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On the Existence of Learning Effects in Swedish Kraft Paper Mills

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Abstract

This paper presents an alternative approach in estimating the effect learning has on the cost structure facing individual firms. The suggested method is applied to the Swedish kraft paper industry and relies on a comprehensive dataset for eight individual integrated kraft paper mills. The analysis is conducted through two steps. *First*, using a flexible cost function, utilizing mill-specific dummy variables, a cost reduction index can be estimated devoid of scale and price effects that if not dealt with can produce spurious results when estimating learning effects. The *second* step is to regress the estimated cost reduction index on the traditional determinants that are thought to influence the learning process. The results suggest that the Swedish kraft paper industry has relatively little to gain in terms of cost reduction through a further learning process. However, the method performed well, producing intuitive and statistically significant estimates indicating its usefulness in further analyses.

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On the Existence of Learning Effects in Swedish Kraft Paper Mills

Robert Lundmark

1 Introduction

The fact that the workforce, management and even machines improve their manufacturing performance as experience is gained by increases in cumulative production is an accepted concept in the economic debate. By gaining experience as production accumulates the workforce will be able to achieve higher output at lower cost. Hence, learning effects can have a profound impact on the cost structure facing a firm. As a consequence, on an aggregate level, the productivity within an industry sector might improve as production accumulates, which might contribute to overall economic growth in a region or in a country. Another aspect of firm behavior derived from learning effects involves pricing strategies. For example, the existence of learning effects might provide a rationale for firms to price low — even predatory pricing might be rational — in the hope of gaining increasing market shares and thereby speeding up their production and gaining learning effects faster. It has also been argued that the existence of learning effects might create entry barriers and protection from competition by conferring cost advantages on early entrants and on those who achieve large market shares (Spence, 1981). Moreover, in the formulation of trade policy it has also been argued that governments should provide limited and temporary protection to domestic firms from foreign competitors (e.g., Helpman and Krugman, 1985). Thus, the existence of learning effects can provide strategy and policy instruments, not only for firms but also for policy makers.

Industries vary considerably in the rates at which they learn. Whereas some sectors show extraordinary rates of productivity growth as cumulative production increases, others fail to show expected productivity gains from learning. As a general rule, it may be stated that the more capital-intensive the industry is, the lower the elasticity of the learning curve (Isoard and Soria, 2001). A capital-intensive industry, which also has a considerable impact on national and local economies in Sweden, is the pulp and paper industry. Given the economic importance the pulp and paper industry has on the Swedish economy, it is surprising how little empirical research on learning effects has been done. The present paper will attempt to remedy this research gap by not only providing an analysis regarding the learning effects for the pulp and paper industry but also by presenting an alternative procedure in the estimation of learning elasticities. Thus, the purpose of this paper is to estimate and analyze the learning effects in the Swedish kraft paper industry using an alternative two-step procedure.

Figure 1 depicts the relation between labor input per unit of output and cumulative production for eight kraft mills in Sweden over the period 1975–1994. Due to different levels of cumulative production the units have been omitted. As a consequence, comparison between the mills is not possible but Figure 1 still suggests some interesting findings. As is evident in the Figure, all eight kraft mills exhibit a decreasing trend in the labor input needed as the cumulative production increases, indicating that the workforce has gained some type of experience as the cumulative production increased. Furthermore, the latter part of the curves in Figure 1 suggests that some degree of maturity is reached where additional gains in experience have little to no effect on the cumulative production.

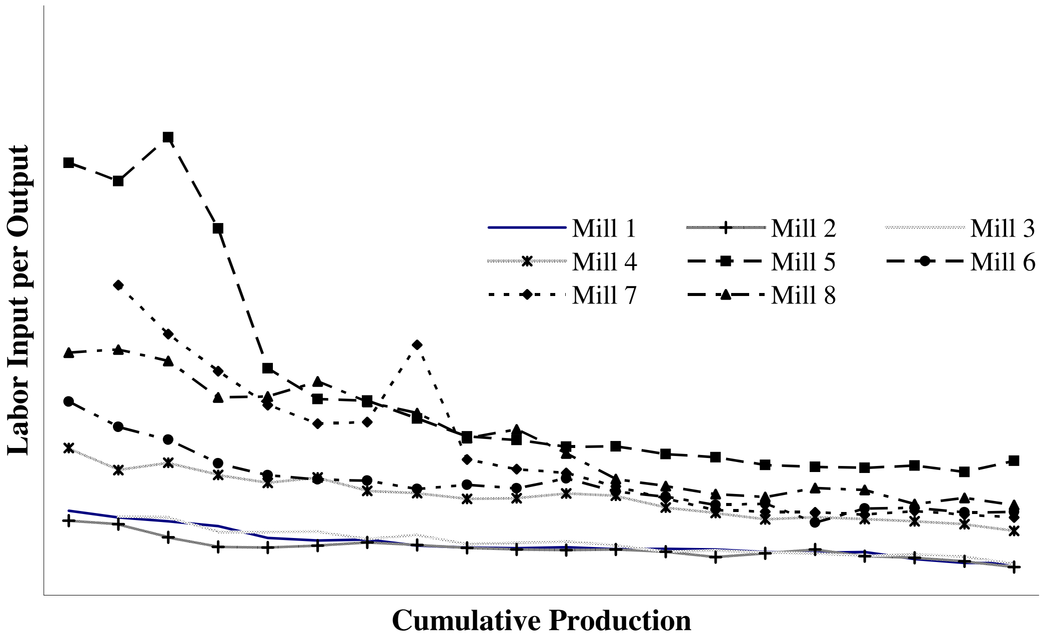

Figure 1: Relation between labor input per unit of output and cumulative production for eight kraft mills in Sweden (units omitted).

However, as mentioned above and what will be further developed in latter sections in this paper, learning effects can also include the learning of capital equipment or infrastructure. For these reasons no decisive conclusions can be drawn from Figure 1 without considering the effects of learning by capital equipment. Since, in the kraft industry, a large part of the capital equipment is conceived, manufactured and supplied by other firms it becomes important to distinguish between embodied and disembodied learning effects of capital equipment. The embodied learning effects are defined as the learning effects achieved by suppliers of capital equipment, while the disembodied learning effects are the learning effects achieved by individual kraft mill operators.

The paper proceeds with a short presentation of the fundamental aspects of the learning concepts, which are followed by theoretical models. In section four the empirical specifications are introduced together with a description of the data. Finally, the results and conclusions are presented in the last two sections.

2 Learning Effects Fundamentals

Since its inception, the learning effect concept has found a solid place in economic literature (e.g., Wright, 1936; Hirsch, 1952; Andress, 1954). The first applications involved a manufacturing process that had high labor intensity. For example, Wright (1936) reported that unit labor costs in airframe production declined with cumulative output. Learning effects can arise from at least three different sources. First, the labor force will accumulate experience over time, which reduces the labor input needed to produce a constant level of output, *ceteris paribus*. Second, managers can also gain experience and thereby improve the management of the production process by, for example, modifying work task assignments. Finally, technical improvement due to repeated use might be considered as experience gained by the infrastructure of the production process, e.g., machines, tools, etc. Machines that have a new technology embodied might even replace older machines that are based upon an obsolete technology.

As a consequence, unit costs incline to decrease as these different aspects of experience accumulate. Some of the literature makes a distinction between these learning concepts; however, in the following text the term 'learning curve' will be used as the measurement of all the learning effects on the cost patterns, whatever their source might be.[1] Hence, the learning effects and the associated learning curve concepts represent the "technological progress associated with a technology, i.e., the improvements induced by experimentation, implementation and research and development throughout the production process, directed by social and economic policies as well as economic opportunities" (Isoard and Soria, 2001). It is an indicator of the marginal innovation, which occurred in a technology or, alternatively, is the product of increasing productivity induced by experience (Arrow, 1962).

3 Theoretical Framework

The effect learning has on the cost structure facing a firm can be formulated in a variety of ways. It is crucial, though, to adjust the modeling so that it fits the industry or sector under investigation. The focus here is to analyze the effect learning has on the cost structure for kraft paper producing mills in Sweden. In general terms, the unit cost of production is, for a specific mill, depending upon learning processes undertaken by its staff and machinery. In addition, kraft production is using substantial capital equipment developed and manufactured by other firms, hence, making it necessary to also include "supplier learning" so that the entire learning aspect is captured (Joskow and Rozanski, 1979; Chung, 2001). The learning curve can then be expressed as:

$$c_u = g(y)h(q) \ , \qquad [1]$$

where c_u is the unit costs of production, y and q are increasing measures of experience by the operator and supplier, respectively. The functions $g(y)$ and $h(q)$ describe the

[1] The distinction is usually made between learning curve effects and experience curve, or organizational curve, effects, e.g., Argote and Epple (1990) and Isoard and Soria (2001). The former is defined as the learning effects of workers on unit costs, while the latter incorporates all of the effects of experience on unit costs, e.g., workers learning, and technical and managerial improvements.

disembodied learning process by operators and the embodied learning process by suppliers. The distinction between the two learning concepts is presented in Figure 2 where *A* is the asymptotic value of the cost reduction.

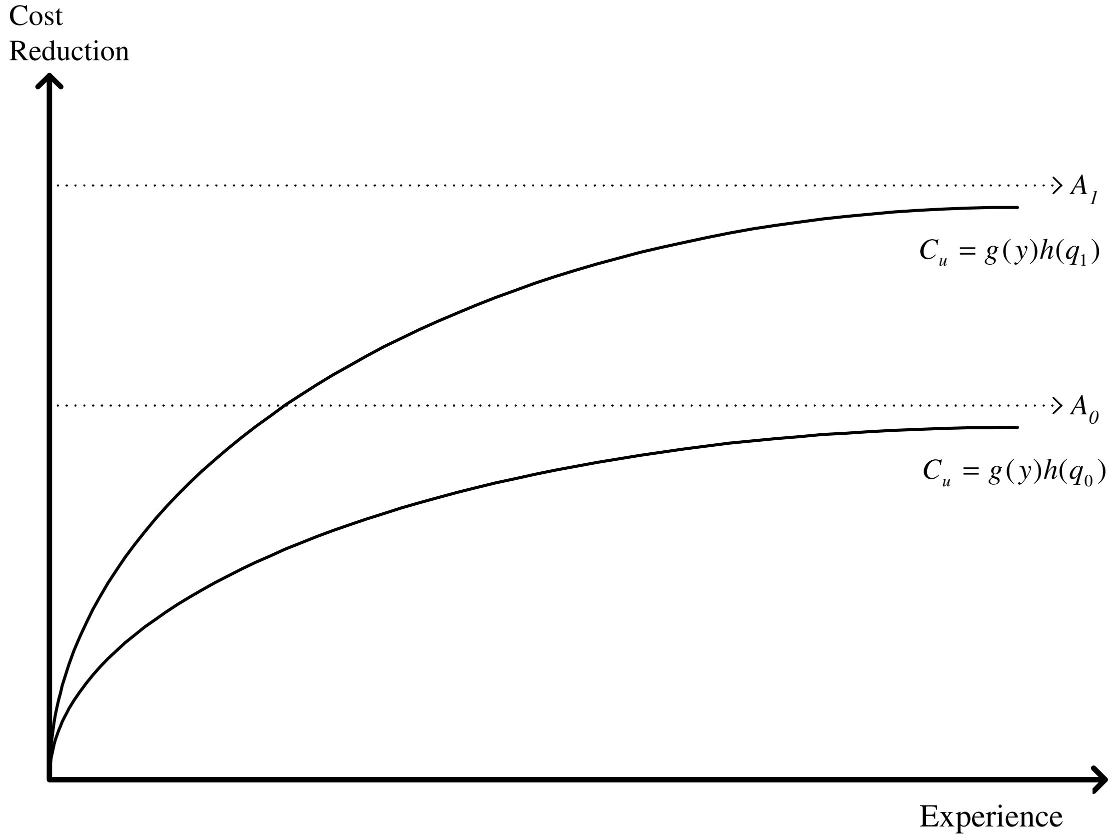

Figure 2: Schematic representation of learning concepts.

The cost function for a representative pulp and paper mill can be expressed as:

$$c = c[y, \mathbf{w}, A(t)] \equiv \min_{\mathbf{x} \geq 0} \{\mathbf{wx} : \mathbf{x} \in V(y)\}, \qquad [2]$$

where *y* is the level of output, **w** is a vector of strictly positive input prices, **wx** is the inner product, *A(t)* represents the state of technological knowledge at time *t* and *V(y)* is the input requirement set, i.e., all input combinations capable of producing output level *y*. Equation [2] allows for the separation of scale effects, price effects and technological knowledge in the cost structure for specific mills. Devoid of scale and price effects, the technological knowledge represents pure cost reductions over time or, using another terminology, the learning effects present in the Swedish kraft industry.

4 The Empirical Specification

Technological knowledge and economies of scale are two important variables when assessing cost reductions in the production process for industry sectors of an economy. While economies of scale represent a movement along the average cost curve, technological knowledge represents a shift in the same. Other important variables that affect the cost structure are, of course, the input prices. When empirically estimating learning curves it is important to employ a cost variable that reflects only the pure cost reductions over time devoid of any scale or input price effects unless these effects are explicitly accounted for in the model. To reflect this, the approach suggested in this paper relies on a two-step estimation procedure. *First*, a variable Translog cost function is derived containing a technological knowledge index using -pecific dummy variables. This step allows for the separation of the scale and price effects from the learning effect. Furthermore, the technological knowledge index is constructed so that it can be decomposed showing technical biases as well as a pure technological knowledge index, i.e., a pure cost reduction over time devoid of other effects than time itself. *Second*, the estimated technological knowledge index is then used to estimate the learning curve and the associated learning elasticities using a two-factor learning curve (2FLC) model.

4.1 Variable Translog Cost Function

Empirical studies analyzing learning curves have often relied on different specifications of the traditional Cobb-Douglas functional form for their cost- or production functions. This approach has the same disadvantages as employing the Cobb-Douglas function in other empirical economic analyses, namely, the inability to allow a desirable flexibility in the estimated parameters. Using a transcendental logarithmic (Translog) approximation function permits the estimation of the parameters of the underlying production technology as well as a technological knowledge index, i.e., unaccounted cost reductions over time, which may be both scale augmenting and non-neutral. Hence, to impose as few restrictions on the variable cost function as possible, a Translog approximation of the cost function is used. This function is obtained by a second-order Taylor expansion of the logarithm of equation [2] (Christensen *et al*., 1971; 1973).[2] Furthermore, we also assume the existence of a short-run cost function, i.e., one in which the capital stock, z, might be fixed at a level other than its full-equilibrium value. In most previous studies long-run cost functions are employed to analyze the cost structure of the pulp and paper industries in various countries (for a review see Stier and Bengston, 1992). Implicit in the long-run formulation is, however, the assumption that the industry is in (long-run) static equilibrium at all times. This assumption is not likely to be valid for industries where the capital embodied has a long lifetime, and where adjustments are costly. This is particularly true for heavy industries, such as the pulp and paper industry, where capacities are planned and built on long-term forecasts, which can easily be inaccurate. In addition, excess capacity is often maintained to meet sudden increases in demand. This implies that the capital stock is quasi-fixed and that the firms are often not in static equilibrium. Under such circumstances a variable (short-run) cost function represents a more appropriate representation of the underlying production structure. Moreover, our choice of estimating a short-run cost function also appears

[2] While the development of flexible functional forms has facilitated a more complex representation of production technologies, such forms do not guarantee meaningful results. The Translog functional form, for example, can yield unrestricted estimates of substitution elasticities, but at the cost of possibly violating global regularity conditions on the concavity of a production function (or the convexity of a cost function). A comparison of the properties of the most common flexible functional forms and their implications for the estimation of parameters of the production technology can be found in Fuss and McFadden (1978).

appealing since short-run disequilibria are likely to have been operative during the period under study (1975–1994). For instance, the sudden energy price increases following the oil crises in the 1970s represent important causes of such disequilibria.

Since *A(t)* in equation [2] is unobservable, it is impossible to derive an approximation that is directly possible to estimate. However, by employing time-specific dummy variables and a pooled data set it is possible to derive a variable Translog cost function that is possible to estimate (Baltagi and Griffin, 1988; Lundmark and Söderholm, 2003). The Translog variable cost function can then be formulated as:

$$\begin{aligned} \ln VC = & \sum_{m=1}^{M-1} \lambda_m D_m + \sum_{t=1}^{T-1} \eta_t D_t + \beta_{yz} \ln y \ln z + \sum_{i=1}^{N} \beta_{iy} \ln w_i \ln y + \sum_{i=1}^{N} \beta_{iz} \ln w_i \ln z + \\ & + \tfrac{1}{2} \left\{ \beta_{yy} (\ln y)^2 + \sum_{i=1}^{N} \sum_{j=1}^{N} \beta_{ij} \ln w_i \ln w_j + \beta_{zz} (\ln z)^2 \right\} + \\ & + \sum_{t=1}^{T-1} \sum_{i=1}^{N} \alpha_{it}^{*} D_t \ln w_i + \sum_{t=1}^{T-1} \alpha_{yt}^{*} D_t \ln y + \sum_{t=1}^{T-1} \alpha_{zt}^{*} D_t \ln z \end{aligned} \quad , \qquad [3]$$

where the subscript $m=1,\ldots,M$ indexes the number of kraft paper mills. D_m represents mill-specific dummy variables. *VC* is the variable costs of production, and is a function of *N* variable input prices (w_i, $i=1,\ldots,N$), the level of paper output (y), the amount of quasi-fixed input (z), in our case the capital stock. The index of technical change [$A(t)$] is replaced by time-specific dummy variables denoted by D_t ($t=1,\ldots,T$).

By differentiating the variable cost function with respect to input prices and employing Shephard's lemma, the corresponding cost share equations (for inputs $i=1,\ldots,N$) can be derived:

$$S_i = \frac{\partial \ln VC}{\partial \ln w_i} = \beta_{iy} \ln y + \beta_{iz} \ln z + \sum_{j=1}^{N} \beta_{ij} \ln w_j + \sum_{t=1}^{T-1} \alpha_{it}^{*} D_t \quad . \qquad [4]$$

The symmetry restriction, $\beta_{ij}=\beta_{ji}$, is imposed on the model. To ensure that the cost shares add up to one (1) and that the cost function is linearly homogenous in input prices, the following parameter restrictions are also imposed:

$$\sum_{i=1}^{N} \alpha_i = 1 \ \forall t, \sum_{i=1}^{N} \beta_{ij} = 0 \ \forall j, \sum_{i=1}^{N} \beta_{iy} = 0, \ and \ \sum_{i=1}^{N} \beta_{iz} = 0 \quad . \qquad [5]$$

The rate of technological knowledge, $\dot{T}$, can be obtained by differentiating the variable cost function with respect to time (t). We then obtain:

$$c_u = \frac{\partial \ln VC}{\partial t} \quad . \qquad [6]$$

Technological knowledge is defined here as cost diminution over time, *ceteris paribus*. Thus, in equation [6] a negative sign indicates technical progress while a positive sign is a sign of technical regress.[3]

4.2 The Two Factor Learning Model

In general, the learning curve specification estimates the extent to which accumulation of production experience contributes to the reduction of costs. Incorporating the notion of embodied and disembodied learning effects mentioned above, the functional form for the learning curve can be written as:

$$c_u = c_1 y^{\alpha_1} q^{\alpha_2} e^{\varepsilon} \ , \qquad [7]$$

where c_1 is the initial cost reduction, y is the cumulative production of kraft paper, q is the gross mill capacity (i.e., rated capacity), the α´s is the learning elasticities to be estimated ($0 \geq \alpha_i \geq -1$) and ε is a stochastic disturbance term. The time notion has been dropped for convenience. It is important to notice that even though the capacity is used as a measure for supplier learning, it will only measure the cost reduction associated with learning effects since the scale effects has been removed in the Translog variable cost function. Taking the logarithm of equation [7] it becomes possible to estimate using least squares methods:

$$\ln c_u = \ln c_1 + \alpha_1 \ln y + \alpha_2 \ln q + \varepsilon \ . \qquad [8]$$

Furthermore, since panel data is employed and because it is of interest to capture within-mill variations among the kraft industry, a fixed effect error specification is chosen. The fixed effects specification assumes that all mills have the same slope on the learning curve, i.e., the same slope parameter, but that they have different intercepts.

4.3 Data

The data employed is a panel set consisting of eight integrated kraft paper mills over the period 1975–1994 resulting in a total of 152 observations.[4, 5] The variable cost function of kraft paper production equals the sum spent on the following inputs: labor, energy, recycled paper, woodpulp, pulpwood and woodchips. The data have been

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[3] The possibility of increasing costs over time (or negative technical change) deserves some further attention. In the case of constant returns to scale, any improvement in efficiency or productivity must be attributed solely to technical change. When, as in this paper, no restrictions on the returns to scale parameters are imposed, any change in productivity must be divided between returns to scale (movements along the production function) and technical change (shifts in the production function). Thus, negative technical change implies that after gains owing to scale are removed there has been a decrease in productivity. Hence, the gross effect on productivity might be positive even though technical change has been negative.

[4] 1994 was the last year that Statistic Sweden (SCB) collected the necessary data for the present analysis.

[5] The kraft paper mills correspond to branch code 341 according to SNI 69 and branch code 21 according to SNI 92, where SNI refers to the Swedish industrial classification systems. Furthermore, only mills producing at least 90% of its output of the good categories 4801, 4804 and 4805 are included (with subcategories).

obtained from Statistic Sweden's annual Industrial Statistics. The corresponding input prices have been derived from the ratio between expenditures and consumed quantities and are measured in 1,000 SEK/metric ton for woodpulp and recycled paper, in 1,000 SEK/m^3 for pulpwood and woodchips, in 1,000 SEK/MWh for energy and, finally, in 1,000 SEK/employee for labor. Production data are measured in 1,000 metric tons. The determinants of the learning curve, the cumulative production and production capacity are also derived from statistics obtained by Statistic Sweden's Industrial Statistics and are measured in 1,000 metric tons.

The capital stock variable was constructed using the perpetual inventory method as outlined in equation [9]:

$$z_t = I_t + (1 - \delta) z_{t-1} \ , \qquad [9]$$

where z_t is the capital stock in time t, I_t is the investment and δ is the capital depreciation rate. The capital stock for the initial year was constructed by using a industry-specific aggregate capital stock obtained from Statistic Sweden, weighted by mill-specific production. Unfortunately, investment data could only be obtained on the firm level and not on the mill level. This problem was solved by disaggregating the firm-level investment data by using the increases in mill-specific production levels between year t and t+1 as weights.[6] The depreciation rate is assumed to be constant over time as well as across mills. Following Samakovlis (2001) and Hetemäki (1990), δ is set at 7%. Descriptive statistics can be found in Table A1 in the Appendix.

Some mills do not use all of the four raw materials, and the prices for these can only be derived conditionally on the realization of a strictly positive demand for that raw material (see above), i.e., the mills must have purchased the raw material. This implies that for some observations we have zero cost shares and missing price observations, and this can cause biased estimates of the parameters (e.g., Bousquet and Ivaldi, 1998). With no special account of zero expenditure, standard estimation methods, such as the maximum likelihood estimator, may yield inconsistent estimates. However, simply deleting observations containing zero expenditure does not cure the problem as it instead may lead to a sample selection bias. In addition, it reduces the sample size. In this paper an approach suggested by Lee and Pitt (1986, 1987) (see also Samakovlis, 2001) is used by replacing the missing price observations by price averages.

In order to estimate the system of equations given by the Translog cost function in equation [3], the N-1 of the factor cost shares in equation [4], and with the parameter restrictions in equation [5] as well as the symmetry condition imposed, we have to specify the stochastic framework. Error terms, ε_{mt}^{VC} and ε_{mt}^{i}, are added to the VC- and share-equations, respectively. Furthermore, the error term of the variable cost function is decomposed so that:

$$\varepsilon_{mt}^{VC} = \mu_m + v_{mt} \ , \qquad [10]$$

[6] The rationale behind this procedure is that it can be expected that mills that expand their production more rapidly than others would be more likely to have invested relatively much in the near past. Regardless of whether the mills have invested in order to replace worn-out capital or to meet higher demand, investments at time period t are likely to result in a higher production level at t+1 than would otherwise have been the case.

where μ_m is the mill-specific component, and v_{mt} is the white noise component, which varies randomly across mills and over time. The mill-specific errors are interpreted as unobserved differences in the cost structure due to, for instance, remaining differences in the output mix (although these should not be large given that mills with relatively low product shares have been removed from the sample). We assume that these differences are fixed over time for a given mill, and we can then eliminate the mill-specific disturbance component by introducing dummy variables for each mill. This fixed effects approach overcomes the bias of the estimation results that can occur in the presence of unobserved mill-specific effects that are correlated with the regressors (e.g., Baltagi, 1995). The disturbance vector for the cost share equations, ε^i_{mt}, are assumed to be multivariate normally distributed with mean vector zero and constant covariance matrix.

Finally, the energy cost share equation is dropped from the estimation to avoid singularity in the disturbance covariance matrix. Since the system of equations is estimated by the method of maximum likelihood (using the TSP software) the results are invariant to the choice of cost share equation dropped (Berndt, 1991).

5 Results

The regression results from the Translog variable cost function and from the learning function is presented in Table A2 in the Appendix and in Table 1, respectively.[7] The changes in unit costs over time and between mills are estimated by the Translog variable cost function. In the estimation procedure, the derived unit cost estimates are cleared from scale and price effects leaving an index of pure technological knowledge. The unit cost changes are plotted in Figure 3 by mill. As seen in the Figure, all mills have had a positive cost reduction over time of about 0.25% annually due to learning effects. Most mills experienced a significant decrease in cost reductions in the late 70s and early 80s indicating that some occurrences affecting most of the industry happened. It is difficult to pinpoint events that might have caused the decline in the unit cost during this time. A low capacity utilization during that late 70s and early 80s together with the aftershocks of the oil crises might explain part of it.

As seen in Table 1, the regression results for the learning function is in line with expectation ($0 \geq \alpha_i \geq -1$) and exhibits at least a 10% statistical significant. It is also noteworthy that a likelihood ratio test indicates that a common intercept for the mills can be rejected supporting the use of a fixed effect model. This suggests that significant within-mill variations exist. In the specific context of this study it means that every mill has the same learning parameter, i.e., slope of the learning curve, but the specific unit cost decline at unit cumulative production and unit capacity are different between the mills.

[7] The theoretical consistency of the Translog variable cost function is presented together with the estimates in the Appendix.

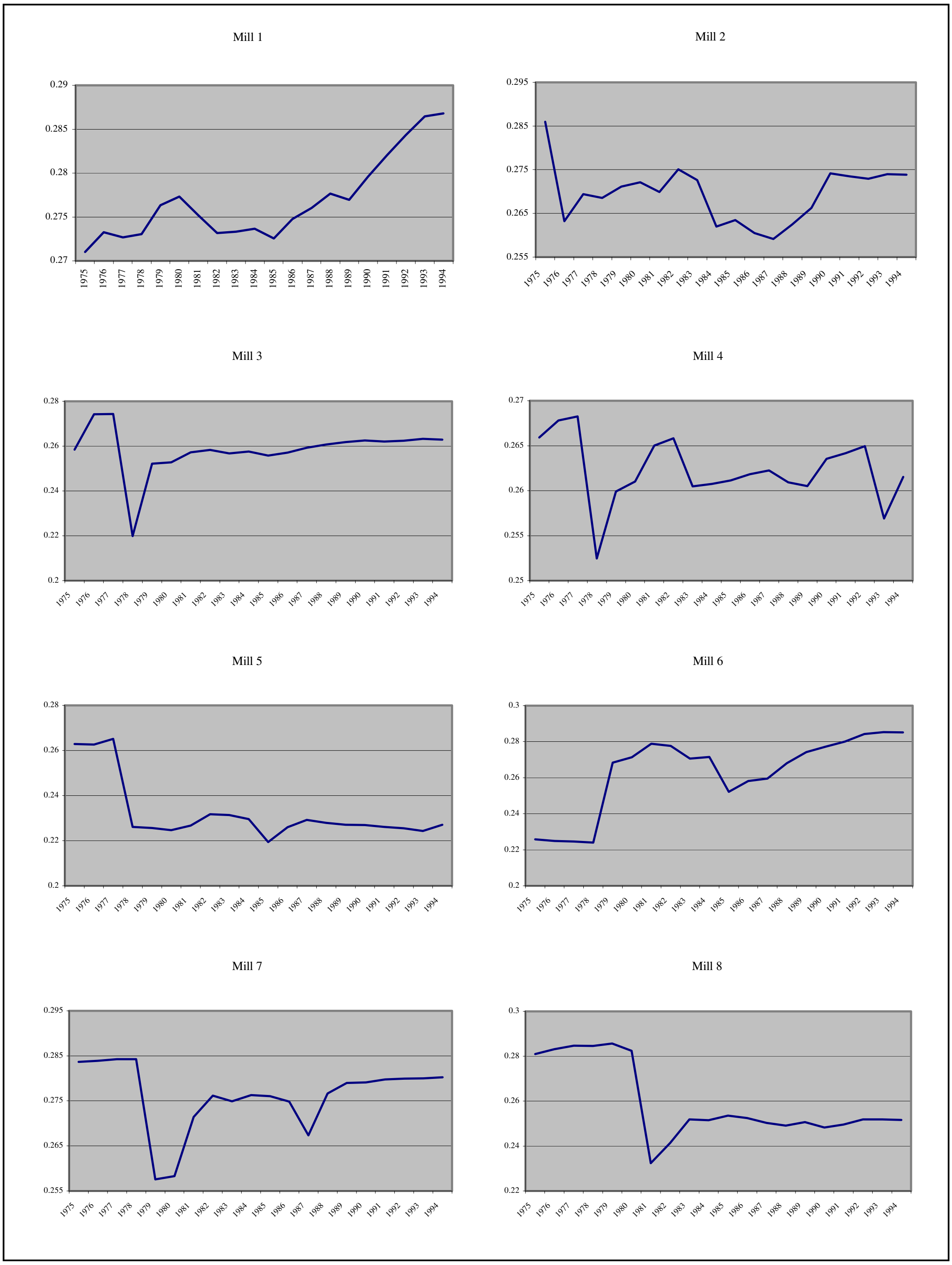

Figure 3: Changes in unit cost reductions over time and by mill.

Table 1: Least squares estimates for 2FLC.

	Coefficient	***t*-ratio**
Capacity	-0.04	1.84
Cumulative Production	-0.03	2.01
Mill 1	-1.20	3.64
Mill 2	-1.25	3.91
Mill 3	-1.29	4.03
Mill 4	-1.28	4.20
Mill 5	-1.44	5.41
Mill 6	-1.24	3.77
Mill 7	-1.22	3.82
Mill 8	-1.31	4.59
R^2 *(adj)*	*0.37 (0.33)*	

Note: *t*-ratios are presented in absolute values.

Since the learning curve function is specified as a logarithmic function the estimated parameters can be interpreted as elasticities. Hence, a 1% increase in cumulative production would result in a cost reduction of 0.03%. Likewise, a 1% increase in the capacity would result in a cost reduction of 0.04%. The low elasticities reflect the fact that the pulp and paper industry is a capital-intensive sector, which, in the manufacturing process from wood chips to finished kraft, is fully automated leaving little room for quality variations.

Alternatively, many studies report the learning rates, which, for example, state the effect that a doubling of cumulative production has on the cost. The learning rates are defined as 2^{α_i}. This indicates a disembodied learning rate of 2.06% and an embodied learning rate of 2.73%. In other words, a doubling of cumulative production would reduce the unit cost to 97.9% of its previous value while a doubling of capacity would reduce the unit cost to 97.3% of its previous value.

Although relatively low, the learning rates are similar in magnitude indicating that learning effects are present both within a specific mill and for the supplier to the mills. The reason for this relative low learning rate can be traced to the fact that the kraft industry is capital-intensive, as mentioned above, and has reached a high degree of maturity. The level of maturity can be illustrated by Figure 2 in which the cost reduction increases with learning but at a diminishing rate. The results would thus indicate that the kraft industry has reached a point where further cost reduction through learning is small.

It is, however, difficult to compare the results to other studies concerning the kraft industry mainly because of the scarcity of previous studies. But examining studies of other capital-intensive industry sectors the estimated learning elasticities and learning rates seems reasonable. For example, Kouvaritakis *et al.* (2000) found similar low learning elasticities and learning rates for large hydroelectric power plants and nuclear power plants.

6 Conclusions

Although learning effects can be found in many industry sectors, there is a great variation in the rate at which various industries learn, ranging from little or no learning to those with impressive productivity growth. This paper limits the analysis of learning effects to the Swedish kraft paper industry, which is an important and relatively homogenous part of the pulp and paper industry. The method proposed herein consists of two steps. First, specifying a flexible cost function that includes a technological knowledge parameter, i.e., by utilizing mill-specific dummy variables, allows for the estimation of a pure cost reduction index over time and by mill. This cost reduction index has the advantage of being devoid of scale and price effects that could otherwise produce spurious results when estimating the learning curve. Second, building on the learning curve literature, the estimated cost reduction index is then regressed on cumulative production as well as on capacity data to reflect both operator and supplier learning effects.

The result suggests the presence of small learning effects for Swedish kraft paper mills, which is consistent with previous findings regarding capital-intensive industries. In addition, the kraft industry has reached a relatively mature state where additional learning effects are difficult to achieve. These two notions can, at least in part, explain the relatively inelastic learning effects. As a consequence, arguments that support the implementation of protective measures — as mentioned in the introduction — on international kraft paper trade to shield the domestic production from competition until sufficient cost reduction through the learning process has been achieved may fall short. Furthermore, predatory pricing is unlikely since larger market shares, and thereby an increasing cumulative production than would otherwise be the case, would not result in any significant cost reduction.

Overall, the methods presented herein could provide policy makers with a tool when assessing aimed subsidies, regulations or specific research programs. For example, technology policies that stimulate innovation could make it possible to recoup high up-front costs in the long-run after achieving cost reduction gained through learning.

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APPENDIX

Table A1: Descriptive statistics.

Variable	Definition	Mean	Std. Dev.	Min	Max	Skewness	Kurtosis
VC	Variable Costs	626341	436216	44494	1615559	0.80	-0.59
SRP	Recycled Paper Share	0.05	0.07	0.00	0.26	1.19	0.02
SPW	Pulpwood Share	0.16	0.22	0.00	0.76	1.22	0.24
SWP	Woodpulp Share	0.27	0.19	0.00	0.73	0.19	-0.61
SCH	Woodchips Share	0.17	0.10	0.00	0.39	-0.10	-0.73
SWA	Labor Share	0.22	0.10	0.12	0.62	2.13	4.26
SEN	Energy Share	0.13	0.07	0.02	0.49	3.06	11.00
RP	Price recycled Paper	1.13	0.56	0.59	5.32	3.17	19
PW	Price Pulpwood	3.44	1.28	1.87	7.08	0.82	-0.02
WP	Price Woodpulp	417	93	212	907	2.04	7.69
CH	Price Woodchips	164	52	98	433	2.96	9.82
WA	Price Labor	172	24	75	246	0.63	2.28
EN	Price Energy	0.22	0.06	0.09	0.50	0.90	3.56
Y	Production	240191	150071	16986	610608	0.24	-0.85
Z	Capital Stock	1181900	948681	79512	4202241	0.95	0.11
y	Cumulative Production	2212761	2046955	23596	8562433	1.09	3.43
q	Capacity	262240	161615	18854	659456	0.20	2.09
Obs.	152						

Table A2: Estimation results from the Translog variable cost function.

Coefficient	Estimation	*t*-ratio	Coefficient	Estimation	*t*-ratio
α_{RP}	21 DV		β_{WPWP}	0.22	5.85
α_{PW}	21 DV		β_{RPWP}	-0.08	5.31
α_{WP}	21 DV		β_{PWPW}	0.01	0.15
α_{CH}	21 DV		β_{RPPW}	0.06	2.77
α_{WA}	21 DV		β_{RPRP}	0.02	1.17
α_{EN}	21 DV		β_{PWZ}	0.03	2.47
α_{Y}	21 DV		β_{WPZ}	0.07	4.29
α_{Z}	21 DV		β_{CHZ}	0.00	0.48
η	21 DV		β_{WAZ}	-0.02	3.24
Mill 1	0.49	5.49	β_{RPZ}	-0.04	7.47
Mill 2	0.17	2.75	β_{PWY}	0.08	5.66
Mill 3	0.17	2.46	β_{WPY}	-0.18	9.34
Mill 4	0.05	1.07	β_{CHY}	0.05	5.38
Mill 5	-0.36	5.95	β_{WAY}	-0.02	2.84
Mill 6	0.96	10.9	β_{RPY}	0.06	9.94
Mill 7	0.70	10.2	β_{YZ}	0.06	2.38
Mill 8	0.57	4.54	β_{YY}	-0.33	3.77
β_{PWWA}	0.03	1.64	β_{ZZ}	0.05	2.25
β_{WPWA}	0.00	0.21	β_{ENY}	0.01	1.20
β_{CHWA}	-0.01	0.91	β_{ENZ}	-0.03	6.25
β_{WAWA}	-0.04	1.56	β_{RPEN}	-0.04	3.50
β_{RPWA}	0.06	4.25	β_{PWEN}	-0.03	2.46
β_{PWCH}	0.08	2.88	β_{WPEN}	0.07	6.23
β_{WPCH}	-0.07	3.02	β_{CHEN}	-0.04	3.54
β_{CHCH}	0.07	2.39	β_{WAEN}	-0.04	3.22
β_{RPCH}	-0.02	1.40	β_{ENEN}	0.08	7.60
β_{PWWP}	-0.14	4.14			
Log	*1343*				

Theoretical consistency of the Translog variable cost function is important to establish so that inference regarding the behavior of the model can be made. First, monotoncity of the variable cost function was checked by determining if the fitted factor cost shares were positive. This check showed that 65 out of a total of 912 fitted cost shares had a negative sign. Second, concavity in input prices were checked by examining whether the bordered Hessian matrix is negative semi-definite, which is a necessary and sufficient condition. The test indicates that 155 of the observations do not fulfill the requirements. Even though not completely satisfactory the Translog variable cost function is behaving reasonably well.