Estimation & Decomposition of Productivity Change in Food, Beverages & Tobacco Products Using Frontier Approaches

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The study estimates and decomposes the sources of productivity change of the 4-digit food, beverages and tobacco industries in India during 1998/99 – 2017/18, pre-economic crises period (1998-99 to 2007-08) and post-economic crises period (2008-09 to 2017-18) using Data Envelop Analysis (DEA) and Stochastic Frontier Approach (SFA). The study decomposes the sources of TFPG into technological change (TP), technical efficiency change (TEC) and economic scale change (SC). It was found that the growth rates of TFP in most of the 4-digit industries of food, beverages and tobacco products in India have declined during the post financial meltdown period (2008/09 – 2017/18) and the decline in TFPG of them during the period is mainly accounted for by the decline in technological progress (TP).

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Introduction

Together with the tobacco industry, the Food and beverages sector is a large source of manufacturing output and employment. However, productivity growth of this sector remains very low as it faces a conflux of challenges such as climate change, changes in food supply and demand and imbalances in the governance of food production systems, food price volatility, and food security (Roy & Das, 2018). The objective of this paper is to illustrate how we can use frontier estimation methods to obtain estimates of total factor productivity growth (TFPG), and decompose it into various sources such as technological change (TP), technical efficiency change (TEC) and economic scale change (SC) of the 4-digit manufacturing industries of food, beverages and tobacco products in India during the period from 1998-99 to 2017-18, and during two sub-periods of 1998-99 to 2007-08 and 2008-09 to 2017-18- the pre-and post-financial melt-down periods (the years are also said to be pre-and post-financial break-down periods respectively). The 4-digit manufacturing industries of food, beverages and tobacco products considered in our study are: production, processing and preserving of meat and meat products [1010(1511)], processing and preserving of fish and fish products [1020(1512)], processing and preserving of fruit and vegetables [1030(1513)], vegetable and animal oils and fats [1040(1514)], dairy products[1050(1520)], grain mill products [1061(1531)], starches and starch products [1062(1532)], bakery products [1071(1541)], sugar [1072(1542)], cocoa, chocolate and sugar confectionery [1073(1543)], macaroni, noodles, couscous and similar farinaceous products [1074(1544)], other food products n.e.c.[1079(1549)], prepared animal feeds [1080(1533)], distilling, rectifying and blending of spirits; ethyl alcohol production from fermented materials [1101(1551)], wines [1102(1552)], malt liquors and malt [1103(1553)], soft drinks; production of mineral waters [1104 (1554)] and tobacco products [1200 (1600)].

Literature Review

Fare, Grosskopf, Norris and Zhang (1994) took the Malmquist index of TFP change, defined in Caves, Christensen and Diewert (1982), and described how we can decompose the Malmquist TFP change measures into various components, including technological change (TP) and technical efficiency change (TEC). They also showed how these measures could be calculated using distances measured relative to DEA frontiers. Ray (1997) used a non-parametric method of DEA to measure Malmquist productivity index for manufacturing sector in the different states in India for the period 1969-84. The measured Malmquist productivity index is decomposed to separate the contribution of technological change (TP), change in technical efficiency (TEC) and change in scale efficiency (SC). The analysis depicted that in most of the states productivity decline is due to technological regress. Ray (2002) examined the impact of reforms on efficiency and productivity in the manufacturing sector of Indian states for the period 1986–87 through 1995–96. Using data envelopment analysis, the study noted an improvement in TFPG in most of the states during the reforms period (1991–92 to 1995–96). The study showed that improvement in technical efficiency as well as faster technological progress had contributed to the observed acceleration in productivity growth. Mahadevan (2001, 2002) used both stochastic frontier approach and DEA separately to calculate the TFPG of Malaysian manufacturing industries during 1981 - 1996. He used the same data set to make comparison between the two approaches and concluded that both methods demonstrated a decline of TFPG after 1990, increasing contribution of technological progress (TP) and declining contribution of technical efficiency change (TEC). Kumar (2004) decomposed total factor productivity growth (TFPG) in industrial manufacturing in 15 major Indian states for the period 1982-83 to 2000-01 using non-parametric linear programming methods. He decomposed TFPG into efficiency and technological changes and level of biasness in technological change. The resulting information is used to examine whether the post-reform period shows any improvement in productivity and efficiency in comparison to the pre-reform one. Joshi and Singh (2010) measured the TFPG and identifies its sources through applying a non-parametric DEA-based MPI (Malmquist productivity index) approach. The productivity growth was decomposed into technical efficiency change (TEC) and technological change (TP). Heshmati and Kumbhakar (2010) in their study used panel data on Chinese provinces and identified a number of key technology shifters and their effect on technological change (TP) and TFPG. Using input-output data from the Annual Survey of Industries for the period 1970-71 through 2007-08, Deb and Ray (2014) compares the pre-and post-reform performances of Indian manufacturing in terms of total factor productivity growth (TFPG). They used Data Envelopment Analysis to construct a Biennial Malmquist Index of total factor productivity for individual states. Results showed that at the all-India level, total factor productivity growth rate in manufacturing is higher during the post-reform period. Although the majority of states experienced accelerated productivity growth, some states did experience decline in productivity after the reforms. Both before and after the reforms technological progress (TP) was the most important component of productivity growth in Indian manufacturing.

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On the other hand, stochastic frontier model was pioneered by Aigner, Lovell and Schmidt (1977) and Meeusen and van den Broeck (1977). Nishimizu and Page (1982) was the first to propose de-composition of TFP into efficiency changes and technological changes using stochastic frontier approach. He used a deterministic translog production frontier to decompose productivity change in Yugoslavia into two aforementioned components. Bauer (1990) estimated a translog cost frontier using data on the US airline industry to decompose TFP growth into efficiency, technical progress, and scale components. Kaliranjan et al (1996) used stochastic frontier approach to decompose the sources of total factor productivity (TFP) growth into technological progress and changes in technical efficiency within the framework of the varying coefficients frontier production function using the Chinese provincial-level agricultural data covering the period 1970–87. By applying a flexible stochastic translog production function, Kumbhakar and Lovell (2000), Kim and Han (2001) and Sharma et al (2007) decompose TFP growth into four components: technological progress, changes in technical efficiency, changes in allocative efficiency and scale changes. Kim and

Han (2001) applied a stochastic frontier production model to Korean manufacturing industries to decompose the sources of total productivity (TFP) growth into technological progress (TP), changes in technical efficiency (TEC), and changes in allocative efficiency (AEC), and scale changes (SC). Empirical results based on data of Korean manufacturing industries from 1980 to 1994 showed that productivity growth was mainly driven by technological progress, that changes in technical efficiency had a significant positive effect, and that allocative efficiency had a negative effect. They suggested that specific guidelines are required to promote productivity in each industry, and provided additional insights into understanding the recent debate about TFP growth in Korean manufacturing. Using the stochastic frontier production function and the decomposition method of total factor productivity made by Kunbhakar and Lovell (2000), Liu and Huang (2009) studied the total factor productivity of China's steel industry during 1981-2003. They found: capital and TFP play more important roles for output growth while the contribution of labor input is negative. Of all the factors for the growth of TFP, scale economy contributes the most, followed by allocation efficiency of resources. Though technical efficiency has been keeping pace with TFP, it contributes little to TFP growth and thus the improvement of technical efficiency is the key element for improving the efficiency of China's steel industry. Roy, Das and Pal (2017) decomposed the sources of TFPG of the thirteen 2-digit manufacturing industries as well as total manufacturing industry in West Bengal into technological progress (TP), changes in technical efficiency (TEC), economic scale effect (SC) and allocation efficiency effect (AEC) during the period from 1981-82 to 2010-11, during the pre-reform period (1981-82 to 1990- 91) and post-reform period (1991-92 to 2010-11) by using a stochastic frontier approach. According to their estimated results TFPG of almost all the 2-digit manufacturing industries in West Bengal have declined during the post-reform period which is mainly accounted for by the decline in technological progress (TP) of the same during this period. The change in allocation efficiency component, however, found that resource allocation in almost all the 2-digit industries in West Bengal has improved during the post-reform period. Njuki, Bravo-Ureta and O'Donnell (2018) estimated a stochastic production frontier model using U.S. state-level agricultural data incorporating growing season temperature and precipitation, and intra-annual standard deviations of temperature and precipitation for the period 1960–2004. They used the estimated parameters of the model to compute a TFP index that has good axiomatic properties. They then decomposed TFP growth in each U.S. state into weather effects, technological progress, technical efficiency, and scale-mix efficiency changes. Roy & Das (2018) applied stochastic frontier approach to decompose the sources of total factor productivity growth (TFPG) of the manufacturing industries of food, beverages and tobacco products in India into technological progress (TP), changes in technical efficiency (TEC), economic scale effect

Technological progress (TP) and allocative efficiency effect (AEC) are the major contributors to TFPG of the 3-Digit manufacturing industries of food, beverages and tobacco products in India during 1981-82 to 2010-11.

(SC) and allocative efficiency effect (AEC) during the period from 1981-82 to 2010-11 and during the pre- and post-reform period (1981-82 to 1990-91 and 1991-92 to 2010-11) at the 3-Digit level of disaggregation of industries by NIC'04 and NIC'98. According to their results, technological progress (TP) and allocative efficiency effect (AEC) are the major contributors to TFPG of the 3-Digit manufacturing industries of food, beverages and tobacco products in India during 1981-82 to 2010-11.

The Malmquist TFP Index

The Malmquist TFP index measures the TFP change between two data points by calculating the ratio of the distances of each data point relative to a common technology. If the period 't' technology is used as the reference technology, the Malmquist (output-oriented) TFP change index between period 's' (the base period) and period 't' can be written as

$$m_0^t(q_s,x_s,q_t,x_t)=d_0^t(q_t,x_t)/d_0^t(q_s,x_s) \ldots\ldots. (1)$$

Alternatively, if the period's reference technology is used it is defined as

$$m_0^s(q_s,x_s,q_t,x_t)=d_0^s(q_t,x_t)/d_0^s(q_s,x_s) \ldots\ldots..(2)$$

Note that in the above equations the notation $d_0^s(q_t,x_t)$ represents the distance from the period 't' observation to the period 's' technology, and all other notations have been previously defined. A value of m_0 greater than one indicates positive TFP growth from period's' to period't' while a value less than one indicates a TFP decline.

As noted by Fare, Grosskopf and Roos (1998), these two (period's' and period't') indices are only equivalent if the technology is Hicks output neutral, that is, if the output distance functions are represented as $d_0^t(q_t,x_t)=A(t)d_0(q_t,x_t)$, for all 't'. To avoid the necessity to either impose this restriction or to arbitrarily choose one of the two technologies, the Malmquist TFP index is often defined as the geometric mean of these two indices, in the spirit of Fisher (1922) and Caves, Christensen and Diewert (1982). That is,

$$m_0(q_s,x_s,q_t,x_t)=[d_0^s(q_t,x_t)\, d_0^s(q_s,x_s)*\, d_0^t(q_t,x_t)\, d_0^t(q_s,x_s)]^{1/2} \ldots\ldots.(3)$$

The distance functions in this productivity index can be rearranged to show that it is equivalent to the product of a technical efficiency change index and an index of technological change.

$$m_0(q_s,x_s,q_t,x_t)= d_0^s(q_t,x_t)/\, d_0^s(q_s,x_s)\ [d_0^s(q_t,x_t)/\, d_0^t(q_t,x_t)*\, d_0^s(q_s,x_s)\, d_0^t(q_s,x_s)]^{1/2} \ldots\ldots\ldots..(4)$$

The ratio outside the square brackets in the equation (4) measures the change in the output-oriented measure of

Farrell technical efficiency change between periods 's' and 't'. That is, the efficiency change index is equivalent to the ratio of the Farrell technical efficiency in period't' to the Farrell technical efficiency in period's'. The remaining part of the index in equation (4) is a measure of technological change. It is the geometric mean of the shift in technology between the two periods, calculated at x_t and also at x_s. Thus, the two terms in equation (4) are:

Technical efficiency change= $d_0^t(q_t,x_t)/ d_0^s(q_s,x_s)$……..………(5)

Technological change= $[d_0^s(q_t,x_t)\ d_0^t(q_t,x_t)^*\ d_0^s(q_s,x_s)\ d_0^t(q_s,x_s)]^{1/2}$…(6)

Fare et al (1994) suggested that technical efficiency change in equation (5) could be decomposed into scale efficiency and pure technical efficiency components. This could be done only when the distance functions in the above equations are estimated considering a CRS (constant returns to scale) technology. This Fare et al (1994) decomposition involving scale efficiency has been widely used. The decomposition procedure involves taking the technical efficiency change measure in equation (5) which we now need to assume involves the ratio of the two CRS distance functions and decomposing it into a pure efficiency change component measured relative to the true VRS (varied returns to scale) frontier.

Pure efficiency change= $d_{ov}^t(q_t,x_t)$ / $d_{ov}^s(q_s,x_s)$………………………………(7)

and the scale efficiency change=$[d_{ov}^t(q_t,x_t)/ d_{ov}^t(q_t,x_t)^*\ d_{ov}^s(q_s,x_s)/ d_{ov}^s(q_s,x_s)^*\ d_{ov}^t(q_t,x_t)/ d_{ov}^t(q_t,x_t)^*\ d_{ov}^s(q_s,x_s)/ d_{ov}^s(q_s,x_s)]^{1/2}$……(8)

The scale efficiency change component in equation (8) is actually the geometric mean of two scale efficiency change measures. The first one is relative to the period 't' technology and the second one is relative to the period's' technology. Note that the extra subscripts, 'v' and 'c', relate to the VRS and CRS technologies respectively. Also note that if this extra decomposition is used, the distance functions in equations (1) to (6) would all need to be relative to a CRS technology, and hence have an extra c-subscript added.

But the above-suggested method of introducing a scale efficiency change component in the Malmquist TFP index decomposition has been the source of considerable debate in recent years. The main point of criticism is essentially that if there is scale efficiency change then this implies that the true production technology must be VRS. However, the Fare et al (1994) decomposition reports a technological change measure (equation 6) that reflects the movement along a CRS frontier and not the VRS frontier.

Calculation Using DEA Frontiers

There are a number of different methods that could be used to estimate a production technology and, hence, measure the distance functions that are used in the construction of the Malmquist TFP index. To date, the most popular method has been the DEA-like linear programming methods suggested by Fare et al (1994), which we discuss here. The alternative approach is the use of stochastic frontier methods (Aigner, Lovell& Schmidt, 1977; Meeusen & Van den Broeck, 1977), which are described later.

Following Fare et al (1994), and given that suitable panel data are available, we can calculate the distance measures (equation 3) using DEA-like linear programs. For the i-th industry, we must calculate four distance functions to measure the TFP change between two periods. This requires the solving of four linear programming (LP) problems. As noted earlier, Fare et al. (1994) utilize constant returns to scale (CRS) technology in their TFP calculations. This ensures that resulting TFP change measures satisfy the fundamental property that if all inputs are multiplied by the (positive) scalar 'δ' and all outputs are multiplied by the (non-negative) scalar 'α', then the resulting TFP change index will equal α/δ. The required LPs are:

$$[d_0^t(q_t,x_t)]^{-1}=\max_{\phi,\lambda}\phi$$
$$\text{st } -\phi q_{it}+Q_t\lambda\geq 0,$$
$$x_{it}-X_t\lambda\geq 0,$$
$$\lambda\geq 0, \quad (9)$$

$$[d_0^t(q_s,x_s)]^{-1}=\max_{\phi,\lambda}\phi,$$
$$\text{st } -\phi q_{is}+Q_s\lambda\geq 0,$$
$$x_{is}-X_s\lambda\geq 0,$$
$$\lambda\geq 0, \quad (10)$$

$$[d_0^t(q_s,x_t)]^{-1}=\max_{\phi,\lambda}\phi,$$
$$\text{st } -\phi q_{is}+Q_t\lambda\geq 0,$$
$$x_{is}-X_t\lambda\geq 0,$$
$$\lambda\geq 0, \quad (11)$$

and

$$[d_0^s(q_t,x_t)]^{-1}=\max_{\phi,\lambda}\phi,$$
$$\text{st } -\phi q_{it}+Q_s\lambda\geq 0,$$
$$x_{it}-X_s\lambda\geq 0,$$
$$\lambda\geq 0, \quad (12)$$

Note that in LP's (11) and (12), where production points are compared with technologies from different time periods, the ϕ parameter need not be greater than or equal to one, as it must be when calculating Farrell output-oriented technical efficiencies. The data point could lie above the feasible production set. This will most likely occur in LP (12) where a production point from period 't' is compared with technology in an earlier period, 's'. If technological progress occurs, then a value of $\phi<1$ is possible. Note that it could also possibly occur in LP (11) if technological regress has occurred, but this is less likely.

It is important to note that the ϕs and λs are likely to take different values in the above four LPs. Furthermore, the above four LPs must be solved for each industry in the sample. Thus, if there are eighteen 4-digit industries of food, beverages and tobacco products and two time periods, 72 LPs must be solved. Note also that as extra time periods are added, one must solve an extra three LP's for each industry (to construct a chained index). If there are T time periods, then (3T-2) LPs must be solved for each industry in the sample. Hence, if there are I industries, then there are I*(3T-2) LPs to be solved. In this study, with I=18 industries and T=20 time periods, this would involve 18*(3*20-2) =1044 LPs.

As noted previously, the above approach can be extended by decomposing the technical efficiency change measure into scale efficiency measure and a pure technical efficiency measure (equations 7 and 8). This requires the solution of two additional LPs (when comparing two production points). These would involve repeating LPs (9) and (10) with the convexity restriction added to each. This provides estimates of distance functions relative to a variable returns to scale (VRS) technology. For the case of I industries and T time periods, this would increase the number of LPs to be performed from I*(3T-2) to I*(4T-2).

Calculation Using SFA Frontiers

The distance measures required for the Malmquist TFP index calculations can also be measured relative to a parametric technology. A number of papers have been written in recent years that describe the ways in which this can be done. The majority of these can be classified into two groups: those that derive the measures using the derivative-based techniques (e.g. Kumbhakar & Lovell, 2000) and those that seek to use explicit distance measures (e.g. Fuentes, Grifell-Tatje& Perelman, 2001). The two approaches tend to provide same TFP formulae and decompositions that are quite similar too. In this study we confine our attention to the former approach (stochastic frontier approach) to see whether there exists any consistency with the Malmquist index concepts (DEA approach).

We consider a translog stochastic frontier production function defined as:

$$\ln y_{it}=\beta_0+\Sigma_j\beta_j \ln x_{jit}+\beta_t t+1/2\Sigma_j\Sigma_k\beta_{jk} \ln x_{jit}.\ln x_{kit}+1/2\beta_{tt}t^2+\Sigma_j\beta_{tj}\, t\ln x_{jit}+v_{it}-u_{it};\ j,k=L,\ K \ldots\ldots(13)$$

In equation (13), y_{it} is the output of the i^{th} industry in the t^{th} year,'t' is the time trend representing technological change and 'x' variables are inputs, subscripts 'j' and 'k' are index inputs. The inefficiency error, u_{it}, accounting for production loss due to unit-specific technical inefficiency, is always greater than or equal to zero and assumed to be independent of the random error (v_{it}); v_{it}, the random error, is assumed to have the usual properties, i.e., [$\sim iidN(0,\sigma^2_v)$]. The βs are unknown parameters to be estimated.

The technical inefficiency function is assumed to be defined by

$$u_{it}=\delta_0+\ \delta_1 SK_{it}+\ \delta_2 KI_{it}+\ \delta_3 D_{it}+w_{it} \ldots\ldots(14)$$

where Y_{it}, L_{it} and K_{it} are respectively output, labor input, and capital input for the aggregate manufacturing industry in industry 'i' at time 't'; SK_{it} denotes the index of employers' skill in the manufacturing industries of food, beverages and tobacco products (FBT) of the i^{th} industry in the year 't' measured by the ratio of the number of employees other than workers to total number of employees; KI_{it} denotes the capital intensity of the manufacturing industries of FBT of the i^{th} industry in the year 't' measured by the ratio of the stock of fixed capital to total number of employees and D_{it} denotes industrial dummy (crises-dummy) which shows the impact of economic crises on productivity growth (D_{it} takes the value '0' during the pre-crises period and it takes the value '1' during the post-crises period); w_{it} is the random error term, distributed as N(0, ^{2}) truncated at $-z_{it}\delta$, which ensures that u_{it}e"0, where z_{it} is the matrix of explanatory variables associated with the technical inefficiency effects of the i-th production unit in year't' and ä is a vector of unknown parameters to be estimated. Equation (14) shows that technical efficiency component has been correlated to the skill of employees, capital intensity and the effects of economic crises that is measured by industrial dummies.

TEC is the change in technical efficiency (TE_{it}) represented by $-du_{it}/dt$, and the rate of technological change (TP_{it}) is defined by

$$TPit= [1+ \partial \ln f(x_{it},\beta,t) /\partial t]*[1+\partial \ln f(x_{it+1,}\beta,t+1)/\partial t+1]^{1/2}-1 \ldots\ldots\ldots\ldots\ldots (15)$$

TE_{it} and TP_{it} are estimated simultaneously using maximum likelihood method, where the maximum likelihood function is based on a joint density function for the composite error term ($v_{it}+u_{it}$). Both TE_{it} and TP_{it} vary over time and across industries.

The component of scale change of the TFP measure is defined as

$$\text{Scale Change} = (\in-1)\Sigma_j \lambda_j x_{jt} \ldots\ldots (16)$$

where $\in=\Sigma_j \varepsilon_j$ denotes the measurement of returns to scale (RTS) [output elasticity of input 'j', $\varepsilon_j=\partial \ln f(x_{it},\beta,t)/\partial \ln x_{jt}$], $\lambda_j=\varepsilon_j/\varepsilon$ and x_{jt} denotes rate of growth of input use.

Data & Variables

The study is based on panel data collected from various issues of Annual Survey of Industries (ASI) and National Accounts Statistics (NAS) published by Central Statistical Organization (CSO). The concordance of data between NIC-2004 and NIC-2008 are mentioned in the Appendix. The variables used in this exercise are output and labor and capital inputs. Deflated gross value added has been taken as the measure of output. The ratio of nominal and real output, the values of which are obtained from different volumes of NAS is treated as deflator. Total number of persons engaged is used as the measure of labor input. Since working proprietors, owners and supervisory, managerial staff have a significant influence on the productivity of industries, the number of persons engaged is preferred to number of workers only. Net fixed capital stock at constant prices has been taken as the measure of capital input. The net fixed capital stock series has been constructed from the series on gross fixed capital formation (at constant prices) using the perpetual inventory accumulation method (PIAM) [Goldsmith, 1951]. The annual rate of depreciation of fixed assets has been taken as 5 per cent.

Empirical Results

The empirical analysis utilizes manufacturing of food, beverages and tobacco industry data [NIC 4-Digit level] to construct indices of TFP growth using the methods already mentioned above i.e., data envelop analysis and stochastic frontier approach. The sample data comprise annual measures of output (real gross value added) and the two inputs (labor and capital) for eighteen 4-digit manufacturing industries of food, beverages and tobacco products in India over the years from 1998-99 to 2017-18.

Results of the Stochastic Frontier Approach

In the stochastic frontier approach, we specify a translog-stochastic frontier production function for these industries, with non-neutral technological change, as shown by Equation 13. The u_{it}s are assumed to be i.i.d.$N^{+}(0,ó^{2}_{u})$ random variables. Thus, the model assumes that technical inefficiency is time variant in nature. This permits the greatest degree of flexibility in the possible patterns of technical efficiency, both for a particular industry over time and among industries. However, with a more restrictive parametric structure, the approaches used here would not be the right approach as this information of restrictive parametric structure would not be used by these approaches. If applied, they would produce estimators with larger variances.

The maximum-likelihood estimates of the parameters of translog stochastic frontier model are obtained by using the computer program, FRONTIER Version 4.1. These estimates are presented in Table 1. Asymptotic standard errors are presented beside each estimate. Also

Table 1 Maximum-Likelihood Estimates of the Stochastic Frontier Model

Coefficients	Estimates	Standard-Errors	t-ratios
β_0	1.90	1.27	1.50
β_L	-0.18	0.43	-0.43
β_K	0.92	0.50	1.86
β_t	0.10	0.04	2.30
β_L^2	0.16	0.02	7.04
β_K^2	0.11	0.04	2.44
β_t^2	-0.0002	0.0007	-0.24
β_{LK}	-0.26	0.06	-4.30
β_{Lt}	0.01	0.005	2.52
β_{Kt}	-0.02	0.007	-2.62
δ_0	0.32	0.15	2.11
δ_1	-1.02	0.14	-7.32
δ_2	0.06	0.02	3.76
δ_3	-0.48	0.17	-2.72
sigma-squared (σ^2)	0.23	0.05	5.04
Gamma (γ)	0.73	0.09	7.90

log likelihood function = -150.65
Source: Authors' Own Calculation

note that the data were mean corrected prior to estimation. Hence, the first-order parameters are interpreted as the elasticities at the sample means. The model also includes a time-squared variable, to allow for non-monotonic technological change, plus time interacted with each (log) input variable, to allow for non-neutral technological change. Table 1 shows that almost all the included variables are statistically significant at the 5% level of significance.

A significant amount of output variation is due to the presence of technical inefficiency effect.

Further, all the coefficients of the technical inefficiency effects are also found to be statistically significant which implies that a significant amount of output variation is due to the presence of technical inefficiency effect. The estimated values of δ_1 and δ_3 are found to be negative and they are statistically significant too which implies that an increase in employees' skill and industrial dummy (crises dummy) lower technical inefficiency effects. However, the estimated value of δ_2 is found to be positive and statistically significant, indicating that capital intensity boosted technical inefficiency effects in the organized manufacturing industries of food, beverages and tobacco products in India. The estimates of the variance parameters σ^2 and γ that test for the validity of technical inefficiency effect are found to be statistically significant at less than 1% probability level which confirms the presence of technical inefficiency effect in the output residual. The estimated value of gamma (γ) is found to be 0.73. This implies that output variation in the organized manufacturing industries of food, beverages and tobacco products in India is significantly dominated by inefficiency error (u_{it}).

The coefficient of time is 0.10, which indicates mean technological progress of 10% per year.

As is noticed in the analyses of the estimates mentioned in Table 1, the elasticity associated with capital is the largest in most of the industries. The sum of the two production elasticities are less than unity, suggesting decreasing returns to scale (DRS) at the sample data point. The coefficient of time is 0.10, which indicates mean technological progress of 10% per year. The coefficient of time squared is negative, indicating that the rate of technological change increases at a decreasing rate over time. However, the time square coefficient is not statistically significant even at less than 5% (or more) probability level. The coefficients of time interacted with labor and capital input variables are positive and negative, respectively, indicating that technological change has been labor saving but capital using over time. Visually, this indicates that the isoquant is shifting inwards at a faster rate over time in the labor intensive part of the input space. This is most likely a consequence of the rising relative cost of labor as the process of development continues in India.

Average annual percentage change measures of technical efficiency change

TFPG of eleven out of eighteen 4-digit industries of food, beverages and tobacco products in India declined during the period of post-economic crisis

(TEC), technological progress (TP), scale change (SC) and total factor productivity growth (TFPG) were calculated for each industry are presented in Table 2. We see that over this twenty-year period (1998-99 to 2017-18), TFPG of eleven out of eighteen 4-digit industries of food, beverages and tobacco products in India declined during the period of post-economic crisis (2008-09 to 2017-18) which is mainly due to the decline in TP of the same during that period. TEC and SC in most of these eleven industries have also declined during this period. These eleven industries are, namely, production, processing and preserving of meat and meat products [1010(1511)], vegetable and animal oils and fats [1040(1514)], dairy products [1050 (1520)], grain mill products [1061(1531)], bakery products [1071(1541)], cocoa, chocolate and sugar confectionery [1073(1543)], macaroni, noodles, couscous and similar farinaceous products [1074(1544)], distilling, rectifying and blending of spirits; ethyl alcohol production from fermented materials [1101 (1551)], malt liquors and malt [1103 (1553)], soft drinks; production of mineral waters [1104(1554)]and tobacco products [1200(1600)].In the remaining seven industries {[processing and preserving of fish and fish products [1020(1512)], processing and preserving of fruits and vegetables [1030(1513)], starches and starch products [1062 (1532)], sugar [1072(1542)], other food products n.e.c.[1079(1549)], prepared animal feeds [1080(1533)]and wines [1102(1552)]}, TFPG increased during the post-crisis period (2008-09 to 2017-18) which may be attributed to the increase in TEC and SC of the same during that period although TP of them have declined during the same period of time. However, the size of the scale effects in all the eighteen 4-digit industries of food, beverages and tobacco products are found to be very small (or negative in many cases) during the study periods. This is not surprising given that the estimated technology had scale economies of less than unity, indicating that the production function followed approximately DRS in all the 4-digit industries of food, beverages and tobacco products in India during the sample period.

DEA Results & Comparisons with SFA Results

The same sample data were used to calculate indices of TEC, TP, SC and TFPG using the DEA-like methods already described. Calculations were done using the DEAP Version 2.1 computer program. These indices were converted into percentage change measures to facilitate easy comparison with the SFA results. The DEA results are summarized in Table 3. The DEA results found that in case of thirteen out of eighteen industries, namely, processing and preserving of fruit and vegetables [1030(1513)], grain mill products [1061(1531)], starches and starch products [1062(1532)], bakery products [1071(1541)], sugar [1072(1542)], cocoa, chocolate and sugar confectionery [1073(1543)], other food products n.e.c.[1079(1549)], prepared animal feeds [1080(1533)], distilling, rectifying and blending of spirits; ethyl alcohol production from fermented materials [1101(1551)], wines [1102(1552)], malt liquors and malt [1103(1553)], soft drinks; production of mineral waters [1104 (1554)] and tobacco products [1200 (1600)] TFPG declined during the post-crises period (2008-09 to 2017-18) and the decline in TFPG in those industries is mainly due to decline in TP of the same during that period. Whereas in case of remaining five industries, i.e., production, processing and preserving of meat and meat products [1010(1511)], processing and preserving of fish and fish products [1020(1512)], vegetable and animal oils and fats [1040(1514)], dairy products[1050(1520)], macaroni, noodles, couscous and similar farinaceous products [1074(1544)]TFPG increased during the post-crisis period and the increase in TFPG of these industries during this period is mainly due to the increase in TEC and SC of the same during that period.

It is to be noted that the DEA results differ from the SFA results in a number of aspects. First, SFA results show that TFPG of production, processing and preserving of meat and meat products [1010(1511)], vegetable and animal oils and fats [1040(1514)], dairy products [1050(1520)] and macaroni, noodles, couscous and similar farinaceous products [1074(1544)] declined during the post-crisis period (2008-09 to 2017-18), whereas DEA results show that TFPG of those industries increased during that period. Further, SFA results show that TFPG of processing and preserving of fruits and vegetables [1030(1513)], starches and starch products [1062 (1532)], sugar [1072(1542)], other food products n.e.c. [1079(1549)], prepared animal feeds [1080(1533)] and wines [1102(1552)] increased during the post-crisis period whereas DEA results show that they have declined during the post-crises period. Second, the DEA TFPG measures are more stochastic than the SFA measures. This is not surprising, given that the DEA method involves the calculation of a separate frontier in each year, while the SFA method uses all the twenty years, with smooth changes in the frontier allowed via the time trend specification of technological change. Another point of difference is that due to the stochastic nature of the DEA, TFPG is relatively greater due to TP in most of the industries. This is mainly due to the above-mentioned year-to-year flexibility embedded in the DEA method. When all industries face a bad year in terms bad weather conditions or a pandemic like the case of Corona virus (Covid-19), the DEA method tends to interpret this as technological regress (i.e. negative TP) while the SFA method interprets it as a decline in TEC.

To obtain a better idea of how the two TFPG measures compare, we plot them in Fig.1 (a) through Fig.1(c), along with SFA TFPG measures calculated using the same data. We observe: first, the two measures do not follow a very similar pattern over the twenty-year period. Second, the DEA TFPG measure is

Table 2 Average Annual Rate (%) of TFPG and its Components using SFA

Time Periods	INDUSTRIES											
	1010(1511)				1020(1512)				1030(1513)			
	TP	TEC	SC	TFPG	TP	TEC	SC	TFPG	TP	TEC	SC	TFPG
Entire Study Period(1998-99 to 2017-18)	0.87	3.23	0.63	4.73	1.68	2.07	-0.09	3.64	0.80	2.00	-0.07	2.73
Pre-crises Period(1998-99 to 2007-08)	0.96	5.16	1.06	7.19	2.14	0.22	-0.39	1.97	1.57	-0.83	-0.34	0.40
Post-crises Period(2008-09 to 2017-18)	0.78	1.29	0.19	2.26	1.21	3.92	0.21	5.30	0.03	4.82	0.19	5.06
Time Periods	INDUSTRIES											
	1040(1514)				1050(1520)				1061(1531)			
	TP	TEC	SC	TFPG	TP	TEC	SC	TFPG	TP	TEC	SC	TFPG
Entire Study Period(1998-99 to 2017-18)	-0.37	0.43	-0.03	0.08	0.39	-0.28	-0.11	0.05	1.29	0.42	0.05	1.76
Pre-crises Period(1998-99 to 2007-08)	0.36	1.35	-0.03	1.68	1.34	-1.07	-0.07	0.20	2.45	-0.48	-0.09	1.88
Post-crises Period(2008-09 to 2017-18)	-1.10	-0.49	-0.03	-1.52	-0.56	0.52	-0.16	-0.09	0.12	1.33	0.19	1.64
Time Periods	INDUSTRIES											
	1062(1532)				1071(1541)				1072(1542)			
	TP	TEC	SC	TFPG	TP	TEC	SC	TFPG	TP	TEC	SC	TFPG
Entire Study Period(1998-99 to 2017-18)	0.67	-2.53	-0.59	-2.44	1.76	0.21	-0.09	1.86	-1.06	-1.52	-0.13	-2.64
Pre-crises Period(1998-99 to 2007-08)	1.68	-4.86	-0.99	-4.17	2.53	0.19	-0.21	2.51	-0.05	-6.38	-0.27	-6.70
Post-crises Period(2008-09 to 2017-18)	-0.34	-0.20	-0.20	-0.70	0.99	0.22	0.03	1.21	-2.07	3.33	0.02	1.41

Time Periods	INDUSTRIES											
	1073(1543)				1074(1544)				1079(1549)			
	TP	TEC	SC	TFPG	TP	TEC	SC	TFPG	TP	TEC	SC	TFPG
Entire Study Period(1998-99 to 2017-18)	0.61	-0.15	-0.14	0.35	1.17	-3.06	0.05	-1.81	1.70	0.50	0.04	2.25
Pre-crises Period(1998-99 to 2007-08)	1.54	0.67	-0.04	2.17	2.17	-0.76	0.61	2.03	2.63	-2.91	-0.17	-0.45
Post-crises Period(2008-09 to 2017-18)	-0.31	-0.97	-0.25	-1.47	0.18	-5.36	-0.51	-5.65	0.76	3.91	0.26	4.94
Time Periods	INDUSTRIES											
	1080(1533)				1101(1551)				1102(1552)			
	TP	TEC	SC	TFPG	TP	TEC	SC	TFPG	TP	TEC	SC	TFPG
Entire Study Period(1998-99 to 2017-18)	1.37	0.01	-0.18	1.21	-0.14	-0.47	-0.13	-0.69	1.52	-0.32	-0.07	1.12
Pre-crises Period(1998-99 to 2007-08)	2.27	-1.64	-0.24	0.39	0.76	-0.16	-0.06	0.54	1.95	-0.83	-0.13	0.99
Post-crises Period(2008-09 to 2017-18)	0.47	1.66	-0.12	2.04	-1.04	-0.77	-0.19	-1.93	1.09	0.19	-0.01	1.24
Time Periods	INDUSTRIES											
	1103(1553)				1104(1554)				1200(1600)			
	TP	TEC	SC	TFPG	TP	TEC	SC	TFPG	TP	TEC	SC	TFPG
Entire Study Period(1998-99 to 2017-18)	-0.10	-0.70	-0.16	-0.93	-0.73	0.33	-0.10	-0.46	3.70	0.81	0.07	4.58
Pre-crises Period(1998-99 to 2007-08)	0.73	-0.75	-0.22	-0.25	-0.34	2.55	-0.12	2.09	4.52	0.70	0.12	5.33
Post-crises Period(2008-09 to 2017-18)	-0.93	-0.65	-0.10	-1.61	-1.13	-1.90	-0.08	-3.01	2.89	0.91	0.03	3.83

Source: Authors' Own Calculations

Table 3 Average Annual Rate (%) of TFPG and its Components using DEA

Time Periods	INDUSTRIES											
	1010(1511)				1020(1512)				1030(1513)			
	TP	TEC	SC	TFPG	TP	TEC	SC	TFPG	TP	TEC	SC	TFPG
Entire Study Period(1998-99 to 2017-18)	-2	0.6	1.6	-1.4	-1.4	1.4	1.2	0.1	-0.2	3	0.9	2.8
Pre-crises Period(1998-99 to 2007-08)	8.2	-11.5	-11.5	-4.2	9.9	-11.4	-12.4	-2.6	10.6	-4.4	-3.8	5.7
Post-crises Period(2008-09 to 2017-18)	-3.6	0.4	-1.3	-3.2	1.6	-1.4	-1.4	0.2	5.3	-0.8	1.3	4.5
Time Periods	INDUSTRIES											
	1040(1514)				1050(1520)				1061(1531)			
	TP	TEC	SC	TFPG	TP	TEC	SC	TFPG	TP	TEC	SC	TFPG
Entire Study Period(1998-99 to 2017-18)	-1.1	5.3	0.7	4.1	1.5	3.1	0.5	4.7	0.2	6	6	6.2
Pre-crises Period(1998-99 to 2007-08)	11.7	-8	-2.8	2.7	12.1	-12.3	-4.1	-1.7	10.3	4.6	4.6	15.4
Post-crises Period(2008-09 to 2017-18)	2.4	4.4	1.5	6.9	2	5.4	1.1	7.6	2.1	5.3	0.5	7.5
Time Periods	INDUSTRIES											
	1062(1532)				1071(1541)				1072(1542)			
	TP	TEC	SC	TFPG	TP	TEC	SC	TFPG	TP	TEC	SC	TFPG
Entire Study Period(1998-99 to 2017-18)	-0.8	5.7	1.5	4.8	-0.6	3.8	-0.2	3.2	0.1	4.2	4.2	4.3
Pre-crises Period(1998-99 to 2007-08)	11	7.9	1.8	19.7	14.6	4.1	0	19.3	19.9	-0.8	-0.8	19
Post-crises Period(2008-09 to 2017-18)	1.2	-0.6	-0.6	0.5	10	1.6	-2.3	11.8	9.5	4.8	4.8	14.7

Time Periods	INDUSTRIES											
	1073(1543)				1074(1544)				1079(1549)			
	TP	TEC	SC	TFPG	TP	TEC	SC	TFPG	TP	TEC	SC	TFPG
ntire Study Period(1998-99 to 2017-18)	-4	2.8	0.7	-1.3	-3.5	2	-0.2	-1.6	-3.8	0.4	0.9	-3.4
Pre-crises Period(1998-99 to 2007-08)	17.4	1.1	1	18.8	13.7	-1	-0.3	12.5	16.5	3.1	0.5	20.2
Post-crises Period(2008-09 to 2017-18)	6.6	3.8	0.5	10.6	7.3	5.9	-0.3	13.7	5.5	3.7	5.5	9.4

Time Periods	INDUSTRIES											
	1080(1533)				1101(1551)				1102(1552)			
	TP	TEC	SC	TFPG	TP	TEC	SC	TFPG	TP	TEC	SC	TFPG
Entire Study Period(1998-99 to 2017-18)	-1.1	0.2	0.2	-0.9	-1	1.9	0.3	0.8	-1.3	2.3	0.2	1
Pre-crises Period(1998-99 to 2007-08)	17.9	5.4	1.2	24.2	18.9	-1.7	-0.4	16.8	14.6	-0.1	0	14.5
Post-crises Period(2008-09 to 2017-18)	4.8	2.6	1.1	7.6	5.8	1.5	0.8	7.4	5.2	7.6	0.8	13.2

Time Periods	INDUSTRIES											
	1103(1553)				1104(1554)				1200(1600)			
	TP	TEC	SC	TFPG	TP	TEC	SC	TFPG	TP	TEC	SC	TFPG
Entire Study Period(1998-99 to 2017-18)	12.3	2.7	0.2	15.3	11.5	-0.6	-0.2	10.8	11.1	1.4	-0.2	12.7
Pre-crises Period(1998-99 to 2007-08)	16.2	6.2	0.2	23.5	16.5	2.6	0.2	19.5	14.2	2.1	0.7	16.7
Post-crises Period(2008-09 to 2017-18)	7.3	7.7	0.2	15.5	4.7	4.4	-0.1	9.3	7.2	3.7	0.6	11.2

Source: Authors' Own Calculations

the most volatile, most likely for the reasons discussed above. Third, the annual average measures of TFPG range from 24.2% to -4.2% for DEA down to -6.7% from 7.19% for SFA.

The above discussion helps us to explain why the measures of TFPG and its various components differ across the methods. However, it does not give us much guidance as to which measure is

Fig.1 (a) Average Annual Rate (%) of TFPG using SFA & DEA

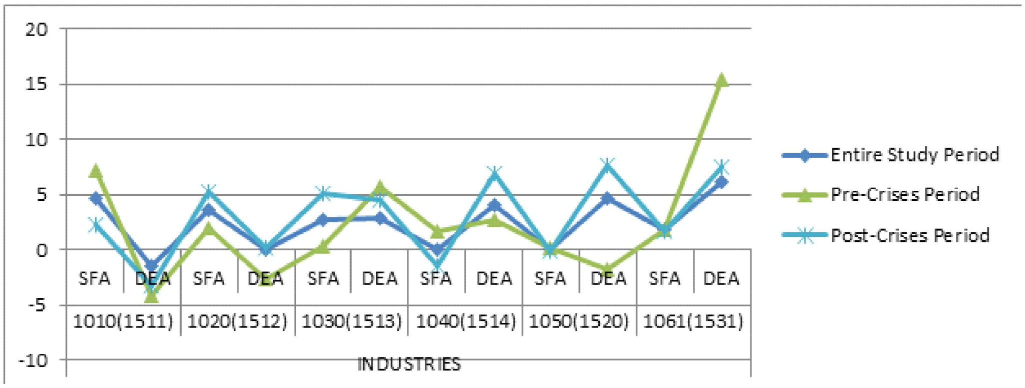


Fig. 1(b) Average Annual Rate (%) of TFPG using SFA & DEA

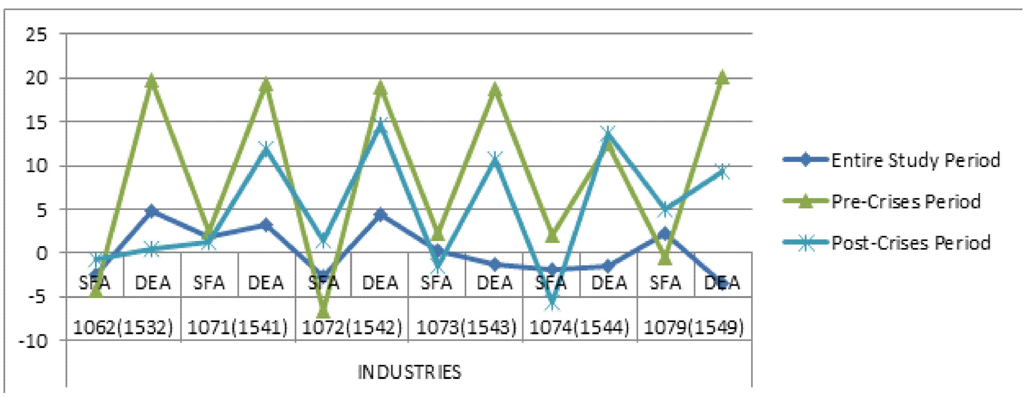
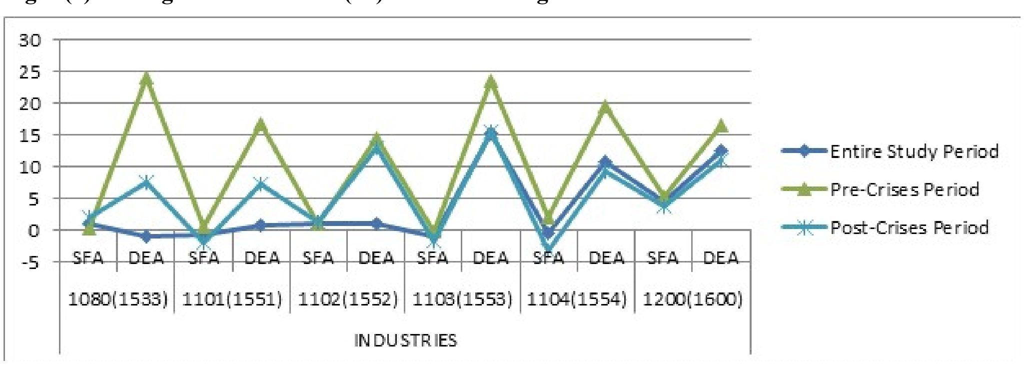


Fig. 1(c) Average Annual Rates (%) of TFPG using SFA & DEA



more correct. The answer to this question is rarely straight forward, and tends to differ according to the industry being studied, the quality of the data and the purpose for which we wish to use the TFPG measures obtained. However, in this particular industry the data noise is quite high, so we would like to prefer SFA to DEA.

Conclusion

We conclude by summarizing the relative merits of the two frontier approaches SFA and DEA for measuring TFPG. Some of the relative merits of both the approaches are:

- Both the approaches do not require price information.
- Both the approaches do not assume all firms are fully efficient.
- They do not need to assume a behavioral objective such as cost minimization or revenue maximization.
- Both the approaches permit TFP change (TFPG) to be decomposed into components, such as technological change (TP), technical efficiency change (TEC) and scale change (SC).
- Both the approaches show that TFPG of most of the 4-digit manufacturing industries of food, beverages and tobacco products declined during the period of post-economic crises (2008-09 to 2017-18) which may be largely accounted for by the decline in technological progress (TP) of the same during that period.

Whatever are the reasons, and their relative importance, for the decline in TFPG of the 4-digit manufacturing industries of food, beverages and tobacco products in India during the post-economic crisis period (2008-09 to 2017-18), policies should be geared to allocate resources optimally and to use factor inputs more efficiently. Policies should further be taken to increase scale of production so that per unit cost of production declines and price tends towards marginal costs. Policy measures intended to improve TFP growth might be misdirected if they focus mainly on accelerating the rate of innovation in circumstances where the low rate of TFP growth is brought about by suboptimal size of the firms and low rate of technology diffusion (technical inefficiency), which really happened in the case of organized manufacturing sector in general. A thorough examination of industrial policy resolution reveals that the importance and contribution of efficiency factor in industrial growth has been neglected or given less priority in the framework of industrial strategy. In this context, the governments should take some policy initiatives to improve productive efficiency of the 4-digit manufacturing industries of food, beverages and tobacco in India. Once efficiency increases, it enhances

A thorough examination of industrial policy resolution reveals that the importance and contribution of efficiency factor in industrial growth has been neglected or given less priority in the framework of industrial strategy.

competitiveness (thereby enhances technological progress) by realizing the potential productivity growth of the 4-digit manufacturing industries of food, beverages and tobacco products in India.

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Appendix

Concordance between NIC-2004 and NIC-2008	NIC2004	NIC2008
Production, processing and preserving of meat and meat products [1010(1511)]	1511	1010
Processing and preserving of fish and fish products [1020(1512)]	1512	1020
Processing and preserving of fruit and vegetables [1030(1513)]	1513	1030
Vegetable and animal oils and fats [1040(1514)]	1514	1040
Dairy products [1050(1520)]	1520	1050
Grain mill products [1061(1531)]	1531	1061
Starches and starch products [1062(1532)]	1532	1062
Bakery products [1071(1541)]	1541	1071
Sugar [1072(1542)]	1542	1072
Cocoa, chocolate and sugar confectionery [1073(1543)]	1543	1073
Macaroni, noodles, couscous and similar farinaceous products [1074(1544)]	1544	1074
Other food products n.e.c. [1079(1549)]*	1549	1079
Prepared animal feeds [1080(1533)]	1533	1080
Distilling, rectifying and blending of spirits; ethyl alcohol production from fermented materials [1101(1551)]	1551	1101
Wines [1102(1552)]	1552	1102
Malt liquors and malt [1103(1553)]	1553	1103
Soft drinks; production of mineral waters [1104(1554)]	1554	1104
Tobacco products [1200(1600)]	1600	1200

*This class includes:

- manufacture of soups and broths
- manufacture of artificial honey and caramel
- manufacture of perishable prepared foods, such as:
- sandwiches
- fresh (uncooked) pizza
- Manufacture of food supplements and other food products n.e.c.

This class also includes:

- manufacture of yeast
- manufacture of extracts and juices of meat, fish, crustaceans or molluscs
- manufacture of non-dairy milk and cheese substitutes
- manufacture of egg products, egg albumin
- manufacture of artificial concentrates