Productivity Growth in the US Food and Kindred Products Industry

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Abstract

The paper provides estimates of productivity growth in the 4-digit SIC food and beverages manufacturing industries in the US for the period 1986-96 using Balk's (2001) decomposition of the Malmquist productivity index (MPI). The empirical results suggest that for the overwhelming majority of industries productivity changes we driven primarily by technical change and technical efficiency change. A comparison between the Divisia index estimates provided by the US NBER and the MPI estimates shows that they had different distributions and the former were systematically lower than the latter.

Key Words: *Productivity Growth, Food and Beverages, US*

JEL Classification: *D24, L66*

Introduction

The Food and Kindred products industry in the US includes firms and their establishments that manufacture or process food and beverage for human consumption and other related products such as vegetable and animal fats and oils and prepared feeds for animals and fowls. According to the US National Bureau of Economic Research (NBER) the industry in the recent years contributes to the manufacturing sector almost 9 percent of the total employment, 12 percent of the total value of shipments, and 10 percent of the total value added. It, therefore, not only exercises significant influence backwards (to farmers) and forward (to distributors and consumers) but it may affect the health of the US economy as a whole (McKinsey Global Institute, 1993).

In the last twenty years a large number of studies have been carried out on the behavior and conduct of the US Food and Kindred products industry. To mention a few, Ball and Chambers (1982), Mullen et al. (1988), and Huang (1991) investigated input demand and input substitutability; McCorkle et al. (1988), analyzed the industry dynamics and the role of economic policy; Gisser (1982), Azzam and Schroeter (1991) and (1995), Bhuyan and Lopez (1997) and (1998) and Lopez et al. (2002) obtained measures of oligopoly and oligopsony power and quantified the welfare losses associated with non competitive practices.

Less attention, however, has been paid to the industry's performance (efficiency and productivity). Heien (1983), used a Divisia (growth accounting) approach to estimate Total Factor Productivity (TFP) growth in US food processing and distribution sector for the period 1950-77. Jayanthi et al. (1996) assessed the efficiency of 20 food manu-

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facturing plants employing the Operational Competitiveness Ratings Analysis (OCRA) (Parkan, 1994). Also, the NBER reports rates of TFP growth for all four hundreds and fifty 4-digit SIC manufacturing industries in the US (among them are industries belonging to Food and Kindred products group) using the Divisia index and information from the Manufacturing Productivity (MP) Database.

The small number of studies on efficiency and productivity in food manufacturing is quite disconcerting. According to McKinsey Global Institute (1993) product standardization among the US food manufacturers has reached such level that production efficiency and productivity growth are the keys to competing in the industry. For Miller and Roth (1994) food manufacturers should be viewed as the "marketeers" who compete primarily through infrastructural changes aiming at cutting costs.

The objective of the present paper to measure productivity growth in each of the forty nine 4-digit SIC food and beverage manufacturing industries in the U.S for the period 1986-1996. To this end, the paper utilizes exactly the same output and input data as the NBER study but a different analytical approach. In particular, the empirical analysis here relies on the Malmquist Productivity Index (MPI) and its decomposition as recently developed by Balk (2001). Both the Divisia and the Malmquist indices are non parametric. They are also proper indices in the sense that they satisfy the desirable properties of identity, monotonicity, separability, and proportionality (Orea, 2002). The Divisia index assumes perfect competition in output and input markets in order to obtain weights for the time rates of changes of the individual production inputs (Bartelsman and Gray, 1996). The assumption of perfect competition, however, is not very plausible for the Food and Kindred products industry in the US. Relevant information suggests that the degree of concentration in the industry as a whole has been rising very fast since the early 80's (Harris, 2002). Moreover, econometric studies in the New Empirical Industrial Organization (NEIO) framework (e.g. Azzam and Schroeter 1995; Bhuyan and Lopez, 1997 and 1998; Lopez et al., 2002) have provided solid evidence on the existence of monopoly or monopsony power in a considerable number of the 4-digit SIC food and beverage manufacturing industries. The MPI requires data on output and inputs only and dispenses altogether with behavioral assumptions. Therefore, it appears to be more appropriate for measuring productivity growth in the sector. The present study compares estimates from the two alternative approaches (MPI and Divisia) to assess the impact of using a potentially implausible behavioral assumption on the resulting rates of TFP growth.

Estimation of productivity growth is important for evaluating changes in the performance of an industry over time. Of equal importance, however, is the identification and quantification of factors driving productivity changes. Balk's (2001) approach allows for a meaningful decomposition of the MPI into four independent factors making, thus, possible to obtain richer insights into the sources of growth. The paper is structured as follows: Section 2 presents the analytical framework and Section 3 the data and the empirical model. Section 4 contains the empirical results, while Section 5 offers conclusions and implications. Appendix A provides a brief description of the industries considered and Appendix B certain technical details.

The MPI Index and Its Decomposition

Let the input quantities be represented by an N-dimensional vector of non-negative real values $x = (x_1,\ x_2,\ .....\ ,\ x_N) \in R_+^N$ and the output by the non negative scalar y. The technology at period t is given by the set S^t of all feasible input-output combinations and the input sets are defined by $L^t(y^t) = \{x^t : (x^t, y^t) \in S^t\}$. An input distance function (D_i^t) is the maximum feasible radial contraction of the input vector with output held fixed. Formally,

$$D_i^t(x^t, y^t) = \sup\{\delta > 0 : x^t / \delta \in L^t(y^t)\} \tag{1}$$

For any input quantity vector x^t, x^t / D_i^t is the smallest input vector from the origin through x^t that is able to produce y^t. The input distance function is linear homogenous in x^t and increasing in y^t. It takes values greater than or equal to one if the input vector x^t is an element of $L^t(y^t)$, where the value of 1 implies that there is technical efficiency in production.

Balk (2001) extended the traditional Malmquist productivity index (Caves, Christensen, and Diewert, 1982) by comprising measures of technical change (TC), technical efficiency change (EC), scale efficiency change (SEC), and an input-mix effect (IME). An input-oriented measure of TFP growth between periods t and $t+1$ encompassing all four factors may be written as

$$MPI_i^{t,t+1} = (TC_i^{t,t+1}) * (EC_i^{t,t+1}) * (SEC_i^{t,t+1}) * (IME^{t,t+1}) \tag*{(2),}$$

where

$$MPI_i^{t,t+1} = \left[\frac{\check{D}_i^t(x^t, y^t)}{\check{D}_i^t(x^{t+1}, y^{t+1})} * \frac{\check{D}_i^{t+1}(x^t, y^t)}{\check{D}_i^{t+1}(x^{t+1}, y^{t+1})} \right]^{0.5} \tag*{(3),}$$

$$TC_i^{t,t+1} = \left[\frac{D_i^{t+1}(x^{t+1}, y^{t+1})}{D_i^t(x^{t+1}, y^{t+1})} * \frac{D_i^{t+1}(x^t, y^t)}{D_i^t(x^t, y^t)} \right]^{0.5} \tag*{(4),}$$

$$EC_i^{t,t+1} = \frac{D_i^t(x^t, y^t)}{D_i^{t+1}(x^{t+1}, y^{t+1})} \tag*{(5),}$$

$$SEC_i^{t,t+1} = \left[\frac{\dfrac{D_i^t(x^t, y^{t+1})}{\check{D}_i^t(x^t, y^{t+1})}}{\dfrac{D_i^t(x^t, y^t)}{\check{D}_i^t(x^t, y^t)}} * \frac{\dfrac{D_i^{t+1}(x^{t+1}, y^{t+1})}{\check{D}_i^{t+1}(x^{t+1}, y^{t+1})}}{\dfrac{D_i^{t+1}(x^{t+1}, y^t)}{\check{D}_i^{t+1}(x^{t+1}, y^t)}} \right]^{0.5} \tag*{(6),}$$

and
$$IME_i^{t,t+1} = \left[\frac{\dfrac{D_i^t(x^{t+1}, y^{t+1})}{\overset{\vee}{D_i^t}(x^{t+1}, y^{t+1})}}{\dfrac{D_i^t(x^t, y^{t+1})}{\overset{\vee}{D_i^t}(x^t, y^{t+1})}} * \frac{\dfrac{D_i^{t+1}(x^{t+1}, y^t)}{\overset{\vee}{D_i^{t+1}}(x^{t+1}, y^t)}}{\dfrac{D_i^{t+1}(x^t, y^t)}{\overset{\vee}{D_i^{t+1}}(x^t, y^t)}} \right]^{0.5} \tag{7}$$

In the above, the symbol $\vee$ denotes the cone (constant global returns to scale) technology which is associated with the actual production technology, S^t.

An output-oriented measure can be derived as well which in the place of the IME contains an output-mix effect (OME). For the single-output production process as the one considered here, however, the OME effect is always equal to unity. The input-orientation in this case provides a richer decomposition of the MPI and it is also consistent with the effort of food manufacturing firms to reduce costs by economizing on inputs (Miller and Roth, 1994). It should be emphasized that because the MPI is defined for a cone technology it makes no difference for the estimates of the productivity growth rates (derived from equation (3)) whether one uses an input- or an output- orientation.[1] A value larger (smaller) than unity in any component of the MPI, implies an improvement (deterioration) in that component. The overall effect of the four independent components is reflected in the MPI where values of it above unity indicate increases in TFP while values below unity indicate declines.

The Data and the Empirical Model

The data for the empirical application were obtained from the Manufacturing Productivity (MP) database of the NBER (2002). A distinct advantage of the MP Database is that it gathers together many years of data, adjusts for changes in the industry definitions over time, and links in a few additional key variables (i.e., capital stocks and price deflators). A detailed documentation of the MP database can be found in Bartelsman and Gray (1996).

The MP Database has been used (expect for calculating TFP growth rates for the 4-digit SIC industries) in a variety of research projects. Bartelsman et al. (1994) and Bartlesman (1995) estimated production functions using industry-level data. Dunne and Schmitz (1995) and Berman et al. (1994) analyzed the links between wages and industry characteristics and the demand for skilled labour. Bhuyan and Lopez (1997) investigated the degree of oligopoly power in food and tobacco manufacturing. In a some studies (e.g. Gray, 1987; Amato and Amato, 2001) the TFP productivity growth estimates from the MP Database have been employed as dependent variables in regression models looking at a variety of possible influences on productivity.

As in the NBER study, the output in this paper is the value of shipments which is assumed to be produced with the use of 4 inputs, namely, production labor, non production labor, materials (non energy and energy ones), and capital. The production labor is measured in terms of the number of production worker hours (millions) and the non production labor in terms of the number of non production employees (thousands). The value of shipments, the cost of materials, and the capital stock are expressed in real (1987) prices.

The Empirical Results

The distance functions involved in the components of MPI have been calculated for each year in 1986-96 using the OnFront 2 program (Fare and Grosskopf, 2000).[2] Table 1 presents average values for each independent effect, by industry. Starting from the TC component, we observe that technical change was progressive in forty one and regressive in seven out of forty nine industries, while the technology level of industry 2043 exhibited no change. Very strong rates of technological progress were achieved by industries 2075, 2082, 2084, 2086, 2087, and 2096. At the same time, the industries 2051, 2068, 2092, and 2097 appear to have experienced sizable technical regress. Turning to technical efficiency change, we observe that technical efficiency deteriorated in twenty one, improved in fourteen, and exhibited no change in fourteen industries. The largest (in percentage terms) declines occurred in industries 2023, 2077, 2052, 2084, and 2092 whereas the largest improvements occurred in industries 2063, 2044, and 2032. Technical efficiency levels have been calculated for each individual industry and year.[3] Mindful of space limitations we discuss here only the general picture emerging from the relevant calculations. Eleven industries (2011, 2021, 2043, 2067, 2068, 2075, 2076, 2082, 2086, 2087, and 2097) were technically efficient in all periods. Six industries (2013, 2015, 2022, 2051, 2053, 2083) attained (on the average) levels of technical efficiency above 0.9, while seven (2024, 2034, 2035, 2045, 2069, 2077, and 2084) attained (on the average) levels below 0.7; industry 2077 was the least technically efficient with an average level of only 0.52.

With regard to scale efficiency change, it appears that scale efficiency declined in twenty four, increased in twenty four, and showed no change in one industry. The largest (in percentage terms) declines occurred in industries 2038, 2075, and 2096 whereas the largest improvements occurred in industries 2053 and 2094. Scale efficiency levels have been calculated for each individual industry and year.[4] Three industries (2043, 2075, 2087) where scale efficient in all periods. Twenty two industries (2011, 2021, 2022, 2023, 2024, 2032, 2036, 2035, 2037, 2041, 2045, 2046, 2047, 2062, 2063, 2066, 2068, 2079, 2084, 2085, 2092, and 2096) attained (on the average) scale efficiency levels above 0.9, while seven industries (2026, 2053, 2074, 2076, 2080, 2091, and 2099) attained scale efficiency levels below 0.7.[5]

With regard to the input-mix effect, it appears that mix efficiency has improved in 29 industries and declined in the rest. The largest (in percentage terms) improvements occurred in industries 2011, 2021, and 2091, while the largest declines occurred in industries 2078 and 2064. It would be useful to identify the input mix changes which are associated with positive or negative input-mix effects. To this end, we constructed all possible input ratios and we calculated their rates of change for every time period. Then we estimated Pearson correlation coefficients between each of the later variables and the input-mix effect variable. Only two coefficients turned out to be statistically significant at the conventional levels. Namely, those involving the time rate of change of the ratio production worker hours to materials and the time rate of change of the ratio capital to materials. Both coefficients were positive indicating a positive association between the ratio of production workers to materials and that of capital to materials with input-mix efficiency.[6]

Technical change was the largest (in absolute value terms) component of the MPI for more than half (twenty five) industries. Technical efficiency change was the largest component in seventeen, scale efficiency change in five, and input-mix efficiency change in two industries. We may conclude, therefore, that for the period considered and for the overwhelming majority of industries technical change and technical efficiency change were the most important factors behind productivity changes, while the role of scale efficiency change and input-mix efficiency change was limited.

Table 1. The Components of the Malmquist Indices of TFP Growth* (geometric averages from 1986/87 to 1995/96) %

Industry Code	(1)	(2)	(3)	(4)	Industry Code	(1)	(2)	(3)	(4)
2011	-0.10	0	-0.11	1.61	2062	0.67	-0.51	0.21	0.07
2013	0.69	0.53	-0.49	-0.55	2063	0.33	3.28	0.54	0.8
2015	2.14	1.40	-2.30	0.92	2064	1.99	1.06	-1.89	0.66
2021	-0.97	0	-0.58	1.59	2066	1.41	-1.63	0.21	-0.29
2022	-0.03	-0.41	-0.06	0.28	2067	0.80	0	0.23	-0.18
2023	1.36	-4.51	-0.06	-0.18	2068	-1.9	0	0.77	-0.56
2024	1.75	1.1	0.52	-0.06	2074	0.41	1.65	-1.21	0.9
2026	1.35	-2.36	0.27	-0.08	2075	6.13	0	-4.72	0.89
2032	0.14	1.72	0.21	-0.08	2076	3.95	0	-1.79	-2.39
2033	1.99	-2.26	-0.51	0.96	2077	2.45	-3.48	-0.24	0.76
2034	0.91	-2.65	0.68	0.39	2079	1.35	-0.5	-0.33	-0.29
2035	1.04	-2.48	0.29	-0.52	2082	4.56	0	-1.5	-0.11
2037	0.58	1.34	-1.24	0.81	2083	2.27	0	0.88	-1.07
2038	2.53	1.68	-2.62	0.83	2084	3.52	-2.84	0.33	0.39
2041	0.64	-1.97	0.05	0.28	2085	0.96	-0.51	-0.4	0.55
2043	0	0	-0.62	0.38	2086	4.01	0	-1.52	0.17
2044	1.07	2.04	0.53	-1.04	2087	4.62	0	-1.59	0.57
2045	1.56	0.85	0.99	0.54	2091	0.40	-2.69	1.15	2.44
2046	1.66	0	0.15	-0.03	2092	-1.05	-2.71	0	0.31
2047	0.32	0	0.14	-0.31	2095	2.33	0.37	0.17	-0.57
2048	1.85	-0.97	-0.46	0.88	2096	5.98	1.17	-3.42	0.75
2051	-1.13	-0.94	1.01	-0.36	2097	-2.19	0	2.24	0.6
2052	3.46	-3.1	-1.9	0.64	2098	0.62	-2.3	0.86	0.05
2053	0.05	-1.05	2.99	0.28	2099	1.65	-0.21	-1.42	-0.03
2061	1.4	0.17	0.01	-0.28					

* Obtained by subtracting 100 from the respective components

(1): TC; (2): EC; (3): SEC; (4): IME

Table 2 presents the average rates of TFP growth as implied by MPI approach and the Divisia approach, by industry. According to the MPI approach, thirty two industries experienced productivity gains from 1986/87 to 1995/96. The highest rates of productivity growth were attained by industries 2045, 2053, 2087, and 2096. The largest declines occurred in industries 2033, 2035, 2068, and 2092. According to the Divisia approach, twenty five industries experienced productivity gains.

Table 2. The Rates of TFP Growth From the Two Approaches (geometric averages from 1986/87 to 1995/96) %

Industry Code	Malmquist*	Divisia	Industry Code	Malmquist*	Divisia
2011	1.39	-0.48	2062	0.43	-0.35
2013	0.16	0.51	2063	5.02	2.13
2015	2.12	1.25	2064	1.80	0.88
2021	0.03	3.51	2066	-0.33	-0.82
2022	-0.23	-0.66	2067	0.85	0.73
2023	-3.44	-2.88	2068	-1.71	-0.65
2024	3.34	1.71	2074	1.74	-0.85
2026	-0.85	-0.78	2075	2.03	0.59
2032	1.99	0.02	2076	-0.35	-1.08
2033	0.14	-1.46	2077	-0.51	-1.24
2034	-0.70	-1.80	2079	0.22	-0.76
2035	-1.69	-1.72	2082	2.87	2.84
2037	1.48	0.17	2083	2.06	0.62
2038	2.38	1.05	2084	1.33	1.04
2041	-1.02	-2.12	2085	0.57	-0.86
2043	-0.24	-4.23	2086	2.60	1.04
2044	2.6	1.11	2087	3.56	2.44
2045	4.00	1.63	2091	1.23	-1.31
2046	1.78	0.18	2092	-3.43	-2.16
2047	0.15	-1.48	2095	2.30	1.96
2048	1.28	-0.10	2096	4.37	1.08
2051	-1.44	-2.50	2097	0.61	1.50
2052	-1.03	-1.82	2098	-0.81	-1.08
2053	2.25	0.75	2099	-0.03	0.07
2061	1.31	1.70			

* Obtained by subtracting 100 from the MPI Index

It is obvious that the results from the two indices differ not only in the implied (average) magnitudes of productivity change but, in a number of cases, in implied direction of the change (positive or negative). It would be certainly interesting to examine whether the observed differences are systematic. To this end we employed the non parametric Wilcoxon Signed Ranks Test (Cooper et al., 2000). The relevant test statistic

$$T = \frac{R_D - n(2n+1)/2}{\sqrt{n^2(2n+1)/12}} \tag{8},$$

where n is the sample size and R_D is the sum of rankings corresponding to the Divisia rates of productivity growth follows the standard normal distribution. The empirical value of T is –4.45 implying that the rates of productivity growth from the two approaches have different distributions. Moreover, since the sign of the statistic is negative and R_D comes from the Divisia approach, the Wilcoxon test implies that the productivity growth rates from the latter index are systematically lower than those from the Malmquist index.

The productivity growth rates from the 4-digit SIC industries were aggregated using shares in the value of shipments as weights to assess productivity growth for the 2-digit SIC Food and Kindred products industry. Figure 1 presents the results. As expected, the MPI suggests a better performance of the industry under consideration relative to the Divisia index and this holds for all but one (1992/93) periods of observation. The average annual rate of productivity growth from the MPI was 0.99 percent indicating a moderate improvement, while from the Divisia was –0.009 percent indicating no change over the ten year period considered.

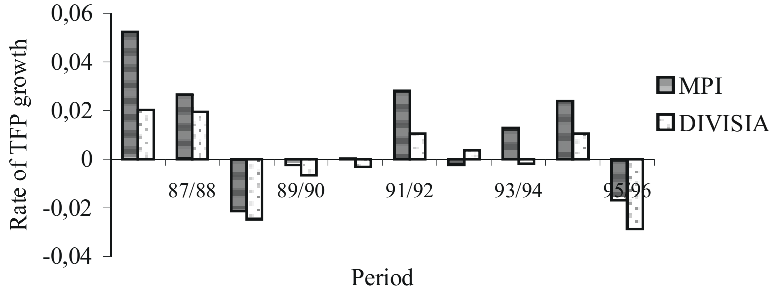

Figure 1. Rates of Productivity Growth for the Food and Kindred Products Industry

Conclusions

The objective of the present paper has been to obtain estimates of productivity growth for the 4-digit SIC food and beverage manufacturing industries in the US. To this end, it utilized detailed information on output and inputs available by the NBER and Balk's (2001) decomposition of the Malmquist productivity index. According to the empirical results:

a) The individual industries exhibited quite different patterns of productivity growth. Some experienced very strong productivity gains, while in others productivity followed a downward trend.

b) For the overwhelming majority of industries technical change and technical efficiency change appeared to be the main forces behind productivity changes, while the role of scale efficiency and input-mix efficiency changes was limited.

c) The Divisia index of the NBER which relies on the highly implausible assumption of perfect competition in both output and input markets results in a distribution of productivity estimates that differs from the one implied by the MPI. The Wilcoxon test offers evidence that the Divisia estimates are systematically lower than the MPI estimates.

The NBER manufacturing productivity growth estimates have been used as a dependent variable in regression models looking at a variety of possible influences (e.g. government regulation, global competition, risk, and concentration) on productivity in US manufacturing. Given the statistically significant difference between the estimates from Malmquist and the Divisia (growth accounting) approach considered in this paper, future research should assess whether the empirical results of works concerning potential influences on productivity are sensitive to the choice of the dependent variable (that is, sensitive to the choice of the index used in productivity calculations). This will certainly allow economists to provide more robust guidelines to the policy makers for fostering productivity growth.

Notes

1. This holds since for a cone technology an input distance function is the reciprocal of the corresponding output distance function, i.e., $\overset{\vee}{D}_i^t = \frac{1}{\overset{\vee}{D}_o^t}$.
2. 1996 is the most recent year in which detailed data on output and inputs are available by the NBER at the 4-digit SIC level.
3. The level of technical efficiency with respect to the period t technology (S^t) is obtained as the reciprocal of $D_i^t(x^t, y^t)$ (Coelli et al. 1998).
4. The level of scale efficiency with respect to the S^t technology is obtained as the ratio $ES^t = \frac{D_i^t(x^t, y^t)^t}{\overset{\vee}{D}_i^t(x^t, y^t)}$ (Balk, 2001; Coelli, et al., 1998).
5. Industries 2043, 2075, and 2087 were scale efficient in all periods according to the measure of scale efficiency with respect to the period t technology (S^t). In Table 1, however, they appear to have experienced declines in scale efficiency over 1986-96. The relevant question is whether here there is a contradiction. The answer is no. The change in scale efficiency between two periods is not calculated as $\frac{ES^{t+1}}{ES^t}$ (that is, as the ratio of scale efficiencies in two production points belonging to *different* technology frontiers). According to equation (6) the change in scale efficiency is actually calculated from movements along *the same* technology frontier. In particular, the first term in the brackets in (6) is the change in scale efficiency calculated from movements along the frontier of S^t while the second term is the change in scale efficiency calculated from movements along the frontier of S^{t+1}. Therefore, a constant scale efficiency along points belonging to different period frontiers by no means imply that there is no change in scale efficiency (for additional details see Balk (2001), pp. 168-71 and 173-75).

6. The former coefficient had a value of 0.11 and the later a value of 0.09. The statistic $\frac{\hat{\rho}\sqrt{n-2}}{\sqrt{1-(\hat{\rho})^2}}$, where $\hat{\rho}$ is the Pearson coefficient estimate and n is the sample size follows the t-distribution with $n-2$ degrees of freedom (Kintis, 1994). With 490 observations, the values of the statistic were 2.34 and 2.01, respectively, which exceed the critical value at the 5 percent level (1.96).

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Appendix A:

Industry Codes and Descriptions

Industry Code	Industry Description	Industry Code	Industry Description
2011	Meat Packing	2062	Cane Sugar Refining
2013	Sausages and Other Prepared Meats	2063	Beet Sugar
2015	Poultry Slaughtering and Processing	2064	Candy and confectionary
2021	Creamery Butter	2066	Chocolate and Cocoa
2022	Cheese	2067	Chewing Gum
2023	Dry, Condensed, Evaporated Dairy	2068	Salted and roasted nuts and Seeds
2024	Ice Cream and Frozen Deserts	2074	Cottonseed Oil Mills
2026	Fluid Milk	2075	Soybean Oil Mills
2032	Canned Specialities	2076	Vegetable Oil Mills
2033	Canned Fruits and Vegetables	2077	Animal and Marine Fats and Oils
2034	Dehydrated Fruits and Vegetables	2079	Edible Fats and Oils
2035	Pickles, Sauces, and Salad Dressings	2082	Malt Beverages
2037	Frozen Fruits and Vegetables	2083	Malt
2038	Frozen Specialities	2084	Wines, Brandy, Brandy Spirits
2041	Flour and Other Grain Mill Products	2085	Liquors
2043	Cereal Breakfast	2086	Soft Drinks
2044	Rice milling	2087	Flavoring Extracts and Syrups
2045	Prepared Flour Mixes and Doughs	2091	Canned and Cured Fish and Sea Foods
2046	Wet Corn Milling	2092	Fresh or Frozen Prepared Fish
2047	Dog and Fat Food	2095	Roasted Coffee
2048	Prepared Feeds	2096	Potato Chips and Similar Snacks
2051	Bread and Cakes	2097	Manufactured Ice
2052	Cookies and Crackers	2098	Macaroni and Spaghetti
2053	Frozen Bakery Products	2099	Food Preparations
2061	Raw Cane Sugar		

Appendix B:

Derivation of the Distance Functions Involved in Components of the MPI

The distance functions for the actual technology in period t were derived using Data Envelopment Analysis (DEA) (Banker, Charnes, and Cooper, 1984). In particular, for industry j

$$[D_i^{j,t}(y^{jt}, x^{jt})]^{-1} = \min \ \varphi^{jt}$$

subject to

$$\begin{aligned} &-y^{jt} + Y^t \lambda \geq 0 \\ &\varphi^{jt} x^{jt} - X^t \lambda \geq 0 \\ &K' \lambda = 1 \\ &\lambda \geq 0 \end{aligned}$$

where Y^t is an 1X49 vector of outputs, X^t is a 4X49 vector of inputs, K is a 49X1 vector of ones, and λ is a 49X1 vector of intensity variables. The distance functions for the cone technology corresponding to the actual technology, $[\overset{\vee}{D}_i^{j,t}(y^{jt}, x^{jt})]$, was derived from the problem above by dropping the constraint that the sum of the intensity variables equals 1. Finally, distance functions involving inputs or/outputs from different periods (e.g. $D_i^t(x^t, y^{t+1})$, $D_i^{t+1}(x^t, y^t)$, etc) have been calculated using the Simulation procedure (OnFront 2, User's Guide, pp. 11-12)