The Impact of Supervisory Monitoring On High-End Retail Sales Productivity

Rajiv D. Banker
Temple University

Seok-Young Lee
Sungshin Women’s University

Gordon Potter
Cornell University

Dhinu Srinivasan
University of Pittsburgh

Author Note:

Rajiv D. Banker, Fox School of Business and Management, Temple University, Philadelphia, PA, e-mail: banker@temple.edu

Seok-Young Lee, Department of Management, Sungshin Women’s University, Seoul, South Korea e-mail: sylee@sungshin.ac.kr

Gordon Potter, School of Hotel Administration, Cornell University, Ithaca, NY, e-mail: gsp6@cornell.edu

Dhinu Srinivasan, Katz School of Business, University of Pittsburgh, Pittsburgh, PA, e-mail: dhinus@katz.pitt.edu

Abstract

Based on a two-stage analysis of a panel of data on 12 outlets of a high-end retailer for 24 months, we investigate how the level of supervisory monitoring affects retail sales productivity. In the first stage, we use Data Envelopment Analysis (DEA) to compute the relative productivity of retail outlets in using their labor and capital resources to generate store sales. In the second stage, we regress the logarithm of DEA scores on contextual variables to obtain consistent estimators of the impact of contextual variables on productivity (Banker and Natarajan in Operation Research 56:48-58, 2008). Contrary to agency theoretic prediction that supervisory monitoring leads to an increase in retail sales productivity, our empirical results indicate that the higher the level of supervisory monitoring, the lower is the retail sales productivity for high-end retail outlets.

Keywords: Efficiency • DEA • Retail sector

The impact of supervisory monitoring on high-end retail sales productivity

Introduction

Improving productivity is an increasingly important objective of many retailers. To achieve this objective, many retailers employ supervisory monitoring to motivate and direct their salesforce. There has been little formal empirical evidence, however, on whether supervisory monitoring increases retail sales productivity. To explore this issue, we perform a two-stage analysis of the impact of supervisory monitoring on the productivity of 12 high-end retail outlets over 24 months. We first estimate the productivity of each outlet in each month using the nonparametric Data Envelopment Analysis (DEA) method. Next, we regress the productivity score on potential contextual factors that affect it to obtain consistent estimators of the impact of key performance drivers at our research site (Banker and Natarajan 2008).

Agency theoretic research in marketing has examined the role of monitoring of salesperson's effort to alleviate moral hazard (Basu et al. 1985; Lal and Srinivasan 1993; Joseph and Thevaranjan 1998) Agency theory suggests that monitoring provides an imperfect signal on the salesperson's effort, and compensating the salesperson based on this signal induces higher effort. This imperfect monitoring signal can be interpreted similar to behavior-based control (e.g. Anderson and Oliver 1987, p. 77) which posits that supervisors who "have a well-defined idea of what they want salespeople to do" can work to ensure that the salesforce behaves accordingly. Therefore, retailers are likely to employ the monitoring ability of supervisors to increase the productivity of retail selling activities. There has been little empirical evidence, however, to assess whether this agency theoretic prediction holds for high-end retail outlets in which customer-focused service involves greater worker empowerment and task ambiguity.

In contrast to agency theory, organizational control theory suggests that behavior-based control requiring high level of supervisory monitoring is not appropriate in an environment characterized by low task programmability (Anderson and Oliver 1987; Eisenhardt 1985, 1988; Ouchi 1979). In high-end retail organizations, customer-focused service is likely to involve greater worker empowerment and lower task programmability. Supervisory monitoring is likely to constrain the salespeople from exploring creative new ways to provide higher levels of customer service. Therefore, increasing the level of supervisory monitoring is likely to undermine retail sales productivity.

We evaluate these two competing hypotheses using data on input, output, supervisory monitoring and other contextual variables collected from 12 retail outlets of a department store company for 24 months. Our research site is a company positioned at the high end of the department store industry. Its strategic positioning is to command premium prices for its merchandise by providing exceptionally high level of service to its customers, going beyond simply ringing up the cash register or responding to customers' requests.

We use Data Envelopment Analysis (DEA) to first assess the relative productivity of each retail outlet in each month in using its labor and capital resources to generate store sales. We rely on the theoretical results of Banker and Natarajan (2008) for a formal justification of the use of the two-stage method in DEA. They show that the DEA estimator of productivity obtained from the usual analysis of input-output data can be regressed in the second stage on contextual factors believed to contribute to productivity differences. Specifically, they prove that the second-stage regression provides consistent estimators of the impact of the contextual factors on productivity. Their simulation results indicate that the two-stage DEA- based procedure performs substantially better than the one-stage parametric methods that rely on commonly used parametric functional forms such as translog and Cobb-Douglas to specify the production correspondence, which in turn outperform the two-stage parametric methods to evaluate the impact of contextual variables on productivity.[1] Using this two-stage approach, we find that contrary to agency theoretic prediction, supervisory monitoring leads to an increase in retail sales productivity. The higher the level of supervisory monitoring, the lower is the retail sales productivity for the high-end department store that emphasizes customer-focused service as a way to gain strategic competitive advantage.

The remainder of this paper is organized as follows. Section 2 discusses our research hypothesis. Section 3 describes the data and the estimation model employed for the empirical analysis. Section 4 contains the results of our analysis. Section 5 summarizes and concludes.

Hypothesis development

Competition in the retail industry has become very intense in recent years. To survive and continue to prosper in this competitive environment, increasing productivity is viewed as a necessity. Our research site is a retailer positioned at the high end of the spectrum for department stores. It offers service that is perceived by its customers to be superior and unique relative to service provided by its competitors. It has achieved differentiation through its innovative customer-focused service, resulting in the willingness of customers to pay premium prices

[1] Their simulation results also indicate that DEA-based methods perform significantly better than one-stage and two-stage parametric methods in the estimation of individual decision making unit (DMU) productivity. More recent research documents that it outperforms bootstrap methods.

(Porter 1996). Customer-focused service involves understanding and satisfying individual needs, which differ widely across customers. Therefore, the tasks performed by its salespeople are more challenging, more difficult to prescribe and less programmable than the tasks required for a more conventional, mass-production-style service at a low-end department or discount store. The main role of supervisors at a low-end retail outlet is to have a well-defined idea of what the salespeople should do and to monitor them closely to ensure that they comply with the prescribed activities. At a high-end retail outlet, the role of the supervisors is much more ambiguous in supporting the salespeople.

Agency theory argues that if an agent’s actions can be monitored more precisely, desired actions can be induced with lower risk premium costs, which in turn leads to an improvement in organizational productivity (Lambert 2001). There has been little empirical evidence, however, on whether this agency theoretic prediction holds for high-end retail outlets in which customer-focused service involves greater worker empowerment and task ambiguity. This is especially important since monitoring of ambiguous tasks may not provide more informative signals, and the simple interpretation of the theoretical analysis may not apply.

Organizational control theory suggests behavior-based control requiring a high level of supervisory monitoring is not appropriate in an environment characterized by low task programmability (Anderson and Oliver 1987; Eisenhardt 1985, 1988; Ouchi 1979). Workers involved in customer service need to be empowered because the exact tasks required to improve customer satisfaction cannot be prespecified, as different customers have different needs, and their service expectations often differ from those of the management (Schlesinger and Heskett 1991). Therefore, in high-end retail organizations, customer-focused service is likely to involve greater worker empowerment and task ambiguity, and increasing the level of supervisory monitoring is less likely to improve retail sales productivity.

The employee motivation literature has built on Vroom's (1964) expectancy theory and posits that workers will exert a level of effort in their jobs that they believe will lead to desired outcome. The theory suggests that employee perceptions are moderated by the degree to which she believes that the reward is possible (Pool 1997; Churchill et al. 1979). If at our research site salespeople are internally motivated to exert more effort in their jobs because of the intrinsic value of the work to them, and not because they are closely monitored by supervisors, excessive monitoring by supervisors may actually stifle creativity and innovation from the salespeople (Maslow 1954). The literature on employee creativity also finds that most creative work occurs when work is complex and challenging, and supervision is supportive and noncontrolling (Oldham and Cummings 1996). In a similar vein, Zhou (2003) demonstrates that when creative coworkers are present, the less supervisors engage in close monitoring, the more the employees exhibit creativity.

Therefore, we state our main research hypothesis formally as follows:

H_0 The impact of supervisory monitoring on retail sales productivity is negative.

Data description and estimation model

Data and variables

Each individual store-month in our sample represents a decision-making unit (DMU). We model the production function relating the output of each DMU as a function of its inputs such as labor and capital, and contextual variables including supervisory monitoring. Goodman (1985) and Thurik and Kooiman (1986) argue that sales should be the principal measure of output to identify ineffective use of inputs. Achabal et al. (1984) suggest that additional measures of ability to produce also need to be included as control variables. In our empirical setting, we measure output as monthly sales (SALES) in deflated dollars.[2] Since sales alone may not capture the strategies pursued by retail units, we consider multiple contextual variables (Venkatraman and Ramanujam 1986; Chakravarthy 1986; Lewin and Minton 1986).

Past research has included store size, labor usage, and capital investment as inputs in the production function (Nooteboom 1983; Ingene 1982, 1985; Hise et al. 1983; Good 1984; Lusch and Moon 1984; Doutt 1984; Ratchford and Brown 1985; Thurik and Kooiman 1986; Kamakura et al. 1996; Samiee 1990). To capture the labor input in the production function, we utilize the number of selling hours in each store each month (HOURS). The two major forms of capital investments in the retail setting are the selling space utilized and the merchandise carried by the store. Accordingly, we include the size of the store in square feet (SIZE) and the dollar value of average inventory of merchandise (INVENTORY). INVENTORY is calculated as the mean of the opening and closing inventories carried by the store for a given month. To reflect input factors other than labor and capital, we include support activity expenses (SUPPORT) measured as other operating expenses exclusive of cost of goods sold, managerial and supervisory salaries, and wages for the sales personnel.[3]

---

[2] Banker et al. (2007) prove that DEA using the aggregate sales measure provides an aggregate measure of managerial and allocative efficiency in choosing the optimal mix of merchandise sold.

[3] All variables measured in dollars are deflated by the Department Store Merchandise Price Index calculated by the Bureau of Labor Statistics to make them comparable over different months.

We also include several contextual variables. The retail manager does not control the area in which each store is located, the demographics of the store location in terms of median household income, median age, median family size, percentage of the population with college education, size of county population, and the intensity of the competition faced by each retail store. To capture the differences in the location of the stores, we include an indicator variable RURAL whose value is 1 if the store is located in a rural area, otherwise 0. To account for different demographics of the store locations, we include INCOME to represent median household income, AGE to reflect median age of county population, FAMSIZE to measure median family size, COLLEGE to reflect the percentage of the population with college education, POPUL to control for total population size in a specific geographical area. Stores in upscale and less heavily populated markets are likely to enjoy higher productivity as upscale customers value customer service and are attracted by enhanced customer service more than other customers (Peterson et al. 1989; Banker et al. 1996). Specifically, retail sales productivity is likely to be higher for stores located in those regions where customers have higher household incomes, there is a higher proportion of older households with greater wealth, the family size is smaller, and the proportion of better-educated customers is higher. To capture the differences in the intensity of the competitive environment, we include the index COMPET constructed at our research site to measure the number and quality of competitors. Stores in a more competitive environment are likely to be less productive in generating retail sales. However, with greater competition, higher levels of quality may play a more critical role in attracting and retaining customers. Therefore, the impact of competition on retail sales productivity is an empirical question.

The contextual variable included to evaluate our principal hypothesis is supervisory monitoring (MONITOR) constructed as the ratio of the number of managers supervising the salespeople to the number of salespeople at each store. Furthermore, we include monthly sales index for other high-end department stores (SINDEX) obtained from the company to control for economy-wide and industry-wide effects and an indicator variable, SEASON, whose value is 1 during the holiday sales season spanning October, November, and December, and 0 otherwise, to control for the seasonal nature of the retail business. The relationship between inputs, output and contextual variables is depicted in Fig. 1.

Insert Figure 1 Here

Basic model to evaluate the impact of contextual variables on productivity

Consider observations on $j = 1, \dots, 12$ stores for $t = 1, \dots, 24$ months. Each observation (j, t) comprises one output y_{jt}, a vector of inputs $X_{jt} \equiv (x_{1jt}, \dots, x_{Ijt})$, and a vector of contextual variables $Z_{jt} \equiv (z_{1jt}, \dots, z_{Sjt})$ that may influence the overall retail selling productivity. The non-negative scalar y_{jt}, and vectors X_{jt} and Z_{jt} are strictly positive in at least one dimension.

We specify the true production function $y = \phi(X)$ and an error term ε. The production function $y = \phi(\cdot)$ is monotone increasing and concave in X, and relates the input vector X to the output y as specific by the equation

$$y_{jt} = \phi(X_{jt}) \cdot e^{\varepsilon_{jt}^*} \qquad j = 1, \dots, 12; t = 1, \dots, 24$$

The random variable representing the error ε^* is itself generated by the process

$$\varepsilon_{jt}^{*} = v_{jt} - u_{jt} - \sum_{s=1}^{S} \beta_s Z_{sjt}$$

where v_{jt} represents random noise for observation (j, t) and has a two-sided distribution, u_{jt} represents technical inefficiency and has a one-sided distribution and the contextual variables Z_{sjt} are all non-negative. The error attributable to only noise and technical inefficiency is specified as $\varepsilon_{jt} = v_{jt} - u_{jt}$.

Following Banker and Natarajan (2008), we impose the following structure on the probability density functions generating the various variables:

$$f_{xi}(x_i) = 0 \quad \text{for all } x_i < 0$$

$$f_{zs}(z_s) = 0 \quad \text{for all } z_s < 0$$

$$f_u(u) = 0 \quad \text{for all } u < 0$$

$$f_v(v) = 0 \quad \text{for all } |v| > V^M$$

Further, the probability density functions $f_{xi}(x_i)$, $f_{zs}(z_s)$, $f_u(u)$ and $f_v(v)$ are all independent of each other. Each stochastic variable has finite variance and the mean of the noise variable, $E(v)$, is zero.

This representation as in Banker and Natarajan (2008) specifies output as a general nonparametric function of inputs and an error term, and the error term as consisting of three distinct components: a linear function of contextual variables, a one-sided inefficiency term and a two-sided random noise term bounded above. Except for the additional component involving the contextual variables, this specification of the error term is analogous to composed error term formulations in parametric stochastic frontier models. Banker and Natarajan (2008) provide theoretical and simulation-based justification for the use of a two-stage method that uses DEA in the first stage and OLS regression in the second stage to evaluate the impact of contextual variables on productivity.

Estimation models

Following Banker and Natarajan (2008), we use the DEA model of Banker, Charnes and Cooper (BCC) (1984) in the first stage of the empirical analysis to evaluate the productivity scores of the different observations represented as DMU_{jt} for store $j = 1, \ldots, 12$, and month $t = 1, \ldots, 24$. There are $288 (= 12 \times 24)$ observations. We use the output-oriented BCC model to evaluate the productivity scores using a set of four inputs to produce one output. Recall that the single output is monthly sales in deflated dollars (SALES), and the four inputs are the number of selling hours (HOURS), the size of the store in square feet (SIZE), the dollar value of average inventory of merchandise (INVENTORY), and support activity expense (SUPPORT). The formulation of this output-oriented BCC model for estimating the productivity $\ddot{\theta}_{j^*t^*} = 1/\hat{p}_{j^*t^*}$ of an observation (j^*, t^*) is given by the following linear program:

$$\hat{p}_{j^*t^*} = \max p_{j^*t^*}$$

subject to

$$\sum_{t=1}^{24} \sum_{j=1}^{12} \lambda_{jt} x_{ijt} \leq x_{ij^*t^*} \qquad i = 1, \ldots, 4$$

$$-\sum_{t=1}^{24} \sum_{j=1}^{12} \lambda_{jt} y_{jt} + p_{j^*t^*} y_{j^*t^*} \leq 0$$

$$\sum_{t=1}^{24} \sum_{j=1}^{12} \lambda_{jt} = 1$$

$$\lambda_{jt}, p_{j^*t^*} \geq 0$$

where

x_{ijt}:	quantity of input i consumed by DMU_{jt}
y_{jt}:	quantity of output r produced by DMU_{jt}
λ_{jt}:	weight placed on inputs/outputs of DMU_{jt}
x_{ijt}, y_{jt}:	quantities of inputs, output for DMU_{jt} being evaluated

The linear program is solved for each observation (j^*, t^*) for $j^* = 1, \dots, 12$ and $t^* = 1, \dots, 24$.

To evaluate our main hypothesis about the impact of supervisory monitoring, we regress the logarithm of the productivity estimator $\ddot{\theta}_{jt}$ (reciprocal of the estimated inefficiency p_{jt}) on the contextual variables in the second stage, using the full panel of pooled data. Banker and Natarajan (2008) show that this two-stage procedure involving nonparametric estimation of productivity in the first stage followed by OLS regression provides statistically consistent estimators. Specifically the regression we estimate is represented as:

$$\ln \hat{\theta}_{jt} = \beta_0 + \beta_1^* MONITOR_j + \beta_2^* SINDEX_t + \beta_3^* SEASON_t + \beta_4^* INCOME_j + \beta_5^* AGE_j + \beta_6^* FAMSIZE_j + \beta_7^* COLLEGE_j + \beta_8^* POPUL_j + \beta_9^* RURAL_j + \beta_{10}^* COMPET_j + \varepsilon_{jt}$$

where

$\ln \hat{\theta}_{jt} =$	the logarithm of productivity for store j in month t,
$MONITOR_j =$	the ratio of the number of managers to the number of salespeople in store j,
$SINDEX_t =$	monthly sales index for other high-end department stores in month t,
$SEASON_t =$	1 if month t is October, November, or December, otherwise zero,
$INCOME_j =$	median household income of the county in which store j is located,
$AGE_j =$	median age of population in the county in which store j is located,
$FAMSIZE_j =$	median family size for county in which store j is located,
$COLLEGE_j =$	the percentage of the population with college education for the county in which store j is located,

$POPUL_j =$ population size in the county in which store j is located,

$RURAL_j =$ 1 if store j is located in a rural area, otherwise 0,

$COMPET_j =$ the competition intensity of store j's market,

$\varepsilon_{jt} =$ are random errors, $j = 1, \ldots, 12$, and $t = 1, \ldots, 24$.

Empirical results

Table 1 provides descriptive statistics on output, inputs and contextual variables. The median values of the output variable (SALES) and the four input variables (HOURS, SIZE, INVENTORY, SUPPORT) are all smaller than their mean values, indicating that the data are skewed to the right. The contextual variable representing our principal hypothesis is MONITOR, its mean is 24% and its median is 23%.

Figure 2 shows the frequency curve for DEA productivity scores for our pooled sample of 288 observations computed using the BCC model in (4). The interquartile range for the productivity scores is from 0.53 to 0.75. The mean of the DEA productivity scores is 0.66 and the median is 0.65. Out of the 288 observations, 33 observations are on the production frontier.

Table 2 presents Pearson and Spearman correlations between DEA productivity score and contextual variables used in estimation model (5). There is a statistically insignificant negative correlation between $\ln \hat{\theta}$ and MONITOR, before controlling for the impact of the contextual variables.

In the second stage of our empirical analysis, we regress the logarithm of DEA productivity scores on the contextual variables. Because pooled cross-sectional and times-series information is used to estimate the impact of contextual variables on retail sales productivity, there is the potential for serial correlation biasing the standard errors of the coefficients.

Therefore, we performed specification tests for residuals to check serial correlations and found that there exists substantial positive serial correlation (parameter estimate = 0.197, $t = 3.11$). We address this problem by using a variant of the Prais-Winsten (1954) estimator proposed by Park and Mitchell (1980) to make first-order autocorrelation adjustments to the variables. This estimator is consistent and performs especially well for short time series and trended data in relation to several other estimates (Doran and Griffiths 1983). It also reduces the extent to which the serial correlation coefficient tends to be underestimated by simpler methods (Kmenta and Gilbert 1970). We test our hypothesis using the parameter estimates from the regression using the transformed variables.

We present the empirical results in Table 3. The coefficients on all the control variables except INCOME are statistically significant. The estimated coefficient on MONITOR is negative and significant (t = -3.64) at the 1% level. Thus, after controlling for economy-wide effects, the differences in the location of each store, the demographics of the store locations, and the intensity of the competitive environment, the results provide strong support for our main hypothesis that supervisory monitoring has a negative impact on retail sales productivity in high-end stores.

Insert Table 1 Here

Insert Table 2 Here

Insert Table 3 Here

Insert Figure 2 Here

Conclusion

In this study, we investigated how the level of supervisory monitoring affects retail sales productivity using a panel of data for 12 outlets of a high-end retailer for 24 months. First, using Data Envelopment Analysis (DEA), we computed the relative productivity of retail outlets in using their labor, capital and other resources (represented by total selling hours, store size, average inventory, and support activities) in order to generate (deflated) store sales. We then regressed the logarithm of DEA productivity scores on contextual variables to consistently estimate the impact of the contextual factors on productivity and evaluate their statistical significance (Banker and Natarajan 2008).

Contrary to conventional wisdom in agency theory that supervisory monitoring leads to an increase in retail sales productivity, our empirical results indicate that supervisory monitoring results in a negative impact on retail sales productivity for the high-end department store that emphasizes customer-focused service as a way to gain strategic competitive advantage.

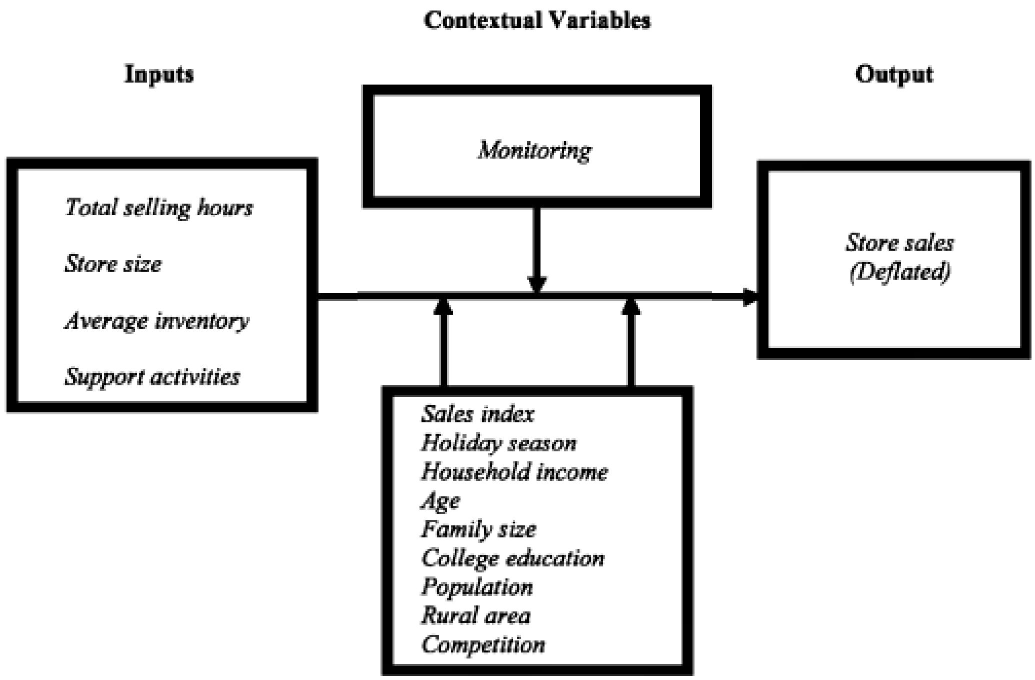

Figure 1. Input-output model.

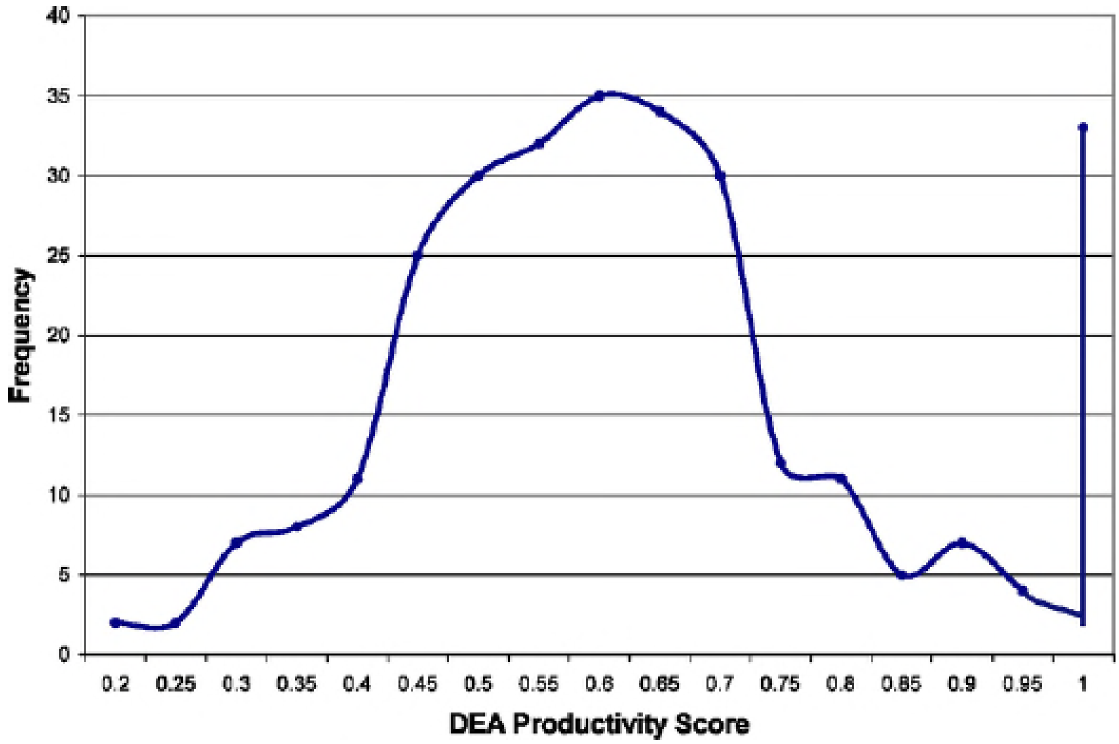

Figure 2. Frequency curve for DEA productivity scores.

Table 1. Descriptive statistics on output, inputs and contextual variables (N = 288).

	Mean	SD	Q1	Median	Q3
Output					
SALES	\$3.40M	\$2.52M	\$1.66M	\$2.61M	\$4.20M
Inputs					
HOURS	39,551.61	23,767.93	22,802.50	32,744.30	47,077.80
SIZE	225.17	150.74	123.00	183.50	230.00
INVENTORY	\$13.73M	\$8.35M	\$7.87M	\$11.35M	\$16.30M
SUPPORT	\$115.46K	\$84.24K	\$65.42K	\$92.58K	\$130.59K
Contextual variables					
MONITOR	0.2383	0.0577	0.1950	0.2300	0.2800
SINDEX	\$2.97M	\$1.22M	\$2.23M	\$2.87M	\$3.24M
INCOME	\$37,093	\$7,174	\$30,349	\$35,383	\$42,213
AGE	32.54	1.91	31.60	32.30	33.40
FAMSIZE	2.59	0.21	2.45.	2.59	2.75
COLLEGE	39.59%	7.17%	34.65%	40.05%	45.60%
POPUL	370,694	182,349	186,302	407,959	496,924
RURAL	0.3333	0.4722	0	0	1
COMPET	19.17	4.97	16.50	19.00	22.00

Variable definitions:
SALES = monthly deflated store sales, expressed in million dollars (\$M)
HOURS = the number of monthly selling hours in a store
SIZE = the size of a store in square feet
INVENTORY = the deflated dollar value of average inventory of merchandise, expressed in million dollars (\$M)
SUPPORT = a store's deflated support activity, expressed in thousand dollars (\$K)
MONITOR = the ratio of the number of managers to the number of salespeople in a store
SINDEX = monthly sales index for other high-end department stores
INCOME = median household income of the county in which a store is located
AGE = median age of population in the county in which a store is located
FAMSIZE = median family size for county in which a store is located
COLLEGE = the percentage of the population with college education for the county in which a store is located
POPUL = population size in the county in which a store is located
RURAL = 1 if a store is located in a rural area, otherwise 0
COMPET = the competition intensity of a store's market

Table 2. Correlation matrix (p-value in parentheses)

	$\ln\hat{\theta}$	MONITOR	SINDEX	SEASON	INCOME	AGE	FAMSIZE	COLLEGE	POPUL	RURAL	COMPET
$\ln\hat{\theta}$		−0.0008	0.48411	0.4844	−0.3702	−0.1685	0.0994	−0.2914	−0.2503	0.0807	0.1372
		(0.9896)	(0.0001)	(0.0001)	(0.0001)	(0.0041)	(0.0923)	(0.0001)	(0.0001)	(0.1721)	(0.0199)
MONITOR	−0.04377		0.0000	0.0000	−0.5474	−0.4737	−0.2316	−0.3088	−0.5158	−0.1542	−0.5132
	(0.4590)		(1.0000)	(1.0000)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0088)	(0.0001)
SINDEX	0.51166	0.0000		0.7090	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	(0.0001)	(1.0000)		(0.0001)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)
SEASON	0.43861	0.0000	0.6768		0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	(0.0001)	(1.0000)	(0.0001)		(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)
INCOME	−0.23866	−0.6071	0.0000	0.0000		0.3217	0.3776	0.5944	0.3357	0.0512	0.1607
	(0.0001)	(0.0001)	(1.0000)	(1.0000)		(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.3866)	(0.0063)
AGE	−0.06892	−0.3749	0.00000	0.0000	0.2057		−0.3636	0.3636	0.7552	0.0512	0.2630
	(0.2437)	(0.0001)	(1.0000)	(1.0000)	(0.0004)		(0.0001)	(0.0001)	(0.0001)	(0.3866)	(0.0001)
FAMSIZE	0.10681	−0.1708	0.00000	0.0000	0.3885	−0.4938		−0.2797	−0.2448	0.1536	0.4822
	(0.0703)	(0.0036)	(1.0000)	(1.0000)	(0.0001)	(0.0001)		(0.0001)	(0.0001)	(0.0090)	(0.0001)
COLLEGE	−0.25746	−0.2893	0.00000	0.0000	0.5378	0.3119	−0.3675		0.2098	0.2048	−0.3069
	(0.0001)	(0.0001)	(1.0000)	(1.0000)	(0.0001)	(0.0001)	(0.0001)		(0.0003)	(0.0005)	(0.0001)
POPUL	−0.17246	−0.4187	0.00000	0.0000	0.1790	0.6979	−0.2522	0.0768		0.3072	0.4530
	(0.0033)	(0.0001)	(1.0000)	(1.0000)	(0.0023)	(0.0001)	(0.0001)	(0.1937)		(0.0001)	(0.0001)
RURAL	0.07195	−0.1638	0.0000	0.0000	0.0070	−0.0155	0.0885	0.2305	0.3480		0.1070
	(0.2235)	(0.0053)	(1.0000)	(1.0000)	(0.9063)	(0.7937)	(0.1340)	(0.0001)	(0.0001)		(0.0698)
COMPET	0.09099	−0.4132	0.0000	0.0000	0.0924	0.1712	0.3716	−0.4639	0.5256	0.0831	
	(0.1234)	(0.0001)	(1.0000)	(1.0000)	(0.1177)	(0.0036)	(0.0001)	(0.0001)	(0.0001)	(0.1596)	

Pearson correlations are below the diagonal, and Spearman correlations are above the diagonal.
$\ln\hat{\theta}$: the logarithm of DEA productivity score, other variables are defined as in Table 1

Table 3. Estimated of regression of logarith of productivity estimates on contextual variables (t statistics in paraentheses) $1\text{n}\,\hat{\theta}_{jt} = \beta_0 + \beta_1^*\ \text{MONITOR}_j + \beta_2^*\ \text{SINDEX}_j + \beta_3^*\ \text{SEASON}_j + \beta_4^*\text{INCOME}_j + \beta_5^*\ \text{AGE}_j + \beta_6^*\ \text{FAMSIZE}_j + \beta_7^*\ \text{COLLEGE}_j + \beta_8^*\ \text{POPUL}_j + \beta_9^*\ \text{RURAL}_j + \beta_{10}^*\ \text{COMPET}_j + \varepsilon_{jt}$

	Parameter	Expected sign	Parameter estimate
Intercept	β_0	?	-0.528^{**}
			(-2.18)
MONITOR	β_1	−	-1.367^{***}
			(-3.64)
SINDEX (in millions)	β_2	+	0.103^{***}
			(8.94)
SEASON	β_3	+	0.154^{***}
			(4.18)
INCOME (in millions)	β_4	+	6.170
			(0.96)
AGE	β_5	+	0.080^{***}
			(6.89)
FAMSIZE	β_6	−	-0.483^{***}
			(-2.76)
COLLEGE	β_7	+	-0.028^{***}
			(-4.97)
POPUL (in millions)	β_8	−	-1.600^{***}
			(-7.03)
RURAL	β_9	+	0.348^{***}
			(5.69)
COMPET	β_{10}	+	0.010^{*}
			(1.76)
p (model)			0.0001
Adjusted R^2			0.564

Variables definitions:
$\ln\hat{\theta}_{jt}$ = the logarithm of DEA productivity score for store j in month t
MONITOR_j = the ratio of the number of managers to the number of salespeople in store j
SINDEX_t = monthly sales index for other high-end department stores in month t, expressed in million dollars
SEASON_t = 1 if month t is October, November, or December, otherwise zero
INCOME_j = median household income of the county in which store j is located, expressed in million dollars
AGE_j = median age of population in the county in which store j is located
FAMSIZE_j = median family size for county in which store j is located
COLLEGE_j = the percentage of the population with college education for the county in which store j is located
POPUL_j = population size in the county in which store j is located, expressed in millions
RURAL_j = 1 if store j is located in a rural area, otherwise 0
COMPET_j = the competition intensity of store j's market
ε_{jt} are random errors

*Indicates statistical significance at 10% levels

**Indicates statistical significance at 5% levels

***Indicates statistical significance at 1% levels

References

Achabal, D. D., Heineke, J. M., & McIntyre, S. H. (1984). Issues and perspectives on retail productivity. *Journal of Retailing*, 60, 107-127.

Anderson, E., & Oliver, R. L. (1987). Perspectives on behavior-based versus outcome-based salesforce control systems. *Journal of Marketing*, 57, 76-88.

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

Banker, R. D., & Natarajan, R. (2008). Evaluating contextual variables affecting productivity using data envelopment analysis. *Operation Research*, 56, 48-58.

Banker, R. D., Chang, H., & Natarajan, R. (2007). Estimating DEA technical and allocative inefficiency using aggregate cost or revenue data. *Journal of Productivity Analysis*, 27, 115-121.

Banker, R. D., Lee, S.-Y., Potter, G., & Srinivasan, D. (1996). Contextual analysis of performance impacts of outcome-based incentive compensation. *Academy of Management Journal*, 39, 920-948.

Basu, A. K., Lal, R., Srinivasan, V., & Staelin, R. (1985). Salesforce compensation plans: an agency theoretic perspective. *Marketing Science*, 4, 267-291.

Chakravarthy, B. S. (1986). Measuring strategic performance. *Strategic Management Journal*, 7, 437-458.

Churchill, G., Ford, N. M., & Walker, O. C. (1979). Personal characteristics of sales people and the attractiveness of alternative rewards. *Journal of Business Research*, 7, 25-50.

Doran, H. E., & Griffiths, W. E. (1983). On the relative efficiency of estimators which include the initial observations in the estimation of seemingly unrelated regressions with first-order autoregressive disturbances. *Journal of Econometrics*, 23, 165-191.

Doutt, J. T. (1984). Comparative productivity performance in fast-food retail distribution. *Journal of Retailing*, 60, 98-106.

Eisenhardt, K. M. (1985). Control: organizational and economic approaches. *Management Science*, 31, 134-149.

Eisenhardt, K. M. (1988). Agency- and institutional-theory explanations: the case of retail sales compensation. *Academy of Management Journal*, 31, 488-511.

Good, W. S. (1984). Productivity in the retail grocery trade. *Journal of Retailing*, 60, 81-97.

Goodman, C. S. (1985). Comments: on output measures of retail performance. *Journal of Retailing*, 61, 7782.

Hise, R. T., Kelly, J. P., Gable, M., & McDonald, J. B. (1983). Factors affecting the performance of individual chain store units: an empirical analysis. *Journal of Retailing*, 59, 22-29.

Ingene, C. A. (1982). Labor productivity in retailing. *Journal of Marketing*, 46, 75-90.

Ingene, C. A. (1985). Labor productivity in retailing: what do we know and how do we know it? *Journal of Marketing*, 49, 99-106.

Joseph, K., & Thevaranjan, A. (1998). Monitoring and incentives in sales organizations: an agency-theoretic perspective. *Marketing Science*, 17(2), 1998.

Kamakura, W. A., Lenartowicz, T., & Ratchford, B. T. (1996). Productivity assessment of multiple retail outlets. *Journal of Retailing*, 72, 333-356.

Kmenta, J., & Gilbert, R. F. (1970). Estimation of seemingly unrelated regressions with autoregressive disturbances. *Journal of the American Statistical Association*, 65, 186-197.

Lal, R., & Srinivasan, V. (1993). Compensation plans for single- and multi-product salesforces: an application of the Holmstrom-Milgrom model. *Management Science*, 39, 777-793.

Lambert, R. A. (2001). Contracting theory and accounting. *Journal of Accounting and Economics*, 32, 3-87.

Lewin, A. Y., & Minton, J. W. (1986). Determining organizational effectiveness: another look, and an agenda for research. *Management Science*, 32, 514-53.

Lusch, R. F., & Moon, S. Y (1984). An exploratory analysis of the correlates of labor productivity in retailing. *Journal of Retailing*, 60, 37-61.

Maslow, A. H. (1954). *Motivation and personality*. New York: Harper.

Nooteboom, B. (1983). Productivity Growth in the Grocery Trade. *Applied Economics*, 15, 649-64.

Oldham, G. R., & Cummings, A. (1996). Employee creativity: personal and contextual factors at work. *Academy of Management Journal*, 98, 607-634.

Ouchi, W. G. (1979). A conceptual framework for the design of organizational control mechanisms. *Administrative Science Quarterly*, 24, 833-848.

Park, R. E., & Mitchell, B. M. (1980). Estimating the autocorrelated error model with trended data. *Journal of Econometrics*, 13, 185-201.

Peterson, R. A., Albaum, G., & Ridgway, N. M. (1989). Consumers who buy from direct sales companies. *Journal of Retailing*, 65, 273-286.

Pool, S. W. (1997). The relationship of job satisfaction, substitute of leadership, leadership behavior, and work motivations. *Journal of Psychology*, 131, 271-283.

Porter, M. E. (1996). What is strategy? *Harvard Business Review*, 74(6), 61-78.

Prais, S. J., & Winsten, C. B. (1954). *Trend estimators and serial correlation*. Cowles Commission Discussion Paper, No. 383, Chicago.

Ratchford, B. T., & Brown, J. R. (1985). A study of productivity changes in food retailing. *Marketing Science*, 4, 292-311.

Samiee, S. (1990). Productivity planning and strategy in retailing. *California Management Review*, 32(2), 54-76.

Schlesinger, L. A., & Heskett, J. L. (1991). The service-driven service company. *Harvard Business Review*, 69(5), 71-81.

Thurik, R., & Kooiman, P. (1986). Research note: modelling retail floorspace productivity. *Journal of Retailing*, 62, 431-445.

Venkatraman, N., & Ramanujam, V. (1986). Measurement of business performance in strategy research: a comparison of approaches. *Academy of Management Review*, 11, 801-814.

Vroom, V. H. (1964). *Work and Motivation*. New York: Wiley.

Zhou, J. (2003). When the presence of creative coworkers is related to creativity: role of supervisor close monitoring, development feedback, and creative personality. *Journal of Applied Psychology*, 88, 413-422.