An Analysis of Multi-Period Agricultural Credit Classification Models for New York Dairy Farms

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AN ANALYSIS OF MULTI-PERIOD AGRICULTURAL CREDIT CLASSIFICATION MODELS FOR NEW YORK DAIRY FARMS

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One of the most important factors influencing the quality of a lender's loan portfolio is the character of the loans selected for inclusion. As lenders search for ways to improve the selection process, the use of credit scoring or credit screening models has been given increased consideration. The initial models (Johnson and Hagan; Dunn and Frey; Hardy and Weed; Hardy and Adrian; Hardy, Spurlock, Parrish and Benoist; Mortensen, Watt and Leistritz) reported in the agricultural literature validated their models with within sample statistics only. That is, the effectiveness was measured by the proportion of the fitted sample that were correctly classified by the model. This procedure was improved upon by later researchers who used hold out samples or cross validation methods to validate the models (Lufburrow, Barry and Dixon; Miller and LaDue). Of course, these methods also use the same basic data set, or part of it, as the test data for validation. Therefore, the test data were from the same basic group of farms, for the same year.

More recently, Turvey and Brown found that models developed under the economic conditions of any one year may be unreliable predictors in years with different economic conditions. Model parameter estimates and significance levels may be unstable over time for models fit to data for different time periods. The ability of fitted models to predict whether a borrower will default or be creditworthy next year or in some future year is poor. Since the most frequent application of such models by lenders is to use a model fit using data from one period to classify loans for a future period, this shortcoming of previously developed models severely limits their usefulness.

The objectives of this study are to test the conclusions reached by Turvey and Brown using a different data set and evaluate the use of a multi-period model, employing Farm Financial Standards Task Force (FFSTF) ratios and economic environment indicators, as a method of reducing parameter estimate instability and increasing model usefulness. To meet these objectives we (1) develop a set of single period best-fit models for a series of years, (2) fit a prespecified model to several years of data, and (3) developed multi-period models with economic environment indicators for two and three year periods.

In the remainder of this article we describe the creditworthiness model used, explain the data set used for the analysis and present the results obtained with the best-fit, prespecified and multi-period models. Finally, we present some conclusions.

The Creditworthiness Model

Previous research on agricultural credit evaluation models has largely been concentrated on loan review or credit screening, where the credit classifications are related to a pre-existing, mutually exclusive, loan classification schemes. Most commonly, these schemes establish two groups, one denoting a "good" loan and the other a "bad" loan. "Good" loans are paid current and "bad" loans are in some form of default, including slow paying, delinquency, bank examiner classification, and official default (Betubiza and Leatham).

A problem with the default oriented classification methods is that they can be influenced by the borrower's or lender's subjective behavior (Miller and LaDue; Lufburrow, et al.). The lender can influence the classification by decisions to forbear, restructure or grant additional credit to repay a

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delinquent loan. A borrower with split credit may have one loan paid current and classified as "good" with one lender, and another loan that is delinquent and classified as "bad" with another lender. Borrowers may also have avoided a current default status because they have made payments by selling assets or through other unrepeatable means. An infusion of funds from inheritance when aunt Sara dies or sale of the combine cannot be repeated next year, or in any future year. Such behavior on the part of the borrower or the lender can result in intrinsic errors in credit evaluation models.

One alternative to default measures is a lender classification where the lender identifies good and bad borrowers or uses the examiner evaluations. However, this introduces a high level of subjectivity.

This study avoids these borrower and lender influences without introducing added subjectivity by measuring creditworthiness rather than default. A creditworthy borrower is defined as one with a positive capital replacement and term debt repayment margin. Two debt repayment margin definitions are used. The first, called the **farm and nonfarm** debt repayment margin, uses the FFSTF definition where the debt repayment margin equals

Net farm income
\+ Nonfarm income
\+ Interest expense
\+ Depreciation expense
\- Personal withdrawals
\- Personal income taxes
\- Planned principal and interest payments

The second definition, called the **farm** debt repayment margin, is calculated in the same manner, except that nonfarm income is excluded. The rationale for this measure is that in many cases the lender and/or farmer is most interested in whether the farm business generates sufficient income to make the necessary payments. Businesses with loans that can be repaid from farm sources without an infusion of funds from nonfarm sources may be lower risk than when loan repayment is dependent on nonfarm income. This approach views the farm operation as a business unit separate from the operation's nonfarm and family activities.

The creditworthiness measure has the advantage that it can be applied to any set of financial statements. It does not depend upon lender default classifications. It can be applied to businesses that provide financial statements but for which the evaluator does not have data on past debt payment history. Thus, it can be used in either credit scoring or credit screening situations.

The model used in this study is a qualitative, lagged-dummy model. The model is expressed as:

$$Y_{i,t+1} = \beta_1 Y_{i,t} + \beta_2 P_t + \sum_{k=3}^{N} \beta_k X_{k,i,t} + u_t$$

where $i = 1,2,\ldots M$ refers to the individual farm, and
$t = 1,2,\ldots T$ refers to a single year. Thus,
$y_{i,t+1}$ is the dependent variable representing creditworthiness for farm i in time period t+1. Similarly, $Y_{i,t}$ is a lagged dependent variable representing creditworthiness for farm i in time period t. The creditworthiness measure is a binary dependent variable. That is, a positive repayment margin is converted to one, and a negative repayment margin is converted to zero.
P, is the economic environment indicator,
$X_{k,i,t}$ refers to the (N-2) explanatory variables for farm i in time period t, and β is the corresponding coefficient for the explanatory variables.

The logit statistical method was employed. It was chosen over the linear probability model and discriminate analysis based on the logit's favorable statistical properties and the ability to translate credit classifications into creditworthiness scores. The choice of the logit over the probit method was based on the fact that the logit coefficients are not affected by the unequal sampling rates of creditworthy and less creditworthy farms. Only the constant term is affected, therefore, there is no need to weight the observations before estimation (Maddala).

The logit model is specified as:

$$P_i = \frac{1}{1+e^{-(x_i B)}}$$

where e is the base of natural logarithms and P_i is the probability of the ith farm being creditworthy, given knowledge of X_i, the set of financial and production ratios and measures.

For estimation purposes this equation is restated as:

$$\ln \frac{P_i}{1-P_i} = x_i B$$

The dependent variable is the logarithm of the odds that a particular farm will be creditworthy. β is a 1 by (N-2) vector of regressor coefficients corresponding to the (N-2) by 1 independent variables in X for the ith farm. The model was estimated using the maximum likelihood method.

The economic environment indicator is designed to reflect the differences in the year to year economic environment in which the farms operate. A major factor contributing to inaccurate model predictions of borrower creditworthiness is variation in the basic profitability of the type of business being evaluated. On dairy farms, most costs tend to move upward with inflation. These cost shifts tend to influence profitability, and thus, creditworthiness, in a somewhat predictable way. The primary exception would be feed costs which show somewhat more variability. On the other side of the profit equation, however, the milk price swings widely. Thus, year to year variability is caused largely by fluctuation in milk prices. To reflect this variability, the percent change in the New York blend milk price was used as the economic environment indicator. For validation and general use of the model, where the future price change is not known, blend price projections as published by the Department of Agricultural Economics at Cornell University (New York Economic Handbook: Agricultural Situation and Outlook) were used.

Two basic principles were used in selecting the remaining individual farm variables. First, model is to include only one explanatory measure from each of the factor categories. Multivariate analysis requires that each ratio or measure in the model convey as much information as possible (Beaver). In other words, ratios or measures with similar components should not be used in the same credit evaluation model (Chen and Shimerda). Financial ratios and measures from the same factor category usually have a higher occurrence of multicollinearity which can confound the interpretation of the individual ratio coefficient and overall production ability of the models. Therefore, it is important that one measure in most cases be selected to represent each factor category in a multivariate statistical analysis. In this study, no two measures from the same factor category will be used in the creditworthiness evaluation model, except for production measures. The production measures may exceed the one measure limit because these measures are not usually derived from the same components, unlike many of the financial measures.

The second procedure is to use the FFSTF recommended ratio and measure definitions to represent the factor categories whenever possible. In previous research, the financial ratios' and measures' definitions have varied considerably (Betubiza and Leatham). This variation has largely been due to researchers selecting ratios and measures they deem as important or were accessible from the data available. As a consequence, these predispositions and limitations have precluded comparison between credit evaluation models and data sets. Hopefully, by employing the FFSTF recommended ratios and measures, it will initiate a foundation for future comparison of credit evaluation models. By using the same ratio and measure definitions, credit evaluation models can be tested on alternative data sets.

Selection of individual variables largely draws from previous empirical agricultural credit evaluation studies and the results of a regional survey on credit evaluating procedures in agricultural banks (LaDue, Lee, Hanson, Hanson, and Kohl).

The measure that was used most consistently, that is in 89 percent of the previous studies (Table 1) was a measure of solvency. This usage can be attributed to the concept that credit evaluation models are loosely analogous to capital structure theory, where an increase in leverage is directly related to an increase in financial risk (Miller). However, the analogy stops there, for farms with a higher debt/asset ratio usually have a higher degree of financial risk, but a higher degree of financial risk does not always necessarily mean a greater degree of financial stress (Lins, Ellinger, and Lattz). This is especially true for highly profitable farms which can sustain high debt levels. Furthermore, the results of a regional survey on credit evaluation procedures were consistent with previous studies where 100 percent of the banks responding used a solvency measure in their credit evaluation. This study will use the debt/asset ratio as a measure of solvency.

Table 1. Summary Factor Categories and Related Measure for Credit Scoring Models

Factor Category	Usage in: Prior Research[a]	Usage in: Bank Evaluation[b]	Measures Used
	percent		
Solvency	89	100	Debt/Asset Ratio[c]
Liquidity	33	57	Current Ratio[c]
Profitability	22	14	Rate of Return on Assets[c]
Repayment Capacity	67	100	Repayment Trend
Financial Efficiency	33	36	Asset Turnover
Collateral	22	71	None
Production			Milk Per Cow (1,000 lbs) Hay Per Acre
Economic Risk			% Change in Milk Price

[a] The percentage of prior research that included the factor.
[b] The percentage of agricultural banks that include the factor in their credit evaluation procedures.
[c] FFSTF recommended calculations.

Two other factor categories included in 33 and 22 percent of the previous studies were liquidity and profitability, respectively. In addition, these categories were used by 57 and 14 percent, respectively, of the banks surveyed. While these two categories have been used extensively in nonagricultural credit evaluation, the adaptation to agriculture has been limited. This study will include the current ratio as a liquidity measure and the rate of return on assets as a profitability measure. The relatively low use of profitability in previous credit evaluation studies is perhaps a reflection of the historical emphasis on loan default, not creditworthiness.

Only 33 percent of the previous studies included some type of repayment capacity measure, while the survey found that 100 percent of the banks used a repayment capacity measure. This study will incorporate a lagged dependent variable. The lagged dependent variable will represent whether a farm was able to make its debt payments the previous year using the same debt repayment margin calculation.

The factor category efficiency encompasses various titles in previous research such as financial, capital, and economic efficiency. An aggregate of the three was found significant in 33 percent of the previous studies. However, limiting this category to just financial efficiency, the survey results showed that 36 percent of the banks used some type of financial efficiency measure. This study will use an asset turnover ratio as a measure of financial efficiency. Collateral was used in 33 percent of the previous studies and by 71 percent of the banks surveyed. A collateral measure may be a viable explanatory variable in a single loan default model, however, in a creditworthiness model a solvency measure may be more appropriate because it can be viewed as a claim on the entire farm's assets, not collateral on a single loan.

The primary nonfinancial measures found significant in previous studies were production measures. Given that this study is limited to the dairy industry, the production management measures selected are pounds of milk produced per cow, and tons of hay crop harvested per acre.

Turvey and Brown also showed that commodity types and geographical regions can be used as indicators of credit risk. However, neither commodity type nor geographic region will be included in the model because the data are all dairy farms located in New York State where creditworthiness is not expected to differ much by region. Based on previous studies, a creditworthiness model can appropriately be expressed as a function of solvency, liquidity, profitability, repayment capacity, financial efficiency, and production management measures.

The Data Set

The data for this study were collected from New York State dairy farms in a program jointly sponsored by Cornell Cooperative Extension, and the Department of Agricultural Economics at the New York State College of Agricultural and Life Sciences, Cornell University. The information collected includes a complete set of financial statements with the essential components for deriving a complete set of financial ratios and measures as recommended by the FFSTF. One key component available was each farm's planned debt payment for the subsequent year.

The number of participants in this program averaged 410 per year for the 1986-91 sample period. Since participation is on a volunteer basis, not all farms submit data each consecutive year. There were 155 farms that did submit data for each year of this particular time period, and of these farms, only 138 used debt in their capital structure. Data for these 138 farms are analyzed in this study.

Due to the procedure used to select participating farms, this is not a random sample. However, the sample does provide consistent information for 138 farms over the sample period. Such a data set is critical in studying the dynamic effects on farm creditworthiness.

The nonrandomness of the data does not pose a problem for the credit evaluation model estimation. Loan portfolios of financial institutions are by nature nonrandom.

Table 2 exhibits the annual mean value of the financial and production measures for the 138 farms. All financial ratios and measures have been calculated according to the FFSTF Guidelines (1991). The production measures, in general, are fairly specific to the dairy industry and were selected because of their historical use as proxies for the production management capabilities of the farm operators.

Table 2. Average Financial and Selected Production Measures, 138 New York Dairy Farms, 1987-91

	Year				
Measures	**1987**	**1988**	**1989**	**1990**	**1991**
Liquidity					
Current Ratio	3.23	3.49	3.83	3.12	2.84
Solvency					
Debt/Asset Ratio	.38	.36	.34	.35	.35
Repayment Capacity					
Term Debt and Capital Lease Coverage Ratio	1.86	1.57	1.90	1.69	1.08
Profitability					
Return on Assets	4.56	4.07	5.72	3.69	1.07
Other					
Milk Sold/Cow (lbs)	16,576	17,091	17,516	17,815	18,222
Hay Crop (T/A)	2.8	2.7	2.7	2.9	2.7

This group of farms could be viewed as a combination commercial lender and FmHA portfolio. It contains more marginal borrowers than a typical commercial lender portfolio where they have eliminated many of the marginal borrowers by not making loans to them.

Single Period Best-Fit Models

To test the basic conclusions of Turvey and Brown that model parameters and levels of significance of single period models are unstable, a series of single period best-fit models were estimated (Table 3). These models used the farm definition of creditworthiness; nonfarm income was excluded. The models were estimated using a 95 percent confidence level decision rule, stepwise variable selection procedure. The initial set of variables incorporated were those identified for the basic creditworthiness model (above) except that the economic environment indicator was excluded. The resulting models are similar to the types of single period models reported in most earlier studies. Researchers with data covering only one year could be expected to report such model results with some confidence in their value.

For both models, statistics are not excellent but are quite acceptable for individual farm data. The within sample prediction rate is similar to that found in previous studies. However, the out of sample prediction rate is much lower. Part of this low out of sample prediction rate results from the fact that 1991 was used for out of sample evaluation. 1991 was one of the worst years for the dairy industry for some time. The observed very high rate of false positives likely results from these unusually poor economic conditions.

The basic instability of such models is clearly indicated by these two models. Even though the same farms are used in both years, the variables included change completely from one year to the next. This confirms, in a rather significant way, that the magnitude, sign and/or significance of single period model coefficients can be much different from year to year. It is not surprising that ex ante prediction rates using such models are poor.

Table 3. **Two Best-Fit Single Period Farm Creditworthiness Evaluation Models 138 New York Dairy Farms**

Variable	1989 Model (P-Value)	1990 Model (P-Value)
Intercept	-5.56 (0.00)	0.65 (0.49)
Lagged Dependent	1.49 (0.00)	
Milk/Cow	0.25 (0.01)	
Working Capital	0.10 (0.04)	
Debt/Asset		-5.21 (0.00)
Debt Repayment Margin		0.20 (0.01)
Milk/Worker		0.04 (0.02)
Operating Expense Ratio		4.51 (0.05)
R	0.42	0.45
Model X^2	39.19	38.76
Within Sample Prediction (%)		
False Positive	24.1	15.7
False Negative	32.7	43.3
Positive	77.8	87.5
Negative	64.9	50.0
Total Correct	72.5	78.3
Out of Sample Prediction (1991) (%)		
False Positive	53.7	56.3
False Negative	25.4	11.4
Positive	63.3	91.8
Negative	59.6	34.8
Total Correct	60.9	55.1

Single Period Prespecified Models

Credit scoring or screening models are usually factor-based because there is no well developed theoretical foundation for their design (Marais, Patell, and Wolfson). To compensate for this lack of theory, a starting point for developing a model and selecting a useful set of factor categories, is prior empirical research (Chen and Shimerda). However, if the prior research is complete and correctly interpreted, once a basic model has been developed it should be appropriate for all years. The type of results that researchers could expect to obtain, depending upon the particular year for which they had data, are illustrated in Table 4. In this case the prespecified model is used in all years. The variables included are those indicated in the model description above.

Table 4. Two Prespecified Single Period Farm Creditworthiness Evaluation Models 138 New York Dairy Farms

Variable	1989 Model (P-Value)	1990 Model (P-Value)
Intercept	-6.93	-2.20
	(0.00)	(0.30)
Debt/Asset Ratio	0.11	-5.11
	(0.94)	(0.00)
ROA	0.01	0.15
	(0.91)	(0.03)
Current Ratio	0.08	0.16
	(0.21)	(0.30)
Lagged Dependent	1.39	-0.30
	(0.03)	(0.62)
Capital Turnover	-0.22	3.85
	(0.92)	(0.19)
Milk/Cow	2.87	0.11
	(0.01)	(0.31)
Hay/Acre	0.41	0.38
	(0.11)	(0.24)
R	0.37	0.39
Model X^2	39.12	37.24
Within Sample Prediction (%)		
False Positive	25.9	15.0
False Negative	36.8	32.0
Positive	74.1	92.3
Negative	63.2	50.0
Total Correct	69.3	81.9
Out of Sample Prediction (1991) (%)		
False Positive	52.2	59.3
False Negative	23.2	5.0
Positive	67.4	98.0
Negative	59.6	21.3
Total Correct	62.3	48.6

The statistical properties are slightly poorer than those obtained with the best-fit models, but are still in the reasonable range for individual farm data. The out of sample prediction rate is still much lower that the within sample rate with a large number of false positive. The 1990 model was much superior in within sample prediction but much poorer in out of sample prediction.

The sign, magnitude and significance of the variables changes significantly from year to year. For example, the parameter value for the debt/asset ratio goes from being small, positive and insignificant with 1989 data to being much larger, negative and significant with 1990 data. The lagged dependent variable is positive and significant in 1989 and negative and insignificant in 1990.

Clearly, the characteristics of these confirm the Turvey and Brown results that single period models have unstable parameters that could be expected to make them unreliable in predicting borrower performance. There is good reason for nonadaption of such models by lenders.

Multi-Period Models

In an attempt to develop models with improved stability and predictive ability, the complete model including the economic indicator variable was fit to two and three years of data (Table 5). Model statistics were similar to, or better than, those obtained for single period models. Parameter values and levels of significance were much more stable. Comparing the two year model with the three year model showed no sign changes and all had the expected sign.

Within sample prediction rates were within the range of those found with the single period models, however, there is less variation between years. The multi-period model had rates of 77.5 to 73.7 percent compared to 69.3 to 81.9 percent for the single period models. Since a model is less likely to be able to fit to the specific characteristics of one year's economic conditions, it is expected that the within sample prediction rates would be similar to those found with single year models. The predictive results are also similar to those obtained by previous research. It, thus, appears that use of the FFSTF categories did not significantly improve model performance. It is likely that this results from the fact that the FFSTF ideas are not new and many of the suggested variables have been used in prior research.

The out of sample prediction rates were better, 63.0 to 64.5 compared to 48.6 to 62.3, than those found with any of the single period models. This indicates the superiority of the multi-period model. However, the absolute improvement achieved was not great. There were still a large number of false positives. The unusual economic conditions of 1991 are not well predicted with any of the models fit.

The economic environment indicator appears to be of value in bridging the interyear gap. Although its coefficient is quite small, the level of significance is quite high in both multi-period models. One shortcoming that this variable has, of course, is the fact that it must be estimated to use the model for predicting. Economists performance in predicting future prices has been reasonable, but is not perfect.

Based on this experience, it appears that multiple period models may be an improvement over single period models. The peculiarities of any individual year have less influence on the model.

Including Farm and Nonfarm Income

The models presented in Tables 3 through 5 use the farm definition of creditworthiness; nonfarm income is excluded. Including both farm and nonfarm income is consistent with the FFSTF definition of repayment capacity (term debt and capital lease coverage ratio), represents the ability of the family to make debt payments, and is closer to a default equivalent. For many farm situations, including nonfarm income provides a more accurate measure of creditworthiness.

Using the basic model with the farm and nonfarm definition of creditworthiness (Table 6) resulted in considerably poorer results. Model statistics were not as good; both the R and X^2 were lower. Also, both within and out of sample predictions were lower. However, the biggest problem is that the sign on the ROA is negative. The coefficient is not large and the level of significance waivers, but the sign is negative.

Re-examination of the model indicates that all of the explanatory variables are farm based in nature and that possibly a nonfarm income indicator should be included. Do to its character, the number of variables available to predict nonfarm income are few. In an effort to correct the situation, the previous years level of nonfarm income was added to represent predicted nonfarm income (Table 7).

Table 5. Two Multi-Period Farm Creditworthiness Evaluation Models 138 New York Dairy Farms

Variable	1988-89 Model (P-Value)	1988-90 Model (P-Value)
Intercept	-4.47	-4.59
	(0.00)	(0.00)
Debt/Asset Ratio	-3.79	-2.25
	(0.00)	(0.01)
ROA	0.13	0.06
	(0.01)	(0.09)
Current Ratio	0.11	0.09
	(0.17)	(0.08)
Lagged Dependent	0.30	0.62
	(0.46)	(0.05)
Capital Turnover	3.28	1.46
	(0.06)	(0.22)
Milk/Cow	0.19	0.19
	(0.02)	(0.00)
Hay/Acre	0.33	0.38
	(0.11)	(0.01)
Milk Price Change	0.07	0.07
	(0.00)	(0.00)
R	0.47	0.42
Model X^2	92.24	112.3
Within Sample Prediction (%)		
False Positive	17.3	19.8
False Negative	34.1	37.7
Positive	84.5	78.7
Negative	62.9	64.4
Total Correct	77.5	73.7
Out of Sample Prediction (1991) (%)		
False Positive	52.0	50.0
False Negative	28.4	31.5
Positive	49.0	30.6
Negative	70.8	83.1
Total Correct	63.0	64.5

The nonfarm income parameter value was negative. This is consistent the net effect many believe nonfarm income may have on dairy farms. There are two possible explanations (1) as nonfarm income increases, the amount of time and attention that is focused on the farm, and thus, farm income, declines, or (2) the farmers that are not very good managers, and have low farm incomes as a result, have to get nonfarm jobs to make debt payments. However, adding the nonfarm variable did not help with our sign problem on ROA. It continues to be negative with variable levels of significance.

At this point we do not have a solution to the problem. If this group of geniuses has suggestions on the cause of, or solutions to the problem, we would be glad to hear them!

Table 6. Two Multi-Period Farm and Nonfarm Creditworthiness Evaluation Models 138 New York Dairy Farms

Variable	1988-89 Model (P-Value)	1988-90 Model (P-Value)
Intercept	-2.71	-4.23
	(0.06)	(0.00)
Debt/Asset Ratio	-1.72	-1.33
	(0.07)	(0.07)
ROA	-0.03	-0.06
	(0.45)	(0.09)
Current Ratio	0.17	0.05
	(0.09)	(0.25)
Lagged Dependent	1.13	1.10
	(0.00)	(0.00)
Capital Turnover	3.50	1.99
	(0.05)	(0.10)
Milk/Cow	0.05	0.16
	(0.56)	(0.01)
Hay/Acre	0.33	0.41
	(0.11)	(0.01)
Milk Price Change	0.07	0.06
	(0.01)	(0.01)
R	0.37	0.34
Model X^2	59.62	76.3
Within Sample Prediction (%)		
False Positive	15.7	19.4
False Negative	49.9	50.9
Positive	81.0	71.3
Negative	56.3	61.7
Total Correct	74.9	68.4
Out of Sample Prediction (1991) (%)		
False Positive	44.1	50.0
False Negative	36.5	40.0
Positive	33.3	15.8
Negative	81.5	88.9
Total Correct	61.6	58.7

Table 7. Two Multi-Period Farm and Nonfarm Creditworthiness Evaluation Models 138 New York Dairy Farms

Variable	1988-89 Model (P-Value)	1988-90 Model (P-Value)
Intercept	-2.46	-3.81
	(0.08)	(0.00)
Debt/Asset Ratio	-1.64	-1.04
	(0.09)	(0.18)
ROA	-0.03	-0.08
	(0.57)	(0.04)
Current Ratio	0.25	0.07
	(0.02)	(0.15)
Lagged Dependent[a]	0.36	0.87
	(0.41)	(0.01)
Capital Turnover	3.55	2.12
	(0.04)	(0.08)
Milk/Cow	0.29	1.37
	(0.72)	(0.02)
Hay/Acre	0.51	0.49
	(0.01)	(0.00)
Nonfarm Income	-0.28	-0.25
	(0.14)	(0.01)
Milk Price Change	0.06	0.06
	(0.02)	(0.06)
R	0.34	0.33
Model X^2	53.64	72.71
Within Sample Prediction (%)		
False Positive	16.8	19.4
False Negative	51.9	52.9
Positive	80.0	69.6
Negative	53.5	69.6
Total Correct	73.2	67.4
Out of Sample Prediction (1991) (%)		
False Positive	43.6	48.0
False Negative	35.4	38.9
Positive	38.6	52.0
Negative	79.0	61.1
Total Correct	62.3	59.4

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