International technology diffusion and productivity

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Abstract: This paper analyses the productivity growth of a panel of 26 Indian manufacturing industries for the period 1991 to 2001. Data envelopment analysis (DEA) is used to estimate total factor productivity growth of the industries during the period. Using the Malmquist productivity index the components of the TFGP growth is captured in terms of change in technical efficiency and technological change. The results reveal that TFPG has declined for all the sectors during the period. Technical efficiency change has been positive in most of the industries. However, technical change has been declined in all the industries, leading to the conclusion that it has been dragging down TFPG in all the sectors. In the second stage the productivity estimates have been used in Tobit regression to compare the differential role of imported inputs and technology between low, medium and high tech industries.

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1. Introduction

The Solow growth model specified that long term per capita growth can come only from technological change. However the source of technological change was exogenous to the model. The later endogenous growth models underlined the role of knowledge generation of profit maximizing firms leading to growth and thus offsetting the diminishing returns from capital accumulation. However in developing countries, the amount of domestic R&D is small. In developing countries, more than innovation and R&D, diffusion of technologies developed elsewhere and learning play a more significant role in the development of technological capabilities. Thus capital accumulation while it may not lead to sustained economic growth in the long run, can act as a vehicle for embodied technical change. Also in developing countries imported machinery plays a significant role in advancing knowledge or promoting learning. However capturing learning is far from easy.

Advances in technology lead to shifting of the frontier. However firms can move towards the best practice frontier either by learning or through changes in efficiency or both. In the context of developing countries, technological change measured in terms of purely R&D intensity or patenting activity, which are the conventional forms of measuring such change, are also likely to be small since either there is underreporting in case of R&D or patent regimes are weak. As a result of all this, learning from doing and other forms of learning emphasized by Lall and others may not be adequately captured using the conventional approaches. A lot of such learning in developing countries is likely to come from the low and medium technology sectors as opposed to the high technology sectors.

Also, in the context of low and medium tech industries, the process of learning may be quite different from the high tech industries. As observed by von Tunzelmann and Acha (2005), very few industries today in the developed world are what can typically be understood as low tech[1] and the importance of knowledge for LMT industries has been

[1] Classification of industries into high tech, medium and low tech is usually done using the OECD classification. The OECD classification is based on R&D intensities though there is a debate in the literature whether R&D intensity alone is sufficient to capture the complex learning processes. According to von Tunzelman and Acha (2005), the LMT industries are the mature industries where market conditions and technologies change more slowly than the high tech industries. Subsequently the OECD classification

neglected. Hirsch-Kreinsen et al (2006) suggest that the performance of the LMT sectors is not fully represented by the conventional indicators and hence there is need to throw light on this aspect. Hence, there is need to focus on firm level knowledge to understand the process of learning in the LMT industries. In the context of such firms, innovation involves a process of modifying generally well known knowledge and technologies developed elsewhere or in other sectors. In this respect LMT firms are very much like developing countries as far as borrowing knowledge is concerned. Hence examining the issue of LMT firms from the perspective of a developing country may be very relevant. This paper will seek to understand the process of learning in large Indian manufacturing firms in some sectors by characterizing the changes in total factor productivity (TFP), and the underlying factors explaining changes in TFPG to shed some light on the nature of the learning process in India during the decade of the 1990s. Data envelopment analysis (DEA) is used to characterize the changes in TFPG and technical efficiency. We look at the differences in performance of the industries by classifying them into low, medium and high technology sectors and throwing some light on the nature of the factors that affect productivity or performance in different sectors.[2] The LMT sectors are important not only for the scores of goods they produce in an economy but also in the context of developing countries like India, the employment potential of these sectors is tremendous (Economic Survey 2006-07).

2. Literature survey

The dynamic effects of liberalization are thought to enhance learning, technological change and economic growth. The relationship between protection and poor technological performance has been shown in the literature by firm level case studies, cross industry studies of technical efficiency and productivity change and cross

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was expanded to include R&D embodied in intermediate and capital inputs to low tech industries (Hatzichronoglou 1997). Several other classifications have been suggested like Peneder (2001), Pavitt (1984), Davies and Lyons (1996) as discussed in von Tunzelmann and Acha (2005). Von Tunzelamann and Acha suggest that approaches that blend the technology dimension (as emphasized by Pavitt) with the product dimension (as done by Peneder) are most useful in this context. Palmberg (2001) also uses the term low tech industries with industries that are traditional or more mature.

[2] Classification of industries into high tech, medium and low tech has been done using the OECD classification as the literature has failed to suggest an alternative classification that incorporates all the above criticism.

country studies of economic growth.[3] The firm level case studies of technological change like Katz (1987), Lall (1987) and Pack (1987) do not lead to any generalizations regarding the extent to which trade regimes affect the pace of learning. Nelson (1981) has emphasized the importance of technological change on a firm's productivity growth. To understand how technology affects efficiency one has to examine how it diffuses through the economy. The impact of technological changes on productivity and efficiency depends on whether these changes are incremental or paradigmatic.[4] Incremental changes are movement along the trajectories while paradigmatic changes involve changes in the frontier itself. Paradigmatic changes lead to increased efficiency for the firms adopting it, but this may raise the distance between the frontier and the average firms. This may result in a decline in average efficiency of the industry. Thus the effect of technology on efficiency is ambiguous (see Caves 1992). Technology usage also has complementarity with skill. Other studies have looked at the effect of multinational firms on domestic technological effort.

Many studies have documented that exporting plants have higher productivity for example Bernard and Jensen (1995) and Aw, Chen and Roberts (2001) though there is debate about the causality of the relation. Some like Clerides, Lach and Tybout (1998) and Bernard and Jensen (1995) have argued that this positive correlation between productivity and exports is due to self-selection process of the most productive producers in to the export market. Alternatively, others have argued that there is a role of learning by exporting as suggested by Van Biesebrock (2003). However, the mechanisms for such learning are not understood clearly though some anecdotal evidence has been presented by some researchers. We refer to these studies to understand the factors that could lead to productivity growth in countries.[5] Learning is industry specific and as Pavitt (1984)

[3] The empirical evidence on trade and growth based on the cross-country studies have shown that increased trade has improved growth. These studies suffer from many problems according to Rodrik (1995) including endogenity of the trade regime variable, causality between the relationships specified, failure to specify the mechanism which leads to growth and measurement problems in the sense that trade regime variables are confused with macroeconomic variables.

[4] See Dosi (1988)

[5] The recent surge in productivity in the US is attributed to the information and communication technology (ICT) producing industry. There are two channels through which this works: the investment in education which is thought to have raised productivity by 0.2 to 0.3 percentage points in the period 1995-99 compared to the early 1990s. The second channel through which ICT affects labour productivity and output is through accumulation of physical capital or the expansion of capital stock as a result of investment in

concludes the drivers of innovation and technological change is also industry specific. Teece and Pisano (1994) provide the dynamic capabilities framework to help in understanding firm specific factors that are important in explaining innovation.

The literature on the LMT sectors suggests that high tech countries are not necessarily high growth countries. Summarizing the literature on the LMT industries Hirsch-Kreinsen at al (2006) conclude that LMT sectors can be innovative. A major criticism of the classification using R&D intensities only, is that it ignores the inter industry flows of embodied and disembodied technology flows and the knowledge spillovers thereof (Robertson et al 2000). Using R&D intensity also ignores the differences of the nature and societal effects of innovation and thus overemphasize the importance of in –house R&D. The way in which the Frascati Manual defines R&D, tends to favour the engineering sciences over the natural sciences. Further as observed by Goedhueys et al (2008), sources of knowledge are also industry specific in the context LMT industries of some developing countries.

In the context of India, the contribution of the LMT sector to employment and exports is significant. Manufactured goods accounted for 74.2 percent of total exports in 2004-05. Sectors like textiles, gems and jewellery, leather and handicrafts accounted for nearly 36 percent of total exports in that year (Economic Survey 2006-07). Manufacturing industries employed about 13 percent of the population in 2004-05 (NSS 2005-06) and among the manufacturing industries, employment is mostly in the low tech sectors like textiles and metal products, and except for chemicals and pharmaceuticals none of the other high tech sectors employ a significant portion of the population.

3. Methodology

Total factor productivity (TFP) is defined as the ratio of output over an index of inputs. Changes in the total factor productivity or total factor productivity growth (TFPG) reflect the ability to produce more and more output per bundle of inputs. Productivity changes occur due to technological change, change in technical efficiency and changes in allocative efficiency. Technological changes reflect the creation of knowledge and lead to shift in the frontier production function. Changes in technical efficiency represent

ICT which made a contribution of about 20 percent annually to overall output growth in the US (OECD, *Measuring productivity*, OECD Manual, 2001).

movement towards the frontier as all producers who are not using the best practice use fewer inputs to produce the same output resulting in greater technical efficiency. Allocative efficiency changes results in resource reallocation as changes in output composition occur due to the right input mix being used in production and hence also contribute to overall productivity changes. Changes in productivity can be measured using the growth accounting approach. Using this approach, the contributions to growth are the residual of the growth of output due to the growth of the factor inputs such as labour and capital. However using this approach, while it is possible to separate out the effect of technological change,[6] it is not possible to decompose the growth in total factor productivity to changes in technical efficiency or allocative efficiency. Moreover, this approach assumes that factors are paid the value of their marginal product under the assumption of perfect competition and marginal cost pricing. There are two alternative ways of estimating the frontier and compute the changes in productivity: the first is the stochastic frontier approach (SFA) and the second is the data envelopment analysis (DEA).[7] We have used the Malmquist index of productivity change, which is based on the Shepard's distance function. Fare et al (1994) decomposed this index into two components, changes in technical efficiency and technological change.

Data

We have data on the firms for the period 1991 to 2001 from Capitaline Ole′ database provided by Capital Markets (I) Pvt. Ltd. We have data on firms for 26 industry groups for the years 1991 to 2001. For each year after cleaning the data[8] we have estimated productivity for each industry group. We have estimated the productivity using the DEA approach with value added[9] as output and capital[10] and labour[11] as inputs.

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[6] The correlation between the components of output growth and measured productivity is known as Verdoon's law and taken to reflect embodiment of new technologies during periods of rapid investment and economies of scale.

[7] For a discussion on the relative merits and demerits of the SFA and other methods see Van Biesebroeck (2003)

[8] We have cleaned the data by omitting firms not belonging to manufacturing and then those with value added, salaries, employee cost or capital equal to or less than zero.

[9] Value added has been defined as gross profit plus depreciation plus excise duty plus interest plus employee cost.

[10] Capital is obtained by adding depreciation, 15% of fixed assets and inventories.

[11] We do not have data on employment and so some proxy has to be used. One alternative is to obtain a value of labour using the wages and wage bill for that industry group from Annual Survey of Industries (ASI). However the assumption underlying this method is that the wages are the same in the entire industry,

Econometric model and estimation

We investigate the relationship between productivity growth and the role of imported inputs in explaining the productivity growth.

TFP $_{i,\,t} = \alpha_{0} + \alpha_{jt}$ (independent variable) $+ \alpha_{k} T_{t} + \varepsilon_{i\,t}$ $\qquad (i \neq j,\ j \neq k)$

Variables

Total factor productivity growth forms the dependent variable in the regression exercise. The independent variables are taken from the literature survey and explained in Appendix B. Technical change has also been used as independent variable. Year Dummies are added to account for differences in productivity. Though we have data for eleven years, one year was lost in estimation of the Malmquist index and so the panel that has been run is for ten years. Hence nine year dummies were given.

4. Results

Trends in productivity growth and its components

In the table below, we present the results of the Malmquist index decomposed into technical efficiency change, technical change and total factor productivity. The table has been subdivided to present the results of the low, medium and high tech industries together.[12] As discussed in the literature survey, there is a debate on the efficacy of such a classification based on R&D intensity alone.

Table 1: Technical efficiency, technical change and total factor productivity

	Δ TE	**Δ TC**	**Δ TFPG**
Low tech industries			
BREW	1.000	0.804	0.804
FOOD	1.002	0.808	0.809
PAPER	1.002	0.798	0.799
SUGAR	1.002	0.795	0.795
TEXTILES	0.998	0.793	0.793
Medium low tech industries			
ALUMINIUM	0.998	0.797	0.796
CEMENT	1.006	0.795	0.799
GLASS	1.004	0.792	0.795

which may not be true. Hence we have used employee cost of the firm. Compensation has been used by Caves (1992).

[12] Classification of industries into high tech, medium and low tech using the OECD classification. We differ form the classification proposed by Hatzichronoglou (1997) only as far as non electrical machinery featuring in the medium low tech as opposed to the medium high tech cohort.

NON ELECTRICAL MACHINERY	1.005	0.802	0.810
METAL PRODUCTS	0.992	0.806	0.804
PLASTICS	0.972	0.831	0.818
STEEL	0.999	0.787	0.787
Medium high tech industries			
AUTO	1.001	0.788	0.788
AUTO ANCILLIARIES	1.010	0.790	0.794
CABLES	0.998	0.785	0.783
CHEMICALS	1.004	0.794	0.797
ELECTRICAL EQUIPMENT	0.999	0.798	0.797
ENGINEERING	1.010	0.795	0.796
FERTILIZERS	0.999	0.796	0.795
PAINTS	1.009	0.793	0.801
PETROCHEM	1.011	0.815	0.824
SOLVENT EXTRCATION	1.009	0.798	0.818
High tech industries			
ELECTRONICS	0.998	0.917	0.919
PHARMA	1.005	0.787	0.790
TELECOM	0.976	0.802	0.783
Diversified			
PERSONAL CARE	1.005	0.816	0.811

Source: author's calculations
Note: Δ TE: change in technical efficiency, Δ TC: technical change, Δ TFPG: change in total factor productivity
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From the table we see that over the period 1991 to 2001, the total factor productivity (last column) has declined in all the industries.[13] Goldar (2004) has also been documented this using a very different approach. On the other hand, technical efficiency and technical change has been different for different industries; while technical efficiency has declined in textiles, aluminum, metal products, plastics, steel, cables, electrical equipment, fertilizers, electronics, and telecom, it has increased for the other industries except breweries where it has remained constant. So on the balance, the technical efficiency change has been positive in most of the industries and no generalization can be made either of increase/decline in terms of low, medium and high tech industries. However,

[13] The industries are automobiles, breweries, cement, chemicals, electronics, food, fertilizers & pesticides, non electrical machinery, steel, paper, pharmaceuticals, plastics, glass & ceramic tiles, textiles, paints, petrochemicals, personal care, engineering, sugar, cables, metal products and parts, aluminum, electrical equipment, auto ancillaries, solvent extraction and telecom.

technical change has been declined in all the industries, leading to the conclusion that it has been dragging down TFPG in all the sectors.

For the low-tech industries, technical efficiency increased by 2 percent for paper and food, and sugar. Technical change as well as productivity change declined for all these sectors in period under consideration. The medium low industries showed increase in technical efficiency for cement, glass and non-electrical machinery but decline in technical change and productivity change for all the industries in the period. The medium high tech industries showed increase in technical efficiency (except electrical machinery, cables an fertilizers) but decline in technical change and change in productivity. In fact the highest increase in technical efficiency has come in this segment in the petrochemical industries. The high tech sectors also show decline in technical change and productivity change as well as technical efficiency, with only the pharmaceutical sector showing increase in technical efficiency.

Econometric results

The industries have been subdivided into three broad groups; low, medium and high technology. The medium technology industries can be further classified as medium low tech and medium high tech industries. The following table summarizes the results for the determinants of total factor productivity growth in all the industries (for details of results see Appendix A).

Table 2: Summary of results

Determinants of TFPG				
Low tech industries				
BREW		CAPVINT (-)		
FOOD	PRODIFF (-)	RDCAP (+)	IMPC (+)	
PAPER	CAPVINT (-)			TECHCH
SUGAR	RDREC (-)	TECHCH	IMPORTS (+)	
TEXTILES	IMPR (+)			
Medium low tech industries				
ALUMINIUM	AGE (-)			TECHCH
CEMENT	TECHCH			
GLASS	RDREC (-)			
NON ELECTRICAL MACHINERY				
METAL	TECHCH			

PRODUCTS				
PLASTICS	CAPINT (+)			
STEEL	TECHCH			
Medium high tech industries				
AUTO	RDCAP (+)	TECHCH		
AUTO ANCIL	CAPINT (+)	RDREC (-)		
CABLES	RDREC (-)	TECHCH		
CHEMICALS	EXPORTS (+)	RDREC (-)	ROYAL (+)	
ELECTRICAL EQUIPMENT	CAPINT (+)	TECHCH		
ENGINEERING	TECHCH			
FERTILIZERS	FUELINT (-)	CAPINT (+)	RDREC (-)	
PAINTS	PRODIFF (-)	IMPC (+)	TECHCH	
PETROCHEM	CAPINT (+)	TECHCH		
SOLVENT EXTRCATION	AGE (-)	PRODIFF (-)	TECHCH	
High tech industries				
ELECTRONICS	EXPORTS (+)	IMPC (+)	TECHCH	
PHARMA	EXPORTS (+)	TECHCH		
TELECOM	CAPVINT (-)	RDCAP (+)	TECHCH	
Diversified				
PERSONAL CARE	AGE (-)	CAPINT (+)		

Source: Author's calculations. Only variables that are significant and with the expected sign are reported in the table.

Looking at the table, certain conclusions can be drawn: technical change affects productivity growth in most industries except some low tech industries. Second, productivity increase in all the industries, barring a few, relies on one of the following source of technology transfer: trade either exports or imports or more direct channels of technology transfer that is reflected in royalty payments. However, exports are significant only in some of the high tech industries like electronics, pharmaceuticals and chemicals (incidentally these are the industries that figure prominently in India's exports).

Discussion

Low- tech industries

Breweries

The significant variables affecting productivity growth in the breweries industry are age of plant and machinery and vintage of capital. Vintage of capital is insignificant when age of plant and machinery is included in the same equation. The age of plant and machinery, however, has the wrong sign though vintage of capital has the right sign. Technical change plays no role in explaining productivity in this industry.

Food

The food industry has the variables export intensity, imports of capital goods, product differentiation and capital expenditure on R&D significantly explaining productivity. All these variables except for export have the right sign. The inclusion of technical change in the productivity equation makes exports insignificant.

Paper

For the paper industry, the variables that are significant are vintage of capital and the import of capital goods, though the import of capital goods has the wrong sign. However, when technical change is inserted into the equation, both the variables become insignificant. The year dummies all become insignificant when technical change is introduced and also change sign.

Sugar

In the sugar industry, imports as well as recurring expenditure on R&D play a significant role in explaining productivity growth. However, the other variables that is significant, i.e. product differentiation has the wrong sign. In any case, the role of advertising is hard to explain in the context of productivity growth in the sugar industry. However, dropping this variable from the regression makes the other variables insignificant. All these variables become insignificant with the inclusion of technical change in the equation, except the product differentiation variable and capital intensity. The year dummies all are insignificant with technical change and also change sign.

Textiles

For the textile industry, technical change does not play any role in explaining productivity growth and hence is not included in the equation showing the results. The variables affecting productivity change in this industry are the age of import of raw materials, royalty payments and the age of plant and machinery (though the latter two have the wrong sign).

Medium low- tech industries

Aluminum

The variables that are significant in this industry are age of plant and machinery, import of capital goods and royalty payments intensity (again the latter two have the wrong sign). However none of the variables are significant when technical change is introduced.

Cement

The cement industry is characterized by the presence of market power, hence the variable that is significant in explaining productivity growth is MP. Only in the presence of this variable, do other variables like royalty payments and export intensity (though these variables have the wrong sign) become significant. The inclusion of the technical change variable in the productivity growth equation renders all the variables except market power insignificant. The year dummies all become insignificant too and change sign.

Glass

For the glass industry, the only variable that seems to explain productivity growth is recurring expenditure on R&D, with a negative sign. None of the other variables or technical change seems to have any effect in explaining productivity growth.

Non-electrical machinery

Productivity growth in the non-electrical machinery industry is also explained by recurring R&D expenditure (though with the wrong sign). Technical change has no significant role in explaining productivity growth in this industry.

Metal products

Fuel intensity is significant in explaining productivity growth in the metal products industry and so is royalty payments. However both have the wrong sign. Adding technical change to the equation improves the explanatory power of the equation considerably but renders the other variables insignificant.

Plastics

The variables explaining productivity growth in the plastics industry are age of plant and machinery, royalty payments intensity and capital intensity. Royalty payments and the age of plant have the wrong sign. Capital intensity becomes insignificant when technical change is included in the equation.

Steel

Capital intensity is significant in explaining productivity growth in the steel industry but has the wrong sign. Also, when included in the same equation as technical change, it becomes insignificant.

Medium high tech industries

Auto

In the automobile industry, technical change is a significant explanatory variable of productivity growth. The other variable that is significant is capital expenditure on R&D and has the right sign but only when capital intensity is included in the equation, though capital intensity is itself not significant.

Auto ancillaries

Technical change is the only variable that is significant by itself in explaining productivity growth in this industry, apart from the year dummies. The auto ancillary industry is characterized by market power and hence the only other variables that are significant in explaining productivity growth are significant when an index of market power is included in the equation. These variables are capital intensity, export intensity and recurring expenditure on R&D, though among them the only the last two have the correct sign.

Cables

The cable industry is similar to the auto ancillary industry in that technical change is the only variable that is significant by itself in explaining productivity growth. The other variables that are significant in explaining productivity growth are capital intensity and recurring expenditure on R&D though only the latter has the correct sign but are significant only when technical change is also present in the equation. The year dummies are insignificant.

Chemicals

Like the previous two industries, in this industry too technical change and the index of market power are the only significant explanators of productivity growth. Also, with the inclusion of technical change, the year dummies all become insignificant and change sign too. The other variables that become significant in the presence of the index of market power are exports intensity, royalty payments intensity and recurring expenditure on R&D. Of these all except the first one, have the correct sign.

Electrical equipment

In the electrical equipment industry the variable that is significant in explaining productivity growth is capital intensity and it has a positive sign. The other variable that is significant is capital intensity only if the index of market power is present in the equation. The presence of technical change in the equation alters the sign of the year dummies though they remain significant.

Engineering

In the engineering industry, royalty payments intensity is significant by itself with a negative sign. The inclusion of technical change in the equation explaining productivity growth makes the year dummies insignificant and also changes their sign.

Fertilizers

In this industry, the variables that are significant in explaining productivity growth are fuel intensity and capital expenditure on R&D. However both these variable are significant only when the index of market power is included in the equation. The inclusion of technical change in the equation makes both fuel intensity and capital expenditure on R&D insignificant, and by dropping these and including capital intensity significant. The year dummies become insignificant and change sign with the inclusion of technical change.

Paints

In the paints industry, capital intensity, import of capital goods and product differentiation proxied by advertising intensity are significant in explaining productivity growth (though capital intensity does not have the right sign). However the inclusion of technical change in the equation makes all the variables except import of capital goods insignificant. The inclusion of technical change makes the year dummies insignificant and change sign.

Petrochemicals

In the petrochemical industry the variables that are significant in explaining productivity growth are age of plant and machinery (wrong sign), and capital intensity with a positive sign. Adding technical change to the equation makes the age of plan and machinery insignificant. Fuel intensity is also significant if capital intensity is present in the equation but with a negative sign as expected and if technical change is added to the equation, both capital and fuel intensity becomes insignificant. .

Solvent extraction

In this industry, the age of plant and machinery is significant when included in the same equation as technical change for explaining productivity growth, along with vintage of capital and product differentiation. The latter two become significant only when an index of market power is included in the equation.

High tech industries

Electronics

Several variables are significant in explaining productivity growth in this industry: these include age of plant and machinery, export intensity, import of capital and fuel intensity. All except the last are positive and all except the first have the correct sign. However none of the variables (except export intensity) is significant when technical change is included in the equation. Upon inclusion of technical change, the year dummies change sign and become insignificant.

Pharmaceuticals

In the pharmaceutical industry export intensity is a significant variable in explaining productivity growth and has the correct sign too. However when technical change is included in the equation, it becomes insignificant. The year dummies change sign though remain significant due to the inclusion of technical change.

Telecom

In the telecom industry, capital expenditure on R&D and import of raw materials are significant, though the latter has the wrong sign. Technical change is significant only if import of raw materials is included in the equation.

Diversified

Personal care

In this industry, the variables that are significant in explaining productivity growth are age of plant and machinery and capital intensity. All the variables have the correct sign. However, technical change plays no role in explaining productivity in this industry.

5. Conclusions

The picture that emerges in the context of the productivity growth of the Indian manufacturing sector for the decade of the 1990s, is that once we classify the industries into high tech and low-tech industries, several facts emerge. First the variables that are significant in explaining productivity are similar for certain group of industries according to whether they are low or high tech. This highlights the differential role of factors in understanding the process of learning in different industries. This also suggests that a policy that promotes learning in a high tech industry may not work as well in the case of a low-tech industry. Hence the role of technology policy which also targets the innovative and learning process in low and medium tech industries is obvious. Also, as pointed out by Robertson and Patel (2006), any policy towards innovation should focus on the economy as a whole since productivity in the low tech sectors is based also on high tech innovations and hence the interdependence and diffusion of knowledge between the sectors is important.

Finally in the context of the low and medium tech industries, we find the importance of R&D whether it is recurring or capital expenditure. Innovation in the low tech sectors is not a "contradiction in terms" as observed by Hirsch-Kreinsen et al (2006) and low tech industry is not synonymous with low tech manufacturing. Also as discussed in the introduction, even within these sectors, learning may play a role (von Tunzelmann and Acha 2005), which is corroborated in our case. There is a significant role played by technical change in explaining productivity growth in the Indian manufacturing over the decade of the nineties. Learning has occurred both through the embodied and the disembodied forms of technical change. Further, interdependence of countries in terms of knowledge flows cannot be ignored. The understanding of the process of growth of countries like China and India in fuelling demand for innovations in the high tech countries and high tech industries will go a long way in providing directions for the future.

References

Aw, B. Y., Chen, X., and M. J. Roberts (2001) Firm level evidence on Productivity differentials and Turnover in Taiwanese Manufacturing, Journal of Development Economics, 66, 51-86.

Bernard, A. B., and J. B. Jensen (1995) Exporters, Jobs and Wages in US Manufacturing Plants, 1976-1987, Brookings papers on Economic Activity, Microeconomics, 67-119, Washington DC.

Caves, R. E. (1992) Industrial Efficiency in Six Nations, MIT Press, Cambridge, Massachusetts.

Clerides, S. K., Lach, S., and J. R. Tybout (1998) Is Learning by exporting Important? Micro-Dynamic Evidence form Colombia, Mexico and Morocco, Quarterly Journal of Economics, 113 (3), 903-947.

Dosi, G. (1988) Sources, Procedures and Microeconomic Effects of Innovation, Journal of Economic Literature, XXVI, pp. 1120-71.

Economic Survey (2006-07) Ministry of Finance, Government of India.

Fare, R., Grosskopf, S., Norris, M., and Z., Zhang, 1994, Productivity growth, Technical progress, and Efficiency changes in Industrial Country, American Economic Review, 84, 66-83.

Goedhueys, M. Jnaz, N. and Mohnen, P. (2008) Knowledge-based productivity in 'low-tech' industries: evidence form firms in developing countries. Working paper series 2008-007, UNU-Merit.

Goldar, B.N. (2004) Indian Manufacturing: Productivity Trends in Pre and Post Reform Periods, Economic and Political Weekly, November 20.

Hatzichronoglou, T. (1997) Revision of the high- technology sector and product classification, Working papers 1997/2, Paris, OECD.

Hirsch-Kreinsen, H. Jacobson, D. and Robertson, P. (2006) Low-tech industries: Innovativeness and Development Perspective – A Summary of a European Research Project, Prometheus, 24, 1, 3-21.

Katz, J. M., (ed.) (1987) Technology Generation in Latin American Manufacturing Industries, London, Macmillan.

Lall, S. (1987) Learning to Industrialize: The Acquisition of Technological Capability in India, Basingstoke and London, Macmillan.

NSS (2005-06) National Sample Survey, Government of India.

Nelson, R. R. (1981) Research on Productivity Growth and Productivity Differences: Dead Ends and New Departures, Journal of Economic Literature, Vol.19, No.3, 1029-64.

Pack, H. (1987), Productivity, Technology and Industrial Development, New York Oxford University Press.

Palmberg, C. (2001) Sectoral patterns of innovation and competence requirements: a closer look at low-tech industries, SITRA Report Series 8.

Pavitt, K. (1984) Sectoral patterns of technical change-towards a taxonomy and theory, Research Policy, 13, 343-373.

Robertson, P. and Patel, P. (2006) New wine in old bottles: technological diffusion and growth in developed economies, in Bender, G. Jacobson, D. and Robertson, P. (eds.) Non-research intensive Industries in the Knowledge economy, Perspectives on Economic Political and Social Integration, Special Issue I, Catholic University, Lublin.

Robertson, P. et al (2000) Classification of industries by level of technology: an appraisal and some implications, Draft paper presented at the seminar on low tech industries in Oslo.

Rodrik, D. (1995), Trade and Industrial Policy Reform, in J. Behrman and T. N. Srinivasan (eds.), *Handbook in Development Economics*, Vol. 3B, Amsterdam, North Holland.

Teece, D. J. and Pisano, G. (1994) The Dynamic Capabilities of Firms: An Introduction, Industrial and Corporate Change, 3, 3.

Van Biesebroeck, J., (2003) Revisiting some productivity debates, NBER working paper # 10065, Cambridge MA.

Von Tunzelmannn, N. and Acha, V. (2005) Innovation in low-tech industries, in J. Fagerberg, D. C. Mowery, and R.R. Nelson (eds.) *The Oxford Handbook of Innovation*, Oxford.

Appendix A

Low- tech industries

Table A1: Productivity growth in Breweries industry

TFPG change			
Y3	0.139 (6.55) ***	Y3	0.150 (7.34) ***
Y4	0.271 (6.56) ***	Y4	0.264 (7.66) ***
Y5	0.237 (10.40) ***	Y5	0.234 (11.41) ***
Y6	0.268 (11.81) ***	Y6	0.262 (13.32) ***
Y7	0.295 (13.31) ***	Y7	0.274 (13.04) ***
Y8	0.273 (7.56) ***	Y8	0.254 (6.41) ***
Y9	0.334 (16.04) ***	Y9	0.319 (12.98) ***
Y10	0.354 (12.35) ***	Y10	0.338 (15.98) ***
Y11	0.396 (8.77) ***	Y11	0.373 (14.04) ***
CAPVINT	-0.352 (-1.95) ***	AGE	0.085 (3.00) ***
EX	-2.99 (-2.67) ***	EX	-3.086 (-2.93) ***
RDREC	228.04 (2.04) ***	RDREC	408.17 (3.25) ***
Adj. R^2	0.83		0.87

Note: Censored Normal Tobit with Huber White standard errors and covariance.

Other statistics: log likelihood for Tobit: 74.74. Total number of observations = 40 of which uncensored = 40, ***-1 % significant, ** - 5% significant, * - 10% significant

Table A2: Productivity growth in Food industry

TFPG change			
Y3	0.168 (8.11) ***	Y3	0.043 (1.59)
Y4	0.237 (10.91) ***	Y4	0.068 (2.04) ***
Y5	0.270 (12.16) ***	Y5	0.099 (2.48) ***
Y6	0.257 (10.73) ***	Y6	0.059 (1.41)
Y7	0.318 (10.48) ***	Y7	0.089 (2.01) ***
Y8	0.305 (14.95) ***	Y8	0.096 (2.29) ***
Y9	0.348 (14.05) ***	Y9	0.112 (2.46) ***
Y10	0.334 (15.73) ***	Y10	0.084 (1.91) ***
Y11	0.385 (17.47) ***	Y11	0.125 (2.75) ***
PRODIFF	-0.425 (-2.81) ***	PRODIFF	-0.312 (-2.47) ***
IMPC	0.761 (3.13) ***	IMPC	0.844 (3.49) ***
RDCAP	12.68 (1.85) ***	RDCAP	1.282 (1.94) ***
EXPORTS	- 0.071 (-2.08) ***	TECHCH	0.666 (5.87) ***
Adj. R^2	0.69		0.74

Note: Censored Normal Tobit with Huber White standard errors and covariance.

Other statistics: log likelihood for Tobit: 231.47 and 247.86, Total number of observations = 180 of which uncensored = 180, ***-1 % significant, ** - 5% significant, * - 10% significant

Table A3: Productivity growth in Paper industry

TFPG change			
Y3	0.147 (6.29)***	Y3	-0.008 (-0.85)
Y4	0.191 (7.93) ***	Y4	-0.014 (-1.09)
Y5	0.249 (10.53)***	Y5	-0.003 (-0.19)
Y6	0.282 (12.50) ***	Y6	-0.008 (-0.56)
Y7	0.361 (9.49) ***	Y7	-0.012 (-0.72)
Y8	0.342 (15.30) ***	Y8	-0.008 (-0.50)
Y9	0.355 (14.28) ***	Y9	-0.018 (-1.05)
Y10	0.362 (15.35) ***	Y10	-0.015 (-0.86)
Y11	0.365 (15.89) ***	Y11	-0.013 (-0.74)
CAPVINT	-0.429 (-1.88) ***	IMPC	0.050 (1.97) ***
IMPC	-0.229 (-2.13)***	MP	0.055 (2.20) ***
		TECHCH	1.013 (28.39) ***
Adj. R^2	0.78		0.98

Note: Censored Normal Tobit with Huber White standard errors and covariance. Other statistics: log likelihood for Tobit: 237.43 and 464.83, Total number of observations = 170 of which uncensored = 170,

***-1 % significant, ** - 5% significant, * - 10% significant

Table A4: Productivity growth in Sugar industry

TFPG change			
Y3	0.186 (9.52) ***	Y3	-0.005 (-0.19)
Y4	0.315 (9.21) ***	Y4	-0.033 (-0.84)
Y5	0.239 (6.10) ***	Y5	-0.006 (-0.20)
Y6	0.296 (13.06) ***	Y6	-0.038 (-0.97)
Y7	0.433 (9.05) ***	Y7	-0.022 (-0.45)
Y8	0.404 (8.83) ***	Y8	-0.021 (-0.41)
Y9	0.448 (7.52) ***	Y9	0.016 (0.44)
Y10	0.363 (9.68) ***	Y10	0.038 (0.96)
Y11	0.406 (13.98) ***	Y11	-0.103 (-1.68)
IMPORTS	0.356 (1.77) ***	CAPINT	-0.003 (-2.97) ***
PRODIFF	54.74 (1.74) ***	PRODIFF	20.53 (2.34) ***
RDREC	-0.738 (-1.80) ***	TECHCH	1.06 (8.80) ***
Adj. R^2	0.51		0.84

Note: Censored Normal Tobit with Huber White standard errors and covariance. Other statistics: log likelihood for Tobit: 88.88 and 156.45, Total number of observations = 120 of which uncensored = 120,

***-1 % significant, ** - 5% significant, * - 10% significant

Table A5: Productivity growth in Textiles industry

Y3	-0.036 (-2.15) ***
Y4	0.047 (2.79) ***
Y5	0.093 (5.11) ***
Y6	0.155 (3.69) ***
Y7	0.150 (9.02) ***
Y8	0.170 (9.96) ***
Y9	0.249 (1.87) ***
Y10	0.163 (7.96) ***
AGE	0.048 (2.40) ***
IMPR	0.123 (2.19) ***
ROYAL	-10.59 (-1.72)
Adj. R^2	0.22

Note: Censored Normal Tobit with Huber White standard errors and covariance. Other statistics: log likelihood for Tobit: 265.36, Total number of observations = 899 of which uncensored = 899

***-1 % significant, ** - 5% significant, * - 10% significant

Medium low tech

Table A6: Productivity growth in Aluminum industry

TFPG change			
Y3	0.131 (3.24) ***	Y3	0.017 (1.21)
Y4	0.212 (5.26) ***	Y4	0.013 (0.67)
Y5	0.214 (4.69) ***	Y5	0.040 (1.54)
Y6	0.273 (6.52) ***	Y6	0.021 (0.67)
Y7	0.324 (8.50) ***	Y7	0.042 (1.41)
Y8	0.350 (8.64) ***	Y8	0.045 (1.43)
Y9	0.380 (8.07) ***	Y9	0.049 (1.46)
Y10	0.364 (9.51) ***	Y10	0.046 (1.43)
Y11	0.379 (9.90) ***	Y11	0.048 (1.43)
AGE	-0.016 (-1.89) ***	TECHCH	0.866 (10.22) ***
IMPC	-0.164 (-1.83) ***		
ROYAL	-4.802 (-2.03) ***		
Adj. R^2	0.84		0.96

Note: Censored Normal Tobit with Huber White standard errors and covariance. Other statistics: log likelihood for Tobit: 113.19 and 174.40, Total number of observations = 70 of which uncensored = 70

***-1 % significant, ** - 5% significant, * - 10% significant

Table A7: Productivity growth in Cement industry

TFPG change			
Y3	0.163 (5.28) ***	Y3	-0.025 (-0.76)
Y4	0.226 (11.48) ***	Y4	-0.066 (-1.27)
Y5	0.268 (13.76) ***	Y5	-0.080 (-1.29)
Y6	0.306 (14.65) ***	Y6	-0.068 (-1.02)
Y7	0.298 (13.36) ***	Y7	-0.092 (-1.34)
Y8	0.351 (14.73) ***	Y8	-0.079 (-0.99)
Y9	0.351 (10.62) ***	Y9	-0.125 (-1.54)
Y10	0.369 (12.81) ***	Y10	-0.122 (-1.49)
Y11	0.345 (13.72) ***	Y11	-0.108 (-1.39)
EX	-0.183 (-2.33) ***	MP	0.328 (1.81) ***
MP	0.474 (2.71) ***	RD	-0.316 (-1.80) ***
RD	-0.270 (-1.71) ***	TECHCH	1.22 (6.21) ***
ROYAL	-49.67 (-2.11) ***		
Adj. R^2	0.69		0.79

Note: Censored Normal Tobit with Huber White standard errors and covariance. Other statistics: log likelihood for Tobit: 244.64 and 289.11, Total number of observations = 220 of which uncensored = 220,

***-1 % significant, ** - 5% significant, * - 10% significant

Table A8: Productivity growth in Glass industry

TFPG change	
Y3	0.172 (28.14) ***
Y4	0.263 (25.22) ***
Y5	0.221 (3.39) ***
Y6	0.342 (40.64) ***
Y7	0.354 (28.93) ***
Y8	0.389 (24.47) ***
Y9	0.430 (8.81) ***
Y10	0.412 (49.47) ***
Y11	0.447 (12.86) ***
RDREC	-1.409 (-19.40) ***
Adj. R^2	0.61

Note: Censored Normal Tobit with Huber White standard errors and covariance. Other statistics: log likelihood for Tobit: 184.45 (for efficiency change) and 314.75 (for productivity change), Total number of observations = 120 of which uncensored = 120

***-1 % significant, ** - 5% significant, * - 10% significant

Table A9: Productivity growth in Non electrical machinery industry

TFPG change			
Y3	0.111 (1.51)	Y3	0.116 (1.72)
Y4	0.160 (2.28) ***	Y4	0.158 (2.88) ***
Y5	0.209 (2.53) ***	Y5	0.197 (3.54) ***
Y6	0.252 (3.71) ***	Y6	0.240 (4.16) ***
Y7	0.324 (4.48) ***	Y7	0.294 (4.38) ***
Y8	0.280 (3.81) ***	Y8	0.266 (3.98) ***
Y9	0.597 (2.15) ***	Y9	0.407 (3.39) ***
Y10	0.270 (4.08) ***	Y10	0.206 (2.33) ***
Y11	0.349 (5.25) ***	Y11	0.253 (3.12) ***
RDREC	0.069 (3.45) ***	MP	0.985 (1.93) ***
Adj. R^2	0.07		0.41

Note: Censored Normal Tobit with Huber White standard errors and covariance. Other statistics: log likelihood for Tobit: -59.21 and –25.25, Total number of observations = 149 of which uncensored = 149,

***-1 % significant, ** - 5% significant, * - 10% significant

Table A10: Productivity growth in Metal products industry

TFPG change					
Y3	0.166 (5.07) ***	Y3	0.159 (5.05) ***	Y3	0.082 (2.37) ***
Y4	0.244 (8.70) ***	Y4	0.238 (10.32) ***	Y4	0.058 (1.38)
Y5	0.366 (3.48) ***	Y5	0.282 (13.99) ***	Y5	0.082 (1.82) ***
Y6	0.259 (7.39) ***	Y6	0.261 (6.01) ***	Y6	0.092 (1.74) ***
Y7	0.310 (15.01) ***	Y7	0.311 (14.61) ***	Y7	0.109 (2.14) ***
Y8	0.331 (15.69) ***	Y8	0.331 (16.70) ***	Y8	0.114 (2.14) ***
Y9	0.350 (16.10) ***	Y9	0.350 (17.29) ***	Y9	0.119 (2.15) ***
Y10	0.356 (16.51) ***	Y10	0.375 (18.23) ***	Y10	0.126 (2.16) ***
Y11	0.365 (16.10) ***	Y11	0.373 (16.07) ***	Y11	0.123 (2.16) ***
FUEL INT	0.258 (1.89) ***	AGE	-0.040 (-2.88) ***	ROYAL	0.701 (2.29) ***
		ROYAL	1.128 (1.76) ***	MP	0.134 (2.04) ***
		FUEL INT	-0.237 (-1.82) ***	TECHCH	0.633 (3.80) ***
		MP	0.390 (10.21) ***		
Adj. R^2	0.34		0.82		0.91

Note: Censored Normal Tobit with Huber White standard errors and covariance. Other statistics: log likelihood for Tobit: 80.18 and 231.95, Total number of observations = 150 of which uncensored = 150,

***-1 % significant, ** - 5% significant, * - 10% significant

Table A11: Productivity growth in Plastics industry

		TFPG change			
Y3	0.170 (3.55) ***	Y3	0.043 (1.04)	Y3	0.060 (1.49)
Y4	0.232 (4.91) ***	Y4	0.102 (2.40) ***	Y4	0.099 (2.43) ***
Y5	0.269 (5.70) ***	Y5	0.107 (2.37) ***	Y5	0.086 (1.96) ***
Y6	0.285 (6.04) ***	Y6	0.108 (2.38) ***	Y6	0.094 (2.14) ***
Y7	0.293 (6.19) ***	Y7	0.070 (1.45)	Y7	0.055 (1.18)
Y8	0.373 (7.84) ***	Y8	0.166 (3.59) ***	Y8	0.160 (3.59) ***
Y9	0.328 (6.90) ***	Y9	0.090 (1.82) ***	Y9	0.070 (1.48)
Y10	0.403 (8.44) ***	Y10	0.148 (2.96) ***	Y10	0.137 (2.86) ***
Y11	0.425 (8.85) ***	Y11	0.159 (3.15) ***	Y11	0.146 (3.01) ***
CAPINT	0.004 (2.11) ***	EX	-0.157 (-2.21) ***	EX	0.068 (0.069)
ROYAL	-7.26 (-2.96) ***	TECHCH	0.686 (7.94) ***	ROYAL	-8.99 (-3.17) ***
				TECHCH	0.71 (8.55) ***
Adj. R^2	0.46		0.62		0.65

Note: Censored Normal Tobit with Huber White standard errors and covariance. Other statistics: log likelihood for Tobit: 88.71 and 115.1, Total number of observations = 120 of which uncensored = 120,

***-1 % significant, ** - 5% significant, * - 10% significant

Table A12: Productivity growth in Steel industry

TFPG change			
Y3	0.018 (1.15)	Y3	0.180 (13.55) ***
Y4	0.025 (1.08)	Y4	0.264 (19.72) ***
Y5	0.032 (1.11)	Y5	0.332 (12.39) ***
Y6	0.035 (1.21)	Y6	0.336 (24.97) ***
Y7	0.028 (0.90)	Y7	0.355 (22.69) ***
Y8	0.037 (1.10)	Y8	0.385 (31.04) ***
Y9	0.044 (1.06)	Y9	0.397 (27.96) ***
Y10	0.035 (0.96)	Y10	0.414 (30.34) ***
Y11	0.065 (1.27)	Y11	0.444 (15.52) ***
CAPINT	- 8.42 E –05 (-1.75) ***	CAPINT	-0.000 (-1.72) **
IMPR	-0.025 (-1.01)		
TECHCH	0.920 (9.92) ***		

Adj. R^2	0.87		0.77

Note: Censored Normal Tobit with Huber White standard errors and covariance. Other statistics: log likelihood for Tobit: 445.99 and 358.48, Total number of observations = 280 of which uncensored = 280,

***-1 % significant, ** - 5% significant, * - 10% significant

Medium high tech

Table A13: Productivity growth in Auto industry

TFPG change	
Y3	0.033 (1.87) ***
Y4	0.046 (1.83) ***
Y5	0.056 (1.89) ***
Y6	0.059 (1.84) ***
Y7	0.066 (1.87) ***
Y8	0.069 (1.81) ***
Y9	0.073 (1.84) ***
Y10	0.073 (1.85) ***
Y11	0.085 (1.87) ***
CAPINT	-0.000 (-1.36)
RDCAP	0.075 (1.75) ***
TECHCH	0.817 (8.15) ***
Adj. R^2	0.99

Note: Censored Normal Tobit with Huber White standard errors and covariance. Other statistics: log likelihood for Tobit: 516.88, Total number of observations = 170 of which uncensored = 170

***-1 % significant, ** - 5% significant, * - 10% significant

Table A14: Productivity growth in Auto ancillaries industry

TFPG change	
Y3	0.082 (2.12) ***
Y4	0.117 (2.21) ***
Y5	0.132 (2.15) ***
Y6	0.157 (2.16) ***
Y7	0.157 (1.96) ***
Y8	0.153 (1.72) ***
Y9	0.170 (1.84) ***
Y10	0.175 (2.01) ***
Y11	0.183 (2.07) ***
CAPINT	0.003 (2.41) ***
EX	-0.151 (-2.51) ***
MP	0.196 (3.48) ***

RDREC	-0.686 (-1.85) ***
TECHCH	0.574 (2.53) ***
Adj. R^2	0.85

Note: Censored Normal Tobit with Huber White standard errors and covariance. Other statistics: log likelihood for Tobit: 635.19, Total number of observations = 420 of which uncensored = 420,

***-1 % significant, ** - 5% significant, * - 10% significant

Table A15: Productivity growth in Chemicals industry

TFPG change	
Y3	-0.057 (-0.73)
Y4	-0.119 (-0.99)
Y5	-0.144 (-1.01)
Y6	-0.126 (-0.86)
Y7	-0.182 (-1.06)
Y8	-0.181 (-1.01)
Y9	-0.158 (-0.91)
Y10	-0.238 (-1.19)
Y11	-0.195 (-1.07)
CAPVINT	0.005 (3.56) ***
EX	0.116 (3.25) ***
MP	1.431 (4.40) ***
ROYAL	6.637 (3.23) ***
RDREC	-8.563 (-2.50) ***
TECHCH	1.511 (3.25) ***
Adj. R^2	0.81

Note: Censored Normal Tobit with Huber White standard errors and covariance. Other statistics: log likelihood for Tobit: 170.57, Total number of observations = 450 of which uncensored = 450,

***-1 % significant, ** - 5% significant, * - 10% significant

Table A16: Productivity growth in Cables industry

TFPG change	
Y3	0.083 (1.53)
Y4	0.088 (1.46)
Y5	0.077 (1.33)
Y6	0.110 (1.72)
Y7	0.119 (1.50)
Y8	0.144 (1.69)
Y9	0.123 (1.74) ***
Y10	0.132 (1.69)

Y11	0.143 (1.86) ***
CAPINT	-0.002 (-2.32) ***
RDREC	-93.63 (-2.21) ***
TECHCH	0.724 (4.17) ***
Adj. R^2	0.79

Note: Censored Normal Tobit with Huber White standard errors and covariance. Other statistics: log likelihood for Tobit: 95.11, Total number of observations = 90 of which uncensored = 90,

***-1 % significant, ** - 5% significant, * - 10% significant

Table A17: Productivity growth in Electrical equipment industry

TFPG change	
Y3	-0.015 (-2.11) ***
Y4	-0.030 (-2.17) ***
Y5	-0.025 (-2.41) ***
Y6	-0.028 (-1.85) ***
Y7	-0.030 (-1.87) ***
Y8	-0.030 (-2.03) ***
Y9	-0.042 (-2.50) ***
Y10	-0.030 (-1.82) ***
Y11	-0.054 (-2.89) ***
CAPINT	0.001 (2.15) ***
MP	0.041 (2.73) ***
TECHCH	1.098 (25.10) ***
Adj. R^2	0.98

Note: Censored Normal Tobit with Huber White standard errors and covariance. Other statistics: log likelihood for Tobit: 550.09, Total number of observations = 200 of which uncensored = 200

***-1 % significant, ** - 5% significant, * - 10% significant

Table A18: Productivity growth in engineering industry

TFPG change			
Y3	0.193 (11.14) ***	Y3	0.192 (10.93) ***
Y4	0.249 (40.11) ***	Y4	0.247 (40.44) ***
Y5	0.307 (26.68) ***	Y5	0.305 (26.33) ***
Y6	0.324 (35.88) ***	Y6	0.322 (36.16) ***
Y7	0.356 (47.43) ***	Y7	0.354 (47.70) ***
Y8	0.412 (14.92) ***	Y8	0.408 (16.06) ***
Y9	0.385 (29.40) ***	Y9	0.378 (28.43) ***
Y10	0.412 (44.84) ***	Y10	0.405 (40.63) ***
Y11	0.408 (64.80) ***	Y11	0.400 (54.40) ***
ROYAL	-0.483 (-1.77) ***	MP	0.051 (1.78) ***

		CAPVINT	-0.019 (-1.73) ***
Adj. R^2	0.70		0.71

Note: Censored Normal Tobit with Huber White standard errors and covariance. Other statistics: log likelihood for Tobit: 460.42 and 464.37, Total number of observations = 410 of which uncensored = 41

***-1 % significant, ** - 5% significant, * - 10% significant

Table A19: Productivity growth in Fertilizers industry

TFPG change			
Y3	0.165 (9.32) ***	Y3	0.011 (1.42)
Y4	0.218 (9.30) ***	Y4	0.010 (0.95)
Y5	0.267 (21.73) ***	Y5	0.007 (0.67)
Y6	0.315 (24.75) ***	Y6	0.008 (0.73)
Y7	0.342 (23.38) ***	Y7	-0.008 (-0.57)
Y8	0.364 (23.06) ***	Y8	0.007 (0.50)
Y9	0.389 (15.51) ***	Y9	-0.016 (-1.00)
Y10	0.356 (16.25) ***	Y10	0.028 (1.79) ***
Y11	0.431 (10.64) ***	Y11	-0.020 (-1.01)
MP	0.177 (2.92) ***	CAPINT	0.001 (1.83) ***
RDC	-7.07 (-1.86) ***	MP	0.102 (3.80) ***
FUEL	-0.110 (-2.43) ***	TECHCH	0.969 (26.42) ***
Adj. R^2	0.72		0.95

Note: Censored Normal Tobit with Huber White standard errors and covariance. Other statistics: log likelihood for Tobit: 194.95 and 347.74, Total number of observations = 160 of which uncensored = 160

***-1 % significant, ** - 5% significant, * - 10% significant

Table A20: Productivity growth in Paints industry

TFPG change			
Y3	0.160 (9.03) ***	Y3	0.140 (0.25)
Y4	0.165 (5.76) ***	Y4	-0.002 (-0.03)
Y5	0.268 (11.81) ***	Y5	0.014 (0.12)
Y6	0.269 (12.36) ***	Y6	0.010 (0.08)
Y7	0.311 (10.49) ***	Y7	-0.059 (-0.34)
Y8	0.311 (8.19) ***	Y8	0.020 (0.14)
Y9	0.462 (8.08) ***	Y9	0.099 (0.57)
Y10	0.428 (13.63) ***	Y10	-0.034 (-0.16)
Y11	0.528 (4.95) ***	Y11	0.056 (0.41)

IMPC	2.040 (4.81) ***	IMPC	1.235 (1.86) ***
CAPINT	-0.004 (-2.70) ***	TECHCH	1.039 (2.26) ***
PRODIFF	-3.010 (-2.32) ***		
Adj. R^2	0.42		0.55

Note: Censored Normal Tobit with Huber White standard errors and covariance. Other statistics: log likelihood for Tobit: 52.55 and 71.22, Total number of observations = 150 of which uncensored = 150 ***- 1 % significant, ** - 5% significant, * - 10% significant

Table A21: Productivity growth in Petrochemicals industry

TFPG change			
Y3	0.206 (6.40) ***	Y3	-0.001 (-0.03)
Y4	0.388 (4.28) ***	Y4	-0.021 (-0.40)
Y5	0.257 (8.15) ***	Y5	-0.021 (-0.35)
Y6	0.320 (12.77) ***	Y6	0.024 (0.39)
Y7	0.385 (12.23) ***	Y7	0.186 (0.26)
Y8	0.419 (12.44) ***	Y8	0.013 (0.17)
Y9	0.357 (14.02) ***	Y9	0.388 (0.58)
Y10	0.393 (15.54) ***	Y10	0.012 (0.16)
Y11	0.365 (13.44) ***	Y11	0.037 (0.55)
CAPINT	0.001 (2.60) ***	CAPINT	0.001 (2.12) ***
AGE	0.024 (4.03) ***	MP	0.164 (2.50) ***
		TECHCH	0.771 (5.60) ***
Adj. R^2	0.54		0.85

Note: Censored Normal Tobit with Huber White standard errors and covariance. Other statistics: log likelihood for Tobit: 82.48 and 141.63, Total number of observations = 100 of which uncensored = 100.***-1 % significant, ** - 5% significant, * - 10% significant

Table A22: Productivity growth in Solvent extraction industry

TFPG change	
Y3	-0.0.36 (-0.39)
Y4	0.007 (0.08)
Y5	-0.067 (-0.61)
Y6	-0.065 (-0.60)
Y7	-0.074 (-0.72)
Y8	0.008 (0.07)
Y9	0.094 (0.92)
Y10	0.038 (0.38)

Y11	-0.055 (-0.44)
AGE	-0.258 (-3.34) ***
CAPVINT	0.678 (2.55) ***
PRODIFF	-10.74 (-6.18) ***
MP	0.654 (6.13) ***
TECHCH	0.596 (3.13) ***
Adj. R^2	0.53

Note: Censored Normal Tobit with Huber White standard errors and covariance. Other statistics: log likelihood for Tobit: 49.01, Total number of observations = 60 of which uncensored = 60

***-1 % significant, ** - 5% significant, * - 10% significant

High tech industries

Table A23: Productivity growth in Electronics industry

TFPG change			
Y3	0.191 (8.90) ***	Y3	-0.015 (-1.18)
Y4	0.285 (9.63) ***	Y4	-0.009 (-0.65)
Y5	0.309 (15.02) ***	Y5	-0.017 (-0.89)
Y6	0.347 (14.77) ***	Y6	0.002 (0.11)
Y7	0.314 (10.78) ***	Y7	-0.010 (-0.50)
Y8	0.391 (14.54) ***	Y8	-0.021 (-0.90)
Y9	0.348 (13.81) ***	Y9	-0.006 (-0.26)
Y10	0.364 (14.27) ***	Y10	-0.027 (-1.11)
Y11	0.373 (14.36) ***	Y11	-0.020 (-0.82)
AGE	0.070 (2.57) ***	TECHCH	1.084 (18.14) ***
CAPVINT	0.033 (2.21) ***		
EX	0.147 (1.97) ***		
FUELINT	-0.631 (-2.20) ***		
IMPC	1.106 (2.06) ***		
Adj. R^2	0.68		0.97

Note: Censored Normal Tobit with Huber White standard errors and covariance. Other statistics: log likelihood for Tobit: 253.70 (for efficiency change) and 282.33 (for productivity change), Total number of observations = 260 of which uncensored = 260

***-1 % significant, ** - 5% significant, * - 10% significant

Table A24: Productivity growth in Pharmaceutical industry

TFPG change			
Y3	0.174 (26.45) ***	Y3	-0. 104 (-1.18)
Y4	0.243 (36.74) ***	Y4	-0.125 (-1.07)
Y5	0.280 (31.59) ***	Y5	-0.152 (-1.11)

Y6	0.333 (34.67) ***	Y6	-0.170 (-1.07)
Y7	0.349 (41.47) ***	Y7	-0.168 (-1.03)
Y8	0.367 (50.17) ***	Y8	-0.196 (-1.10)
Y9	0.365 (36.93) ***	Y9	-0.203 (-1.12)
Y10	0.565 (3.68) ***	Y10	-0.194 (-1.01)
Y11	0.400 (9.53) ***	Y11	-0.167 (-0.79) ***
EX	0.028 (3.02) ***	MP	0.360 (15.73)
		TECHCH	1.521 (3.21) ***
Adj. R^2	0.19	Adj. R^2	0.93

Note: Censored Normal Tobit with Huber White standard errors and covariance. Other statistics: log likelihood for Tobit: -24.22 and 308.93, Total number of observations = 260 of which uncensored = 260,

***-1 % significant, ** - 5% significant, * - 10% significant

Table A25: Productivity growth in Telecom industry

TFPG change			
Y3	0.076 (1.22)	Y3	0.010 (0.185)
Y4	0.182 (4.53) ***	Y4	0.102 (2.13) ***
Y5	0.134 (1.89) ***	Y5	0.063 (0.086)
Y6	0.257 (6.64) ***	Y6	0.155 (2.83) ***
Y7	0.370 (6.91) ***	Y7	0.239 (3.35) ***
Y8	0.340 (6.35) ***	Y8	0.226 (3.17) ***
Y9	0.382 (6.47) ***	Y9	0.188 (2.01) ***
Y10	0.317 (7.52) ***	Y10	0.214 (3.50) ***
Y11	0.308 (7.70) ***	Y11	0.199 (3.64) ***
IMPR	-0.263 (-2.02) ***	IMPR	-0.296 (-2.46) ***
RDCAP	1.661 (5.93) ***	RDCAP	2.12 (9.19) ***
CAPVINT	-0.332 (-1.69)	TECHCH	0.414 (2.04) ***
Adj. R^2	0.61		0.65

Note: Censored Normal Tobit with Huber White standard errors and covariance. Other statistics: log likelihood for Tobit: 54.49 and 57.69, Total number of observations = 50 of which uncensored = 50,

***-1 % significant, ** - 5% significant, * - 10% significant

Diversified

Table A26: Productivity growth in Personal care industry

TFPG change	
Y3	0.196 (7.23) ***
Y4	0.281 (7.11) ***
Y5	0.304 (9.29) ***
Y6	0.493 (4.19) ***
Y7	0.393 (6.76) ***
Y8	0.546 (5.83) ***
Y9	0.620 (5.09) ***

Y10	0.532 (10.26) ***
Y11	0.556 (7.71) ***
AGE	-0.116 (-2.53) ***
CAPINT	0.0114 (2.49) ***
IMPC	-2.253 (-2.50) ***
RDCAP	-9.734 (-2.20) ***
Adj. R^2	0.35

Note: Censored Normal Tobit with Huber White standard errors and covariance. Other statistics: log likelihood for Tobit: 20.84, Total number of observations = 100 of which uncensored = 100,

***-1 % significant, ** - 5% significant, * - 10% significant

Table B: variables explained

	Variable	**Definition**	**Expected sign**
1	AGE (of machinery)	accumulated depreciation /capital	(-)
2	CAPINT (Capital intensity)	Capital /EMC	(+)
3	CAPVINT (vintage of capital)	Depreciation allowance /value of plant and machinery	(-)
4	EXPORTS	Total exports / STO	(+)
5	FUELINT	Power and fuel cost / STO	(-)
6	IMPORTS	Total imports / STO	(+)
7	IMPC	Capital imported /STO	(+)
8	IMPR	Raw materials imported /STO	(+)
9	PRODIFF	Advertisement expenditure /STO	(-)
10	RDCAP	R&D expenditure (capital) /STO	(+)
11	RDREC	R&D expenditure (recurring) /STO	(-)
12	ROYAL	Royalty payments / STO	(+)
13	TECHCH	Technical change	(+)
13	Y	Year dummies	(+)