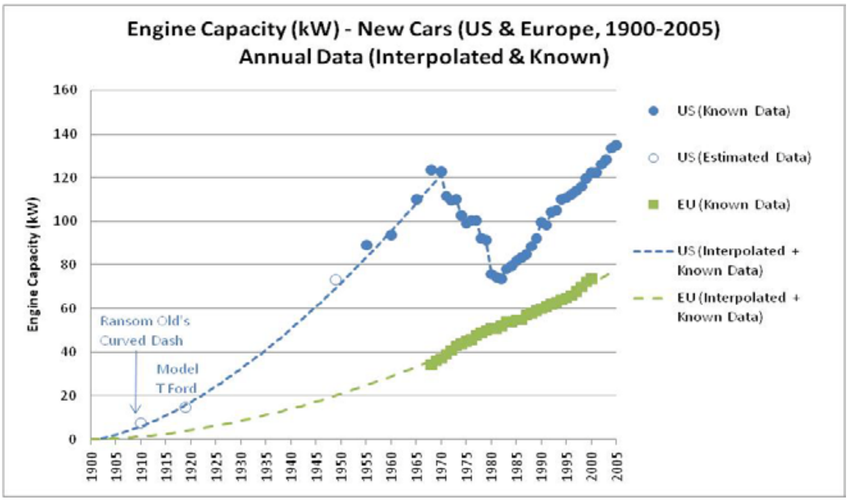
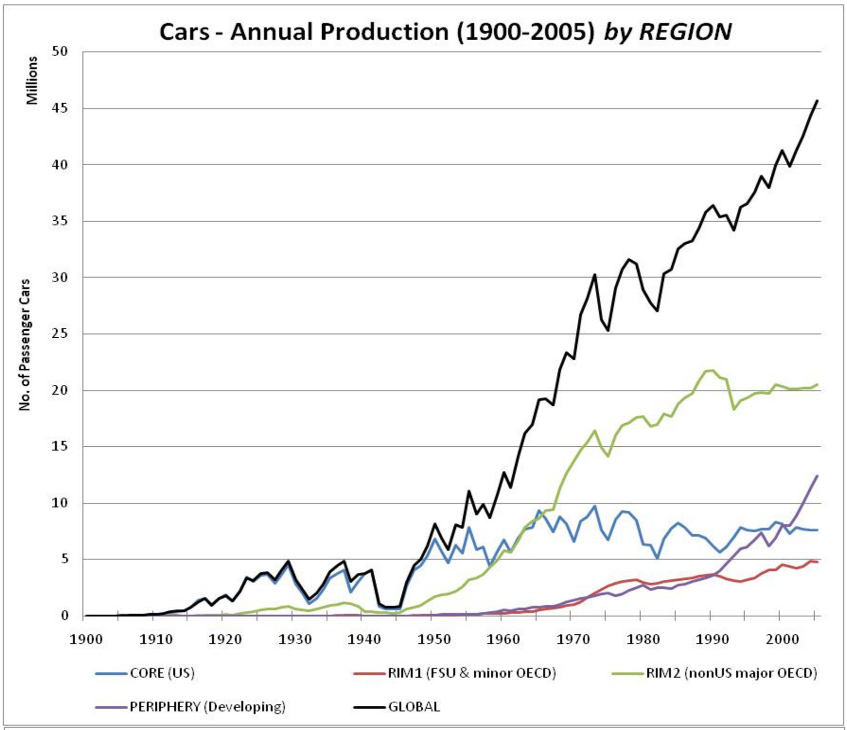


Figure A.19. Cars: Engine Capacities. Markers show known and estimated average engine capacities of new cars in the US and Western Europe; dotted lines show interpolated and back extrapolated data. [Data from various sources; see text for details].



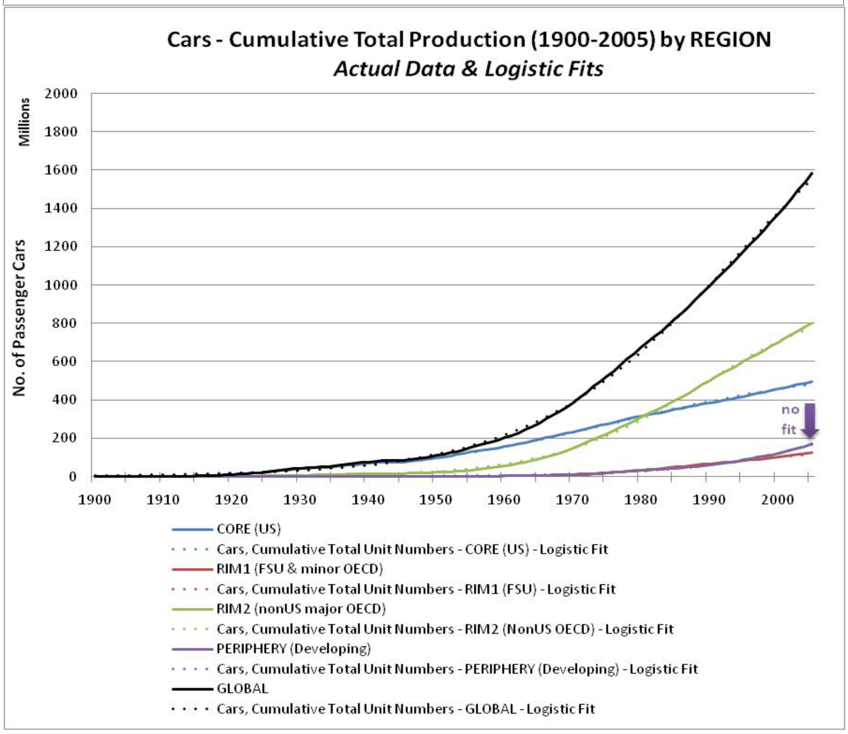


Figure A.20. Cars: Cumulative Total Production. Annual total (upper graph) and cumulative total number of cars (lower graph) produced globally and in 4 regions. Dotted lines on lower graph show logistic fits. 'No fit' marker indicates insufficient data (< 60% of K) for reliable estimation of logistic model. [Data from various sources; see text for details].

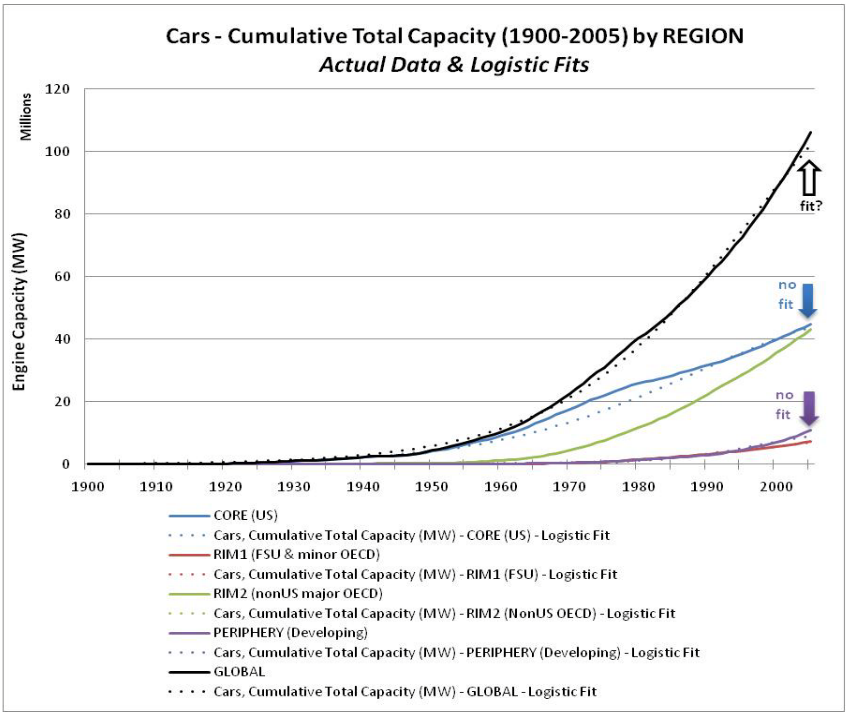


Figure A.21. Cars: Cumulative Total Capacity. Cumulative total engine capacity (MW) produced globally and in 4 regions. Dotted lines show logistic fits. ‘No fit’ marker indicates insufficient data (< 60% of K) for reliable estimation of logistic model. [Data from various sources; see text for details].

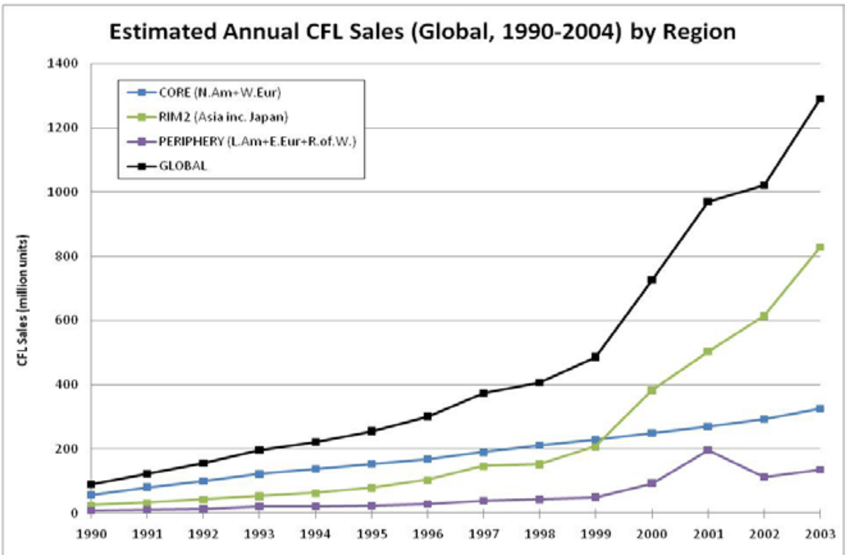


Figure A.22. Compact Fluorescent Light Bulb Sales. Annual sales of 'energy efficient' compact fluorescent light bulbs from 1990-2004 globally and in 3 regions. [Data from (IEA 2006); see text for details].

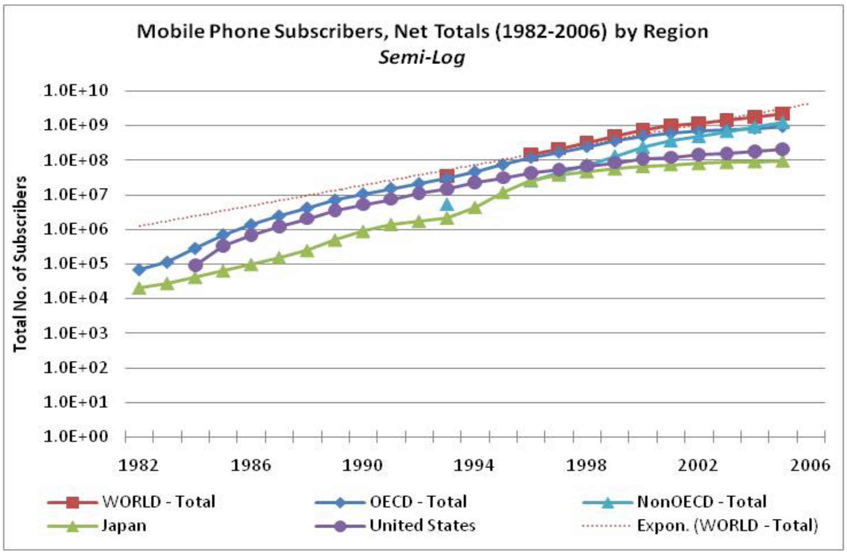


Figure A.23. Mobile Phone Subscribers. Total number of mobile phone subscribers globally and in various regions. Note log scale y-axis. [Data from (OECD 2007; OECD 2009); see text for details].

Appendix B: Scenario Data & Logistic Fits

This Appendix provides detailed information on the scenario data used for each technology. All scenarios are taken from IIASA's Integrated Assessment Modelling Framework described in detail in a special issue of *Technological Forecasting and Social Change* (Riahi et al., 2007). Graphs are included in this Appendix, and underlying data are available online with the historical data; see the Transitions to New Technologies program on the IIASA website: http://www.iiasa.ac.at/Research/TNT/WEB/Publications/Scaling_Dynamics_of_Energy_Technologies/ .

The methodology for data compilation and analysis, including fitting logistic models, is identical to that used for the historical data (described in Section 3 and the previous Appendix) with some exceptions:

i. Scenario data were compiled from outputs of the MESSAGE model rather than primary sources;
ii. Scenario data were only available for industry scaling in terms of cumulative total capacity (MW); no data were available for total unit numbers nor unit capacities.

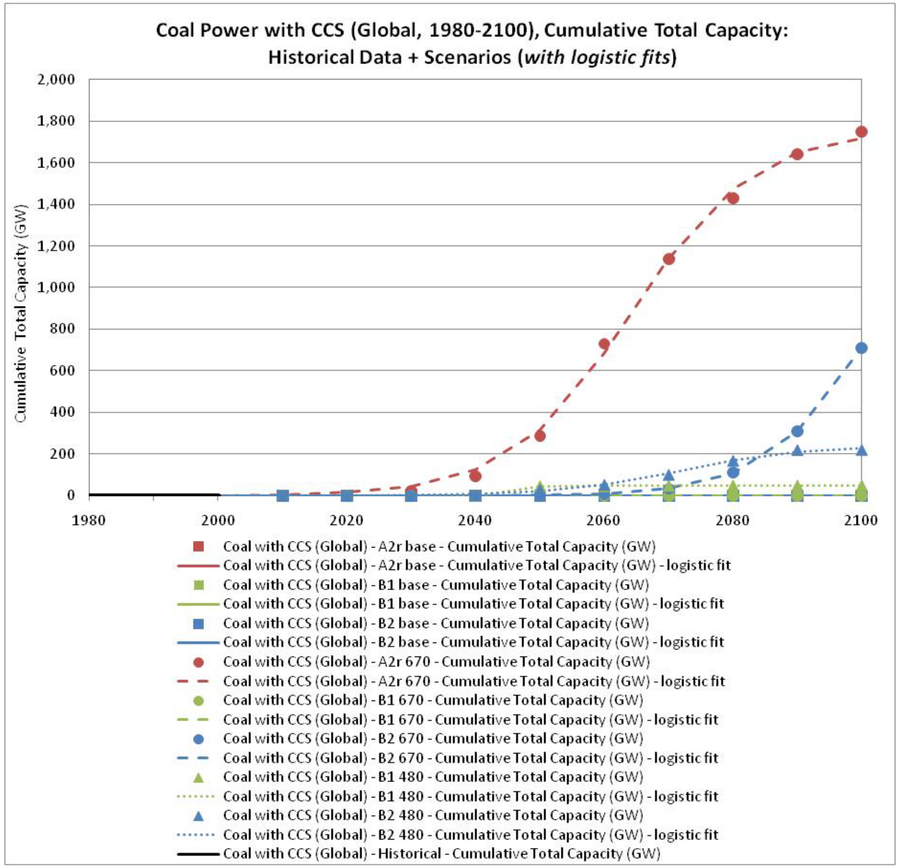
Although MESSAGE tracks cumulative total capacities, as an explicit model of capital stock turnover its emphasis is on production and net installed capacities. Cumulative total capacity data from MESSAGE were cross-checked against net total capacities combined with a simple capital stock turnover model assuming 30 year plant lifetimes. Differences were <5% despite the simplifying assumptions of the validation so cumulative total capacity data were considered robust.

CCS is modelled in MESSAGE in terms of generation (in EJ). CCS imposes a 15-25% production penalty on plant output so coal power plants with CCS have lower effective capacity factors.

Coal, nuclear and natural gas power are modelled in MESSAGE as different technology types: conventional, integrated gasification combined cycle, and fuel cell for coal power; light water reactor, fast breeder reactor, higher temperature reactor for nuclear power; conventional, combined cycle, and fuel cell for natural gas power. In all cases, the different technology types were aggregated into a single data series for each technology.

Solar PV is modelled in MESSAGE as both centralised and decentralised applications. The maximum shares of centralised solar PV are low: 0.5 - 1% in the A2r family; 6-7% in the B1 family; 2-9% in the B2 family. As a result, solar PV cumulative installed capacity data are aggregated across both applications.

Figure B.1 shows cumulative total capacity (MW) of 6 technologies under 8 scenarios from 3 scenario families (A2r base & 670 ppmv; B1 base, 670 ppmv & 480 ppmv; B2 base, 670 ppmv & 480 ppmv). Data are global for 1980 – 2100.Solid black line shows historical data. Markers show decadal MESSAGE output data. Dotted lines show logistic fits. Note different y-axes for each graph.



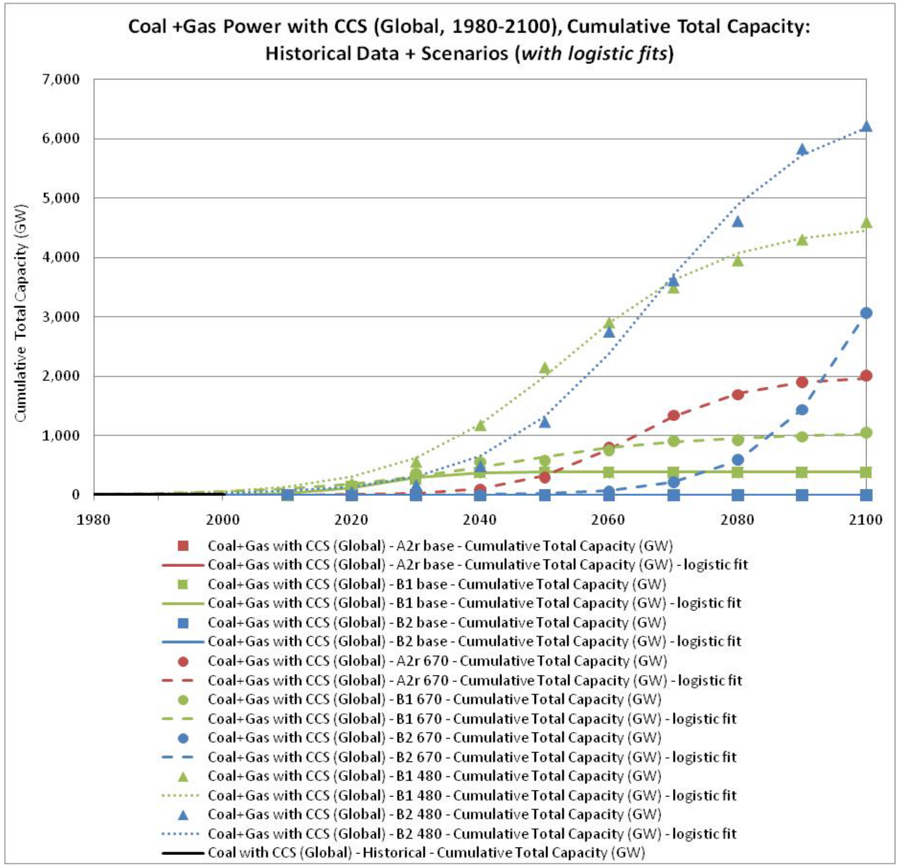
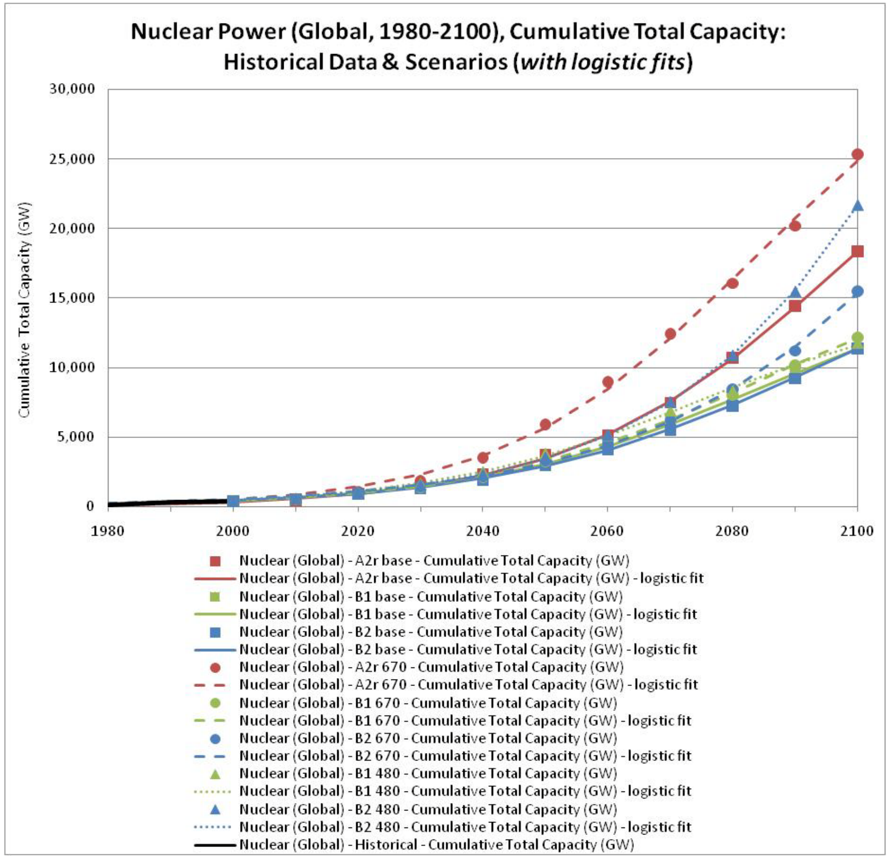


Figure B.1. Scenarios of Low Carbon Technology Scaling. [Data from IIASA's Integrated Assessment Modelling Framework (Riahi et al. 2007); see text for details].



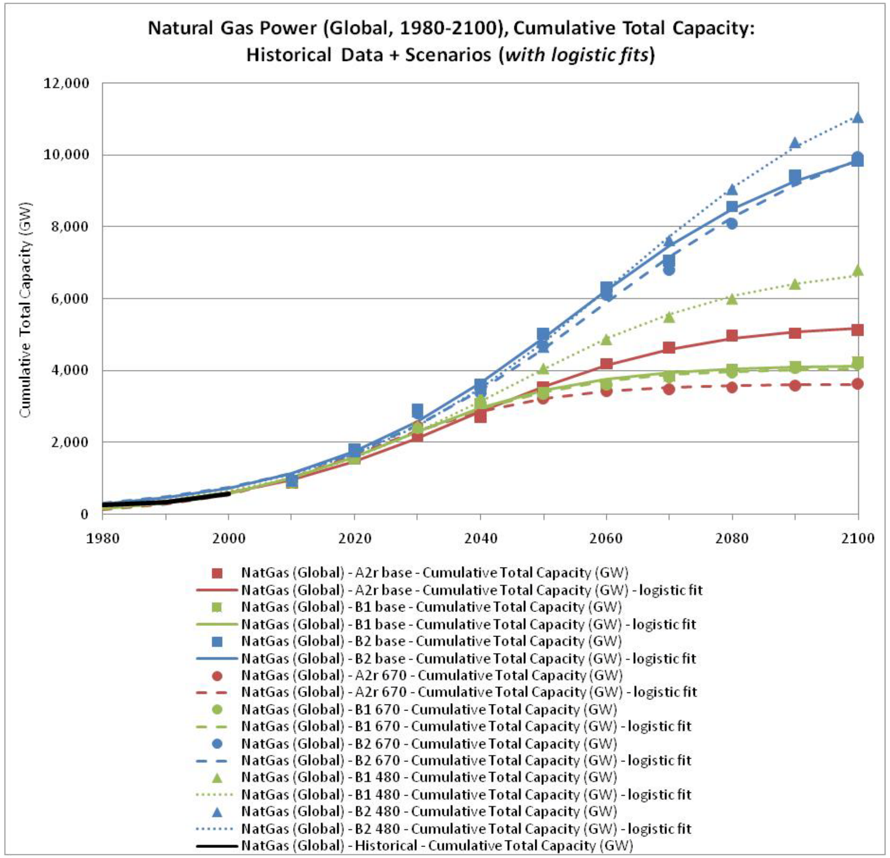
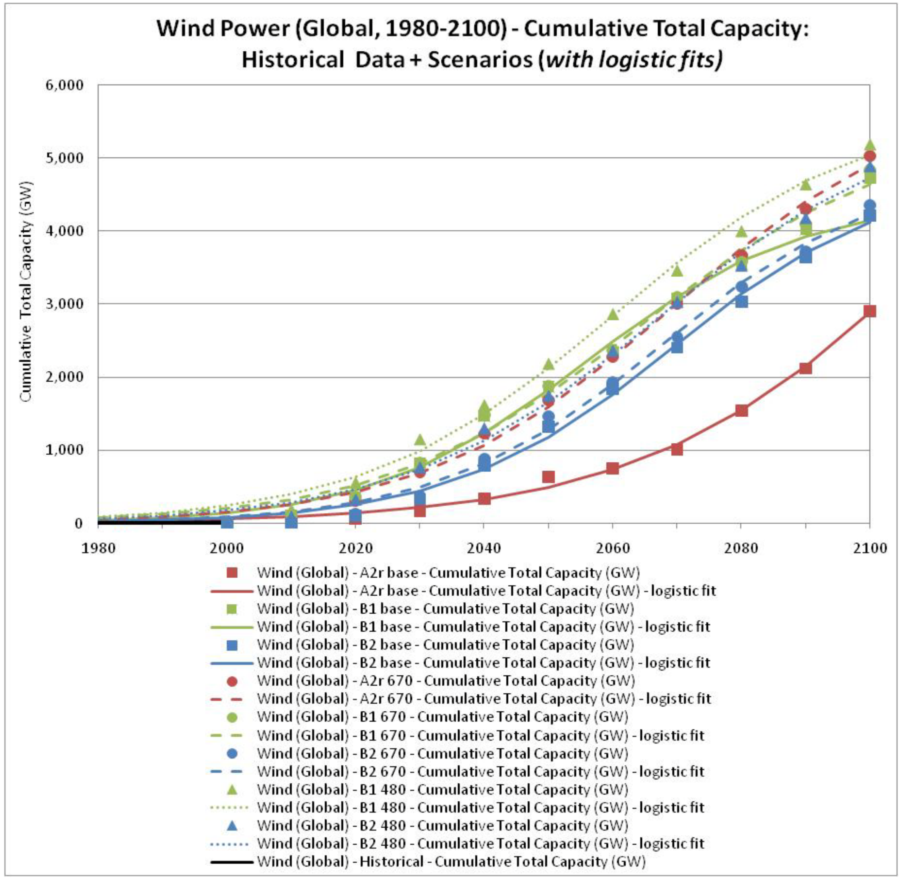


Figure B.1.(continued).



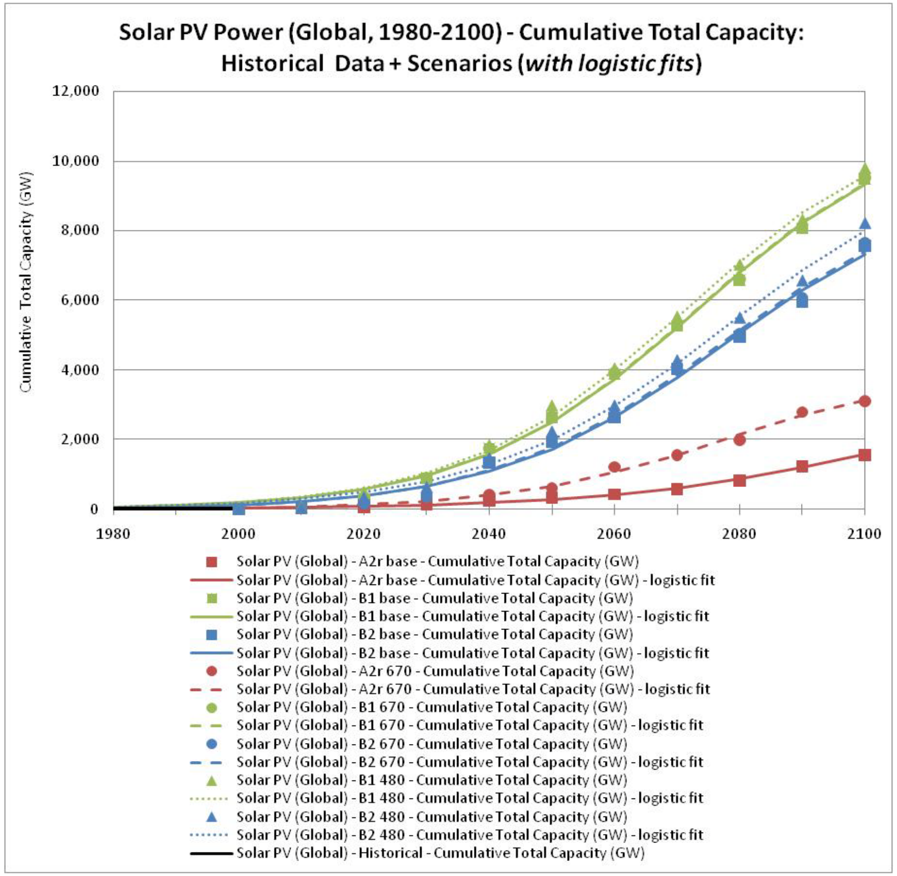


Figure B.1.(continued).

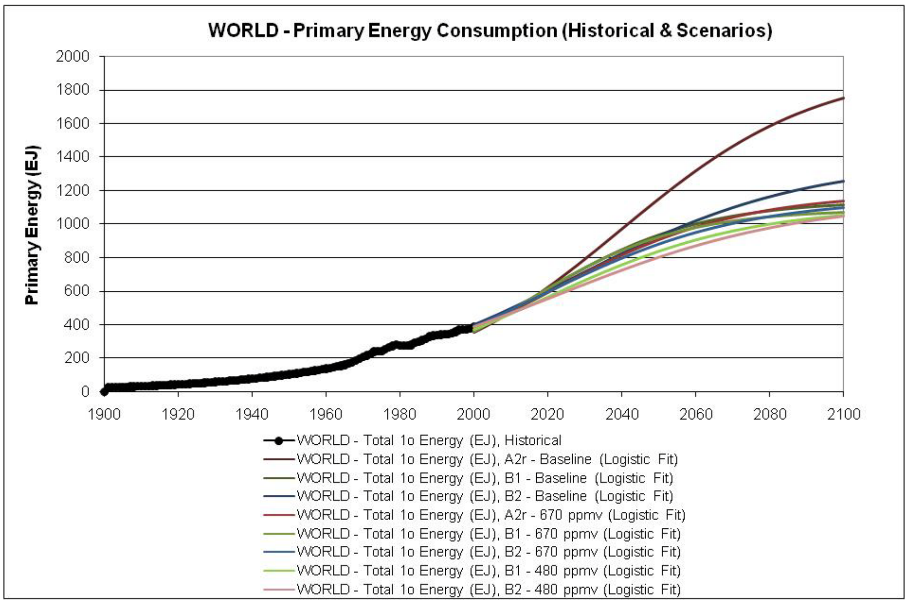


Figure B.2. Scenarios of Total Primary Energy. Total primary energy consumption (EJ) globally both historically(1900-2000) and for 8 scenarios (2000-2100).Primary energy data are used to normalise the fitted K parameters of the industry scaling logistic functions to account for changes in system size. [Historical data from (Smil 2000); scenario data from (Riahi et al. 2007)].

Appendix C. Unit Scale Economies in Energy Technologies

Isolating Unit Scale Economies from Other Cost Drivers

In this context, unit scale economies for energy technologies describe an increase in capacity per unit (MW/unit) resulting in a decrease in cost per unit capacity ($/MW). Data on both unit capacity and cost per unit capacity are generally available for the energy technologies analysed in this study. However, simple unit scale economies are difficult to isolate from economies of scale at other levels and also from learning effects.

Observed unit cost reductions during commercialisation and deployment most commonly conflate unit scale economies with more conventional economies of scale in terms of manufacturing and production. In one recent study, the capital cost per unit capacity ($/MW) of wind power in California was found to have fallen by a factor of four since 1980, but the relative influences of unit and manufacturing scale economies were not isolated (Nemet 2009b).

Ultimately, cost reductions may result from scale economies at many different levels:

- <u>unit level</u>: e.g., increased technical efficiency at larger unit capacities (*holding unit numbers constant*);
- <u>plant level</u> (also facility level or installation level): e.g., spreading fixed balance of installed system components over larger unit numbers and/or unit capacity;
- <u>manufacturing level</u> (also production level): e.g., spreading fixed capital inputs over larger unit numbers (*holding unit capacity constant*);
- <u>organisational level</u>: e.g., labour productivity or lower cost volume purchases of material inputs;
- <u>industry level</u>: e.g., greater potential to exercise market power or political economic influence;
- <u>system level</u>: e.g., greater availability of required infrastructure and supporting institutions.

Another recent modelling study of integrated gasification combined cycle (‘IGCC’) plants with carbon capture and storage (‘CCS’) assumed cost reductions of 17.5% for a doubling of unit capacity from 250 to 500MW, and again from 500MW to 1000MW (Al-Juaied & Whitmore 2009). This unit scaling effect, however, did not hold constant all other drivers of cost reduction including the likely returns to scaling up a new industry.

Isolating Unit Scale Economies (1): Econometric Models

Two approaches have been used to disaggregate scale economies from other influences on the unit cost of energy technologies. The first are econometric models with distinct scale, learning, factor input and productivity variables. The second are bottom-up engineering models disaggregating the cost drivers by component.

Econometric approaches typically use a Cobb-Douglas functional form to explain the logarithm of unit cost as a function of the logarithm of unit capacity. An early example examined the relative influence of unit scale economies and learning effects on the construction cost of the first 41 nuclear power plants built in the US to 1978 (Zimmerman 1982). A doubling of unit scale (MW/unit) reduced the cost per unit capacity ($/MW) by 12%, although the effect was not significant.[46] The effect of unit scale economies was also weaker than that of construction lead times and delays coupled with rising factor prices pushing costs up, and both appropriable (construction firm) and non-appropriable (industry wide) learning effects pushing costs up.

A similar model fitted to data on coal power plants built in the US from 1960-1980 showed a doubling of unit scale reducing the cost per unit capacity by 12%, controlling for learning effects (also both appropriable and non-appropriable), compliance with environmental regulation (scrubbers, cooling towers), and time as a proxy for productivity changes (controlling for changes in input prices) (Joskow & Rose 1985). Unit scale economies were also found to differ between technological variants: scaling of super-critical units reduced unit costs further than sub-critical units.[47]

A later study of steam turbine units in both coal power plants (1960-1980) and nuclear power plants (1967-1988) in the US similarly found significant unit scale economies controlling for environmental regulation, changes in factor inputs, and learning by both design and construction agents and utility principals(McCabe 1996). In the case of coal, a doubling of unit capacity reduced unit costs by 20-24%, and in the case of nuclear by 15-19% (although with higher uncertainty).

Interestingly, the data period to which both these nuclear and coal unit models are fitted describes the rapid growth phase of unit scaling dynamics during which unit scale economies might be expected to be most evident. This supports the general contention in Section 4.2 that the rate of observed unit scaling is a rough proxy for the availability of unit scale economies. Although learning effects are concurrent with unit scale economies, it seems likely that they - or other drivers of cost reduction - would exert greater influence on similar models fitted to earlier data periods (say: from 1910-1940).

Another interesting finding from the study of coal power unit economies was a reversal of utilities' preference for super-critical over sub-critical designs towards the end of the 1970s despite the latter's weaker scale economies and lower fuel efficiencies (Joskow & Rose 1985). One explanation was the weakening of electricity demand following the oil shocks which increased the risk to utilities of large construction projects with long lead times. This illustrates the trade-offs between scale economies and demand constraints in determining preferred unit capacities (see Section 4.2).

Isolating Unit Scale Economies (2): Bottom-Up Engineering Models

As an example of the bottom-up engineering approach to cost drivers, a model disaggregating the determinants of solar photovoltaic ('PV') module cost ($/Wpeak) found manufacturing scale economies explained 43% of observed cost reductions from 1980-2001 (Nemet 2006). During this period, manufacturing plant output had scaled by

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[46] The unit cost reduction from a doubling of cumulative production or, in the case of power plant construction, cumulative installed capacity is known as the 'learning rate'. As noted, however, this often aggregates 'true' learning effects with scale economies that are availed concurrently.

[47] Above a critical pressure threshold of 3206 psi, water heated to 706°F or above directly vaporizes to dry superheated steam, foregoing the need for equipment to extract and recycle saturated steam.

two orders of magnitude from 125 kW/yr to 14 MW/yr. Improvements in module efficiency explained a further 30% of cost reductions, with combined changes in yield, input materials, input costs, and wafer size explaining a further 22%.[48]

Note that for solar PV, three quarters of the 3.5% average annual decline in PV system costs between 1998-2007 in the US are attributable to non-module costs, which comprise around 50% of total installed costs and demonstrate clear economies of scale(Wiser et al. 2009).[49] In the terms used here, these are equivalent to 'plant level' economies of scale achieved through balance of system components (e.g., wiring, inverters, installation costs) rather than the PV modules. Large systems (>750kW) installed in 2006 or 2007 averaged \$6.8/W whereas small systems (<2kW) averaged \$9.0/W. As the average size of PV systems has increased over time, these plant level scale economies help explain the decline in PV system costs whereas module costs fell only marginally from 1998-2003 and actually increased somewhat from 2003-2007 (Wiser et al. 2009).

[48] Specified over a longer period (1975-2001), manufacturing scale economies explained only 19% of observed cost reductions and improvements in module efficiency a further 26%. The residual 40% of cost reductions not explained by the model were attributed to changes in quality, price sensitivity, market concentration and standardisation as the market for PV applications shifted from space to terrestrial at the end of the 1970s.

[49] Non-module costs include balance of system components (inverters, mounting hardware), labour, permitting and fees, shipping, overhead, taxes and profit (Wiser et al. 2009).

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