Successful Dairy Farm Management Strategies Identified by Stochastic Dominance Analyses of Farm Records

Jonas B. Kauffman, III and Loren W. Tauer

First-degree and second-degree stochastic dominance were used to separate a panel of 112 dairy farms with ten annual observations per farm into successful and less successful groups using four different performance measures. Logit regression using 16 independent variables was then used to determine important farm characteristics leading to farm success. High milk production and controlling hired labor and purchased feed expenses were important. The selective adoption of new technologies was also important. Optimal debt-asset ratios varied over the 10-year period.

Introduction

The 1970s and early 1980s were periods of change for dairy farmers. Largely as a result of the developments during these periods, dairy farmers are currently facing increasing financial stress. In this environment, it has become more important for farmers to effectively manage their farms since much of the difference in profitability among dairy farms can be attributed to managerial performance. A study of management practices on New York dairy farms (Bratton) found that while utilizing essentially the same amounts of land, labor, and capital, farms with incomes in the top 20 percent had an average net cash farm income nearly three times that of those in the lowest 20 percent.

The purpose of this article is to identify management strategies that have been successful on commercial dairy farms in New York using farm records as data. Logit regression is used to identify the strategies, and stochastic dominance is used to classify farms as successful. A strategy is a series of steps or actions that, when taken together, are a plan or method for achieving a specific goal; a farm management strategy is used herein to denote a plan for the utilization of resources to produce and market the farm output and finance the farm business, with the goal of attaining the highest possible level of satisfaction for the farm family. In this study, the success of a management strategy is assumed to be reflected in a farm's profitability as measured by annual observations on labor and management income or rate of return to equity capital.

Several efficiency criteria are available for the analysis of distributions of outcomes including E-V analysis. However, if one is unwilling to assume that the utility function is quadratic, nonnormality of the distributions precludes the use of E-V analysis. Stochastic dominance is an efficiency criterion which is less restrictive as to the shape of the utility function and distribution of outcomes. By making pair-wise comparisons between alternative cumulative outcome distributions and eliminating those which are dominated, stochastic dominance partitions the distributions into efficient and inefficient sets. With first-degree stochastic dominance (FSD), the utility function is restricted to be monotonically increasing. Second-degree stochastic dominance (SSD) requires the additional restriction that the utility function be strictly concave, i.e., that one assumes the decision maker to be risk averse. Stochastic dominance also uses the entire empirical distribution of the outcomes rather than a limited number of moments which may not completely specify the distribution.

Kauffman is a cooperative extension agent in Genesee County, New York. Tauer is an associate professor of agricultural economics. Cornell University. The authors thank B.F. Stanton and R.N. Boisvert for their comments and advice in completing this research.

Stochastic dominance has been applied to a variety of decision situations in agriculture including (1) adoption of new technologies (Hardaker and Tanago; Danok, McCarl, and White; Schoney and McGuckin), (2) participation in government programs (Kramer and pope; Richardson and Nixon (1982)), (3) evaluation of cropping strategies (McGuckin; peder son; Zacharias and Grube), and (4) selection among management strategies (Richardson and Nixon (1984); Wilson and Eidman).

Schurle and Williams used stochastic dominance to determine what farm characteristics generate outcomes that are preferred by farmers. Annual net farm income on 128 Kansas farms over a seven-year period was used to generate outcome probability distributions for comparisons by stochastic dominance. The researchers separated the farms by FSD and SSD into efficiency groups by using an iterative procedure that removed the dominant distributions after each stochastic dominance comparison and re compared the remaining distributions. They then compared the efficiency groups based on averages of various farm characteristics such as size, age of operator, and diversification.

The procedure used in this paper is similar to that used by Schurle and Williams. The farms are grouped by FSD and SSD by the same iterative procedure described above. However, the performance measures used are adjusted for the size of the operation. Rather than using simple averages to study differences between groups, logit regression analysis is used since the farms are placed into two groups. With regression analysis, the importance of various characteristics of a farm management strategy in explaining the stochastic dominance partitioning can be examined.

Data

The data used for this study are annual New York dairy farm business summary records. Data for the 1974 through 1983 ten-year period contain a panel of 112 farms with 10 annual observations per farm. The 112 sample farms are well dispersed geographically, located in 34 of the 55 upstate New York counties. The maximum number of farms in any one county is 9.

The sample is diverse in farm size; farms with herd sizes from 32 cows to over 300 are represented, as are farms with crop acreages ranging from 32 to over 1,000. The average sample farm was found to be somewhat larger than the average New York and the average United States dairy farm. Despite this size difference, the results should have useful implications for a broad group of commercial dairy farms. First, analysis of the diverse sample group was performed on a per unit of output or input basis. Second, the average sample farm in the study represents the size toward which many small farms will be moving. Therefore, the sample farms can be considered harbingers of the future and, as such, could be a valuable source of information for other farmers.

The sample decade, 1974 to 1983, comprises a period of high, medium, and low dairy farm profitability. Such a cycle in farm profitability has occurred regularly in the past and is likely to recur. Therefore, the sample period seems an appropriate one from which to draw conclusions about dairy farm management strategies and to make inferences about future strategies.

Stochastic Dominance Analysis

Stochastic dominance analysis was performed on probability distributions of four different performance measures: labor and management income per operator (LMIO), labor and management income per operator per cow (LMIOC), rate of return on equity capital (RREQ), and rate of return on equity capital excluding appreciation (RREQEA). Labor and management income, and return on equity capital are commonly used measures of farm performance. Since business analysis is often performed on a per cow basis, labor and management income per operator was divided by the number of cows as well as used undivided. Appreciation was estimated by the summary participants and may be especially subject to bias or erroneous reporting, so rate of return was used with and without appreciation included. These are defined and measured in this study consistent with the procedures used in the annual New York Dairy Farm Business Summary Program.

The annual observations on the performance measures for each farm were first indexed by dividing each year's observations by the average of the performance measures for all 112 farms for that year. A farm's annual performance then is in reference to the average for the group in a particular year. This type of data adjustment is reasonable since many farmers compare their performance to their peers for the year. The indexing also permits using the ten annual observations as ten equal likelihood outcomes for any given year. Indexing by the annual average farm performance is also preferable to using price indexes which are often not strongly correlated with annual farm performance. Four cumulative distributions, one for each performance measure, were constructed for each farm.

An iterative procedure was used to partition the sample farms into two groups. A stochastic dominance program was used with all 112 farms to determine which farms dominated.[1] A farm would dominate by FSD if its cumulative distribution lay entirely to the right of another farm and no other farm's cumulative distribution lay to its right. Thus if more than one farm dominated by FSD, they had cumulative distributions that crossed at least once. Often fewer than six farms were dominating with the first application of the stochastic dominance program. After removing these dominant farms and placing them into the successful group, the remaining farms were again partitioned by stochastic dominance, and the new dominant farms were also placed into the successful group. This iterative procedure was repeated until over half the farms were placed into the successful group. For first-degree dominance this required two, three, or four iterations depending upon the particular performance criterion. Second-degree dominance required seven or eight iterations. All farms were then categorized as either "successful" or "less successful." With this procedure, all farms in the successful group individually dominate all farms in the less successful group. However, within the successful group there are farms that dominate others in the successful group.

The consistency of the results of the stochastic dominance analyses across the four performance measures can be compared by the use of a simple proportion. A farm is categorized as either successful or less successful under each of the four performance measures. Drawing pairwise comparisons between performance measures, two possible

Table 1. Proportion of the 112 Sample Farms Classified Similarly by the Different Performance Measures

Performance Measure	Performance Measure: LMIOC	RREQ	RREQEA
	First-Degree Stochastic Dominance Analysis		
LMIO	0.71	0.85	0.71
LMIOC	—	0.76	0.68
RREQ	—	—	0.88
	Second-Degree Stochastic Dominance Analysis		
LMIO	0.85	0.86	0.81
LMIOC	—	0.80	0.77
RREQ	—	—	0.81

outcomes exist for each farm: (1) the farm is classified the same, either "successful" or "less successful" under both measures or (2) the farm is classified successful by one measure and less successful by the other. The proportion used to test the similarity of two measures is that fraction of the 112 farms falling under the first of these two outcomes—farms classified similarly by two measures. If two measures classified all of the farms identically, the test proportion would be 112/112 or one.[2] With random classification of farms into successful and less successful groups, one would expect a proportion of 56/112 or 0.5. Thus the values of the test proportion are expected to fall between 0.5 and 1.0, with values closer to 1.0 indicating greater similarity between measures. As shown in Table 1, the test proportion values ranged from 0.68 to 0.88. The most closely related measures were rate of return on equity capital (RREQ) and labor and management income per operator (LMIO); the two measures of rate of return on equity capital (i.e., including and excluding appreciation) were also closely related. The least closely related measures were rate of return on equity capital excluding appreciation (RREQEA) and labor and management income per operator per cow (LMIOC).

Logit Regression

After establishing the successful/less successful groupings, the characteristics of dairy farm

[1] The computer program in Anderson, Dillion, and Hardaker was

[2] Because none of the groups being compared contain exactly the same number of "successful" farms, the maximum test proportion is actually less than 1.0.

Table 2. Independent Variables for Logit Regression

Variable	Units	Defination
~~	Production Variables	
BARN	(0,1)	Housing system = 0 for stanchion = 1 for other
COWS	Head	Number of milk cows
MILKC	Cwt.	Cwt. milk sold per cow
YHAY	Tons/acre	Yield of hay (dry matter)
PFEEDC	Dollars	.Purchased feed per cow
HLABC	Dollars	Hired labor per cow
HAYR	(ratio)	Haylage as proportion of all hay (dry matter)
FERTA	Dollars	Fertilizer expense per acre
		Marketing Variables
MILKP	Dollars	Price received per cwt. milk sold
DIV	(ratio)	Measure of diversification = value of crop sales/ total cash receipts
		Financial Variables
DA74-79	(ratio)	Debt-asset ratio for 1974 to 1979
DA74-79SQ	(ratio)	Squared debt-asset ratio, 1974-79
DA80-83	(ratio)	Debt-asset ratio for 1980 to 1983
DA80-83SQ	(ratio)	Squared debt-asset ratio, 1980-83
TYPE	(0,1)	Type of business organization = 0 for sole proprietorship 1 for multiowner business
AGE	Years	Average age of operator(s)

management strategies responsible for this separation were investigated with a logit regression model. Each farm was assigned a value of 1 or 0, according to its classification as successful or less successful, respectively. A set of farm characteristics representing management strategies was then regressed on this (0,1) dependent variable. The logit model is specified as

$$P_i = \frac{1}{1 + e^{-(\alpha + \beta X)}}$$

where e is the base of natural logarithms, and PS is the probability of farm i being successful, given knowledge of X, the set of farm management characteristics for that farm. For estimation purposes this equation can be manipulated to the form

The dependent variable is the logarithm of the odds that a particular farm will be successful, ct is an intercept, and p is a 1 by j matrix of regressor coefficients corresponding to the j by 1 independent variables in X.

Sixteen independent variables were selected as representative of management strategies in the regression analysis. The variables were chosen to encompass the three areas of concern in developing a farm management strategy—production, marketing, and finance—and are summarized in Table 2.

The results of the logit model regressions are presented in Tables 3 and 4.[3] The dependent variable in all cases is a binary variable having the value of 1 when a farm is in the successful group and 0 when it is in the less successful group. The specific values of the dependent variable for each farm may differ among the models due to differences in the stochastic dominance results for the four performance measures. By specifying the dependent variable in this way, a positive sign on a regressor coefficient indicates that an increase in the variable's value will increase a farm's chances of being in the successful group; a negative sign indicates that an increase in the variable's value would decrease a farm's chances of being in the successful group.

Results

The statistical importance of the logit regression in explaining the successful/less successful division of farms varied from model to model. Table 5 provides a qualitative summary of the importance of the different independent variables. The maximum likelihood chi-square statistic (Wald statistic) was used to test the null hypothesis that a parameter was zero since parameter estimates are asymptotically normal. The statistic was computed by dividing the parameter estimate by its standard error and squaring the result. An R^2 for each equation was calculated using the model likelihood ratio chi-square and maximum log-likelihood, correcting for the number of variables. This R^2 is similar to the multiple correlation coefficient (correcting for the number of parameters) that is familiar to most readers.

The quantity of milk sold per cow is the most consistently important variable in the models. The sign of the MILKC coefficient is positive in all cases. The logit model predicts a change in the probability of farm success that is dependent on the level of the variable (e.g., MILKC). Figure 1 demonstrates the nonlinear change in the probability of a farm being in the

[3] The LOGIST routine from SAS was used which utilizes a maximum likelihood estimation procedure.

Table 3. Logit Regression Models Based on First-Degree Stochastic Dominance Analysis of 112 New York State Dairy Farms

Independent Variable	LMIO	LMIOC	RREQ	RREQEA
Intercept	4.30	16.3	3.95	-6.99
	(0.13)*	(1.68)	(0.16)	(0.44)
MILKC	0.0517	0.0552	0.0359	0.0696
	(4.36)	(5.89)	(3.11)	(9.65)
PFEEDC	-0.00266	-0.00394	-0.00177	-0.00512
	(1.09)	(2.80)	(0.65)	(4.82)
HLABC	-0.00363	-0.0124	-0.000435	-0.00470
	(0.64)	(5.77)	(0.01)	(1.44)
HAYR	1.19	-0.133	2.05	0.0118
	(0.65)	(0.01)	(2.50)	(0.00)
COWS	0.0297	-0.00165	0.00574	0.0196
	(4.84)	(0.02)	(0.47)	(5.04)
YHAY	-0.224	0.217	0.519	-0.605
	(0.15)	(0.14)	(1.16)	(1.32)
BARN	0.988	0.139	-0.1460	0.32
	(1.81)	(0.04)	(0.05)	(0.22)
FERTA	0.0243	0.00611	-0.0126	-0.0205
	(0.55)	(0.03)	(0.19)	(0.44)
MILKP	-0.802	-1.62	-0.673	-0.0781
	(0.80)	(2.95)	(0.85)	(0.01)
DIV	3.85	-0.683	-2.36	-0.340
	(0.23)	(0.01)	(0.13)	(0.00)
DA74-79	3.97	11.1	-2.12	-10.2
	(0.14)	(1.40)	(0.07)	(1.48)
DA74-79SO	-10.3	-23.2	6.630	29.7
	(0.23)	(1.81)	(0.19)	(3.26)
DA80-83	-15.5	-18.7	-11.0	-6.86
	(5.16)	(8.65)	(4.38)	(1-70)
DA80-83SO	14.6	21.7	13.4	9.82
	(2.86)	(7.68)	(4.22)	(2.18)
TYPE	-1.77	-3.03	-1.52	-1.48
	(5-13)	(9.91)	(5.00)	(4.26)
AGE	-0.0488	-0.0300	-0.0273	0.0485
	(0.87)	(0.40)	(0.38)	(1-22)
R-Squared	0.41	0.36	0.09	0.05

* Numbers in parentheses are chi-square values.

successful group as MILKC changes. The probabilities in Figure 1 are based on the first-degree logit model for the RREQEA performance variable; they were determined by varying MILKC from 80 to 220 cwt. per cow while holding all of the other explanatory variables constant at their mean values. The greatest change in the likelihood of a farm being in the successful group for a given change in MILKC occurs around the 0.5 probability level. At a production level of 151 cwt., the probability of a farm being classified as successful is 0.5; an increase of 1,000 Ibs. to 161 cwt. increases that probability by 0.17. At the extremes of the distribution the change in probability is lower given a change in MILKC. For example, an increase in production from 100 to 110 cwt. raises the probability of a farm being in the successful group by about 0.03.

Purchased feed per cow and hired labor per cow were two production "expenditure" variables that were important in explaining differences in farm success. Their negative relationship with success, when examined in the context of the gains from additional milk per cow, reflects the value of improving production efficiency. It also signifies the importance of a farm's endowment of family labor and high quality crop land.

Changes in the expenditures for hired labor have a greater effect on the chances of farm success by first-degree stochastic dominance criteria than by second-degree criteria. The results infer that the amount of hired labor can affect the variability of labor and management income, additional hired labor being less detrimental to income distributions preferred by risk-averse decision makers. Thus, although

Table 4. Logit Regression Models Based on Second-Degree Stochastic Dominance Analysis ot 112 New York Dairy Farms

Independent Variable	Binary Dependent Variable Performance Measure			
	LMIO	LMIOC	RREQ	RREQEA
Intercept	13.7	22.5	1.43	5.90
	(1.48)*	(3.46)	(0.02)	(0.29)
MILKC	0.0301	0.0419	0.0422	0.0463
	(2.00)	(3.46)	(3.80)	(4.62)
PFEEDC	-	-0.00501	-0.00355	-0.00505
	(2.13)	(3.86)	(2.35)	(3.65)
HLABC	-	-0.00601	-0.00467	-0.0047
	(0.22)	(1.90)	(1.24)	(1-12)
HAYR	1.64	-0.141	2.47	3.12
	(1.42)	(0.01)	(3.19)	(4.09)
COWS	0.00467	-0.00826	0.00727	0.0175
	(0.26)	(0.83)	(0.66)	(2.77)
YHAY	0.473	0.755	0.779	0.211
	(0.86)	(1-82)	(2.35)	(0.15)
BARN	0.570	0.0437	-0.243	-0.791
	(0.71)	(0.00)	(0.12)	(1.20)
FERTA	-0.0283	-0.0165	-0.0606	-0.0434
	(0.87)	(0.27)	(3.65)	(1.69)
MILKP	-1.28	-1.97	-0.105	-1.01
	(2.17)	(4.58)	(0.02)	(1.56)
DIV	-4.99	-1.03	-12.7	-7.12
	(0.34)	(0.01)	(2.50)	(0.61)
DA74-79	1.59	11.5	2.21	0.841
	(0.03)	(1-45)	(0.06)	(0.01)
DA74-79SQ	-7.97	-26.6	-5.65	-10.5
	(0.17)	(1.89)	(0.12)	(0.27)
DA80-83	-8.49	-11.7	-13.0	-10.1
	(2.09)	(3.62)	(4.77)	(2.77)
DA80-83SQ	4.68	8.12	11.3	7,97
	(0.32)	(0.99)	(2.40)	(0.92)
TYPE	0.121	0.0447	-0.796	-0.243
	(0.03)	(0.00)	(1.33)	(0,12)
AGE	-0.0523	-0.0673	-0.0794	0.0453
	(1.22)	(2.11)	(2.77)	(0.79)
R-Squared	0.26	0.35	0.25	0.37

* Numbers in parentheses are chi-square values.

hired labor may lower the profitability of a farm, it may allow for timely farm operations and stable income. The overall implication of the HLABC results appears to be that the less labor a manager hires (or at least the less he expends for hired labor per cow), and thus, the more labor provided by the manager and his family, the greater is the probability that the farm will be successful. However, as one reviewer noted, this conclusion depends criti-

Table 5. Statistical Importance of the Independent Variables in Regression Models Examining Farm Success

Consistently Important		Inconsistent	Consistently Unimportant
MILKC	(+)*	COWS	BARN
PFEEDC	(-)	YHAY	FERTA
HLABC	(-)	MILKP	DIV
HAYR	(+)	TYPE	AGE
DA80-83	(-)	DA74-79	
DA80-83SQ	(+)	DA74-79SQ	

* The sign indicates the direction of the relationship between the consistently important variables and farm success.

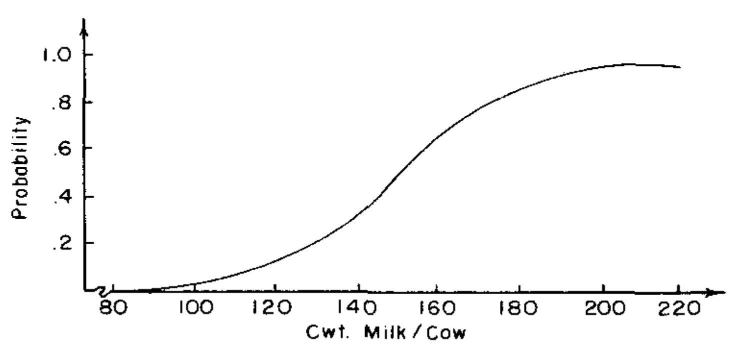

Figure 1. Predictions Using the Logit Model

cally upon whether the farmers are dependent solely on farm income. A farm operator may generate a higher total net income by combining on-farm and off-farm work while hiring on-farm labor rather than utilizing more family labor on-farm. If some of the farms have off-farm earned income, then the recommendation to control hired labor may contribute to higher on-farm returns but lower farm household income levels. Unfortunately, off-farm income was not collected as part of the business summary program during the years 1974 through 1983. Beginning in 1985 that information is collected and 26 percent of the participants from a sample of counties recorded $5,000 or more in off-farm income from labor and investments.

The important influence that the hay ratio (haylage as a proportion of all hay) has on the chances for farm success is one of the more notable results of this study. Farmers who adopted the technology necessary for haylage production and who emphasized haylage over dry hay significantly improved their farm's probability of success. The haying season in New York is rainy and humid so the ability to hasten the hay harvesting process can produce substantially higher quality hay. The adoption of haylage technology would also increase labor efficiency.

The two debt-asset ratios in their linear and squared forms offer some interesting regression results. The DA74-79 and DA80-83 variables represent a farm's average annual debt-asset ratio during the respective periods. The expected result was that the model would be concave with respect to the debt-asset variables—that is, the linear term would be positive and the squared term negative. If this were the case, the curve would exhibit a maximum at the optimal debt-asset level—the leverage ratio that would give the farm the highest probability of success. That optimal ratio was hypothesized to be higher for the 1974 through 1979 period than for the last four years of the sample period.

As expected, debt-asset levels substantially larger than zero for the period 1974-79 generally improved the probability of farm success. However, during the 1980-83 period, in-Screases in the debt-asset ratio were found to have a significant negative impact on a farm's chances of being in the successful group. The coefficient for the linear debt-asset variable in this latter period was negative and highly statistically significant in most models. Thus, the regression models suggest that the optimal debt-asset ratio during the 1980-83 period was zero. Over the ten-year sample period, the best chances of farm success *ceteris paribus,* were obtained by dramatically changing debt strategy near the middle of the period. These results confirm empirically what is theoretically expected: higher levels of debt may not be detrimental (and may, in fact, be beneficial) during periods of rising prices, while high real interest rates, such as have occurred in the 1980s, significantly affect optimum level of debt for farmers.

Several of the variables were inconsistent with respect to their importance in influencing farm success. Among these was the average number of cows on the farms during the sample period. Especially in the case of risk-averse decision makers, increasing herd size was shown not to be important in generating preferred distributions of the performance measures.

Hay yield per acre shows very little consistency among the different models; in some of the models higher yields slightly improved a farm's chances of being in the successful group.

It was hypothesized that farmers who were able to market milk at a higher average price would increase their farms' chances of success. Although the coefficients in the regression models were frequently not statistically different from zero, the sign for the parameter was negative in most of the models—the opposite of what was expected. This result was caused by the inclusion of a number of farms with low milk production per cow and high milk price typical of the colored dairy cattle breeds.[4]

The TYPE variable was used to indicate the form of business organization chosen for the farm operation, either sole proprietorship or one of several multiowner forms (e.g., partnership or corporation). The coefficient for the variable was statistically significant in the first-degree models and generally insignificant in the second-degree models. In all of the models where the coefficient was important, it had a negative sign, indicating that the sole proprietorship form increased a farm's chances of being in the successful group. We believe this is due to the dilution of earnings by excess labor. Often a child joins a farming

[4] Dairy cattle breed data were not obtainable from these farm records, and therefore, could not be introduced as a variable.

operation without a compensating increase in farm size or volume. The additional operator #ould lower labor and management income per operator or increase labor expenses in computing returns to equity.

The variables measuring the livestock housing system, fertilizer per acre, diversification, and operator(s) age were all found to be unimportant in influencing the likelihood of farm success. The appearance in this group of the variable for livestock housing system (BARN), which was also a proxy for type of milking system, was the least expected. The BARN variable is similar to the hay ratio variable (HAYR) in that both are indicators of adoption of newer technologies; however, HAYR was an important variable and BARN was not. The use of stanchion barns is still a viable technology.

Predictions

A test of the regression model could be performed by utilizing the estimated models to predict the success of individual farms. Ideally, data from outside the sample panel should be used for such a test. However, suitable outside data (i.e., individual farm data for 10 years for each of the model variables) were not readily available. As an alternative, five farms were chosen randomly from the 112 sample farms to test the model. Since no one farm in the sample is likely to have significantly influenced the estimated regression models, random selection of farms should offer a valid test of the model.

The 10-year average values for the regressor variables on the five test farms are presented in Table 6. Table 7 reports the probabilities which result when the test farm values are substituted into the regression models. These values are the predicted probabilities that the farm is in the successful group. Values greater than 0.5 are interpreted to predict a farm will be in the successful group; values less than 0.5 predict a farm will be in the less successful group. Also shown by the value of 1 is whether each farm was in the successful group.

The models did very well in "predicting" the actual case. In 34 out of 40 tries (5 farms x 8 models) the predictions were correct. The models performed especially well where the farm was consistently either in the successful group or the less successful group (e.g., farm 75 and 38). Even where there was an isolated case of a farm being classified as successful when the farm was typically not so designated, the models were often sensitive enough to predict correctly (e.g., farm 92). Interestingly, there was no difference between the first- and second-degree models in the number of correct predictions.

Conclusions

Stochastic dominance was used to separate successful from less successful dairy farms.

Table 6. Values of the Independent Variables for Five Randomly Selected Sample Farms

Independent Variable	7	38	69	75	92
MILKC	136.6	126.1	146.9	142.0	160.4
PFEEDC	269	565	412	275	379
HLABC	272.42	165.49	231.37	83.78	91.36
HAYR	0.908	0.205	0.000	0.015	0.424
COWS	285.5	61.5	49.1	38.3	75.3
YHAY	2.58	1.39	2.30	2.78	2.50
BARN	1	0	0	0	0
FERTA	51.59	11.26	16.47	17.90	28.04
MILKP	10.84	11.58	11.31	11.05	10.88
DIV	0.0571	0.0009	0.000*	0.1150	0.0988
0A74-79	0.281	0.242	.000	.000	0.196
DA74-79SO	0.079	0.059	.000	.000	0.038
DA80-83	0.374	0.172	.000	.000	0.487
DA80-83SQ	0.140	0.030	.000	.000	0.237
TYPE	1	0	0	0	1
AGE	33.5	28.3	51.6	47.3	36.8

Table 7. Predicted Probability of Success on Five Randomly Selected Sample Farms

Regression Model	LMIO	LMIOC	RREQ	RREQEA
	Farm No. 7			
FSD Logit	1.00	0.01	0.53	0.67
(Actual)	(1)	(0)	(0)	(0)
SSD Logit	0.73	0.14	0.38	0.83
(Actual)	(1)	(0)	(0)	(0)
	Farm No. 38			
FSD Logit	0.14	0.16	0.19	0.05
(Actual)	(0)	(0)	(0)	(0)
SSD Logit	0.17	0.27	0.54	0.06
(Actual)	(0)	(0)	(0)	(0)
	Farm No. 69			
FSD Logit	0.43	0.64	0.66	0.71
(Actual)	(0)	(1)	(0)	(1)
SSD Logit	0.47	0.63	0.72	0.75
(Actual)	(1)	(1)	(1)	(1)
	Farm No.			
FSD Logit	0.70	0.96	0.73	0.77
(Actual)	(1)	(1)	(1)	(1)
SSD Logit	0.66	0.95	0.75	0.80
(Actual)	(1)	(1)	(1)	(1)
	Farm No. 92			
FSD Logit	0.18	0.19	0.24	0.22
(Actual)	(0)	(0)	(0)	(0)
SSD Logit	0.31	0.73	0.22	0.35
(Actual)	(0)	(1)	(0)	(0)

The technique was reasonably consistent across different performance measures in ranking successful farms. The results of the stochastic dominance analysis thus provided a solid basis upon which to examine the importance of selected characteristics of dairy farm management strategies using logit regression models.

Three general conclusions can be drawn from this study which should be applicable in establishing dairy farm management strategies. Further, these conclusions appear relevant across a wide diversity of dairy farm sizes and types. First, achieving high levels of milk production, while closely controlling use of hired labor and purchased feed, can greatly improve a farm's chances of being successful. Second, choice of hay-making techniques is important to dairy farm success; utilization of the technology necessary for production of hay crop silage is superior to dry hay production as a hay-making strategy. By implication, selective adoption of new technologies is itself an important management strategy. Third, the drastic change in optimal debt-asset levels within a very short period of time demonstrates the importance of maintaining flexibility in farm management strategies and the benefits which can accrue to those who are alert to, or even better, able to anticipate changing circumstances. The farm manager should avail himself or herself of the information necessary to make intelligent judgments as to the conditions he or she will face in the future.

Dairy farmers confront myriad and complex management decisions. While the conclusions reached in this study may not be startling, they do indicate where farm managers should place emphasis when developing their management strategies. Further, this study demonstrates the usefulness of stochastic dominance analysis in classifying farms and their success in operation.

References

Anderson, J.R., J.L. Dillon and J.B. Hardaker. *Agricultural Decision Analysis.* Ames: The Iowa State University Press, 1977.

Bratton, C.A. "Dairy Management Practices and New York Dairy Farm Incomes," A.E. Research 84-6 Department of Agricultural Economics, Cornell University, 1982.

Danok, Abdulla B., Bruce A. McCarl, and T. Kelley White. "Machinery Selection Modeling: Incorporation of Weather Variability," *American Journal of Agricultural Economics,* 62(1980):700-708.

Hardaker, J.B., and A.G. Tanago. "Assessment of the Output of a Stochastic Decision Model." *The Australian Journal of Agricultural Economics,* 17(1973): 170-178.

Kramer, Randall A., andRulon D, Pope. "Participation in Farm Commodity Programs: A Stochastic Dominance Analysis." *American Journal of Agricultural Economics,* 63(1981): 119-128.

McGuckin, Tom. "Alfalfa Management Strategies for a Wisconsin Dairy Farm—An Application of Stochastic Dominance." *North Central Journal of Agricultural Economics,* 5(1983):43-49.

Pederson, Glenn D. "Selection of Risk-Preferred Rent Strategies: An Application of Simulation and Stochastic Dominance." *North Central Journal of Agricultural Economics,* 6(1984): 17-27.

Richardson, James W., and Clair J. Nixon. "Producer's Preference for a Cotton Farmer Owned Reserve: An Application of Simulation and Stochastic Dominance." *Western Journal of Agricultural Economics,* 7(1982):123-132.

Richardson, James W., and Clair J. Nixon. "Selecting Among Alternative Depreciation Methods: A Stochastic Dominance Approach." Paper presented at the A.A.E.A. annual meeting, Ithaca, NY, August 1984.

Schoney, Richard A., and J. Thomas McGuckin. "Economics of the Wet Fractionation System in Alfalfa Harvesting." *American Journal of Agricultural Economics,* 65(1983):38-44.

Schurle, Bryan W., and Jeffrey R. Williams. "Application of Stochastic Dominance Criteria to Farm Data." Kansas Agricultural Experiment Station Contribution Number 42-400-A, Department of Agricultural Economics, Kansas State University, 1982.

Wilson, Paul N., and Vernon R. Eidman. "Dominant Enterprises Size in the Swine Production Industry." *American Journal of Agricultural Economics,* 67(1985): 279-288.

Zacharias, Thomas P., and Arthur H. Grube. "An Economic Evaluation of Weed Control Methods Used in Combination with Crop Rotation: A Stochastic Dominance Approach." *North Central Journal of Agricultural Economics,* 6(1984):113-120.