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Estimates of Learning by Doing in the Manufacture of Electric Power Gas Turbines

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ABSTRACT

This paper investigates LBD in prices and heat rates of gas turbines. We test whether the LBD spills over from production experience with smaller units. Progress ratios range from 0.83 to 0.95 for price and 0.89 to 0.94 for the heat rate. We do not find that learning spills over from the smaller size class. Since lower heat rates have an upward effect on price, the two learning effects offset one another so that the reduced form of experience on price is not significantly different from zero. The net result is that LBD has a large effect, but does not result in lower prices per se. The effects of cumulative experience are simultaneous increases in the performance, which tends to increase the value hence the price, and reductions in production costs, which allow the better unit to be sold for roughly the same price as the newer unit.

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Introduction

There is no single driver to the changes that are occurring in the electricity industry. However, it is safe to say that gas turbines are a component of that change, even if it is not possible to determine whether the gas turbine is the driver or a passenger. Even if gas turbines are just "along for the ride" in the changes in the electric sector, a better understanding of the economic forces leading to change in the gas turbine itself is important. This paper examines the role of learning by doing (LBD) in this rapidly growing technology for electric power generation. Gas turbines are not a new technology. Gas combustion turbines are a conventional technology that have improved substantially and have recently experienced a growing role in power plant capacity additions. Unlike coal-fired and nuclear plants, most of the cost in gas turbine power plants is in manufactured factory equipment. Since this technology is changing and its use is expanding, LBD in manufacturing may contribute to lower costs and higher performance, which could result in further expansion of their market share and even more impact on the energy industries.

It is clear that the technology changes in gas turbines have resulted in the units becoming "more economical" in the electric generation market than their predecessors. Prices for similar units have fallen; performance has improved. This paper investigates how LBD may have provided an impetus to those two dimensions of technical change. Dar-El (2000) illustrates how the simple observation that human experience with repetitive tasks results in improved performance can be represented by measurable *learning curves*. Dar-El cites psychology that shows that this phenomenon generalizes to a wide range of tasks and similarly wide range of implications. One such implication is the impact on the productivity of labor. Whether the labor in question is a factory worker assembling components or the engineer tackling another design issue, the experience gained from previous similar tasks makes the new task easier to accomplish. Initially, this effect may be quite dramatic. The second time something is done, it is much easier, but the marginal effect of the 100th or 1000th repetition diminishes. The impact of this improved productivity on a production process is that fewer hours of labor are required to produce a product as experience is gained with its assembly. Many economic studies have observed and measured the effect of cumulative experience on the labor component of production; more experience results in less labor hours and lower costs per unit. Studies have measured how the cumulative production experience in building war ships and planes to making computer chips have resulted in lower labor inputs and lower production costs. The impact of LBD has been seen to vary across products and industries. How large this effect is in the manufacture of gas turbines is the focus of this study.

Similarly, the designs of a product may improve with subsequent generations of a product that incorporate better ideas gained from designing *and producing* the earlier models. This type of experience may result in lower costs, e.g. better designs for manufacturing, but may also result in better performance. In economic terms, this is a change in *quality* rather than production *costs*. Since there is strong anecdotal evidence that the performance of gas turbines has improved, this study also examines LBD. The potential synergy between LBD and market growth discussed above is what makes this issue even more important. If the impact of LBD is a large component of the change, then we might expect the cost to continue to fall and performance of the technology to continue to improve.

Many learning studies focus narrowly on a production task, e.g. building a particular model of airplane in a particular factory. Other studies look at the experience of an entire industry. The latter is the case for gas turbines. In addition, when we talk about "experience" in gas turbines production we are talking about a variety of products with similar, but not identical characteristics. It may be that the experience gained in producing one type of turbine readily applies, or "spills over," to other models. In particular we look at whether experience in producing small size turbines has any impact on larger models. We are interested in this because the markets for the small and large turbine are quite different, but LBD may provide a connection between these markets.

Islas (1999) chronicles the historical technological evolution of gas turbine systems. He focuses on the changes in size and thermal efficiency over time and alludes to the role of 'learning' in this process. Although he compares the variable and production costs of the gas turbine with other conventional technology, he does not examine how the price of this technology may have changed alongside its performance. LBD typically results in lower production costs and thereby prices when markets are competitive. However, when the cost of the turbine alone is examined, one expects that a tradeoff may be made between capital cost and performance. Higher performance, either in such characteristics as reliability or heat rate, is likely to be more expensive. In this case, LBD may actually be associated with rising prices, if LBD manifests in changes in performance. Bahk and Gort (1993) argue that either case may equally be associated with LBD, so this paper considers how learning may effect both the performance and cost of gas turbines.

The paper is organized as follows. First we explore some of the basics of LBD and discuss some related empirical studies. The purpose of this empirical review is to give the reader that is not familiar with the LBD literature some context for our own estimates. Next, we discuss our data sources. Finally, we present a recursive system of two equations, which forms the basic regression model we specify for LBD in gas turbine manufacturing.

Learning Curve Fundamentals

The learning curve expresses the cost of producing some item as a function of experience in such production. The empirical formulations have employed a variety of metrics for cost and a variety of definitions for the scope of experience. Costs may be total dollar investment in all aspects of production or some subset thereof. Labor hours has been a common measure of "cost," but clearly reflects a narrower focus. Total cost or labor hours have been defined as instantaneous, recent average, or cumulative average. Experience is more consistently represented as total cumulative production, but the scope of experience may encompass a plant, a firm (or subset thereof), a collection of firms or an entire industry.

It is not surprising that the time required to perform a task or series of tasks declines with experience. It is also not surprising that decline is less dramatic as experience accumulates. What is surprising, is that the reduction in labor requirements seems to be well represented by a simple mathematical formulation. The generally-cited first documentation of this realization was published by T.P. Wright in the Journal of Aeronautical Sciences in 1936 (Argote and Apple 1990). What Wright reported was that the decline in labor requirement for production of a single air-frame could be represented by the following formulation:

$$C_Q = C_I \bullet Q^a \tag{1}$$

where

C_Q is the cumulative average cost for Q units

C_I is the cost of the first unit

Q is the cumulative production

a is the learning parameter

While referred to here as the learning curve, this relationship is also commonly called the progress curve, progress function, or experience curve. The progress function can be used to represent cost reductions or productivity improvements due to materials changes, process improvements, management innovations, and production scale in addition to labor experience (Dutton and Thomas 1984). Such a broadly defined learning curve concept has application to current industrial cost engineering (Smith 1989).

Other differences in LBD analysis focus on such issues as the appropriate proxy for experience or how experience may be transferred or depreciate. Experience is typically represented as total cumulative production, but the scope of experience may encompass a plant, a firm (or subset thereof), a collection of empirical studies e.g.(Irwin and Klenow 1994), Jarmin 1994), Jarmin 1996), and including those of the electric sector, Zimmerman (1982), Joskow and Rose (1985), and Lester and McCabe (1993).

Learning reflects the observation that unit production costs or input requirements decline over time, due to experience with the production process. This experience may come from cumulative production, which we will call learning by doing, or from other sources over time. Declining unit costs or input requirements over time can arise from a variety of sources, not all of which one would strictly label by doing. Failure to control for these other sources of cost reduction may bias an attempt to estimate learning by doing. This bias could introduce errors in forecasting or policy inferences. Therefor it is very important to understand these other sources of cost reduction and how they might be associated with learning. Some of these sources include:

- Economies of scale
- Product innovation, i.e. improvement in the technology that change the quality of the product (better performance, lifetime, features) that increase its value.
- Process innovation, i.e. significant improvements in production technique.

Economies of Scale

It is important to keep in mind that the focus of this paper is to estimate the impacts of experience on the manufacturing cost of gas turbine generating *capacity*, not on the cost of electric generation. In particular, electricity generation economies of scale are often cited as important factors in the busbar cost of electricity. This study examines the industries that build power generating capacity or its major component parts. The unit costs that are represented here are capacity, i.e. kW, not generation, kWh. There are two possible types of economies of scale in our context. The first is the manufacturing economies of scale in turbine production. The second is the effect of larger sized turbines on the per kW cost. We are able to investigate the latter in our study, but do not have data on the former. It is possible that if there are increases in the scale of manufacturing of gas turbines and they have contributed to lower costs over the period of time we investigate, our estimates will be biasing toward more LBD. We also investigate the role of LBD on turbine performance. We feel it is unlikely that scale of manufacturing would have any effect there.

Product Innovation

Product innovation implies that the product is more useful and has a higher value. In the context of generation technologies, while *capacity (kW) costs* may not be declining, the same kW of capacity can have a higher value. This may be very important for electric generating technologies, like gas turbines, where the focus of learning may be building lower heat rate, higher reliability, and larger scale units. In electric generation technologies, higher value of the product may be embodied in a performance variable like heat rate. Lower heat rates imply lower cost of operation and lower unit costs of electricity production. This means that each unit of capacity is worth more than before the improvements. Another element of value would be an inherently 'cleaner' technology, in terms of lower emission and lower add-on control costs. Bahk and Gort (1992) argue that product quality changes and innovations may be viewed as part of 'learning'.

Most learning studies assume that the product, or technology, is unchanging.

The focus is on producing the same "widget" with less input, hence at a lower cost per widget. The approach suggested by Bahk and Gort is that producing a "better widget" is a valid form of learning. This will only produce reasonable empirical estimates if the prices of the improved products rise to reflect their inherent value or we can observe a hedonic characteristic. In our case, it is the latter, since we observe the heat rate of different types of gas turbines.

Process Innovation

Process innovation, better production techniques or process changes, can be important sources of cost reduction. Within the context of learning by doing, it is important to distinguish between

(a) innovations that arise from new technical information that is developed over time, and

(b) process changes that are embodied in new capital equipment versus improvements that arise from incorporating this new information and fine tuning these process changes with operating experience.

The latter source we characterize as learning by doing, while the former is a source of exogenous technical advance. For example, aeroderivative turbines may be a technology that was developed from military R&D but found its way into power generation. However, learning by doing cost improvements in manufacturing of these newer design turbines would arise from the application of this knowledge and experience in using it related to rated levels of capacity, maintenance and the use of physical capital in place. This does not imply that 'learning' is not involved in the creation of innovation, but that the focus of learning by doing is typically on productivity rather than process changes.

Empirical Studies

Most, if not all, empirical studies assume the exponential (log-linear) functional form of learning that is discussed above. Everett and Farghal (1994) report on the usefulness of the exponential function form that is so commonly applied in empirical studies. (Badiru 1992) investigates the proliferation of functional forms for estimation of LBD, but admits that the simple model performs well.

While many studies in the literature use some form of learning cost curve or progress function, the notation and method of reporting the results also varies. To summarize the studies we have examined we follow Dutton and Thomas (1984) and report the progress ratio. The progress ratio is defined as the fraction of cost that remains when production doubles. In terms of equation 1, costs decline to the progress ratio, d, of its previous level with each doubling of cumulative production, with $d=2^{\alpha}$. Thus if $\alpha = -.33$, then $d=.8$ and costs fall by 20 percent each time cumulative production doubles; or if $\alpha = -.25$, then d=.84 and costs fall by 16 percent with each doubling of cumulative production.

Dutton and Thomas report the distribution of progress ratios observed in over 100 studies. The median progress ratio, d, is about 80%, i.e. a 20% cost reduction for each doubling of production. Lieberman finds progress ratios of 70-80% in a study of 37 different chemical products. Gruber (1994) estimates a 79% progress ratio for one class of semiconductor memory chips, EPROMS, but no statistically significant results for other classes of chips. Both Lieberman and Gruber use industry level price data in their studies. It is interesting to note that both chemicals and semiconductors are high tech products, but may also be viewed as commodities with a high degree of 'mass production'.

It is results like these that lead to the '80% rule' to generalize learning by doing. However, Dutton and Thomas suggest caution in using this level of performance to predict future trends. A high degree of variability, even within products or industries exists in the studies they review. They argue that the level of learning is a managerial target to work toward, not necessarily an inherent aspect of production.

In another study of LBD, firm level data at the Census Bureau was employed (Bahk and Gort 1992). Their work covers a wide range of manufactured products, using a production function approach. They explicitly control for two other sources of productivity change, 1) human capital effects and 2) process innovation. They proxy human capital with a plant level wage rate and the vintage of capital equipment is used as a proxy for process innovation. They find that industry-wide learning is directly related to the vintage of capital. When this source of industry-wide productivity change is controlled for they find statistically significant learning by doing at the individual firm level. However, they find much smaller progress ratios than the earlier studies review by Dutton and Thomas. Progress ratios range from 99% to 95%[1], depending on model specification and industry type. Typical estimates were only 97% - 98%.

Joskow and Rose (1985) have done the only major study of learning in fossil-fired electric generation plant costs. They control for a variety of time, technology, and size effects. In particular they examine whether learning is technology specific, i.e. depends on the specific costs and experience in coal plants of different pressure classes. They also examine whether the experience is specific to the utility or to the architect and engineering (A&E) firm. They find that both of these factors are statistically significant and induce some change in the estimates of the learning parameter. The learning effects found by Joskow and Rose are much closer to those found by study of manufacturing firm learning conducted by the Census mentioned above. The progress ratios range from 98%-94%, depending on technology class and whether the experience comes from the A&E firm or the utility as the general

[1] One pooled specification yielded an estimate as high as 90 %, but this was rather out of the ordinary

contractor. The highest progress ratios were for supercritical units. These were 96% and 94% for the utility and A&E firm experience, respectively.

There is an extensive empirical literature on learning, though it is often based on price rather than on cost data, which is typically confidential. Lieberman (1984) argues that prices are a reasonable inference to costs if the price/cost margins are constant, change very little, or are controlled for, in some way, by the analysis. While these assumptions appear strong, it is often difficult to get firm or industry cost data to test the assumption that prices are proportional to unit costs. The more competitive the industry the better this assumption will be.

A major distinction may be made between studies like Joskow and Rose and Bahk and Gort. The former examines the field construction costs of a major facility while the latter examines learning by doing in manufactured products. While the sources of learning by doing should be conceptually the same, we must distinguish between the two situations in applying these results to the gas turbine technology. Some electric generation technologies have more investment in field construction while others have more investment in manufactured components. For example, the coal fired generating plants examined by Joskow and Rose have a high field-construction component, while gas turbine plants have the majority of their cost embodied in the manufactured turbine. Learning due to construction experience will have a much smaller impact on total costs for the gas technology than for traditional coal technologies. In general, the relative proportion of plant investment in capital equipment and in site labor is expected to be a determinant of the learning parameter. This is due, in part, to differences in the learning rate for these two types of activities. The difference will also reflect the fact that the experience measure is quite different for the two activities.

We have examined power plant costs for factory equipment, construction labor, and site materials. Pulverized coal plants have the breakdown: 55% factory equipment, 30% construction labor, and 15% site materials. The natural gas combined cycle has a substantially higher proportion of factory equipment. The breakdown is 80% for factory equipment, 12% for construction labour and 8% for site materials. Combustion turbine plants are expected to have an even higher fraction of costs attributed to factory equipment.

Data

The data used to estimate the learning curves came from two sources. Price data for gas turbine systems was taken from issues of the "Gas Turbine World Handbook." The issues were from 1987, 1988-89, 1990, 1991, and 1992-93. These issues gave us data for the years 1987, 1988, 1990, 1991, and 1992. After 1993, this price data was no longer published, restricting our analysis to these years. The GTW Handbook also gave the heat rate and capacity of the model. Manufacturing cost would be preferable to the market price data. However, if the markup over marginal cost is constant over the period, an assumption that is discussed below, then price data will reflect the learning. The data set includes 188 observations, mostly of very small size units. Nearly ½ are 25 MW or less. There are 40 observations with sizes 100 MW or greater. The larger size units are the focus of our analysis, as explained below. Estimating the learning in factory equipment requires that cost adjustments only remove inflation, not learning. The producer price index was used to deflate the data to constant dollars.

The second piece of data required is a measure of the cumulative production of gas turbines used for electricity generation. Argonne has developed a database of generating capacity. That database contains the plant type, size, year built, and fuel used by the generating facility. To create a variable for cumulative production of gas turbines, data for the year on-line and capacity for all gas turbine units in the U.S. electric utility industry were used. Based on the population of gas turbine units in operation in 1992 the cumulative sum of capacity, based on the year on-line was constructed. This resulted in a time series of total newly installed gas turbine capacity. Summing the time series up to but not including each year arrives at the cumulative production of gas turbines for use by the electric utility industry. A similar measure of cumulative production was calculated which excluded all units below 100 MW. The rationale for these alternative variables is that most of the more important innovations in gas turbines are in the large size categories. These variables allow us to test for a 'technology size' component of learning. In addition, the larger size gas turbines are more important in light of the changes the industry is undergoing.

There are problems with the use of these variables, which are discussed in more detail below. The first is that the data covers only U.S. utilities. Industrial gas turbine units, independent power producers, and co-generators are not accounted for. Moreover, if learning can occur across applications, e.g. from airplane engines to electric generation, then this measure of cumulative output understates the 'true' cumulative output and the learning effect will be overstated. On the other hand, if learning is of greatest interest in the larger capacity sizes that are currently of interest to the electric sector, then this omission is less important. We return to the issue of learning across applications in model results below.

Growth in the Market Segment

It was observed that there was a dramatic increase in the gas segment of the electric utility capacity market in the mid-1980s. Between 1986 and 1992, our measure of cumulative production of gas turbines increased by 22 percent. This increase in market segment may bias the results of our regressions since we do not account for shifts in demand for gas turbines. The percentage growth in cumulative production of units over 100MW (48%) is even larger.

A rapid or large change in the demand for any product will have an impact on its price. If the demand for turbines increases, then the pressure on the market price of gas turbines is upward. In the long run, new suppliers will enter the market and the supply curve will shift downward. In the short run, the price markup assumption is likely to be violated. The increase in installed capacity and high level of new orders suggest that this may present problems with the use of price data, without a complete treatment of supply and demand. However, the market for gas turbines is very competitive. During the 80's and 90's competition and tight profits has lead to industry consolidation, not higher prices. For this reason, we expect our analysis to be reasonable.

Hedonic Price Issues

Characteristics of the gas turbines will affect the price. The two most important hedonic variables are the size of the turbine and the conversion efficiency. The latter matters largely because the demand for gas turbines is a derived demand for electricity, hence the efficiency with which it converts gas to electricity matters a lot. The price / size relationship of the turbine may also not be linear. The value of small or large turbines will depend on what market niches for electricity they are intended to satisfy. Similarly, larger turbines may be cheaper to manufacture on a per kW basis.

It was observed that the price per kW of gas turbines declines with increasing size. For example, the price in 1988 is $509 per kW for 1 MW (Saturn model) and $154 per kW for 20.2 MW (model PG9281F). We also observed that the efficiency of different models generally increased with larger models. To account for these differences, we included size as a variable in the regressions that were estimated.

Heat rate also influences the price. One would expect that units that are more efficient are more expensive to manufacture. The decision on which to *buy* is based on fuel prices and appropriate discount rates. Our data does not allow us to estimate a complete supply and demand model, so we include heat rate, along with size, as a hedonic characteristic in the price equation. These variables appear in log form in the regressions.

There may be other unobservable characteristics of the technology that would influence the price. Newer gas turbines may be more reliable, require less maintenance, etc. To the extent that there are some unobservable qualities of newer turbines that would raise the price, then our estimate of learning would be biased downward (i.e. less learning).

Performance Embodied Learning

Since the performance of gas turbines has changed, even over this six-year period, we consider the possible effect of LBD on performance, specifically the heat rate. Changes in heat rate are expected to effect the cost of the turbine, as described above. However, LBD may have influenced the turbine technology by improving the quality of the product. Since we have a directly observable measure of quality, a separate equation relating heat rate and learning is estimated as well.

Basic Regression Results

The basic price equation is given by the following:[2]

$$\ln(P_{i,t}) = k_p + \beta_p \ln(S_{i,t}) + \gamma \ln(h_{i,t}) + \alpha_p \ln(Q_t) + \varepsilon_{i,t} \qquad (2)$$

In addition to the price equation, a heat rate equation is specified.

$$\ln(h_{i,t}) = k_h + \beta_h \ln(S_{i,t}) + \alpha_h \ln(Q_t) + \varepsilon_{i,t} \qquad (3)$$

Where,	i,t	are the model and year, respectively
	$P_{i,t}$	is the price of the gas turbine model,
	$S_{i,t}$	is the size,
	$h_{i,t}$	is the heat rate,
	$Q_{,t}$	is cumulative production,
	$\varepsilon_{i,t}$	is the usual error term, and
	k, β, γ, α	are parameters to be estimated.

In preliminary analysis no significant trends were found in price or heat rate as a function of cumulative production or time for the entire sample. However, the most dramatic growth has been in the introduction and installation of large turbines. In 1987 there were only two models over 100 MW with prices reported in the data set. By 1992, there were thirteen models. Similarly, there was a 48% growth in cumulative production of units greater than 100 MW while there was only an 18% growth in units under 100 MW. This suggested that the technical change / LBD may have occurred primarily in larger units. Restricting the sample to units with capacity 100 MW, the two equations were estimated as a system using generalized least squares (GLS).

A major issue that has arisen in recent LBD literature is the transfer, or spillover, of LBD. Spillover may occur across plants, firms, or technologies. The degree of spillover has important theoretical and empirical implications. Since we do not have data on cumulative output on individual firms we cannot test for the firm specific LBD vs. industry-wide LBD. However, we can test to see if LBD in smaller units has any influence on the cost and performance of the large units. To test this we ran three models. One defines cumulative production for large units only, the second for all

[2] In earlier versions of the paper, other regressions were examined, such as non-log formulations equations which dropped the size and/or heat rate variables, various price deflators, and size cutoff.

units, and the third measure is for units under 100 MW. The first model is based on large unit experience only. The second is based on all experience. The third model is the same as the first, but includes experience in small units as well. Summary statistics for the data set are shown in Table 1. The results are presented below in Table 2.

Table 1: Sample Statistics (Observations = 40)

				Cumulative Production		
	Price (million)	Size (MW)	Heat Rate	All	<100 MW	Price per kW (1992$)
Mean	$26.06	141.3	9979	21186	2652	$ 165.85
Standard Deviation	0.99	5.5	49	243	64	1.48
Minimum	$17.50	100.5	9260	18734	2148	$ 149.30
Maximum	$41.50	226.5	10430	22802	3180	$1 85.13

Table 2: GLS Results for three specifications of LBD
(Standard errors reported below coefficients)

	k	β	γ	α >100 MW	α all	α <100 MW
Price	18.68 3.66	0.77 0.04	-1.48 0.30		-0.18 0.10	
Heat Rate	11.77 0.43	-0.07 0.01			-0.17 0.04	
Price	17.12 3.31	0.77 0.04	-1.44 0.31	-0.08 0.05		
Heat rate	10.74 0.20	-0.07 0.01		-0.08 0.02		
Price	19.04 3.86	0.77 0.04	-1.47 0.30	-0.22 0.16		-0.26* 0.28
Heat rate	11.29 0.91	-0.07 0.01		-0.13 0.08		-0.09* 0.14

*Not significantly different in a one-tailed t-test at 90% confidence or better.

All coefficients presented in table 2 have the expected sign. All estimates are significant in a one-tailed t-test, except for experience with small units in the third model. We reject the hypothesis that learning "spills over" from the less-than 100 MW unit experience to the larger-than 100 MW group. On the other hand, all models fit equally well (R^2 is 0.97 and 0.59 for price and heat rate, respectively) making it difficult to choose the best set of parameters. The estimated progress ratios for price range from 0.83 to 0.95, and .89 to 0.94 for heat rate performance.

Since LBD has an impact on both price and performance and the system is recursive, the LBD coefficients from the price equation represent only the partial effect. To obtain the reduced form, we substitute the heat rate equation into the price equation and solve. Since lower heat rates tend to raise the price (or cost) of a unit the separate effects of LBD are offsetting. The reduced form coefficients for LBD are 0.07 and 0.04 for the first 2 models. The reduced form coefficients for the two types of LBD experience in the third model are –0.03 and –0.13. None of these reduced form coefficients are significant in a Wald test at any reasonable confidence level.

Discussion and Caveats

This paper investigates the role of LBD in the technology change for a rapidly expanding electric generation technology, gas turbines. LBD analyses typically focus on the reduction of cost per unit of production as a function of experience. We do not directly observe the cost of gas turbine manufacture, so we follow the approach used by others by taking market price as a proxy for cost. Since other researchers have argued that quality improvements are a valid form of LBD, we also estimate the impact of experience on an important performance variable, the heat rate. The dramatic improvement in heat rate for gas turbines makes this a particularly important empirical extension of LBD analysis. The result is a recursive system of two equations, with LBD entering price equation and heat rate equation with heat rate also influencing the market price. Preliminary analysis lead our investigation to the large (>100 MW) sized units. These units have experienced the most growth and are arguably more important in the changes that are ongoing in the electric industry. We test whether the LBD is specific to the large unit size class or spills over from production experience with smaller units.

We find that LBD is significant in both the price and heat rate equations. The LBD estimates, in the form of progress ratios, range from 0.83 to 0.95 for the price equation and 0.89 to 0.94 for the heat rate equation. We do not find that learning spills over from the smaller size class in either price or performance. Since lower heat rates have an estimated upward effect on price, the indirect LBD effect in heat rate improvement is in the opposite direction from the direct LBD effect on price. The two significant learning effects offset one another so that the reduced form of experience on price is not significantly different from zero. The net result is much like the Red Queen and Alice in the Lewis Carroll novel, "running very fast to stay in one place."

This result seems to be a good explanation for one of the reasons gas turbines have received so much attention in the changing electric market. Learning has improved the technology performance while at the same time kept the costs down. This, along with low gas prices and short construction times, has allowed for increasing opportunities for gas turbine penetration. The synergy between expanded adoption and more LBD suggest that gas turbines will continue to be even more attractive as time goes on.

How realistic might the magnitudes of the individual estimates of LBD be? Based on information from a manufacturing plant manager at the GE turbine division, learning curves *are* used to forecast production costs in *aircraft engines*. A typical assumption would be a progress ratio of 92%.[3] This is much lower than the "80% rule" derived from earlier studies, which this manager suggested would be 'very optimistic', and much closer to the estimate we obtained. Our estimates are also much closer to those obtained by Joskow and Rose for fossil power plant *construction costs* and for cross-sectional estimates of plant specific learning in manufacturing productivity (Bahk and Gort, 1993).

There are some unavoidable shortcomings to the data we use and hence our results. The time-period over which the data was published is rather short. Other measures of performance would be interesting, like maintenance cost or reliability of the newer turbines. Actual manufacturing cost data would also be preferred over the market price data we used. Firm or company level information would allow the testing for industry vs. firm specific learning. Nevertheless, without access to information that is typically proprietary, like company level production and costs, we have made use of market data to estimate a set of LBD relationships that seem quite consistent.

These estimates rely on a measure of cumulative production value based on U.S. utility gas turbine capacity. We are faced with the untested assumption that the ratio of U.S. experience is proportional to the world (i.e. the rate of change is the same). If world experience with gas turbines is actually growing faster than U.S. experience, then our estimate will be biased. In recent years, the increased interest in gas turbine generation in the newly deregulated markets of Britain and elsewhere might strain this assumption. However, for the time-period 1987-1992 the assumption that the growth in U.S. and world experience is the about same does not seem an unreasonable first approximation.

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[3] Private communication Kent Kueman, General Electric.

References

Argote, Linda, and Dennis Apple, 1990, "Learning Curve in Manufacturing", *Science*, 247 (Feb) : 920-4.

Badiru, A. B. (1992). "Computational Survey of Univariate and Multivariate Learning Curve Models", *IEEE Transactions on Engineering Management* 39(2): 176-188.

Bahk, B.-H. and M. Gort (1993). "Decomposing Learning by Doing in New Plants", *Journal of Political Economy* 101(4): 561-583.

Dutton, John M., and Annie Thomas, 1984, "Treating Progress Functions as a Managerial Opportunity", *Academy of Management Review*, 9 (2) : 235-247.

Everett, John, and Sherif Farghal, 1994, "Learning Curve Predictors for Construction Field Operations", *Journal of Construction Engineering and Management*, 120 (3) : 603-16.

Gruber, Harald, 1994, "Learning and Strategic Product Innovation: Theory and Evidence for the Semiconductor Industry", Edited by H. Glejser and S. Martin, *Studies in Mathematical and Managerial Economics*, Amsterdam: North-Holland.

Irwin, D. A. and P. J. Klenow (1994). "Learning by doing spillovers in the semiconductor industry", *Journal of Political Economy* 102: 1200-1227.

Islas, J. (1999). "The Gas Turbine: A New Technological Paradigm in Electricity Generation", *Technological Forecasting and Social Change* 60(2): 129-148.

Jarmin, R. S. (1994). "Learning by doing and competition in early rayon industry", *RAND Journal of Economics* 25(3): 441-454.

Jarmin, R. S. (1996). "Learning by doing and Plant Characteristics", Washington, D.C., *Center for Economic Studies- U.S. Bureau of the Census*: 37.

Joskow, Paul L., and Nancy L. Rose, 1985, "The effects of technology change, experience, and environmental regulation on the construction cost of coal-burning generating units", *Rand Journal of Economics*, 16 (1) : 1-26.

Lester, R. and M. McCabe (1993). "The effect of industrial structure on learning by doing in nuclear power plant operation", *RAND Journal of Economics* 24(3): 418-38.

Lieberman, Marvin B., 1984, "The learning curve and pricing in the chemical processing industries", *Rand Journal of Economics*, 15 (2) : 213-28.

Smith, J., 1989, "Learning Curve for Cost Control", *Institute of Industrial Engineers*.

Zimmerman, Martin, 1982, "Learning Effects and the Commercialization of New Energy Technologies: The Case of Nuclear Power", *Bell Journal of Economics*, 13 (Autumn): 297-310.