MEASUREMENT OF TOTAL FACTOR INPUT, TECHNICAL CHANGE AND OUTPUT BY INDUSTRY IN THE FEDERAL REPUBLIC OF GERMANY 1958–1968

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This paper deals with some results of an extended investigation which was carried out by the German Institute of Economic Research, Berlin, and the Ifo-Institute, Munich, and financed by the Stiftung Volkswagenwerk. For 29 sectors of manufacturing Cobb-Douglas production functions have been calculated, based on quarterly figures 1958–1968 of value added, input of hours worked, input of utilized capital stock (net of scrappage), and of potential value added, potential labor input and total capital stock. The income distribution is used as production elasticities. For each of the 29 sectors 12 time series of quarterly indices of total factor input and technical change have been computed, using utilized data (variation 1-6) and capacity data (variation 7-12). Two different time series of α are used, taking quarterly interpolated data (variation 1, 3, 5, 7, 9, 11) and the geometric mean 1958–1968 (variation 2, 4, 6, 8, 10, 12). Moreover three different parameters of homogeneity are introduced, taking $r = 1$ (variation 1, 2, 7, 8), $r = 1.1$ (variation 3, 4, 9, 10) and $r = 1.25$ (variation 5, 6, 11, 12). Seven of the 29 sectors show a very high sensitivity of the rate of technical change due to the assumed r, six sectors a rather high sensitivity. Ten of the 29 sectors show a rather small sensitivity of technical change due to the assumed r, six sectors a very small or even negative sensitivity, i.e. an increasing r creates an increasing technical change. These results can be explained by taking account of the fact that total factor input in many branches increased very slowly or even decreased (labor input alone decreased in nearly all branches). A hierarchy of technical change has been calculated; this hierarchy is difficult to explain, because fast growing industries as well as industries with a small or a negative growth rate of output rank in both the leading and the last group of technical change. Very high rates of output result in high rates of technical change (chemicals, mineral oil refining, plastics manufactures), but some industries with a rather small growth of output (shipbuilding, fine ceramics, steel drawing, and cold rolling mills) show a high rate of technical change too.

INTRODUCTION

Most of the papers concerned with empirical results of growth theory have served to explain the growth of the total economy or of some broad sectors. Normally, yearly figures are used. In this paper I deal with some results of an experiment to compute quarterly figures of output, total factor input, and technical change of 29 sectors of manufacturing. Data cover the period I/1958 to IV/1968, i.e., 44 quarters. All data refer to the Federal Republic of Germany and include West-Berlin. The results given in the statistical annex are a small part of an extended investigation, which has been financed by the Stiftung Volkswagenwerk and carried out by the German Institute of Economic Research (DIW), Berlin, and the Ifo-Institute, Munich [1].

Empirical results of growth theory have shown (1) that numerical differences in the elasticity of substitution have only a very limited influence on the development of output and (2) that for practical purposes the Cobb-Douglas function in most cases explains the growth of output quite well [2]. Therefore I have used a CD-function with its well known restrictions.

The Production Function

We start from a CD-production function

(1) $$Y_t = A \cdot L_t^{ra} \cdot K_t^{rb}\, e^{\lambda t} \cdot \epsilon_t$$

with the usual denotation, where A is the scale parameter and ϵ_t the random variable. As we have no chance to separate $e^{\lambda t}$ from ϵ_t, we write

(2) $$e^{\lambda t} \cdot \epsilon_t = \lambda_t$$

assuming that the technical change λ_t includes the random ϵ_t with $E(\epsilon_t) = 1$.

In a more simplified form we write

(3) $$Y_t = L_t^{ra} \cdot K_t^{rb} \cdot \lambda_t.$$

Using income shares instead of production elasticities we write

(4) $$Y_t = L_t^{r\alpha} \cdot K_t^{r(1-\alpha)} \cdot \lambda_t.$$

Statistical experience has shown that if we fit statistical data to (4) the λ_t-time series is normally biased by cyclical fluctuations [3]. This is due to some misspecification of the statistical data: some of these (Y_t, L_t) are more or less influenced by cyclical fluctuations, whereas K_t normally is not influenced by short term fluctuations.

We introduce the subscripts u (utilized) and c (capacity) into (4) and write

(4a) $$Y_{ut} = L_{ut}^{r\alpha} \cdot K_{ut}^{r(1-\alpha)} \cdot \lambda_{ut}$$

(4b) $$Y_{ct} = L_{ct}^{r\alpha} \cdot K_{ct}^{r(1-\alpha)} \cdot \lambda_{ct}$$

where λ_{ut} will resemble the realized, λ_{ct} the planned technical change.

The Questions to the Model

The main purpose of this paper is to find an answer to the following questions:

(1) How great is the sensitivity of the results, if we compute total factor input and technical change using different variables and parameters for each sector?

(2) What happens to the hierarchy of technical change and its stability, if we use different variables and parameters for each sector?

Twelve Different Calculations For Each Sector

For each of the 29 sectors we computed 12 time series of total factor input and of technical change. We used utilized data (variation 1–6) and capacity data (variation 7–12). We changed r, assuming $r = 1$ in variation 1, 2, 7, 8, assuming $r = 1{\cdot}1$ in variation 3, 4, 9, 10, and finally $r = 1{\cdot}25$ in variation 5, 6, 11, 12. Moreover, we used two different time series of α, taking quarterly interpolated data (α_t) in variation 1, 3, 5, 7, 9, 11 and taking the geometric mean ($\bar{\alpha}$) of the original yearly α 1958–1968, which we derived from income statistics, in variation 2, 4, 6, 8, 10, 12. Thus the following computations were made:

Variation 1: Utilized Data, $r = 1$, $\alpha = \alpha_t$
Variation 2: Utilized Data, $r = 1$, $\alpha = \bar{\alpha}$
Variation 3: Utilized Data, $r = 1{\cdot}1$, $\alpha = \alpha_t$
Variation 4: Utilized Data, $r = 1{\cdot}1$, $\alpha = \bar{\alpha}$
Variation 5: Utilized Data, $r = 1{\cdot}25$, $\alpha = \alpha_t$
Variation 6: Utilized Data, $r = 1{\cdot}25$, $\alpha = \bar{\alpha}$
Variation 7: Capacity Data, $r = 1$, $\alpha = \alpha_t$
Variation 8: Capacity Data, $r = 1$, $\alpha = \bar{\alpha}$
Variation 9: Capacity Data, $r = 1{\cdot}1$, $\alpha = \alpha_t$
Variation 10: Capacity Data, $r = 1{\cdot}1$, $\alpha = \bar{\alpha}$
Variation 11: Capacity Data, $r = 1{\cdot}25$, $\alpha = \alpha_t$
Variation 12: Capacity Data, $r = 1{\cdot}25$, $\alpha = \bar{\alpha}$

Sources of Data Used

A detailed description of the data will be given in [1]. In this paper only some short remarks are possible:

Y_{ut} = Actual gross value added at 1962 prices, I/1958–IV/1968, 29 sectors, 4 sector groups, manufacturing. Data were computed by the DIW, combining the calculation of sectoral gross value added of 1962 with the official indices of sectoral production. The sectoral indices were weighted with their 1962 gross value added.

Y_{ct} = Calculation of DIW, following methods developed in the institute [4, 5, 6]. It is assumed that the Y_t/K_t ratio is a smooth function of time working under conditions of full utilization of capacity.

L_{ut} = Calculation of DIW. Official data on white-collar and blue-collar workers and hours worked by blue-collar workers are used. It is assumed that the average individual working time of all employed persons is in any quarter the same as the average individual working time of blue-collar workers. Based on this assumption we get quarterly data of total hours worked by all employed persons.

L_{ct} = Calculation of DIW, following the same methods as described above. This time the L_t/K_t ratio is smoothed over time.

K_{ct} = Capital stock, as shown in current capital-stock accounting of manufacturing of DIW. Methods of new calculation are published in [7]. Gross as well as net, i.e., allowing for scrappage or depreciation, capital stock figures are compiled by the institute. In this calculation we have used the gross capital stock data as K_{ct}. Some time ago there was some discussion of the question whether gross or net capital stock data should be used in macro-economic analysis (I remember a discussion with Simon Kuznets in Saltsjöbaden in 1965). This question was important for the German scholar for a rather long period after the war because the net-gross ratio of industrial assets increased very quickly in the fifties. That is why in this period growth rates of capital stock net of scrappage were substantially lower than those of capital stock net of depreciation in the Federal Republic of Germany. In most sectors of manufacturing the highest net-gross ratio was reached in 1962–1963. Since then the ratios more or less declined in practically all sectors. From 1958–1968 the ratio remained much more stable than in the fifties. Therefore the net and gross growth rates of K_{ct} were not as divergent in recent years as they had been in the fifties. I myself have never ceased to think that from the *capacity* point of view only the gross capital stock should be used. But for the period covered here it is not very important whether we take net or gross capital stock data.

K_{ut} = Actually used capital stock. No statistical information is available. To cover this gap we assume that the Y_{ut}/Y_{ct} ratio varies in the same way as the K_{ut}/K_{ct} ratio, that is we compute

$$K_{ut} = Y_{ut} \cdot Y_{ct}^{-1} \cdot K_{ct}. \tag{5}$$

α = Income of labour's share of gross value added. No official statistical data are available, at least not for each of our 29 sectors of manufacturing. Therefore we computed the ratio of capital-income to labour-income of stock companies and transferred this ratio to the other enterprises of each sector. All computations of α and $1-\alpha$ were made for 29 sectors, 4 groups of sectors, and for manufacturing as a whole. No quarterly data can be computed, as the computations of stock companies are based on the published balances, i.e., yearly figures.

The following disaggregation has been taken:

100 Manufacturing

200 Primary Metals and Basic Products
201 Building Materials
202 Iron and Steel
203 Iron and Steel Foundries
204 Steel Drawing and Cold Rolling Mills
205 Non-Ferrous Metals
206 Chemicals
207 Mineral Oil Refining
208 Rubber and Asbestos Manufactures
209 Sawmills and Timber Processing
210 Cellulose and Paper

300 Engineering Industries
301 Constructional Steel
302 Machinery
303 Vehicles
304 Shipbuilding

305 Electrical Engineering and Electronics
306 Precision Engineering and Optics
307 Steel Forging, Hardware, Metal Goods

400 Consumers' Products
401 Fine Ceramics
402 Glass
403 Timber Manufactures
404 Paper and Board Manufactures
405 Printing and Duplicating
406 Plastics Manufactures
407 Leather
408 Textiles
409 Clothing

500 Food, Beverages and Tobacco
501 Edible Oils and Margarine
502 Sugar
503 Brewing and Malting

Sensitivity of Total Factor Input Data

The indices of computed total factor input are given in the statistical annex; quarterly and yearly data and growth rates are shown.

It is impossible to go into details of our results. I am restricting my remarks to the comparison of the 12 computations of 1968 total factor input (1958 = 100) and will mainly deal with the capacity data which I call "planned total factor input".

Out of our 29 sectors 7 sectors show a very high sensitivity of the rate of growth of total factor input to the assumed r (= 1·0 or 1·25):

Plastic manufactures
Vehicles
Brewing and malting
Mineral oil refining
Chemicals
Paper and board manufactures
Building materials

The next group with a still rather high sensitivity of total factor input to the assumed r consists of the following sectors:

Glass
Rubber and asbestos manufactures
Electrotechnical engineering and electronics
Printing and duplicating
Clothing
Machinery.

The third group with a medium to small sensitivity of 1968 total factor input data consists of 10 sectors:

Iron and steel
Non-ferrous metals
Steel forging, hardware, metal goods
Sugar
Steel drawing and cold rolling mills
Cellulose and paper
Precision engineering and optics
Timber manufactures
Sawmills
Constructional steel.

The last group consists of 6 sectors, which show no or a *negative* sensitivity of results as r increases:

Edible oils	Iron and steel foundries
Fine ceramics	Leather
Textiles	Shipbuilding.

How can these results be explained? There seems to be some connection between the rate of growth of output of the sectors and their sensitivity of computed total factor inputs to an increasing r. This looks quite reasonable, if we consider the following facts. If we combine an increasing input both of labour and of capital and weight them with different r's, the difference between the total factor input ($r = 1{\cdot}25$) and ($r = 1{\cdot}0$) must be higher than if we combine a decreasing labour input with an increasing capital input and increase the assumed r's. If we weight a decreasing input of labour with an increasing r, the decrease of the labour component is amplified. Whether the total factor input in such a case decreases or increases depends upon whether the negative labour component ($L_{ct}{}^{r\alpha}$) is stronger than the positive capital component ($K_{ct}{}^{r(1-\alpha)}$) or not.

In the Federal Republic of Germany from I/58 to IV/68 the labour component of total factor input due to the reduction of individual working time decreased in 19 of 29 sectors.

From the groups of sectors mentioned before only one industry of the first group shows a negative labour component (building materials). From the second group, two sectors have a negative labour component (glass, clothing). All sectors belonging to the third and fourth group are distinguished by a negative labour component.

We may draw the following conclusion from these results. The computation of total factor input of most sectors of manufacturing in the Federal Republic of Germany in the later fifties and sixties is much less influenced by the assumption of a changing r than it had been influenced in the early fifties, when both labour and capital components were growing rather quickly and an increasing r amplified both components.

Sensitivity of Technical Change Data

If we compute technical change data using different r's ($1{\cdot}0$, $1{\cdot}1$, $1{\cdot}25$) and rank the sectors by their sensitivity of results, we get the inverse picture as given before. For instance the group of 6 sectors with no or a negative sensitivity of total factor input data show no or a positive sensitivity of technical change data if we assume an increasing r. On the other hand all the sectors with a fast growth of output like plastics manufactures and so on show a high negative sensitivity of technical change data if we assume an increasing r.

Some Remarks on a Hierarchy of Technical Change in the Federal Republic of Germany

If we rank the industries by their rate of growth of technical change 1958–1968, we obtain something close to a hierarchy of technical change in the Federal Republic of Germany.

It would seem quite reasonable that sectors with a high rate of growth of output reach a high rate of growth of technical change and vice-versa. But reality is more complicated (table 2). From the leading group of 10 sectors only three show a high rate of growth of production potential and they are the leading sectors in the hierarchy of technical change. But the following seven sectors did not reach the average rate of growth of production potential of manufacturing. Moreover some of these sectors belong to those which are distinguished by a very low rate of growth of output.

Also the second group of 10 sectors looks very unhomogeneous. It contains such industries as electrotechnical engineering (rate of growth of production potential +6·7 %) and iron and steel foundries (+0·1 %).

The third group of 9 sectors contains two branches with rather high growth rates of production potential (brewing and malting, vehicles). Nevertheless, these sectors are the last industries within the hierarchy of technical change!

I am unable to explain these results of our computations. In some cases, official index figures of production are suspect. In machinery and vehicles, production seems to be underestimated. In other cases a substantial shift of production within the sectors took place (e.g., brewing and malting: shifting to bottled beer). In such cases production and technical change may be underestimated, that is the hierarchy might be biased in some way. But the whole picture seems to show the following. Those industries which feel themselves to be in a dangerous position or which are threatened by heavy competition (e.g., shipbuilding, textiles, fine ceramics in the Federal Republic of Germany) or which are subject to substitution from other industries (e.g., leather in the Federal Republic of Germany) are willing and able to endure a high rate of technical change. For them technical change is the most important weapon to solve their problems. As has been demonstrated by textiles, cellulose and paper, and, just recently, shipbuilding in the Federal Republic of Germany, it is entirely possible to restore the viability of those industries which some years ago seemed to be sentenced to agony or even death.

Stability of the Hierarchy of Technical Change

In order to test the stability of the sectoral hierarchy of technical change we computed the ranks of the 29 sectors. We limited our computations to capacity data, using the geometric mean of α and taking $r = 1{\cdot}0$ or $1{\cdot}25$ respectively.

Fifteen sectors show no substantial change of rank in the hierarchy of technical change, whether we use $r = 1{\cdot}0$ or $1{\cdot}24$ (difference +1 to −1 rank):

Chemicals
Steel forging, hardware
Timber manufactures
Textiles
Mineral oil refining
Clothing
Steel drawing and cold rolling mills
Rubber and asbestos manufactures
Sawmills and timber processing
Cellulose and paper
Machinery
Vehicles
Printing and duplicating
Sugar
Brewing and malting.

Seven sectors show a positive sensitivity (+5 to +2 ranks):

Shipbuilding	Edible oils and margarine
Leather	Constructional steel
Iron and steel foundries	Fine ceramics.
Iron and steel	

Seven sectors show a negative sensitivity (−2 to −4 ranks):

Building materials	Paper and board manufactures
Non-ferrous metals	Plastic manufactures
Precision engineering and optics	Electronical engineering and electronics.
Glass	

The *stability* of ranking within the hierarchy of technical change is nearly uncorrelated with the *rank* which is held within the hierarchy. Within the first group of 15 sectors mentioned before (high stability of ranking with increasing r) are chemicals and mineral refining (the leading sectors in the hierarchy of technical change) as well as machinery and vehicles (vehicles are the last sector within the hierarchy of technical change).

Some Preliminary Conclusions

In this paper I have confined the inputs to labour and capital. It is true we have just now finished four input-output tables with 56 production sectors, but the data are limited to the years 1954, 1958, 1962, and 1966. In principle such tables are suited as a basis for future research of sectoral output measurement. Input–output tables normally contain current price information. They must be converted to a fixed price level. Using this method we hope to be able sooner or later to include the purchases from other industries as a third production factor, but at the moment independent information about the first quadrant of the input–output tables is insufficient to do so.

Therefore I tried to calculate value added data at 1962 prices and I extended this calculation to quarterly figures. A desired improvement of the method used for measuring value added requires more independent statistical information than we have at the moment. My calculation cannot give more than a rough and preliminary picture of reality.

The measurement of total factor input requires a model and cannot be made in an unequivocal way. The measurement of capital is complicated. Independent information about the useful lifetime of assets is lacking. The model assumes a survival function, which might describe reality inadequately. Moreover, there arises the question whether the capital stock data should be measured gross or net, that is net of scrappage or net of depreciation. It has been shown that in the Federal Republic of Germany, at least for the time included in this experiment, the gross-net question of capital stock is not very important (it was very important in the fifties, when the net-gross ratio increased quickly).

The question as to which parameters should be used to combine labour and capital fills a library. The CES function unfortunately is of limited usefulness for sectoral measurement. But the influence of a change of the σ-values ($= 1$ in the CD function) is limited too. Therefore I decided to take CD functions for all sectors and I calculated the income distribution to get the production elasticities.

This function of course is very simple. To test its usefulness, I decided to calculate the sensitivity of our model using different parameters of homogeneity (r) and different production elasticities (α_t or $\bar{\alpha}$). The results in some cases are puzzling. In a good number of sectors the assumption of an increasing r leads to a decreasing total input of labour and capital, because the labour component in many of the 29 sectors of manufacturing in the Federal Republic of Germany decreased in the time period taken into account here.

The attempt was made to calculate a hierarchy of technical change. The results are difficult to explain. Very large rates of growth of output seem to be accompanied by large rates of growth of technical change, but in some cases the inverse is true. On the other hand, some branches which seemed to be sentenced to agony or death were able to keep up high rates of growth of technical change. A theory of sectoral technical change is needed which is able to explain better the rank of the different branches within the hierarchy.

The sensitivity of the place which is held by the different branches in this hierarchy is rather limited, if the utilized r's are changed. In most cases the rank held is rather stable.

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TABLE 1

INDICES OF THE TOTAL FACTOR INPUT 1968 IN THE MANUFACTURING INDUSTRIES OF THE FEDERAL REPUBLIC OF GERMANY

Capacity data 1958 = 100

Sector	$r = 1{\cdot}0$		$r = 1{\cdot}1$		$r = 1{\cdot}25$	
	α_t	$\bar{\alpha}$	α_t	$\bar{\alpha}$	α_t	$\bar{\alpha}$
Manufacturing	124·9	126·2	127·7	129·2	132·0	133·8
Primary Metals and Basic Products	130·2	128·7	133·6	132·0	139·0	137·1
Building Materials	145·7	140·9	151·3	145·9	160·1	153·6
Iron and Steel	117·0	115·4	118·8	117·1	121·7	119·7
Iron and Steel Foundries	84·0	87·8	82·5	86·7	80·4	85·0
Steel Drawing and Cold Rolling Mills	106·9	107·0	107·6	107·7	108·6	108·8
Non-Ferrous Metals	120·9	121·4	123·2	123·8	126·7	127·5
Chemicals	147·8	146·7	153·6	152·5	162·9	161·5
Mineral Oil Refining	175·5	168·6	185·7	177·6	202·0	192·1
Rubber and Asbestos Manufactures	134·8	139·5	138·8	144·2	145·2	151·5
Sawmills and Timber Processing	105·9	102·8	106·5	103·0	107·4	103·5
Cellulose and Paper	109·6	109·7	110·6	110·7	112·1	112·3
Engineering Industries	128·6	131·8	131·8	135·5	136·9	141·3
Constructional Steel	98·9	105·5	98·8	106·1	98·7	106·9
Machinery	123·3	125·0	125·9	127·9	129·9	132·2
Vehicles	184·2	191·7	195·8	204·6	214·6	225·6
Shipbuilding	72·8	74·8	70·6	72·6	67·3	69·5
Electrical Engineering and Electronics	148·7	136·1	154·7	140·4	164·2	147·0
Precision Engineering and Optics	107·6	106·6	108·4	107·3	109·6	108·3
Steel Forging, Hardware, Metal Goods	114·3	115·6	115·8	117·3	118·2	119·9
Consumers' Products	109·7	111·7	110·8	112·9	112·3	114·8
Fine Ceramics	85·9	89·5	84·6	88·5	82·7	87·0
Glass	137·4	138·0	141·8	142·5	148·8	149·6
Timber Manufactures	102·2	103·7	102·4	104·0	102·8	104·6
Paper and Board Manufactures	153·0	153·7	159·7	160·5	170·2	171·2
Printing and Duplicating	123·0	125·6	125·5	128·5	129·5	133·0
Plastics Manufactures	248·0	243·4	271·6	266·1	311·2	304·1
Leather	80·7	83·1	79·0	81·6	76·5	79·4
Textiles	90·1	91·4	89·1	90·6	87·7	89·4
Clothing	121·3	121·7	123·7	124·1	127·3	127·8
Food, Beverages and Tobacco	131·1	132·9	134·7	136·7	140·3	142·7
Edible Oils and Margarine	98·1	98·4	97·9	98·2	97·6	98·0
Sugar	109·3	112·5	110·2	113·8	111·7	115·9
Brewing and Malting	167·2	172·2	176·1	181·8	190·2	197·3

TABLE 2

HIERARCHY OF TECHNICAL CHANGE OF MANUFACTURING INDUSTRIES IN THE FRG

Average Growth Rates 1958–1968

	Industry	Planned Technical Change[a]	Production Potential
	(a) Sectors		
1	Mineral Oil Refining	8,5	15,1
2	Chemicals	5,9	10,4
3	Plastics Manufactures	5,4	16,5
4	Timber Manufactures	4,7	5,2
5	Textiles	4,3	3,3
6	Shipbuilding	3,9	0,9
7	Steel Drawing and Cold Rolling Mills	3,8	4,6
8	Fine Ceramics	3,8	2,5
9	Precision Engineering and Optics	3,7	4,5
10	Sawmills and Timber Processing	3,4	3,7
11	Leather	3,1	0,9
12	Cellulose and Paper	3,0	4,1
13	Printing and Duplicating	2,8	5,6
14	Electrical Engineering and Electronics	2,8	6,7
15	Steel Forging, Hardware and Metal Goods	2,6	4,2
16	Non-Ferrous Metals	2,5	4,7
17	Iron and Steel Foundries	2,3	0,1
18	Glass	2,2	5,9
19	Clothing	2,1	4,3
20	Rubber and Asbestos Manufactures	1,7	5,1
21	Paper and Board Manufactures	1,6	6,6
22	Constructional Steel	1,3	1,2
23	Iron and Steel	1,2	2,9
24	Building Materials	1,0	5,1
25	Machinery	0,9	3,3
26	Sugar	0,2	1,5
27	Edible Oils and Margarine	−0,1	−0,3
28	Brewing and Malting	−0,5	5,4
29	Vehicles	−0,6	6,6
	(b) Groups		
1	Consumers' Products	3,6	4,9
2	Primary Metals and Basic Products	3,5	6,4
3	Manufacturing	2,8	5,3
4	Engineering Industries	1,9	4,8
5	Food, Beverages and Tobacco	1,7	4,9

[a] Averaged from six indices computed by different methods.