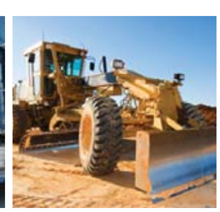
EQUIPMENT LEASING & FINANCE FOUNDATION
Your Eye On The Future

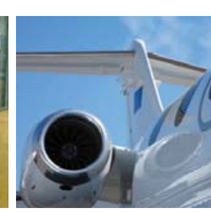
JOURNAL OF EQUIPMENT LEASE FINANCING

VOLUME 27 • NUMBER 1 • WINTER 2009

Articles in the *Journal of Equipment Lease Financing* are intended to offer responsible, timely, in-depth analysis of market segments, finance sourcing, marketing and sales opportunities, liability management, tax laws regulatory issues, and current research in the field. Controversy is not shunned. If you have something important to say and would like to be published in the industry's most valuable educational journal, call 202.238.3400.







The Equipment Leasing & Finance Foundation
1825 K Street NW
Suite 900
Washington, DC 20006
202.238.3400
www.leasefoundation.org

Comparison of Classification Models for Predicting Equipment Lease and Loan Default

By Levon Goukasian and Samuel L. Seaman

Prior to Altman's (1968) influential work on predicting corporate bankruptcy, credit analysis was more art than science, as decision-makers had few mechanisms for accurately quantifying risk. Since then, alternatives to Altman's discriminant model have been used with great success to measure risk and predict default (see for example Ohlson, 1980; Nanda and Pendharkar, 2001).

These now-common procedures, however well known and accepted, require certain assumptions about the data. If the data being analyzed violate some or all of those assumptions, the classification procedures may yield sub-optimal results. This realization has led to an enthusiasm for reportedly more robust approaches to the classification problem, which require fewer assumptions of the data. The most popular such alternative today is artificial neural networks.

Unfortunately, comparative studies of the aforementioned classification procedures generally fail to identify a uniformly superior approach to the classification problem (Michie, Spiegelhalter, and Taylor, 1994). In the end, it seems, the best approach depends in large part on the nature of the unique data set being analyzed.

Our objective, then, has been to compare three default classification procedures—discriminant analysis, logistic regression, and artificial neural networks—to determine which, if any, classification procedure offers the most accurate forecast of lease and/or loan default, and to discover which independent variable(s) is(are) most predictive of default.

Results of the present research offer evidence of an opportunity for marked improvement in forecasting accuracy, when key predictor variables from the PayNet database and an appropriate classification model are used to classify applicants. The PayNet rating score alone has proven to be an outstanding predictor of risk along with past-due history and number of open contracts, and then, to a lesser extent, geographic region, public or private ownership status, government or nongovernment contract status, and ease of credit access.

> Which classification procedure most accurately forecasts lease or loan default? A linear discriminant model appears the most effective for modeling credit risks.

Most surprising, however, has been the superior, comparative performance of an easily applied statistical technique called linear discriminant analysis. This approach to predicting default has yielded classification accuracies as much as 10% higher than some of the most commonly used classification models in the industry—logistic regression and neural network analysis being two such examples. This is not an inconsequential result (statistically or practically speaking) in an industry where analysts often struggle to improve classification accuracies by just 1% or 2%.

In short, we would advise credit analysts in the industry to seriously consider modeling their credit risks (loan/lease default) with a linear discriminant model, using as independent variables the PayNet rating score, history of past due experience, and number of open contracts. Programming this procedure is straightforward for those with access to software such as SPSS or SAS.

THE DATA WE HAVE USED

Data used in the study have been obtained from the PayNet database and consist of 32,852 individual lease/loan contracts obtained over the time period 2002 to 2005. Each contract was identified by a "type" variable with outcomes: conditional sale, loan, lease-purchase, revolver, rental-lease, true-lease, or unknown. In Table 1 we show the number of contracts of each type with associated percents of total sample, and the associated percentage of those contracts in "default" for our final data set.

In addition to contract type, the PayNet database contained much additional information for each contract, including date of contract, location, contract size, asset type, information about contract terms, and many other variables having to do with lessee credit history. Indeed, for each contract there were as many as 78 unique descriptive variables. One of the most important, of course, was the "default status" of the contract, which has been coded as "default" or "not in default," and which represented the outcome variable of interest in our study. The predicate or independent variables used to predict this outcome have been selected from among all remaining variables, including any new variables that we have created ourselves from existing data.

Certainly, there are analysts in the industry with good intuition on these matters. The rest of us generally find it helpful to use an empirical model of the credit-rating process.

Table 1.

Number of Contracts by Type and Percentage of Contracts in Default: Final Data (2002 to 2005)

Contract type	Total number	(% of total)	Number in default	(% of total)
Conditional sale	9026	(27%)	3417	(10%)
Loan	10794	(32%)	5562	(17%)
Lease-purchase	967	(3%)	188	(0.5%)
True-lease	12065	(36%)	4385	(13%)

Research Methodology

The primary objective of this research has been to identify for our readers an optimal set of predictor variables along with an ideal classification model that ought to be used when predicting lease and/or loan default. Certainly, there are analysts in the industry with good intuition on these matters. The rest of us generally find it helpful to use an empirical model of the credit-rating process. Empirical models can be very simple—computing percentiles based on PayNet rating scores—or relatively complex—estimating default risk parameters using learning vector quantization. The literature on default prediction describes a variety of alternative models that lie somewhere along this continuum, three of which stand out for their ease of use and familiarity in the industry: binary logistic regression, discriminant analysis, and neural network analysis.

Binary Logistic Regression

As the name implies, binary logistic regression is simply a variation on regression analysis that is used whenever the outcome variable being studied has only two possible outcomes (i.e., loan status is "default" or "not in default"), and the independent variables are discrete and/or continuous. Of particular importance to the credit analyst is the probability of a "default" outcome, which can be expressed as a function of the predictor variables (X) by,

$$P(default) = \frac{e^{\beta X}}{1 + e^{\beta X}} .$$

If this probability is greater than some predetermined threshold value, say 0.5, the observation will be classified as having come from the "default" outcome group; otherwise, the observation will be classified as having come from the "not in default" outcome group. All logistic regression analyses in this study have been performed using the SPSS software package, by selecting the ANALYZE menu and choosing REGRESSION – BINARY LOGISTIC and choosing appropriate menu settings.

Discriminant Analysis

Linear discriminant analysis, a procedure closely related to both regression and analysis of variance, also can be used to allocate observations into one of two outcome groups (e.g., default versus not in default). A discriminant score, computed as a linear combination of the predictor variables and called the discriminant function, is estimated in such a way that the mean differences between outcome groups will be maximized. An observation is assigned to one of the outcome groups based on the magnitude of this discriminant score. The procedure is easily implemented in SPSS by selecting the ANALYZE menu and then choosing CLASSIFY – DISCRIMINANT and appropriate menu options.

> A discriminant score is estimated in such a way that the mean differences between outcome groups will be maximized.

Neural Network Analysis

Artificial neural networks (neural nets) are machine-based models that learn to recognize patterns in data. The structural design of neural networks, very much inspired by the function of the human brain, consists of layers of interconnected nodes, or neurons, each of which accepts a weighted set of inputs and then passes on output, ultimately, to the output layer of the network. The neural network models used in our analyses were of the back-propagation type with fully connected input, hidden, and output layers. Algorithms for neural network procedures can be found in the SPSS Clementine package.

Statistically Significant Variables and Three Predictive Models

Model 1

Our database contained a PayNet credit rating score for each individual lease/loan contract. The precise manner by which this credit rating score is computed is unknown (proprietary); moreover, we were not told how this score has been used historically to evaluate the risk of an individual contract. Nevertheless, we have assumed that the PayNet score can be used by analysts, even if on an ad hoc basis, to evaluate the likelihood of default, and we believe in fact that it should serve as the gold standard against which all other potential predictor models are compared. Our first model of default using the PayNet rating variable alone will be referred to as model 1.

Model 2

We also hypothesized that a better collection of predictor variables could be found among the remaining PayNet database variables that might yield better classifications. Our search for this ideal set of variables involved a careful assessment of all PayNet variables—as well as a few newly created variables of our own design. Of the 70 or so possible predictor variables available, only eight have proven to be statistically significant for prediction of the binary outcome categories. We identify those statistically significant variables by category, and we provide the observed default frequencies associated with those variables in tables 2–7 below. We hereafter refer to this combination of predictor variables as model 2.

Table 2.

Past Due Experience and Default Frequencies (as Percentages of Sample Total)

(2002 to 2005)

	Default status of contract	
Variable name (value)	**In default**	**Not in default**
Lessee with one or more 31-60 days past due experience	37.9%	34.6%
Lessee with no 31-60 days past due experience	2.3%	25.1%
Lessee with one or more 61-90 days past due experience	35.0%	24.2%
Lessee with no 61-90 days past due experience	5.2%	35.6%
Lessee with one or more > 90 days past due experience	31.6%	19.6%
Lessee with no > 90 days past due experience	8.7%	40.1%

Notice in Table 2 that for a lessee/borrower with one or more 31–60 days past due experience, the probability of a "default" outcome for our sample observations would have been about 0.379 and the probability of a "not in default" outcome would have been about the same, at 0.346. If, however, the lessee/borrower had no historical evidence of a 31–60 days past due experience, the probability of a "default" outcome would have been substantially smaller (inconsequential really) at about 0.023, while the probability of a "not in default" outcome would still have been quite large, roughly 0.251.

As the severity of past due experience intensifies, the probability of a contract being in "default" grows larger as well. Notice, for example, that among applicants with one or more >90 days past due experience (the most severe past due history), the probability that a related contract will be in default is almost twice the probability that it is not in default (0.31 versus 0.19). Yet for those applicants with no history of a >90 days past due experience, probability of a contract in default is small (0.08), while the probability of a not-in-default contract remains large (0.40). Clearly, a past due history is strongly associated with the "default" versus "not in default" status, and should be considered, carefully, when evaluating the risk of a particular lessee/borrower.

> As the severity of past due experience intensifies, the probability of a contract being in "default" grows larger as well.

Five additional predictor variables have proven to be statistically significant in our study: number of open contracts; geographic region; public versus private ownership status; government versus nongovernment status; and ease of access to credit. We present these variables in a similar way in tables 3–7 and discussions that follow.

Another statistically significant PayNet variable from our analysis is "number of open contracts." For illustrative purposes we have created a categorical variable out of this otherwise quantitative predictor. In Table 3, default outcome frequencies have been tabulated for four categories of the "number of open contracts" variable (0, 1–5, 6–10, and more than 10).

It is clear that as the number of open contracts with an individual customer increases, the probability of default for that customer decreases dramatically. First-time customers (i.e., 0 open contracts), for example, have a 29.9% default rate, while high-volume customers (over 10 open contracts) have a nominal 0.5% default rate.

Anticipating a regional effect, we have created a qualitative "geographic region" variable with five levels (1 = Northeast, 2 = South, 3 = Midwest, 4 = Northwest, and 5 = Southwest). While statistically significant, patterns of the default rates in Table 3 would indicate that this is not a particularly compelling predictor variable. Most of the contracts in the sample derive from businesses on the East Coast (North and South) and in the Midwest, with very little data for other regions of the country. Perhaps the only observation worth making is that the Southeast and

Table 3.

Number of Open Contracts and Default Frequencies (as Percentages of Total)

(2002 to 2005)

	Default status of contract	
Variable name (value)	**In default**	**Not in default**
Number of open contracts (0)	29.9%	10.5%
Number of open contracts (1–5)	8.9%	42.0%
Number of open contracts (6–10)	0.9%	4.1%
Number of open contracts (over 10)	0.5%	3.1%

Table 4.

Geographic Region and Default Frequencies (as Percentages of Sample Total)

(2002 to 2005)

	Default status of contract	
Variable name (value)	**In default**	**Not in default**
Region = 1	12.9%	22.2%
Region = 2	10.9%	12.8%
Region = 3	10.9%	13.7%
Region = 4	1.8%	2.8%
Region = 5	3.7%	8.2%

Table 5.

Public/Private Ownership and Default Frequencies (as Percentages of Total)

(2002 to 2005)

	Default status of contract	
Variable name (value)	**In default**	**Not in default**
Publicly traded (yes)	0.2%	2.1%
Publicly traded (no)	40.1%	58.7%

Midwest regions tend to have slightly higher relative default rates, on average, than other regions.

Also included in the PayNet database was a variable indicating public or private ownership of the firm (if a firm was publicly traded, the variable was coded as "yes"; privately held firms were coded as "no"). This variable, too, was statistically significant in our analysis, but like the region variable, it appears to be of minimal consequence for prediction of default outcomes.

Customers in the PayNet database have also been characterized as government-related or not-government-related businesses (for government-related businesses this variable was coded with a "yes"; nongovernmental entities were coded as "no"). Given the default frequencies in Table 6, it would appear that government-related firms have lower default rates, on average, than the nongovernmental firms of the sample data. Again, data for government-related businesses seems to have been very sparse, however, making any broad generalizations precarious at best.

Finally, wondering about the possible effects of access to credit, we have created an "ease of credit" variable, believing that a borrower located in a state with many major financial centers would have easier access to credit than customers in states having few major financial centers. A new variable, then, was created with two levels: "easy access to credit" or "difficult access to credit." This variable proved to be statistically significant in all predictive models, and the default frequencies posted in Table 7 lead one to believe that there might be a slightly higher default rate, on average, when access to credit is plentiful.

A new variable was created with two levels: "easy access to credit" or "difficult access to credit." This variable proved to be statistically significant in all predictive models.

Table 6.

Government/Nongovernment Contracts and Default Frequencies (% of Total)
(2002 to 2005)

	Default status of contract	
Variable name (value)	**In default**	**Not in default**
Government related (yes)	0.3%	1.1%
Government related (no)	40.0%	58.7%

Table 7.

Easy Access to Credit and Default Frequencies (as Percentages of Sample Total)
(2002 to 2005)

	Default status of contract	
Variable name (value)	**In default**	**Not in default**
Credit access (easy)	14.8%	21.2%
Credit access (difficult)	25.4%	38.6%

Model 3

Lastly, we believed that if a model based on the PayNet rating score (model 1) was expanded to include variables we discovered in model 2, the combined effectiveness of this grander, collective model would be even more potent than either one of those models individually. We therefore investigated the qualities of a third model, consisting of the combined variables of models 1 and 2, which we refer to hereafter as model 3.

Classification Results

In tables 8–11(page 6), we present the overall classification accuracies obtained for the three predictive models described above, using each of the three classification procedures described in the previous section for each of four contract types (conditional sale, loans, lease-purchase, and true lease). Each value in these tables is an estimated probability of correct classification, and it provides an indication of how well a particular model has performed when classifying observations into the two outcome groups ("default" or "not in default").

The most surprising result in the tables above is the comparatively superior performance of the linear discriminant analysis procedure. Much has been written of late suggesting that neural networks and logistic regression models typically outperform linear discriminant analysis, since they tend to be more robust to data deficiencies and violations of important distributional assumptions.

For nearly every model and type of contract analyzed using the sample PayNet data, the discriminant analysis

Table 8.

Classification Accuracies (Proportion Correctly Classified) for Conditional Sale Contracts

(2002 to 2005)

Model	Logistic regression	Linear discrimination	Neural network
Model 1	0.87	0.96	0.83
Model 2	0.84	0.88	0.87
Model 3	0.89	0.94	0.92

Table 9.

Classification Accuracies (Proportion Correctly Classified) for Loan Contracts

(2002 to 2005)

Model	Logistic regression	Linear discrimination	Neural network
Model 1	0.89	0.98	0.85
Model 2	0.88	0.82	0.87
Model 3	0.95	0.94	0.96

model in our study has been as good as or better than both the logistic regression and neural network models. Notice, for example, that the probabilities of correct classification for the linear discriminant classifier are always larger (sometimes by as much as 10%) than those obtained with logistic regression or neural networks, when using model 1 (PayNet rating score).

Also worth mentioning is the admirable performance, comparatively speaking, of the PayNet rating score. While we do not have details on the exact nature of the score, it appears to be a powerful predictor of the "default" outcome when compared to other sets of predictor variables. Still, the classification accuracies obtained with the PayNet rating score alone can be improved with the addition of the variables identified in model 2. In summary, for each contract type, the best classification probabilities are realized by using the linear discriminant model and the combined set of predictor variables in model 3.

Table 10.

Classification Accuracies (Proportion Correctly Classified) for Lease-Purchase Contracts

(2002 to 2005)

Model	Logistic regression	Linear discrimination	Neural network
Model 1	0.69	0.98	0.89
Model 2	0.83	0.92	0.94
Model 3	0.97	0.97	0.99

Table 11.

Classification Accuracies (Proportion Correctly Classified) for True Lease Contracts

(2002 to 2005)

Model	Logistic regression	Linear discrimination	Neural network
Model 1	0.89	0.96	0.87
Model 2	0.83	0.91	0.85
Model 3	0.90	0.94	0.93

COMMENTS AND CONCLUSIONS

Several of the results presented above appear to be quite compelling for risk analysts in the lease/finance industry. First, the linear discriminant model has emerged as the best overall classification algorithm among those investigated in this study—sometimes markedly so. Moreover, risk analysts with access to readily available software like SAS or SPSS will find that discrimant analysis is, computationally, as straightforward as any of the other analytical procedures being used in the industry. Practitioners, then, should consider applying the discriminant model recommended in this study when evaluating the potential default risk of a lessee/borrower.

> The linear discriminant model has emerged as the best overall classification algorithm among those investigated in this study—sometimes markedly so.

Secondly, very accurate predictions of default risk have been obtained using the PayNet rating score alone in the linear discriminant model. However, analysts with easy access to one or two additional predictive variables available in the PayNet database—history of past due experiences (over 90 days) and number of open contracts—should realize significant improvements in predicting default by simply adding these two variables to a model with the PayNet rating score. Those without access to PayNet data or the PayNet rating score may find equally accurate proprietary models, using their own variations of the predictor variables discovered in model 2 from this study.

We have also found some evidence of four additional predictive effects worth pursuing in future research: a geographic effect, a public/private ownership effect, a government contract effect, and an ease of access to credit effect. Analysts with more representative data sets could contribute to this ongoing research on default prediction by investigating the importance of these variables to new and improved models of risk.

Acknowledgment

The Equipment Leasing and Finance Foundation and the authors would like to acknowledge PayNet Inc. for providing the data used in developing this article.

References

Altman, E.I. (1968). Financial ratios, discriminant analysis, and the prediction of corporate bankruptcy. *Journal of Finance,* 23 (4) (September 1968), 589–609.

Ohlson, J. (1980). Financial ratios and the probabilistic prediction of bankruptcy. *Journal of Accounting Research,* 18 (1) (Spring 1980), 109–131.

Michie, D., Spiegelhalter, D.J., and Taylor, C.C. (1994). *Machine learning, neural and statistical classification.* New York: Ellis Horwood.

Nanda, S., and Pendharkar, P.C. (2001). Development and comparison of analytical techniques for predicting insolvency risk. *International Journal of Intelligent Systems in Accounting, Finance, and Management,* 10, 155–168.

Levon Goukasian, PhD

levon.goukasian@pepperdine.edu.

Levon Goukasian, PhD, is an associate professor of finance and the John and Francis Duggan Professor of Business at Pepperdine University. He conducts active research in risk management, asset pricing, corporate social responsibility, ethics in corporations, and quantitative portfolio management. His consulting interests include risk management for corporations and hedge funds. Dr. Goukasian's papers have been published in such journals as *Management Science, Journal of Fixed Income,* and *Journal of Public Economic Theory.* He received his PhD from the University of Southern California, Los Angeles, in 2001.

Samuel L. Seaman, PhD

samuel.seaman@pepperdine.edu

Samuel L. Seaman, PhD, is professor of decision sciences in the Graziadio School of Business and Management at Pepperdine University, Malibu, Calif. He teaches graduate courses in applied statistics and evidence-based decision analysis and has an applied research agenda that focuses on the use of mathematical models to solve dilemmas in economics, finance, healthcare, and marketing. His consulting engagements have led to meaningful improvements in credit-scoring models, predictive models of charitable giving, and assessment models used to evaluate the efficacy of strategic initiatives on corporate financial performance. Dr. Seaman has published in a variety of academic journals including *Business Economics, Communications in Statistics, Head & Neck Surgery, Journal of Business Forecasting, Journal of Business Research, Journal of Business Venturing,* and *Strategic Management Journal.* His true passion is the ongoing search for an optimal solution to the particle/wave duality paradox in his other lab, at Malibu's Surfrider Beach. Dr. Seaman received his PhD from the University of Florida, Gainesville, in 1984.