Knowledge Accumulation and Productivity Growth In Swedish Manufacturing Industries 1952-2001

‘What Technical Change really is in a Disaggregate Production Function’

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Abstract

This paper tries out a new method to distinguish between different growth generating mechanisms and measure their separate effects on output growth. Swedish data is disaggregated in accordance to industries method of production. Total factor productivity ‘TFP’ is then calculated by traditional growth accounting on each industry-specific data set so that effects originating from quantitative aspects of the production factors are separated from those deriving from changes in factor quality and/or economies of scale. The innovative ingredient in this paper is to analyse how TFP interacts or ‘cointegrates’ with qualitative measurements of labour and capital along with demand in a full equation system using the cointegrated VAR model. In this way various hypotheses on steady state relations and causality between variables, suggested in the ‘growth literature’, can be examined. Results show that changes in factor quality can be pinpointed as specific sorts of knowledge accumulating mechanisms such as embodied technological change, learning-by-doing, technology based R&D or sales and organisational based R&D. The main finding is that industries’ knowledge accumulating mechanisms are firmly connected to what they produce and what technology they use.

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Introduction

In Robert Solow's famous article "Technical change and the aggregate production function" (1957), 'technical change' expresses any kind of shift in the production function, and subsequently all sorts of things appear as 'technical change'. Eventually, strict application of neoclassical marginal theory originating from the micro level on growth dynamics on the macro level has reached a dead end. However, throughout the last two decades, the analysis of technical change and economic growth has made remarkable progress, mainly consisting of various ways of bringing together the earlier qualitative endogenous technology models based on Joseph Schumpeter with the standard neoclassical model. Mainly two approaches has developed along this line: the first implies to develop empirical methodologies to measure and distinguish between different sources of growth, aiming to reduce the size of the residual by adding more and more 'qualitative' variables. Examples in this field are improved growth accounting models in which new technology is embodied in capital goods, and years of schooling is regarded as a quality improver of labour rather than forming externalities to physical and human capital accumulation. The most important works are by Zvi Griliches and Dale Jorgenson. Yet, this method has little aspiration to theoretically explain growth in terms of modelling its underlying mechanisms. Another approach aims to produce general or multiple equilibrium models addressing how and under what condition growth is generated theoretically. The typical examples are alternatives based on the endogenous growth models introduced by Paul Romer and Robert Lucas. These, however, generally have little interest in and/or prospect of measuring various sources of growth. Besides from the two main approaches, there have also been important progresses in evolutionary theory of in particular Richard Nelson and Sidney Winter, not to forget Brian Arthur's new insights in the path dependency of technical progress. These approaches all aim at deepening our analytical understanding of the complexities that arise when 'knowledge' is regarded both as a production factor and as a produced good. Nevertheless, it is unclear how much these new agendas in fact have lighten up our empirical understanding of 'what sort of things' that hides in the Solow residual. It has lately been stressed that none of these new methods and theories are able to distinguish the internal mechanisms causing growth, and therefore the 'modus operandi' of learning and knowledge accumulation still remains in a black box (see e.g. Wright, 1997 and Ruttan, 2001). A more and more accepted proposal is that all approaches should be regarded as components of a more general theory explaining technical change (see e.g. the proposed model in Ruttan, 2001). It is true that as long as these approaches are carried out separately they are missing the main point, namely finding ‘what sources generate growth in what way’ given the *actual* conditions. However, I propose that there is no such thing as a general growth model, on the contrary, growth is generated by different mechanisms in different firms or industries depending on their specific method of production. By considering the possibility of technical change reflecting various growth mechanisms such as learning-by-doing, embodied technological change, research and even economies of scale for diverse industries, this paper suggests a method that can distinguish between various sources of growth, theoretically explaining through what mechanisms they work as well as measure their separate impact on growth.

A common feature of endogenous growth models is the representation of knowledge generating activities as homogeneous. However, knowledge and skills can be accumulated in different ways, e.g. formal education, vocational training, research, learning by doing and embodied technological change. It is generally recognised that industries show different growth patterns, and yet so far, there has been a general lack of analyses based on disaggregated data; most researchers have addressed growth on a national scale or analysed output growth in the manufacturing sector as a whole. Provided that the sources of productivity growth differ between industries with different methods of production, it is of great importance to separate the analyses of productivity growth for industries using different production methods. This paper uses a unique data set including more than 100 time series covering 50 years, which makes it feasible to divide the Swedish manufacturing industry into labour-intensive, capital-intensive and knowledge-intensive industries.

This paper shows that in order to analyse economic growth it is advantageous to first remove the quantitative effect of labour and capital growth on output growth in each industry-specific data set, and then analyse how the ‘qualitative’ part, i.e. TFP, cointegrates with variables representing various knowledge accumulating mechanisms and demand. However, when the cointegration relations are identified the quantitative and the qualitative measures are both be included in a growth accounting framework to demonstrate their individual and total effect on output growth.

How to distinguish between different industries when carrying out disaggregation

It is feasible to distinguish among industries with different method of production by considering both the production factor that receives the relative largest share of total factor remuneration and the capital/output ratio. The relative size of remuneration to different factor inputs are indicated by the shares of blue collar workers, white collar workers and capital. The idea is that industries that are comparatively similar in terms of wage share and capital/output ratio form a group of industries sharing common growth mechanisms. Labour-intensive industries are characterised by a high total wage share, low white collar share and low capital/output ratio, capital-intensive industries are characterised by a relatively lower wage share and high capital/output ratios, whereas knowledge-intensive industries are characterised by a high white-collar wage share and low capital/output ratio. The graphs below show that the three sectors, into which Swedish manufacturing industries have been divided are largely coherent. Each sector essentially maintains its own level in relation to the others. The capital/output ratio – calculated on capital stocks and value added in fixed prices – shows a distinctly higher level in capital-intensive industries than in the other two groups of industries. The capital/output ratio is particularly low in knowledge-intensive industries. In the latter group of industries, however, the white collar share is permanently at a distinctly higher level.

The wage share gives a slightly more complex picture. Basically, it reflects the fact that human capital is the most important factor in knowledge-intensive industries with high wage shares, that remuneration in labour-intensive industries is somewhat more balanced between labour and capital and that capital takes a greater share in capital-intensive industries. There are, however, great variations in the profit share due to the occurrence of crises and instabilities. Thus during the problematic period from 1975 to 1980 the total wage share in capital-intensive industry exceeded the wage share in labour-intensive industry, due to the strongly decreasing demand after OPEC I. The high wage share was maintained only for a short time through subsidies from the Swedish government to crisis-stricken heavy industries.

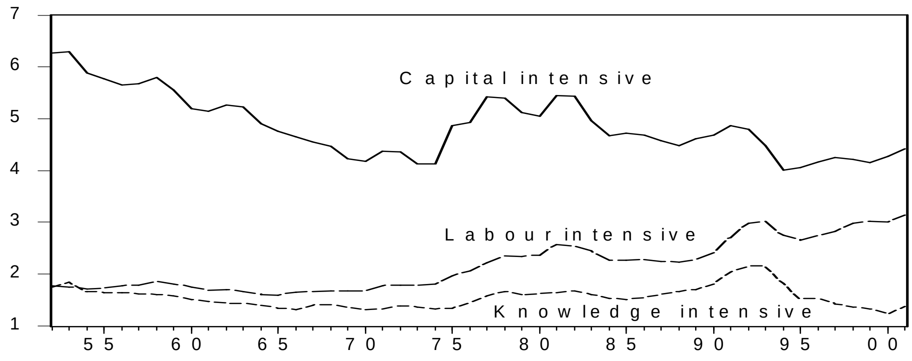


Figure 1 Capital/output ratio in labour-intensive, capital-intensive and knowledge-intensive industries 1952-2001

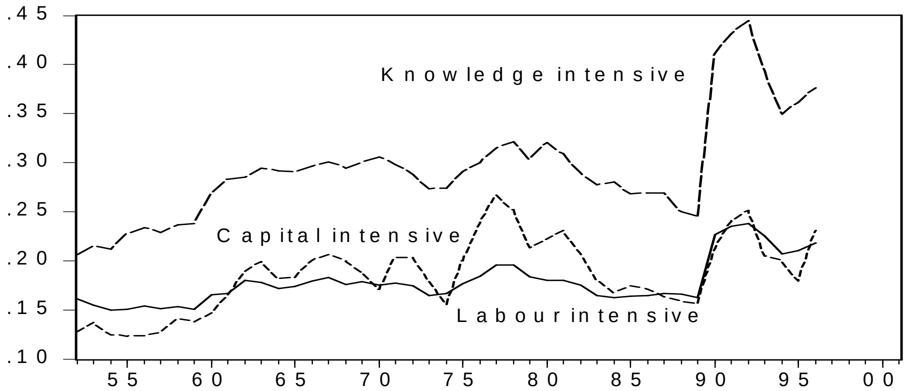


Figure 2 White-collar wage share of value added in labour-intensive, capital-intensive and knowledge-intensive industries 1952-1996 calculated using current prices

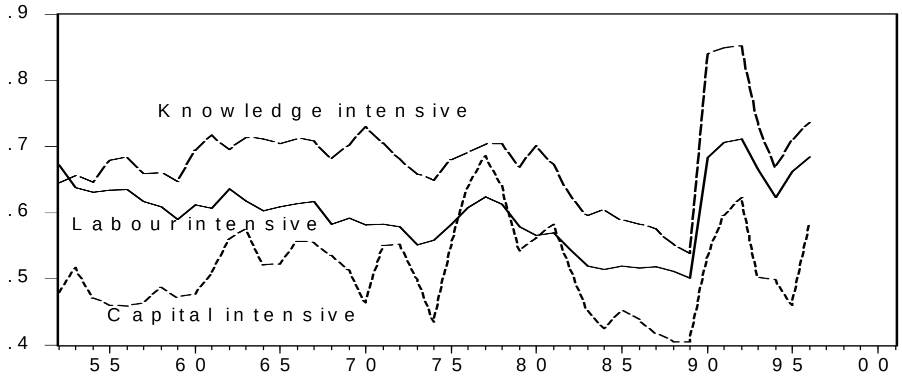


Figure 3 Total wage share of value added in labour-intensive, capital-intensive and knowledge-intensive industries 1952-1996 calculated using current prices. Source: Output from Historiska nationalräkenskaper för Sverige: Industri och hantverk 1800-1980, Statistiska Meddelanden I of Statistics Sweden (SCB) and especially ordered statistics from SCB data base. Capital stocks from Statistiska Meddelanden N of Statistics Sweden (SCB).Wages from Swedish wage statistics (SOS Löner) Note: Aggregate series on wage shares are complete to 1996 only, while series on white-collar workers in different positions cover the whole period up to 2001. The calculation of the total wage share, as well as of the white-collar wage share is based on total wage sum and value added in current prices.

Table 1 Total wage share and white-collar wage share for the period 1952-1996, capital/output ratio for the period 1952-2001, labour-intensive, capital-intensive and knowledge-intensive industries

Industry	Total wage share		White-collar wage share		Capital/output ratio	
	Mean	St.d.	Mean	St.d.	Mean	St.d.
Labour-intensive	0.60	0.05	0.18	0.02	2.16	0.48
Earth and clay	0.57	0.06	0.18	0.04	2.48	0.47
Wood	0.62	0.07	0.14	0.03	2.83	0.96
Food and beverages	0.51	0.07	0.17	0.03	2.02	0.37
Textiles and clothing	0.70	0.05	0.21	0.02	1.94	0.56
Metal manufacturing	0.65	0.05	0.20	0.02	1.96	0.37
Capital-intensive	0.51	0.06	0.19	0.04	4.86	0.59
Steel and metal works	0.63	0.12	0.20	0.05	5.84	0.81
Pulp and paper mills	0.49	0.09	0.13	0.04	7.59	0.62
Chemical industries	0.46	0.04	0.22	0.02	2.60	0.50
Knowledge-intensive	0.68	0.06	0.29	0.05	1.54	0.26
Engineering industries	0.69	0.07	0.29	0.05	1.66	0.26
Printing industries	0.65	0.08	0.31	0.07	1.22	0.27

Source: See figure 3

Labour-intensive industries include earth and clay, wood, food and beverages, textiles and clothing, and metal manufacturing. Remuneration to labour, foremost blue-collar workers, constitutes the largest factor expenditure. The mean value for the wage share 1952-2001 is 0.60, the mean value for the shares of white-collar workers is 0.18 and the mean capital/output ratio is 2.16, although the values differ between industries. The mean value for the wage share of the food and beverage industry is only 0.51, in the textiles and clothing industry it is 0.70, yet both show a capital/output ratio around two. The reason for the textile industry's high wage share is its strongly falling profits, especially in the 1960s and 1970s.

Remuneration to capital constitutes the largest factor expense in the capital-intensive industry including steel and metal works, pulp and paper mills, and chemical industries. The mean value for the wage share is 0.51, the mean value for the shares of white-collar workers is 0.19 and the mean capital/output ratio is 4.86. Hence, it is foremost the capital/output ratio that distinguishes capital industries from labour-intensive and knowledge-intensive industries. The wage share for steel and metal works is higher than for some labour-intensive industries, due to extraordinary low profit levels in the 1970s and early 1980s. Its capital/output ratio of 5.84 shows, however, that it is clearly a capital-intensive and not labour-intensive industry. I may also note that the standard error for steel and metal works unveils high fluctuations. For several years in the 1970s and 1980s the Swedish state bore the wage cost in order to save jobs when profits fell drastically, hence the ‘real’ wage share would otherwise have been much lower. Clearly the chemical industry shows a rather low capital/output ratio of 2.60, and a slightly higher white-collar wage share than the other capital-intensive industries. The chemical industry consists of a number of different industries, of which some actually could have been included in labour-intensive industry, e.g. the industry for rubber products. It would have been desirable to include the pharmaceutical industry in knowledge-intensive industry instead of capital-intensive industry but this could not be done since disaggregation was limited by the lack of capital stocks and investment data for the entire period.

Salaries to white-collar workers constitute the largest factor cost in knowledge- intensive industry including the engineering and printing industries. The mean value for the wage share is 0.68, the mean value for the shares of white-collar workers is 0.29 and the mean capital/output ratio is 1.54. It may appear remarkable to combine engineering industries and printing industries in the same aggregate, and perhaps it is. Since the engineering industry is so dominant, the effects of including the printing industry are marginal. However, when analysed separately the industries tend to show rather similar patterns.

The variables included in this study

The data set used in this study is quite unique. Not only is it the first time that growth is analysed in diverse groups of industries conditioned to what method of production they use, it is also the first time that detailed data on an industry level on machinery investments, two types of human capital and export is put together for this period in Sweden.

Output, the capital stock and working hours

Figure 4 Output, capital stock and labour hours in labour intensive industry 1952-2001, log scale

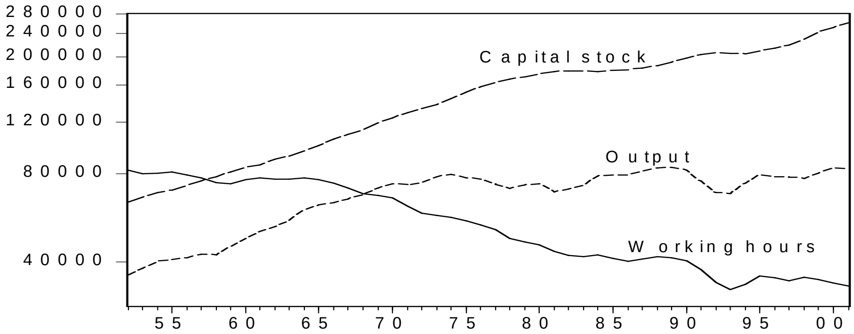


Figure 5 Output, capital stock and labour hours in capital intensive industry, 1952-2001, log scale

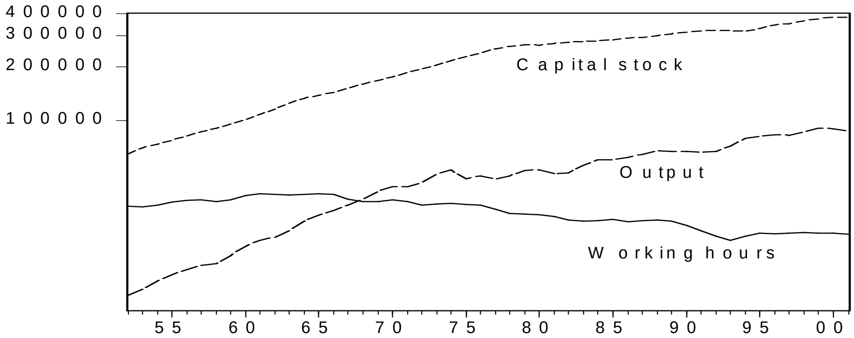
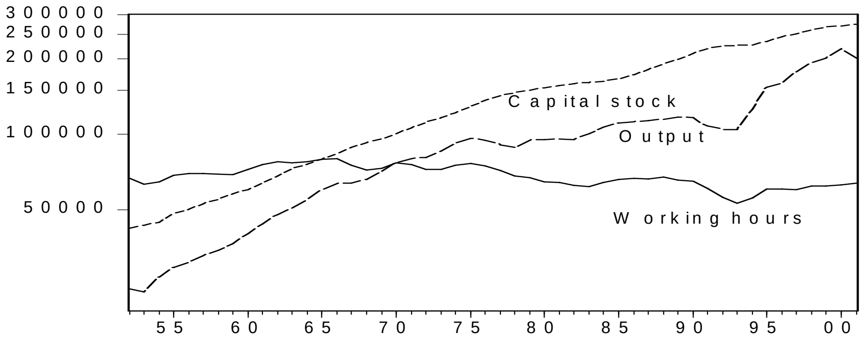


Figure 6 Output, capital stock and labour hours in knowledge intensive industry 1952-2001, log scale



Source: For the period 1950-1953 the series are from Schön, *Historiska nationalräkenskaper för Sverige: Industri och hantverk 1800-1980*. The data is rearranged for the present groups from the sub-sectors in the material for the Historical National Accounts. For the period 1952-1994 the series are from *Statistiska Meddelanden I* of Statistics Sweden (SCB) and for the period 1994-2001 the branch series are constructed from an SCB data base that has been arranged in accordance with SNI69 and where the value added figures in current prices have been deflated by the branch producer price index (PPI). The branch series have been aggregated to the respective industrial sector of labour, capital and knowledge-intensive industries with the value added weights of 1960 for the period 1952-1980 and the weights of 1991 for the period 1980-2001. Since there are only small structural changes at branch level within each group, the choice of deflation periods is of minor importance.[1] The series are in 1991 price levels. The series on capital stocks build on machinery capital and total capital in fixed prices at branch level in *Statistiska Meddelanden N* of Statistics Sweden (SCB) for the period 1950-1994. The series from the Reports are linked 1970 and 1980. For the period 1994-2001 the series are constructed from investment figures in the SCB data base mentioned above, using the Perpetual Inventory Method with an annual depreciation allowance of 4 percents for machinery capital and 2 percent for building capital. The number of worked hours for blue-collar workers is directly reported in the official industrial statistics, whereas white-collar workers are reported in number of workers, which have to be recalculated to hours. In doing so reduction in working hours have been considered. All data is reported for individual industries on the two-digit level and is then aggregated by summing up the measurements for industries with similar methods of production.

There are some similarities and some differences between the sectors. Figures 1-3 show that the capital stock increases in all industries whereas working hours are decreasing. In capital intensive and knowledge intensive industries the capital stock and output develops rather closely together, whereas the capital stock in labour intensive industry shows a much stronger increase than output. The deviation occurs after 1975; in labour intensive industry output only increases until 1975 and thereafter levels out, while the capital stock continues to increase with a somewhat reduced rate. Labour intensive industry also shows the strongest decrease in working hours for the whole period.

TFP

I use the traditional neo-classical way to measure TFP, i.e. a growth-accounting procedure according to a linear homogeneous Cobb-Douglas production function of first degree[2]. $Y = F(A, K, L)$, with Y being value added, A the level of technology, K the capital stock and L the quantity of labour. Y and K are in fixed prices whereas L is in working hours. The usual specification of a standard Cobb-Douglas model takes the form:

$$\dot{Y}\Big/Y = g + \left(\frac{F_K K}{Y}\right)\left(\dot{K}/K\right) - \left(\frac{F_L L}{Y}\right)\left(\dot{L}/L\right) \qquad (1)$$

with F_K and F_L the factor marginal products.

[1] The output aggregates are sensitive to the choice of base year only if there are changes in both the relative price levels and the quantity shares within each subgroup.

[2] A function is homogeneous if all its terms are of the same dimension, that is, if the sums of the exponents of the variables in all its separate terms are equal; it is homogeneous of first degree if these sums are equal to unity. When such production function obeys constant return to scale and there are at least two factors, the forces are always complements i.e. increasing the amount of one factor in isolation lowers its own marginal product but necessarily raises the marginal product of the other factors.

The rate of technical progress i.e. TFP growth or the Solow residual, can then be written as:

$$g = \dot{Y}/Y - s_K\left(\dot{K}/K\right) - s_L\left(\dot{L}/L\right) \quad (2)$$

where $s_K \equiv RK/Y$ and $s_L \equiv \omega L/Y$ are the respective shares of each factor payment in total product, R is the cost of capital and ω is the cost of labour. The classical assumption is that the production function obeys conditions of constant returns to scale, meaning that all the income associated to Y is attributed to one of the factors K and L. The exponents expressing marginal products of labour and capital must consequently sum to unity: $s_K + s_L = 1$. I use equation (2) directly to estimate g by means of time series data without econometric techniques - known as growth accounting. Hereby I avoid econometric drawbacks such as simultaneity problems i.e. technical change may for example affect factors accumulation so that when g is estimated by regressing the growth rate of output on the growth rates of input as in equation (1), where g is measured by the intercept, the rate of growth of capital and the rate of growth of labour may vary together with g.

TFP is calculated for the three groups of industries according to equation (2) with elasticities of capital and labour in each group derived from their respective share of value added. Labour elasticity of the sub sectors is set at 0.6 for labour-intensive industry, 0.4 for capital-intensive industry and 0.7 for knowledge-intensive industry; consequently capital elasticity is set at 0.4 for labour-intensive industry, 0.6 for capital-intensive industry and 0.3 for knowledge intensive industry. In accordance with the Cobb-Douglas production function fixed shares have been used, however varying the shares each year is shown to affect the results very little.

The variations in TFP growth 1951-2001 are striking. There are however some broad regularities among the industries: TFP growth in all industries is above zero for the period 1953-1975, whereas it is heavily fluctuating close to zero from 1975-2001. All industries show a remarkable drop in TFP during the 1974-75 crises. TFP growths in the three different industries tend to move together i.e. once one sector is above or below zero others tend to appear in a similar position. Thus there is a tendency for co-movements across sectors within manufacturing industry.

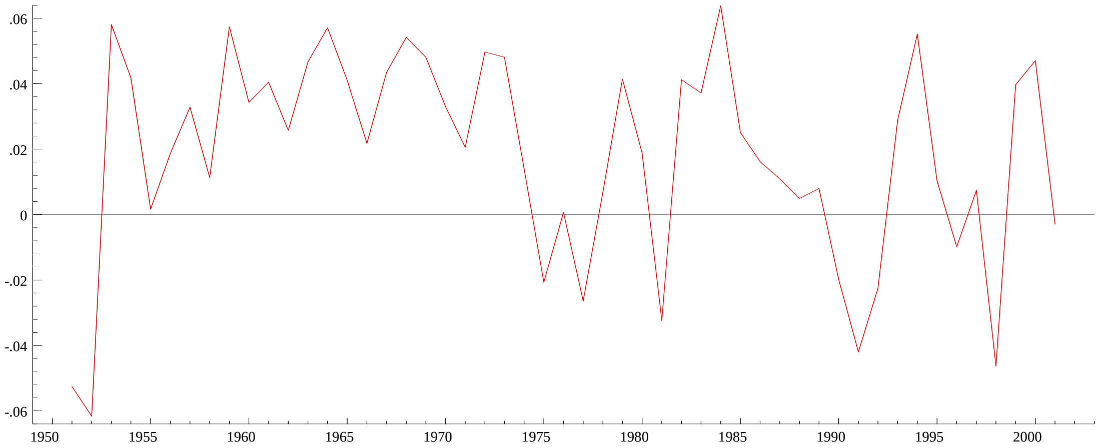


Figure 7 TFP in Labour-intensive industry 1951-2001

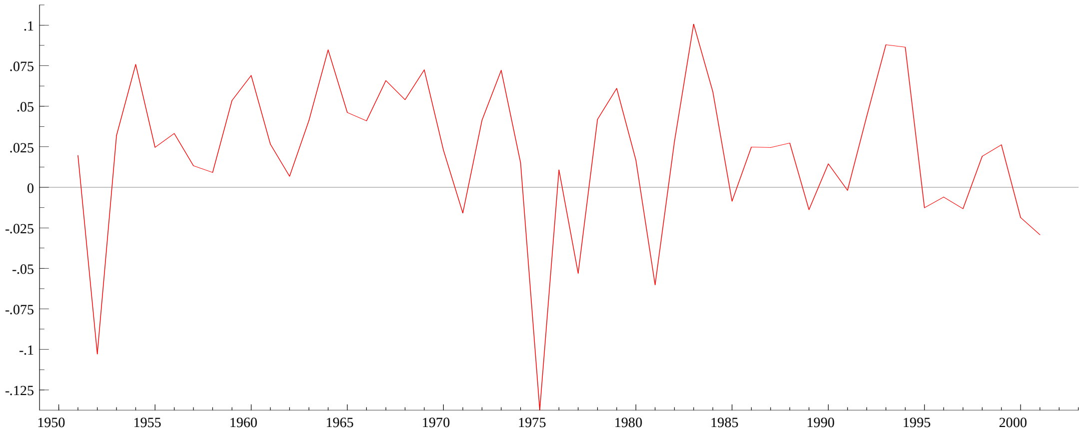


Figure 8 TFP in Capital-intensive industry 1951-2001

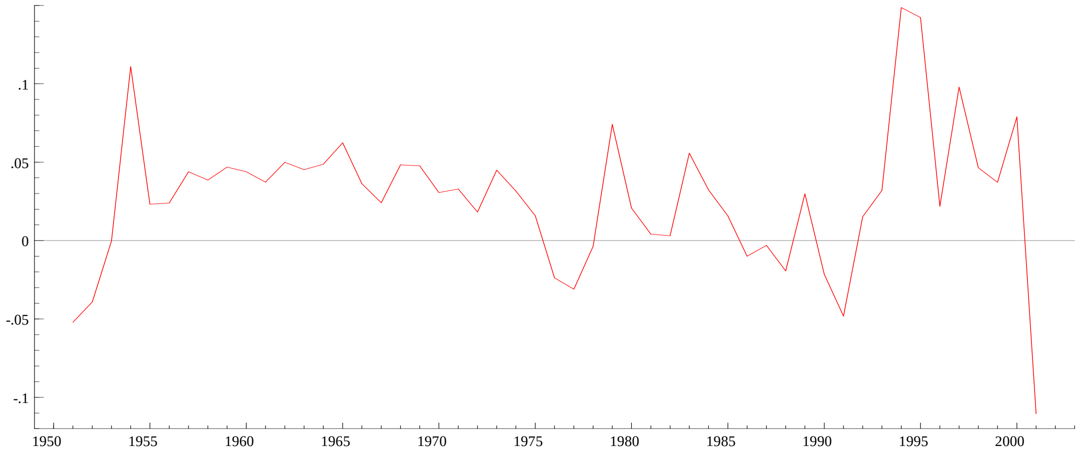


Figure 9 TFP in Knowledge-intensive industry 1951-2001. Source: My own Calculations according to equation 2 based on the data presented in figures 4-6

Measuring two different types of human capital

The quality of the labour input is one of the crucial components in the analysis of TFP growth. There is no available data on the employees' education in each industry, the average number of years of schooling on a national level usually constitutes a proxy. Yet, even if such data were available I could not be sure that employees with longer education necessarily have occupational positions in which they can use all their additional education. Nonetheless, I can make the opposite assumption; certain occupational positions imply the use of a certain amount of human capital and thus require knowledge either gained from schooling or on the job training. The endogenous growth model distinguishes itself from neo-classical models by emphasising that economic growth is an outcome of people's ability to generate useful ideas. The possession of human capital is a necessary, yet not sufficient condition to generate useful ideas, which in turn create growth; it is the ability and willingness to use human capital in such a way that generates growth. Hence the share of qualified positions compared to the whole work force seems an appropriate measure of human capital.

SOS Löner (Swedish official wage statistics) for white-collar workers contain detailed data on the number of employees in different occupational levels within different fields. The fields are: 1. administration, organisation, office-work and selling,[3] 2. technical and engineering work, and 3. product developing work and research. Within each field the number of employees in each of four different occupational levels is shown: 1. leading position, 2. independent / self-governed work, 3. qualified / skilled work, and 4. routine work. This study assumes that the first three levels imply a rather large use of human capital for generate useful ideas, whereas the fourth level does not. Therefore the total number of positions in which the use of human capital is essential, divided by the total number of workers within the industry (including blue-collar workers), constitutes our relative measure of human capital. This study chooses to distinguish between two fields and construct a measurement of human capital for each field; one measuring the share of human capital in organisation, administration and sales – referred to as human capital in "D", and the other measuring the rate of human capital within research, engineering and product-developing work – referred to as human capital in "R". The measurement of human capital in administration, organisation and sales is transformed to an average of the 'human capital share' in the preceding three years. That is, the model estimates the impact on TFP of a build-up of human

[3] Office-work and selling will be referred to as 'sales' in the rest of the thesis.

capital. Yet, the measurement of human capital within technical, engineering product-developing work and research is based on its yearly fluctuations. This different measurement manoeuvre for the two human capital variables helps to distinguish the direct effects of labour hoarding from the effects of a build up in administrative and organisational human capital, as well as from the direct effects from human capital in technical knowledge. These two measurements are yet no more than a qualified approximation of human capital, particularly since the level of skills in general have risen considerably over the period.

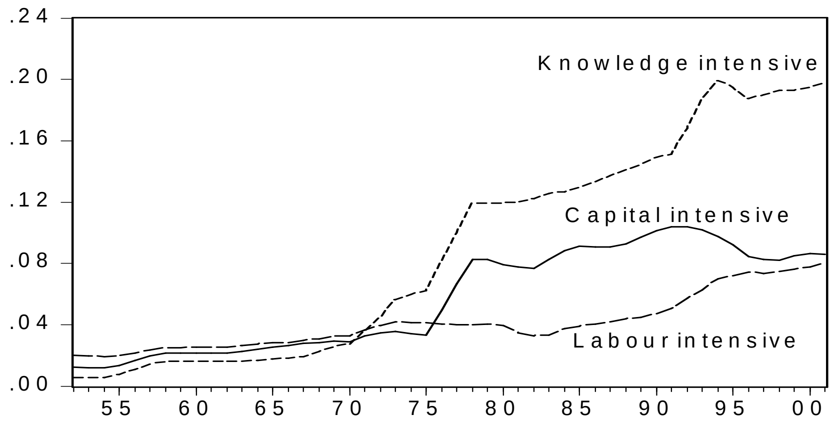


Figure 10 Human capital in "D" organisation, administration and sales in labour-, capital-, and knowledge-intensive industries as shares of total labour force 1952- 2001, linear scale

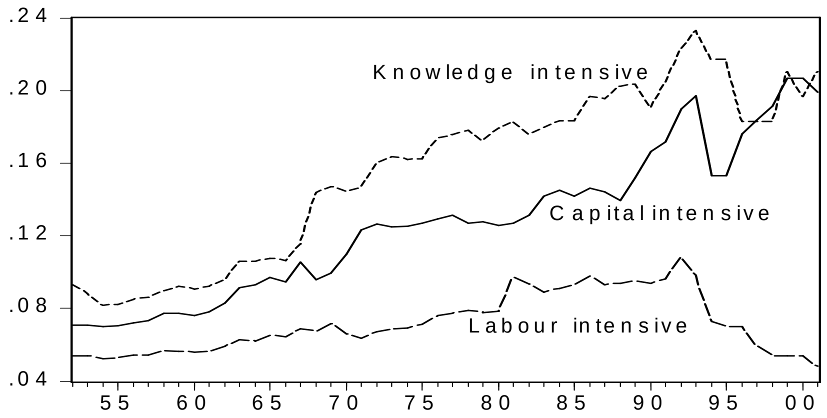


Figure 11 Human capital in "R" research, engineering and product development in labour-, capital-, and knowledge-intensive industries as shares of total labour force 1952-2001, linear scale. *Source*: SOS Löner, Swedish official wage statistics

The share of higher occupational positions in administration, organisation and sales of the total work force, referred to as human capital in “D”, increases rather strongly from 1970 in knowledge-intensive industry and from 1975 in capital-intensive industry; however after 1977 growth slows down, and capital intensive industry shows a negative growth for the next couples of years. Labour-intensive industry shows quite the opposite behaviour; human capital in “D” increases rather slowly until 1983, where after it grows faster. The financial crisis in 1991/1992 seems to have a positive effect on human capital in “D” in both knowledge-intensive and labour-intensive industries, whereas capital-intensive industry shows a delayed negative effect. The growth pattern in human capital in “R” looks similar in knowledge- and capital-intensive industries, although the growth rate is at a higher level in knowledge-intensive industry. In labour-intensive industry human capital in “R” increases in a somewhat stable rate until 1992 and then falls for the rest of the period. The financial crisis hit industries oriented to the home market particularly hard due to the strong depreciation of the Swedish crown and a more restrictive Swedish monetary policy. The crisis struck metal manufacturing and building material especially hard due to a slump in construction, and these industries have the highest share of technical workers and engineers within the labour-intensive industries. Knowledge-intensive and capital-intensive industries show three periods of approximately 3-5 years each, in which human capital in “R” grows relatively stronger: the first period starts around 1966/1967, the second period starts in 1988/1990, and the third one begins after 1995. After the financial crisis 1991/92 human capital in “R” falls drastically in both capital- and knowledge-intensive industries.

Not only have the shares of qualified positions within each field increased but also the employees in these positions have in general become much higher educated. The percentage of all people in Sweden in the age group 22-44 that have started a university education before the age of 22 has increased strongly in the last 50 years. In 1952 only 4 percent in the age group had enrolled in university, whereas 34 percent did so in 2001.

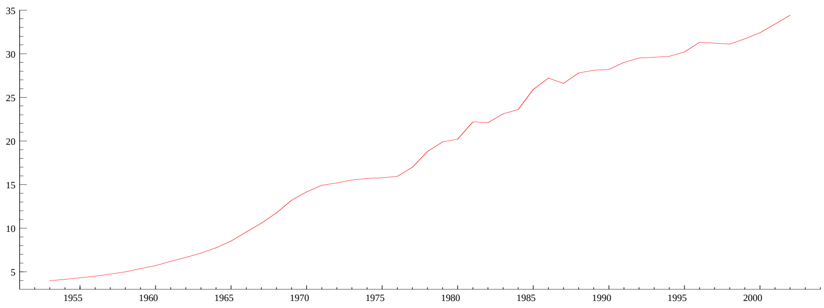


Figure 12 Percentage of people in Sweden 22-44 years old enrolled in university before the age of 22 during the years 1952-2001, linear scale. *Source:* Arbetsmarknaden i siffror 1970-1988. SM AM 12 (1989-2000: 2001)

Machinery investments and exports

Machinery investments represent the injection of new capital equipment. Some degree of new technology is already accounted for by the capital stock, measured in fixed prices (see Schön 2004). Yet, I do not know exactly how much of the improved quality of capital is already accounted for. This variable is included in the study in order to consider the quality of capital that is not accounted for by the capital stock. Machinery investment is also a very useful variable when considering learning-by-investing. Investments in machinery equipment constitute an appropriate indicator of new technology in physical terms embodied into capital.

The export variable is included in the study in order to represent variations in demand. Since Sweden is a small open economy with a high degree of export dependency in manufacturing, export is a rather good measure of demand. Branch specific data are used for capital-intensive and knowledge intensive industries, whereas output from labour-intensive industries is sold to a large extent on the domestic market. Since total export through its effect on derived demand, better reflects the domestic level of activity than export of labour-intensive goods, it is used as a measure of demand in labour-intensive industry. Estimates of domestic consumption show roughly the same pattern as total export; hence replacing the latter measurement with the former would not make much difference (Schön, 2000).

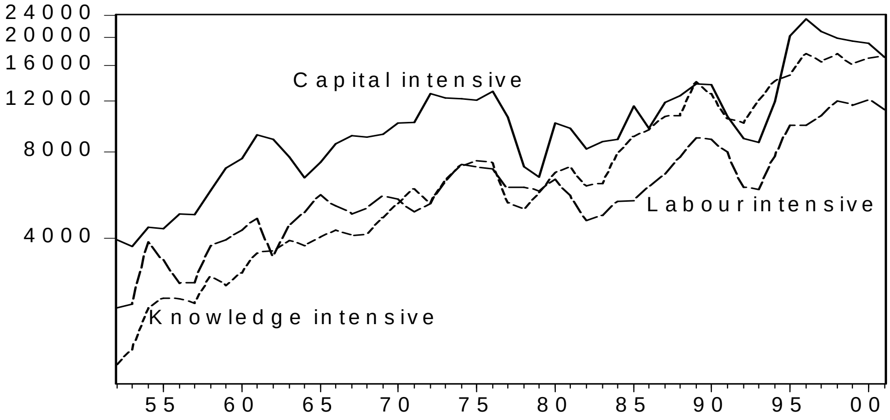


Figure13 Machinery investments in labour-, capital-, and knowledge-intensive industries 1952-2001 Mill. SEK in 1991 price level, log scale. *Source*: 1950-1962 from Kommersiella Meddelanden, Kommerskollegium, 1962-1994 from Statistiska Meddelanden N, the series are spliced in 1962, 1969, 1975, 1982 and 1991. From 1994 to 2001 from SCB data base.

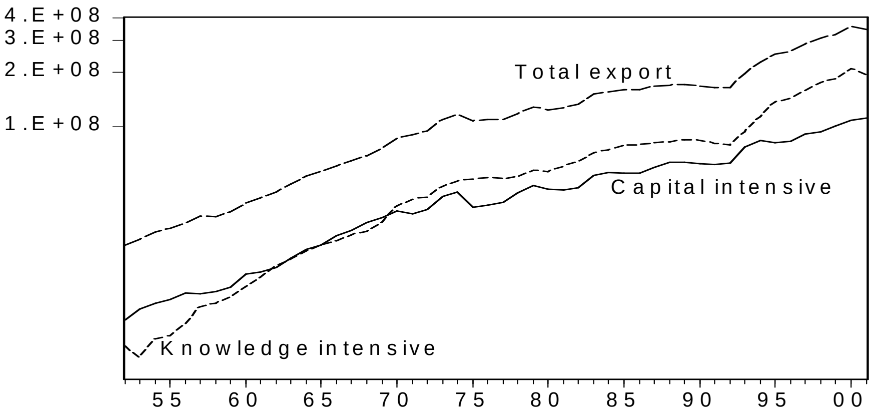


Figure14 Total export and export in capital-, and knowledge-intensive industries 1952-2001, 1000 SEK in 1991 price level, log scale. *Source*: SOS Utrikeshandel, the official industrial statistics for foreign trade contain data on the value and quantity of each type of good that is imported and exported. The branch-specific measures of export are produced by combining all exported goods produced by a certain industry and calculating the total value of these goods. A branch-specific PPI is used when deflating exports in each branch.

All three industries show a rather similar behaviour in machinery investments yet with different levels and magnitudes: they all show a strongly fluctuating yet solidly increasing growth in machinery investment until 1975/76 when investments fall for one or a couple of years. From around 1980 investments increase persistently for about ten years until 1990 where after there is another drop due to the financial crisis. From 1993 investments increase strongly once again.

All industries show a rather smooth and quite strong increase in exports from 1950 to 1974. Then all show a slower growth rate in export until 1992, but thereafter the increase is stronger again. Hence, export evolves in three different periods, starting with a phase of strong growth, broken by a period of slower growth and finishes with a new period of stronger growth. The knowledge-intensive industry has the strongest growth rate over the whole period, overtaking capital-intensive industry as the most important export sector around 1970.

Describing and specifying the cointegrated VAR model

The cointegrated 'VAR' (Vector Auto Regressive) model has cointegration restrictions built into the specification and hence is designed for use with nonstationary time series. Analysing a 'vector' process containing the variables of interest instead of examining each variable individually, gives us a statistical model based on a full equation system, which provides information about the dynamic relationship between all variables simultaneously without any *a priori* assumptions about variables' dependency or endogeneity. This paper aims at sorting out the complexity enfolding the 'raw' measurement of TFP by analysing the establishment of 'steady state' or 'cointegration' relations between TFP and other 'non-stationary' variables in the long run. In order to find the engine of TFP growth in the long run eight hypothesis reflecting long-run 'homogeneity'[4] between TFP and other variables are formulated and tested by analysing a covariance matrix of the data[5]. The difference between the observed value of the process and its conditional mean, i.e. the homogeneous steady state tested for, constitutes the cointegration relation often referred to as the vector error correction term. To carry this out, an error correction model is specified. The empirical analysis follows the general-to-specific approach of Hendry (1993) based on a VAR model with I(1) restrictions (Johansen 1996).

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[4] A homogeneous relation between two variables i.e. TFP and human capital means that any changes in TFP growth is proportional to changes in human capital in a one to one relation: if human capital changes by 0.07 TFP also changes by 0.07. It is important to mention that homogeneity does not reveal causality between variables.

[5] The VAR model is fundamentally a reformulation of the covariances of the data. Instead of studying the covariances for two variables separately, I make use of a covariance matrix, which provides a complete general

The variables described earlier are included in the variable vector $X_{t,}$ defined as

$$X_{t} = \left[\; Y_t \quad M_t \quad D_t \quad R_t \quad E_t \; \right] \qquad (3)$$

where Y_t is total factor productivity (TFP), M_t is machinery investments, D_t the share of employees in higher occupational positions in organisation, administration and sales of the total work force, R_t the share of employees in higher occupational positions in research, engineering and product development of the total work force, E_t is export, and t express time. All variables are in natural logarithms. The empirical analysis in this study applies to estimations based on the variable vector X_t using the cointegrated VAR approach. Since the asymptotic distribution of the likelihood ratio (LR) test statistic for the reduced rank test depends on the assumptions made concerning deterministic trends, I must choose one of five possibilities considered by Johansen (see Johansen 1996. pp. 80–4 for details). In our case a constant and a linear trend in both stationary and non-stationary directions describe the data best, hence this possibility is chosen for our models. Some of the variables in the vector X_t contain a deterministic linear trend. I include a trend since it may act as a proxy for missing variables outside the information set, meaning that I allow for both stochastic and deterministic trends. The vector error correction form used in this study then looks as follows:

$$\Delta X_t = \Pi X_{t-1} + \sum_{i=1}^{k-1} \Gamma_i \Delta X_{t-i} + \mu_0 + \alpha\beta'_{0\,t} + \Phi D_t + \varepsilon_t \qquad (4)$$

The long-run matrix Π can be decomposed as $\Pi = \alpha\beta'$ where α and β are two matrices of the dimension (p x r), where p is the number of variables and r is the cointegration rank, i.e. the number of cointegration relations. The β matrix represents cointegration vectors, which contain the cointegration parameters, that is, the parameters that indicate an equilibrium or long-run relation between the time series. The adjustment parameters α reflect the speed with which variables are drawn back to or drift further away from the equilibrium relation after a shock in the system. Furthermore Γ_i are p x p dimensional matrices of autoregressive coefficients. The

description of a multivariate vector time series process describing the interrelations of all variables included in the system. As a result I can study the covariances between all variables simultaneously.

elements $\mu_0 + \alpha\beta'_0 t$ imply that a constant is included and that coefficients are restricted to the trend term, so that a linear trend is permitted in both stationary and non-stationary directions. Any dummies included in the model are denoted ΦD_t. Finally ε_t is the residual. Together with the dummies, the constant and the trend terms constitute the only deterministic components in the model.[6] Information criteria such as Hannan-Quinn and Schwartz suggest one lag length in the VAR model for each industry.

How many cointegration relations are there?

Next step is to find out the number of cointegration relations. The procedure of finding out whether a vector can be made stationary by making linear combinations of time series in the vector is called cointegration testing or testing the rank. CATS software implements VAR-based cointegration tests (the trace test) using the methodology developed by Johansen (1995; 1996). In order to determine the rank I proceed sequentially from $r = 0$ to $r = p - 1$ until I fail to reject the hypothesis. First, I test whether there is no cointegration relation (r=0) against the alternative of a stationary model ($r = p$). If that hypothesis is rejected I continue by testing whether there is at most one cointegration relation and so on until I fail to reject.

[6] Dummy variables are added for each industry depending on the data structure. Studying the residuals' standard deviations is usually a good way of finding any outliers; the following dummies are shown to be significant: In labour-intensive industry an intervention dummy or so-called blip dummy Φp is added for the year 1981 due to an outlier in human capital in "D". The model for labour-intensive industry has also been estimated with different types of dummies for 1994 in order to adjust for the behaviour in human capital in "R" research, engineering and product development, but human capital in "R" was still not required in the steady state relation. In capital-intensive industry two transitory dummies are added for 1975 due to outliers in TFP and export and for 1994 due to outliers in human capital in "R". For knowledge-intensive industry a shift dummy Φs is added for 1968 due to a shift in human capital in "R". Since the shift dummy is restricted not to be included in the cointegration space, it does not affect the asymptotic distribution by giving lower t-values.

Table 2 Testing for cointegration in each branch-specific data set

Rank	Labour-intensive		Capital-intensive		Knowledge-intensive	
	Eigenvalues	p-value	Eigenvalues	p-value	Eigenvalues	p-value
$r = 0$	0.77	0.00	0.81	0.00	0.68	0.00
$r \leq 1$	0.57	0.03	0.53	0.01	0.47	0.00
$r \leq 2$	0.28	0.78	0.35	0.31	0.41	0.07
$r \leq 3$	0.10	0.95	0.18	0.77	0.25	0.50
$r \leq 4$	0.08	0.72	0.05	0.90	0.04	0.95

The first column presents the eigenvalues, and the second column gives the *p*-values for the null hypothesis: the process can be made stationary in at most *r* cointegration relations. Using a critical value at five per cent implies that p-values above 0.05 cannot reject the null hypothesis, and that the number of cointegration relations equals the rank tested for. The lowest rank that fails to reject should be applied in the model.

The trace test clearly suggests rank two for capital-intensive and labour-intensive industry. The number of cointegration relations in knowledge-intensive industry is less certain, however. The p-values for two cointegration relations are 0.07. When the test results are uncertain, I can obtain more information by considering the number of roots inside the unit circle in the companion matrix, and the number of columns in which coefficients show significant t-values in the α-matrix. The α-coefficients present the speed of adjustment back to equilibrium, and the first column in the α-matrix corresponds to the first cointegration relation. I can thus expect significant coefficients in as many columns in the α-matrix as there are cointegration relations. The speed of adjustment to additional cointegration relations is nonsignificant or very slow (Juselius 2003 chapter 5). Knowledge-intensive industry shows two roots inside the unit-root circle, and only the first two columns have significant α coefficients; therefore rank two is chosen for knowledge-intensive industry as well.

Merging economic theory with empirical results

All three industries have rank two, hence two cointegration relations or stationary linear combinations of variables need to be identified. Identifying the cointegration relations means setting restrictions on their statistical structure at the same time as giving each stationary linear combination an economically meaningful interpretation. Economic theory may suggest that the cointegration relations take a specific form, which broadens the understanding of the statistical processes. First, eight theoretical hypotheses about homogeneous interrelations of variables is formulated, then a design matrix is used, in which the cointegration vector can be restricted to reflect each hypotheses, finally I test whether the cointegrating space can be structured in the suggested way. The intention is to choose a formulation of the design matrix that can spot the steady state relation appearing in the data, which is realised by finding a linear combination of $\beta_{1,\ldots,}\beta_r$ that produces a vector not significantly different from the estimated parameters in the cointegration relation.[7] The null-hypothesis is that a linear combination is stationary, which means that the stochastic trend is cancelled and a steady state relation is identified. A model where identifying restrictions are set on all cointegration vectors is known as the equilibrium error correction term.

Formulating the eight hypotheses

Each hypothesis is formulated as a restricted linear combination of certain variables, which corresponds to a steady state relation supported by economic theory. I argue in line with Romer (1990) and Lucas (1988) that the underlying source of sustained growth in per capita income is the endogenous accumulation of knowledge.[8] Both Romer and Lucas assume that the economic growth rate is proportional to the rate of growth in human capital so that when the amount of knowledge increases by one unit, growth increases by one unit as well. This kind of one-to-one relation is referred to as homogeneity.[9] It is feasible to test whether a homogenous relation prevails between e.g. human capital in "R" research engineering and product development and TFP growth by restricting the linear combination of these variables to being homogeneous. I set up eight hypotheses reflecting a distinct homogenous relation between TFP and the other variables. Each hypothesis is formulated as a restricted linear combination of certain variables, which corresponds to a steady state relation supported by economic theory – such as Arrow's theory on learning-by-investing, Romer's endogenous growth theory and the economies of scale argument .[10] Hence, testing H1 to H8 gives information of vital importance in identifying the

[7] For a more detailed explanation see Johansen (1996).

[8] In endogenous growth models, in contrast to neo-classical models, markets are assumed to be imperfectly rather than perfectly competitive: firstly, in order to create an incentive for firms to invest in research and development, firms must be able to maintain ownership of at least some of the value of the increased productivity gained through their investments, secondly, since technology to some degree is proprietary and since the support of research and development is feasible only if price exceeds production cost by some margin.

[9] A homogeneous relation between certain variables implies that their β-coefficients sum to zero. All hypotheses in this study are restricted so that TFP should be positive and all coefficients within a homogeneous relation should be negative in order to confirm the economic motivation for the hypothesis.

[10] For a more detailed explanation see Johansen (1996).

growth mechanisms reflected by the time series long-run properties. I should, however, be very clear about one thing: In a case where homogeneity between TFP and human capital in "R" cannot be rejected, it only points towards a consistent one-to-one relation between these variables over time, and does not reveal the causality between them. In order to identify which variable is dependent and which is exogenous I need to analyse the α coefficients for speed of adjustment. First I impose restrictions on just one of the vectors, leaving the second vector unrestricted. However, due to lack of space I only present the joint identification of both cointegration relation in this paper. The null-hypothesis is that a linear combination is stationary, which means that the stochastic trend is cancelled and a steady state relation is identified. I raise the usual critical level of significance of 0.05 to 0.1; accordingly p-values above 0.1 imply that the hypothesis of stationarity cannot be rejected. However, large p-values only confirm that the linear combination of variables is stationary. It is, therefore, important to interpret the coefficients' signs and size in order to determine whether the time series' behaviour reflects the growth mechanism presented in the hypothesis. When the variables are in logarithms, as in this study, the coefficients constitute elasticities.

(H1) Productivity growth through embodied technical progress and learning-by-investing

Changes in the capital stock are sometimes necessary to achieve technical progress. When technical improvements are embodied in the capital stock is referred to as embodied technical progress. The idea is that net or replacement investment increases the extent of embodied technical progress because the equipment available on the market embodies the latest technology. Learning-by-investing means that diminishing factor returns are offset because knowledge creation is a side product of investment. A firm that increases its physical capital learns simultaneously how to produce more efficiently (Arrow, 1962). This hypothesis assumes that embodied technical progress and learning-by-investing are both connected with machinery investments and go hand in hand. The hypothesis is tested through restrictions to only allow homogeneity between TFP and machinery investments, meaning that TFP will increase in the same proportion as machinery investments. The following linear combination is tested for stationarity:

$$\beta_1(Y\text{-}M) + \beta_2 D + \beta_3 R + \beta_4 E \sim I(0) \qquad (4)$$

(H2) Productivity growth through human capital accumulation in “D”

This hypothesis implies that specifically human capital in “D” generates productivity growth; hence the share of highly skilled employees in administration, organisation, and sales, of the total work force, is the most essential factor causing TFP growth. The hypothesis is tested through restrictions to only allow homogeneity between TFP and human capital in “D”. The following linear combination is tested for stationarity:

$$\beta_1(Y\text{-}D) + \beta_2 M + \beta_3 R + \beta_4 E \sim I(0) \qquad (5)$$

(H3) Productivity growth through human capital accumulation in “R”

This hypothesis implies that exclusively human capital in “R” generates productivity growth; hence, the share of highly skilled employees in research, engineering and product development, of the total work force, is the most important determinant of TFP growth. The hypothesis is tested through restrictions to only allow homogeneity between TFP, and “R”. The following linear combination is tested for stationarity:

$$\beta_1(Y\text{-}R) + \beta_2 M + \beta_3 D + \beta_4 E \sim I(0) \qquad (6)$$

(H4) Productivity growth through human capital accumulation in "D" and “R”

This hypothesis implies that human capital in both “D” and “R” is essential for growth in TFP. The motivation reads that highly skilled workers in both fields: administration, organisation and sales on the one hand and research, engineering and product development on the other are complementary and may only cause TFP growth together. The hypothesis is tested through restrictions to only allow homogeneity between TFP, "D" and "R". The following linear combination is tested for stationarity:

$$\beta_1(Y\text{-}D) + \beta_2(Y\text{-}R) + \beta_3 M + \beta_4 E \sim I(0) \qquad (7)$$

(H5) Productivity growth through embodied technical progress, learning-by-investing and human capital accumulation in "D"

This hypothesis implies that investments in both human capital and physical capital are essential for productivity growth. More than leading to embodied technical progress and learning-by-investing, machinery investments may call forth changes in the administration and/or the organisation, which also affect productivity. This hypothesis implies that human capital in "D" and machinery investment constitutes complements which only together are able to cause TFP growth. The hypothesis is tested through restrictions to only allow homogeneity between TFP, machinery investments and "D". The following linear combination is tested for stationarity:

$$\beta_1(Y\text{-}M) + \beta_2(Y\text{-}D) + \beta_3 R + \beta_4 E \sim I(0) \quad (8)$$

(H6) Productivity growth through embodied technical progress, learning-by-investing and human capital accumulation in "R"

This hypothesis implies that human capital in "R" research, engineering and product development constitutes a complement to machinery investments. Hence, human capital in “R” can only generate productivity growth if accompanied by machinery investments, and vice versa. The hypothesis is tested through restrictions to only allow homogeneity between TFP, machinery investments and "R". The following linear combination is tested for stationarity:

$$\beta_1(Y\text{-}M) + \beta_2(Y\text{-}R) + \beta_3 D + \beta_4 E \sim I(0) \quad (9)$$

(H7) Productivity growth through embodied technical progress, learning-by-investing and human capital accumulation in "D" and "R"

This hypothesis implies that human capital in "D" and "R" and machinery investments together constitute complements, which generate productivity together. The hypothesis is tested through restrictions to only allow homogeneity between TFP, machinery investments, "D" and "R". The following linear combination is tested for stationarity:

$$\beta_1(Y\text{-}M) + \beta_2(Y\text{-}D) + \beta_3(Y\text{-}R) + \beta_4 E \sim I(0) \quad (10)$$

(H8) Productivity growth through economies of scale

This hypothesis implies that increased exports generate economies of scale and affect capacity utilisation, both of which give rise to increased productivity: the former by means of lowering costs and the latter by higher efficiency. The hypothesis is tested through restriction to only allow homogeneity between TFP and export. The following linear combination is tested for stationarity:

$$\beta_1(Y\text{-}E) + \beta_2 M + \beta_3 D + \beta_4 R \sim I(0) \quad (11)$$

Joint identification of the two cointegration relations

In table 3 each pairs of cointegration relations suggested for each industry are jointly tested. By setting identifying restrictions on both cointegration relations simultaneously I can test whether they identify one cointegration relation each and hence are significantly different from each other. Identifying the cointegration relations jointly derives the definitive t-values for all β coefficients and for the α coefficients. As mentioned, the variables' role in the cointegration relations is expressed by the β coefficient, whereas the speed, with which variables are drawn back to the steady state relation, or drift further away from it after a shock in the system, is expressed by the α coefficient. For the moment I concentrate on the β coefficients, whereas the α coefficients are presented and further discussed in the following section. Empty boxes indicate excluded variables due to coefficients very close to zero having no power, meaning that the variables are not required for cancelling the common stochastic trend. The null-hypothesis is that the two cointegration relations are not significantly different; p-values above 0.10 reject the hypothesis. Since I have normalised on TFP, the β coefficient for TFP is always 1[11].

Table 3 Jointly identified cointegration relations in labour-intensive, capital-intensive and knowledge-intensive industries

Labour-intensive industry χ^2 *0.08, df 2, p-value 0.96*						
Hypothesis	β Y	B M	β D	β R	β E	β T
H1	1	-1	0.97	0.07	-0.13	0.01
H2	1	1.27	-1			-0.01
Capital-intensive industry χ^2 *1.16, df 2, p-value 0.56*						
Hypothesis	β Y	β M	β D	β R	β E	β T
H3	1	0.04		-1	0.24	0.01
H8	1		0.15	3.68	-1	-0.05
Knowledge-intensive industry χ^2 *0.47, df 2, p-value 0.79*						
Hypothesis	β Y	β M	β D	β R	β E	β T
H3	1	0.42	0.14	-1		-0.01
H5	1	-0.78	-0.22	1.84		0.02

Note: Y is TFP, M is machinery investments, D is human capital in administration, organisation and sales, R is human capital in research, engineering and product development, E is export, T is the trend, df is degrees of freedom

[11] To be able to interpret a cointegration relation as primarily connected with a particular variable, I may normalize the former on the variable of interest, in this case, TFP. In practice, normalization means setting a chosen variable *X* to unity and then dividing all variables' coefficients with the *X*-coefficient so that *X* becomes 1 (Juselius 2003). Hence, normalising on TFP implies that all variables are divided by the TFP coefficient so that TFP becomes 1, which facilitates the interpretation of the proportional relation between the variables.

The results of joint identification in table 3 show that *p*-values in all industries are far above 0.10 and thus strongly indicating that the two hypotheses suggested in each industry are significantly different from each other. Accordingly, I claim the first cointegration relation in labour-intensive industry is identified as H1 *Productivity growth through embodied technical progress and learning-by-investing*, whereas the second cointegration relation is identified as H2 *Productivity growth through human capital accumulation in "D"*. In capital-intensive industry I assert that H3 *Productivity growth through human capital accumulation in "R"* and H8 *Productivity growth through economies of scale* represent the two steady state relations. Finally, I state that the two cointegration relations in knowledge-intensive industry are identified as H3 *Productivity growth through human capital accumulation in "R"* and H5 *Productivity growth through embodied technical progress, learning-by-investing and human capital accumulation in "D"*.

Revealing the causality in the steady states

The most important feature of cointegrated variables is that their time paths are influenced by the extent of any deviation from the steady state relation or equilibrium. If the system is to return to the long-run steady state relation, the movements of at least some of the variables must respond to the effects of the disequilibrium i.e. deviation from the steady state relation. The long-run steady state relation constitutes an attractor set towards which endogenous variables are drawn back after a shock in the system. For example, endogenous growth theory identifies a long-run relationship between output growth and human capital, to find out whether such a relation exists empirically, I may test for homogeneity between output and human capital by restricting the cointegration properties in such a way. Provided that such a relation exists, I now imagine that a situation occurs in which the gap between output and human capital widens considerably such that human capital accumulation grow relatively faster than output. There are several ways to close the gap e.g: (*a*) an increase in output or a decrease in human capital accumulation; (*b*) an increase in the accumulation of human capital with a commensurately greater increase in output; or (*c*) a fall in human capital accumulation with a smaller fall in output. Without a full dynamic specification of the particular model, however, it is impossible to determine which of the possibilities will occur. What I do know is that the short-run dynamics must be influenced by deviations from the long-run relationship in order to re-establish the steady state relation. Given that output and human capital are cointegrated, the short-run dynamics of at least one of the two variables are influenced by the deviation from their steady state relation. Thus, in order to determine the behaviour of each variable, I need information on how output and human capital accumulation respond to stochastic shocks and to the previous period's deviation from the steady state relation, α coefficients contain exactly this information.[12] Analysing the α coefficients for speed of adjustment is useful for distinguishing between endogenous variables and variables which do not react to deviations in the steady state.[13] Variables showing no adjustments are in a way the 'causing elements', since they trigger off adjustments in the other variables included in the homogeneous relation. Given that the coefficients are significant, the larger the α coefficient the more dependent and, hence, more affected by changes in the steady state relation is the variable. Variables need not necessarily react to deviations in the steady state by adjusting back and re-establishing the steady state; they may also respond by drifting further away from the steady state. The latter behaviour, however, means stronger adjustment behaviour for other endogenous variables. When a variable's α and β coefficients have opposite signs, it means that the variable adjusts towards equilibrium at the speed of α. However, if the α and β coefficients show the same sign, the variable drifts further away from the steady state relation at the speed of α. If a variable adjusts to the steady state with a speed of 1, it adjusts fully to equilibrium after one time period, which in this study is one year. If a variable's speed of adjustment is less than 1, the variable does not fully adjust to equilibrium within one time period. Finally, if a variable's speed of adjustment is above 1, the variable 'over-adjusts' and passes through equilibrium to the other side. It is important to mention that since I are using log values, the behaviour of α coefficients is always related to a one unit change in the steady state. Hence, a large α coefficient does not necessarily mean that the cointegration relation has a large influence on the variable. Provided that the changes in the steady state are only small; the real effect on variables' speed of adjustment is still small although the α coefficient is large. The behaviour of α coefficients continues until the next shock hits the system and calls forth new reactions.

[12] See Juselius (1996; 1998a; 1998b; 2000; 2003) and Juselius and Toro (2005) for a methodical approach on money demand.

[13] Notice that variables with low or non-significant α coefficient are not necessarily the 'causing' factor, but the common stochastic trend is the 'disturbing phenomenon'.

Table 4 Speed of adjustment towards the two identified cointegration relations in each industry

	Labour-intensive		Capital-intensive		Knowledge-intensive	
	H1	H2	H3	H8	H3	H5
α Y	-0.44	-0.42	-0.68	-0.14	-0.47	-0.20
α M	1.29	0.66	1.10	0.21	0.50	0.66
α D			-0.60			-0.29
α R	-0.36			-0.21		-0.29
α E	0.26			0.11		

Note: *Y is TFP, M is machinery investments, D is human capital in administration, organisation and sales, R is human capital in research, engineering and product development, E is export*

Interpreting the α coefficients in labour-intensive industry

The first cointegration relation identified as *Productivity growth through embodied technical progress and learning-by-investing* provokes the following adjustment behaviour: TFP adjusts by -0.44 after a shock in the system and machinery investment shows an even faster speed of adjustment of 1.29 and is hence over adjusting. Since the steady state reflects homogeneity between TFP and machinery investments and both are adjusting, it is not possible to reveal any causality between them, the most probable reason being that they are both dependent on a third variable, e.g. demand, although demand itself adjusts by 0.26. Human capital in ”D” administration and organisation shows no adjustment whereas human capital in ”R” research, engineering and product development adjusts to the steady state relation with a speed of -0.36. The second cointegration relation is identified as H2 Productivity growth through human capital accumulation in “D”, towards which TFP adjusts at a speed of -0.42 after a shock in the system. Machinery investment moves further away from the steady state relation with a speed of 0.66 (since both the α coefficient and the β coefficient are positive). The second steady state reflects homogeneity between TFP and human capital in “D” administration, organisation and sales. Since TFP adjusts back to the steady state whereas human capital in “D” does not, it is strongly indicated that TFP is the dependent variable which is affected by human capital in “D”.

Interpreting the α coefficients in capital-intensive industry

H3 *Productivity growth through human capital accumulation in "R"* identifies the first cointegration relation, which is tested by homogeneity between TFP and human capital in "R" research, engineering and product development. TFP adjusts to the steady state relation with a speed of -0.68 after a shock in the system. Machinery investments move further away from the steady state with a speed of 1.10. Since human capital in "R" has no significant α coefficient, I can conclude that TFP is the dependent variable, which is influenced by human capital in "R". Furthermore, as "R" does not adjust to the steady state after a shock, I can exclude labour hoarding due to a recession as a possible interpretation. Although human capital in "D" administration, organisation and sales does not take part in the cointegration relation, it still reacts to deviations in the steady state by drifting further away with a speed of -0.60.[14] This possibly implies that human capital in organisation, administration and sales decreases in periods of falling demand and large investments in human capital in "R", which is supported by the fact that H4, implying complementarity between the two types of human capital, was rejected. The second cointegration relation is identified by H8 Productivity growth through economies of scale. The hypothesis implies homogeneity between TFP and export. However, in this case both variables react to deviations from the steady state by slowly adjusting back after a shock in the system; TFP with a speed of -0.14 and export with 0.11. Hence, there is no statistical indication that TFP is affected by demand and not the other way round. However, large-scale generally lowers production costs and increases TFP, hence, there is a strong theoretical argument for that TFP is affected by demand. Although machinery investment is not part of the steady state, it adjusts to disturbances with a speed of 0.21, which make sense since economies of scale call forth machinery investment. Human capital in "R" adjusts back with a speed of -0.21, indicating that increased scale brings about an increased share of less-skilled workers.

Interpreting the α coefficients in knowledge-intensive industry

H3 *Productivity growth through human capital accumulation in "R"* constitutes the first cointegration relation reflecting homogeneity between TFP and human capital in "R" research,

[14] Generally I know that variables drift further away from the steady state when the α and β coefficients have opposite signs. When β is zero, as in this case, I assume that negative α coefficients drift further away whereas positive α coefficients adjust to the steady state.

engineering and product development. TFP adjusts to the steady state relation with a speed of -0.47 after a shock in the system, whereas "R" shows no adjustment, indicating that human capital in "R" causes long-run growth in TFP. Machinery investment moves further away from the steady state with a speed of 0.50. The second cointegration relation is identified as H5 Productivity growth through embodied technical progress, learning-by-investing and human capital accumulation in "D", which reflects homogeneity between TFP machinery investments and human capital in "D" administration, organisation and sales. TFP adjusts back to the steady state with a speed of -0.20, machinery investments adjust back at 0.66, whereas human capital in "D" drifts further away with a speed of -0.29 (since it has the same sign as the β coefficient) after a shock in the steady state. Since all variables included in the homogeneous relation respond to deviations in the steady state, I cannot draw any conclusions about causality. Human capital in "R" adjusts back at -0.29 whereas export shows no adjustment. The adjustment of human capital in "R" indicates new hiring of less skilled workers, whereas the movement away from the steady state in human capital in "D" indicates that human capital in administration, organisation and marketing is increasing with current production. It seems likely that investments in machinery and enlarged hiring of lower skilled workers call forth more expertise in organisation and administration. It further indicates that learning-by-investing foremost concerns lower skilled workers rather than researchers, as with labour intensive industry.

For all three industries TFP is the only variable that reacts by adjusting back to both steady state relations after shocks in the system, whereas machinery investment is the variable most sensitive to deviations from the long-run equilibrium relation although it reacts by moving further away from the steady state in one of the cointegration relations.

Combining the quantitative and the qualitative measurements of output growth

In the beginning of this paper I argued that in order to analyse economic growth it is desirable to remove the quantitative effect of labour and capital growth on output growth, and then analyse how what is left , TFP, cointegrates with qualitative variables. The steady state relations are analysed by using the information given by the α and β coefficients. The β matrix represents cointegration vectors, which contain the cointegration parameters, that is, the parameters that indicate an equilibrium or long-run relation between the time series. The adjustment parameters α reflect the speed with which variables are drawn back to or drift further away from the equilibrium relation after a shock in the system. By using the β coefficients at their estimated values for each variable in the cointegration relation I construct a variable that reflects the 'hypothesis' tested for. Then I weight them by the α coefficients and construct a growth accounting framework which combines the quantitative contribution of labour and capital and the results of cointegration analysis measuring the 'qualitative' or 'technical' contribution to growth.

Table 5 Growth accounting framework with output as the dependent variable in labour-intensive, capital-intensive and knowledge-intensive industries

Industry	Capital stock	Working hours	CR1	CR2
Labour intensive	0.4	0.6	0.44	0.42
Capital intensive	0.6	0.4	0.68	0.14
Knowledge intensive	0.3	0.7	0.47	0.20

Note: Table 5 displays a growth accounting model for each industry showing the capital stock in fixed prices, the number of working hours and the two identified cointegration relations for each industry. The shares of factor payment are used as in the original equations measuring TFP from equation 2.

The adjustment coefficients of table 4 constitute the weights for the two cointegration relations. Using the information in table 5, the equation for output in labour-intensive industry according to a growth accounting procedure would be:

$$dlO = 0{,}4dlK + 0{,}6dlW + 0{,}44CR1 + 0{,}42CR2 \qquad (13)$$

Where *O* is output, *K* is the capital stock, *W* is working hours and *CR* represents the cointegration relations. In order to compare these estimates with real output, the two variables appear together in figures 15 to 17. The figures reveal that the new growth measurement replicates changes in output rather well. Hence, to combine qualitative and quantitative aspects of the causes of growth, by first removing the quantitative effect of labour and capital growth from output growth, and then analysing the interrelations of the residual i.e. TFP and qualitative variables for labour and capital and demand in a full equation system such as the cointegrated VAR model, and then combining the two measurements in a growth accounting framework, turns out to be an appropriate and successful method.

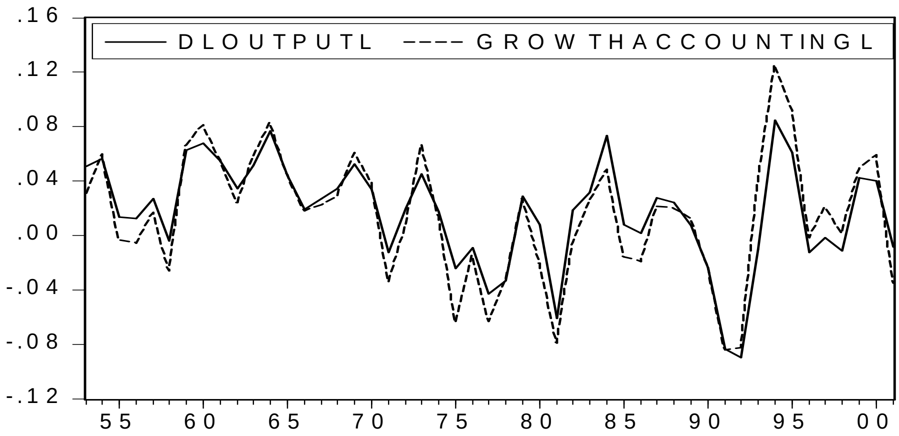

Figure 15 Output in first difference log scale and the new growth measurement, labour-intensive industry 1953-2001

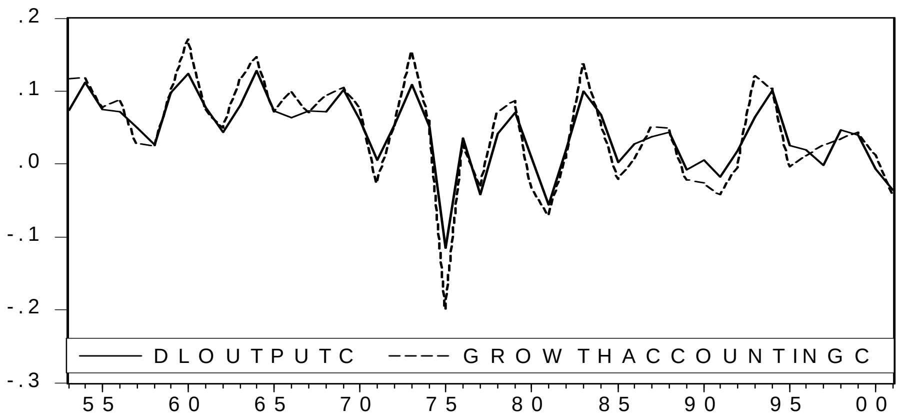

Figure 16 Output in first difference log scale and the new growth measurement, capital-intensive industry 1953-2001

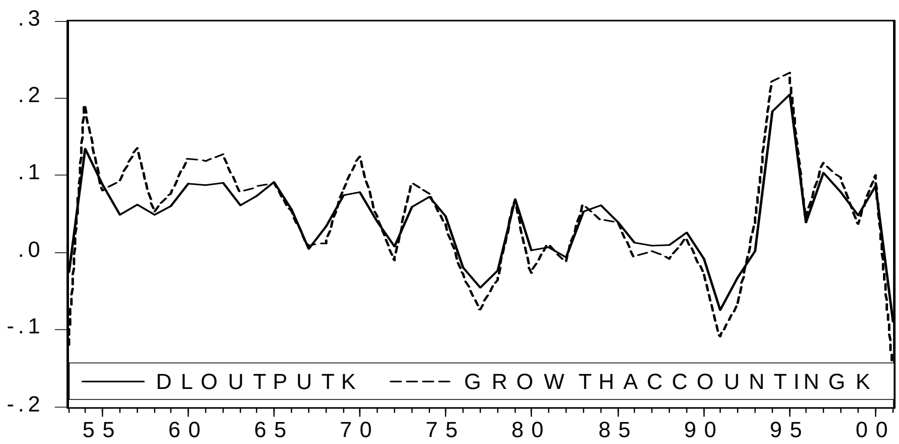

Figure 17 Output in first difference log scale and the new growth measurement, knowledge-intensive industry 1953-2001

Conclusion

This paper propose an original method to distinguish between different growth generating mechanisms and measure their separate effects on output growth. There are two innovative elements involved in this method: the first implies to disaggregate the data on Swedish manufacturing industries according to what sorts of goods industries produce and what technology they use. Data is split up in three industry-specific datasets: labor-intensive, capital-intensive and knowledge-intensive data sets. Total factor productivity 'TFP' is then calculated for each data set using a linear Cobb-Douglas growth accounting framework in order that effects originating from quantitative aspects of the production factors are separated from those deriving from changes in factor quality, technical change and/or economies of scale. Using a Cobb-Douglas production function under the presumption of perfect competition and constant returns to scale has been heavily criticised for leaving a rather complex residual 'TFP' in a black box beyond reach to analyse. However, by means of the second pioneering element; analysing how TFP interacts or 'cointegrates' with qualitative measurements of labour and capital plus demand in a full equation system using the cointegrated VAR model, it is possible to straighten out a great deal of the intricacy surrounding such 'raw' measurement of TFP by exploring the 'steady state' or 'cointegration relations' that TFP establishes with other variables in the long run.

The relation between human capital formation and productivity growth can be outlined in much greater detail when combining the two novelties 'disaggregation' and 'cointegration' in the analysis. Empirical results show that the 'sort of things' that actually do show up as 'technical change' in the raw TFP measurement, often referred to the 'Solow residual', to a large extent can be explained by various sorts of learning and knowledge accumulating mechanisms, and economies of scale. Moreover, there can be more than one type of knowledge accumulating mechanism affecting TFP growth in each type of industry, in the Swedish case I found two mechanisms affecting TFP growth in each industry. In labour-intensive industry the important factors for growth are embodied technological progress and learning-by-investing on the one hand, and human capital in administration, organisation and sales on the other. Capital-intensive industry has a large share of fixed capital; therefore, economies of scale is crucial for productivity growth. It is also shown that human capital in research, engineering and product development is necessary for improving the technologically advanced production process. In knowledge-intensive industry human capital in research, engineering and product development is important both for developing the production process and for the invention of new products or better functions in old products. Furthermore, it is shown that human capital in administration, organisation and sales is complementary to embodied technological progress and learning-by-investing; together they constitute the second source of productivity growth in knowledge-intensive industry.

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