Credit Scoring Models

HOW TO EFFECTIVELY RATE YOUR CREDIT RISK

EQUIPMENT LEASING & FINANCE
FOUNDATION
Your Eye On The Future

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The Foundation is the only research organization dedicated solely to the equipment finance industry.

The Foundation accomplishes its mission through development of future-focused studies and reports identifying critical issues that could impact the industry.

The Foundation research is independent, predictive and peer-reviewed by industry experts. The Foundation is funded solely through contributions. Contributions to the Foundation are tax deductible.

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Preface

The Equipment Leasing & Finance Foundation (the Foundation) is the leading provider of research funding for evaluating current trends, their potential impact on the equipment finance industry and to help provide a sense of direction for the industry's future. The Foundation, recognizing the proliferation of credit scoring models in the industry, decided to evaluate the impact of these models and to try to determine whether this technology is being used to its best advantage within the industry.

The Foundation postulated that credit scoring models have affected the risk-analysis process in the equipment leasing and finance industry and that many companies may have become increasingly dependent on these tools. Recent lending institution failures outside the leasing industry may have underscored the risk of over-reliance on automated scoring models in place of human judgment, and the Foundation wanted to identify trends that might indicate similarities or difference between the industries' practices.

Many recent failures may also have underscored the risks of stressing scoring models beyond the scope of their original design. Therefore, the Foundation set out to determine how credit scoring models are affecting industry credit decisioning and, furthermore, whether the current economic downturn has had any impact on the predictive capacity of these scoring models.

To aid the Foundation in preparing its review of the state of credit scoring models within the leasing industry, PredictiveMetrics, Inc. (PMI) was selected to create an industry wide survey that would provide the information necessary for evaluating the industry's use of credit scoring models and their overall viability

PMI was selected to work with the Foundation in preparing this report because of its expertise in the development and performance evaluation of credit scoring models. PMI is one of the leading providers of statistical-based predictive scoring models and analytical decision solutions for both the B2C and B2B markets. PMI's custom analytics and industry/finance decision technology spans many industries, types of financing, and debt.

How Good is Your Scoring Model? – Report Overview

This report begins with a general review of model usage, followed by a specific analysis of the use of statistical-based and judgmental-based models. This is followed by an analysis of the impact of current economic conditions on model usage and other factors that are affecting model performance and scope of usage. Additionally, the various data sources that are most commonly used in credit scoring models are reviewed and evaluated followed, most importantly, by the answer to the question – How Good is Your Scoring Model? A summary and suggestions for future industry attention ends the report.

Survey Approach

The industry survey encompassed a highly structured questionnaire that contained 87 questions and addressed all of the salient points that the Foundation's research committee requested be considered. Survey responses were gathered from February 2009 through April 2009. During the survey period, business in general was sluggish and particularly bad for the leasing industry. As an example, as reported by the Equipment Leasing and Financing Association (ELFA) in their Monthly Leasing and Financing Index Report for April 2009, in February 2009 new leasing business was down 37.7% compared to February 2008, down 30.9% in March 2009 compared to March 2008 and down 42.3% in April 2009 compared to April 2008. During the same period charge-offs as a percentage of net receivables were up 75.8% in February 2009, up 104.6% for March 2009 and up 72.1 for April 2009 compared to the same months in the previous year. Additionally, credit approvals as a percentage of decisions submitted on a current month this year compared to the same month last year basis were down 12.1%, 10.9% and 17.3% for the period February 2009 through April 2009, respectively.

Given the current leasing environment, the following questions were considered important and are included in the report's summary:

1. Do recent lending institution failures outside the

equipment leasing industry underscore the risk of over-reliance on automated scoring models as opposed to human judgment, or are these practices primarily confined to other lenders?

2. What is the incidence of models designed for a specific application being used for an application for which they were not designed?

3. What is the impact of the current economic downturn on the predictive capacity of scoring models? Specifically, do factors such as the mortgage industry crisis or fuel prices affect scorecard results?

4. Are there specific trends, practices and industry controls that exist which will affect the nature of potential exposures within the equipment leasing and finance industry?

5. What are specific recommendations for remedial action in areas where such problems exist?

6. With respect to the future of credit models are there other factors, not usually included as model variables that should be considered for inclusion in future models?

7. What are the prevalent technologies utilized in developing credit models? And is any one technology superior and if so how?

Number of Respondents

The survey was e-mailed to over 500 members of the ELFA. We received 81 survey responses and in many cases more than one individual from a given company participated (124 in total). Many of the respondents did not complete the entire survey. However, we believe that sufficient data was obtained so that certain valuable conclusions can be made about the industry's use of credit scoring models and how well models are performing.

Market Segment Classification

Consistent with "traditional" segmentation of the industry and in prior surveys, respondents were placed into three categories: Banks (either separately-operating subsidiary or integrated), Captives, and Independent Financial Services companies. Definitions of these various financing categories are as follows:

Bank - Equipment finance activities intermingled with other bank functions, utilizing internal funding sources; jurisdiction by Comptroller of the Currency (24.3% of respondents).

Captive - At least 51 percent of equipment finance portfolio consists of products produced by parent and/or affiliates (24.3% of respondents).

Independent, Financial Services - A company with a portfolio for its own account that may provide a broad range of financial products and services including leasing, lending, and may arrange transactions (51.4% of respondents).

The survey captures four leasing market segments: micro-ticket, small-ticket, middle ticket, and large-ticket. Defined as:

Micro-Ticket – The majority of the new business volume booked in fiscal year 2008 had a transaction size of less than $25,000 (14.9% of respondents).

Small-Ticket – The majority of the new business volume booked in fiscal year 2008 had a transaction size between $25,000 and $250,000 (50.0% of respondents).

Middle-Ticket – The majority of the new business volume booked in fiscal year 2008 had a transaction size between $250,000 and $5,000,000 (25.7% of respondents).

Large-Ticket – The majority of the new business volume booked in fiscal year 2008 had a transaction size over $5,000,000 (9.5% of respondents).

Note: The "majority" of new business volume is not necessarily over 50% of the total new volume. For instance, if the company booked $120,000,000 in new business volume, of which $40,000,000 was in Small-Ticket, $50,000,000 in Middle-Ticket and $30,000,000 in Large-Ticket, the majority of the new business volume would be in the Middle-Ticket segment.

PredictiveMetrics, Inc. (PMI) has certain opinions, based on our knowledge and experience, with respect to the industry's use and maintenance of credit scoring models and whether or not best practices are being utilized in specific areas. Our feelings are provided in the Summary and Conclusions section at the end of this report.

PredictiveMetrics, Inc.
Albert Fensterstock, Senior Consultant

Executive Summary

Objective

This study was designed to determine how well credit scoring models are performing within the leasing industry and whether there is over-reliance on automated scoring models as opposed to human judgment. Have these tools been used beyond the scope of their original design, and is the current economic downturn having an impact on the predictive capacity of scoring models? To answer these questions the survey was designed to examine trends, practices and controls so that it would be possible to either refute or confirm whether potential exposures exist within the equipment leasing and finance industry and, thereby, recommend where attention may be warranted both now and in the future.

Model Origination and Application

Of the companies that use statistical-based models, 32.4% utilize internal modeling groups to develop them, while 37.8% use outside contractors, and 29.7% utilize a combination of both. With respect to judgmental-based models, 68.6% of the companies' model development is done by in-house senior risk management/credit staff, 5.7% utilize outside contractors, and 27.5% of the companies use a combination of both.

The credit scoring models, both statistical and judgmental appear to be used mostly to aid in the evaluation of smaller sized transactions. Almost half of the respondents utilized both types of models. Statistical-based models were used to evaluate 96.6% of the total number of micro-ticket (<$25,000) transactions, 100% of the total number of small-ticket ($25,000 to $250,000) transactions, 62.5% of the total number of middle-ticket ($250,000 to $5,000,000) and 31.6% of the total number of large-ticket (>$5,000,000) transactions, while judgmental-based models were used to evaluate 86.7% of the total number of micro-ticket transactions, 88.2% of the total number of small-ticket transactions, 62.5% of the total number of middle-ticket transactions and 36.8% of the total number of large-ticket transactions.

Current Model Performance

Almost 78% of the companies that responded to the survey are using some form of credit scoring model; however, there was a strong indication from respondents that the downturn in the economy has and will produce a significant increase in manual review of model results. This was underscored by the fact that almost 66% of the companies' feel that their model results have been affected by the current economic conditions and 96.3% believe that the models are less accurate.

Current Impact

About 48.0% of the companies believe that there are specific trends, practices and industry controls being deployed which will affect delinquency and loss rates within the equipment leasing and finance industry. Most frequently mentioned as steps that are being taken were the tightening of credit requirements and that lenders are demanding more favorable transaction structures together with limiting their exposure. Additionally, there has already been a notable increase in the manual review of model decisions and markets that are considered marginal or more risky are being de-emphasized or avoided entirely, however the actual markets were not disclosed for competitive reasons. There is also serious consideration of revalidation and adjustment of existing models; however the frequency of future planned revalidation was also not explicitly stated. For the short term, prior to refitting or re-estimating existing models many companies have raised their cut-off levels for credit acceptance, thereby making it more difficult for all but the best credit risks to obtain credit.

Future Impact

Some respondents thought that certain operating procedures should be put into place, as soon as possible, with the hope of mitigating some of the additional risk perceived by their companies. Specifically, the increased use of business rules to guarantee manual review of applications from businesses in stressed sectors would very likely be accelerated together with requiring additional underwriting data (financial statements, credit references, etc.) for applications from businesses in stressed sectors. Additionally, for consumer models where the model is being used to evaluate a business owner, it was suggested that an improvement would be to rely less on off-the-shelf consumer-type scores. It should be noted that the Industry does not include consumer financing and is limited to commercial transactions only.

In the short term, putting more focus and reliance on collection staff efforts and tools to effectively manage portfolios and reduce delinquencies and write-offs is something that is being considered. Additionally, another short term strategy that may help to mitigate losses is to workout extensions for existing troubled customers, where possible.

In the longer term, developing new models using information from this significant downturn as part of the model development database was indicated as something that should be considered and although this recession may be an anomaly, it would be a good idea not to overly weight or under-weight the history from this period, so that profitable lending opportunities in the future will not be unnecessarily restricted. Additionally, as part of the model development process, if statistical- based models are being developed, it can be determined which factors have the greatest impact on losses during a downturn, which might provide an early warning system in the future.

How Good is Your Scoring Model?

According to the survey findings a majority of the leasing industry's model users are not utilizing any type of consistent statistically-based scoring performance evaluation system and, therefore, may not really know how well their models are performing. Only 25.9% of the respondents indicated that they were receiving regularly scheduled credit scoring performance evaluation reports and of these respondents only 51% indicated they were revalidating models on an annual frequency or less.

Overview of Model Types

In general, judgmental and statistical-based systems utilize a similar set of information about a company. In the judgmental-based system, the information is weighted by the senior risk management/credit personnel developing the system according to their past experience, judgment, defined credit policy and personal bias. Alternatively, in the statistical-based system, the weights are determined through a rigorous statistical analysis performed by professional statisticians who are familiar with these types of models. If desired, credit and collection policy rules can be incorporated into a statistical-based model to improve model performance. In the development of a "new application" statistical-based model the following steps are typically performed:

1. The model developers are provided with 18 to 24 and perhaps 36 months or more of historical data, at the customer level from a variety of sources including internal data, commercial bureau data, consumer bureau data and financial statement data.

2. This data serves as the basis for predicting future customer payment activity.

3. The model is developed from the data by uncovering past trends, magnitudes and payment patterns, and formulizing this information to predict future payment performance.

4. Model results are validated by using actual customer payment activity, subsequent to the time of score, to evaluate the model's ability to differentiate future problem payers from future timely payers.

5. The validation quantifies how accurately the model predicted future customer payment behavior.

In the development of a statistical based model for "existing accounts", the lessor's accounts receivable, application data and other internal data is the basis for model development. The addition of bureau, financial and other external data is optional based upon availability and cost.

In both judgmental-based and statistical-based model development, the data used by the models consists of information such as: payment histories; bank and trade references; commercial and consumer credit agency information; applicant financial statements; and various financial ratios to name some of the sources.

Model Assessment

Given both judgmental-based and statistical-based models can utilize the same data, some of the critical differences between them are:

1. It is unlikely that any two judgmental-based model developers would agree on the variables or the weights to be assigned for a given model. The factors and their weights would be biased based upon each individual's past experience and judgment, which is unlikely to be the same. In a statistical-based model, once the factors to be included in the model have been determined by various statistical tests, and statisticians may differ on which and how many variables to include, the weights are assigned by the statistical software used for that purpose. Given the variables selected, there will be one best fitting model with some differences based upon the model developers skill set.

2. If the judgmental model, for what ever reason, is not performing as well as hoped, it is extremely difficult to determine which factor(s) and weight(s) need to be adjusted. In a statistical-based model, it is a straight forward process to determine which variables are causing the problem and fix the model.

3. Judgmental models are rarely, if ever, validated. After the model is determined the developers do not go back in time and say, "if we had this model six months ago how well would it have predicted the next six months?" A statistical-based system should always be validated. It's the validation process that tells how good the model is, and helps the developer determine whether it's adequate for the purpose for which it has been developed.

4. Judgmental systems are not easy to build. And, this is probably the main reason that once in place, they are not frequently changed. Alternatively, because of the availability of sophisticated and relatively inexpensive statistical software, a statistical-based model can be developed in less time than a judgmental model that uses a wide range of input variables.

5. Judgmental systems can not quantify risk. They are essentially ranking systems where the company with the highest score is considered the best risk. A judgmental-model produced score cannot predict the probability or odds that a given company will pay its bill within any particular time period, which statistical-based models do as a matter of course.

Credit Scoring Model Usage by Respondents

The distribution by type of credit scoring model usage by the respondents was as follows:

Model Usage	Percentage of Respondents
Statistical-based	16.7%
Judgmental-based	15.3%
Statistical-based and judgmental-based	45.8%
No scoring models	22.2%
	100.0%

Only 32.4% of the model users indicated that they used different models for "new applicants" than for "existing customers". It should be noted that the payment behavior of existing customers is at the granular level (detailed payment history and monthly aged accounts receivable balances) - data which has been proven to be the most predictive for risk management purposes. This is data which if we have interpreted this answer correctly is not used by 67.6% of the respondents for evaluating existing customers requesting additional credit. We arrived at this conclusion because these companies indicated that they are using the same model for existing customers as they are for new applicants, where granular level payment data is not available and only payment history at a higher level with previous lenders is possible model input.

Separate models are used by 42.3% of the respondents to deal with different lines of business and 43.1% of the respondents use different models depending on the transaction size. It should be noted that the more sophisticated the model user, the more granular the model development, providing there is sufficient data available to develop segmented models, i.e. develop alternative models for different lines of business and/or different transaction sizes. One of the criteria used for determining whether it is possible to segment a population is the number of "BADs", i.e., the population of customers that meet the definition of a bad account in the data sample. If there are not a sufficient number in the data sample, and statisticians differ as to how many are required (this is one of the areas where statistics is an art rather than a science), you do not have sufficient data to segment the model. This does not necessarily mean that the companies that answered "yes" achieve better predictability. The companies that answered "no" could use more frequent and detailed manual reviews to achieve their required level of comfort for a given risk analysis.

About 21% of the respondents are using models to evaluate transactions and/or lines of business that the models were not designed for. These companies may be taking a larger risk then they think they are, and as was indicated by the original model development work. In general, you do not want to use a model developed to evaluate a particular population to evaluate a different population as the risk metrics can be completely different. In fact, independent modeling companies will usually not warrant models developed from one population that are used to evaluate a different population. Fortunately, however, for our sample population there was no indication that this practice was causing a significant problem.

Some Thoughts on Generic Scorecards

About 65.7% believe that there are benefits in using generic scorecards compared to or together with custom scorecards. The benefits most frequently mentioned were:

• Provides additional input data in both judgmental and statistical-based custom models.

• They can help to evaluate smaller deals not covered by models.

• They are a good starting point for deciding whether to submit the transaction for detailed financial review.

• They are useful in business segments where prior history is not available.

• They are useful in smaller shops where the economic basis or volume to support the use of custom models does not exist.

•They can provide a benchmark to determine whether a customer is performing above or below industry norms.

•They provide sufficient predictability for smaller portfolios where the cost of developing a custom model is not justified.

Planned Changes

When asked what, if anything, survey respondents were planning with respect to their current scoring practices, the respondents indicated that some combination of the following was most likely to occur:

•Increase reliance on manual/judgmental decisions – 50.0%

•Revalidate and adjust existing scorecards – 42.2%

•Develop new scorecards – 21.9%

•Raise cut-off scores as a means of tightening credit – 16.0%

•Increase due diligence and apply stricter manual and judgmental evaluation – 9.4%

•Increase the amount of down payments – 3.1%.

STATISTICAL-BASED MODELS

The technology used to develop statistical-based models is centered on two methodologies. Approximately 85% are using either or both logistic regression and discriminant analysis, predominately for transactions up to $250,000. Other technologies mentioned were, other types of regression analysis, and genetic algorithms. No respondent mentioned they were using neural network technology. Additionally, 12.1% use generic scorecards either as a stand-alone evaluator or as input to their models, and 3.0% use a technique called reject inference.

The personnel used to develop models are about evenly split among three categories: 32.3% are developed in-house, 37.8% utilized an outside contractor and 29.7% used a combination of both. As for the number of models in use for a given company, one company utilized more than 50 models, two companies utilized between 21 and 50 models and one company utilized between 11 and 20 models. The average number of models utilized by the remaining 89.5% of the respondents was between 3 and 4. As mentioned previously, the more sophisticated model user, provided the data is available, will build numerous models as a function of business type and/or transaction size as a method to provide additional model predictiveness. For example, a model developed specifically for a given business segment and transaction size, say office equipment leasing less than $10,000 will most likely do a better job on that class of customers than a general model developed for any type of lessor for any transaction size if for no other reason than the variance between possible customers has been significantly reduced..

When and how are Models Used?

Models are used 3.4 times more frequently to aid in the evaluation of transactions up to $250,000 than for larger transactions and 89.5% use some type of auto-decisioning either for approval or decline. However, it was also indicated that there will be increased manual review of model decisions in the future.

Manual reviews are performed greater than 50.0% of the time by from 34.5% to 60.0% of the respondents, based on the transaction size. This seems to indicate that regardless of the transaction size, there is a general feeling that models are not perfect and professional judgment needs to be applied frequently to support a model's decision. Additionally, in most instances, the greater the risk, the more likely a manual review will be performed.

Based on the survey responses, manual reviews frequently wind up changing a model's auto-decision. On average, only 15.1% of the respondents indicated that a manual review never changes a model's auto-approval decision, 74.2% indicated it changed the model's decision up to 50.0% of the time and 10.8% indicated it changed the model's decision over 50.0% of the time. Alternatively, if the auto-decision was negative, only 12.0% of the respondents indicated that a manual review had never changed a model's decision, 53.0% indicated it changed the model's decision up to 50% of the time and 35.0% indicated it changed the model's decision over 50% of the time. Of interest here is the high percentage of the time a negative decision was overridden. Companies do not want to lose business because of a model's decision and many companies have a policy of reviewing all model declines over a certain amount.

Another thing of note is that almost 40.0% of the respondents have raised their auto-approval cut-off as a method of tightening credit due to the current economic conditions, and that as a result there was from a 5.0% to 25.0% decrease in auto-approvals with about the same number above as below the mean value of a 15.0% decrease. As expected, increasing the cut-off definitely has a material impact and will significantly reduce the amount of credit granted by auto-approvals and, thereby, the risk a leasing company is willing to assume.

With respect to the maximum portfolio exposure a respondent was willing to take on an "existing customer" based purely on a model's auto-approval, 37.5% would not be willing to risk any exposure, essentially indicating that they do not use auto-approvals. The complete distribution of the maximum portfolio risk that the 24 respondents were willing to assume is:

Maximum Portfolio Exposure ($)	Percentage of Respondents
0	37.5%
>0 to 50,000	8.3%
>50,000 to 100,000	29.2%
>100,000 to 500,000	8.3%
>500,000 to 1,000,000	16.7%
	100.0%

JUDGMENTAL-BASED MODELS

Model development by senior risk management/credit staff accounts for 68.6% of development, outside contractors were used only 5.7% of the time and a combination of both accounted for 25.7%. As for the number of judgmental models in use, in a given company, only three companies indicated that they were using more that five models. On average, companies that use judgmental-based models use slightly fewer models than companies that use statistical-based models.

In most cases, when the information is available, the data used by a judgmental system consists of: payment histories; bank and trade references; credit agency ratings and financial statements and ratios. The factors and weights used by a given company are based on the past experience and judgment of the credit personnel developing the system.

When and How are Models Used?

Similar to the use of statistical-based models, judgmental-based models are used far more frequently to aid in the evaluation of transactions up to $250,000 than for larger transactions. In our experience, there is a limit which differs from company to company, beyond which a company will not risk a credit decision based solely on a model's judgment. Beyond that point, a financial analyst will always be involved in the final decision.

Manual reviews are performed greater than 50% of the time by from 31.0% to 47.8% of the respondents, based on the transaction size. Therefore, whether the model is statistical or judgmental the use of professional judgment to support a model's decision was widely utilized.

Manual reviews frequently change a judgmental model's auto-decision. On average, only 19.4% of the respondents indicated that a manual review never changes a model's auto-approval decision, 72.4% indicated it changed the model's decision up to 50.0% of the time and 7.1% indicated it changed the model's decision over 50.0% of the time. Alternatively, if the auto-decision was negative, 23.0% of the respondents indicated that a manual review had never changed a model's decision, 67.0% indicated it changed the model's decision up to 50% of the time and 10.0% indicated it changed the model's decision over 50.0% of the time compared to 35% of statistical-based model users. As noted previously, companies do not want to lose business based on a model's decision without some level of manual financial review that supports the model.

With respect to the maximum portfolio exposure a respondent was willing to risk on an "existing customer" based purely on a model's auto-approval, 47.8% would not be willing to risk any exposure, i.e., they do not use auto-decisioning, The complete distribution of the maximum portfolio risk that the 23 respondents were willing to assume is:

Maximum Portfolio Exposure ($)	Percentage of Respondents
0	47.8%
>0 to 50,000	17.4%
>50,000 to 100,000	13.0%
>100,000 to 250,000	13.0%
>250,000 to 500,000	4.3%
>500,000 to 750,000	4.3%
	100.0%

For "new applicants" 45.5% were not willing to take any risk based on a model's auto-approval: The complete distribution of the maximum portfolio risk that the 22 respondents were willing to assume is:

Maximum Portfolio Exposure ($)	Percentage of Respondents
0	45.5%
>0 to 50,000	27.3%
>50,000 to 100,000	4.5%
>100,000 to 500,000	22.7%
>500,000 to 1,000,000	0.0%
	100.0%

GENERAL MODEL QUESTIONS

During the last twelve months economic conditions have significantly affected their models' predictiveness according to 65.9% of the respondents. Additionally, of those that indicated there had been a change, 96.3% said their models have been less accurate in predicting delinquency or loss.

Assuming that the accuracy of models has been affected, we wanted to know what has been the positive or negative percent change in predicting delinquency or loss? According to the 19 companies that provided actual percentage information the impact of the change in model accuracy ran the entire gamut from 0% change in accuracy of loss prediction or estimated bad rate to 100%, as follows:

% Change in Model Accuracy	Percentage of Respondents
0%	10.5%
>0% to 5%	10.5%
>5% to 10%	26.3%
>10 to 20%	26.3%
>20% to 30%	10.5%
>30% to 50%	10.5%
>50% to 99%	0.0%
>99%	5.3%

Expected Changes in the Industry That Might Affect Delinquency and Loss Rates

Respondents were about evenly split as to whether there were specific trends, practices and industry controls in existence which will effect current delinquency and loss rates within the equipment leasing and finance industry. Of the companies that thought such factors were in existence, the following activities were the only ones mentioned by more than one respondent:

•Credit requirements have tightened and lenders are demanding more favorable transaction structures, and reduced exposure limits.

•Additional manual reviews are occurring.

•Marginal markets have been exited.

•Revalidation and adjustment of models is more prevalent.

When asked what remedial action they recommended in areas where problems were perceived the following were recommended:

•Increased use of business rules to ensure manual review of applications from businesses in stressed sectors.

•Increased requirements for additional underwriting data (i.e., financial statements, credit references, etc.) for applications from businesses in stressed sectors.

•Redlining industries at a more granular level - For example 4-digit SIC rather than 2-digit industry segments at the filter level (i.e. 65xx - Real Estate whereas 4-digits distinguish between commercial and consumer real estate segments).

•For consumer models, rely less on off-the-shelf consumer-type scores.

•Developing new models using data from this significant downturn as part of the basis. However, it was suggested not to overly weight the history from this recession, as the future may not look like the recent past and you do not want to unnecessarily restrict profitable lending opportunities in the future.

•Use the current recession as an opportunity to examine which factors have the greatest impact on losses during a downturn the like of which has not been experienced since the depression.

•Workout extensions for existing troubled customers, if possible.

•Aggressively monitor all significant exposures and take immediate action to protect the value of assets. These measures may vary based on the specific collateral and customer relationship.

•The industry should develop true peer group data similar to FDIC bank peer data to assist equipment finance firms in monitoring the quality of their portfolios, in general.

•Focus and rely more on collection staff efforts and tools to effectively manage portfolios and reduce delinquency/write-off roll rates.

•Change how rating agencies are compensated. The issuer who seeks a rating is paying their bill. To create a more arms length transaction, the investor or conduit should be paying this bill, thereby ensuring that the rating agencies are working in their best interest and not for the issuers.

New Generic Scores

Only 23.3% of the companies that responded were aware of new generic scores that are available or under development that might be applicable to the equipment leasing industry. Of those companies that were aware of new developments, the following were mentioned as new capabilities available to the industry:

•Additional Paynet functionality.

•New products from D&B.

•Oliver Wyman LGD studies.

•Revised lease analysis product suite from PMI.

Product Types

Application Only Leases

A little over 82% of the companies that answered the question (37 companies) accept application only leases where additional financial information beyond that requested on the application is not required. The maximum exposure these companies were willing to accept ranged from $0 to $750,000. The distribution of the 24 companies that provided dollar limits is:

Maximum Portfolio Exposure ($)	Percentage of Respondents
0	4.2%
>0 to 50,000	12.5%
>50,000 to 100,000	41.7%
>100,000 to 250,000	20.8%
>250,000 to 500,000	16.7%
>500,000 to 750,000	4.2%
	100.0%

Only 23% of the respondents indicated that there had been a significant increase in requests for application only leases over the last year.

Deferred Payment Programs

A little over 59.0% of the companies that answered the question (26 companies) provide deferred payment programs. The maximum exposure these companies were willing to accept ranged from $5,000 to $20,000,000. One company was willing to accept $5,000,000 and one company was willing to accept $20,000,000. The distribution of the 12 companies that provided dollar limits is:

Maximum Portfolio Exposure ($)	Percentage of Respondents
0	0.0%
>0 to 50,000	16.7%
>50,000 to 100,000	16.7%
>100,000 to 500,000	41.7%
>500,000 to 1,000,000	8.3%
>1,00,000 to 5,000,000	8.3%
>5,000,000	8.3%
	100.0%

Only 25% of the respondents indicated that there had been a significant increase in requests for deferred payment programs over the last year.

Step-up Payment Programs

About 45% of the companies that answered the question (18 companies) provide step-up payment programs. The maximum exposure these companies were willing to accept ranged from $25,000 to $20,000,000. One company was willing to accept $10,000,000 and one company was willing to accept $20,000,000. The distribution of the 8 companies that provided dollar limits is:

Maximum Portfolio Exposure ($)	Percentage of Respondents
0	0.0%
>0 to 50,000	12.5%
>50,000 to 100,000	25.0%
>100,000 to 500,000	37.5%
>500,000 to 1,000,000	0.0%
>1,00,000 to 5,000,000	0.0%
>5,000,000	25.0%
	100.0%

Only 5% of the respondents indicated that there had been a significant increase in requests for step-up payment programs over the last year.

No-Money-Down Payment Programs

About 49.0% of the companies that answered the question (21 companies) provide no- money-down payment programs. The maximum exposure these companies were willing to accept ranged from $25,000 to $20,000,000. One company was willing to accept $2,000,000 and one company was willing to accept $20,000,000. The distribution of the 9 companies that provided dollar limits is:

Maximum Portfolio Exposure ($)	Percentage of Respondents
0	0.0%
>0 to 50,000	11.1%
>50,000 to 100,000	22.2%
>100,000 to 500,000	44.4%
>500,000 to 1,000,000	0.0%
>1,00,000 to 5,000,000	11.1%
>5,000,000	11.1%
	100.0%

None of the respondents indicated that there had been a significant increase in requests for no-money-down payment programs over the last year.

MODEL VARIABLES – WHAT'S IMPORTANT?

The following information was provided to respondents with respect to the major data sources together with some sample variables within each data source to guide their answers to the questions in this section.

Internal Data: Account Tenure; Collection Effort; Credit Balance; Current Aging; Date of Last Payment; Historical Aging; Late Fees; NSF Checks; Days Beyond Terms; Payment Amounts; Write-Off Amounts; Application Date; Application Decision; Funding Date; Trade and Bank References, Etc.

Commercial Bureau Data: Various Bureau Predictive Indicators – Paydex; CCS; FSS; Intelliscore, etc.; Company History; Industry/Geography; Negative Payment Experiences; Previous Bankruptcy; Secured Financing; Size of Company; Suits/Liens/Judgments; UCC Filings; Years in Business; Trade Interchange Data; Etc

Consumer Bureau Data: Various Bureau Predictive Indicators – FICO, etc.; Age of Newest Trade; Average Trade Balance; Charge-Offs; Collection Inquiries; Credit Limit; Current Balance; Delinquent Trade Lines; Number of Inquiries; Public Records; Time On File; Total Trades; Etc.

Financial Statement Data: Leverage Ratios; Working Capital; Net Liquid Balance; Net Worth; Solvency Ratios; Cash Position; Profit Returns; Industry Norm Information; Total Liabilities; Gross Profit Margin; Etc.

New Applicant Model Data Sources

The most commonly used data in new applicant models was commercial bureau and consumer bureau data. About 83% of the respondents indicated they use both followed by 73% that also use internal data and only 56% ask for financial statement data. About 32% of the respondents utilize some variables not usually classified in the above categories, specifically mentioned were: specific professional licenses information, news research, Certificate of Good Standing, and competitive analysis.

Existing Customer Model Data Sources

The most commonly used data in existing customer models was internal data, About 90% indicated they use it followed by consumer and commercial bureau data, about 80% for each and only 54% use or ask for financial statement data. About 27% of the respondents utilize some variables not usually classified in the above categories, specifically mentioned were: news research, collateral value and competitive analysis.

Most Frequently Used Variables

Of the variables used in respondent's models, the five specific variables most frequently represented in their models and the percentage of occurrence was: Time in Business - 75.8%; Payment History - 39.4%; FICO - 39.4%; Paydex - 18.2% and Paynet Business Credit Scores - 9.1%

For the five most critical variables used in their models, the respondents were asked whether there had been any change in the variable's importance over the last two years. There were 32 responses, as follows:

	Percentage of Respondents		
Variable	No Change	Little Change	Significant Change
Variable 1	46.9%	31.3%	21.9%
Variable 2	45.2%	32.3%	22.6%
Variable 3	41.4%	44.8%	13.8%
Variable 4	33.3%	44.4%	22.2%
Variable 5	41.7%	50.0%	8.3%
Total	42.0%	39.9%	18.2%

The above indicates that it is very likely that the weights of certain key variables may need to be recomputed. For statistically-based models this is normally done through a process that refits the model, i.e., changes the underlying weights assigned to the same variables based on a revalidation. If a refit does not improve model performance then a complete reestimation may be necessary.

Model Accuracy

The responses shown above indicate that the problem may lie in the weights attached to what the respondents consider to be their most critical variables. It should be noted that in the development of statistical-based models, the variable weights are determined by the process employed and would be optimized by the system which is not the case in the development of judgmental-based models where the developers may not be able to measure with any accuracy the predictiveness of any variable in the model. In either case, models deteriorate over time and need to maintained on a regular basis.

PERFORMANCE EVALUATION OVERVIEW

The OCC's Bulletin 2000-16 states that "once in use, model estimates should continually be compared to actual results". In other words, a credit scoring model's performance, including the performance of overrides, should be reviewed regularly and appropriate action taken when the credit scoring model's performance begins to deteriorate, and, if at all possible, these evaluations should be done by an independent party (i.e., independent from the end-user).

In evaluating scorecard performance there is both a front-end and back-end reporting requirement. Front-end reports allow a creditor to measure changes in the population between the time the model was developed and the time of customer application and, thereby, serve as an early warning of deterioration in the model's performance. While back-end reports provide for a measure of portfolio quality.

Front-end reports include: population stability analysis or a comparison of the actual and expected score distributions; characteristic analysis or a comparison of applicants' score distributions by individual characteristics or model variables over time; and final score reports or approve and deny score distribution analysis.

Back-end reports may reveal differences between expected and actual results. These reports may identify shifts in applicant behavior suggesting a model no longer effectively separates good from bad accounts (see note below) and may identify deterioration in the model's ability to rank risk performance of the company's current or future applicant pool.

Note: The definition of a bad account is usually based upon the account becoming severely delinquent or going to loss or bankruptcy over a specified performance period. A common form for a Bad Definition might be that: *an account is considered bad if more than 15% of the monthly outstanding balance ages to over 180 days past due, or incident of write-off, or bankruptcy occurs within 18 months (the performance period) of scoring.* Accounts that do not reach this state of delinquency are considered good. The bad rate is the percentage of the accounts in the total population, for a given period, that meet the Bad Definition.

Frequency of Performance Evaluation and Content

Only 21 of the respondents stated that they were performing some type of regularly scheduled performance evaluation. Given the small number of responses, we can not state with any assurance what the non-respondents are doing to evaluate their models' performance. As this question was answered by only 36 of the respondents, the implication is that 74.1% of the total respondents are not regularly evaluating their model's performance. Again due to the small number of responses we can not infer what the general population is doing with any degree of certainty. Of the 21 companies doing scheduled performance evaluation, 71.4% are using personnel to evaluate model performance that are independent of model development.

Even among respondents that are doing some type of model evaluation there was no consistency of review. In other words, for the same respondent, some models were evaluated every six months and some were evaluated every 36 months, if at all.

If a respondent is doing performance evaluation then the system always contains back-end reports and 90% of the time front-end reports as well.

Model Performance

It was hoped that it would be possible to find out how well scoring models were performing. One way of determining how well a model is performing is to compare its development sample bad rate to a validation sample bad rate. Another way is to compare the average credit score in the development sample to the average credit score in a validation sample. Unfortunately too few respondents answered these questions, so, we cannot state with any assurance that the results are representative of how models are performing. The above procedure is usually only applicable for statistical-based models as the modeling procedure produces these statistics as a matter of course. It is possible to gather similar statistics for judgmental-based models, however, the back testing required is rarely performed.

Of those that responded, only 50.1% of the models were evidencing a difference between the development sample bad rate and the validation sample bad rate of between 5% and -5% which might indicate that the other 49.9% of the models need to be modified (refitted) with respect to the weights of certain variables, or if the percent difference is very large completely re-estimated.

Additionally, about half the models are showing little change in the average risk score and half are evidencing a measurable difference. Those companies that indicated that the validation bad rate or average risk score for a model is greater than 5% of the development sample bad rate or average risk score should consider revalidating those models and, thereby, determine whether a model refit or a re-estimate is called for. The revalidation process would examine bad capture curves, KS statistics, among other statistical measures.

Alternatives Utilized Instead of a Regularly Scheduled Scoring Performance Evaluation

Fifteen companies replied that they do not have any type of formal scoring performance evaluation system. They indicated that they use the procedures listed below to determine how well their models are performing. Most of the procedures identified below are designed to address portfolio performance, but do not provide information as to how well the model is performing.

- Perform a static pool analysis. This is a procedure where a pool of loans from a specific time period has ongoing analysis conducted upon it. Analysis would examine such things as delinquency, prepayments and rate of return and, thereby, provide a true return on a pool of loans. As an example, for a given time period the following might be determined:

- o Beginning/ending number of leases in period still active
- o Amortization during period
- o Prepayments during period
- o Delinquencies at end of period
- o Gross/net losses during period

•Independent portfolio analysis by an outside contractor.

•Use of monthly and historical delinquency data/loss data to monitor applications that were approved under application only guidelines.

•Review samples of non-performing loans and evaluate various factors such as geographic location, time in business and commercial/personal credit scores to determine if any of these factors could have predicted the lease defaulting.

•Utilize a tracking report that measures population stability and model characteristic analysis that also checks that the score, and its component elements, are rank ordering risk.

•Analyze actual vs. predicted loan results over time.

•Perform an analysis each quarter utilizing a system developed in-house.

•Review delinquencies and repossessions.

•Evaluate each incident of loss to understand what went wrong in the underwriting and modify their risk tolerance for that specific category of customer or asset category. Additionally, look at portfolio composition quarterly and monitor exposures.

•Perform various types of internal analyses, such as profit margin and delinquency based on FICO, balance, equipment, and equipment supplier.

•Evaluate portfolio performance within various credit score ranges.

Summary and Conclusions

At the beginning of this report, a number of questions were listed that this survey was designed to answer. These questions were considered to be of significant interest to the industry as specified by the Equipment Leasing and Finance Foundation. The following are the answers to the questions, based on the information provided by the respondents:

1. Do recent lending institution failures outside the equipment leasing industry underscore the risk of over-reliance on automated scoring models in place of human judgment, or are these practices primarily confined to other lenders?

The lessors that responded are not placing an over-reliance on automated scoring models. In excess of 80% of the respondents perform manual reviews of both judgmental-based and statistical-based model results. In addition many of the respondents indicated that the manual review may change the model's decision regardless of whether it was an accept or a decline.

PredictiveMetrics' Observation:

To a great extent the lending institution failures outside of the equipment leasing industry were consumer based - the so called sub-prime crisis. These failures were triggered by a lack of any type of credit evaluation - sometimes called "liars loans" by the press. In other words, there was no reliance on automated scoring models as they weren't used or if they were their judgment was ignored. The leasing industry did not utilize these practices, but was affected because of the almost complete collapse of our financial system and its effect on many of the industries that are major leasers. These companies found the demand for both their products and services significantly reduced and this caused them to significantly reduce their demand for leasing services.

2. What is the incidence of models designed for a specific application being used for an application for which they were not designed?

Models are used by 21.1% of the respondents for transactions and/or lines of business for which they were not designed. Only 20% of the respondents indicated that the results were a little worse than usual, and none of the respondents indicated that the results were a lot worse than usual.

PredictiveMetrics' Observation:

It is PMI's opinion that using a model designed for one population to evaluate a different population is a risky practice and, furthermore, the amount of risk being taken is unknown. Only if a validation is performed for the population not originally included in a model's development where the risk is determined can the user have an understanding of the risk they are actually taking.

An analogous situation is that only 32.4% of the model users indicated that they used different models for "new applicants" than for "existing customers". As noted previously, the payment behavior of existing customers is at the granular level (detailed payment history and monthly aged accounts receivable balances) - data which has been proven to be the most predictive for risk management purposes. This is data that is not used by 67.6% of the respondents for evaluating existing customers requesting additional credit.

It is PMI's judgment that if you are trying to estimate the risk inherent risk in a customer's payments over time, not using the actual payment data available will very likely provide far less than the optimum result.

3. What is the impact of the current economic downturn on the predictive capacity of scoring models? Specifically, do factors such as the mortgage industry crisis or fuel prices affect scorecard results?

A significant majority of the respondents (65.9%) indicated that the current economic conditions have affected their models predictiveness. And, 96.3% of those indicated that their models were less accurate in predicting delinquency or loss. One company indicated it had experienced a 50% negative increase and one company experienced a 100% negative increase in loss prediction or estimated bad rate. The balance of the responses ranged from negative increases of 2% to 25% and averaged about 15% in increased estimated bad rate. There was no indication of the specific factors that might have affected model accuracy.

PredictiveMetrics' Observation:

Based on PMI's experience, the decrease in model accuracy may not necessarily have been caused by the current economic downturn. A model measures credit worthiness, and in an economic downturn a model may evidence a decrease in credit worthiness through an increase in applicant bad rates over the through the door population (new applicants) or a decrease in the average applicant credit score indicating higher credit risk. Both of which would affect model results, but does not necessarily mean that the model is not working if the applicant population has become riskier. Furthermore, the use of Behavior Score technology (portfolio scoring models) would help to make a current assessment of any change in risk since origination. Additionally, models deteriorate over time, and if a model has not been revalidated within the last 12 to 18 months, it is possible that the model is no longer measuring credit risk accurately. Therefore, it may not be the economy that is the problem, but just a lack of proper model maintenance.

4. Are there specific trends, practices and industry controls that exist which will affect the nature of potential exposures that exist within the equipment leasing and finance industry?

Approximately 50% of the respondents answered this question affirmatively. Most frequently mentioned was that credit requirements are tightening and lenders are demanding more favorable transaction structures, and reduced exposure limits. Additionally:

•Companies have increased the percentage of manual reviews

•Certain marginal markets are not being serviced any more.

•Revalidation and adjustment of models is occurring on a more frequent basis.

PredictiveMetrics' Observation:

Our recent experience indicates that many of our clients are using two basic strategies to reduce their potential exposure to future loss:

•They are raising their auto-approval cut-off levels, thereby making it more difficult for riskier applicants to get credit without a manual review. This is very likely evidenced by the fact that 35% of the respondents who used statistical-based models indicated that auto-decline decisions were changed over 50% of the time by a manual review.

•A higher percentage of our clients are requesting that we perform model revalidations on a more frequent basis. Many of which result in either a model refit or a model re-estimation.

5. What are specific recommendations for remedial action in areas where such problems exist?

Respondents provided the following suggested actions to address critical problem areas:

•Increased use of business rules to ensure manual review of applications from businesses in stressed sectors.

•Require additional underwriting data (financial statements, credit references) for applications from businesses in stressed sectors.

•Redline industries at a more granular level. For example, 4-digit SIC rather than 2-digit industry segments at the filter level (i.e. 65xx - Real Estate whereas 4-digits distinguish between commercial and consumer real estate segments).

•For consumer models, rely less on off-the-shelf consumer-type scores.

•Develop new models using more current data, i.e., from this significant downturn as part of the basis. However, do not overly weight the history from the recession, as the future may not look like the recent past and that profitable lending opportunities in the future are not unnecessarily restricted.

•Additionally, use this as an opportunity to examine which factors have the greatest impact on losses during a downturn.

•Workout extensions for existing troubled customers, if possible.

•Aggressively monitor all significant exposures and take immediate action to protect the value of assets. These measures should vary based on the specific collateral and customer relationship.

•The industry should develop true peer group data similar to FDIC bank peer data to assist equipment finance firms in monitoring the quality of their portfolios, in general.

•More focus and reliance on collection staff efforts and tools to effectively manage portfolios and reduce delinquency/write-off roll rates.

•Change how rating agencies are compensated. The issuer who seeks a rating is paying the rating agency bill. The investor or conduit should be paying this bill thereby creating a more arms length transaction and ensuring that rating agencies are truly independent.

PredictiveMetrics' Observation:

If you are not doing proper credit model performance evaluation and you are not sure if a model is producing the desired results, you are going to have to revalidate it, and thereby determine whether or not you have a problem, and if so fix it by either a refit or a re-estimation.

For clarification purposes the refit process entails deriving new coefficients from the original model's specifications. This simply changes the underlying weights assigned to the same variables and is the most efficient way to restore a model's predictiveness and also minimizes a company's need for extensive changes to its credit underwriting systems. The refit is conducted using validation data provided by the company as specified in the original model specifications. Unfortunately, the refit process is not always successful and may not materially increase a model's predictiveness.

If a refit is not successful then a complete re-estimation is necessary. A re-estimation involves a complete new modeling effort beginning with using the validation sample to perform updated bivariate analysis and multivariate model estimation. The re-estimation will most likely result in both new variables and new weights being introduced into the model. This will require extensive re-programming on the part of the company and may lead to additional external cost for the purchase of archived bureau data. Therefore, unless re-estimation is required due to sufficient deterioration of overall predictiveness, the refit is the fastest and most economical method to restore predictiveness.

If a company is using judgmental-based models the refit/re-estimate process described above is not applicable. The least expensive way to control model results, in the case of judgmental-based models, would be to expand the use of manual reviews to all but the least risky applicants. Alternatively, a complete judgmental-based remodeling effort is required.

6. With respect to the future of credit models are there other factors, not usually included as model variables that should be considered for inclusion in future models?

Respondents did not provide much additional information. Specifically:

- Professional license information.
- News research. (Google and Hoover for example, would be good sources).
- Certificate of good standing.
- Competitive analysis

PredictiveMetrics' Observation:

In many of our models, we utilize various types of econometric and demographic data which are evaluated for applicability during the model development process. Many of these are leading indicators of economic behavior and can provide some additional predictiveness, particularly in times of rapid economic change.

7. What are the prevalent technologies utilized in developing credit models? And is any one technology superior and if so how?

Only 22.2% of the respondents indicated that they do not use any type of scoring model. For the other respondents the percentage using statistical-based vs. judgmental-based was roughly the same.

With respect to the use of statistical-based technologies: 51.5% are using logistic regression; 33.3% are using discriminant analysis; 9.1% are using other types of regression analysis and 9.1% are using genetic algorithms. Neural network technology was not mentioned by any of the respondents.

PredictiveMetrics' Observation:

As to which technology is superior, you can find professional statisticians that will line up behind each of them. In general, based on PMI's experience, if the technology is producing predicted results and you are comfortable with it, you'll probably not want to change.

And finally, the question that is the title of the report and the underlying reason for this survey:

8. How good is your scoring model?

As noted previously, only 36 of the respondents answered the question; "Does your company utilize some type of scheduled scoring performance evaluation system or methodology?" and only 21 indicated that they were performing some type of scheduled credit scoring performance evaluation. The implication of these responses is that 74.1% of the respondents are not evaluating their models' predictiveness on a regular basis.

PredictiveMetrics' Observation:

Given the above; it is possible that a significant majority of the survey respondents do not know how well their credit scoring models are performing. Furthermore, it is very likely that many industry members are not able to accurately measure the value- at-risk inherent in their portfolios. Additionally, it is not apparent that the respondents appreciate how regularly scheduled credit scoring performance evaluation can be used to improve model results.

Based on the assumption that this survey is an accurate depiction of the leasing industry, PMI believes that it would be to the industry's benefit for its members to be educated on the value of scheduled credit scoring performance evaluation. Whether the lessor is responsible to the OCC or not, the OCC recommendations, as briefly described in the introduction to Performance Evaluation Overview, should be considered for applicability by every lessor. If this practice is followed it will ensure that a company's' models are working properly and will provide significant additional confidence in model estimates. If the practice is not considered applicable than some other consistent performance evaluation process should be implemented that produces similar results.

If the OCC recommendations or similar systems are followed, the lessors will know exactly how good their models are, and be able to determine more accurately what the inherent risk is in their portfolios. It should be noted that to utilize a scoring performance evaluation system, it does not matter whether the lessor is using judgmental-based or statistical-based models as long as the models are applied consistently over time.

It is PMI's experience, however, that judgmental-based models are rarely evaluated because validation requires a significant background in statistics which the developers of judgmental models rarely possess. It is PMI's judgment that credit scoring models should be evaluated every 12 to 18 months as a reasonable way to ensure that a company's models are producing the desired results.

Additionally, many portfolios are evaluated by applying a company's credit model to its existing leases and developing current credit scores as the basis for determining the inherent risk in its portfolio. It should be noted, that if the model has not been properly validated and maintained, it is problematic as to how useful it is for directly evaluating current portfolio risk as the risk inherent in using the model may not be known.

Appendix A: About Predictivemetrics

Founded in 1995, PredictiveMetrics was established to provide higher-quality analytics and predictive scoring models in a customer oriented environment. Our customer focus is to work with you to create a strategic relationship ensuring your company's resources are optimally utilized to make automated, knowledge-based, profitable decisions that are proven accurate through statistical validation. We deliver you cost-effective solutions, on time, to specifications, requiring limited IT resources, with proven results. We are there before, during, and after the analytical process begins. PredictiveMetrics offers custom and/or industry specific statistical decision models for collections, debt buying, portfolio management, and underwriting. Our analytical staff, which is comprised of Ph.D. and masters level statisticians and econometricians, apply their data and statistical modeling expertise and combine it with advanced technology enabling our customers to continually improve their profit margins. We leverage internal performance data, data which is free and is proven to be the most powerful predictor of risk and collections, and blends it with external data when economically justified. PredictiveMetrics has proprietary software systems and state-of-the-art hardware designed specifically to conduct vigorous and sophisticated analytics. We offer our clients seamless implementation through secure FTP Internet or our web-hosted report and query system, ScoreMiner(SM), for portfolio management. Armed with the scientific knowledge, data expertise, technical qualifications, and systems capabilities, PredictiveMetrics provides the most unsurpassed predictive analytics in the market today!

PredictiveMetrics
Turning Probabilities into Profits™

Appendix B: Survey Questions and Responses

SURVEY DEMOGRAPHICS

1. Who Responded?

A total of 124 individuals responded to the survey. Their corporate function was:

Corporate Function	Percentage of Respondents
Officer	15.3%
Other Executive	16.9%
Credit	32.3%
Collections	5.6%
Risk	13.7%
Other	16.1%
	100.0%

2. Where Did the Respondents Come From?

The nature of the companies that responded was:

Nature of Instituton	Percentage of Respondents
BANK	24.3%
CAPTIVE	24.3%
INDEPENDENT, FINANCIAL SERVICES	51.4%
	100.0%

3. What Was the Market Segment That Most Closely Described the Majority of New Business Volume Represented By the Respondents?

Note: The "majority" of new business volume is not necessarily over 50% of the total new volume. For instance, if the company booked $120,000,000 in new business volume, of which $40,000,000 was in Small-Ticket, $50,000,000 in Middle-Ticket and $30,000,000 in Large-Ticket, the majority of the new business volume would be in the Middle-Ticket segment.

Majority Market Segment	Percentage of Respondents
MICRO-TICKET	14.9%
SMALL-TICKET	50.0%
MIDDDLE-TICKET	25.7%
LARGE-TICKET	9.5%
	100.0%

OVERVIEW OF MODEL USAGE

1. What was the distribution of credit scoring model usage among the respondents?

Model Usage	Percentage of Respondents
Statistical-based	16.7%
Judgmental-based	15.3%
Statistical-based and judgmental-based	45.8%
No scoring models	22.2%
	100.0%

2. Are different models used for "new credit applicants" then are used for "existing customers" applying for additional credit?

Response	Percentage of Respondents
Yes	32.4%
No	67.6%
	100.0%

3. Are separate models used that are designed to deal specifically with different lines of business?

Response	Percentage of Respondents
Yes	42.3%
No	57.7%
	100.0%

4. Are different models used as a function of the transaction size?

Response	Percentage of Respondents
Yes	43.1%
No	56.9%
	100.0%

5. Are models ever used to evaluate a transaction and/or line of business for which the model was not specifically designed?

Response	Percentage of Respondents
Yes	21.1%
No	78.9%
	100.0%

6. If you answered yes to the previous question, on average how would you compare the model's results when used for transactions for which it was not specifically designed?

Response	Percentage of Respondents
Better than usual	13.3%
About the same as usual	66.7%
A little bit worse than usual	20.0%
A lot worse than usual	0.0%
	100.0%

7. Is there any benefit or trade off in using generic pooled scorecards such as Paydex, FICO, D&B's Commercial Credit Score, etc., versus custom scorecards?

Response	Percentage of Respondents
Yes	65.7%
No	34.3%
	100.0%

8. Respondents that answered yes to the previous question, provided the following additional information:

The following were the most frequently mentioned benefits or reasons for using generic pooled scorecards:

- Provides additional input data in both judgmental and statistical-based custom models.
- Used to valuate smaller deals not covered by models.
- Good starting point, used as the basis for determining whether to submit for detailed financial review.
- Useful in business segments where prior history is not available.
- Used by smaller shops where the economic basis or volume to support the use of custom models does not exist.
- Useful as a benchmark to determine whether customer is performing above or below industry norms.
- Provides sufficient predictability for smaller portfolios where the cost of developing a custom model is a factor.

9. Based on the current economy, are you planning any changes to your current scoring methodology? Please check all that apply.

Response	Percentage of Respondents
Development of new scorecards	21.9%
Revalidation and adjustment of existing scorecards	42.2%
Increased reliance on manual/judgmental decisions	50.0%
Other	18.8%

10. Those who answered Other above, are planning to take one or more of the following actions:

- Raise cut-off score as a means of tightening credit.
- Increase due diligence and apply stricter manual and judgmental evaluation.
- Increase the amount of down payments.

STATISTICAL-BASED MODELS

These questions were answered by companies currently using statistical-based models. There were 38 respondents to the questions in this section.

1. What statistical modeling technology is utilized?

Technology Used	Percentage of Respondents
Logistic Regression	51.5%
Discriminant Analysis	33.3%
Other Types of Regression Analysis	9.1%
Neural Network Analysis	0.0%
Genetic Algorithms	9.1%
Other	18.2%

2. Those companies that answered Other indicated that they use the following technology:

- 67% use generic scorecards developed by Fair Isaac.
- One company indicated that they use reject inference.
- One company indicated they use another type of statistical-based predictive analysis, but did not want to specify the underlying technology.

3. For companies that utilized statistical-based models, the models were developed by:

Response	Percentage of Respondents
Internal modeling group	32.4%
Outside contractor	37.8%
Combination of both	29.7%
	100.0%

4. If a company utilized statistical-based scoring models, how many different models were used for credit decisioning?

Number of Models	Percentage of Respondents
1 to 5	73.7%
6 to 10	15.8%
11 to 20	2.6%
21 to 50	5.3%
> 50	2.6%
	100.0%

One company utilized more than 50 models, two companies utilized between 21 and 50 models and one company utilized between 11 and 20 models. The average number of models utilized by the remaining 34 respondents was between 3 and 4.

5. During fiscal year 2008, by transaction size, what percentage of the time were statistical-based models utilized to aid in credit evaluation?

Transaction Size	Percentage Models Utilized
Micro-Ticket -<$25,000	96.6%
Small-Ticket - $25,000 to $250,000	100.0%
Middle-Ticket - $250,000 to $5,000,000	62.5%
Large-Ticket - >$5,000,000	31.6%

6. Of the companies that use statistical-based models, what percentage utilizes auto-approval, auto-decline or both?

Response	Percentage of Respondents
Auto-approval only	23.7%
Auto-decline only	26.3%
Both	39.5%
No auto-decisioning	10.5%
	100.0%

Of the respondents, 89.5% utilize some form of auto-decisioning.

7. By transaction size, if the statistical-based scoring decision was positive, what percentage of the time was a manual review performed that might change the decision? It was assumed that if there was no manual review, the model's decision would stand, i.e., auto-approval was used.

	Percentage of Respondents				
Transaction Size	0% of the Time	>0% to 10% of the Time	>10% to 25% of the Time	>25% to 50% of the Time	>50% of the Time
Micro-Ticket - <$25,000	13.8%	34.5%	13.8%	3.4%	34.5%
Small-Ticket - $25,000 to $250,000	6.1%	30.3%	12.1%	12.1%	39.4%
Middle-Ticket - $250,000 to $5,000,000	20.0%	10.0%	5.0%	5.0%	60.0%
Large-Ticket ->$5,000,000	38.5%	0.0%	7.7%	7.7%	46.2%
Total	15.8%	23.2%	10.5%	7.4%	43.2%

8. For existing customers, what is the maximum portfolio exposure that a respondent was willing to risk based on an auto-approval decision of a statistical-based model?

Maximum Portfolio Exposure ($)	Percentage of Respondents
0	37.5%
>0 to 50,000	8.3%
>50,000 to 100,000	29.2%
>100,000 to 500,000	8.3%
>500,000 to 1,000,000	16.7%
	100.0%

9. For new applicants, what is the maximum transaction value that a respondent was willing to risk based on an auto-approval decision of a statistical-based model?

Maximum Portfolio Exposure ($)	Percentage of Respondents
0	37.5%
>0 to 50,000	12.5%
>50,000 to 100,000	25.0%
>100,000 to 500,000	25.0%
	100.0%

10. By transaction size, if the statistical-based scoring decision was positive, what percentage of the time did the manual review change the model's decision?

	Percentage of Respondents				
Transaction Size	0% of the Time	>0% to 10% of theTime	>10% to 25% of the Time	>25% to 50% of theTime	>50% of theTime
Micro-Ticket - <$25,000	6.9%	55.2%	24.1%	6.9%	6.9%
Small-Ticket - $25,000 to $250,000	3.2%	58.1%	22.6%	9.7%	9.7%
Middle-Ticket - $250,000 to $5,000,000	25.0%	30.0%	25.0%	10.0%	10.0%
Large-Ticket ->$5,000,000	46.2%	15.4%	7.7%	23.1%	23.1%
Total	15.1%	45.2%	21.5%	7.5%	10.8%

11. If a company used statistical-based models and auto-decisioning, have they adjusted the cut-off upward as a method of tightening credit, during the last twelve months?

Response	Percentage of Respondents
Yes	37.9%
No	62.1%
	100.0%

12. If a company answered yes to the previous question, what percent decrease in positive auto-decisions has occurred?

The responses were evenly distributed from 5% to 25% decrease in positive auto-approvals with no apparent central tendency, that is about the same number were above as were below a 15% decease. There was one outlier of approximately 90%. As expected, increasing the cut-off will definitely have a material impact in that it will significantly reduce the amount of credit granted by auto-approvals.

13. By transaction size, if the statistical-based scoring decision is negative, what percentage of the time is a manual review performed that might change the decision?

Transaction Size	0% of the Time	>0% to 10% of the Time	>10% to 25% of the Time	>25% to 50% of the Time	>50% of the Time
Micro-Ticket - <$25,000	6.5%	38.7%	22.6%	6.5%	25.8%
Small-Ticket - $25,000 to $250,000	0.0%	42.4%	12.1%	15.2%	30.3%
Middle-Ticket - $250,000 to $5,000,000	18.2%	18.2%	0.0%	13.6%	50.0%
Large-Ticket ->$5,000,000	42.9%	7.1%	0.0%	7.1%	42.9%
Total	12.0%	31.0%	11.0%	11.0%	35.0%

14. By transaction size, if the statistical-based scoring decision was negative, what percentage of the time did the manual review change the model's decision?

	Percentage of Respondents				
Transaction Size	0% of the Time	>0% to 10% of the Time	>10% to 25% of the Time	>25% to 50% of the Time	>50% of the Time
Micro-Ticket - <$25,000	6.5%	67.7%	12.9%	6.5%	6.5%
Small-Ticket - $25,000 to $250,000	0.0%	66.7%	18.2%	9.1%	6.1%
Middle-Ticket - $250,000 to $5,000,000	20.0%	40.0%	10.0%	20.0%	10.0%
Large-Ticket ->$5,000,000	53.8%	15.4%	7.7%	7.7%	15.4%
Total	13.4%	54.6%	13.4%	10.3%	8.2%

JUDGMENTAL-BASED MODELS

These questions were answered by companies currently using judgmental-based models. There were 35 respondents to the questions in this section.

1. For companies that utilized judgmental-based models, the models were developed by:

Response	Percentage of Respondents
Internal senior risk management/credit staff	68.6%
Outside contractor	5.7%
Combination of both	25.7%
	100.0%

2. If a company utilized judgmental-based scoring models, how many different models were used for credit decisioning?

Number of Models	Percentage of Respondents
1 to 5	90.9%
6 to 10	3.0%
11 to 20	3.0%
21 to 50	3.0%
> 50	0.0%
	100.0%

3. During fiscal year 2008, by transaction size, what percentage of the time were judgmental-based models utilized to aid in credit evaluation?

Transaction Size	Percentage Models Utilized
Micro-Ticket -<$25,000	86.7%
Small-Ticket - $25,000 to $250,000	88.2%
Middle-Ticket - $250,000 to $5,000,000	62.5%
Large-Ticket - >$5,000,000	36.8%

4. By transaction size, if the judgmental-based scoring decision was positive, what percentage of the time was a manual review performed that might change the decision? It was assumed that if there was no manual review, the model's decision would stand, i.e., auto-approval was used.

	Percentage of Respondents				
Transaction Size	0% of the Time	>0% to 10% of theTime	>10% to 25% of the Time	>25% to 50% of theTime	>50% of theTime
Micro-Ticket - <$25,000	13.8%	34.5%	13.8%	6.9%	31.0%
Small-Ticket - $25,000 to $250,000	6.7%	36.7%	3.3%	13.3%	40.0%
Middle-Ticket - $250,000 to $5,000,000	17.4%	13.0%	4.3%	17.4%	47.8%
Large-Ticket ->$5,000,000	41.2%	11.8%	0.0%	11.8%	35.3%
Total	17.2%	26.3%	6.1%	12.1%	38.4%

5. For existing customers, what is the maximum portfolio exposure that a respondent was willing to risk based on an auto-approval decision of a judgmental-based model?

Maximum Portfolio Exposure ($)	Percentage of Respondents
0	47.8%
>0 to 50,000	17.4%
>50,000 to 100,000	13.0%
>100,000 to 500,000	17.4%
>500,000 to 1,000,000	4.3%
	100.0%

6. For new applicants, what is the maximum portfolio exposure that a respondent was willing to risk based on an auto-approval decision of a judgmental-based model?

Maximum Portfolio Exposure ($)	Percentage of Respondents
0	45.5%
>0 to 50,000	27.3%
>50,000 to 100,000	4.5%
>100,000 to 500,000	22.7%
>500,000 to 1,000,000	0.0%
	100.0%

7. By transaction size, if the judgmental-based scoring decision was positive, what percentage of the time did the manual review change the model's decision?

	Percentage of Respondents				
Transaction Size	0% of the Time	>0% to 10% of the Time	>10% to 25% of the Time	>25% to 50% of the Time	>50% of the Time
Micro-Ticket - <$25,000	10.3%	62.1%	17.2%	6.9%	3.4%
Small-Ticket - $25,000 to $250,000	6.7%	56.7%	20.0%	13.3%	3.3%
Middle-Ticket - $250,000 to $5,000,000	26.1%	30.4%	13.0%	21.7%	8.7%
Large-Ticket ->$5,000,000	50.0%	12.5%	12.5%	6.3%	18.8%
Total	19.4%	44.9%	16.3%	12.2%	7.1%

8. If a company used judgmental-based models and auto-decisioning, have they adjusted the cut-off upward as a method of tightening credit, during the last twelve months?

Response	Percentage of Respondents
Yes	30.8%
No	69.2%
	100.0%

9. If a company answered yes to the previous question, what percent decrease in positive auto-decisions has occurred?

There were too few responses to this question for us to present a definitive answer. The answers that were received ranged from a 10% to 25% decrease.

10. By transaction size, if the judgmental-based scoring decision is negative, what percentage of the time was a manual review performed that might change the decision?

	Percentage of Respondents				
Transaction Size	0% of the Time	>0% to 10% of the Time	>10% to 25% of the Time	>25% to 50% of the Time	>50% of the Time
Micro-Ticket - <$25,000	13.3%	36.7%	13.3%	10.0%	26.7%
Small-Ticket - $25,000 to $250,000	6.3%	34.4%	15.6%	12.5%	31.3%
Middle-Ticket - $250,000 to $5,000,000	39.1%	8.7%	8.7%	13.0%	30.4%
Large-Ticket ->$5,000,000	55.6%	11.1%	0.0%	11.1%	22.2%
Total	24.3%	25.2%	10.7%	11.7%	28.2%

11. By transaction size, if the judgmental-based scoring decision was negative, what percentage of the time did the manual review change the model's decision?

	Percentage of Respondents				
Transaction Size	0% of the Time	>0% to 10% of the Time	>10% to 25% of the Time	>25% to 50% of the Time	>50% of the Time
Micro-Ticket - <$25,000	13.3%	53.3%	10.0%	13.3%	10.0%
Small-Ticket - $25,000 to $250,000	6.5%	58.1%	16.1%	9.7%	9.7%
Middle-Ticket - $250,000 to $5,000,000	36.4%	31.8%	9.1%	13.6%	9.1%
Large-Ticket ->$5,000,000	52.9%	17.6%	11.8%	5.9%	11.8%
Total	23.0%	44.0%	12.0%	11.0%	10.0%

GENERAL MODEL QUESTIONS

1. Have leasers found, during the last twelve months, that current economic conditions have affected their credit scoring models' predictiveness?

Response	Percentage of Respondents
Yes	65.9%
No	34.1%
	100.0%

2. Of those companies that answered yes above, have their models been more or less accurate in predicting delinquency or loss?

Response	Percentage of Respondents
More accurate	3.7%
Less accurate	96.3%
	100.0%

3. Given that the accuracy of models has been affected, what has been the positive or negative percent change in predicting delinquency or loss?

The impact of the change in model accuracy ran the entire gamut from one company indicating they had no discernable change in accuracy of loss prediction or estimated bad rate to one company indicating they had experienced a 50% negative increase and one company experiencing a 100% negative increase in loss prediction. The balance of the responses ranged from negative increases of 2% to 25% and averaged about 15% in increased estimated bad rate.

4. Are there are specific trends, practices and industry controls in existence which will effect delinquency and loss rates within the equipment leasing and finance industry?

Response	Percentage of Respondents
Yes	47.6%
No	52.4%
	100.0%

6. The companies that answered yes to the above question cited the following:

- Most frequently mentioned was that credit requirements are tightening and lenders are demanding more favorable transaction structures, and reduced exposure limits.
- Some companies noted that additional manual review was occurring.
- Additionally, marginal markets are being exited.
- Revalidation and adjustment of models is more prevalent.

7. As a follow-up to the above, certain companies provided the following thoughts for remedial action in areas where problems were perceived:

- Increased use of business rules to ensure manual review of applications from businesses in stressed sectors. Also, increased requirements for additional underwriting data (financial statements, credit references) for applications from businesses in stressed sectors.
- Redlining industries at a more granular level - For example 4-digit SIC rather than 2-digit industry segments at the filter level (i.e. 65xx - Real Estate whereas 4-digits distinguish between commercial and consumer real estate segments). For consumer models, rely less on off-the-shelf FICO-type scores.
- Developing new models using data from this significant downturn as part of the basis. Try not to overly weight the history from this recession, as the future may not look like the recent past so that profitable lending opportunities in the future are not unnecessarily restricted. Additionally, use this as an opportunity to examine which factors have the greatest impact on losses during a downturn.
- Workout extensions for existing troubled customers, if possible.
- Aggressively monitor all significant exposures and take immediate action to protect the value of assets. These measures may vary based on the specific collateral and customer relationship. Additionally, it would be advisable for the industry to develop true peer group data similar to FDIC bank peer data to assist equipment finance firms in monitoring the quality of their portfolios in general.
- More focus and reliance on collection staff efforts and tools to effectively manage portfolios and reduce delinquency/write-off roll rates.
- One of the biggest problems from an issuing standpoint is how rating agencies are compensated. The issuer who seeks a rating is paying their bill. I believe it should be the investor or conduit that should be paying this bill to create a more arms length transaction and ensure the rating agencies are working in their best interest and not the issuers.

8. Are there any new generic scores that are available or under development that might be applicable to the equipment leasing industry?

Response	Percentage of Respondents
Yes	23.3%
No	76.7%
	100.0%

9. Those companies that answered yes above, said the following were new capabilities available to the industry:

- Additional Paynet functionality.
- New products from D&B.
- Oliver Wyman LGD studies.
- PMI's revised LeaseRiskScore.

10. Of the companies that responded, what percent provide application only leases, i.e., additional financial information is not required?

Response	Percentage of Respondents
Yes	82.2%
No	17.8%
	100.0%

11. Of those companies that provide application only leases, what is the maximum dollar exposure they will accept?

Maximum Portfolio Exposure ($)	Percentage of Respondents
0	4.2%
>0 to 50,000	12.5%
>50,000 to 100,000	41.7%
>100,000 to 500,000	37.5%
>500,000 to 1,000,000	4.2%
	100.0%

12. Of those companies that provide application only leases, how has the number of requests changed over the last year?

Response	Percentage of Respondents
Significant increase	22.9%
Significant decrease	8.6%
No significant change	68.6%
	100.1%

13. Of the companies that responded, what percent provide deferred payment programs?

Response	Percentage of Respondents
Yes	59.1%
No	40.9%
	100.0%

14. Of those companies that provide deferred payment programs, what is the maximum dollar exposure they will accept?

Maximum Portfolio Exposure ($)	Percentage of Respondents
0	0.0%
>0 to 50,000	16.7%
>50,000 to 100,000	16.7%
>100,000 to 500,000	41.7%
>500,000 to 1,000,000	8.3%
>1,00,000 to 5,000,000	8.3%
>5,000,000	8.3%
	100.0%

15. Of those companies that provide deferred payment programs, how has the number of requests changed over the last year?

Response	Percentage of Respondents
Significant increase	25.0%
Significant decrease	4.2%
No significant change	70.8%
	100.0%

16. Of the companies that responded, what percent provide step-up payment programs?

Response	Percentage of Respondents
Yes	45.0%
No	55.0%
	100.0%

17. Of those companies that provide step-up payment programs, what is the maximum dollar exposure they will accept?

Maximum Portfolio Exposure ($)	Percentage of Respondents
0	0.0%
>0 to 50,000	12.5%
>50,000 to 100,000	25.0%
>100,000 to 500,000	37.5%
>500,000 to 1,000,000	0.0%
>1,00,000 to 5,000,000	0.0%
>5,000,000	25.0%
	100.0%

18. Of those companies that provide step-up payment programs, how has the number of requests changed over the last year?

Response	Percentage of Respondents
Significant increase	5.0%
Significant decrease	0.0%
No significant change	95.0%
	100.0%

19. Of the companies that responded, what percent provide no money down payment programs?

Response	Percentage of Respondents
Yes	48.8%
No	51.2%
	100.0%

20. Of those companies that provide no money payment programs, what is the maximum dollar exposure they will accept?

Maximum Portfolio Exposure ($)	Percentage of Respondents
0	0.0%
>0 to 50,000	11.1%
>50,000 to 100,000	22.2%
>100,000 to 500,000	44.4%
>500,000 to 1,000,000	0.0%
>1,00,000 to 5,000,000	11.1%
>5,000,000	11.1%
	100.0%

21. Of those companies that provide no money down payment programs, how has the number of requests changed over the last year?

Response	Percentage of Respondents
Significant increase	0.0%
Significant decrease	5.3%
No significant change	94.7%
	100.0%

MODEL VARIABLES – WHAT'S IMPORTANT?

1. What data sources do respondents include in New Applicant models?

Response	Percentage of Respondents
Internal Data	73.2%
Commercial Bureau Data	82.9%
Consumer Bureau Data	82.9%
Financial Statement Data	56.1%

2. Are other variable sources included in New Applicant models that are not mentioned in the above classifications?

Response	Percentage of Respondents
Yes	31.7%
No	68.3%
	100.0%

3. The respondents that answered yes, indicated that these other data sources and types of variables are used in their New Applicant credit evaluations:

- Specific professional licenses information.
- News research.
- Certificate of Good Standing.
- Competitive analysis.

4. What data sources do respondents include in Existing Customer models?

Response	Percentage of Respondents
Internal Data	90.2%
Commercial Bureau Data	78.0%
Consumer Bureau Data	80.5%
Financial Statement Data	53.7%

5. Are other variable sources included in Existing Customer models that are not mentioned in the above classifications?

Response	Percentage of Respondents
Yes	26.8%
No	73.2%
	100.0%

6. The respondents that answered yes, indicated that these other data sources and types of variables are used in their Existing Customer credit evaluations:

- News research
- Collateral value
- Competitive analysis

7. Of the variables used in the respondent's models, these five specific variables were most frequently represented in their models:

Variable	Percentage of Occurrence
Time in Business	75.8%
Payment History	39.4%
FICO	39.4%
Paydex	18.2%
Paynet	9.1%

8. Has the importance of the most critical five variables listed by respondents changed over the last two years?

	Percentage of Respondents		
Variable	No Change	Little Change	Significant Change
Variable 1	46.9%	31.3%	21.9%
Variable 2	45.2%	32.3%	22.6%
Variable 3	41.4%	44.8%	13.8%
Variable 4	33.3%	44.4%	22.2%
Variable 5	41.7%	50.0%	8.3%
Total	42.0%	39.9%	18.2%

PERFORMANCE EVALUATION

1. Does your company utilize some type of scheduled Performance Evaluation system or methodology?

Response	Percentage of Respondents
Yes	58.3%
No	41.7%
	100.0%

This question was answered by only 36 of the respondents, only 21 of which indicated that they were performing some type of scheduled Performance Evaluation.

2. Is the Performance Evaluation performed by individuals who are independent, in other words not the original model developers?

Response	Percentage of Respondents
Yes	71.4%
No	28.6%
	100.0%

3. How frequently do the respondents evaluate their models?

Evaluation Frequency	Percentage of Models
Every 6 months or less	22.4%
Every 6 to 12 months	28.6%
Every 12 to 24 months	24.5%
Every 24 to 36 months	12.2%
Greater than 36 months or never	12.2%
	100.0%

4. What reports are contained in the Performance Evaluation system?

Response	Percentage of Respondents
Only front-end reports	0.0%
Only back-end reports	9.5%
Both	90.5%
	100.0%

5. One way of determining how well a model is performing is to compare its development sample bad rate to its validation sample bad rate. (For example, if the development sample bad rate was 8.0% and the validation sample bad rate is 10.0%, the change would be -2.0%/8.0% or -25%).

Percentage Difference	Percentage of Models
>30%	6.3%
>5 to 30%	18.8%
>0% to 5%	18.8%
0% to -5%	31.3%
<--5% to -30%	18.8%
<-30%	6.3%
	100.0%

Unfortunately only 10 respondents answered this question. So, we cannot state with any assurance that these results are representative of how models are performing. Here, only 50.1% of the models were evidencing a difference between the development sample bad rate and the validation sample bad rate of between 5% and -5% which might indicate that the other 49.9% of the models need to be modified (refitted) with respect to the weights of certain variables or if the percent difference is very large completely re-estimated.

6. Another way to determine how well a model is performing is to compare the average credit score in the development sample to the average credit score in the validation samples.

Nature of Difference	Percentage of Models
Decrease in average risk, i.e., there was an increase in the average credit score of applicants in the validation samples relative to development samples	23.1%
Increase in average risk, i.e., there was a decrease in the average credit score of applicants in the validation samples relative to development samples	30.8%
Small/No Change in average risk, i.e., neither an increase or decrease in credit average score	46.2%
	100.0%

These results are consistent with the previous question in that about half the models are showing little change in the average risk score and half are evidencing a measurable difference. Again, the response was small, only 17 respondents, so we can not state with any assurance that this represents a population trend.

7. For those models that evidenced a decrease or increase in the average score of applicants between development and validation samples, what was the average percentage change in risk observed?

	Percent of Models		
Nature of Change	0% to 20%	>20% to 40%	Total
Decrease in average risk	85.7%	14.3%	100.0%
Increase in average risk	77.8%	22.2%	100.0%

Again, the number of respondents was small so no population characteristic can be projected.

8. Fifteen companies that indicated that they do not have some type of formal Performance Evaluation System indicated that they use the following procedures to determine how well their models are performing:

- Performing a static pool analysis. This is a procedure where a pool of loans from a specific time period has on-going analysis conducted upon it. Analysis would examine such things as delinquency, prepayments and rate of return and, thereby, provide a true return on a pool of loans.
- Independent portfolio analysis by an outside contractor.
- Use of monthly and historical delinquency data/loss data to monitor applications that were approved under application only guidelines.
- Review samples of non-performing loans and evaluate various factors such as geographic location, time in business and commercial/personal credit scores to determine if any of them could have predicted the lease defaulting. If it appears that there is one major factor is occurring quite often then the credit decision model could be changed accordingly.
- Utilize a tracking report that measures population stability and model characteristic analysis also checks that the score, and its component elements, are rank ordering risk.
- Analyze actual vs. predicted loan results over time.
- Perform an analysis each quarter utilizing a system developed in-house.
- Review of delinquencies and repossessions.
- Evaluate each incident of loss to understand what went wrong in the underwriting and modify their risk tolerance for the specific category of customer or asset category. Additionally, look at portfolio composition quarterly and monitor exposures.
- Perform various types of internal analyses, such as profit margin and delinquency based on FICO, balance, equipment, and equipment supplier.
- Evaluate portfolio performance within various credit score ranges.

2009 Credit Scoring Model Study Steering Committee

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