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ABSTRACT

The main purpose of this study is to characterize and analyze high technology industrial firms in Israel. We are able to advance beyond previous empirical studies of high technology because we have access to a unique individual firm data set, a sample of 670 establishments in Israel for the year 1982. Not only do we have basic production data at the individual firm level, but also each firm's capital stock revalued to 1982 dollars. A technology index is constructed from three technological indicators -- substantial R & D investment, a high proportion of the work force consisting of engineers and technicians, and a high proportion of the capital stock being of recent vintages. This technology index is used to classify firms. The largest concentration of High Tech firms are found in electronics and transport equipment industries, and the lowest in textiles and clothing. High Tech firms appear to be more productive, pay higher wages, and earn higher rates of return. Part of the higher wages to workers in High Tech firms accrue in the form of rents whereby workers in these firms exappropriate a portion of monopoly profits, a phenomenon which does not appear to be the case for Low Tech firms.

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1. Introduction

In recent years industrial policy in the developed countries has focused on the encouragement of high technology product and process innovation as a means of sustaining economic growth. This is reflected in the economic literature by phrases such as: "In the mid-1980's high technology has become the Economy Holy Grail" (Markusen, et. al. (1986)); or "If in the course of history a single phrase becomes associated with the 1980's it is likely to be "high technology" (Breheny & McQuaid (1987)).

For less developed countries, the issue has often been addressed by the question of whether export orientation or import substitution yields a path of higher productivity gain (Pack (1988)). Since High Tech firms are very export-oriented[1], encouragement of high technology development is closely connected to a growth strategy which is export-oriented.

Israel is an excellent example of a developing country in which high technology production and export orientation are becoming increasingly important phenomena. This process is aided by an explicit government industrial policy. The Government of Israel Investment Authority makes the following statement in its information pamphlet given to potential new investors:

> "The Government of Israel considers the encouragement of foreign investment to be a matter of the highest priority. ...to further this goal, we provide financial incentives to those who invest in export-oriented industries and to those who create jobs in development areas. We are particularly interested in attracting investors in high-technology industries, as this is an area where

Israel has a great abundance of highly-skilled labor, and an export sector which we hope to greatly expand."

As we will show, High Tech firms produce the majority of output in the electronics, transport equipment, metal, chemical, and mineral industries. In 1965 these industries accounted for 37% of Israel's industrial output. By 1985, these industries produced 56% of industrial output. In the high technology industries, exports grew at a 16% annual rate between 1965 and 1985. For the other industries the per annum growth rate of exports was only 9% (Bregman (1988)).

The main purpose of this study is to characterize and analyze high technology industrial firms in Israel. We are particularly interested in whether such firms could be considered more productive than other firms, given the question of the relationship between high technology development, export orientation, and productivity improvement. We are able to advance beyond previous empirical studies because we have access to a unique individual firm data set. Our study is based on empirical analysis of a sample of 670 establishments in Israel for the year 1982. Not only do we have basic production data at the individual firm level, but also each firm's capital stock revalued to 1982 dollars, the result of a special capital stock survey of the 670 firms. To our knowledge this is the first time that a broadly-based disaggregated data set has been used to examine the nature of high technology. The new data base enables us to identify the components of the firm's production function (output and factors of production - materials, labour, and capital services); as well as supplementary variables necessary to understand the high technology nature of the production process, such as investment in

R & D and the use of high quality labour and capital.

The conceptual framework is presented in section 2. Our data set is described in more detail in section 3. Sections 4 and 5 contain the empirical results. Section 6 concludes the paper with summary remarks and suggestions for further research.

2. The Conceptual Framework

We assume that the firm produces output (Q) using labor (L), capital (K), and materials (M), subject to a state of technology (T). The firm's production function is:

$$Q = F\ (L,\ K,\ M,\ T) \tag{1}$$

We will use the state of technology to distinguish "High Tech" firms from other firms. Recent research (Markusen et. al. (1986), Breheny & McQuaid (1987), U.N. Report (1987)) has shown that there is no standard definition of high technology, and no single indicator can be taken as a measure of it. The main aspects of high technology are: growth, new products, labour saving production processes, etc. Achieving those goals demands investment in knowledge (R & D or acquired know-how), the use of more sophisticated capital goods and the use of more technically educated workers. In short, High Tech production requires a sophistication of product line and production process.

Compared to the general population of manufacturing firms, High Tech firms are likely to be characterized by a greater proportion of technical labour, modern capital equipment, and intensity of R & D activity - a continuous effort to develop new products and to find ways of producing them more efficiently.

To capture these characteristics of the High Tech firm, we specify T to be a 3 dimensional vector containing indices of (1) the technical quality of labor (QL) - the proportion of engineers and technicians in the labor force, (2) the quality of capital (QK) - the proportion of capital that is less than six years old[2], and (3) an index of R & D activity (INRD).[3,4] The production function (1) then becomes an "augmented" production function,

$$Q = F\ (L,\ K,\ M,\ T\ (QL,\ QK,\ INRD)) \qquad (2).$$

We will estimate two forms of the production function - the Cobb-Douglas (CD) and Translog (TL) functional forms. The CD function can be viewed as a first order approximation to any production function, and takes the form:

$$\log Q = \log A + \sum_{i=1}^{3} a_i \log T_i + \sum_{j=1}^{3} b_j \log X_j \quad ; \qquad (3)$$

where $T = (T_1,\ T_2,\ T_3) = (QL,\ QK,\ INRD)$

$X = (X_1,\ X_2,\ X_3) = (L,\ K,\ M)$

and $\log A$, a_i, b_j are parameters to be estimated.

The TL function is a second order approximation to any production function, and takes the form:

$$\log Q = \log A + \sum_{i=1}^{3} a_i \log T_i + \sum_{j=1}^{3} b_j \log X_j$$

$$+ \frac{1}{2} \Sigma b_{jj} (\log X_j)^2 + \sum_{\substack{j \\ j<k}} \sum_{k} b_{jk} \log X_j \log X_k \tag{4}$$

where we have assumed that the technology index T is additively separable from the remainder of the production function.[5] Under these circumstances a natural measure of the technology index is:

$$\log T = \sum_{i=1}^{3} a_i \log T_i \tag{5}$$

We will define High Tech firms as those which have large values of log T. Since $a_i > 0$, i = 1, 2, 3 (see empirical results), such firms will also be those which have large amounts of at least some of the T_i, so that there will be consistency between the use of log T as a "High Tech indicator" and the descriptive nature of High Tech firms presented earlier.

In both equations (4) and (5), differences in the technology index represent differences in output levels for firms which use the same amounts of inputs L, K and M, but differ in "High Techness". To see this, we can apply Diewert's (1976) Quadratic Lemma to (3), (4) and (5) to obtain:

$$\log Q^2 - \log Q^1 = \Sigma a_i (\log T_i^2 - \log T_i^1)$$

$$+ \frac{1}{2} \sum_j \left[\frac{\partial \log Q^2}{\partial \log X_j} + \frac{\partial \log Q^1}{\partial \log X_j} \right] \cdot (\log X_j^2 - \log X_j^1) \tag{6}$$

where 1 and 2 index firms 1 and 2.

$$\frac{\partial \log Q}{\partial \log X_j} = b_j \qquad \text{(Cobb-Douglas)}$$

$$= b_j + \sum_k b_{jk} \log X_k \qquad \text{(Translog)}$$

When $X_j^2 = X_j^1$, $\log Q^2 - \log Q^1 = \Sigma\, a_i\, (\log T_i^2 - \log T_i^1)$ $= \log T^2 - \log T^1$. Thus firm differences in the technology index represent differences in total factor productivity or efficiency, in the sense of Solow (1957).[6] High Tech firms are, by definition, more technically efficient firms as long as $a_i > 0$, $i = 1,2,3$. But such firms are not necessarily more cost-efficient or profitable, since to be High Tech requires a higher cost production process. In the empirical results, we not only present productivity differences between High Tech and other firms, but also an analysis of their relative cost and profitability positions.

3. The Data

A new data base, built by the Israel Central Bureau of Statistics (CBS) in the last two years, enabled us to use a subsample of 670 industrial firms out of approximately 2,000 firms participating in the current Industrial Survey for 1982/83 (CBS(1982)). The limiting factor as to the size of the sample was the number of firms contained in the special survey of fixed capital and investment by vintage (CBS (1986)). The firm data include the values of output and materials input, the total wage bill, number of employees, hours worked, and capital stock by kind of capital (buildings, equipment and machinery, and vehicles). The industry the firm belongs to and other characteristics of the firm were also available.

This data set was merged with two other sources of firm information: a series of R & D surveys that were conducted from 1970 onwards and the distribution of labour by profession. The R & D Surveys gathered firm data on R & D expenditures - wages, materials and capital investments, and the number of workers of various professional capacities involved in R & D activity. The skill distribution of labour in the firm was obtained from a file made available by the Ministry of Industry and Trade. This file contained a breakdown of employees into 6 categories: non-technical university educated (called academicians), engineers, technicians, other professionals, clerks and unskilled workers. These data were matched with the other sources of firm data, and where data were incomplete (approximately 40% of firms) imputations were utilized.

The technological indicators have been defined in section 2. The output and inputs into the production process were defined as follows:

Output: value of sales during 1982 (adjusted for inventory changes and price inflation over the year).

Materials input: value of materials purchased (also adjusted for inventory changes and inflation).

Labour input: hours worked.

Capital input: capital services obtained by aggregating the three components of capital utilizing component-specific depreciation rates and a real return of 5% (Levy (1987)).

4. Empirical Results

(a) Estimation of the Production Function

Cobb-Douglas and Translog production functions were estimated using a cross-section of 628 firms. The additional 42 firms in the original 670 firm sample were deemed to be non-comparable and were eliminated from consideration (see Bregman, Fuss and Regev (1989) for further details).

Because we are dealing with a single period cross-section, our output data are in value terms (gross revenue). Hence any positive relationship between the technology index and output due to inter-industry price effects may distort our results. For example, if high technology firms are situated in industries where firms possess monopoly power, the greater value of output generated by High Tech firms may be due to monopoly pricing rather than increased efficiency. To control for this possibility we need to model inter-firm variations in output prices. We assume that the firm's output price p can be expressed as:

$$p = f\,(\bar{p},\ \underline{D},\ CON,\ WE) \qquad (7)$$

where $\bar{p}$ is a constant base reference price

$\underline{D}$ is a vector of industry-specific dummy variables

CON is the three firm concentration ratio (at a 3 digit industry level).

WE is a measure of the extent to which the firm's wage rate exceeds the average wage rate in its industrial group, after correcting for the occupational composition of the firm's labour force. The variable WE is designed to capture the interaction of firm and union market power, where high wages are passed on to consumers in the form of high prices. This variable will also be effective when firms in a competitive industry employ labour which can exercise monopoly power.

A possible alternative interpretation of WE is that it measures human capital effects and thus is a labour quality variable. This would occur if the payment of higher than average wages within a skill category implied the use of more productive labour within that category. The fact that WE is on average substantially higher for High Tech versus Low Tech firms lends support to this interpretation. We will be sensitive to this possibility when interpreting the empirical results.

The dependent variable, revenue, is now given by:

$$\begin{aligned} \log R &= \log Q + \log p \\ &= \log F\,(L,\, K,\, M,\, T) + \log f\,(\bar{p};\, \underline{D},\, CON,\, WE) \end{aligned} \tag{8}$$

Assuming that the price function (7) can be approximated by a linear-in-logarithms function, equation (8) becomes, for the Cobb-Douglas production function,

$$\begin{aligned} \log R = {} & \log A^1 + \Sigma\, a_i \log T_i + \Sigma\, b_j \log X_j \; + \\ & \Sigma\, d_m D_m + c_1 \,.\, \log CON + c_2 \,.\, \log WE \end{aligned} \tag{9}$$

where $\log A^1 = \log A + \log \bar{p}$.

Similarly, for the Translog function, (8) becomes:

$$\log R = \log A^1 + \Sigma a_i \log T_i + \Sigma b_j \log X_j + \frac{1}{2} \Sigma b_{jj} (\log X_j)^2 + \sum_{j<k}\Sigma b_{jk} \log X_j \log X_k + \Sigma d_m D_m + c_1 \log CON + c_2 \log WE \qquad (10)$$

Table 1 presents the results of estimating equations (9) and (10) by ordinary least squares, with and without the industrial group dummy variables.[7] All parameters are statistically significant at conventional levels. As noted earlier, the coefficients a_i of the components of the technology index are positive, so that increases in these components lead to increased output. A 1% increase in the technical capability of labor, or in the proportion of modern capital, or in the intensity of R & D activity results in .02 to .03 percent more output. When the industrial group dummy variables are included, the values of the technical indicator coefficients decline in magnitude. This is to be expected, since the dummy variables will capture some of the inter-industry high technology effects, as High Tech firms tend to be concentrated in certain industries. Nevertheless, the coefficients remain positive and statistically significant.

The input coefficients for the Cobb-Douglas function are the input-output elasticities. All variables are measured as deviations from sample means, so that the Translog coefficients b_j are input-output elasticities for the mean firm. For the mean firm returns to scale are slightly less than unity, but the hypothesis of constant returns to scale would not be rejected. The market power variables are positive and significant, indicating that ignoring inter-industry price effects would bias inter-firm efficiency comparisons. An analysis of the market power results implies that at the mean values of CON (3 firm concentration ratio of 50%) and WE (a firm excess wage of 25%), output price is 20% above the competitive price. Interpreting WE as a labour quality variable, output price is 15% above the competitive price (since only the contribution of CON is included).

The dummy variables were constructed so that textiles is the reference industrial group. Since $d_m > 0$, all other industrial groups have higher output (in value terms) than the textiles industry, ceteris paribus. Several explanations are possible. As noted earlier, the dummy variables will capture part of the technology effect. This is consistent with the results presented in Table 7, where the industry with the largest coefficient -- electronics and transport equipment -- has the highest percentage of output produced by High Tech firms, and textiles has the lowest percentage. The dummy variables may capture a value of product effect -- labor and capital produce a higher value of product in electronics than in textiles. This effect should be mitigated by the fact that the materials input is also in value terms. Finally, the coefficients of the dummy variables may imply inter-industry average efficiency differentials among firms which are unrelated to high technology.

The empirical results relating to the structure of production and the structure of markets have been described in a condensed form since they are not the primary focus of this paper (see Bregman, Fuss and Regev (1989) for additional details). We are mainly interested in the technology index and its components. The production function can be estimated under a variety of assumptions, each of which implies a different method of estimation. We need to demonstrate that the results concerning the technology index are robust to changes in assumptions. The OLS results contained in Table 1 yield consistent estimates of parameters when firms are assumed to be expected profit maximizers or expected cost minimizers, and commit to inputs in advance of output determination (Zellner, Kmenta and Dreze (1966)). If inputs and output are simultaneously determined, OLS is inconsistent. We estimated (9) and (10) by two stage least squares (2SLS) to obtain consistent estimates for this case.[8] We also modelled cost minimization explicitly, by including a second equation in which firms are assumed to choose labour and materials so that the marginal rate of substitution is equal to relative input prices. The two equation system was estimated using the iterative Zellner maximum likelihood procedure (IZEL) -- i.e., ignoring the endogeneity of labour and materials, and the iterative three stage least squares procedure (I3SLS) which recognizes the endogeneity of labour and materials.

Tables 2 and 3 present the results of the robustness analysis for the Cobb-Douglas and Translog functions respectively when industrial group dummy variables are included. The results were similar when the dummy variables were not included. The estimates of the coefficients are robust to alternative assumptions - generally remaining within the .02 to .03 range.[9] This implies that the technology index which will be used to designate firms as High Tech is robust to changes in assumptions.

(b) The Distribution and Characterization of High Technology Production in Israeli Industry

We calculated the technology index T from the OLS Translog production function results, giving equal weights to the regression with and without dummy variables.[10] The resulting index is:

$$\log T = .026 \log QL + .032 \log QK + .021 \log INRD \qquad (11).$$

Firms were ranked according to values of T. Members of the upper quartile were designated "High Tech firms", the lowest quartile designated "Low Tech firms", and the remainder "Medium Tech firms".

In order to fully characterize Israeli industry, Central Bureau of Statistics expansion factors were applied to the sample decomposition described above in order to decompose the population of approximately 5,500 firms. These expansion factors take into account the fact that the original sample was a random stratified sample in which large firms were oversampled.[11]

Table 4 presents average values of T for the three groups of firms, further decomposed by size class. Since the logarithms of QL, QK and INRD are calculated as deviations from population means, the value of T for the mean firm in the population will be 1.00. This value coincides with the average T for Medium Tech firms. Recall that we have associated differences in log T with differences in total factor productivity (see page 6). Corresponding to that interpretation, High Tech firms on average are 20 percentage points more productive than Low Tech firms in Israeli industry. This result will be explored in more detail and interpreted below (see pages 16-18). Size has little effect on T, so that it is unlikely that the technology index is a returns to scale phenomenon in disguise.

Before proceeding to an analysis of productivity differentials between High and Low Tech firms, it is useful to provide a characterization of the incidence of high technology in Israeli industry. In Tables 5-10 we present this characterization.

Table 5 demonstrates that Hi-Tech firms are relatively large, about 16 percent of all manufacturing enterprises produced some 46 percent of total output, employing 40 percent of all workers. It is not surprising that their share in capital stock is even higher (53%) and that 94% of all R & D capital of industrial firms was accumulated in this group of advanced firms. Consistent with the export-orientation of high technology enterprises, High Tech firms produced 71% of Israel's industrial exports, whereas Low Tech firms produced only 5% of exports.

Table 6 shows that High Tech firms are not only human capital intensive but also very intensive in fixed capital: buildings, machinery, and equipment. The average cost of labour per worker in this group of firms is much higher than the cost in Low Tech firms. We also find higher value-added per employee in the High Tech group - 27,000 dollars per annum - as compared to 15,000 in the Low Tech firms.

Additional characteristics of High Tech firms can be seen from Tables 7-10. Table 7, for example, shows that the greatest concentration of High Tech firms can be found in the Electronics and Transport Equipment industries. In these branches 79 percent of production was carried out by High Tech enterprises. On the other hand, only 8 percent of the product in Textiles and Clothing are attributed to this group, which means that most of the production in this field is still done with traditional methods, using old machinery and little human capital.

Approximately two-thirds of value-added and employment in Israeli High Tech firms resides in relatively large establishments, employing more than 500 workers each (table 8). In these 40 firms, the average wage per employee is much higher than the wage rate in large Low Tech firms - $18,000 per year as compared with $11,000 per year (table 9); and also higher than the average wage in the small High Tech firms (1-50 workers). Value-added per worker follows the same pattern as the wage rate -- greater in large High Tech firms than in large Low Tech firms, and greater in large High Tech firms than small High Tech firms. One puzzling aspect is the relationship between small High and Low Tech firms. Value - added per worker is only marginally higher in these High Tech firms and the average wage is the same. Part of the explanation may be that small High Tech firms are the least capital-intensive, so that, ceteris paribus, such firms would have the lowest labour productivity.

We now proceed to a more formal analysis of differences between the labour productivity of High and Low Tech firms. Similar to equation (6), we can apply the Quadratic Lemma to equation (8) and then subtract $\log L^2 - \log L^1$ from both sides of the resulting equation to obtain a decomposition of the difference in labour productivity (in value terms) between High and Low Tech firms.

A detailed derivation of this equation is contained in an Appendix. The results of the decomposition are presented in Table 11.[12] The difference between High and Low Tech firms is represented by the difference between mean firms in each group (i.e., firms which have mean values of the logarithms of the production data). High Tech firms have a 54% higher value of labour productivity than Low Tech firms. This greater productivity is due to the use of more capital and materials intensive production techniques, and a higher level of "High Tech" technology. The labour quality differential is the most important source, whereas the quality of capital difference is the least important source. The three sources of high technology together account for one-half of the difference in labour productivity value between High and Low Tech firms.

Since High Tech firms are, on average, considerably larger than Low Tech firms, the estimated diseconomies of scale translate into a source of labor productivity disadvantage for High Tech firms. The market power variable CON is a source of increased prices and hence increased labour productivity value for High Tech firms. The variable WE is also a source of increased labour productivity value for High Tech firms. Depending on the interpretation, this variable is a source of either increased prices or increased physical labour productivity for High Tech firms.

5. Performance of High Tech Versus Low Tech Firms

We have seen that High Tech firms have higher total factor productivity (in value terms) and higher labour productivity than Low Tech firms. We have also seen that High Tech firms pay higher wages. In Table 12 we consider the wage-productivity comparison in a different light. The value of the marginal product of labour (VMP_L) is calculated from the Translog production function estimates (with and without industry dummy variables). For both High and Low Tech firms, VMP_L exceeds the wage rate (w). However, when the marginal products are purged of market power effects which raise output prices, $w > VMP_L$ for High Tech firms. This result, which tends to hold even when the effect of WE is attributed to differences in labour quality, is consistent with Katz and Summers (1988) conclusion that in the U.S. workers in export-oriented industries earn rents. Table 12 also provides evidence (although somewhat weaker) that $w < VMP_L$ for Low Tech firms.

The results of Table 12 suggest that there are labour market imperfections as well as product market imperfections in Israel. The increase in the size of the export-oriented high technology sector in Israel appears to have led to an increase in the proportion of higher paying jobs, relative to skill levels, to the benefit of workers. Workers in High Tech firms have expropriated a portion of monopoly profits, which does not appear to be the case for Low Tech firms.

Table 13 presents pre-tax rates of return data for high and low technology firms by size class. On an overall basis, rates of return are greater for High Tech firms, which is particularly interesting given the above evidence that profits are shared with workers. One surprising result is the very high rates of return earned by small High Tech firms. Part of the reason is the low capital intensity of these firms. In addition, very small firms may place owners' compensation in the profit rather than the wage category for income tax reasons. This may account for the low average wage in this category (see Table 9). Another surprising result is the low rates of return for large Low Tech firms. Such firms seem to be the poorest performers in Israeli industry - low rates of return, low wages and low productivity.

6. Summary and Conclusions

In this paper we have used a unique individual firm data set to investigate the characteristics of high technology production in Israeli industry. We defined high technology firms as those firms characterized by substantial Research and Development activity, a high proportion of the workforce consisting of engineers and technicians, and a high proportion of the capital stock being of recent vintages. A technology index was constructed from the three technological indicators by estimating a production function, augmented by these indicators. Firms with large values of the technology index were designated High Tech firms. As expected, the largest concentration of such firms is found in electronics and transport equipment industries and the lowest in textiles and clothing. High Tech firms appear to be more productive, pay higher wages, and earn higher rates of return. These firms are also more heavily export-oriented, so that a development strategy which encourages exports will yield a greater proportion of output being produced by the high technology sector, as has been the case for Israel.

In spite of the quality of our data set, the use of a single year cross section has an important limitation. It tells us nothing about the growth process. Our results could be interpreted as establishing a hypothesis that firms with "High Tech" characteristics are more productive. This hypothesis can be tested by seeing whether the technology index which has been estimated and used to decompose the Israeli industrial sector into High Tech and other firms can also predict superior performance over time in such dimensions as output and productivity growth. A panel data set is necessary to test this hypothesis, and we are currently assembling an individual firm data set for the 1970-87 period constructed from the same sources as the data used in this paper.

Footnotes

1. For the sample of firms studied in this paper, High Tech firms exported 37% of output whereas Low Tech firms exported only 8% of output.

2. Our empirical results were not sensitive to changes in the number of years used to calculate QK.

3. This index of R & D activity is an average of three components:

   (a) R & D capital stock, accumulated over 12 years of R & D activity (early years received lower weights).

   (b) The ratio of the number of years that the firm conducted R & D in the last seven years.

   (c) Percent of technical skilled workers who participated in R & D activity in the firm.

4. In a small, open country like Israel a substantial component of technical knowledge is imported in the form of foreign-sourced equipment and patent licenses, which will not be captured in INRD. A part will however be contained in QK.

5. We experimented with non-separable forms of the production function but the results were not particularly successful. While the average value of the technology index was similar to the separable case, the index fluctuated widely among firms which had similar high tech "endowments".

6. This definition of total factor productivity difference (ΔTFP) is net of economics of scale effects. Alternative definitions are possible. For example, the popular Divisia index of ΔTFP, which includes scale effects and the assumption of cost-minimizing behaviour, can be written as

$$\Delta TFP = \log Q^2 - \log Q^1 - \frac{1}{2} \sum_j (S_j^2 + S_j^1) (\log X_j^2 - \log X_j^1)$$

$$= \frac{1}{2} \sum_j \left[S_j^2 (\theta^2 - 1) + S_j^1 (\theta^1 - 1) \right] (\log X_j^2 - \log X_j^1)$$

$$+ \sum_i a_i (\log T_i^2 - \log T_i^1)$$

where S_j is the cost share of the jth input and θ is the scale elasticity. As long as $\theta \neq 1$ or $X_j^2 \neq X_j^1$ for all j, the first term above will measure the total factor productivity effects of departures from constant returns to scale.

7. Because of the wide diversity in size of firms heteroskedasticity of the error terms could be an issue. We ordered the firms by size and analysed the residuals-size interrelationship. We found no evidence that would support the existence of either heteroskedasticity or size-related misspecification.

8. We considered the case where output, labour and materials are chosen simultaneously, subject to a given amount of capital. The 1983 inputs of labour and materials and the 1982 wage rate were used as instruments for the 1982 inputs of labour and materials. While

lagged values of variables are more conventional instruments, future values possess the same properties which render lagged values appropriate instruments. Both lagged and future variables may not be suitable instruments in the presence of strong intertemporal firm - specific effects, and this may be a problem in the current application. Unfortunately, no more suitable instruments were available.

9. The other coefficient estimates remain essentially unchanged under alternative assumptions, with the occasional exception of b_{jk} terms for the Translog functional firm.

10. This procedure is consistent with the argument presented on page 11 that the dummy variables, in part, capture the effects of high technology production.

11. The expansion factors expand from 670 firms to the entire population. The sample was increased from 628 to 670 by assuming that the technology index (11) also represented the state of technology for the 42 excluded firms.

12. The results are based on the Translog OLS regression without industry group dummy variables. The inclusion of industry dummies would render interpretation more difficult since the mean High Tech and Low Tech "firms" could not be allocated to any particular industry group.

References

Bregman, A. (1988), "Technological Progress, Structural Change, and Productivity in Industry: The Case of Israel", Bank of Israel, Jerusalem, Israel, mimeograph.

Bregman A., M. Fuss and H. Regev (1989), "The Production and Cost Structure of Israeli Industry: Evidence from Individual Firm Data", in preparation.

Breheny, M.J. and R. McQuaid (1987), "H.T.U.K.: The Development of the United Kingdom's Major Centre of High Technology Industry", in Breheny and McQuaid, eds., The Development of High Technology Industries, Croom Helm Ltd., pp. 296-354.

CBS (1985), Israel Central Bureau of Statistics, Industry and Crafts Survey, 1982, Jerusalem.

CBS (1986), Israel Central Bureau of Statistics, Survey of Fixed Capital Stock in Industry, 1.1.1982, Jerusalem.

CBS (various years), Surveys on Research and Development in Industry, Jerusalem (1970-1985).

Diewert, W.E. (1976), "Exact and Superlative Index Numbers", Journal of Econometrics, 4, pp. 115-145.

Katz, L. and L. Summers (1988), "Industry Rents and Industrial Policy", paper presented at the Brookings Conference on Microeconomics, Dec. 1, Washington D.C.

Levy, H. and Z. Lerman (1987), "Estimating the Cost of Capital Under Inflation - Israeli Industry, 1971-1980", Bank of Israel, Economic Review, 59 (April).

Markusen, A., P. Hall, and A. Glasmeier (1986), High Tech America, Boston, Allen & Unwin.

Pack, H. (1988), "Industrialization and Trade" in H. Chenery and T.N. Srinivasan, eds., Handbook of Development Economics, forthcoming.

Solow, R. (1957), "Technical Change and the Aggregate Production Function", Review of Economics and Statisitcs, 39, pp. 312-320.

U.N. Report (1987), "Impact of Science and Technology on Long-Term Economic Development", Economic and Social Council.

Zellner, A., J.Kmenta and J. Dreze (1966), "Specification and Estimation of Cobb-Douglas Production Function Models", Econometrica, 34, pp. 784-795.

Table 1

Production Function Estimates for Israeli Industry[1]

Coefficients	Cobb-Douglas		Translog	
a_1	.029 (5.1)[2]	.024 (3.9)	.030 (5.8)	.021 (3.9)
a_2	.037 (3.5)	.033 (3.2)	.034 (3.5)	.030 (3.2)
a_3	.026 (3.2)	.018 (2.3)	.025 (3.4)	.017 (2.4)
b_L	.327 (20.5)	.349 (20.7)	.304 (21.5)	.329 (21.9)
b_K	.066 (6.5)	.055 (5.2)	.071 (7.2)	.061 (6.1)
b_M	.565 (44.1)	.556 (43.3)	.585 (48.7)	.582 (48.3)
b_{LL}			.086 (3.0)	.099 (3.5)
b_{KK}			.028 (2.9)	.031 (3.3)
b_{MM}			.174 (11.9)	.177 (12.5)
b_{LK}			.037 (2.8)	.034 (2.6)
b_{LM}			-.115 (7.0)	-.123 (7.7)
b_{KM}			-.062 (6.2)	-.060 (6.3)
c_1	.076 (4.9)	.066 (4.2)	.056 (4.0)	.047 (3.4)
c_2	.256 (11.4)	.268 (11.9)	.256 (12.6)	.259 (12.7)
d_C		.156[3] (4.8)		.164 (5.6)

d_F		.154 (4.1)		.107 (3.1)
d_W		.095 (2.7)		.117 (3.7)
d_E		.205 (5.7)		.224 (7.0)
d_M		.111 (3.6)		.137 (4.9)
R^2	.983	.984	.986	.988
SEE	.232	.226	.207	.199

Notes:

1. The dependent variable is the logarithm of 1982 revenue of the firm. All right hand side variables except the dummy variables are in logarithms and are computed as differences from sample means.
2. t ratios are in parenthesis.
3. Industry dummy variables:

   d_C - chemical industries and mining
   d_F - food, beverages and tobacco
   d_W - other light industries (wood, paper, printing, rubber and plastics, etc.)
   d_E - electrical and electronic equipment
   d_M - metals, machinery and transport equipment

   The reference industry is textiles (including clothing and leather)

Table 2

Robustness Analysis of the Technological Indicators - Cobb Douglas Case

Coefficient	Estimation Method			
	OLS	2SLS	Cost Minimization (IZEL)	Cost Minimization (I3SLS)
a_1	.024 (3.9)	.022 (3.7)	.023 (3.9)	.021 (3.7)
a_2	.033 (3.2)	.031 (2.9)	.030 (2.9)	.028 (2.8)
a_3	.018 (2.3)	.018 (2.2)	.015 (2.0)	.016 (2.1)

Table 3

Robustness Analysis of the Technological Indicators - Translog Case

Coefficient	Estimation Method			
	OLS	2SLS	Cost Minimization (IZEL)	Cost Minimization (I3SLS)
a_1	.021 (3.9)	.019 (3.4)	.024 (4.6)	.021 (3.7)
a_2	.030 (3.2)	.028 (3.0)	.032 (3.5)	.028 (2.8)
a_3	.017 (2.4)	.016 (2.2)	.019 (2.6)	.016 (2.1)

Table 4

The Technological Index by Type and Size of Firm

		Size (Number of Employees)			
	All Firms	1-50	50-200	200-500	500 +
Low Tech	.91	.90	.91	.93	.92
Med. Tech	1.00	.98	1.00	.99	1.00
High Tech	1.11	1.08	1.10	1.10	1.12

Table 5

Firms, Employment, Production, Capital, R & D and Exports
by Type of Technology, 1982
(percentage)

		Type of Technology		
	Total	High	Medium	Low
Number of Firms	100	16	45	39
Number of Employees	100	40	39	21
Production	100	46	38	16
Fixed Capital	100	53	32	15
R & D Capital	100	94	6	0.2
Exports	100	71	24	5

Table 6

Production, Wages, and Capital per
Employee, by Type of Technology
(Thousands of 1982 Dollars per Year per Employee)

		Type of Technology		
	Total	High Tech	Medium Tech	Low Tech
Production	50	58	48	39
Value Added	20	27	16	15
Cost of Labour	13	16	11	10
Capital Stock	39	52	32	29
R & D Capital	0.6	1.5	0.1	0.01

Table 7

High Tech Firms by Branch, 1982

	Percent of Employees	Percent of Production	K/L	W/L (Thousands of dollars per worker per year)
Total	40	46	52	16
Food, Beverages & Tobacco	29	33	40	12
Textiles and Clothing	8	8	40	8
Light Industries	9	17	35	10
Chemicals & Minerals	41	60	146	21
Metals	50	55	38	17
Electronics, & Transport Equipment	77	79	26	16

Table 8

High Tech Firms by Size
(Percent of Total)

		Size			
	All High Tech Firms	1-50	50-200	200-500	500 +
Number of Firms	100	79	12	5	4
Number of Employees	100	10	11	16	64
Value Added	100	7	11	17	66

Table 9

Wage Per Worker, by Size of Firm
and Level of Technology
(Thousands of dollars per worker per year)

	Type of Technology		
	High	Medium	Low
Size			
Total	16.4	11.4	10.1
1-50	9.9	8.7	9.9
50-200	14.5	11.2	10.8
200-500	15.2	12.8	9.5
500 +	17.9	13.6	10.6

Table 10

Value-added Per Worker, by Size
and Level of Technology
(Thousand of $ per Year)

	Type of Technology		
	High	Medium	Low
Size			
Total	26.6	16.2	14.6
1-50	18.8	11.8	15.2
50-200	27.8	15.5	14.6
200-500	28.3	17.6	13.7
500 +	27.1	21.5	11.9

Table 11

Decomposition of Labour Productivity Difference Between High Tech and Low Tech Firms[1]

Labour Productivity Difference	Sources of Difference (% Contribution)								
	Capital Intensity	Materials Intensity	Scale Economics	Quality of Labour	Quality of Capital	R & D Activity	Concentration	Excess Wage	Estimation Residual
1.54	8	43	-14	27	8	15	5	7	1
					50				

1. Based on Translog OLS regression without industry group dummy variables.

Table 12

Labour Productivity and Wage Rates ($ per day)

	High Tech Firms		Low Tech Firms	
	(1)	(2)	(1)	(2)
Wage Rate	67	67	40	40
Value of the Marginal Product of Labour	70	76	50	54
Value of the Marginal Product of Labour (net of CON and WE market power effects)	55	61	40	44
Value of the Marginal Product of Labour (net of CON market power effects)	58	65	41	46

(1): Labour productivity estimate based on Translog regression without industry group dummy variables.

(2): Labour productivity estimate based on Translog regression with industry group dummy variables.

Table 13

Rates of Return to Capital by Size

Type of Firm	Total	Size Class (No. of Employees)			
		1-50	50-200	200-500	500 +
High Tech	0.20	0.48	0.26	0.24	0.17
Low Tech	0.16	0.20	0.13	0.14	0.03

Capital Intensity by Size (Capital/Labour Ratio)

Type of Firm	Total	Size Class (No. of Employees)			
		1-50	50-200	200-500	500 +
High Tech	52	18	52	55	56
Low Tech	29	27	28	29	41

Appendix

Decomposition of Labour Productivity Differences Between High Tech and Low Tech Firms

We first apply the Quadratic Lemma to equation (10) (without industry dummy variables but with an explicit error term) and obtain:

$$\log R^2 - \log R^1 = \Sigma\, a_i\,(\log T_i^2 - \log T_i^1)$$
$$+ \frac{1}{2} \sum_j \left[\frac{\partial \log R^2}{\partial \log X_j} + \frac{\partial \log R^1}{\partial \log X_j}\right] . (\log X_j^2 - \log X_j^1)$$
$$+ c_1 (\log CON^2 - \log CON^1) + c_2 (\log WE^2 - \log WE^1) \qquad (A.1)$$
$$+ (\varepsilon^2 - \varepsilon^1)$$

where the superscripts 2 and 1 index High Tech and Low Tech firms, respectively. Subtracting $\log L^2 - \log L^1$ from both sides of (A.1) results in (where $L = X_1$):

$$\log \left[\frac{R}{L}\right]^2 - \log \left[\frac{R}{L}\right]^1 = \sum_i a_i (\log T_i^2 - \log T_i^1)$$
$$+ \frac{1}{2} \sum_{j \neq 1} \left[\frac{\partial \log R^2}{\partial \log X_j} + \frac{\partial \log R^1}{\partial \log X_j}\right] \cdot \left[\log \left[\frac{X_j}{L}\right]^2 - \log \left[\frac{X_j}{L}\right]^1\right]$$
$$+ \frac{1}{2} \left[\sum_j \left[\frac{\partial \log R^2}{\partial \log X_j} + \frac{\partial \log R^1}{\partial \log X_j}\right] - 2\right] (\log L^2 - \log L^1)$$
$$+ c_1(\log CON^2 - \log CON^1) + c_2(\log WE^2 - \log WE^1) \qquad (A.2)$$
$$+ (\varepsilon^2 - \varepsilon^1)$$

The RHS of A.2 is the value of labour productivity difference (in percentage terms) between High Tech and Low Tech firms. The decomposition contains the effects due to:

(1) technology: $a_i(\log T_i^2 - \log T_i^1)$

(2) capital and materials deepening: $\frac{1}{2}\left[\frac{\partial \log R^2}{\partial \log X_j} + \frac{\partial \log R^1}{\partial \log X_j}\right] \cdot \left[\log \left[\frac{X_j}{L}\right]^2 - \log \left[\frac{X_j}{L}\right]^1\right]$

j 1

(3) returns to scale: $\frac{1}{2}\left[\sum_j \left[\frac{\partial \log R^2}{\partial \log X_j} + \frac{\partial \log R^1}{\partial \log X_j}\right] - 2\right] \cdot (\log L^2 - \log L^1)$

(since $\frac{\partial \log R}{\partial \log X_j} = \frac{\partial \log F}{\partial \log X_j}$)

(4) market concentration: $c_1(\log CON^2 - \log CON^1)$

(5) excess wages: $c_2(\log WE^2 - \log WE^1)$.

(6) estimation residual: $(\varepsilon^2 - \varepsilon^1)$