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ABSTRACT: This paper presents a new approach to measuring the input productivity gains from information technology (IT) in complex managerial environments. The approach is illustrated in the context of a study of a pilot deployment at Hardee's Inc. of a new cash register point-of-sale and order-coordination technology called "Positran." The method employs *data envelopment analysis* (DEA) and nonparametric production frontier hypothesis testing to determine whether the performance of restaurants that have deployed Positran is better, on average, than for those that have not. The design of the study is of special interest, because it approximates a controlled experiment. Our results show that Positran helped to reduce input materials costs, since restaurants that deployed the technology were less likely to be inefficient. It is further possible to characterize the class of restaurants for which the relationship holds. Operational efficiency measures such as the ones we have developed provide managers with the opportunity to implement deployment strategies for new ITs in order to maximize value.

KEY WORDS AND PHRASES: measuring value of information systems, operational efficiency, productivity gains due to information systems.

1. Introduction

1.1. The Problem: Measuring IT Value in a Service Industry Setting

Today, senior managers in service-industry firms are faced with making decisions about how to spend historically large information technology (IT) budgets without the comfort and guidance of systems of performance measurement that are broadly accepted in practice and well grounded in theory. As a result, there is much confusion about how the measurement of business value impacts of IT should actually be carried out. For example, the results of the *American Banker 1988 Managing Technology Survey* [37] showed that 55 percent of 188 senior executives in bank operations believed that the returns on their investments in IT were either good or excellent, although one-half of them reported that their firms did not have any formal systems in place to measure. Similar results were also found in an Index Group survey of 240 senior IS managers for a broader cross-section of industries. In fact, *Computerworld*, commenting on the Index Group study, reported that only one in ten of the executives polled indicated that he/she knew how to evaluate adequately the business value of IT investments (November 8, 1988, p. 8).

Although investments in information technology made by large service-industry corporations can result in a variety of strategic impacts, the kinds that most senior managers probably feel they best understand are those that lead to relatively direct operating-cost savings, and are thus readily measurable. In other circumstances, measurement by itself does little to help management understand the value that IT can create in a firm's business operations. Instead, the justification for an investment in IT may develop out of a firm's beliefs about how it must respond to recent moves by its competitors just to stay competitive. In addition, rapid changes in technology, customer demand, the competitive environment, and the structure of the industry force managers to take risks and deal with uncertain future outcomes that increase the variance on the potential return to any investment [19, 21].

For many large and well-managed financial and nonfinancial industry companies, the days of easily measurable payoffs from automating operations are long gone. Major corporate investments in IT that lead to operating cost reductions will be made

with the goal of more carefully controlling the effects of previous investments in IT and enhancing the effects of other programs that were meant to improve productive efficiency. In this paper, we present a new approach to understanding the leverage IT investments can have in improving efficiency in production.

1.2. The Case: Hardee's Positran—Promoting Operating Efficiency, Product Differentiation, and Product Quality with IT

Our approach is presented in the context of a case study of "Positran," Hardee's Inc.'s cash register point-of-sale and order-coordination system, which is now widely deployed among its more than 800 company-owned and 2,300 franchised units. In addition to providing support for a restaurant's order-taking and order-preparation activities, management intends Positran to support the firm's ability to deliver an innovative menu of products directly and to maintain the highest levels of product and service quality for its consumers.

Most observers would agree that product differentiation can make or break a competitor in a service industry. Nowhere is this more true than in the fast-food industry, where a couple of percentage points in national market share can translate into tens of millions of dollars of revenue, and the difference between a large operating profit or loss. Carol Levy, an analyst for Shearson Lehman Hutton who follows Hardee's performance, comments:

> The [fast-food] industry is so competitive that you never have a unique product. If you do, you have it for three months max. All that really differentiates you is management, and Hardee's is running their business well. [29, p. D4]

If the quality of management really differentiates a fast-food firm, then consider the background of the present study. Positran was a pilot IT deployment effort that represents as close to a controlled experiment on the value of IT as is possible in most industry settings. Hardee's management chose to deploy Positran in a set of restaurants in which it was expected to perform well, and another set where the performance expectations were less optimistic. In effect, management was funding two treatment groups, and they allowed us to study a control group of restaurants where the technology was not deployed. This control group included restaurants exhibiting the same characteristics as those of restaurants that were expected to leverage the presence of Positran, as well as some that were not, across a market area with broadly similar demographic attributes. The results of this study suggest how much can be learned about the operational efficiency of a fast-food restaurant and an IT deployed to improve it. They also provide feedback to Hardee's management on an initially controversial and expensive IT deployment that is now at the heart of the firm's comprehensive point-of-sale data capture and information-reporting systems.

1.3. Outline of the Paper

The remainder of the paper is organized as follows. Section 2 presents our perspective on prior approaches to the measurement of firm efficiency and IT value in the IS

literature. We argue that a method is needed to capture the impact of IT on operating efficiency, when operating efficiency is potentially influenced by multiple factors in a complex operating environment. Section 3 presents a competitive analysis of Hardee's position in the burger segment of the fast-food industry, and the role that IT plays in helping it to strengthen its competitive position. The section also provides descriptive background on Positran itself, and management's rationale for investing in a technology to control materials waste while delivering a more diverse product mix. We discuss how it was deployed, how it integrates the cash-register, food-preparation, and food-delivery systems in a typical Hardee's restaurant, and what its intended performance effects were. We also describe the components of Hardee's materials input cost function, and the data set used to develop the results presented later in the paper.

Section 4 lays out an operational efficiency evaluation model that incorporates a term for "random" inefficiency. Random inefficiency (which we discuss in greater detail in that section) can stem from a number of possible sources, including the absence of IT. We also discuss how this model can be evaluated using *data envelopment analysis* (DEA). Finally, we discuss the set of variables used to get a reading on the productivity impacts of Positran. Section 5 details the hypotheses we wished to test, our results, and their managerial significance. We conclude the paper with a review of our findings, some remarks about the limitations of our approach, and some directions for future research.

2. Rethinking Efficiency Measurement for IT

AN IN-DEPTH UNDERSTANDING OF INTERMEDIATE PRODUCTION is crucial to ensuring that management deploys IT in a manner that maximizes its competitive and operational value. By *intermediate production process*, we refer to production within a firm that leads to the creation of goods and services, rather than their economic value. The latter is only determined when they are sold on the market. The environments in which intermediate production occur are formalized by Porter's value chain: inbound logistics, operations, outbound logistics, marketing and sales, and after-sales service [31]. Building on the idea of the value chain, Cash, McFarlan, and McKenney [14], for example, suggested a typology of potential impacts of IT, including building barriers to entry, building customer switching costs, changing buyer–supplier power relationships, and providing a basis for the creation of new products. Shaw [32] has discussed how to recast the value chain for application in service-industry companies, to provide other specific avenues along which management can explore the value of IT. One can examine whether the outputs of the process have been produced efficiently in each part of the value chain.

2.1. Perspectives on Firm Efficiency and IT Value

Recent research on IT performance evaluation has emphasized the need to investigate intermediate production as a means to understand how IT leads to the creation of

business value. (For example, see the papers by Benham [12], Crowston and Treacy [20], Banker and Kauffman [7, 8, 9], Kauffman and Kriebel [24, 25], and Parker and Benson [30].) This body of work reflects a recognition among researchers that it is methodologically quite difficult to develop robust measures linking IT investments to bottom-line impacts, without taking some pains to capture how the "conversion" from investment to value occurs, and whether it is effective. (For a fuller discussion of the concept of "conversion effectiveness," see Weill and Olson [36].)

Earlier studies by Stabell [34], Chismar and Kriebel [16], and more recent work by Harris and Katz [23] and Loveman [27], have taken a different approach, concentrating on strategic business-unit and firm-level aggregate analysis. At this level, however, IT has been shown to provide few concrete payoffs to justify the expenditures, although there is a wealth of anecdotal evidence suggesting that some major investments in IT have paid off handsomely [19]. These results argue in favor of research approaches that focus on the IT–performance link more directly than a business-level analysis.

We support the argument that the science of measuring the *effectiveness* of IT investments will improve through the application of multiple approaches that build on the experience gained and methods used in the studies mentioned above. (For a more complete review of the methods associated with IT value measurement, see Kauffman and Weill [26] and Carlson and McNurlin [13].) These include both organizational [35, 36] and economic process models [1, 11] and the use of case-by-case investigation of IT investments [17, 18]. We believe that additional consideration should be given to the theory base for measuring how IT influences *efficiency*, especially in the inbound and outbound logistics, and operations segments of the value chain.

In our current program of research on measuring IT-related gains in firm performance, we distinguish between "competitive efficiency" and "operational efficiency." *Competitive efficiency measures* describe the relationship between technology investments and other major firm-level expenditures, and bottom-line impacts, such as revenues, profitability, return on investment (ROI), and return on assets, among others. Thus, firms exhibiting a high level of competitive efficiency tend to do better in terms of these indicators than other firms that deploy similar levels of resources.

Based on our definition, the firm- and business-level studies mentioned above can be broadly classified as competitive efficiency analyses of IT investment. IT plays an important role in helping some of these firms to secure better performance than their competitors, but competitive efficiency measures alone do little to explain *how* some firms benefit, and *to what extent*. As we observed above, such highly aggregate measures sometimes sidestep the real measurement problem of identifying the contribution of IT, since there will be many influences of firm-level performance that will confound the effect of IT. And, even when ROI is of greatest interest, potential users of the results and the methods employed in those studies need to bear in mind that they are meant to be descriptive rather than normative.

Operational efficiency measures describe IT performance in intermediate production processes. They provide a means to gauge whether conversion of IT investments into business value is occurring in the segments of the service value chain most affected by IT. This is where management efforts to improve operational controls are

centered, so it makes sense that IT performance measures should either directly relate to, or be derived from, the operations the IT supports. Utilizing operational efficiency measures also makes a lot of sense when comparing one unit of a corporation with another. It is usually reasonable to assume that in order to keep costs under control, most corporations attempt to duplicate intermediate production processes across different units of the firm. Comparing operating units can yield targets for performance and suggests dimensions along which efforts to improve control of the operation can be made.

2.2. Assessing IT's Impact on Efficiency in Complex Managerial Environments

Having a method at hand to measure IT-related gains in input efficiency in complex production settings is of particular interest to us, since their complexity makes identifying the factors that lead to improvements in operational control more difficult. By *complex production settings*, we refer to segments in the value chain in which IT is just one among a number of factors in the managerial environment that can affect the use of resources in the production of physical or service outputs. Although IT may affect the outcome, it will be difficult to distinguish its contribution from those of other factors present in the managerial environment. When IT is used to support production, its value can be derived from the extent it improves the likelihood that cost-minimizing production decisions are made by managers. Value will also be created if, on average, IT helps to reduce inventory, cut material waste, and/or control labor overtime.

To address these concerns, we illustrate a method for analyzing the results of a *data envelopment analysis* (DEA) [2, 3, 15] to evaluate a production process involving IT. DEA is well suited to our analysis of Hardee's Positran technology, because it:

- can be used to address the problem of identifying IT's role in complex production environments by modeling the production process;
- provides a mechanism to measure operational inefficiency in a generalized cost function, in which operational inefficiency is represented by a random variable, θ;
- produces results that can be evaluated using new statistical hypothesis testing methods to determine if intermediate production performance improves in the presence of an IT;
- opens up the possibility of creating an IT performance baseline, which can be used for comparison purposes in later periods, or to pinpoint the timing of the impact.

Carrying out hypothesis tests to identify "separation" in the performance frontiers of business units that operate under materially different conditions enables managers to identify more realistic and specific targets for their performance. A sample plot of a performance frontier is shown in Figure 1, for an arbitrary production correspondence involving one input and one output. The hypothesis of interest is whether the performance frontier for the units that have deployed an IT to improve operational performance is farther northwest, on average, than for units that have not deployed the technology.
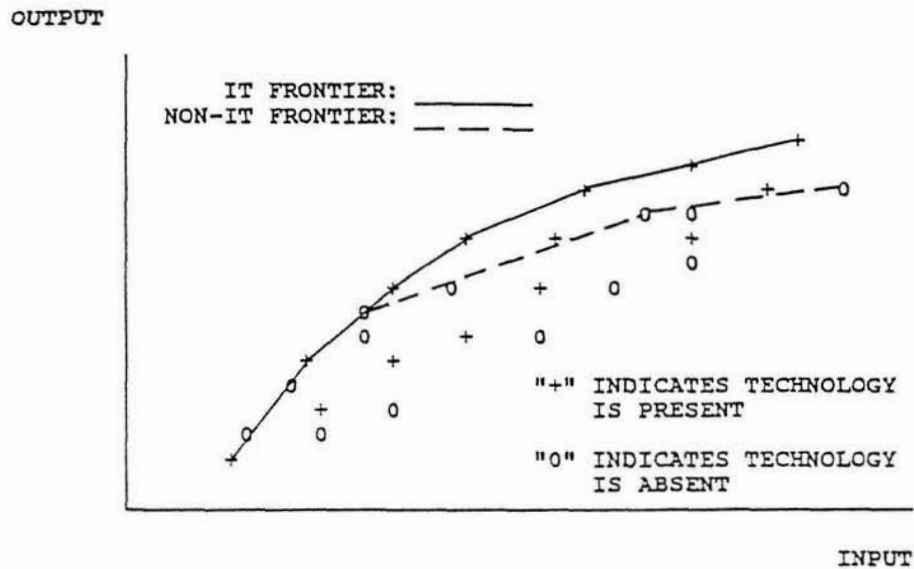
OUTPUT


```
IT FRONTIER:    _____
NON-IT FRONTIER: _ _ _ _


                                    "+" INDICATES TECHNOLOGY
                                        IS PRESENT

                                    "0" INDICATES TECHNOLOGY
                                        IS ABSENT
```

INPUT

Figure 1. The Separation of Nonparametric Frontiers: An Illustration

Although Figure 1 appears to show that the deployment of the IT leads to greater operating efficiency at higher production volumes, a more reliable answer would result by recasting this as a hypothesis and then carrying out a statistical test. Banker [5] developed a formal statistical test that enables such hypotheses regarding efficiency in nonparametric production frontiers to be more thoroughly examined.[1] Restating the question of a "*significant*" difference in the IT and non-IT frontiers in statistical terms provides evidence for an impact. Thus, the primary methodological interest in this paper centers on the way the Hardee's materials cost function is evaluated to determine whether Positran tends, on average, to improve efficiency. We stress the words "on average" here, because of the possible presence of other factors in the production environment that could produce the same outcomes.

3. Positran—Hardee's Inc.'s Cash Register and Order Coordination System

3.1. Hardee's Competitive Background: The Burger Segment of the Fast-Food Industry

Hardee's Inc., a large fast-food retailing firm based in Rocky Mount, North Carolina, opened its first restaurant in 1961. While the majority of its operating units are located in the southeastern and midwestern United States, Hardee's Inc. competes at the national level with such well-known firms as McDonald's, Burger King, Wendy's, and Jack-in-the-Box. The firm's chairman, Jack Laugherty, reported that the firm's

Table 1 Leading Burger Companies: Sales and Units

leading burger firms	1988 sales in $MM (# units)	1987 sales in $MM (# units)
McDonald's	$16,100 (10,513)	$14,330 (9,911)
Burger King	$5,400 (5,793)	$5,000 (5,179)
Wendy's	$2,902 (3,762)	$2,870 (3,816)
Hardee's	$2,733 (3,100)	$2,419 (2,959)
Jack-in-the-Box	$755 (961)	$655 (897)

Source: *Restaurants and Institutions*, 99, 18 (July 10, 1989).

primary strategy is to "seek dominance in those regions where it is established and to expand only into contiguous regions" [29, p. D4].

Table 1 shows the relative sizes of these firms. Previously, Hardee's management viewed its most direct competitor as Burger King, which produces about twice as much revenue each year with slightly less than twice the number of units. McDonald's, as is evident from Table 1, is more than twice as large as Burger King and Hardee's combined. Among the three firms, Burger King and McDonald's tend to focus on serving a mostly blue-collar customer base. Hardee's, meanwhile, has increasingly targeted upscale fast-food customers. Wendy's competes for a similar customer segment, and, although Wendy's has just a slightly larger national market share, Hardee's management increasingly perceives Wendy's to be its primary competitor. In order to remain competitive with Wendy's and to maintain an image of slightly higher quality than McDonald's and Burger King, Hardee's experiments with a wide range of products, so that its menus continue to change to attract the interest of its upscale, health-conscious customers.

Hardee's is recognized in the burger segment as an innovator, and has been first to market in the past with popular menu items, such as breakfast biscuits and bacon burgers. As a result, hamburgers comprised only 45 percent of the firm's revenues by 1988, down from about 65 percent in 1985. Although McDonald's pioneered breakfast fast food, Hardee's is widely credited with offering the broadest, most attractive breakfast menus in the industry. Laugherty comments: "It took the marketing clout of McDonald's to convince the American public that they could get a good breakfast in a hamburger establishment. We were able to capitalize on it with a bigger, better breakfast offering" [29, p. D4]. As a result, Hardee's tends to have a relatively larger portion of its sales derived from breakfast sales than its competitors, amounting to about $900 million or 30 percent of total revenues in 1988.

Hardee's 1983 decision to pilot test Positran, its cash-register and order-coordination automation, is indicative of management's interest in innovating to improve its overall service quality, despite the additional costs. The company has also made a strong commitment over the years to collecting data that can be used to track the

performance of its operations (e.g., data related to pricing, product mix, location quality, restaurant layout, and materials use). Currently, each unit in the chain produces between $500,000 and $1 million per year in revenue. In addition to the one-time cost of purchasing a site and building the new unit, the primary ongoing costs of doing business are labor and materials. Enhanced control of materials usage was of considerable interest to Hardee's management, since the company's estimate of the value of wasted materials was about $20 million, or on the order of 1 percent of sales.
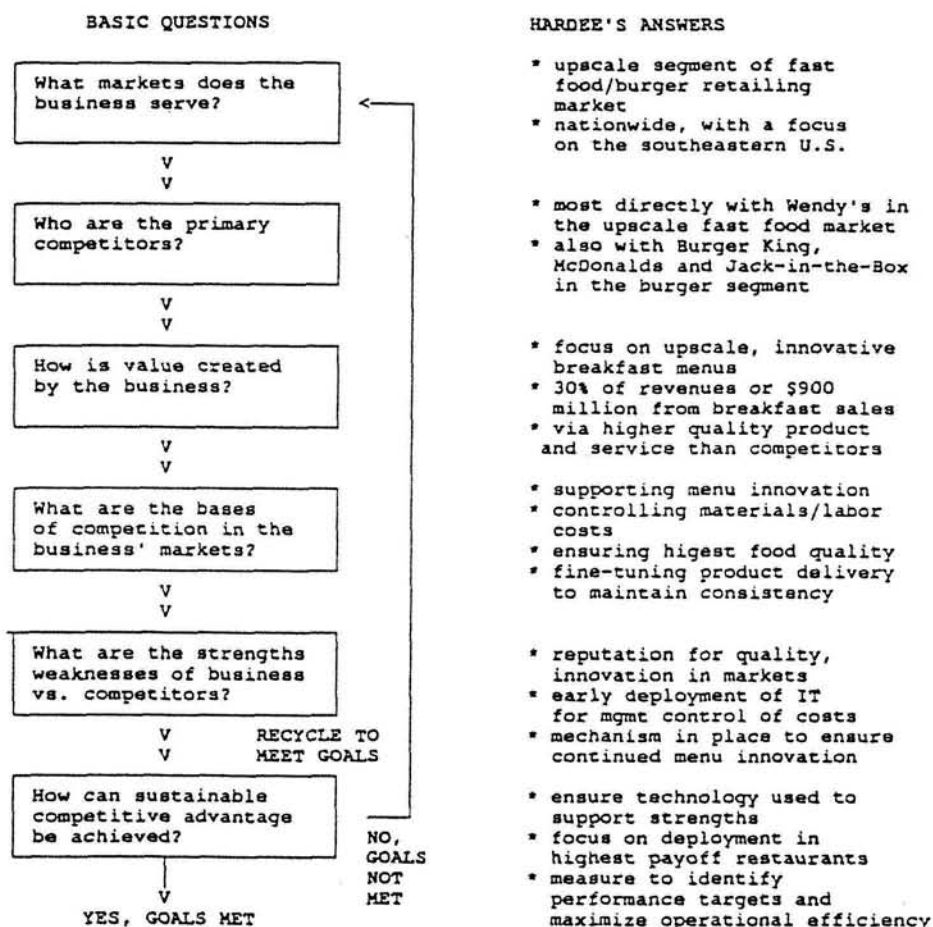
Figure 2, adapted from Shaw [32], summarizes the primary issues that Hardee's faces in maintaining a competitive position in the burger segment of the fast-food industry. It also suggests the roles that IT can play in helping the firm to achieve competitive advantages.

3.2. An Enhanced Cash-Register/Point-of-Sale Device

The Positran technology deployed at Hardee's enhances a standard cash register so that it displays customer orders on a CRT screen as they are entered into the cash register. This enables the customer to provide an initial check to make sure that the order was placed correctly. More importantly, though, Positran transmits the customer order to the food preparation area, where food preparers who were not involved in taking the order set it up and bag it. This replaced the old process, where the order taker called out the order to the food preparation area in a loud voice or via a microphone. There was some likelihood in the old process that the order recorded on the cash register slip would not completely match what was set up and bagged in the food preparation area. This would lead to a slowdown in order throughput, wasted materials, and customer dissatisfaction with the quality of Hardee's service.

Hardee's purchased the Positran technology from an outside vendor, SCAN-DATA Corp. of Morristown, Pennsylvania, at a cost of about $2,500 per installation above the cost of a standard cash register system. Each investment in Positran is depreciated over a life of seven years by Hardee's accounting department, and Positran requires little maintenance besides that needed by the standard cash register. Hardee's management believed that this IT was likely to have beneficial effects on materials waste in restaurants where it was deployed. They recognized that the benefits might be maximized where Positran would help to offset the effects of other cost drivers. For example, materials waste was likely to increase when a unit operated an order counter and a drive-through window, since orders were flowing to the food preparation area from two different locations. This also had the potential to enable Hardee's to increase the diversity of its product line, without sacrificing efficient materials use. Another likely setting where materials waste would be large is high-volume restaurants, particularly at those times of the day when the order flow is large. On the other hand, in restaurants where alternative management control programs were in place (e.g., quality training and improvement programs, or a specially trained workflow coordinator), Positran was believed to reinforce changes that were already being obtained by these other means.

Positran was initially deployed by Hardee's in 1983 and 1984. At that time, the

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BASIC QUESTIONS                              HARDEE'S ANSWERS

┌─────────────────────┐        * upscale segment of fast
│ What markets does the│          food/burger retailing
│ business serve?      │ <──        market
└─────────────────────┘        * nationwide, with a focus
         v                        on the southeastern U.S.
         v
┌─────────────────────┐        * most directly with Wendy's in
│ Who are the primary  │          the upscale fast food market
│ competitors?         │        * also with Burger King,
└─────────────────────┘          McDonalds and Jack-in-the-Box
         v                        in the burger segment
         v
┌─────────────────────┐        * focus on upscale, innovative
│ How is value created │          breakfast menus
│ by the business?     │        * 30% of revenues or $900
└─────────────────────┘          million from breakfast sales
         v                      * via higher quality product
         v                        and service than competitors
┌─────────────────────┐        * supporting menu innovation
│ What are the bases   │        * controlling materials/labor
│ of competition in the│          costs
│ business' markets?   │        * ensuring higest food quality
└─────────────────────┘        * fine-tuning product delivery
         v                        to maintain consistency
         v
┌─────────────────────┐        * reputation for quality,
│ What are the strengths│         innovation in markets
│ weaknesses of business│       * early deployment of IT
│ vs. competitors?     │          for mgmt control of costs
└─────────────────────┘        * mechanism in place to ensure
         v    RECYCLE TO          continued menu innovation
         v    MEET GOALS
┌─────────────────────┐        * ensure technology used to
│ How can sustainable  │          support strengths
│ competitive advantage│── NO,  * focus on deployment in
│ be achieved?         │  GOALS   highest payoff restaurants
└─────────────────────┘  NOT    * measure to identify
         v               MET      performance targets and
  YES, GOALS MET                  maximize operational efficiency
```

(Note: This figure is adapted from Shaw (1990), p. 2.)

Figure 2. A Competitive Analysis of Hardee's Inc.

chain comprised some 2,600 units, and management was interested in identifying the value of deploying Positran more widely. But before proceeding with this program, more evidence was required about how Positran improved control of input material usage by reducing waste. Hardee's management also intended to work out the bugs and understand how Positran affected a restaurant's workflow and order throughput at peak order volume hours. From the outset, management's plan was to take a "rifle-shot" approach; they hoped to determine some rules of thumb for which kinds of units would derive the greatest value from the technology.

3.3. Hardee's Positran Data Set and Input Materials Cost Function

Hardee's management provided us with quarterly data on input material use and related descriptive information for 89 restaurants located in the state of North Carolina. All data collected reflect observations for individual restaurants for a representative

quarter of the same year. Hardee's had implemented Positran at 48 of its units a minimum of three months (one quarter) or more prior to the period for which we obtained data. The remaining 41 restaurants did not have the new technology. Hardee's management indicated that this was a sufficient amount of time for the technology to be accepted and used appropriately in day-to-day operations by restaurant staff.[2]

The Hardee's Positran data set is shown in Table 2.

Comparing restaurant operations with and without Positran provides a natural and scientific test-bed for identifying its impacts on materials waste and productive efficiency. The restaurants that did not have Positran act as a control group. Hardee's management chose to deploy Positran to a *random selection* of locations in North Carolina, where the performance of the IT could be monitored closely by headquarters staff in Rocky Mount. As a result, we expect that no systematic selection biases were introduced in the data, and this was reinforced by our examination of the other descriptive variables mentioned above. Although we believe that the best test for the value of Positran would come from examining input material usage efficiency before and after Positran deployment, time-series data were not available. Cross-sectional analysis was an acceptable "next best" approach, especially in view of the time lag between the initial deployment of Positran and when our measurements occurred.

The primary materials cost driver was the overall volume of sales at a restaurant. Since Hardee's breakfast sales are relatively large in terms of total unit sales compared to its competitors, we collected data on sales volume in two categories: breakfast and other nonbreakfast menu sales. The additional data that were made available on individual restaurants included the presence of Positran, quarterly volume of restaurant sales, square feet of restaurant floor space, number of cashier positions and drive-up windows, number of new menu items, and staffing levels. However, a number of the restaurant descriptors generally were found to have little influence on input materials use.

In other situations, where a case could be made for the impact of a characteristic on materials usage efficiency, we observed relatively little variation. For example, all of the 89 restaurants in the sample had drive-through windows, which tend to increase the complexity of coordinating product delivery, and thus increase the potential for inefficiency. Another potential cost driver was the extent to which a unit was implementing new menu items; with more new menu items, more learning is required on the part of the staff, and input costs are likely to rise. We chose not to include this in the cost function, however, since new menu items were relatively uniform among the units for the quarter we studied.

Other factors examined included the quality of the local workforce, and managerial experience and training. Since we evaluated Hardee's units in North Carolina only, however, the quality of the workforce is fairly homogeneous across restaurants. Omitting this variable would have a greater impact on the quality of the results we might obtain if the initial deployment of Positran had not been limited to that single geographic area.

Table 2 Hardee's Restaurant Data Set

obs #	quarterly breakfast sales ($000)	quarterly other sales ($000)	quarterly materials costs ($000)	Positran present?
1	40.879	114.229	55.012	Y
2	26.372	74.834	36.061	N
3	32.698	153.780	68.158	N
4	49.764	111.459	57.400	Y
5	35.500	173.784	77.488	Y
6	52.672	108.448	56.710	N
7	33.034	85.111	42.776	N
8	42.402	177.471	74.347	Y
9	50.002	66.303	44.564	N
10	29.746	83.038	43.215	N
11	42.123	132.799	61.042	N
12	54.245	149.541	70.261	Y
13	32.327	74.681	40.477	Y
14	39.601	137.539	59.068	Y
15	44.648	247.207	99.091	Y
16	42.704	128.989	·59.210	N
17	36.791	108.169	48.107	N
18	44.701	124.006	62.729	N
19	36.048	108.614	52.704	Y
20	41.948	80.564	43.191	N
21	40.957	175.371	73.507	Y
22	36.295	93.826	47.073	N
23	29.025	45.989	25.672	N
24	27.592	76.046	37.744	N
25	25.692	101.165	41.633	Y
26	28.814	74.222	38.140	N
27	35.585	97.039	49.076	N
28	44.287	141.882	62.958	N
29	25.060	83.220	40.563	N
30	38.375	98.028	48.745	Y
31	41.779	111.336	54.098	N
32	40.977	75.968	39.650	N
33	25.974	105.448	45.546	N
34	26.943	90.568	44.452	Y
35	26.179	68.609	37.378	N
36	49.953	154.970	69.526	Y
37	38.789	66.301	37.322	Y
38	38.173	148.637	62.031	Y
39	41.322	102.247	52.617	N
40	35.195	83.948	40.745	N
41	26.470	63.822	32.534	N
42	26.454	133.664	67.782	Y
43	32.026	98.565	47.038	Y
44	34.817	61.282	34.040	N
45	26.470	88.795	43.058	N

Table 2   Hardee's Restaurant Data Set (continued)

obs #	quarterly breakfast sales ($000)	quarterly other sales ($000)	quarterly materials costs ($000)	Positran present?
46	26.454	47.745	27.464	N
47	33.263	91.503	45.293	N
48	44.359	126.443	60.998	N
49	21.926	81.385	36.738	N
50	41.560	100.484	48.195	Y
51	32.920	54.163	29.676	Y
52	24.492	102.847	46.428	Y
53	40.643	160.200	68.124	Y
54	51.996	127.689	64.048	Y
55	29.726	96.914	42.395	Y
56	22.714	165.672	69.124	Y
57	35.915	126.002	54.022	N
58	38.125	112.743	44.552	N
59	38.610	100.485	48.029	N
60	28.154	105.645	46.039	N
61	43.625	135.839	69.378	Y
62	8.209	72.173	30.252	N
63	52.817	109.103	57.769	N
64	20.927	85.839	38.531	N
65	32.717	102.614	47.362	N
66	30.521	133.356	56.589	Y
67	38.897	136.013	62.041	N
68	33.311	130.533	57.071	Y
69	50.523	89.599	45.909	N
70	45.455	137.071	75.766	Y
71	50.788	150.627	70.788	Y
72	26.913	77.553	37.021	Y
73	39.584	145.039	61.972	N
74	31.812	72.658	37.227	Y
75	41.050	156.179	67.455	Y
76	37.807	102.271	48.204	Y
77	28.108	62.938	32.185	N
78	41.809	142.510	63.925	Y
79	40.245	113.638	54.989	Y
80	21.877	78.337	38.419	Y
81	30.393	89.254	41.408	Y
82	59.308	170.017	79.473	Y
83	37.388	83.689	42.060	Y
84	25.594	85.220	42.096	Y
85	27.057	80.505	39.157	Y
86	32.345	97.194	44.006	Y
87	29.885	95.073	43.184	Y
88	48.948	158.843	68.285	Y
89	28.205	99.894	44.592	Y

4. A Model that Captures Positran's Effects on Input Inefficiency

4.1. A Generalized Cost Function Incorporating Random Inefficiency

As a basis for an illustration of our ideas and measurement of the impacts of Positran on aggregate materials cost efficiency, we employ a simplified cost function. This cost function maps a set of outputs into input use. This relation includes a *random inefficiency* component, which represents the effects of the way an operation is managed, the impact of IT on the operation, and other variables that cannot be measured directly. The generalized cost function (which we will shortly specify for Hardee's) is written as follows:

$$c = f(Y) * \theta$$

where

    c = observed use of input materials;

    Y = vector of outputs in production process;

    θ = a random variable for inefficiency, whose values range between 1 and infinity.

In this model the variable, θ, is assumed to be exponentially distributed with $E[\theta] = (1 + 1/\delta)$, and the probability density function, $g(\bullet)$, given by $g(\theta \mid \delta) = \delta e^{-\delta(\theta - 1)}$, for $\theta \geq 1$, and 0 otherwise.[3]

We further assume that the function $f(Y)$ is monotone increasing and convex in the variables described. These assumptions place minimal structure on the form of the function, and enable the application of our method to a wide range of production environments influenced by IT. By including the random variable for inefficiency, θ, the method also directly addresses concerns that have been raised about the utilization of nonparametric production frontiers in the econometrics literature (for example, see Schmidt [33]) in situations where hypothesis testing is necessary.

Our formulation of the cost function implies that variables omitted from the function $f(Y)$ are reflected in the random variable, θ. If the presence of IT causes input use to decline, then it will cause the distribution of inefficiency scores across the restaurants to shift to the left. That is, while it is not certain that efficiencies will decline in all cases in the presence of IT (because other variables may counteract the effect of IT), lower inefficiency values will become more likely. The main challenge is to detect such a shift and support the argument that reduction in waste is attributable to IT.

4.2. DEA Model and Analytic Approach

We next present a model based on this approach to gauge the impact of Positran on input use in Hardee's restaurants. Rewriting the generalized cost function presented above to incorporate the relevant variables, we have the following:

$$c = f(y_{BRK\_SALES}, y_{OTHER\_SALES}) \cdot \theta$$

where the variables y_{BRK_SALES} and y_{OTHER_SALES} represent quarterly breakfast and nonbreakfast sales volumes, respectively. The distribution of the random inefficiency variable θ is affected by the presence of Positran, among other factors, which we omit to focus our analysis on IT. In this case, the variable c is the actual quarterly materials cost.

Our measurement approach makes use of all the information present in Hardee's aggregate materials input cost function via a two-step analysis. The first step is to run a deterministic DEA model (see [3]) to obtain inefficiency scores for input resource use. The mathematical program that structures this analysis is based on a DEA model incorporating categorical variables, as discussed in Banker and Morey [10]. Using the model shown below enables us to estimate the efficiency h_0 (reciprocal of the inefficiency θ_0) for any specific restaurant distinguished here by the subscript 0.

(1)   Minimize h_0

subject to

(2)
$$\sum_{j=1}^{89} y_{OTHER\_SALES,j}\,\lambda_j \geq y_{OTHER\_SALES,0}$$

(3)
$$\sum_{j=1}^{89} y_{BRK\_SALES,j}\,\lambda_j \geq y_{BRK\_SALES,0}$$

(4)
$$\sum_{j=1}^{89} w_j \lambda_j \geq w_j$$

(5)
$$\sum_{j=1}^{89} c_j \lambda_j \leq h_0 c_0$$

(6)
$$\sum_{j=1}^{89} \lambda_j = 1$$

(7) $c_j, \lambda_j \geq 0 \quad (j = 1, 2, \ldots, 89)$

This program models one input, aggregate materials cost (c), and two outputs (y), breakfast and nonbreakfast sales. The reciprocal of the solution h_0^{*} to the program for restaurant 0 provides a measure for input use inefficiency ($\theta^{*} = 1 / h_0^{*}$). Also obtained by solving the math program is a set of λ_j^{*}'s identifying the restaurants to which the restaurant being evaluated is compared. The variable w codes the presence ($w = 0$) or the absence ($w = 1$) of Positran at any of the 89 restaurants identified by the subscript j.

The first two constraints (represented by equations 2 and 3) in the math program ensure that the output levels of inefficient restaurants are compared to the output levels of a convex combination of restaurants at least as large. The next constraint (4) ensures that restaurants without Positran only are compared to restaurants that also have not

deployed Positran. On the other hand, restaurants that have deployed Positran may be compared to both Positran and non-Positran restaurants. This formulation recognizes that it will be harder to achieve efficient performance in the absence of Positran, because the conditions of production are more constrained. The following constraint (5) maintains the envelopment conditions for the input (i.e., that all observed input combinations lie on or within the production space defined by the production frontier) and provides a means to enable the analyst to interpret the h_0^*'s as input use efficiency scores. The next constraint (6) implements convexity in the production correspondence. The last constraint (7) ensures that all values of the production correspondence convexity weights, λ_j, and the materials costs, c_j, be greater than or equal to zero.

Once the DEA scores, h_0^*, have been obtained by iteratively running 89 DEA programs, the second step is to classify restaurants into groups with similar characteristics and test hypotheses about the differential effects of Positran on materials use efficiency. We provide a more complete discussion of the hypothesis tests in the following section.

5. Hypothesis Tests and Results

5.1. Hypothesis Tests for the Operational Efficiency Effects of Positran

For the purpose of testing the hypothesis that the presence of Positran technology improves input productivity at a Hardee's restaurant, let j represent a restaurant in the overall data set. The set J of restaurants consists of two subsets, A_1 and A_2. Restaurant j is an element of the subset A_1 if management has not installed Positran on its premises, and an element of A_2 if Positran has been installed. We will denote the inefficiency of restaurant j in group A_i by θ^i_j to distinguish it, and allow for the possibility that the probability distribution of θ^1_j differs from that of θ^2_j. Let the distribution of θ^1 be exponential with mean $1 + (1/\delta_1)$, and θ^2 be exponential with mean $1 + (1/\delta_2)$. Thus, the simplest null hypothesis is that Positran deployment does not influence the random inefficiency scores:

$$H_{01} : \delta_1 = \delta_2 .$$

The alternate hypothesis is:

$$H_{01'} : \delta_1 < \delta_2 ,$$

i.e., that Positran deployment leads to a *reduction* in input inefficiency on average for this data set.

This kind of hypothesis test is of general interest whenever management wishes to determine whether the differential efficiency of two groups of business units can be attributed in some way to factors within or beyond the control of management. Charnes, Cooper, and Rhodes [15], for example, compared school performance with and without an accountability program. Banker, Datar, and Kemerer [6], using software develop-
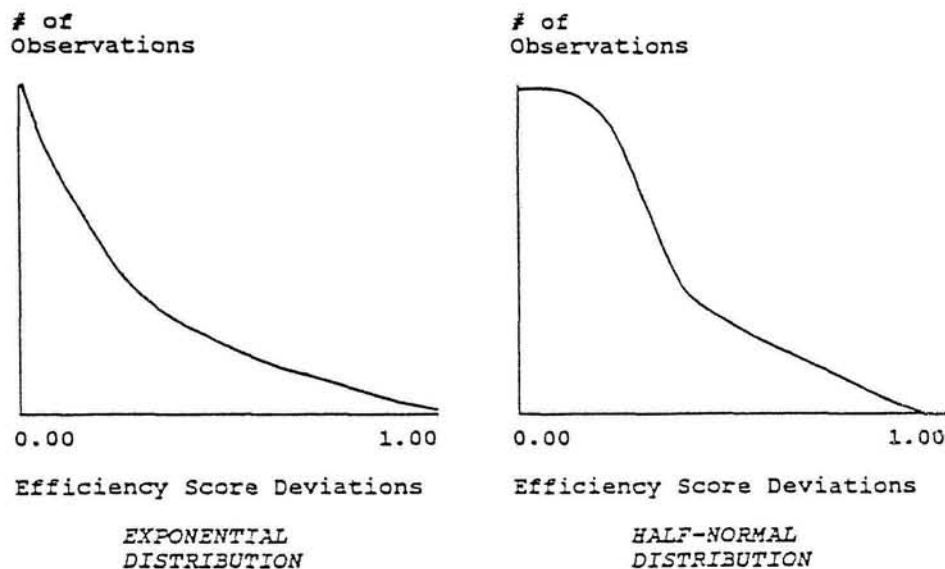
Note: The efficiency score deviation is given by $1 - h_0$, for restaurant 0.

Figure 3. Exponential and Half-Normal Distributions for Efficiency Score Deviations

ment projects as their unit of analysis, attempted to correlate software maintenance labor productivity with the use of a structured development methodology.

Generally speaking, the probability of a small amount of inefficiency in production is high, while the probability of highly inefficient operations is low. An exponential distribution for the DEA inefficiency scores, θ, is appropriate whenever the analyst believes that most of the observations are close to the frontier. If fewer observations are expected to be close to the frontier, then it is appropriate to use a half-normal distribution to represent θ's probability distribution. Both distributions capture the idea that the likelihood of inefficient observations decreases for larger inefficiency levels (see Figure 3). To illustrate, we will examine results related to both distribution assumptions and discuss how they can be interpreted.

After solving the DEA models discussed above to determine the set of inefficiency scores, we carried out hypothesis tests to determine whether the means of the Positran and non-Positran inefficiency score probability distributions were actually different. The relevant test statistic assuming an exponential distribution of inefficiency scores has been suggested by Banker [5]. We assume a large sample of DEA inefficiency scores, θ_j. Under the null hypothesis, we perform a statistical test using the following statistic:

$$\frac{\sum_{j \in A_2} (\theta_j^2 - 1)/a_1}{\sum_{j \in A_1} (\theta_j^1 - 1)/a_2}$$

This statistic asymptotically follows the F-distribution with $(2a_2, 2a_1)$ degrees of freedom, where a_i, $i = 1, 2$ is the number of observations in the sets A_i.

Assuming a half-normal distribution of inefficiency scores requires the following test statistic instead:

$$\frac{\sum_{j \in A_2} (\theta_j^2 - 1)^2 / a_1}{\sum_{j \in A_1} (\theta_j^1 - 1)^2 / a_2}$$

This statistic also follows an F-distribution, however, with (a_2, a_1) degrees of freedom. Banker [5] contains additional details for this test as well.

A second set of hypotheses was also of interest to Hardee's management. This involved attempting to identify whether Positran has a different impact on restaurants with a high percentage of breakfast sales versus those that do not. We further divided the subsets A_1 and A_2 into $A_{1, \text{HIGH}}$ and $A_{1, \text{LOW}}$, and $A_{2, \text{HIGH}}$ and $A_{2, \text{LOW}}$, respectively. The subscript HIGH indicates a high percentage of breakfast sales relative to the average, and the subscript LOW indicates a lower than average percentage of breakfast sales.[4]

The rationale for the significant impact of Positran in restaurants with a higher percentage of breakfast sales is that the breakfast menus are more complicated than those offered during nonbreakfast hours. This provides additional opportunities for mismatching orders, and Positran appears to provide management with some additional control over the production process.

The relevant null hypothesis here is that the presence of Positran does not lead to observed productivity differences in Hardee's restaurants with a relatively larger percentage of breakfast sales than the mean across all restaurants in the data set:

$$H_{02}: \delta_{1,\text{HIGH}} = \delta_{2,\text{HIGH}}$$

Since Hardee's management believed that Positran would pay off to a greater extent in high-breakfast-percentage restaurants, where menu complexity increases the likelihood of materials waste, it was expected that our tests would show that H_{02} was rejected in favor of:

$$H_{02}': \delta_{1,\text{HIGH}} < \delta_{2,\text{HIGH}}$$

As we indicated above, Hardee's management did not expect Positran to be as influential in improving productivity in low-breakfast-percentage sales restaurants. This yielded a third hypothesis:

$$H_{03}: \lambda_{1,\text{LOW}} = \lambda_{2,\text{LOW}}$$

To test the null hypotheses, H_{02} and H_{03}, assuming an exponential distribution of inefficiency scores, a similar test statistic is utilized. However, it must be adjusted to reflect the number of elements in the smaller subsets (e.g., $A_{1,\text{HIGH}}$ contains $a_{1,\text{HIGH}}$ restaurants, $A_{2,\text{HIGH}}$ contains $a_{2,\text{HIGH}}$ restaurants, and so on). So, for H_{02}, we have:

$$\frac{\sum_{j \in A_{2,\text{HIGH}}} (\theta_j^{2,\text{HIGH}} - 1)^r / a_{1,\text{HIGH}}}{\sum_{j \in A_{1,\text{HIGH}}} (\theta_j^{1,\text{HIGH}} - 1)^r / a_{2,\text{HIGH}}}$$

This also follows the F-distribution with $(2a_{2,\text{HIGH}}, 2a_{1,\text{HIGH}})$ degrees of freedom, where $a_{1,\text{HIGH}}$ and $a_{2,\text{HIGH}}$ are the number of observations in the sets $A_{1,\text{HIGH}}$ and $A_{2,\text{HIGH}}$. (The statistical test for H_{03} is identical, requiring the substitution of LOW whenever HIGH appears in the test statistic above.) Testing the null hypotheses under the assumption of a half-normal distribution of θ requires additional modification of the test statistic, the number of observations in the data set, and the degrees of freedom.

This general approach can also be used to examine the extent to which the physical size, number of cashier positions, and presence of a drive-up window in a restaurant affect input use inefficiency. Management will want to use as much information as it has available to enhance the usefulness of the results for managers.

5.2. Results of Hypothesis Tests

Table 3 summarizes the outcomes of the hypothesis tests of the DEA results. (For a fuller presentation of the DEA results, and a more detailed methodological treatment of the estimation issues, see Banker and Morey [10].) $H_{01} : \delta_1 = \delta_2$, tested under the assumptions of an exponential and half-normal for the inefficiency scores, could not be rejected at the 10 percent significance level (exponential case: F-statistic = 1.214 with (82, 96) degrees of freedom; half-normal case: F-statistic = 1.265 with (41, 48) degrees of freedom). Although we observed somewhat different mean inefficiency scores, they proved not to be statistically different for our sample of 48 restaurants with and 41 without Positran. The mean inefficiency score for the entire data set of 89 restaurants was 1.057; this implies that material costs could be reduced by 5.7 percent if all restaurants exhibited 100 percent efficient operation.

The results of the test for the null hypothesis, $H_{02} : \delta_{1,\text{HIGH}} = \delta_{2,\text{HIGH}}$, were more interesting to Hardee's management. When we focused only on the 44 higher-percentage-breakfast-sales restaurants, the mean of the inefficiency scores appeared to be significantly larger for non-Positran, as compared to Positran restaurants. Under the assumption of a half-normal distribution of inefficiency scores, the null hypothesis was rejected at an 8.7 percent significance level (F-statistic = 1.89 with (27, 17) degrees of freedom). However, when an exponential distribution is assumed for the inefficiency scores instead, this result no longer was evident (F-statistic = 1.199 with (54, 34) degrees of freedom).

Our test of the null hypothesis, $H_{03} : \delta_{1,\text{LOW}} = \delta_{2,\text{LOW}}$, that the presence or absence of Positran has little influence on productivity in low-percentage-breakfast sales restaurants, confirmed management's intuition. The null hypothesis could not be rejected for the 44 low-percentage-breakfast sales stores for an exponential (F-statistic = 1.128 with (28, 60) degrees of freedom) or a half-normal (F-statistic = 1.00 with (14, 30) degrees of freedom) distribution of inefficiency scores.

Table 3 Results of Six Hypothesis Tests

characteristics of restaurants	assumed distribution for normalized deviations	value of F-test statistic	significance level
all stores * Positran: 48 * non-Positran: 41	exponential	$\dfrac{0.07318}{0.0603} = 1.214$	0.18
	half-normal	$\dfrac{0.0071}{0.00562} = 1.265$	0.22
high-percentage-breakfast-sales stores * Positran: 17 * non-Positran: 27	exponential	$\dfrac{0.07567}{0.0631} = 1.199$	0.29
	half-normal	$\dfrac{0.0094}{0.00498} = 1.89$	**0.087**
low-percentage-breakfast-sales stores * Positran: 30 * non-Positran: 14	exponential	$\dfrac{0.06689}{0.0593} = 1.1282$	0.34
	half-normal	$\dfrac{0.006}{0.006} = 1.00$	0.48

5.3. Managerial Significance of Results

Since the Positran device costs about $2,500 over the cost of a standard cash register, and Hardee's had some 2,600 outlets at the time of the study, at risk was an investment of $6.5 million in IT. Of particular interest to Hardee's management was the ability to develop a Positran deployment policy that would lead to maximal business value.

Table 2 indicates that quarterly materials cost averaged $51,161 and ranged between $25,652 and $77,488. Since the difference in average inefficiency between the restaurants without and with Positran was about 7.32 percent – 6.03 percent = 1.29 percent, we estimated the annual value of Positran in reducing input waste to be about $51,161 × 1.29 percent × 4 quarters = $2,660 for an average restaurant. Clearly, the deployment of the Positran technology to an appropriate location would enable an almost immediate payback of the initial investment and provide the basis for additional future savings. Extrapolating from our data set, there were about 1,000 (40 percent) of the firm's restaurants that might have been classified as high-percentage-breakfast sales outlets, offering the firm an opportunity to reduce input resource costs by nearly

$2.7 million per annum. Since the firm's strategy involved increasing the proportion and volume of profitable breakfast sales in many of its units, system-wide deployment had the potential to save the firm even more money.

Results such as these were useful to Hardee's management in planning the invest-ment and installation of Positran in its company-owned outlets and in advising its franchisees about the business value of Positran. Most large fast-food restaurant chains are able to muster significant expertise to identify revenue-maximizing locations. Often the operator of a chain retains ownership of the locations it believes will be the most profitable. In the case of Hardee's, offering to install Positran in franchised locations can provide the franchisees additional profit opportunities through cost control. This serves to maintain the value of existing franchises and also gives Hardee's some leverage to attract new investors as franchisees. Still, our results highlight the fact that Positran makes a difference, but only in restaurants with selected characteristics. Thus, management must exercise special care in selecting where to deploy the Positran technology so as to maximize its contribution to the operational performance of the firm.

6. Concluding Remarks

POSITRAN IS REPRESENTATIVE OF AN INCREASING NUMBER of restaurant informa-tion technologies that deliver a range of services at the point at which retail sales occur. At the time that Positran was initially deployed, Hardee's was investigating the roles that information technologies might play in changing its business. Based on the firm's success with Positran and other ITs it has deployed, Hardee's commitment to IT has grown significantly over time. As a result, Positran is now a part of an integrated point-of-sale system that is reputed to be the largest and most sophisticated in the industry, linking the firm's restaurants nationwide. According to a report in the *New York Times*:

> The system collects data from every transaction made at every Hardee's res-taurant, including the product sold, the price, the time of sale and whether it was eat-in or take-out. . . . the system enables [senior executives] to monitor sales throughout the chain to within the last 15 minutes. Using this informa-tion, Hardee's can fine-tune its operations in ways that can make it millions of dollars. [29, p. D4]

For example, Hardee's was recently able to utilize data captured by this system concerning the purchase of less popular menu items, such as turkey sandwiches and mushroom and Swiss cheeseburgers, that were discontinued in the early 1980s due to lackluster sales. Analysis of point-of-sale data showed that customers simultaneously purchased one or more higher-margin menu items (such as french fries and soda), and that discontinuing the less popular items caused Hardee's to lose these customers to competitors. This led management to reinstate the discontinued items on Hardee's menus [29, p. D4].

Hardee's has positioned itself so that a technology that continues to provide important operational productivity gains is no longer just a "stand-alone" capability that any of its competitors would be able to purchase off the shelf from a third-party vendor and readily imitate. Instead, Positran offered Hardee's the basis of an infrastructure at the point of sale that is expandable to capture a range of other data that will enable management to make further improvements to the firm's operating efficiency and marketing effectiveness.

6.1. Summary of Results

To summarize, our primary result is that Positran appears to have reduced materials waste in the high-percentage-breakfast sales restaurants where it was deployed. The method we used to obtain this result relies on statistical tests that utilize information about the inefficiency scores of all units in the analysis. We recognized explicitly that input use at Hardee's restaurants can be modeled using a nonparametric frontier, thus requiring minimum assumptions about the form of the production correspondence. This also enabled us to use a standard DEA model to solve for the inefficiency results. Our primary methodological innovation is that random inefficiency results obtained from the DEA model can be used for hypothesis testing. We focused on detecting whether the means of the distributions of inefficiency scores vary across restaurants with different characteristics. When they vary with the presence of an IT variable—in this instance, Positran—we can make a case that the technology influences input use.

Examining the deployment of Positran at Hardee's is insightful, because it allows us to show how to model how IT enters a production process, and probabilistically affects input productivity. We also have shown how to detect such impacts by testing a set of simple hypotheses, utilizing formal statistical tests to examine the influence of varied assumptions that match a reasonable analyst's intuition. Our approach utilizes methods based on production economics, mathematical programming, and statistics, yet it can be applied by analysts who have access to desktop workstations. No doubt, it will continue to be a challenge to collect large and rich samples of data, and to identify instances where a simulated IT value experiment can be carried out with a control group and a test group. Nevertheless, we expect that managers who endeavor to carry out this kind of analysis stand to gain a deeper understanding of the critical environmental factors that lead to differential returns on IT investments in complex managerial environments.

6.2. Limitations and Future Research Directions

Although the importance of the potential contributions of IT in most firms today is unquestioned, the ability of senior management to achieve a positive return on IT investments continues to be a topic of heated debate [19, 24]. As a result, better measurement methods for IT value are critical for senior managements responsible for large, discretionary information systems budgets. Lucas [28] has suggested that substantiating the business value of an IT requires showing two things:

(1) that a performance gain is *correlated with* the deployment of an IT; and

(2) that a performance gain *follows from* the deployment of the IT.

Our results suggest the usefulness of measuring IT impacts in the segments of the value chain in which they occur.

The use of IT for improving operational control places added emphasis on identifying investment and performance evaluation methods, which realistically recognize the variety of factors that can produce results similar to those deriving from the deployment of IT. These include productivity incentive programs, management training, upgraded physical facilities, and so on. Compounding the problem of IT performance assessment is the reality that identical ITs may be utilized in rather different ways in different units of a firm, and that other aspects of managerial control may create the same effects as IT.

As a result, one concern we had in this research was the extent to which management practice in Hardee's restaurants varied from one unit to another. Discussions with management suggested that the primary differences are discernible in units of different size. For example, restaurants with a larger floor area and sales volume normally have managers on-site who act as workflow coordinators and trouble-shooters. In smaller restaurants, managers are more likely to be involved in the work itself, at the cash register, in food preparation, or maintaining the facilities. Thus, any influences from different management practices in restaurants of different size are likely to be captured by the sales volume variable. However, we were not able to obtain results to bear out these assertions.

A natural next step is to extend the present analysis using a time series of quarterly observations on Hardee's materials costs and unit sales. This would support hypothesis tests about how rapidly Positran produced the desired effects in high-breakfast-sales units. It would also allow us to explore in more depth the extent to which a workflow coordinator and Positran provide similar benefits. Given the data available to us, the strongest test we could perform in the present research was a cross-sectional one.

Even recognizing Lucas's requirements stated above, the Hardee's Positran data set is an uncommonly rich one for IS research, since management had installed Positran in roughly half of the sites just prior to the test period. A related issue that could be explored in an extension of this work is the set of conditions that push a unit down the Positran learning curve the fastest. This would enable Hardee's management to take steps to refine other aspects of the workflow in its units at the same time Positran is deployed. Finally, although we have obtained results indicating Positran's value with respect to materials use, there may be labor saving and other dimensions of cost reductions that could be identified by employing alternative models including different outputs.

NOTES

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1. The reader should note that we are *not* employing another relatively newer approach called "stochastic DEA." Stochastic DEA incorporates the possibility of a two-sided error term—inefficiency and random error—directly into the mathematical program that is run to obtain the efficiency scores. For additional details, see Banker [4].

2. Of course, our study requires this to be the case. Otherwise, in view of the well-documented short-term decreases in productivity and performance that are observed when new technologies are introduced within a firm [23], it is possible that non-Positran restaurants might exhibit less resource waste and thus higher levels of operational efficiency.

3. Since inefficiency scores vary between 1 and infinity, we adjust the mean of the standard exponential distribution $(1 / \delta)$ when the random variable varies between 0 and infinity, by adding 1 to it.

4. The median Hardee's restaurant in the data set had a breakfast sales percentage of 23.3 percent, with a minimum of 4 percent and a maximum of 43 percent. The 25th percentile was 21.83 percent, and the 75th percentile about 28.13 percent. The mean percentage of breakfast sales was 24.82 percent across the 89 restaurants.

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