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COMPETITIVE ANALYSIS OF U.S. FOOD PROCESSING PLANTS

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ABSTRACT

This paper presents a model-based approach for competitive analysis of manufacturing plants in the U. S. food processing industry. As part of this approach, plant competitiveness is measured using Operational Competitiveness Ratings Analysis (OCRA) -- a new non-parametric method of computing relative inefficiency. Drivers of competitiveness are identified in terms of policies related to plant structure and infrastructure. Policies related to plant structure are those decisions that are related with "bricks and mortar" and have long term implications, such as decisions related to plant size and capacity. Policies related to plant infrastructure are decisions related to how the " bricks and mortar" are used. These policies are typically under the direct control of the operations managers and have a short-term orientation, such as decisions related to equipment, quality, inventory, workforce and confusion-engendering activities (e.g. new product introductions and product variety). The empirical analysis is based on detailed cross-sectional data on 20 processed food manufacturing plants. With respect to plant structure, the results suggest that small sized food processing plants are competitive, and both capacity underutilization and overutilization are detrimental to plant competitiveness. Among the significant results with respect to plant infrastructure, equipment maintenance, quality management programs, packaging supplies inventory, workforce training and product variety are positively associated with plant competitiveness. The results also suggest that introduction of new products disrupts plant operations, at least in the short run, and is negatively associated with plant competitiveness.

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1. INTRODUCTION

Competitive analysis of plants is fundamental to enhancing the competitiveness of manufacturing firms. Such analysis can guide the process of planning and executing organizational interventions such as process re-engineering, total quality management and continuous improvement programs. However, "most management systems in place do not provide the kind of information needed by companies that seek to create competitive advantage through manufacturing" (Hayes et al. 1988, p. 130). After a review of the models available for economic evaluation of manufacturing operations, Fine (1993, p.723) concludes: "Firms need better models to improve their control and evaluation systems." More specifically, Oral (1993, p. 10) notes: "What is needed is in fact a more formal approach that analytically captures the relationship between strategy and competitive strength."

This paper presents a model-based approach for competitive analysis of manufacturing plants that makes it possible to investigate the relationship between operations strategy and competitive strength of plants. As part of this approach, Operational Competitiveness Ratings Analysis (OCRA) -- a new non-parametric relative inefficiency evaluation method -- is used to measure competitiveness of 20 U.S. food processing plants. Next, regression models are estimated to identify drivers of plant competitiveness in terms of policies related to plant structure and infrastructure. The results of regression analysis are both intuitive and consistent with the qualitative insights from the research and practitioner literature on processed food manufacturing.

The remainder of the paper is organized as follows. Section 2 contains a review of the relevant practitioner and research literature. Section 3 describes the measure of plant competitiveness. Section 4 describes the U. S. processed food manufacturing industry. Section 5 contains a discussion of the research design and the data used to conduct the empirical analysis. Section 6 presents the results of the empirical analysis along with a discussion on the insights obtained from these results, followed by the concluding section 7.

2. LITERATURE REVIEW

2.1 Competitive analysis

Prescott and Grant (1988) were the first, to the best of our knowledge, to review studies on competitive analysis. Their review comprised of 21 studies led to guidelines aimed at helping managers understand the trade-offs associated with the different competitive analysis approaches. More recently, Oral (1993) conducted another comprehensive review of the studies on competitive analyses. His review suggests that the approaches documented in the extant literature can be divided into two categories -- descriptive and analytical:

(i) The *descriptive* approaches are useful for understanding the general nature of competition and its broad strategic implications. They provide a checklist of factors, but contain few measurement guidelines, or actionable procedures for competitive strategy formulation.

(ii) The *analytical* approaches are founded on models whose solutions provide insights for strategy formulation. However, the resulting guidelines are generally not specific enough to be useful for strategic decision making. Furthermore, very few of these analytical approaches have been empirically tested in order to assess their potential for strategy formulation.

Oral and his associates are among the first to systematically conduct competitive analysis using model based approaches. For example, Oral and Dominique (1989) examine competitive strategy formulation with respect to manufacturing-marketing interface and explicitly take into account the context of the firm and the environment in which it operates. They propose an analytical framework which can be used to study how a firm perceives the opportunities and threats in its environment and attempts to optimize its objectives subject to internal and external constraints.

Oral (1993) extends the developments in Oral and Dominque (1989). In this paper he proposes a model to measure the level of industrial competitiveness, and also describes its phase-by-phase implementation in a large glass making company. The competitiveness level of the firm is expressed as a function of two major factors: industrial mastery and cost superiority. Industrial mastery is an indicator of a firm's success compared to its competitors in terms of generating and managing capital and operational resources. Cost superiority, on the other hand, is the indicator of a firm's input usage rates and input costs.

The unit of analysis in these two studies by Oral and his associates[2] or those documented in Prescott and Grant (1987) is either the firm or the business unit. Studies on competitive analysis where the unit of analysis is the operating unit -- i.e. plant or service

[2] There are other papers by Oral and his associates on competitive analysis, including competitive analysis of nations. The two papers referenced here are the ones most relevant to this study.

center -- are relatively rare in the literature. Review of both practitioner and research literature suggests that references to competitive analysis of a firm's manufacturing or service operations are predominantly proprietary or anecdotal in nature. There is a body of practitioner literature on competitive benchmarking which provides normative guidelines for identifying performance gaps between plants, and identifying practices necessary to be at par with, or, outperform one's competitors (Tucker et al. 1987; Hayes et al. 1988, p. 156-157; Camp 1989). In the research literature, references to studies on competitive analysis of manufacturing and service operations of firms are extremely limited. At best, the research literature on competitive analysis of plants can be characterized as being in the developmental stages.

The few studies where model based approaches have been used to conduct competitive analysis of the operating units of a firm are Parkan (1994) and Sinha (1996). Parkan (1994) proposes models for computing "operational competitiveness ratings" of a set of production units. He illustrates the application of these models to evaluate the competitiveness of the branches of a major bank (Parkan 1994).

Sinha (1996) proposes "moving frontier analysis" -- a method for conducting competitive analysis of dynamically-complex operations of a high technology manufacturing plant. Using a wafer fabrication plant of a semiconductor manufacturing company as a research site, he demonstrates the application of moving frontier analysis over a 28-month period to determine (i) the gap between a plant's performance and industry best practices, and (ii) whether it will be possible to close this performance gap, and if so, the time it will take to do so.

Competitive analyses presented in Parkan (1994) and Sinha (1996) focus primarily on the measurement of competitiveness, and do not provide much insight into the drivers of competitiveness. The present study extends the developments documented in these two papers by not only focusing on the measurement of competitiveness, but also investigating the drivers of competitiveness.

2.2 Drivers of plant competitiveness

Drivers refer to choices that a firm makes with reference to its operations function to enhance the competitiveness of its operating units. Understanding these choices and their impact on competitiveness is at the heart of strategic management of a firm's manufacturing and service operations (Hayes et al. 1988; Fitzsimmons and Fitzsimmons 1994). The framework used to organize these choices was first proposed by Hayes and Wheelwright (1984) in their effort to understand the decision patterns in the operations function.[3] Subsequently, the framework proved to be useful in providing a "microeconomic" explanation of productivity differences at the plant level (Hayes and Clark, 1985). According to the framework, there are two categories of drivers -- structural and infrastructural:

[3] The categories in Hayes and Wheelwright's (1984) framework are substantively similar to the categories in the "production process level framework" used in studies commissioned by the McKinsey Global Institute (1993) to investigate the differences in labor productivity in plants across several manufacturing industries in the U.S, Germany and Japan.

(i) *Structural* drivers are decisions related with “bricks and mortar” and are therefore considered to have long-term implications. Examples of structural decisions are those related to plant size, plant capacity, age of equipment in a plant.

(ii) *Infrastructural* drivers are decisions related to policies that determine how the “bricks and mortar” are managed. Typically, these decisions are under the direct control of the operations managers, and are easier to change because they do not require the large and costly modifications that structural decisions do. Infrastructural decisions include policies related to equipment, quality, inventory, workforce and confusion-engendering activities (e.g. new product introductions and product variety) in a plant.

While the categories within this framework are parsimonious, the domain of its application has been restricted to investigating the drivers of plant productivity measured typically in the form of total factor productivity or labor productivity. Productivity measurement using such “traditional approaches” are frequently found, in practice, to be inconsistent with “a firm’s competitive position and its short term and long term profitability” (Banker 1985, p. 240). The domain of application of this framework of structural and infrastructural decisions is expanded in this paper by using it to investigate the drivers of plant competitiveness.

3. MEASURE OF PLANT COMPETITIVENESS

Competitiveness of a plant is measured in terms of its relative efficiency -- that is, efficiency of the plant *relative* to the efficiencies of plants in a sample. A formal econometric approach for estimating relative efficiency is with reference to the “best practice frontier". Best practice frontier, a term originally coined by Farrell (1957), denotes maximal output that can be obtained given a set of input quantities for a given set of plants in a sample[4]. The plants in a sample should be comparable in order to gain insights into how a firm's operations "compares with its best competitors with respect to the manufacturing capabilities upon which its manufacturing strategy is based" (Hayes et al. 1988, p. 148). At a conceptual level, competitive analysis based on such relative efficiency measures is "consistent with the underlying economic theory of optimizing behavior" and is oriented toward extreme observations of a body of data to extract information from them (Bauer 1990, p. 39).

Data Envelopment Analysis (DEA) is probably the most well known econometric method for estimating relative efficiency with reference to best practice frontier (cf. Banker and Khosla 1995; Sinha 1996; Cooper et al. 1996). DEA is a non-parametric method since the frontier is constructed without any assumptions about the functional form of the underlying relationship between the inputs and outputs. With increasing complexity of manufacturing plants, the relationships between the inputs and the outputs are far from well understood. Hence, a non-parametric method for estimating relative

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[4] "Absolute frontier", on the other hand, refers to maximal output which can be attained, given a set of input quantities for all plants which can conceivably exist. From a theoretical standpoint, the distinction between the two types of frontiers is that the best practice frontier is estimated without assuming the form of the distribution of the one-sided error, where as the absolute frontier is estimated by assuming an explicit distributional form for the one-sided error. From a practical standpoint, the distinction between the two types of frontier is not likely to be large since the absolute and best-practice frontier necessarily converge asymptotically. See Forsund, Lovell and Schmidt (1980) for more details.

efficiency is useful because it does not require any *a priori* specification of the relationship between inputs and outputs.[5]

At an intuitive level, estimating relative efficiency using DEA involves defining a piecewise linear frontier using a set of real plants in its corners and “plants” invented by their convex combinations in between. Only the plants on the frontier, real or invented, are judged to be relatively efficient. To estimate the relative efficiency of a plant that is not on the frontier, its position is compared with that of the plant on the frontier. The specific plant on the frontier with which this comparison is made is generally an “invented plant” -- invented through a convex combination of nearby efficient plants that are real, and are also referred to as the reference set of the inefficient plant.[6]

Figure 1 is a geometric portrayal of a frontier using single input-single output example. Let P_1....P_5 represent five plants with coordinate values representing the amount, x, of a single input used to produce an amount y of a single output. The plant P_j with coordinates (x_j,y_j) is introduced to exhibit the phenomena of efficiency dominance. Comparing P_4 with P_j shows that the former obtained more output from the same input. Hence, P_j is output-inefficient in amount $y_4 - y_j$. Similarly, comparison with P_3 shows P_j to be input-inefficient since P_3 achieved the same output as P_j with input less in amount $x_j - x_3$. Next, consider the plant P_1 which may be evaluated from non-negative (convex) combinations of the observed values of efficient plants such as P_3 and P_4. These

[5] See Cooper, Sinha and Sullivan (1996) for more details on reasons for using non-parametric method for efficiency evaluation of complex manufacturing operations.

[6] See Charnes et al. (1978), Banker et al. (1984), and Banker et al. (1989) for a detailed review of DEA.

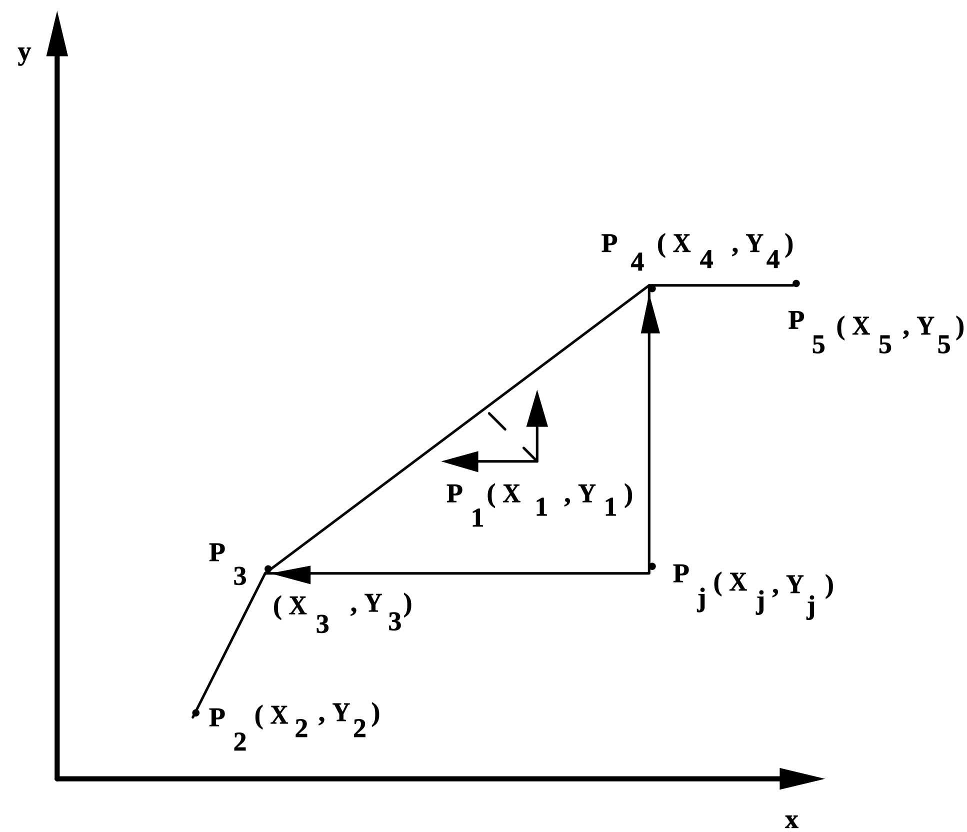

Figure 1. Geometric portrayal of a frontier using a single input-single output example

combinations help to "invent" plants which are also efficient. The vertical arrow in Figure 1 locates a point that assigns all inefficiency to P_1's realized output while the horizontal arrow assigns it to the input utilized. As designated by the broken line, other points may be designated by DEA models. The solid line segments connecting P_2, P_3, P_4, P_5 represent a frontier or the "production possibility set" -- i.e. the set of output and input pairs that have been actually realized. Not all plants on the frontier represent best (i.e. efficient) practice--e.g. P_5's input performance is dominated by P_4 because it uses input quantity that is more than what P_4 uses to produce the same output quantity. The plants P_2, P_3 and P_4 represent the best practice frontier (or, the "efficiency frontier"). A plant is on the best practice frontier if and only if the performance of other plants do not show that some of its inputs or outputs can be improved without worsening some of its other inputs or outputs.

A major problem in implementing DEA is that it may construct a frontier that may contain far too many real plants necessary for estimating relative efficiencies. The problem is particularly exacerbated when the number of production units (e.g. plants) in a sample is small because many of the production units become self-evaluators. Small sample size is a common problem encountered in conducting competitive analysis of plants or other types of operating units of firms (cf. Schefczyk 1993; Sinha 1996), we have identified a method that was developed recently to circumvent such a problem. The method is known as Operational Competitiveness Ratings Analysis (OCRA) and was developed by Parkan (1994). Like DEA, OCRA is a non-parametric method.[7] At an intuitive level, OCRA computes the inefficiency of a plant relative to a set of plants by taking into consideration all the relevant input-consuming and output-generating activities of the plants and assigning ratings to gauge their relative inefficiency in these activities. Mathematical formulation of the OCRA model for computing relative inefficiency is presented in Appendix A.

4. PROCESSED FOOD MANUFACTURING PLANTS

Processed food is defined as all food products that undergo some form of preservation, cooking, reconstitution or packaging before they are sold to the consumers. In practical terms, this includes all food categories except fresh produce, alcoholic and non-alcoholic beverages. This definition covers most of the products which fall under the heading "Food and Kindred Products" (SIC 20).

A recent study by the McKinsey Global Institute (1993, p. 1) shows that the processed food industry " is the largest single consumer goods industry, and as such plays an important role in the health of an economy." In the U.S., food processors account for the largest share of employment in consumer goods manufacturing industry. The importance of food processing is accentuated when one examines the entire food supply system, with the farm sector at one end and consumers at the other end. The food processors transform inputs in the form of raw commodities from the farm sector (using other inputs such as labor, capital, packaging supplies and energy) into a variety of packaged consumer products within the limits imposed by the biological, storage and safety requirements of raw food and agricultural commodities and manufacturing

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[7] For a comparison between OCRA and DEA methods, see Parkan (1994, p. 202).

technology. “It is this segment that largely shapes the time, form and location characteristics of our food supply” (McCorkle Jr. 1988, p. 2).

Processed food manufacturers can be divided into four strategic groups based on the marketing channels used to sell the products:

(i) Firms that sell producer or industrial goods (e.g. flour and sugar) to other manufacturers.

(ii) Firms that cater to food service market (e.g. commercial eating and drinking places, schools, hospitals, airlines and other establishments) that serve food away from home.

(iii) Firms that sell packaged consumer products carrying their own manufacturer’s brand to food stores.

(iv) Firms that sell private label, generic and unbranded products to various distributors or directly through food stores.

The sample of 20 processed food manufacturing plants in this study belong to category (iii). The plants’ output is packaged consumer products that carry their own manufacturer’s brand.

According to the McKinsey Global Institute’s (1993) study, product standardization among the U.S. processed food manufacturers has reached such a level that price is an important factor in competition. Price competition, in turn, puts pressure on the firms to reduce their production costs. Recently, Miller and Roth (1994) conducted an empirical study on manufacturing strategies across several U.S. industries. Their study suggests that the consumer packaged food manufacturers are “marketeers” who compete primarily through infrastructural changes aimed at cutting costs. It is evident from both of these recent studies that production efficiency is key to competing in the food processing industry. Hence, relative efficiency is an appropriate measure of plant competitiveness in this industry.

The Hayes and Wheelwright's (1984) framework, discussed earlier, is followed to organize the ensuing discussion under two headings: structural and infrastructural drivers.

4.1 Structural drivers

Capacity utilization. In spite of the advances in agricultural sciences, climatic conditions and soil characteristics still restrict the production of many important crops to given geographical areas. This restriction leads to heavy on-season use of many food processing facilities and partial or minimal utilization of the capacity in the off-season (McCorkle 1988, p. 4).

Plant size. An optimal size of a plant is one that, under currently available technologies, achieves lowest unit costs. The agricultural economics literature seems to indicate that in food processing, production economies of scale can be substantial. According to Connor and Wills (1988, p. 133-134), economies of scale can be a barrier to entry depending on how great a cost disadvantage the suboptimal plant size poses. Reports in the recent practitioner literature, on the other hand, suggest that small sized food processing plants are competitive because they are more flexible (cf. *Food Processing* 1996, p. 54-55).

4.2 Infrastructural drivers

Equipment policies. The focus here is on equipment maintenance because in a modern food processing plant well-maintained equipment is key to (i) ensuring that food processing is safe, and (ii) effectively utilizing automated processing, packaging and material handling equipment to meet the volume and mix fluctuations in the demand for consumer packaged food products. In food processing operations, scheduled preventive maintenance is less costly than condition-based preventive maintenance, in which performance is monitored for precursors of imminent failure (the monitoring system itself requires maintenance). Efficient corrective maintenance is expensive, because skilled staff have to be kept in readiness, but it offers highest all-round availability of equipment (McFarlane 1995, p. 35).

Quality policies. Processing technologies such as aseptic processing and packaging, and food irradiation[8] that are integral to a modern processed food manufacturing plant require stringent quality control. Furthermore, for a processed and packaged food product to be considered a quality product that will sell in the market place, it must cater to consumers' preferences such as those related to sensory properties (color, flavor, texture and overall appearance), nutritional value, shelf life, packaging, ease of preparation, microbiological safety etc. In essence, competitiveness of a food processing plant is determined by policies related to both internal and external quality.

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[8] "Aseptic processing and packaging" is used to produce food products that are shelf-stable (i.e. free from danger of microbiological spoilage even at room temperature. "Food irradiation" is used to irradiate food products (typically using gamma rays) in order to reduce the population of spoilage organism, kill all non-

Inventory policies. The seasonal nature of agricultural production and perishability of crops make it necessary for the processed food manufacturers to carry raw materials and finished goods inventory. In addition, packaging material inventory constitutes a significant portion of inventory costs of a processed food manufacturer. This is due to the fact that these processors use packaging technologies (e.g. aseptic packaging, and the development of new packaging materials) to improve shelf-life and decrease cost of storage. Further, because of the consumer-oriented nature of processed food product, packaging materials play an important role in differentiating competing products.

Workforce policies. A technologically sophisticated workforce is becoming increasingly necessary to operate, maintain and repair the processing and packaging equipment used in modern food processing operations (McCorkle et al. 1988, p. 430). Hence, food processors need to make substantial investments in technical training of their workforce in order to be competitive.

Confusion related policies. The food processing industry is characterized by product proliferation that is unlike any other industries. According to Kinsey and Heien (1988, p. 63): "There are about 50,000 food items in distribution each year, and about 2,500 net "new" items are introduced every year. The failure rate is about 60 percent per year. Over 90 percent of all "new" food products eventually fail." For food processors, product proliferation can translate into operating at suboptimal production levels. New product introductions, broad product variety and frequent schedule revisions are disruptive and

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spore-forming pathogens, or kill all organisms associated with the product. See Sanderson and Scheigert (1988, p. 93-95) for more details.

detrimental to a plant's performance, at least in the short run (Hayes and Clark, 1985). Confusion related policies are aimed at minimizing the disruptions in the plant.

5. RESEARCH DESIGN

The empirical analysis for this study is based on detailed cross-sectional data from 20 plants of several well-known processed food manufacturing firms for the year 1989. The dataset was made available to us by A. T. Kearney Inc., an international management consulting firm, the industry partner in this study. The identity and the location of the plants cannot be divulged, so numbers 1 to 20 were assigned to the plants and their products are listed in column 1 of Table 1.

The empirical analysis is conducted in two steps:

Step 1. The competitiveness of the 20 plants in the study sample is measured in terms of their relative inefficiencies using the OCRA method. The relative inefficiencies are computed using input data in the form of costs of labor, capital, material and energy, and output data in the form of revenue.

Step 2. Regression models are estimated to investigate the drivers of plant competitiveness. The dependent variables in the regression models are the relative inefficiencies of the plants. The independent variables are the proxies for the infrastructural policies related to equipment, quality, inventory, workforce and confusion-engendering activities. The proxies for structural policies related to plant

Table 1

Food processed at the plants, processed food prices in 1989$, and the sources of the prices.

	Column 1	Column 2	Column 3
Plants	*Products*	*Price (1989$)*	*Source of the price*
1	Ice cream	2.60 (1/2 gal)	Food Cost Review[9], p. 6.
2	Ice cream	2.60 (1/2 gal)	Food Cost Review, p. 6.
3	Potatoes	0.34 (one lb.)	Food Cost Review, p. 6.
4	Packaged meat (turkey)	0.99 (one lb.)	Food Cost Review, p. 6.
5	Packaged meat (chicken)	0.93 (one lb.)	Food Cost Review, p. 20.
6	Snack food	2.86 (one lb.)	Cost of Living Index[10].
7	Cookies	2.38 (one lb.)	Food Cost Review, p. 6.
8	Cereal	1.72 (18 oz)	Cost of Living Index.
9	Cereal	1.72 (18 oz)	Cost of Living Index.
10	Juice	1.86 (one lb.)	Food Cost Review, p. 6.
11	Yogurt	0.55 (half pt= 8 oz)	Cost of Living Index.
12	Spices	2.37 (one lb.)	United Nations Statistics[11].
13	Packaged meat (sausage)	2.12 (one lb.)	Statistical Abstracts of the United States[12].
14	Packaged meat (beef)	1.88 (one lb.)	Statistical Abstracts of the United States.
15	Cookies	2.38 (one lb.)	Food Cost Review, p. 6.
16	Potatoes	0.34 (one lb.)	Food Cost Review, p. 6.
17	Soup	0.69 (10 3/4 oz)	Product Alert[13].
18	Frozen meals	1.40 (11 oz)	Food Cost Review, p. 15.
19	Packaged eggs	1.14 (dozen)	Statistical Abstracts of the United States.
20	Pet food	0.50 (14 oz)	Product Alert[14].

[9] Dunham, D., 1989. *Food Cost Review*, Economic Research Service, U.S. Department of Agriculture, Agricultural Economic Report No. 636.
[10] American Chamber of Consumers Research Association, *Cost of Living Index*, Vol. 22, No. 4.
[11] *United Nations Statistics*, 1989-90, p. 181.
[12] *Statistical Abstracts of the United States*, 1995, p. 503.
[13] *Product Alert*, July 23, 1990. "Campbell's Condensed Soup - Cream of Broccoli."
[14] *Product Alert*, December 18, 1989. "Tyrell's Deluxe Canned Dog Food."

size and capacity utilization are used as the control variables in the regression models.

5.1 Data on inputs and output

Following is a description of the data on the four inputs and one output:

Labor. This includes annual expenditures on direct and indirect labor and salaried employees.

Materials. This includes annual expenditures on raw material and packaging supplies.

Capital. This includes the annual depreciation costs of facilities and equipment. Reliable and consistent estimates of opportunity cost of capital were not available for any of the 20 plants and hence, it is not included in this input cost category.

Energy. This includes the annual costs of energy and utilities.

Revenue. The output data on the plants were available in physical units, and were transformed into revenue by multiplying the annual production volume by the publicly available retail prices for the products. The retail prices used and their sources are listed in columns 2 and 3 of Table 1. This transformation to price-adjusted production volume is necessary to ensure that the output data across plants are comparable (cf. Chew 1988, p. 118).

5.2 Data on plant structure and infrastructure

The data used as proxies for the policies related to plant structure are:

Plant size. This is measured as the total number of hourly and salaried employees in a plant.

Capacity utilization. This is measured as the ratio of physical units of output to production capacity of a plant.

The data used as proxies for the policies related to plant infrastructure are:

Equipment. The proxy is the ratio of annual maintenance costs to book value of facilities and equipment. Maintenance costs include expenditures on maintenance labor, maintenance materials, maintenance contractors and maintenance overhead. Separate costs for preventive and corrective maintenance costs were not available for any of the plants in the sample.

Quality. The proxy is the ratio of annual budget for quality control and laboratory to cost of goods manufactured.

Inventory. The proxies used are the dollar value of annual inventory levels for raw materials, packaging materials and finished goods, respectively. There were numerous missing observations for the data on work-in-process inventory. Hence, we do not include it as a variable in estimating the regression model.

Workforce. The proxies used are the average hours of training per employee, and yearly averages of percentage-absenteeism and percentage-turnover for hourly workers. Data on overtime was not available for any of the plants in the sample. Hence, we do not include overtime as a variable in estimating the regression model.

Confusion. The proxies used are the product (SKU[15]) introductions per year and the average number of products per production line.

[15] SKU (Stock Keeping Unit) is defined as "individual color, size, flavor or pack of a product that requires a separate code number to distinguish it from other items" (Food Marketing Institute 1995, p. 81).

6. DATA ANALYSIS AND RESULTS

6.1 Measurement of plant competitiveness

The descriptive statistics for the input and output data of the 20 plants in this study are presented in Table 2. The material costs are the most significant input costs followed by labor, capital and energy. Figure 2 is a pie-chart showing both the categories and the sub-categories of input costs as a proportion of the total input cost.

Column 1 of Table 3 contains the relative inefficiency scores of the plants computed using the OCRA method16. To highlight the variability in the OCRA relative inefficiency scores, the DEA relative efficiency scores for the plants using the same data on inputs and output were computed. The DEA model used to compute the relative efficiencies was the BCC model (Banker, Charnes and Cooper 1984), the most widely used DEA model for relative efficiency evaluation. Mathematical formulation of the BCC model is presented in Appendix C**.** Column 2 in Table 3 contains the DEA relative efficiency scores. Consistent with the discussion in section 3, the OCRA relative inefficiency scores show more variability than the DEA relative efficiency scores for the same 20 plants. Correlational analysis between the OCRA measure of relative inefficiency

[16] Using expressions (A.6) and (A.7), we determined the following calibration constants that were used in the computation of relative inefficiencies: $a_{materials}$=0.29, a_{labor}=0.06, a_{energy}=0.01, $a_{capital}$=0.05, $b_{revenue}$=0.59.

Table 2

Descriptive statistics for the inputs and output.
(All values in thousands of 1989$)

	Mean	Standard deviation	Minimum	Maximum
Labor	17396	17194	2433	70414
Materials	87970	94209	627	386262
Capital	11311	12183	1190	47000
Energy	2479	2592	332	9000
Revenue	191732	165271	11866	550208

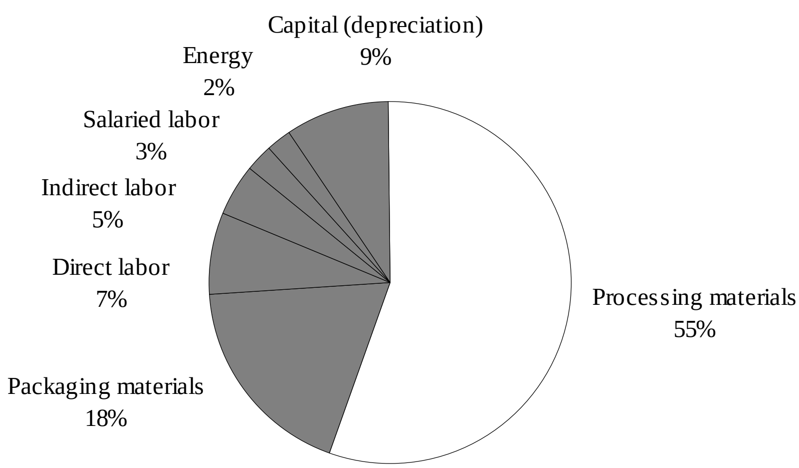

Figure 2. Proportions of the input cost categories and subcategories

Table 3

Relative inefficiency (OCRA), relative efficiency (DEA) and total factor productivity scores of the plants.

	Column 1	Column 2	Column 3
Plants	*Relative inefficiency (OCRA)*	*Relative efficiency (DEA)*	*Total factor productivity*
1	9.81	1.00	1.52
2	14.60	1.00	0.38
3	17.09	0.31	1.63
4	41.41	0.24	0.64
5	91.70	0.26	1.28
6	6.93	0.81	3.28
7	8.75	1.00	2.33
8	28.57	0.27	2.11
9	30.31	0.34	1.99
10	1.33	1.00	4.61
11	24.34	1.00	2.49
12	47.31	0.55	1.01
13	24.66	1.00	2.27
14	164.14	1.00	0.89
15	1.00	1.00	7.41
16	13.86	0.83	0.43
17	38.72	0.52	2.88
18	14.84	0.61	3.93
19	21.44	0.64	1.0003
20	110.04	0.08	0.25

and DEA measure of relative efficiency suggests that the correlation is not significant ($r = -0.34$, $p = 0.14$), implying that when the sample size of plants is small the two measures are not correlated.

Having shown that there is more variability in the OCRA relative inefficiency scores than the DEA relative efficiency scores, the variability in the OCRA relative inefficiency scores is compared to the variability in Total Factor Productivity (TFP) scores, a traditional measure of plant efficiency (cf. Hayes and Clark 1985). Column 3 contains TFP scores -- computed as the ratio of the output to the sum of four inputs -- for the 20 plants. The data on output and inputs are the same as those that were used to compute the OCRA relative inefficiency scores and the DEA relative efficiency scores. The correlation between the OCRA and TFP scores is negative and significant ($r = -0.44$, $p < 0.05$). The substantive difference in the variability between the OCRA and TFP scores is that the OCRA scores can be exploited to obtain insights into drivers of plant competitiveness in terms of policies related to plant structure and infrastructure, where as the TFP scores cannot be exploited to obtain such insights.

6.2 Regression analysis

Regression analysis was conducted to estimate models that relate plant competitiveness with policies related to plant structure and infrastructure. First, a *basic model* was developed containing only the control variables, plant size and capacity utilization,[17] as the predictors. The basic model is of the following form:

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[17] We do not a use a separate control variable to capture the learning curve effect because reliable estimates of cumulative production volume (a commonly used proxy for learning curve effect) were not

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \varepsilon \quad (1)$$

In the above model (1), the random error term, ε, is assumed to be independent and identically distributed as $N(0, \sigma^2)$. Y is the dependent variable that denotes plant competitiveness measured in terms of OCRA scores. X_1 and X_2 are the control variables -- plant size and capacity utilization.

Independent variables were added to this basic model (1) to develop models, one-at-a-time, corresponding to each one of the policies related to plant infrastructure. The rationale for conducting regression analysis corresponding to the infrastructural policies, one-at-a-time, is that the number of plants in the study sample is small (N=20)[18]. Diagnostic tests conducted as part of the regression analysis are discussed in Appendix B.

6.3 Regression results

Table 4 contains the descriptive statistics of the data on the variables in the regression models. The results of the regression analyses for estimating the basic model and the models corresponding to each one of the infrastructural policies are presented in Table 5. Column 1 shows that in the basic model, plant size measured as logarithm of

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available for the plants in the sample. Further, responses to questions in the survey questionnaire for data collection on average age of the processing and packaging equipment indicates that the production technology in the plants had been in use for 3 years or more, implying that the plants had gone down the learning curve.

[18] Hayes and Clark (1985) used a similar strategy for analyzing their data.

Table 4

Descriptive statistics for the data on variables in the regression models

Variables	Mean	Standard Deviation	Minimum	Maximum
OCRA relative inefficiency	35.54	41.16	1.00	164.10
Total factor productivity	2.12	1.72	0.25	7.41
Number of employees	733	842	92	3630
Capacity utilization	0.54	0.21	0.16	0.94
Maintenance cost/book value	0.18	0.13	0.02	0.60
Quality budget/cost of goods manufactured	0.01	0.01	0.0004	0.04
Raw material inventory/cost of goods manufactured	0.03	0.02	0.0008	0.08
Finished goods inventory/cost of goods manufactured	0.17	0.37	0.002	1.60
Packaging supplies inventory/cost of goods manufactured	0.01	0.01	0.001	0.03
Training hours per employee	52.07	134.40	0	600
Percentage-absenteeism	0.04	0.05	0.01	0.24
Percentage-turnover	0.16	0.17	0.01	0.65
Number of new product introductions	277	463	3	1900
Average number of products per line	22	24.5	2	114

Table 5
Estimation of the regression models, dependent variable = ln (OCRA relative inefficiency)
(Standard errors in parentheses)

	Column 1	Column 2	Column 3	Column 4	Column 5	Column 6
Variable	*Basic model*	*Equipment policies*	*Quality policies*	*Inventory policies*	*Workforce policies*	*Policies affecting confusion*
intercept	-2.53 (1.65)	-4.23*** (0.79)	-4.55*** (0.53)	-0.81 (0.86)	-4.89*** (0.89)	-1.27 (0.93)
ln(total number of employees)	0.80*** (0.26)	1.19*** (0.14)	0.65*** (0.11)	0.64*** (0.11)	0.98*** (0.09)	0.58*** (0.19)
capacity utilization	-2.38 (1.40)	-3.04*** (0.66)	-0.35 (0.53)	-0.25 (0.59)	-1.36** (0.52)	-1.32* (0.70)
(capacity utilization)^2	11.96** (5.15)	9.32*** (2.32)	5.35*** (1.48)	5.55** (1.76)	6.24*** (1.60)	6.60** (2.49)
maintenance cost/book value	-	-2.38** (0.98)	-	-	-	-
ln(quality budget/cost of goods manufactured)	-	-	-0.65*** (0.10)	-	-	-
ln(raw materials inventory/cost of goods manufactured)	-	-	-	-0.07 (0.10)	-	-
ln(finished goods inventory/cost of goods manufactured)	-	-	-	0.06 (0.08)	-	-
packaging supplies inventory/cost of goods manufactured	-	-	-	-33.10** (14.05)	-	-
ln(training hours per employee)	-	-	-	-	-0.17*** (0.05)	-
ln(absenteeism)	-	-	-	-	-0.65*** (0.17)	-
ln(turnover)	-	-	-	-	-0.003 (0.08)	-
ln(new product introductions)	-	-	-	-	-	0.47** (0.20)
ln(number of products per line)	-	-	-	-	-	-0.64** (0.23)
	F=4.80 R^2=0.51 *Adjusted* R^2=0.41	F=23.79 R^2=0.90 *Adjusted* R^2=0.86	F=60.34 R^2=0.96 *Adjusted* R^2=0.94	F=76.26 R^2=0.94 *Adjusted* R^2=0.88	F=25.69 R^2=0.93 *Adjusted* R^2=0.90	F=76.86 R^2=0.89 *Adjusted* R^2=0.84

* Statistically significant at the 0.10 level;
** at the 0.05 level;
*** at the 0.01 level.

number of employees in the plant is significant and positively associated with the OCRA measure of relative inefficiency. Also, in the subsequent regression models where proxies of infrastructural policies have been introduced one-at-a-time to the basic model, this association continues to be positive and significant. These results are consistent with the practitioner literature which suggests that small sized food processing plants are flexible and competitive (cf. *Food Processing* 1996, p. 54-55).

In the basic model (1) both a linear and a quadratic term for capacity utilization were used because the relationship between relative inefficiency and capacity utilization is expected to be curvilinear -- i.e. both capacity underutilization and capacity overutilization are detrimental to the competitiveness of a plant. The inclusion of both linear and quadratic terms for capacity utilization caused multicollinearity problems in estimating the regression models. These problems were addressed by re-estimating the models using deviations from the mean capacity utilization. As seen in column 1, the linear term is negative but not significant. However, the quadratic term is positive and significant. In the subsequent models, both the sign and the significance of the quadratic term is similar to the basic model. For the linear term, the signs continue to be negative in the remaining regression models, and is significant in columns 2, 5 and 6 corresponding to equipment, workforce and confusion related policies.

In column 2, the coefficient estimate of the ratio of maintenance cost to book value of equipment, the proxy for equipment policy, is negative and significant. This result indicates that maintenance expenditure is positively associated with a plant's competitiveness. In column 3, the coefficient estimate of the logarithm of ratio of quality budget to cost of goods manufactured, the proxy for quality policy, is also negative and significant. This result provides empirical support to the conventional wisdom that investments in quality management are positively associated with plant competitiveness.

In column 4, it is observed that out of the coefficient estimates of the three variables used as proxy for inventory policy, only the coefficient of the ratio of packaged supplies inventory to cost of goods manufactured is negative and significant. This result is capturing a feature that is unique to the manufacturers of consumer packaged food products. As noted earlier, given the perishable nature of processed foods and the fact that (i) packaging technologies are used to improve shelf-life and decrease cost of storage of food products, and (ii) packaging materials play an important role in differentiating between competitors' products, high inventory level of packaging supplies can be positively associated with competitiveness of processed food manufacturing plants.

In column 5, it is noted that out of the three variables used as proxy for workforce policy training and absenteeism are significant. The coefficient of the training variable is negative, indicating that training is negatively associated with relative inefficiency of a plant. This result empirically supports the fact that investment in training contributes toward improving the competitiveness of a plant. The negative association between absenteeism and relative inefficiency may at first appear to be counterintuitive, but it is not. What this result is capturing is the fact that when workers are absent the remaining workers increase their level of effort so as to fill the gaps left by their absent colleagues. "It is as if when the tenth worker is absent the remaining nine do the work of the 10.5 workers !" (Hayes and Clark, 1985; p. 163).

In column 6, it is noted that coefficient estimates of the two variables used as proxy for policy affecting confusion in operations are significant. However, the sign on the coefficient of logarithm of the number of new product introductions per year is positive. While this result may appear to be counterintuitive, it is actually capturing the short term disruptive impact of new product introductions on plant competitiveness. The long term impact of new product introductions on plant competitiveness can only be investigated through a longitudinal study. The sign on the coefficient of the second proxy variable is negative, indicating that competitiveness of plants is positively associated with product variety per line. This result provides empirical support to the prevailing wisdom in both the research and practitioner literature that the ability of a plant to effectively respond to product variety demanded by the marketplace enhances its competitiveness.

6.4 Comparative regression results

Another set of regression analyses was conducted in order to contrast the results obtained from the regression analyses using OCRA measure of relative inefficiency as the dependent variable. While the estimation procedure, and control and independent variables used in the next set of regression models are the same as in the earlier analyses, the dependent variable is Total Factor Productivity (TFP).

Table 6 contains the regression results using TFP as the dependent variable. It is interesting to note that compared to the earlier set of regression analyses, none of the proxies for any of the infrastructural policies -- with the exception of absenteeism in the workforce regression in column 5 -- is statistically significant. The explanation for positive association between absenteeism and total productivity is the same as the explanation for negative association between absenteeism and relative efficiency, discussed above. In summary, comparing the results of the two sets of regression analyses highlights the promise and potential of the OCRA measure of relative inefficiency for conducting competitive analysis and identifying the drivers of plant competitiveness.

7. CONCLUSION

The study documented in this paper is among the first research initiatives to use a model-based approach for analyzing the competitiveness of manufacturing plants. Integral to this approach is measuring competitiveness of plants using the OCRA method. OCRA circumvents the problems encountered in using DEA to compute relative efficiencies with small sample size of plants. This model-based approach can be used to examine the relationship between plant competitiveness and policies related to plant structure and infrastructure. Structural policies are decisions related to “bricks and mortar” that have long term implications, e.g. policies related to plant size and capacity utilization. Infrastructural policies are decisions related to the use of the “bricks and mortar” that are typically under the direct control of the managers in a plant, e.g. policies related to equipment, quality, inventory, workforce and confusion-engendering activities.

Table 6
Estimation of the regression models, dependent variable = ln (total factor productivity)
(Standard errors in parentheses)

	Column 1	Column 2	Column 3	Column 4	Column 5	Column 6
Variable	*Basic model*	*Equipment policies*	*Quality policies*	*Inventory policies*	*Workforce policies*	*Policies affecting confusion*
intercept	2.32* (1.12)	-2.45* (1.31)	2.40* (1.16)	0.21 (1.47)	3.83** (1.39)	2.49 (1.40)
ln(total number of employees)	-0.21 (0.18)	-0.26 (0.23)	-0.13 (0.25)	-0.02 (0.20)	-0.28 (0.16)	-0.22 (0.28)
capacity utilization	2.70** (0.95)	2.92** (1.10)	2.25 (1.39)	1.71 (1.10)	2.16** (0.81)	2.23* (1.06)
(capacity utilization)^2	-12.32*** (3.50)	-12.43*** (3.76)	-11.74*** (3.81)	-9.16** (3.43)	-12.44*** (2.89)	-11.36** (3.75)
maintenance cost/book value	-	0.78 (1.63)	-	-	-	-
ln(quality budget/cost of goods manufactured)	-	-	0.11 (0.24)	-	-	-
ln(raw materials inventory/cost of goods manufactured)	-	-	-	-0.10 (0.18)	-	-
ln(finished goods inventory/cost of goods manufactured)	-	-	-	-0.003 (0.14)	-	-
packaging supplies inventory/cost of goods manufactured	-	-	-	33.13 (20.53)	-	-
ln(training hours per employee)	-	-	-	-	0.17 (0.10)	-
ln(absenteeism)	-	-	-	-	0.45* (0.24)	-
ln(turnover)	-	-	-	-	-0.08 (0.14)	-
ln(new product introductions)	-	-	-	-	-	0.12 (0.30)
ln(number of products per line)	-	-	-	-	-	-0.24 (0.34)
	F=5.18 R^2=0.52 *Adjusted* R^2=0.42	F=3.44 R^2=0.53 *Adjusted* R^2=0.38	F=3.72 R^2=0.53 *Adjusted* R^2=0.40	F=2.54 R^2=0.66 *Adjusted* R^2=0.40	F=5.08 R^2=0.79 *Adjusted* R^2=0.64	F=2.54 R^2=0.54 *Adjusted* R^2=0.32

* Statistically significant at the 0.10 level;
** at the 0.05 level;
*** at the 0.01 level.

Among the significant results with respect to structural policies, plant size, capacity overutilization and capacity underutilization are negatively associated with plant competitiveness. Among the significant results with respect to infrastructural policies, plant competitiveness is positively associated with expenditures on equipment maintenance, quality management programs, packaging supplies inventory and workforce training, and product variety. The results also suggest that introduction of new products disrupts plant operations, at least in the short run, and is negatively associated with plant competitiveness. Based on the application of this model-based approach for competitive analysis of processed food manufacturing plants in the U.S., it seems that the overall approach and its building blocks are generalizable.

In conclusion, the model-based approach presented in this paper has unified the developments in two bodies of literature: (i) the econometrics literature devoted to developing models for estimating relative [in]efficiency, and (ii) the operations strategy literature devoted to understanding decision patterns in the operations function of firms. While the models for estimating relative [in]efficiency provide an analytically rigorous measure of competitiveness, the econometric studies have largely ignored strategic decision making that underlies competitiveness. On the other hand, studies in operations strategy which have been predominantly concerned with the process and content of strategic decision making in the operations function have largely ignored the need for analytical rigor in measuring competitiveness. This model-based approach, founded on the developments in these two bodies of literature, ensures that (i) the measure of plant competitiveness is analytically rigorous, and (ii) empirical application of the measure yields managerially relevant insights into strategic operations decisions.

7.1 Future research directions

As extensions to the present study, two streams of investigations are being planned. The first stream of investigations will examine how the policies related to plant structure and infrastructure fit -- i.e. complement, substitute, supplement, or contradict each other -- and how this fit impacts plant competitiveness. These investigations will require panel data-set -- cross-sectional and time-series data -- on processed food manufacturing plants. The second stream of investigations will compare the drivers of plant competitiveness within the processed food industry but across countries. Ideally, these investigations will also require panel data-set on processed food manufacturing plants but located in different countries.

Appendix A. OCRA combined relative cost and revenue inefficiency model

Suppose the competitiveness of *K* plants need to be compared that are involved in *I* different types of input-consuming and *J* different types of output-generating activities. Suppose there are separate observations on the amounts of inputs consumed and outputs generated by each of these *K* plants. Let the vectors $\mathbf{x}^k = (x_1^k, x_2^k, \ldots\ldots, x_I^k)$ and $\mathbf{y}^k = (y_1^k, y_2^k, \ldots\ldots, x_J^k)$ represent the *k*th plant's inputs and outputs, respectively. The *i*th element of $\mathbf{x}^k$, x_i^k, denotes the number of units of type *i* input consumed by the *k*th plant. Similarly, the *j*th element of $\mathbf{y}^k$, y_j^k, denotes the number of units of type *j* output generated by the *k*th plant. Suppose separate unit-price observations are also available. Let $\mathbf{p}^k = (p_1^k, p_2^k, \ldots\ldots, p_I^k)$ and $\mathbf{q}^k = (q_1^k, q_2^k, \ldots\ldots, q_J^k)$ be the *k*th plant's input and output unit-price vectors, respectively. The *i*th element of $\mathbf{p}^k$, p_i^k, represents unit-price of the *i*th input consumed by the *k*th plant. Similarly, the *j*th element of $\mathbf{q}^k$, q_j^k, represents unit-price of the *j*th output generated by the *k*th plant. Often, separate data on the amounts of inputs consumed and outputs generated or their unit-price cannot be obtained. Data on the cost of inputs consumed and revenues from outputs generated are generally available. Let the vectors $\mathbf{u}^k = (u_1^k, u_2^k, \ldots\ldots, u_I^k)$ and $\mathbf{v}^k = (v_1^k, v_2^k, \ldots\ldots, v_J^k)$ denote the costs of inputs consumed and revenues from the outputs generated, respectively. The *i*th element of $\mathbf{u}^k$, u_i^k, is the cost of the *i*th input consumed by the *k*th plant. Similarly, the *j*th element of $\mathbf{v}^k$, v_j^k, is the revenue from the *j*th output generated by the *k*th plant, where $u_i^k = p_i^k x_i^k$ and

$v_j^k = q_j^k y_j^k$. It is assumed that amounts of inputs consumed and outputs generated are not zero all at once, and all unit-prices are positive.

Let E(**u,-v)**, a linear function of (**u,-v**), represent the combined relative cost and revenue inefficiency of a plant. The relative inefficiency assigned to the *k*th plant is the minimum value of E^k such that the cost of inputs in any category is not less than the cost actually incurred at the *k*th plant and the revenue generated in any revenue category is not more than the revenue realized from the *k*th plant. This minimization problem can be written as follows:

$$\Delta(\mathbf{u}^k, \mathbf{v}^k) = \mathrm{Min}_{u,v} \left\{ \begin{array}{l} E(\mathbf{u}, -\mathbf{v}) : \mathbf{1u}_i \geq \mathbf{1u}_i^k,\ i = 1, \ldots., I;\ \mathbf{1v}_j \leq \mathbf{1v}_j^k, \\ j = 1, \ldots, J; \mathbf{u}_i, \mathbf{v}_j \geq 0, \mathbf{u}_i, \mathbf{v}_j \neq 0 \end{array} \right\}, k = 1, \ldots., K \tag{A.1}$$

where **1** is the I-component unit vector (1,....,1).

The linear programming formulation whose optimum solution characterizes the solution of the minimization problem (A.1) is as follows:

$$\text{Min} \quad S = \sum\sum_{kn} (s_u^{kn} + s_v^{kn}) \tag{A.2}$$

subject to

$$E^k - E^n + \sum_{i=1}^{I} \left[\mathbf{1}\left(\mathbf{u}_{Ni}^n - \mathbf{u}_{Ni}^k\right) \right] \alpha_i^k - \sum_{j=1}^{J} \left[\mathbf{1}\left(\mathbf{v}_{Nj}^n - \mathbf{v}_{Nj}^k\right) \right] \beta_j^k - s_u^{kn} + s_v^{kn} = 0, k, n = 1, \ldots., K \text{ and } k \neq n$$

$$\alpha_i^k \geq a_i^k > 0,\ i = 1, \ldots\ldots, I;\ \beta_j^k \geq b_j^k > 0,\ j = 1, \ldots\ldots, J\ ;$$

$$E^k, s_u^{kn}, s_v^{kn} \geq 0; k, n = 1, \ldots\ldots., K \text{ and } k \neq n.$$

where: s_u^{kn} and s_v^{kn} are penalty variables; $\mathbf{u}_{Ni}^n = \dfrac{\mathbf{u}_i^n}{\mathbf{1u}_i^k}$ and $\mathbf{v}_{Nj}^n = \dfrac{\mathbf{v}_j^n}{\mathbf{1v}_j^k}$ are vectors of normalized values of the costs of inputs consumed and revenues generated; α_i^k and β_j^k are the Lagrangian multipliers in relation to the constrained optimization problem (A.1) for the *k*th plant; a_i^k and b_j^k are the calibration constants of the model and serve as the lower bounds of α_i^k and β_j^k, respectively -- the procedure for estimating the calibration constants is described in the paragraph to follow. The main constraints of the linear program (A.2) are strict equality because of the linearity assumption of the inefficiency function E(**u**,-**v**). The optimum value of E^k, E^{k*}, represents combined relative cost and revenue inefficiency of *k*th plant.

Calibration constants. The following procedure is used to determine the calibration constants:

(i) For each plant, determine the cost share of the ith input and the revenue share from the jth output

$$Cost_i^k = \text{Cost}_i^k \Big/ \left[\sum_{i=1}^{I} \text{Cost}_i^k + \sum_{j=1}^{J} \text{Revenue}_j^k \right] \tag{A.3}$$

$$Revenue_j^k = \text{Revenue}_j^k \Big/ \left[\sum_{i=1}^{I} \text{Cost}_i^k + \sum_{j=1}^{J} \text{Revenue}_j^k \right] \tag{A.4}$$

for $i = 1,\dots,I$, $j = 1,\dots\dots,J$, and $k = 1,\dots\dots,K$.

Set $a_i^k = Cost_i^k$ and $b_j^k = Revenue_j^k$ (A.5)

(ii) If the values of calibration constants do not change with plants in the sample -- i.e. $a_i^k = a_i$ and $b_j^k = b_j$ -- use the average cost category share as the value of the calibration constant for the cost category, and the average revenue category share as the calibration constant for the revenue category:

$$a_i = \left[\sum_{k=1}^{K} Cost_i^k \right] \Big/ K \text{ for } i = 1,\dots,I \tag{A.6}$$

$$b_j = \left[\sum_{k=1}^{K} Revenue_j^k \right] \Big/ K \text{ for } j = 1,\dots\dots,J \tag{A.7}$$

It should be noted that $\sum_{i=1}^{I} a_i + \sum_{j=1}^{J} b_j = 1$. This normalization is desirable to ensure that the ratings computed for different calibration constant values are comparable. For a detailed discussion on the development of the OCRA models, see Parkan (1994, 1996).

Appendix B. Regression diagnostics

Following Neter et al. (1996), diagnostic tests for the residuals were conducted in order to check for any departures from assumptions of the regression models. If the residuals indicated that the dependent variable had a nonlinear relationship with one of the variables in the model higher order terms of that variable were included. To mitigate the effect of multicollinearity due to presence of higher order terms of the same variable deviations from mean of that variable were used. Variance Inflation Factor (VIF) was employed to detect the presence of multicollinearity. A VIF value greater than 10 was taken as an indication that multicollinearity may be influencing the least squares estimates. If the error variance varied systematically with independent variables, dependent variable, or predicted values of dependent variable, then a transformation on the dependent variable was done to overcome this problem. For example, a logarithmic transformation of the dependent variable helped in dealing with the problem of nonconstancy of variance. There were occasions when a simultaneous transformation of the independent variables was also necessary. For each of the estimated models the normality assumption of the error terms was tested. If the normal probability plot of the error terms was approximately a straight line, then the normality assumption was considered to be valid. However, if the normal probability plot showed departures from the normality assumption, then the dependent variable, independent variables, or both were transformed. The presence of outliers in the data was checked by using leverage values, internally studentized residuals and studentized deleted residuals. Some of the influential observations were identified utilizing Cook's distance. If these diagnostic tests suggested that such observations were present, remedial measures such as mitigating the influence by taking logarithmic transformation of the variables were used.

Appendix C. The DEA-BCC relative efficiency evaluation model

Using notations similar to those used for presenting the OCRA model formulations, the linear programming formulation of the BCC model can be written as follows:

$$Max \qquad \sum_{j=1}^{J} \mu_j v_j^0 \ - \ \rho^0 \tag{C.1}$$

subject to,

$$\sum_{i=1}^{I} \omega_i u_i^0 \qquad = 1$$

$$-\sum_{i=1}^{I} \omega_i u_i^k + \sum_{j=1}^{J} \mu_j v_j^k - \rho^0 \qquad \leq 0 \ ; \quad k = 1,2,....,K$$

$$\mu_j \qquad \geq \varepsilon \ ; \quad j = 1,2,....,J$$

$$\omega_i \qquad \geq \varepsilon \ ; \quad i = 1,2,...., I$$

ρ^0 is unconstrained in sign.

where,

K	=	number of plants, indexed by k = 1, 2,.....,K;
I	=	number of inputs, indexed by i = 1, 2,......,I;
J	=	number of outputs, indexed by j = 1, 2,....,J;
u_i^k	=	cost of ith input of kth plant;
v_j^k	=	revenue from jth output of kth plant;
u_i^0	=	cost of ith input of the plant being evaluated with an index 0;
v_j^0	=	revenue from jth output of the plant being evaluated with an index 0;
ω_i	=	weight to be determined and assigned to the cost of ith input;
μ_j	=	weight to be determined and assigned to the revenues from jth output;
ρ^0	=	a variable to indicate returns to scale possibilities in accordance with the following criteria: $\rho^{0*} < 0$ implies increasing returns

to scale, $\rho^{0*} = 0$ implies constant returns to scale, $\rho^{0*} > 0$ implies non- increasing returns to scale, where ρ^{0*} is the optimum value of ρ^{0};

ε = a positive "non-Archimedean" element -- the reciprocal of the "big M" used with artificial variables in ordinary linear programming.

The dual formulation of (C.1) is as follows:

$$\textit{Minimize} \qquad \theta^0 - \varepsilon\left[\sum_{i=1}^{I} l_i + \sum_{j=1}^{J} l_j\right] \tag{C.2}$$

subject to,

$$-\sum_{k=1}^{K} u_i^k \lambda^k + \theta^0 u_i^0 - l_i = 0;\ i = 1,2,.....,I$$

$$\sum_{k=1}^{K} v_j^k \lambda^k - l_j = v_j^0;\ j = 1,2,......,J$$

$$\sum_{k=1}^{K} \lambda^k = 1;$$

$$\lambda^k,\ l_i,\ l_j \geq 0$$

where l_i and l_j are non-negative input and output slack variables used to convert inequalities to equivalent equations. For a plant under evaluation -- i.e. plant with an index 0 -- the optimal θ^0, θ^{0*}, is a measure of relative efficiency of the plant. The condition $\sum_{k=1}^{K} \lambda^k = 1$ in (C.2) ensures that all solutions and, hence, the relative efficiencies of the plants are evaluated only by reference to input and output data of the plants in a sample and their convex combinations. For details on the development of the BCC model, see Banker et al. (1989, p. 144-146) and Banker (1984).

REFERENCES

Banker, R. D. (1985), "Productivity measurement and management Control," in: P. K. Kleindorfer (ed.), *The Management of Productivity and Technology in Manufacturing*, Plenum Publishing, 239-257.

Banker, R. D. , Charnes, A., and Cooper, W. W. (1984), "Models for estimation of technical and scale inefficiencies in data envelopment analysis," *Management Science* 30/9, 1078-1092.

Banker, R. D. , Charnes, A., Cooper, W. W., Swarts, J., and Thomas, D. A. (1989), "An introduction to data envelopment analysis with some of its models and their uses," *Research in Governmental and Nonprofit Accounting* 5, 125-163.

Banker, R. D., and Khosla, I. (1995), "Economics of operations management: a research perspective," *Journal of Operations Management* 12, 423-435.

Bauer, P. W. (1990), "Recent developments in econometric estimation of frontiers," *Journal of Econometrics* 46/1/2, 39-56.

Camp, R. C. (1989), *Benchmarking: The Search for Industry Best Practices that Lead to Superior Performance*, Quality Press, ASQC, Milwaukee, WI.

Charnes, A., Cooper, W. W., and Rhodes, E. (1978), "Measuring the efficiency of decision making units," *European Journal of Operational Research* 2, 429-444.

Chew, W. B. (1988), " No-nonsense guide to measuring productivity," *Harvard Business Review* 66/1, 110-118.

Cooper W. W., Sinha, K. K., and Sullivan, R. S. (1996), "Evaluating the information content of a measure of plant output: an application to high technology manufacturing," *Annals of Operations Research* (in press).

Farrell, M. J., (1957), "The measurement of production efficiency," *Journal of Royal Statistical Society* 120/ III/A (General), 253-281.

Fine, C., 1993. "Developments in manufacturing technology and economic evaluation models," in: S.C. Graves, A. Rinnoy Kan and P. Zipkin (eds.), *Logistics of Production and Inventory*, Elsevier Science Publishers B. V., Amsterdam, The Netherlands, 711-750.

Fitzsimmons, J. A., and Fitzsimmons, M. J. (1994), *Service Management for Competitive Advantage*, McGraw-Hill, New York, NY.

Food Marketing Institute. (1995), *Category Management 1: Getting Started*, Food Marketing Institute, Washington, D. C.

Food Processing, March 1996, 54-55.

Forsund, F. R., Lovell, C. A., and Schmidt, P. (1980), "A survey of frontier production functions and of their relationships to efficiency measurement," *Journal of Econometrics* 13, 5-25.

Hayes, R. H., and Clark, K. B. (1985), "Exploring the sources of productivity differences at the factory level," in: *The Uneasy Alliance: Managing the Productivity-Technology Dilemma*, Harvard Business School Press, Boston, MA, 151-188.

Hayes, R. H. and Wheelwright, S. C. (1984), *Restoring Our Competitive Edge: Competing Through Manufacturing*, John Wiley & Sons, Inc., New York.

Hayes, R. H., Wheelwright, S. C., and Clark, K. B. (1988), *Dynamic Manufacturing*, The Free Press, New York, NY.

Kinsey, J., and Heien, D. (1988), "Factors influencing the consumption and production of processed foods," in: C. O. McCorkle Jr. (ed.), *Economics of Food Processing in the United States*, Academic Press, Inc., San Diego, CA, 47-81.

McCorkle Jr., C. O., (1988), "U.S. food manufacturing industries: an overview," in: C. O. McCorkle Jr. (ed.), *Economics of Food Processing in the United States*, Academic Press, Inc., San Diego, CA, 2-46.

McCorkle Jr., C. O., Archibald, S. O., and McCalia, A. F. (1988), "Food processing industry dynamics and economic policy," in: C. O. McCorkle Jr. (ed.), *Economics of Food Processing in the United States*, Academic Press, Inc., San Diego, CA, 409-434.

McFarlane, I. (1995), *Automatic Control of Food Manufacturing Processes*, Blackie Academic & Professional, Glasgow, England.

McKinsey Global Institute. (1993), *Manufacturing Productivity*, McKinsey Global Institute Washington, D.C.

Miller, J. G., and Roth, A. V. (1994), "A taxonomy of manufacturing strategies," *Management Science*, 40/ 3, 285-304.

Neter, J., Kutner, M. H., Nachtsheim, C. J., and Wasserman, W. (1996), *Applied Linear Statistical Models*, Irwin, Homewood, IL.

Oral, M.(1993), "A methodology for competitiveness analysis and strategy formulation in glass Industry," *European Journal of Operational Research* 68, 9-22.

Oral, M. and Dominique, C. R. (1989), "An analytical approach to competitive strategy formulation in mature industries," *IIE Transactions* 21/ 3, 271-278.

Parkan, C. (1994), "Operational competitiveness ratings of production units," *Managerial and Decision Economics* 15, 201-221.

Parkan, C. (1996), " Measuring the performance of hotel operations," *Socio-Economic Planning Sciences* (in press).

Prescott, J. E. and Grant, J. H. (1988), "A manager's guide for evaluating competitive analysis techniques," *Interfaces* 18/3, 10-22.

Sanderson, G. W., and Schweigert, B. S. (1988), "Changing technical processes in U.S. food industries," in: C. O. McCorkle Jr. (ed.), *Economics of Food Processing in the United States*, Academic Press, Inc., San Diego, CA, 83-115.

Schefcyzk, M. (1993), "Operational performance of airlines: an extension of traditional measurement paradigms," *Strategic Management Journal* 14, 301-317.

Sinha, K. K. (1996), "Moving frontier analysis: an application of data envelopment analysis for competitive analysis of a high-technology manufacturing plant," *Annals of Operations Research* 66, 197-218.

Tucker, F. G., Zivan, S. M., and Camp, R. C. (1987), "How to measure yourself against the best," *Harvard Business Review* 65/1, 8-10.