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AGRICULTURAL ECONOMICS
STAFF PAPER

NONPARAMETRIC TECHNICAL EFFICIENCY WITH N FIRMS AND M INPUTS: A SIMULATION

Loren W. Tauer
and
John J. Hanchar

July 1993 **No. 93-9**

Department of Agricultural Economics
Cornell University Agricultural Experiment Station
New York State College of Agriculture and Life Sciences
A Statutory College of the State University
Cornell University, Ithaca, New York, 14853

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Abstract

Simulation of nonparametric efficiency shows that even when the number of firms is large, defining ten or more inputs results in most firms being efficient. Comparison of empirical with simulated results suggests that the dimension of the problem rather than actual efficiencies has the greater effect for some empirical results.

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* Professor and extension associate, respectively, Department of Agricultural Economics, Cornell University, Ithaca, NY 14853-7801. Paper delivered at the American Agricultural Economics Association annual meeting, August 2-4, 1993 in Orlando, Florida. R.N. Boisvert and A. Weersink provided useful comments.

NONPARAMETRIC TECHNICAL EFFICIENCY WITH N FIRMS AND M INPUTS: A SIMULATION

Nonparametric or data envelopment techniques using linear programming have become common tools to measure technical and cost efficiency of individual firms. The seminal work was by Farrell, with recent developments reported by Färe, Grosskopf and Lovell. The attraction of the nonparametric approaches is that a functional form need not be specified for the technology of the firm. Although flexible functional forms are available, it is believed by many that complete flexibility is preferred.

One characteristic of data envelopment analysis (DEA) procedures is that computed firm efficiencies appear to be dependent on the number of comparison firms used and the number of defined outputs and inputs -- that is, the dimension of the problem. Nunamaker (1985) examines the sensitivity of DEA-generated efficiency scores to variable set expansion and data variation. He found that variable set expansion through disaggregation or addition of new factors produces an upward trend in efficiency scores. Ahn, Charnes, and Cooper provide a counterexample to Nunamaker's findings. Their counterexample is one that Nunamaker (1988) in reply describes as a trivial case because it is a situation where two firms operate at an identical point. Nunamaker (1988) in his reply computes efficiency scores for 15 hospitals for alternative variable specifications using DEA. He reports that efficiency scores show a general upward trend as the variable set expands. Thrall shows the conditions under which Nunamaker's (1985) original proposition is true, and supplies transition theorems for output and input expansion while holding the number of firms constant. As Leibenstein and Maital state, given enough inputs, all (or most) of the firms are rated efficient. They state that this is a direct result of the dimensionality of the input/output space relative to the number of observations (firms).

The purpose of this paper is to determine the extent of this occurrence by performing a Monte-Carlo simulation of nonparametric efficiency using various combinations of firms and inputs. It is shown that even with a large number of firms, defining ten or more inputs will result in most firms being measured as efficient.

Procedure

The underlying concept of the nonparametric approach is the existence of a bounding technology characterized by an input requirement set L(Y), which can be constructed from observed input-output data from K firms. This set is specified as

$$L(y_1, \ldots, y_m) \equiv \left\{ (x_1, \ldots, x_n):\ y_i \le \sum_{k=1}^{K} \mu_k\, y_{ik},\ i=1, \ldots, m; \right.$$

$$\left. x_j \ge \sum_{k=1}^{K} \mu_k\, x_{jk},\ j=1, \ldots, n; \qquad \mu_k \ge 0,\ k=1, \ldots K \right\},$$

where $\mu = (\mu_1, \ldots, \mu_k)$ is an intensity vector that forms linear combinations of the observed input vectors x_j and output vectors y_i. The technical efficiency of each firm is measured relative to this set. This specification assumes radial technical inefficiency, strong disposability of inputs and outputs, and constant returns to scale, since the summation of the intensity vector μ is not constrained to be equal to one (variable returns to scale) or less than one (increasing returns to scale).

Empirically, the technical efficiency of a firm, k, can be calculated by solving the linear programming problem

$$\min_{\mu_k} \quad \lambda_k$$

$$\text{s.t.} \quad \sum_{k=1}^{K} \mu_k\, y_{ik} \ge y_{ik}, \qquad i=1, \ldots, m,$$

$$\sum_{k=1}^{K} \mu_k x_{jk} \leq \lambda_k x_{jk}, \qquad j=1, ..., n,$$

$$\mu_k \geq 0, k=1, ..., K,$$

where y_{ik} is the output i produced by firm k, and x_{jk} is the input j used by firm k, with m outputs and n inputs. The solution value λ_k shows the fraction by which a firm can multiply its input vector and produce no less output. The solution value $\lambda_k=1$ determines the firm as technically efficient. Any value $\lambda_k<1$ is technically inefficient. To solve for the technical efficiency of all K firms, it is necessary to solve K linear programs where the y_{ik} and x_{jk} on the RHS of the LP are replaced with the outputs and inputs of the k^{th} firm for each LP solution.

By defining just one output and various combinations of input and firm numbers, the technical efficiency of each of K firms was computed from data randomly generated. The output for each firm was defined as y=1, and the quantity of input j for firm k was randomly drawn from the univariate uniform distribution [0, 1]. By randomly specifying the input-output data set this way, the chance that any one firm will lie on the bounding technology is strictly random. The simulations were performed for total inputs of 3, 5, 10 and 15, with the number of firm combinations of 25, 50, 100 and 200. This spans most empirical combinations of inputs and firms. Forty complete replications were completed at each of the 16 firm-input number combinations. The simulation was also performed drawing from a univariate normal distribution.

Results

The results are summarized in Table 1 by the percentage of firms measured as being completely technically efficient ($\lambda_k=1$). These results are also plotted in Figure 1 (see Appendix). With 3 inputs and 25 firms, on average, over the forty replications 22 percent of the firms were technically efficient. The range of firms efficient over the forty

Table 1. Percentage of Firms Technically Efficient from Data Envelopment Simulation of Uniformly Distributed Data*

Number of firms		Number of inputs 3	5	10	15
			--- *percentage* ---		
25	mean	22.0	46.7	87.4	97.5
	s.d.	6.5	9.2	7.3	3.1
	range	(8 - 36)	(24 - 64)	(68 - 96)	(88 - 100)
50	mean	14.4	33.6	76.6	94.2
	s.d.	4.2	6.6	6.1	4.3
	range	(4 - 24)	(20 - 48)	(62 - 86)	(80 - 100)
100	mean	9.4	24.2	65.6	89.2
	s.d.	2.0	4.5	5.4	3.4
	range	(5 - 13)	(17 - 36)	(57 - 75)	(82 - 96)
200	mean	5.3	16.2	53.7	81.6
	s.d.	1.2	2.9	4.8	2.9
	range	(2 - 8)	(8 - 24)	(42 - 62)	(76 - 86)

* Inputs were randomly generated from univariate uniform distribution [0, 1]. Forty replications at each cell.

replications went from a low of 8 percent to a high of 36 percent. With 3 inputs and 200 firms, on average, 5.3 percent of the firms were technically efficient. Table 2 and Figure 2 (Appendix) show the results when the inputs were drawn from a univariate normal distribution. As expected, slightly fewer of the firms are measured as efficient under normality since the distribution tails are less dense.

As the number of firms increase, the computed efficiencies decrease, since it becomes more likely that any firm would then be dominated. What is more striking is the relationship between the number of defined inputs and the computed efficiencies. There is a dramatic increase in the number of firms that are efficient as the number of

Table 2. Percentage of Firms Technically Efficient from Data Envelopment Simulation of Normally Distributed Data*

Number of firms		Number of inputs 3	5	10	15
			--- *percentage* ---		
25	mean	20.4	42.5	79.2	94.5
	s.d.	6.6	8.5	8.0	5.4
	range	(8 - 40)	(24 - 60)	(56 - 96)	(76 - 100)
50	mean	11.6	26.8	66.9	89.0
	s.d.	3.4	5.8	6.8	4.3
	range	(6 - 18)	(16 - 40)	(54 - 84)	(78 - 100)
100	mean	7.0	16.0	52.0	80.0
	s.d.	1.6	3.3	6.1	4.4
	range	(4 - 10)	(8 - 25)	(38 - 63)	(70 - 91)
200	mean	3.7	11.4	38.6	67.4
	s.d.	0.9	2.0	3.7	4.2
	range	(2 - 6)	(7 - 16)	(33 - 47)	(60 - 76)

* Inputs were randomly generated from univariate normal distribution (μ=0, σ=1). Each distribution was then shifted so the minimum value of that distribution was zero. Forty replications at each cell.

inputs increase. When 10 or 15 inputs are used, in all but one case over half of the firms were measured as technically efficient.

The inputs were randomly drawn from a univariate distribution. Empirically, one might expect some dependency between inputs. After all, factor substitution occurs along an isoquant. In addition, some input pairs may be technically complementary or technically competitive, rather than technically independent. Off of the efficient frontier, one might expect strong correlation of input usage inefficiency. If a firm uses one input inefficiently, it may use other inputs inefficiently as well. On balance, however, whether inputs are jointly dependent or not is an empirical issue.

A Comparison Between Simulated and Empirical Results

A comparison of the results of empirical efficiency studies and the simulated nonparametric efficiency results here is useful to determine whether the empirical studies replicate the simulated results. If there are no differences, then the usefulness of the empirical results must be questioned. To identify empirical studies for comparison, attention was limited to studies that utilized nonparametric or data envelopment techniques using linear programming to measure the technical or cost efficiency of individual firms. Sources for the literature review included the electronic databases of Agricola and Econlit and a bibliography by Seiford listing more than 400 data envelopment studies. The list of potential studies available for review included applications in the areas of banking, health care, education and agriculture, among others.

Not all of the empirical studies identified from the review match the assumptions and specification of the simulation. Recall the assumptions used in the specification of the simulation: radial technical inefficiency, strong disposability of inputs and outputs, and constant returns to scale. Also, note that a single output was defined. Points of disagreement include the consideration of nonconstant returns to scale and the inclusion of multiple outputs. Many empirical studies, although consistent with regard to assumptions, report only the average efficiency of all firms used in the analysis and not the number or percentage of observations that were 100 percent efficient. Fifteen empirical studies are listed in Table 3. These are likely representative of studies whose assumptions and specification match those used in the simulations reported here.

One of the fifteen studies is Farrell's seminal article, where he computed the technical efficiency of agricultural production in each of the then 48 united states. He examined situations in which two, three, and four inputs were specified. Using six different combinations of two inputs (ignoring two inputs at a time) he reported that between 4 and 12 percent of the observations were efficient. Using four different combinations of three inputs (ignoring the fourth input) he reported as efficient 15, 12,

Table 3. Percentage of Firms Technically Efficient by Study, Simulated Efficiencies, and Tests of Significance

Study	Number of inputs	Number of firms	Percentage of firms technically efficient	Simulated pct. of firms technically efficient[a]	Standard deviation[a]	test statistic[b]
Farrell (1957)	2	48	4.2[c]	4.4	2.5	0.5
	2	48	8.3	4.4	2.5	- 9.7
	2	48	12.5	4.4	2.5	-20.2
	3	48	8.3	12.3	3.7	6.8
	3	48	12.5	12.3	3.7	- 0.3
	3	48	14.6	12.3	3.7	- 3.9
	3	48	16.7	12.3	3.7	- 7.4
	4	48	18.8	20.2	4.8	1.8
Seitz (1966)	3	81	7.4	8.7	2.3	3.5
Sitoras (1966)	4	58	17.2	18.0	4.3	1.2
	8	58	31.0	48.7	6.2	17.8
Araji (1975)	4	48	10.4	20.2	4.8	12.8
	4	48	12.5	20.2	4.8	10.0
Burley (1980)	4	25	12	31.4	7.6	15.9
Byrnes et al. (1984)	8	15	100	70.0	8.9	-21.1
Grisley and Mascarenhas (1985)	4	160	9	9.1	1.8	0.3
	4	291	7	4.0	0.5	-37.5
	4	153	11	9.4	1.9	- 5.3
	4	97	18	12.0	2.6	-14.4
Grisley and Henson (1986) hen flocks:	4	64	9	17.0	4.0	12.5
	4	36	33	26.1	6.3	- 6.8
	4	65	17	16.9	4.0	- 0.2
tom flocks:	4	63	13	17.2	4.0	6.6
	4	81	11	14.4	3.3	6.4
	4	56	20	18.3	4.3	- 2.5
Byrnes et al. (1988)	9	84	20	49.3	5.9	31.0
	9	113	20	43.3	5.3	27.5
Nunamaker (1988)	2	15	26.7	11.5	7.0	-13.6
	3	15	26.7	23.9	7.9	- 2.2

- continued -

Table 3. Continued

Study	Number of inputs	Number of firms	Percentage of firms technically efficient	Simulated pct. of firms technically efficient[a]	Standard deviation[a]	test statistic[b]
Pozzano and Zaninotto (1988)	2	126	45.2	1.8	0.6	-451.7
	2	61	72.1	3.7	1.9	-224.8
Färe et al. (1989)	3	19	5.3	22.5	7.4	14.5
Diamond and Medewitz (1990)	5	46	34.9	29.3	6.2	- 5.6
	5	23	69.6	43.8	8.7	-18.5
	5	23	43.5	43.8	8.7	0.2
Thompson et al. (1990)	4	32	18.8	28.0	6.7	8.6
Weersink et al. (1990)	7	105	42.9	30.0	4.3	-18.7

[a] Computed using linear interpolations of the data in Table 2.
[b] A t-statistic is used to test the null hypothesis that the mean percent of efficient firms from the simulation is equal to the percent reported for the empirical study. The critical t value for alpha equal to 0.05 and 40 - 1 degrees of freedom is approximately 2.02.
[c] Farrell reports that 4.2 percent of the observations were efficient for four of the two-input combinations.

17, and 8 percent of the observations. These results are within the ranges of 6 to 18 percent found in Table 2 under 3 inputs and 50 firms. Using all four inputs, 19 percent of the observations were efficient. In Table 3 a simple statistical test compares the sample mean percentage of the simulated results to the percentage reported for the empirical study. In six of the eleven situations Farrell examined, the simulated results replicate the empirical results. That is, the sample mean percentage for the simulation does not differ from the empirical result reported.

Seitz used the Farrell approach to examine efficiency measures for steam electric generating plants. Using three inputs and 81 plants, he reported that 7 percent of the plants were technically efficient. The t-statistic in Table 3 for Seitz's study indicates that the sample mean percentage for the simulation and the percentage for the study differ.

Sitoras used the Farrell approach to examine the agriculture sector in the Philippines using 1960 census data. A subsample of 58 agricultural municipalities taken from a total of 431 indicated that for four and eight inputs, 17 and 31 percent of the observations were technically efficient, respectively. In the eight-input case, the simulation result does not replicate the empirical result. The empirical results do illustrate the trend that the percent of technically efficient firms increases as the number of inputs increases, holding the number of observations constant.

Araji examined the production efficiency of 48 beef cattle operations. Using four inputs and two alternative measures of a single output -- pounds and value of livestock products sold -- Araji reported that 10 and 12 percent of the beef cattle operations were technically efficient, respectively. In both cases the null hypothesis of no difference between the simulated result and the empirical result is rejected. Burley illustrated a linear programming analysis developed from the Farrell efficiency system using yearly manufacturing output as observations. Using one output, four inputs, and 25 observations, he reported that 12 percent of the observations were efficient technologies. Byrnes, Färe, and Grosskopf measured the technical efficiencies of 15 Illinois strip mines using eight inputs. They found that all of the mines were technically efficient, although some were not scale-efficient. Based upon the value of the test statistic, the simulation results do not replicate the empirical results reported in Table 3 for the latter two studies.

Grisley and Mascarenhas examined the efficiency of Pennsylvania dairy farms. They divided their sample of dairy farms into four different size groups and assumed constant returns to size within a group. They used four inputs and one output. One size group had 97 dairy farms, and of those 18 percent were efficient. Two other groups had approximately 150 farms and were 9 and 11 percent efficient. The fourth group had 291 farms of which 7 percent were efficient. Only the test statistic for the 160 farm size group is insufficient to reject the null hypothesis. Grisley and Henson used the Farrell efficient unit isoquant technique to examine the technical efficiency of operating input utilization for hen and tom turkey flocks. They divided the 165 hen flocks and 200 tom turkey flocks in their sample into groups based upon the returns to scale exhibited in the econometric analysis of Grisley and Gitu. Sixty-four, 36, and 65 of the 165 hen flocks exhibited constant, increasing, and decreasing returns to scale, respectively. Sixty-three, 81, and 56 of the 200 tom turkey flocks exhibited constant, increasing, and decreasing returns to scale, respectively. Grisley and Henson assumed constant returns to scale within each of these groups and conducted their analysis using one output and four inputs. As in Grisley and Mascarenhas, in only one of the cases examined was the null hypothesis of no difference between simulated and empirical results not rejected.

Byrnes, Färe, Grosskopf, and Lovell used mathematical programming to measure productivity differentials in the U.S. surface coal mining industry. Using one output and nine inputs, they measured the overall technical efficiency of 84 midwestern and 113 western mines. They reported that in each sample fully 20 percent of the surface mines were technically efficient. Nunamaker (1988) applied the data envelopment analysis model to a sample of 15 hospitals. Results using one output and one, two, and three inputs suggest that efficiency scores display a general increasing trend as the variable set expands. For the three input alternatives, he reported that approximately 7, 27, and 27 percent of hospitals were efficient, respectively. The t-statistics in Table 3 for both studies indicate that the simulated results do not replicate the empirical results.

Pozzano and Zaninotto utilized a Farrell-type approach to obtain an index of production efficiency for a sample of large retail units. They reported that for their analysis of one output and two inputs, 45 percent of the 126 supermarkets and 72 percent of the 61 discount stores were efficient. That is, they belonged to a well-behaved production function. Their results appear to be outside the ranges reported in Tables 1 and 2. The values of the test statistic in Table 3 support the observation. Färe, Grosskopf, and Kokkelenberg used efficiency measures closely related to the Farrell-type efficiency measures to examine electric utility data. They examined 19 firms using a single output and three inputs. They reported that 5 percent of the firms were technically efficient. The value of the test statistic indicates that the empirical result does not replicate the simulated result.

Diamond and Medewitz used data envelopment analysis to examine differences in the efficiency of resource use between Developmental Economic Education Program (DEEP) high school classes and non-DEEP classes. Using a single output and five inputs, they reported that 70 percent of the 23 DEEP and 44 percent of the 23 non-DEEP classes were technically efficient. An analysis combining DEEP and non-DEEP classes identified 35 percent of the 46 classes as technically efficient. The result for the 23 non-DEEP classes corresponds closely to the simulated result while the other two empirical results do not.

Thompson, Langemeier, Lee, Lee and Thrall applied efficiency analysis to Kansas farming. Results reported for 32 dryland wheat farms indicated that for one output and four inputs 19 percent of the 32 farms were technically efficient. Based upon the test statistic, the empirical result is not consistent with the simulated result. Weersink, Turvey and Godah computed technical efficiency measures for 105 Ontario dairy farms using one output and seven inputs. They reported that approximately 43 percent of the farms in the sample were technically efficient. The simulated result is not comparable to the empirical result reported in Table 3.

Thus, of the forty empirical results reported here (some of the 15 studies reported results for more than one group) 10 or 25 percent had efficiency measures comparable to the simulated results. This correspondence suggests that a closer look be taken at the research procedures used in empirical studies. It may be that the data used in the ten studies are not correctly defined or measured, such that they are strictly randomly generated as the data generated for the simulation. If the data are correct, then the usefulness and accuracy of nonparametric efficiency analysis must be questioned. These issues should be investigated further.

Conclusions

Previous researchers have observed that use of the nonparametric approach or data envelopment analysis to measure firm efficiency is sensitive to the difference between the number of firms and the sum of inputs and outputs used. This paper explored the severity of this problem by simulating nonparametric efficiency computations using various combinations of inputs and firms. It was discovered that the number of inputs defined, rather than the number of farms used, was a stronger determining factor for higher efficiency measurement. Use of more than ten inputs caused the majority of farms to be measured as efficient.

The comparisons of the results from forty empirical efficiency studies suggest implications for empirical studies of firm efficiency using nonparametric approaches, since 25 percent of those results did not differ from our simulated results from randomly generated data. If a researcher finds that the percentage of firms technically efficient in a study is closely approximated by the simulation results here, those results might simply be due to the dimensionality of the problem (the number of inputs/outputs and firms) rather than actual efficiencies. If empirical results do not approximate the simulated results, it could be more likely that actual differences in efficiencies exist.

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APPENDIX

Figure 1. Graph of Table 1.

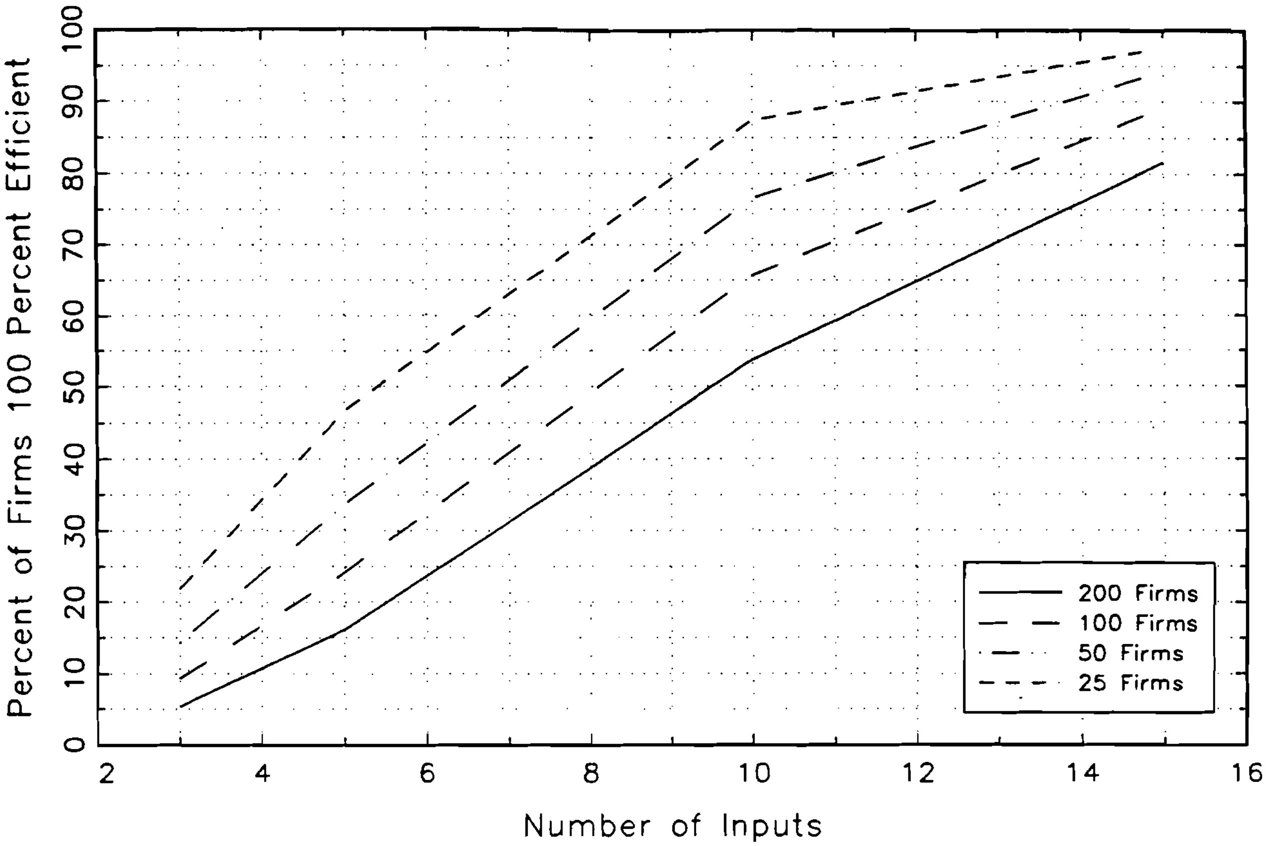
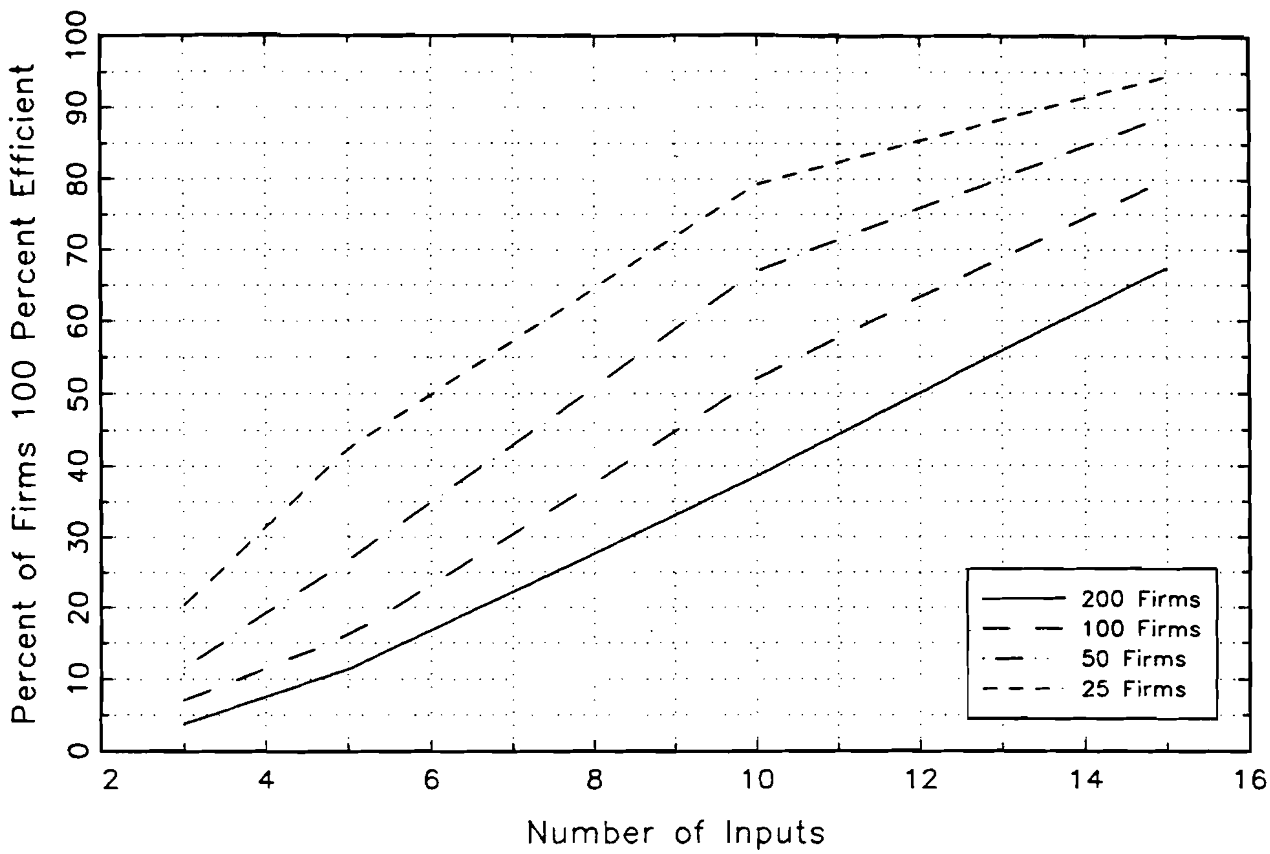


Figure 2. Graph of Table 2.



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