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The learning curve and the yield factor: the case of Korea's semiconductor industry

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This article attempts to find out how the Korean economy has grown so rapidly in a short time span of less than 30 years. For that purpose, it focuses on the development of the Korean semiconductor industry – more specifically, the memory-chip segment of the industry – as a case in point. To test the hypothesis that the learning curve effects have been significant in the memory-chip industry, 'yield factor' (the ratio of sellable chips to total chips in a wafer) in semiconductor production is used as a measure of the learning progression. That is, by tracing how the yield factor for each generation of memory chips has increased, one is able to see how well the Korean chip makers have exploited the learning effects. This article improves the learning-by-doing modelling by introducing a richer set of yield data; and the unit of analysis employed throughout the article is at the firm level, which is not common in the literature dealing with East Asian development as well as the economics of technology, thus enhancing understanding of the industry dynamics.

I. INTRODUCTION

This article focuses on the development of the Korean semiconductor industry which has experienced an impressive growth for little more than 20 years. The country's semiconductor chip producers at the outset focused on producing products relatively easy to manufacture using mature technology imported from abroad. By producing these products in high volume, mainly memory chips such as dynamic random access memories (or DRAMs) and static RAMs (or SRAMs), the Korean producers were able to capture the benefits of learning effects and economies of scale,[1] thus reducing their production costs and diffusing capabilities acquired in the process to other product areas.

From technical perspective, the learning curve effect in the semiconductor industry is represented by yield factor, which is defined as the ratio of nondefective (and sellable) chips to total wafer area fabricated. In an initial production run for a specific generation of chips, the production yield typically remains below 10%. The yield, as the production experience accumulates, in many cases asymptotically increases up to 95%. The trajectory of this increase is called the learning curve, which since the report on the phenomenon at the US airframe (or airplane fuselage) manufacturing site in the 1930s has been extensively used by many economists and management decision makers.[2]

Using the concepts introduced above, i.e., the yield factor and the learning curve, one can begin to analyse the Korea's chip-making industry. That is, by tracing how the yield factor for each subsequent generation of memory chips has increased one can see how well the country's producers exploited the learning effects to increase productivity and reduce costs.

This study relies on the data collected from Dataquest, a US high-tech market research firm, and a Korean semicon-

[1] Learning effects give rise to dynamic economies of scale which differ from (static) economies of scale. In the case of dynamic economies of scale, increasing current production reduces *future* costs, not current costs. In econometric modelling thus, the former concept is usually represented by *cumulative* output and the latter by *current* output.
[2] See Wright (1936). This article is considered the seminal paper on the subject.

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ductor company, then tests the hypothesis that the learning curve effects were significant in the country's industry. The first estimation uses the price data, based on the conventional learning curve models. After finding out that this estimation yields poor results in terms of coefficients well out of expected ranges and low *t*-statistics, the second estimation employs yield data instead of prices as a dependent variable. A significant learning curve effect is found in the estimation, with the learning ratio of 17% for 64K DRAMs and 9% for 256K DRAMs, confirming the learning hypothesis in the case of the Korean industry.

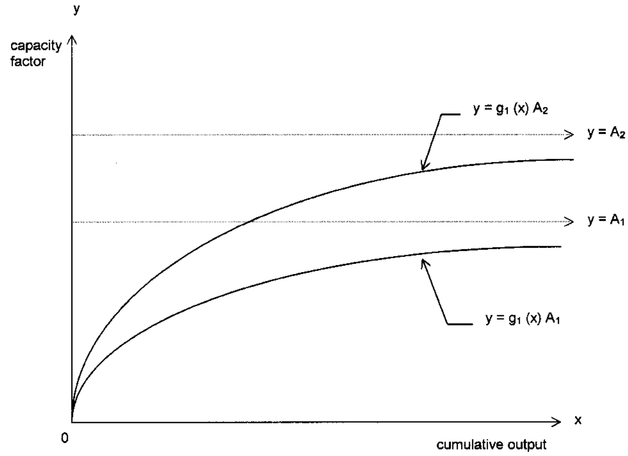

Fig. 1. *Supplier and operator learning*

II. THE ECONOMIC LITERATURE ON LEARNING[3]

Wright, an aeronautical engineer, reported in 1936 that the direct labour cost of producing an airframe (fuselage of an airplane) declined with the accumulated number of airframes of the same type produced. That is:

$$Y = aX^b \quad (1)$$

where Y is the direct labour cost, X is the cumulative output of airframes, a is the cost of the first unit of airframe ($a > 0$), and b is the learning elasticity ($0 \geqslant b \geqslant -1$), which defines the slope of the learning curve.

In so far as Second World War airframe data were concerned, every doubling of cumulative airframe output was accompanied by an average reduction in direct labour requirements of about 20%. This so-called 'eighty per cent curve' is the precursor of the present-day learning curve. Following Wright's article, most research effort has been directed at finding an appropriate functional form of the learning curve and applying the theory to diverse industries, using different proxy variables for learning, such as time, cumulative output, and so on.

Joskow and Rozanski (1979) apply the learning principle to nuclear plant operations. There are two distinctive features in the model: The first one is that, unlike other models, they utilize *capacity factor*[4] of nuclear plants as a dependent variable in their model. For them, capacity factor reflects power generation cost more accurately than do price data, the usual proxy in other models. So the higher its capacity factor, the lower is the average unit cost of power generated.[5]

The general form of the learning curve to be estimated is:

$$y = Ag(x)^{e_u} \quad (2)$$

where $y =$ annual plant capacity factor; $A =$ asymptotic value of the capacity factor; $x =$ increasing measure of experience (i.e., cumulative output) ($x > 0$); and $g(x) =$ function describing the nuclear operators' learning process.

The second feature of their model is that they extend this general model to account for 'supplier learning' in addition to 'operator learning.' As cumulative output increases, capacity factor increases due to learning on the part of the plant's operators. This is depicted as the function $g_1(x)A_1$ in Fig. 1 that approaches an asymptote A_1. The effect of learning by the suppliers (e.g., plant designers and engineers) responsible for building the plant are modelled as a shift upward in the asymptotic capacity factor. This is shown as a shift in the asymptote from A_1 to A_2.

The model to be estimated is:

$$PF = A\ CAP^b e^{cV} g(x) \quad (3)$$

where $PF =$ plant capacity factor (see note 4 for definition); $CAP =$ gross plant capacity (i.e., rated capacity); $V =$ the month during which the plant began commercial

[3] For those interested in history, structure, and dynamics of the semiconductor industry, refer to Kraus (1973), Sciberras (1977), Braun and MacDonald (1978), Hazewindus and Tooker (1982), Dosi (1984), Malerba (1985), United Nations Centre on Transnational Corporations (1986), Steinmueller (1987), Howell *et al.* (1988), Langlois *et al.* (1988), Green (1996) and Flamm (1996). However, most of these studies focus on the US and European semiconductor industry. Some of these deal with the Japanese industry, but only in relation to trade conflict with the United States. In these publications, the semiconductor industry of Korea and Taiwan is only treated as passing notes.

[4] The annual capacity factor of a plant is defined as the energy generated (Y) divided by the rated power output of the plant (CAP) times the number of hours in the year ($H = 8760$ except in leap years). That is, capacity factor $PF_{(\%)} = Y_{(\mathrm{WH})}/[CAP^*_{(\mathrm{W})}H_{\mathrm{Hours}}]$. It is equivalent to saying: capacity factor = [actual energy generated]/[potential capacity*time].

[5] The capacity factor in nuclear power generation is notionally identical to the yield factor in the semiconductor industry.

operation (a measure of the vintage of the plant); and $g(x)$ = operators' learning function.[6]

Except the constant term A, each term in the equation represents a different source of learning: The first term represents supplier learning, the second one the effect of time and the third operator learning. The regression results reported in Joskow and Rozanski (1979) show that the learning effect is important in nuclear plant operations, with learning rate approximately 5% per annum.

Generally, these empirical studies confirm the importance of learning phenomenon in reducing costs in their respective industries. It will now be seen how these learning economies has shaped the structure of the semiconductor industry.

Gruber (1992) comes up with the following learning equation for memory chips:

$$P_{ijt} = AQ_{ijt}^{\beta} V_{ijt}^{\gamma} H_{ijt}^{\delta} \exp(u_{ijt}) \quad (4)$$

where A = constant, price of the first unit produced; P_{ijt} = average real selling price for memory chips of type i and generation j in year t (proxy for cost); Q_{ijt} = annual shipments for memory chips of type i and generation j in year t; β = indicator of static economies of scale ($\beta < 0$); $V_{ijt} = \Sigma Q_{ijt}$, cumulative shipments for memory chips of type i and generation j up to year t; γ = learning elasticity ($\gamma < 0$); H_{ijt} = age of memory device, or time elapsed since production began, i.e., $H_{ijt} = 1$ for the first year when generation j is introduced; δ = indicator of the effect of generation age (alternative indicator for learning by doing); and u_{ijt} = random error term.

Taking log for each term:

$$p_{ijt} = \alpha_i + \beta_i q_{ijt} + \gamma_i \nu_{ijt} + \delta_i h_{ijt} + u_{ijt} \quad (5)$$

where lower cases indicate logarithms. From this he finds the results as shown in Table 1.

Gruber finds no significant learning for DRAMs and SRAMs. Only for EPROM did he find a significant learning, which is somewhat counterintuitive. His model measures the learning effects, with cumulative shipments of semiconductor devices and the elapse of time; as well as static economies of scale, with annual shipments of memory chips. The reason he uses average selling prices as a proxy for costs is not different from others; i.e., the unavailability of cost data. So he reiterates the conditions under which reliable estimates of the learning curve can be obtained from price data. That is, (1) price-cost margins are constant over time, (2) price-cost margins change in a way controlled for by other variables, or (3) changes in the margin are small in relation to changes in marginal cost.[7]

Table 1. *Summary of regression results*

	EPROM	DRAM	SRAM
Economies of scale		*	
Learning curve	*		
Generation age		*	*

Note: * Indicates significant presence.

Then he goes on to say that the condition (1) and possibly condition (3) are hard to apply to the semiconductor production, since it is well known that in this industry profit margins fluctuate considerably over the life cycle of a generation of chips.

Nevertheless, he argues that these fluctuations can be controlled for by using variables that are closely correlated with the margins. That is, he says that the time profile of profit margins for a given generation is U-shaped. In other words, the margins are large at the beginning and at the end of the product life cycle, while in-between margins are depressed due to entry of firms and strong competition. Current shipments for a given generation have a time profile which is inversely related to the time profile of profit margins. Thus the fluctuations of the margins can be controlled for by the current shipments variable. But given the dramatic changes in the conditions of competition over the product cycle, price-cost margins might decline steeply as the product matures, which invalidates the Gruber's procedure to control for fluctuations in price-cost margins.[8]

III. REGRESSION ANALYSIS OF THE LEARNING CURVE MODEL

The learning-by-doing model

In many manufacturing operations in which tasks are performed relatively in a repetitive manner, it has been reported that workers tend to learn from their experiences thereby reducing the time and costs it takes to complete given tasks. Many empirical studies have so far attempted to find out significant cost-reduction effects of a cumulative production experience.

Confining the focus on the semiconductor industry, Webbink (1977) reports a coefficient of −0.40 on cumulative production, indicating that, with every doubling of cumulative output, cumulative average price falls by 24%. Dick (1991) reports regressions of industry price on lagged cumulative production (an aggregate of US and

[6] In Joskow *et al.* $g(x)$ is specified as $e^{k/x}$. They say this form has the advantage that it can be linearized easily and so simplifies estimation.

[7] Lieberman (1984).

[8] For example, each generation of memory chip is introduced by a pioneering firm, and later on faces considerable competition, thus being forced to cut price-cost margins.

Japanese firms) of 1K and 4K DRAMs based on annual data for 1974–1980 and 1976–1981, respectively. He finds a 19% learning curve in 1K DRAMs and a 7% learning curve in 4K DRAMs. Gruber (1992) estimates similar models for DRAMs, EPROMs, and SRAMs, but finds no significant learning for DRAMs. Irwin and Klenow (1994) use broader dataset encompassing quarterly, firm-level data on seven generations of DRAMs over 1974–1992, for which they find average of 20% learning curve on cumulative output.

Since cost data are kept secret by companies and thus difficult, if not impossible, to obtain, most empirical learning curve studies, including those mentioned above, have proxied unit costs with a real price variable and then regressed the log of real price on a constant term and the log of cumulative output. This procedure introduces a major problem and makes separate identification of the learning curve effect very difficult. When one uses price data for the dependent variable, several problems arise. For one thing, the justification for using the proxy is given by the assumption that prices move fairly in synchronization with costs, with a certain constant markup. In other words, it assumes that price-cost margins are constant over time, price-cost margins change in a way controlled for by other variables, or changes in the margin are small in relation to changes in marginal cost.[9]

Yet, given the tumultuous state of competition in the semiconductor market in which each generation of product is introduced by a leading firm and later faces a large number of competitors resulting in a substantial drop in prices as the product matures, price-cost margins cannot be stable over time, rather they decline steeply.[10] It is even more so in the case of the East Asian semiconductor producers, including the Japanese and the Korean firms, who have frequently been the target of dumping accusations which alleged that their semiconductor components were sold at prices below actual production costs.

Aside from this difficulty, there is another problem in using a proxy variable. As evidenced from the 1996–1997 downturn in the semiconductor market, the price movements in the semiconductor market before and during the period have largely been dictated by the forces of supply and demand, rather than by the learning principle by which prices fall continuously over time. Nearly three years from 1993 to 1995, the semiconductor prices, notably those of memory chips, have been propped up by unprecedented high demand from personal computer manufacturers, bringing in profit margins of over 70% for some chip makers. As the market conditions reversed in early 1996, however, the chip prices fell to a level comparable to or lower than its production costs.[11] Under these circumstances, it is hard to expect the price-cost margins are within a certain stable range, let alone constant. This possible wide divergence between prices and costs forces us to reconsider the feasibility of the price proxy.

To see this point more clearly, suppose that there are two firms with identical learning curve experiences. Assume that one firm adopted a forward pricing strategy in which the price was initially set very low, thereby increasing demand, market share, and production, while the other firm adopted a 'cream-skimming' pricing strategy in which the initial price was set very high and lowered gradually (Intel is a typical firm that has adopted the pricing strategy of cream skimming). If one regressed price on cumulative production for these two firms, one would obtain very different estimates of the learning curve elasticity, even though the potential learning curve effects were identical by assumption. If, instead, unit cost data had been adopted, this difference would not have occurred. It shows that it is preferable to adopt unit cost rather than price data in estimating learning curve parameter, since using price data confounds the effects of pricing strategy with 'pure' learning curve effects.

In general, the learning curve model estimates the extent to which the accumulation of production experience contributes to the reduction of costs. The simplest and most commonly used form of the learning curve is as follows:

$$C_t = A V_t^{\alpha_1} \mathrm{e}^{u_t} \tag{6}$$

where C_t is unit cost of production in time period t, V_t is cumulative output produced up to time period t, A is the cost of the first unit of output, α_1 is the learning elasticity ($0 \geqslant \alpha_1 \geqslant -1$), and u_t is a stochastic disturbance term.

Equation 6 can be rewritten in logarithmic form as

$$\ln C_t = \ln A + \alpha_1 \ln V_t + u_t \tag{7}$$

The learning curve elasticity parameter α_1 can be estimated by ordinary least squares, provided that relevant data on unit costs and output are available. The following formula for log transformations implies that every time cumulative experience doubles, cost will decline to s per cent of its previous level:

$$s = 2^{\alpha_1} \tag{8}$$

Therefore, if cost declines to 70% of its previous level as cumulative output doubles, then the learning curve is said to have a 70% slope. However, when one runs a simple regression for a model such as Equation 7, regressing unit

[9] This assumption is found in Lieberman (1984) and Gruber (1994a).
[10] Irwin and Klenow (1994, p. 1209).
[11] For 4M DRAM, the price fell as low as $2.50, a level that industry experts say is below production costs. A break-even point for memory chips is approximately a dollar per megabit; for example, it is $4 for 4M DRAMs and $16 for 16M DRAMs.

production cost on cumulative output, it is often difficult to distinguish the cost-reducing effects of learning from that of scale economies. Thus the learning curve elasticity may be over- or under-estimated by omitting the variable representing scale economies. In order to separate the two effects, we add a current output variable to the Equation 7 as follows:

$$\ln C_t = \ln A + \beta_1 \ln V_t + \beta_2 \ln X_t + \omega_t \tag{9}$$

where X_t is current output, β_2 is a coefficient representing the extent to which economies of scale contribute to cost reduction, and β_1 is same as α_1 in Equation 6, and ω_t is random disturbance term.

By running both the simple regression on Equation 7 and the multiple regression on Equation 9, we can find the difference in coefficients for cumulative output V. The bias resulting from omitting $\ln X_t$ from the learning curve equation is called the 'omitted variable bias.'[12] To analyse the issues of omitted variable bias, it is convenient to introduce a new equation, called an auxiliary regression equation, in which the omitted variable – in this case $\ln X_t$ – is related to the included variable $\ln V_t$ and a disturbance term ε_t.

$$\ln X_t = \delta_0 + \delta_1 \ln V_t + \varepsilon_t \tag{10}$$

Now label the least-squares estimates of the α's, β's, and δ's as a's, b's, and d's, respectively. The relationship between a_1 (the least squares estimate of α_1) and b_1 (the least squares estimate of β_1) can be shown to be as follows:

$$a_1 = b_1 + d_1 b_2 \quad \text{or} \quad a_1 - b_1 = d_1 b_2 \tag{11}$$

The bias from omitting $\ln X_t$ is simply equal to $a_1 - b_1$ which is equal to $d_1 b_2$. This omitted variable bias will be zero only if at least one of the following two conditions is satisfied:

(1) $d_1 = 0$, i.e., the log of current output and cumulative output are uncorrelated;
(2) $b_2 = 0$, i.e., unit cost of production does not depend on current production. Alternatively, returns to scale are constant.

If neither of the two conditions is met, an omitted variable bias will result, meaning that if one estimated the learning curve elasticity using Equation 7 and omitting $\ln X_t$, one would obtain a biased estimate of the true learning curve parameter. In many cases, one might expect returns to scale to be increasing, so it is plausible to expect that $a_1 - b_1$ will be negative. Further, since a_1 and b_1 are typically negative in value, $a_1 - b_1 < 0$ corresponds to b_1 being smaller in absolute value than a_1. In such a case, estimation of the simple learning curve equation yields a larger estimate of the learning curve elasticity (in absolute value) than if one includes the current output variable as in Equation 9. Hence in this case the learning curve elasticity is overestimated in absolute value.[13]

The model with price variable

The first equation to be estimated would be the one based on price dependent variable as in most of the conventional models. This way, the problems of the price proxy explained above can be verified. The model is as follows:

$$P_i = A V_i^{\beta_1} X_i^{\beta_2} e^{u_i} \tag{12}$$

where P is average selling price in real terms, i is type of memory chips, and the rest are identical to the notations in Equations 6 and 9.

Taking log in each term of Equation 12,

$$\ln P_i = \ln A + \beta_1 \ln V_i + \beta_2 \ln X_i + u_i \tag{13}$$

Following the modified model used in Joskow and Rozanski (1979) which employs the inverse of cumulative output:

$$\ln P_i = \ln A + \beta_1 \ln (1/V_i) + \beta_2 X_i + u_i \tag{14}$$

This functional form has the advantage that it can be linearized easily and simplifies estimation.[14] To obtain a real price for the memory chips, the average selling prices have been divided by the US implicit price. There are two reasons for choosing the US price deflator to calculate the real prices: First, the average selling price data provided by Dataquest, the source of the dataset, are quoted in US dollars; and second, the US market has been the largest market for memory chips for most of the observation period.[15]

There are 350 observations from the first quarter of 1994 to the second quarter of 1996 in the dataset for 19 companies (4M DRAMs) and for 16 companies (16M DRAMs). In addition to estimations of individual company learning parameters, industrywide learning curve has been estimated for both memory products. The regression results based on ordinary least squares are reported in Tables 2 and 3.

As can be seen in Tables 2 and 3, regression results are completely out of expectations based on our hypothesis that as cumulative output increases real prices decrease, thus taking negative coefficients in $\ln (1/V_i)$ terms. In the case of 4M DRAMs, all the regressions for 19 individual companies yielded positive coefficients in their cumulative output variable (ranging from 0.044 to 0.490), as opposed

[12] Berndt (1991, pp. 76–8).
[13] For further discussion of omitted variable bias, see Section III subsection 3 – the yield model.
[14] Joskow and Rozanski (1979) p. 164.
[15] Gruber (1994a), p. 47, note 5.

Table 2. *Regression results for 4M DRAMs (price as dependent variable)*

Company	Constant	Cumulative output	Current output	R^2	D–W stat	F-stat
Samsung	−0.334	0.092	0.891	0.890	1.676	28.202
	(−0.554)	(2.804)	(5.989)			
Hyundai	2.047	9.276	0.499	0.819	1.255	15.885
	(7.537)	(5.635)	(4.128)			
LG Semicon	2.217	0.306	0.566	0.821	1.131	16.083
	(1.268)	(5.630)	(4.135)			
Texas Ins	1.132	0.324	0.835	0.727	0.542	9.325
	(1.669)	(4.237)	(2.984)			
Micron Tech	1.818	0.358	0.675	0.871	0.927	23.727
	(7.630)	(6.727)	(5.240)			
Motorola	0.102	0.090	1.264	0.964	2.549	92.906
	(0.377)	(4.545)	(10.925)			
IBM	2.047	0.305	0.578	0.817	0.871	15.611
	(7.819)	(5.556)	(4.037)			
NEC	1.196	0.214	0.658	0.757	1.917	10.905
	(1.956)	(4.377)	(3.359)			
Toshiba	−0.537	0.145	1.140	0.865	3.048	22.364
	(−0.745)	(4.135)	(5.184)			
Hitachi	−0.342	0.232	1.092	0.649	1.171	6.467
	(−0.222)	(5.533)	(2.339)			
Fujitsu	2.201	0.279	0.483	0.506	0.586	3.586
	(3.100)	(2.175)	(1.202)			
Mitsubishi	−1.631	0.198	1.826	0.582	0.954	4.872
	(−0.656)	(2.942)	(1.899)			
Oki	0.781	0.113	0.825	0.928	1.567	45.242
	(2.448)	(4.178)	(7.508)			
Matsushita	3.041	0.044	−0.270	0.586	0.827	4.954
	(14.651)	(0.459)	(−1.422)			
Nippon Steel	2.712	0.184	0.119	0.458	0.690	2.963
	(19.331)	(1.483)	(0.592)			
Sharp	2.485	0.172	0.090	0.548	0.754	4.239
	(16.701)	(1.379)	(0.610)			
Siemens	1.996	0.101	0.365	0.966	2.389	99.070
	(19.107)	(5.793)	(11.464)			
Mosel-Vitelic	2.652	0.122	−0.079	0.629	1.024	5.943
	(22.455)	(1.559)	(−0.916)			
Vanguard	2.502	0.490	0.489	0.993	2.938	72.792
	(48.637)	(9.167)	(6.584)			
Industry Total	−1.209	0.326	1.032	0.808	0.730	14.748
	(−1.009)	(5.421)	(3.970)			

Note: For raw data which these estimates are obtained, see Chung (1998).
t-statistics in parentheses. Number of observation for each company estimation ($= n$) is 10.

to their expected range of −1 to 0. In the case of 16M DRAMs, only five out of 16 regressions yielded negative coefficients in their cumulative output variable (−0.010 to −0.256). For all the five cases, however, coefficients are found to be insignificantly based on t-test (t-statistics below 2.0).

It is also noteworthy that four out of 19 cases in 4M DRAMs and only one out of 16 cases in 16M DRAMs produced the Durbin–Watson statistic higher than 2.0, which indicates the positive serial correlation in disturbance terms.[16] Some of the estimates have low F-statistics,[17] implying that none of the independent variables influences the dependent variable, thus the specification is meaningless. However, the subject is not gone into in detail because the estimates obtained above are well out of the expected range anyway. The results for overall industry estimations

[16] In the next estimation using yield factor data, the problem of positive serial correlation indicated by a low Durbin–Watson statistic will be corrected by adding to the equation the first-order autocorrelation term $AR(1)$.
[17] For example, Fujitsu and Nippon Steel Semiconductor in the case of 4M DRAMs, Micron Technology and Nippon Steel for 16M DRAMs have low F-statistics, assuming the critical value of F-statistic is 4.

Table 3. *Regression results for 16M DRAMs (price as dependent variable)*

Company	Constant	Cumulative output	Current output	R^2	D–W stat	F-stat
Samsung	4.440	0.125	−0.082	0.739	1.202	9.908
	(29.595)	(0.872)	(−0.397)			
Hyundai	4.173	0.513	0.525	0.866	1.655	22.562
	(57.587)	(4.101)	(3.378)			
LG Semicon	4.179	0.364	0.339	0.713	1.148	8.685
	(34.319)	(2.079)	(1.344)			
Texas Ins	4.121	0.294	0.231	0.689	0.973	7.754
	(22.431)	(0.796)	(0.488)			
Micron Tech	3.974	0.240	0.225	0.507	0.898	3.085
	(17.513)	(1.308)	(0.890)			
Motorola	3.940	0.159	0.015	0.713	1.022	8.708
	(18.262)	(0.726)	(0.051)			
IBM	4.057	0.241	0.168	0.659	0.963	6.768
	(11.848)	(0.476)	(0.236)			
NEC	4.318	−0.143	−0.451	0.864	0.535	22.184
	(51.024)	(−1.331)	(−2.813)			
Toshiba	4.372	−0.256	−0.696	0.723	1.442	9.155
	(28.740)	(−0.642)	(−1.052)			
Hitachi	4.282	−0.090	−0.382	0.820	1.398	15.966
	(42.015)	(−0.628)	(−1.862)			
Fujitsu	4.060	0.024	−0.192	0.804	1.342	14.372
	(39.995)	(0.194)	(−1.232)			
Mitsubishi	4.100	−0.010	−0.214	0.673	0.941	7.210
	(33.324)	(−0.032)	(−0.464)			
Oki	4.066	0.273	0.179	0.700	0.871	8.148
	(14.516)	(1.022)	(0.447)			
Matsushita	3.428	−0.074	−0.359	0.966	1.063	99.818
	(58.250)	(−10.803)	(−6.504)			
Nippon Steel	6.454	0.793	1.652	0.870	3.386	3.347
	(1.670)	(1.461)	(0.901)			
Siemens	3.981	0.078	−0.133	0.684	1.125	7.751
	(29.030)	(0.497)	(−0.519)			
Industry Total	4.766	−0.067	−0.320	0.731	1.211	9.531
	(16.068)	(−0.246)	(−0.818)			

Note: t-statistics in parentheses. Number of observation for each company estimation ($= n$) is 10.

(for both 4M and 16M DRAMs) are similar to those of the individual company regressions, yielding positive coefficient for cumulative output variables or negative but insignificant coefficients. Unreported estimations of simple regressions, regressing the log of real price against the log of cumulative output alone, did not improve the results.

The reasons for this 'bad fit' can be found in the following reasons. First the quarterly average rate of price drop has not been high enough to produce a substantial learning curve effect. The quarterly rate of price fall has been 5.30% for 4M DRAMs and 7.84% for 16M DRAMs for the two and half year period. Excluding the last two observations (the first and second quarter of 1996) in which the price drop has been steepest, the average rate of drop has been only 0.44% and 2.44%, respectively. This is because the period from 1993 to 1995 is characterized by a strong demand from PC manufacturers that has propped up the chip prices, reversing the usual pattern of steady and substantial fall in prices. Second, quarterly output has been increasing at a slower rate. Especially in the case of 4M DRAMs, the quarterly rate of increase in industry total output has been only 2.44%.[18] The observation period of 1994 to 1996 has corresponded to the transition period in which the 4M DRAM generation was being phased out, so the output has not been increased in spite of the high demand. Third, the initial period in which the mass production has begun is not captured in the analysis for both products. In the case of 4M DRAMs, the mass production

[18] For 16M DRAMs, the average rate increase in quarterly output has been 35.05%, partially weakening the second claim that the not-high-enough quarterly output increase was responsible for the bad fit.

has started from 1989, while that of 16M DRAMs from 1990. Given the dataset encompasses the years from 1994 to 1996, well after the products were introduced in the market, it is understandable that a substantial part of the learning curve effects is not represented in the observation.

The weak presence of the learning curve effect in the dataset leads one to test if economies of scale have been strong instead. The following model estimates the influence of scale economies on real-price reduction by regressing the log of real price against the log of inverse of shipments:

$$\ln P_i = \ln A + \beta_1(1/X_i) + u_i \qquad (15)$$

Since the serial correlation has been found in most of the estimations, the term $AR(1)$ is added to the equation. Unreported estimations reveal that in the case of 4M DRAMs seven out of 19 individual company regressions had significant economies of scale.[19] For the industry as a whole, the cost-reducing effect coming from economies of scale turned out to be overwhelming 44.02% (corresponding coefficient is −0.837). However, in the case of 16M DRAMs, none out of 16 regressions produced significant economies of scale, all of whose coefficients are positive.

The yield model

Instead of using price data which yielded results that are inconsistent with the learning hypothesis, yield data are used as the dependent variable obtained from a Korean semiconductor company, say Company A, for 64K and 256K DRAMs.[20] This richer set of data includes yield and shipment data for Company A from the first quarter of 1985 to the fourth quarter of 1993, consisting of 36 observations.[21] All the estimates are obtained by ordinary least squares.

The yield factor model to be estimated here is identical to Equation 14 except that the price variable P_i is replaced by the yield variable Y_i as follows:

$$\ln Y_i = \ln A + \beta_1 \ln(1/V_i) + \beta_2 X_i + u_i \qquad (16)$$

where Y is yield factor, and the rest are identical to the notations in Equations 6–12.

A simple regression model is the one without a current output variable $\ln X_i$.

$$\ln Y_i = \ln A + \alpha_1 \ln(1/V_i) + u_i \qquad (17)$$

This way, we can estimate the learning parameter more directly without employing proxy variable or complicated procedures to estimate production costs. The only model which analysed the semiconductor industry based on the yield factor data is found in Gruber (1994a). However, its dataset includes only 7 quarters for 4 generations of a single product, EPROM from one European firm, SGS-Thomson, which is too limited to deduce any meaningful conclusion. Therefore, the current yield model that covers quarterly data of a Korean company for nine years for two important memory items can be considered a major improvement of the model.

First, in the case of 64K DRAMs, if one runs a simple regression where the log of yield factor is regressed against the log of cumulative output, the coefficient for $\ln(1/V_i)$ turns out to be −0.182 with the corresponding learning ratio of 11.843%, which implies that every doubling of cumulative output would result in the yield improvement of 11.8%, which in turn reduces the production costs by the same amount. Then we add a current output variable $\ln X_i$ and run a multiple regression to separate the learning effect from the cost-reducing effect of economies of scale. The estimation results in the learning coefficient of −0.176, slightly lower in absolute value than that of the simple regression with the learning ratio of 11.493%.

To see if omitting the current output variable would result in an estimation bias, an auxiliary regression equation similar to Equation 10 is run.

$$\ln X_i = \delta_0 + \delta_1 \ln(1/V_i) + \varepsilon_i \qquad (10a)$$

According to Equation 11, the sign of the difference between a_1 (the least squares estimate of α_1) and b_1 (the least squares estimate of β_1) determines whether the omitting variable over- or under-estimates the coefficient. That is,

$$a_1 - b_1 = d_1 b_2 \qquad (11)$$

(1) $a_1 - b_1 > 0$ (the learning curve elasticity is underestimated when the current output variable is omitted)
(2) $a_1 - b_1 = 0$ (the current output variable has no correlation with yield; that is, constant returns to scale)
(3) $a_1 - b_1 < 0$ (the learning curve elasticity is overestimated).

Plugging in coefficients obtained from the estimation of the auxiliary regression equation, $a_1 = -0.182$, $b_1 = -0.176$, $d_1 = 0.111$, and $b_2 = -0.051$, it is $-0.006 \approx -0.005661$. Since $a_1 - b_1$ is negative, Equation 16 exhibits increasing returns to scale and the simple regression Equation 17 overestimates the learning curve elasticity.

In the case of 256K DRAMs, the simple regression produces the coefficient of −0.165 for the $\ln(1/V_i)$ term and

[19] 'Significant,' means estimates that satisfy the following conditions: $-1 < \beta_1 < 0$, t-statistic > 2, and Durbin–Watson statistic > 2.
[20] The source for the data, a high-ranking official at the company's corporate research institute, asked for anonymity, which will be maintained throughout.
[21] Actually the number of observation is 26 for 64K DRAMs and 32 for 256K DRAMs.

the corresponding learning ratio of 10.807%. The estimation for the multiple regression with the current output variable $\ln X_i$ results in the learning coefficient of -0.145 with the learning ratio of 9.572%.

Running an auxiliary regression equation to check the presence of omitted variable bias yields following numerical results: $a_1 = -0.165$, $b_1 = -0.145$, $d_1 = -0.277$, and $b_2 = 0.071$; therefore, $a_1 - b_1 = -0.020 \approx d_1 b_2 = -0.019667$. That is, $a_1 - b_1 < 0$ and Equation 16 exhibits increasing returns to scale and the simple regression overestimates the learning curve elasticity. All the estimates for both memory products are reported in Tables 4 and 5.

However, it is notable that Durbin–Watson statistics turn out to be 1.476 for 64K and 0.941 for 256K DRAMs which are well below 2, an indication of the presence of positive serial correlation in the residuals. In order to incorporate the serial correlation in the equation, the first-order autocorrelation term $AR(1)$ is added. With the new regression, there is a better fit in terms of the Durbin–Watson statistics close to or higher than 2 as shown in the fourth row of each table.

As reported in Tables 4 and 5, the learning ratios of 16.841% (for 64K DRAMs) and 9.382% (for 256K DRAMs) are consistent with the hypothesis that with every doubling of cumulative output production yield increases by the same percentage. However, the learning slopes are not as steep as expected, usually reaching as high as 30%. The reason for this rather low ratio can be traced to the following fact: the year when Company A introduced 64K DRAMs to the market was 1984, and the first year for 256K DRAMs was 1985; meanwhile, the observation period in the analysis starts from 1985 and 1986, respectively, one year later than each product's market introduction year. Due to this lack of data for the year the learning curve effect could have been most pronounced, the learning curves for the two memory items are estimated at approximately 17% and 9% as reported in the tables.

Figures 2 and 3 have been plotted using the log of the inverse of cumulative output as X-axis and the log of yield as Y-axis. These learning curve diagrams resemble fairly well the ones drawn by other studies, including, Joskow and Rozanski (1979, p. 163).

Aside from the above empirical evidence which shows that the Korean semiconductor industry has grown by rapidly moving down the learning curve,[22] there is an

Table 4. *Regression results for 64K DRAMs (yield factor as dependent variable)*

Regression type	Constant	Current output	Cumulative output	R^2	D–W stat	F-stat	Learning ratio (%)
Simple	−1.378 (−11.700)	N.A.	−0.182 (−6.763)	0.656	1.455	45.743	11.843
Multiple	−1.268 (−8.883)	−0.051 (−1.319)	−0.176 (−6.569)	0.680	1.476	24.448	11.493
Regression with AR(1)	−1.765 (−11.470)	0.0003 (0.009)	−0.266 (−9.087)	0.860	1.886	43.085	16.841

Note: N.A.: Not applicable.
t-statistics in parentheses. Number of observation ($= n$) is 26.

Table 5. *Regression results for 256K DRAMs (yield factor as dependent variable)*

Regression type	Constant	Current output	Cumulative output	R^2	D–W stat	F-stat	Learning ratio (%)
Simple	−1.228 (−23.871)	N.A.	−0.165 (−15.814)	0.893	0.703	250.085	10.807
Multiple	−1.290 (−27.176)	0.071 (3.463)	−0.145 (−13.690)	0.924	1.941	176.858	9.572
Regression with AR(1)	−1.248 (−5.495)	0.060 (1.484)	−0.142 (−4.180)	0.903	2.119	83.731	9.382

Note: N.A.: Not applicable.
t-statistics in parentheses. Number of observation ($n = 32$)

[22] Although the analysis based on yield and shipment data of a Korean company produced substantial learning effects for both memory products, 17% for 64K DRAMs and 9% or 256K DRAMs, one cannot claim from the results that the Korean companies have moved down the learning curve faster than any other firms in the advanced countries because there is no comparable dataset available for the analysis.

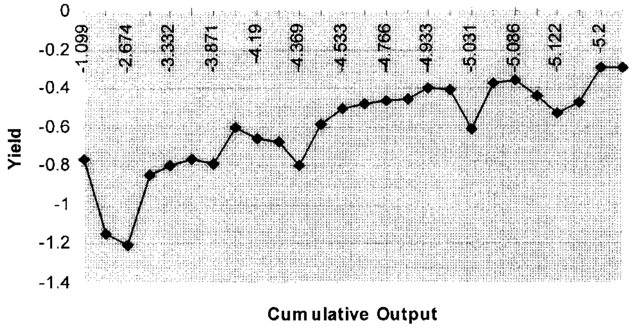

Fig. 2. *Learning curve for 64K DRAMs*

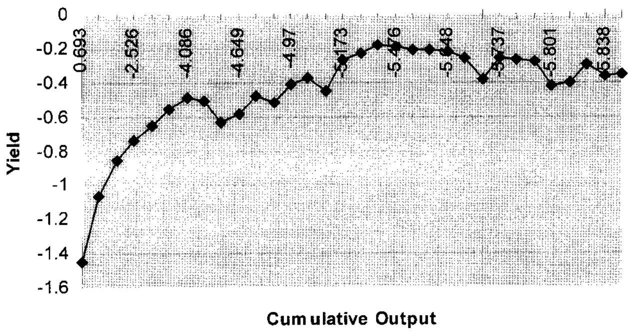

Fig. 3. *Learning curve for 256K DRAMs*

ample amount of anecdotal evidence demonstrating the Korean industry's high production yield and resulting high productivity. The yield of 4M DRAMs produced by the Korean chip makers had, for example, run up to 95% in 1995, the year at which the product had reached the maturity stage. According to officials of a Korean company, although varied by company and product, the yield of the Korean chip makers is in general 10% higher than that of the Japanese, and the yield of Japanese chip makers is again 10% higher than that of the American.

In the semiconductor manufacturing process, from raw wafer manufacturing to circuit design, mask generation and wafer processing, almost all processes are automated, so there is little room for quality variations. In these pre-assembly processes, the purity of silicon wafers, the quality of processing chemicals, and the stricter standard of the clean-room operations are important factors affecting the processing yields. But at the stage of assembly and final inspection, human factors largely determine the production yield. This is where 'finger tips' of young female workers of Korea have proven important. For example, in a Samsung assembly plant that employs 15 000 female workers, the average age of assembly workers is 21, which is 10 years younger than that of their counterparts in Japan.[23] The reason the Korean chip makers have been able to enjoy higher yield is given also by the fact that, similar to the cost advantage of the Japanese makers, most of the Korean firms are large conglomerates with affiliates in consumer electronics, which require components with less stringent performance standards than military or industrial-purpose chips, thus helping to achieve higher yields.

VI. CONCLUSION

The chip-making industry of Korea deserves special attention because of its great reliance of the production technology on foreign sources and its intense efforts to internalize the imported technology into its own production, thus making a good study subject for the learning-by-doing theory. Nevertheless, no full-length academic endeavour has been made on the subject except some of the contributions narrowly focusing on the case of one company. Such examples include Kim (1997) and Choi (1996).

When analysing an industry, there may be two distinct approaches; detailed descriptive approach and quantitative approach. Both are complementary in the sense that what the quantitative part cannot account for can be explained by the rich examples of the country's chip-making industry, thus providing us with the whole picture of the industry and its dynamics. However, this article has employed quantitative approach alone. Those who wish to understand the Korean semiconductor industry more in depth may refer to Chung (1998), which includes descriptive part as well as the quantitative analysis.

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