Predictive Analytics:

Increasing Profitability, Managing Risk, and Enhancing Customer Satisfaction

EQUIPMENT LEASING & FINANCE
FOUNDATION
Your Eye On The Future

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.

Equipment Leasing & Finance Foundation

1825 K Street • Suite 900

Washington, DC 20006

www.leasefoundation.org

202-238-3429

Kelli Jones Nienaber, Executive Director

Foreword

As an industry, equipment leasing and finance continually faces change in its business environment, change it sometimes embraces and sometimes grudgingly accepts. Industry members have traditionally used various methods of analysis to help them make critical decisions while navigating these changes. Yet, we now have an opportunity to improve our decision-making by gathering, analyzing, and using more effectively the vast amounts of information at our disposal.

Equipment financiers have more data today than ever. Yet, the use of this data in decision-making has not changed appreciably in that analysis continues to be based on some form of financial-statement output. This is where the growing use of business intelligence comes in as executives gather and process large amounts of data and quantify, analyze, and deliver sophisticated reports in real time.

Predictive analytics represents the next step in the evolution of business intelligence. It is also critical to becoming a knowledge-based company – a company with knowledge of customers, risks and opportunities. This study allows readers to preview the processes and expertise necessary to implement predictive analytics and benefit from the competitive advantages they can create. In our view, equipment finance companies that proactively embrace predictive analytics and its uses are the ones that will be rewarded in the marketplace.

John Deane
Chief Executive Officer
The Alta Group

The Alta Group℠

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Executive Summary

Predictive analytics is an evolving branch of informatics, or information science that considers and analyzes large amounts of data to help firms better manage risk, improve operations, increase profitability, and make more insightful decisions. Equipment leasing and finance firms can apply predictive analytics to become knowledge-based companies that create competitive advantage through improved decision-making.

To achieve its results, predictive analytics employs a variety of statistical techniques that identify and validate correlations between outcomes and causative variables. Use of these techniques requires enabling technologies and knowledge of applicable markets. In return, predictive analytics allows users to model the future under varying assumptions, in each instance answering the critical question, "What if?"

Applying predictive analytics is not simply a matter of data or the technologies to analyze it, however. The ability to extract useful information from data and make sound decisions based on it is what creates predictive analytics' value. Developing this ability requires corporate commitment, financial resources and highly specialized skills.

As of late 2012, equipment leasing and finance firms surveyed for this study reported applying predictive analytics in three areas of functionality: credit scoring, residual management and portfolio management. Application in credit scoring was reported as most developed.

Industry processes for managing asset/collateral risk were not well enough aligned at the time of the study to leverage the benefits of predictive analytics, and thus, the study suggests actions firms can take to alleviate this situation. This is fitting, since surveyed firms indicated that they expect their use of predictive analytics to increase in the coming year, most by leveraging extant capabilities and personnel. Such an approach should help firms realize early on two primary benefits of predictive analytics: increased efficiencies and reduced costs.

Given predictive analytics' shift away from management's traditional focus on experiential intuition and past performance, it is important to note that a company's leadership and culture play key roles in the creation of a successful predictive analytics program. As one survey respondent observed, "It still takes people to implement a predictive analytics program, no matter how good the informatics."

The study answers many questions about the use of predictive analytics within the equipment finance industry. Yet one vital question remains unanswered: "Will the industry and individual firms within it embrace predictive analytics and apply it to create a competitive edge?" We hope so. But only time will tell.

About the Study

Businesses have always used analysis to help them make the best decisions possible when faced with a given set of facts or assumptions. Applying a range of tools from handwritten spreadsheets to sophisticated software solutions, companies have separated information into multiple components and then examined and evaluated those components in an effort to maximize profitability and enhance customer satisfaction.

At its most basic, information analysis today takes the form of financial statements and footnotes on those statements that explain certain aspects of a company's operations. At a more complex level, information analysis encompasses a broad range of metrics displayed on electronic "dashboards" and known as "business intelligence." Business intelligence is based primarily on historical data and helps firms understand past performance and trends. Predictive analytics is the next generation of business intelligence, leveraging massive amounts of data to predict future performance and trends, allowing businesses to make better-informed decisions.

In the context of deploying this evolving management tool, the Equipment Leasing and Finance Foundation ("the Foundation") established this Study. Through it, the Foundation seeks to identify ways in which companies can use predictive analytics to produce information that can be used to make meaningful business decisions. The Study also considers predictive analytics' impact upon current industry processes, and discusses how "PA," as we shall sometimes refer to it, can be effectively implemented from a business process and technology perspective. The study also examines the potential benefits that might be expected.

The study further focuses on ways equipment leasing and finance companies are already processing and leveraging their data through predictive analytics. These insights are reinforced through practical application of the concepts embodied in the research, and further enhanced through collaboration with industry leaders in the analytics space that currently offer such services.[1]

In the Foundation's view, the key questions every lessor or lender must ask are two: "How can I use predictive analytics to make better decisions?" and "How are my competitors using this powerful data-management tool?" We hope the study will help answer these questions for equipment leasing and finance organizations large and small, both of which contribute significantly to the formation of capital, the success of other businesses, and growth of the U.S. economy as a whole.

[1]Additional information on the Study research resources and project partners can be found in **Appendix Three**.

A Business Intelligence Primer

Much business analysis is based on information contained in financial statements. Making sense of this output, which may come to management as pieces of a jigsaw puzzle, is difficult, because it does not come with a big-picture perspective.

In recent years, however, business intelligence has been employed to reveal not only the big picture, but details behind key drivers of the business. Such detail is critical for employees undertaking investigative analyses of the data in the form of drill-downs, aggregations, correlations and other techniques.

Companies create business intelligence by combining information, data, business models, and human insights. They use tools that include standalone or embedded software systems, existing databases, and presentation capabilities tailored to the users' needs. Loosely speaking, this intelligence may be analytical, predictive, or both, and uses internal information to analyze metrics like financial performance, risk, or operational efficiencies. It then is used to facilitate improved and agile decision-making, helping maximize company performance and market position.

Unlike traditional management information, business intelligence combines data from numerous sources and multiple perspectives to provide a single, overarching version of the truth. This approach provides a holistic view of the business and the integrated analysis that supports the strategic management process.

Traditionally, reporting and analysis of financial and operational data was a manual process that combined multiple data sources. The process created accuracy issues due to rekeying data, and compatibility problems when attempting to merge different sources. Business intelligence automates this process, extracting source data, compiling reports and analyses, and creating important benefits that include quicker report issuance, repeatable processes and superior distribution mechanisms.

Activities inherent in the business intelligence process include monitoring performance, such as profitability; how well the sales force is aligned with profitable opportunities; and analyzing the effectiveness of vendor or broker programs. Activities also involve modeling and managing processes, the most recognizable of which in equipment leasing and finance is credit scoring. Companies may choose to use data-mining techniques, stochastic analysis, predictive analysis, modeling, or a combination of these methods to examine large volumes of data to forecast trends.

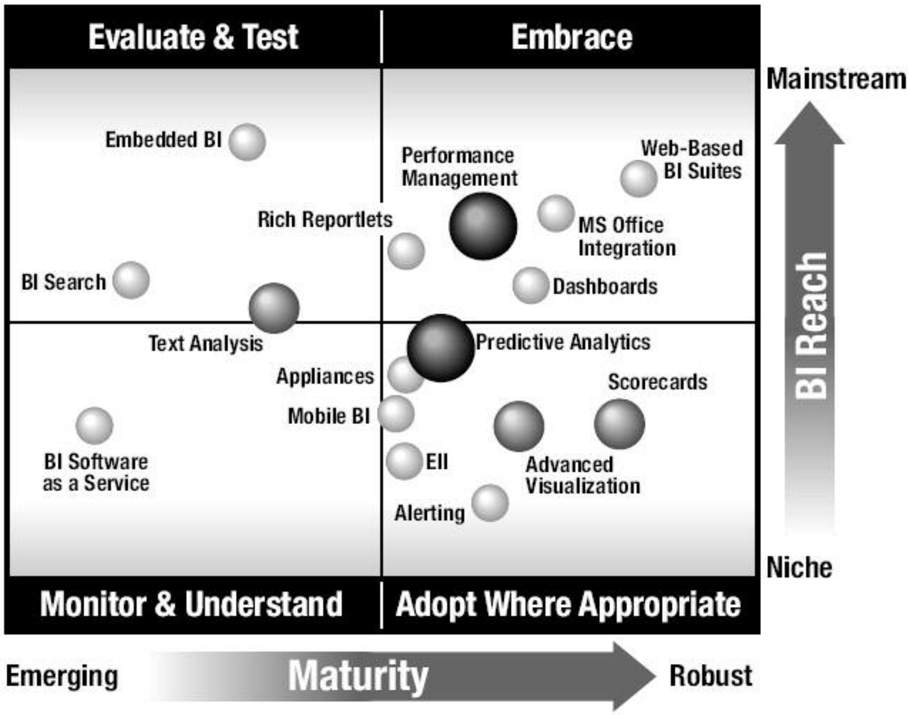
According to the ELFA 2011 Business Technology Performance Index ("BTPI"), organizations surveyed use several business intelligence tools, and a majority aggregate and report data from a data warehouse or other repository of multiple core applications. More than 25% do not use a business intelligence tool, however, choosing instead to manually construct reports from the output of various applications.

Top factors driving the use of business intelligence that were identified in the BTPI are business effectiveness, cost reduction, customer expectations, risk reduction, and statutory obligations, such as bank-reporting requirements. Barriers to using business intelligence include data availability, staff skills and training, user culture, lack of trust, and, to a lesser extent, business processes and organization. **Figure 1**[2] illustrates the evolutionary path a company may travel as it creates a robust and mainstream business intelligence

[2] *Business Intelligence: The Key to Enhanced Profitability*, Paul Bent, Richard Ryan, Scott Thacker, James McKinney, and Michael Donnary, ELFA Annual Convention, October 25, 2011

competency. Also noted are certain tools and capabilities that are required. As can be seen in **Figure 1**, predictive analytics is a component of business intelligence used to make predictions of future behaviors and outcomes. Through its mathematical and statistical methods, predictive analytics represents another step forward in businesses' quest to exploit available information.

Figure 1: Adopting Business Intelligence



The Role of Predictive Analytics

Predictive analytics is thought of more in terms of arcane methodologies than Academy Award-nominated motion pictures. But the film "Moneyball" is a case study in predictive analytics. The movie chronicles how the revenue-constrained Oakland A's assembled a winning team by using performance indicators that defied conventional baseball wisdom and experience. Those performance indicators, or scores in this case, were based on statistical models and a data-driven approach – predictive analytics, in other words.

Although predictive analytics incorporates many of the characteristics of business intelligence, there are differences. **Figure 2** highlights some of these differences and represents the evolution of financial reporting to predictive analytics.

Figure 2
Evolution of Predictive Analytics

Financial reporting

- Historical and internal focus
- Experiential-based
- Flat or silo view of the business
- Multiple sources of the truth
- Tools sort, filter, and summarize data
- Format defined by the systems that produce it
- Supports managing individual business processes
- Proves core systems reconcile and add up
- Monitors activity

Business intelligence

- Integration of external data
- Drill-down reporting and quantification of interrelationships
- 360° view of the business at all levels
- Single source of the truth
- Format defined by the needs of the user
- Supports managing the business as a whole
- Driven by the needs of the business
- Evaluates activity from a strategic perspective
- Answers "Why?"

Predictive analytics

- Forward-looking science
- Predictive models and forecasting tools
- Time series analysis determines trends
- Statistical analysis predicts probability of outcomes
- Correlates multiple sources of data
- Identifies anomalies in data
- Answers "What if?"

Predictive analytics encompasses a variety of statistical techniques that analyze current, historical, economic, and even unstructured data such as texts and pictures. This information is used to identify risks and opportunities and capture relationships among various factors. The results of the analyses are used to make more accurate predictions about future events and to exploit patterns found in that data, thereby resulting in better decision making.

A key difference between predictive analytics and traditional decision making is the nature of the information being considered. Financial statement analysis, for example, looks backwards to determine what happened in the past, and often results in decisions being reactive to that past. Predictive analytics helps management look forward and assess how to address future events such as expected customer behavior.

Predictive analytics also requires a range of enabling technologies and detailed knowledge of the applicable markets. Although advances in technology and computer processing power have enabled development of powerful predictive models and the processing of large volumes of data, simply having the technologies to gather, analyze, and store data is not enough for success.

The value of predictive analytics

Predictive analytics is receiving increasing scrutiny within the equipment leasing and finance industry as finance companies evolve into knowledge-based organizations. Improved information within these organizations allows both executives and front-line staff to make better commercial judgments. This knowledge includes having the right data to glean the best information about one's customers, competitors, and own company, and is essential to generating additional revenue and growth in a competitive environment.

Given today's pressure to achieve more results with fewer resources, companies now must work even harder to eliminate inefficiencies. Access to up-to-the-minute information about customers, operations, funding sources, competitors, and markets is essential to accomplishing this. Applying predictive analytics to this information can assist businesses in turning this data into a competitive advantage.

While there is much to be said about the value of experience, the pace and complexity of today's business environment, along with the massive amounts of data that can be analyzed, require a more dynamic method of making decisions. Predictive analytics helps increase the agility of the decision-making. In traditional analytical decision-making, data is collected, synthesized, and passed to top management, who then must absorb it, formulate responses and disseminate strategies and directives back through the reporting channel.

Markets are shifting too quickly today for this form of decision-making to be effective. The speed to market that predictive analytics helps facilitate is a very real competitive advantage. A good example of this benefit is the equipment finance provider's ability to credit-score a vendor's customer in minutes, thereby taking the transaction off the street and solidifying the vendor's sale. By doing so, the company increases its value to the vendor partner and creates a stronger and longer-lasting relationship.

What's more, predictive models can help companies understand their customers by segmenting them into groups based on measures that matter to the business. Best Buy was able to determine through analyzing customer data that 7% of its customers were responsible for 43% of its sales.[3] This information allowed Best Buy to segment its customers and design marketing programs and retail environments appropriate to each segment.

"The speed to market that predictive analytics helps facilitate is another, very real competitive advantage."

Similarly, equipment finance companies can use segmentation to launch product campaigns or promotions. A company might identify distinct marketing segments based on scores that consider a combination of credit performance, required capital and profitability. The firm could then develop models to reflect the outcomes of these scored customer behaviors. Once predictive outcomes are generated, the customer segment with the highest, potential risk-adjusted return on capital could be assigned a salesperson for a personal visit. The moderately profitable group might be mailed a promotional piece, followed by a telephone call, while the least profitable group might receive an email with a link to the company's website.

Another application of predictive analytics in the equipment leasing and finance space is market forecasting. In a recent project, a finance company client was concerned about the direction of new business, given the volatility and uncertainty of the economy. The finance company wanted to use available internal data and external factors to predict potential demand in order to set investment priorities and identify growth markets.

The company incorporated a multidimensional design into the analysis. Dimensions included asset categories, metrics such as new volumes and market share, external markers like Gross Domestic Product ("GDP") and inflation rates, and the time series for both historical and forecast data. Based on this information and its goals, the company developed a model that allowed it to predict future new volumes by asset

[3]*Why Predictive Analytics Is A Game-Changer,* Dave Rich and Jeanne G. Harris, Forbes.com, April 1, 2010.

category and by market. The model also allowed the company to analyze the effect of changes in external factors on that new volume.

Other areas in which equipment finance companies can use predictive to improve operations, increase profitability, or mitigate risk include:

- Credit scoring and underwriting
- Risk analysis
- Portfolio management
- Strategic planning
- Market analysis
- Customer relationship management
- Cross-selling and up-selling
- Residual value analysis
- Fraud detection
- Collections and delinquency management
- Direct and online marketing
- Asset maintenance
- Customer profitability

Historically, equipment leasing and finance companies have been slow adopters of new technologies and processes. But this study shows they are beginning to seize upon the benefits of predictive analytics. Just as transportation systems use predictive models to estimate the likelihood of system interruptions and mechanical failures, fleet lessors can use the same models to identify the likelihood of maintenance breakdowns to assist in fleet selection and planning. Similarly, finance providers can identify vendor deception, just as the public sector is using predictive analytics to reduce government fraud.

Applying predictive analytics

There is a surfeit of data in most companies, so the ability to extract information from data, recognize its application, and then make good decisions is what creates value. Further to this point, the resultant information must be actionable. All the sophisticated tools and methodologies at one's disposal are of little value if the information cannot be used to make good business decisions.

In this regard, predictive analytics should be viewed more as a business activity than an IT activity. IT support is essential to the process, but the information must be relevant and presented in a way that it can be understood. If the user cannot relate to the information and perceive its value, it will not be trusted or relied upon. Dashboards and other focused reporting mechanisms associated with predictive analytics create value in this area.

Another essential step in developing information that is actionable is establishing the goal of the prediction, as defined by the business problem to be solved. Goals might include allocating capital, avoiding risk, reducing expense, or retaining profitable customers. For example, a company may want to know if customers are more likely to continue leasing on a month-to-month basis if an additional follow-up notification call is made. The income benefits of this information then can be balanced with the cost of the call and any associated customer goodwill consequences.

Properly defining the goal of the prediction ensures that the results are actionable and have the intended impact on business results. This latter determination requires that the prediction results be evaluated and redirected, if appropriate. For instance, the targeted customer behavior on which the decision is being made may not be sufficient to draw meaningful conclusions. Or, there may be flaws in the underlying business assumptions. On the upside, such a review may inspire additional insights or applications of the data. Once the goal of the prediction is defined, a model must be chosen. The model helps develop theories about how a variable will perform in the future. It also suggests remedial actions through a variety of statistical techniques. These theories are represented by formulas or algorithms and represent how a given variable performs.

Formulas must first be used to analyze how the variable performs, based on historical data. In predictive analytics, the model, through its formulas, correlates the performance of the selected variable to changes in various factors, which may be internal or external to the company. This correlation is performed through a variety of statistical techniques.

In the earlier example, a finance company used historical internal and external data to predict new business volumes by developing a model to analyze its data. Specifically, this model calculated regression statistics between GDP and changes in lease volume. It then tested the statistical significance of the relationship between GDP and the changes in lease volume. Once these relationships were established, assumptions regarding the variables were input, and the model calculated the estimated and forecasted change in leasing volumes based on applicable GDP levels.

Although an in-depth understanding of these statistical techniques is not necessary, those considering implementing predictive analytics should at least be familiar with some of the technical jargon and terminology, if not the detail, of these statistical intricacies. A brief overview of some statistical elements of predictive analytics is presented here as background.

Key elements of predictive analytics that may be used by equipment finance organizations include:

- *Descriptive statistics* – basic statistics such as means, maximum, minimum, frequencies, and cross tabulation
- *Bivariate statistics* – statistics examining the relationship between sets of numbers, e.g., t-test, ANOVA, correlation, and non-parametric tests such as Chi-squared
- *Regression analysis* – establishing the relationship between two or more variables, including simple linear regression, multiple linear regression, and non-linear regression
- *Factor and cluster analysis* – techniques for identifying groups within data sets, e.g., identifying customers most likely to default or those most likely to churn
- *Time series analysis* – establishing trends in data over time, measuring seasonality, which is an important technique for forecasting
- *Decision tree models* – a valuable technique for analyzing yes/no type data and employed in applications such as credit scoring
- *Monte Carlo simulation* – a technique for forecasting a range of outcomes and an important tool in risk management
- *Anomaly detection* – the ability to detect extreme or unusual combinations of values within a data set and a technique that is utilized in fraud detection
- *Text analytics* – functionality that identifies trends and patterns from unstructured, textual information such as e-mails, social media, etc.

"At the end of the day, a successful predictive model must produce actionable information."

The predictive elements of a model can profit greatly through the addition of more sophisticated statistical steps, such as correlation and stochastic analysis. In the real world, each analytical object is affected by a number of factors or variables, so correlation analysis evaluates the correlation between all the listed variables. A Pareto plot can then be created to reflect the correlation of a particular variable, such as profitability, to all other variables.

The predictive analytics process also is iterative, so it will have a strong tendency to suggest further questions that may not have been anticipated at the beginning of the analysis, such as why credit risks of type X perform better in territory A than in territory B. A good portion of the value of a model lies in its ability to perform intelligent ad hoc analysis.

Equipment leasing and finance companies have access today to a diverse range of predictive-analytics models and software tools that incorporate these requirements, statistical techniques, and forms of analysis. This broad access has not always been available, although software tools for predictive analytics existed long before the term.

Review of Predictive Analytical Tools

Predictive analytics software can be categorized into three types:

- Enterprise business intelligence software platforms
- Standalone predictive analytics solutions
- Generic desktop applications

An overview of selected tools

Most enterprise business intelligence platforms are modular, with predictive analytics or statistics available as one of a set of modules. SAP's *"BusinessObjects"* is widely used for financial and management reporting and also offers a Predictive Analysis module. IBM *SPSS* is a long established statistical analysis package that offers a range of statistics modules as well as the SPSS Modeler workbench for predictive analytics.

Like IBM SPSS, another vendor, *SAS*, is focused strongly on the business analytics market and meets the requirements of predictive analytics with desktop and server options and an extensive set of data mining and analysis tools. It also enables predictive models to be developed and shared across the enterprise. In addition, SAS has developed *JMP*, a suite of entry-level statistical and predictive-analytics software more focused on ad hoc investigation by individual users.

Information Builders' *WebFOCUS* is more widely used for reporting and business intelligence application, although it has moved into the data mining and predictive analytics sectors. Another enterprise software application, TIBCO's *Spotfire*, places the emphasis on ease of use and data visualization across its business intelligence functionality while its *Spotfire Analyst* option offers an extensive range of predictive analytics suited to the occasional user, as well as expert power users.

There are several standalone predictive analytics solutions available from a wide range of vendors, including Oracle and IBM. Angoss Software Corporation's *KnowledgeSTUDIO*, MicroStrategy's *BI Platform*, and Rapid Insight's *Analytics* are pure-play data mining and business analytics solutions while Statsoft's *Statistica* provides analytical and advanced statistical functionality.

Quantrix Modeler, another standalone solution, is aimed primarily at financial modeling, but contains some statistical functionality and is excellent at handling multidimensional data. The open source statistical programming language *R* is available as a free download from the R Foundation; paid-for, supported versions are available from a number of organizations, including Revolution Computing.

Finally there are popular desktop tools, primarily spreadsheets such as Microsoft *Excel* and *OpenOffice*. These provide a range of statistical and mathematical functions from which basic analysis can be undertaken and simple predictive models developed. While they lack the rich functionality of dedicated predictive analytics applications, spreadsheets do provide a familiar and easy-to-use environment for simple model development, and at a relatively low cost.

Predictive analytics software requirements

Data-mining: Predictive analytics software should have data-mining functionality to analyze and find relationships in data, and statistical functionality to develop predictive models on which forecasts and behavioral assumptions can be made.

Data-visualization: The software also should provide data-visualization capabilities, including the ability to display simple graphics. Many applications support more complex visualizations, such as interactive dashboards, maps, and decision trees.

Visual environment: A number of predictive analytics applications, notably IBM *SPSS Modeler, BusinessObjects,* and *WebFOCUS Developer Studio* also provide a visual environment in which to develop models. This feature assists in the development process and can improve user productivity by placing the emphasis on discovering insights from the data rather than just writing code.

To qualify as a predictive analytics tool, then, the software must provide *statistical and analytic functionality*. This includes basic statistics (mean, standard deviation, correlation coefficients, etc.) and simple modeling, such as linear regression. Most of the dedicated packages provide much more sophisticated functionality, however, including predictive capabilities for identifying groups, like factor and cluster analysis; plus forecasting and decisioning capabilities, such as multiple linear and non-linear regression modeling, decision tree models, and Monte Carlo simulation.

Data integration: Another key functional capability for predictive analytics software is data integration, the tools of which invariably will be used in conjunction with operational data such as originations, credit, delinquencies, and so on. The operational data is drawn from transactional systems such as lease administration, finance and accounting, manufacturing, or banking, and may require extraction from a combination of these to provide the right data for analysis.

Since transaction data usually is not in a format conducive to analysis, functionality must exist to extract data from transactional systems, undertake any transformation, aggregation, or sampling required and load it ready for analysis. Known as *Extract, Transform, Load (ETL)*, this operation sometimes is performed by a separate specialized toolset that extracts and aggregates the data into a data warehouse. The predictive analytics (or reporting tools) then interact with the data in the data warehouse instead of with the live transactional system.

Some predictive analytics software can interact directly with lease administration systems or Enterprise Resource Planning (ERP) databases, while some of the enterprise business intelligence suites offer ETL modules that are used to build a database on which their predictive analytics modules then can be applied. At a minimum level, predictive analytic software needs to import data from other sources, such as Excel spreadsheets, text files (e.g., CSV file format), and, preferably, relational databases used for transactional systems, such as Oracle, Microsoft SQL Server, and IBM DB2.

Examined from another perspective, predictive analytics software requires the user to possess an understanding of the analytical and modeling techniques applied, although the level of expertise varies considerably between packages. At one end of the spectrum, as shown in **Figure 3**, is *R*, a statistical programming language aimed at the statistician and expert programmer. R is command-line-driven and sacrifices ease of use for power and speed, so a solid knowledge of the language is necessary, as there is no user-friendly graphical interface (other than through third party add-ons).

Figure 3
Required Statistical Expertise Spectrum

R	Angoss KnowledgeSTUDIO MicroStrategy BI Platform Statistica Data Miner SAS JMP Pro	Quantrix Modeler TIBCO Spotfire Oracle Crystal Ball Excel

At the other end of the usability spectrum are packages such as *Quantrix Modeler*, TIBCO *Spotfire*, and Oracle *Crystal Ball*. *Quantrix Modeler* is interesting in that, while it possesses a relatively limited range of statistical functions (its primary focus is financial modeling), its ability to handle multidimensional data is extremely user-friendly. It also provides a straightforward approach to building models that are spreadsheet-like in simplicity, although, unlike spreadsheets, it keeps the model logic separate from the data, making it much easier to audit.

TIBCO Spotfire emphasizes data visualization that enables non-expert users to easily identify relationships between data while Oracle *Crystal Ball* focuses on risk analysis. Crystal Ball provides a rich set of functionality for Monte Carlo simulation, but packages this in a simple, step-wise approach to model-building that can be easily understood by non-expert users. It also is implemented as an add-in to Microsoft Excel so the user can work within a familiar environment.

Comparison of selected software tools

The software tools reviewed and compared in this section are listed in **Figure 4**, and include a broad, representative set of tools that meet the range of requirements of leasing companies in terms of functionality, size of business and type of user. These users will range from specialists, such as statisticians and programmers, to senior executives basing their decisions on the output of predictive models.

Since many ELFA members are using platforms from Microsoft, Oracle, SAP and IBM, predictive-analytic solutions from these vendors have been included, along with several independent vendors. Point solutions from well-established vendors in the sector, plus some low-cost, entry level options, also are reviewed. It should be noted that this review is not intended to be exhaustive. Many available software tools have not been included, primarily because they do not offer the requisite statistical or analytical functionality.

Statistical functionality

Statistical functionality, the first core requirement to be reviewed, typically is available in varying degrees, ranging from basic statistical functions in Excel to extensive and complex functionality in packages such as *SAS, Statistica,* and *R*. Bearing in mind the predictive-analytics requirements of equipment-finance organizations, this section reviews the applications in nine key areas, as indicated in **Figure 5**.

Figure 4
Predictive Analytics Software Tools Reviewed

Application reviewed	Software provider	Application type	Brief description
BusinessObjects Predictive Analysis	SAP	Enterprise BI suite	Widely used by finance organizations for reporting and data mining Recently introduced module targeted at the asset finance market
Crystal Ball	Oracle	Standalone PA solution	Relatively inexpensive point solution for modeling and forecasting with specific relevance for risk analysis
SAS JMP Pro	SAS	Standalone PA solution	Broad set of functionality. JMP and JMP Pro offer both entry level and full statistical and data mining functionality, respectively
SPSS Modeler	IBM	Enterprise BI suite	Dedicated platform for predictive models, more easily implemented
SQL Server 2012 Business Intelligence Edition	Microsoft	Enterprise BI suite	Widely adopted database platform
WebFOCUS (Rstat and Developer Studio)	Information Builders	Enterprise BI suite	Well-established BI application and provides extensive predictive analytics capabilities. Also features strongly in its data integration functionality.
KnowledgeSTUDIO	Angoss	Standalone PA solution	Powerful and well-established application
MicroStrategy BI Platform	MicroStrategy	Standalone PA solution	Powerful and well-established application
Modeler Professional	Quantrix	Financial modeling solution	An application with enough functionality to enable simple analytic models to be developed. Also features highly on usability
R	REvolution Analytics	Standalone PA solution	Increasingly adopted by statisticians and expert users and is incorporated in a number of other predictive analytics applications. A number of organizations provide R training, consultancy, and support
Statistica Data Miner	Statistica	Standalone PA solution	Powerful and well-established application
Excel	Microsoft	General purpose desktop application	Widely used in finance organizations, it includes a surprising amount of statistical functionality from which simple models and forecasting applications can be built quickly by non-expert users

Figure 5
Statistical Functionality

	BusinessObjects	Crystal Ball	SAS JMP Pro	SPSS Modeler	SQL Server BI Edition	WebFOCUS	KnowledgeSTUDIO	MicroStrategy	Quantrix Modeler	R	Statistica	Excel
Descriptive statistics	P	P(1)	F	F	P(4)	F	F	F	F	F	F	F
Bivariate statistics	N	P(2)	F	F	P(4)	F	F	F	F	F	F	F
Regression analysis	F	F	F	F	F	F	F	F	P	F	F	P
Factor/cluster analysis	F	N	F	F	F	F	F	F	N	F	F	N
Time series analysis	F	F	F	F	F	F	F	F	N	F	F	N
Decision tree models	F	N	N	F	F	F	F	F	N	F	F	N
Monte Carlo simulation	N	F	F	N	N	F	N	N	N	F	F	P
Anomaly detection	F	N	N	F	N	F	N	N	N	N	F	N
Text analytics	N	N	N	F(3)	F	N	F	N	N	N	F	N

Key: F Functionality fully supported, P functionality partly supported, N functionality not supported
Notes:
(1) Descriptive statistics provided for forecasts only, otherwise use Excel functions
(2) Bivariate statistics provided for forecasts and simulations, otherwise use Excel functions
(3) Text analytics on SPSS Modeler Premium version only
(4) Uses Excel functions
(5) Limited functionality can be enhanced with third party add-ins

All applications reviewed provide descriptive and bivariate statistics, with the exception of BusinessObjects, which offers limited descriptive statistics only, and Oracle Crystal Ball, which provides these for output forecasts only. Crystal Ball is implemented as an add-in to Excel, as is Microsoft SQL Server Analysis Services, so both provide this functionality through Excel functions.

Regression analysis is fully supported by all the applications reviewed with the exception of Quantrix Modeler and Microsoft Excel. These can implement linear and multiple linear regression models, but are less well-suited to more complex regression techniques. Quantrix Modeler and Excel also do not support factor/cluster analysis or time-series analysis, although it is possible to build simple time-series models using basic regression techniques and seasonal analysis in both applications. Of the other applications evaluated, only Crystal Ball does not provide factor and cluster analysis.

Decision tree functionality is available in eight of the twelve software solutions evaluated, while Crystal Ball, Quantrix Modeler, SAS JMP Pro, and Excel do not offer this capability. Monte Carlo simulation is less widely available. Crystal Ball, for example, has extensive capabilities in this area and it also is provided by SAS JMP Pro, WebFOCUS, R, and Statistica. Basic Monte Carlo simulations can be built using Excel and there are third party add-ins available that extend its functionality in this respect.

Of the software solutions reviewed, Statistica offers the most complete set of functionality in the areas evaluated, while SPSS Modeler lacks only Monte Carlo simulation, although it is available in other SPSS modules. Quantrix Modeler and Excel are the most limited in terms of statistical functionality, as these are more general purpose solutions not specifically aimed at predictive analytics.

Usability and data visualization

Usability was assessed in terms of the type of interface available and the extent to which the interface meets the needs of different types of users, as summarized in **Figure 6**. All the software packages reviewed offer a GUI (graphical user interface) with the exception of R, which is command-line-driven only. However, some third party add-ons are available that provide a limited GUI to R functionality. Apart from R, only Microsoft SQL Server Analysis Services provides a command-line interface although, unlike R, it also has a GUI alternative. Some packages also can be integrated with spreadsheets, thereby providing users with a familiar interface.

Some of the software solutions reviewed provide a graphical environment for model development. This typically is represented as a visual workbench in which data sources, statistical/modeling functionality, visualization, and model outputs are represented as icons. Graphic functionality is valuable where complex models are developed using multiple data sources, and where models are run on a regular basis or have to be replicated for multiple users.

The graphic environment enables developers to focus on the business requirement and process in building predictive models without requiring them to learn a programming language. Models also can be more easily understood and audited by other users in such an environment. This graphic development environment is featured mainly in the enterprise business intelligence software suites with BusinessObjects, SPSS Modeler, Microsoft SQL Server, WebFOCUS (through the optional Developer Studio module), SAS Enterprise Miner, and Statistica offering this capability.

Data visualization is a key requirement of any predictive analytics solution, and all the software systems provide simple data visualization with standard bar, line, pie, scatter charts, etc., while most provide more complex visualizations, including dashboards, maps and decision trees. Microsoft SQL Server, Excel, and Quantrix Modeler are the only three solutions that are limited in this respect.

Various types of users are likely to be involved in developing predictive analytics models. They will include specialists such as statisticians and programmers, as well as more generalist power users or analysts and, potentially, executives. Clearly, statisticians are likely to be capable of using all of the software solutions reviewed, although Quantrix Modeler and Excel are unlikely to provide the statistical functionality that this level of expertise would require. **Figure 7** correlates the software tools with the most appropriate user focus.

Figure 6
Usability and Data Visualization

	BusinessObjects	Crystal Ball	SAS JMP Pro	SPSS Modeler	SQL Server BI Edition	WebFOCUS	KnowledgeSTUDIO	MicroStrategy	Quantrix Modeler	R	Statistica	Excel
Graphical user interface	F	F	F	F	F	F	F	F	F	N	F	F
Command-line interface	N	N	N	N	F	N	N	N	N	F	N	N
Spreadsheet integration	N	F	F	N	F	P(3)	N	N	F	N	N	F
Graphical process flow	F	N	N(2)	F	F	P(4)	N	N	N	N	F	N
Data visualization												
Simple data visualization	F	F	F	F	F	F	F	F	F	F	F	F
Complex data visualization	F	F	F	F	N	F	F	F	N	F	F	N

Key: F Functionality fully supported, P functionality partly supported, N functionality not supported
Notes:
(1) Only with third party add-ons
(2) Available in SAS Enterprise Miner, but not JMP Pro
(3) Requires WebFOCUS Quickdata additional module
(4) Requires WebFOCUS Developer Studio additional module

Programmers may be employed in model development when there is a requirement to integrate the model with other business applications, such as real-time credit scoring, but also may be employed when complex models are constructed using a programming language, such as SAS or R. Programming skills may also be required in applications such as Microsoft SQL Server Analysis Services, in which additional database administration expertise is required, or in applications that provide predictive analytics capabilities through embedded R, such as WebFOCUS Rstat.

Most of the applications have been developed with non-specialist users in mind so power users and analysts should be capable of using the systems for data mining and model development. Statistical software tools typically will not be adopted by executive users without a background or training in predictive analytics, however, given the specialization, power, and complexity of the applications. R is the only application that presents more of a challenge, as it has a steep learning curve and a user interface with which most users are unlikely to be familiar.

Figure 7
Type of User Focus

	BusinessObjects	Crystal Ball	SAS MP Pro	SPSS Modeler	SQL Server BI Edition	WebFOCUS	KnowledgeSTUDIO	MicroStrategy	Quantrix Modeler	R	Statistica	Excel
Statistician	Y	Y	Y	Y	Y	Y	Y	Y	N	Y	Y	N
Programmer	N	N	N	N	Y	Y	N	N	N	Y	N	N
Power user	Y	Y	Y	Y	Y	Y	Y	Y	Y	N(1)	Y	Y
Executive user	N	Y	N	N	N	N	N	N	Y	N	N	Y

Key: Y Application well-suited to this type of user, N Application not suited to this type of user
Notes:
(1) R could be used by power users given sufficient training in the application and its statistical functionality

Despite this, there are some applications that can be utilized by users with typical Excel-level skills. Crystal Ball, for example, abstracts the complexity of Monte Carlo simulation through a wizard-style approach to building models in a familiar Excel environment. A simple learning curve and a modest amount of training allows the user to focus on the business requirement, and not the complexity, of the statistics involved.

Quantrix Modeler also provides a user-friendly interface and structure for model development that more than compensates for its limited statistical functionality. As a financial modeling tool, Modeler clearly is intended as an alternative to spreadsheets for executives, analysts and power users. As most executives are familiar with Excel, given the right level of expertise, they should be capable of developing simple predictive models with its standard functionality.

Data integration

Predictive analytics applications will invariably draw data from a variety of operational systems such as lease administration systems, finance systems, data warehouses, credit reference sources, and spreadsheets. For this reason, the ability to extract and integrate data from relational databases and other standard data formats is a key requirement for model developers and analysts using these tools.

Figure 8 shows the software solutions' ability to extract data from relational databases, such as Oracle, Microsoft SQL Server, and IBM DB2; spreadsheets such as Excel; and fixed-format text files in CSV and TXT formats. The applications' ability to handle multiple data sources in a single model also has been assessed, as this is a useful capability in more complex models. Possession of this capability also avoids the need to consolidate the data beforehand in a single source.

Most of the applications are fully capable of importing data from relational databases, spreadsheets, and text files. Solutions more limited in this respect are Oracle Crystal Ball, which effectively runs in an Excel environment, and R. In its open-source version, R only can import data from text files, which is a significant limitation, while JMP Pro Excel will import data from relational databases, but requires the ODBC drivers provided by the database vendors.

A number of applications support a range of data transformation capabilities. While not strictly necessary for predictive model development, they are useful when large datasets have to be manipulated, if data from multiple sources needs to be merged or normalized, or where datasets are incomplete. The assessed functionality includes:

- Availability of rules for data validation
- Ability to impute missing values (important where data is incomplete)
- Data selection, sampling, sorting, and merging
- Data restructuring, partitioning, and transposition

Overall, greater levels of data extract and transformation functionality are found in the enterprise business intelligence suites, primarily SAS, SPSS Modeler, SQL Server, and WebFOCUS, which is not unexpected as these applications are designed to run against operational systems and data warehouses. Of the standalone predictive-analytics applications, KnowledgeSTUDIO, JMP Pro, and Statistica offer the most functionality in this area, while general purpose tools like Excel provide the least.

Reporting and presentation

The output from predictive analytics applications are used in various ways, as indicated in **Figure 9**. It is likely, however, that forecasts, data visualizations, scorecards, etc., will need to be reported and exported to external applications such as Excel or published on Web or mobile platforms.

All the solutions reviewed provide some form of user reporting, whether it is basic output in applications like Excel, or the more complex reporting capabilities in the business intelligence suites. With the exception of R, all the applications also can export data to Excel, although WebFOCUS requires the optional "Quickdata" module to deliver this functionality. Publishing to other platforms is less widely supported, however, as only SQL Server and Microstrategy can publish to Web, PDF/Word, and mobile platforms, although SQL Server requires "Reporting Services" to do so.

Process support

All the solutions are capable of supporting ad hoc investigations in response to specific business issues and questions. However, the output from predictive models is not necessarily used in one-off decisions, but can be applied to operational aspects of the leasing business. Examples include risk-based pricing, using dynamic scorecards, and upsell/cross-sell marketing, using real-time customer relationship management data.

In these cases, the predictive analytics models must be embedded in the organization's operational processes and run automatically as part of a workflow. In order to do so, the application on which the model runs must support real-time analytics or be capable of exporting the model in a format that can be used by another application running as part of the operational process. The process support capabilities of the reviewed software tools are shown in **Figure 10**.

Figure 8
Data Extract and Transformation Functionality

	BusinessObjects	Crystal Ball	SAS JMP Pro	SPSS Modeler	SQL Server BI Edition	WebFOCUS	KnowledgeSTUDIO	MicroStrategy	Quantrix Modeler	R	Statistica	Excel
Import from relational databases	F	N	F	F	P	F(1)	F	F	F	N	F	P(2)
Import from spread-sheets	F	F	F	F	F	F	F	F	F	N	F	F
Import from text files	F	F(3)	F	F	F	F	F	F	F	F	F	F
Multiple data sources	F	N	N	F	F	F	F	N	N	N	F	N
Data validation rules	F	N	N	N	F(4)	F(1)	N	N	N	F	F	N
Manage missing values	P	N	P(5)	F	F(4)	F	F	N	N	F	N	N
Data selection, sorting, etc.	F	N	F	F	F(4)	F	F	N	P	F	F	P
Data restructure-ing	N	N	F	F	F(4)	F	F	N	N	F	F	N

Key: F Functionality fully supported, P functionality partly supported, N functionality not supported

Notes:

(1) Requires iWay optional module
(2) Required ODBC connector from database provider
(3) Via Excel
(4) Functionality available in SQL Server outside of Analysis Services
(5) Limited functionality - can view patterns in missing data and do basic data replace. Full functionality available in SAS Enterprise Miner.

A number of the applications reviewed support automated real-time analytics, including SPSS Modeler, WebFOCUS, KnowledgeSTUDIO, and Statistica. Predictive Modeling Markup Language (PMML) is an open standard for predictive analytics that enables models developed in one application to be read and run by another, thereby allowing models to be ported between systems with different software solutions. A number of the applications evaluated support the reading and exporting of models in PMML.

Figure 9
Reporting and Presentation Functionality

	BusinessObjects	Crystal Ball	SAS JMP Pro	SPSS Modeler	SQL Server BI Edition	WebFOCUS	KnowledgeSTUDIO	MicroStrategy	Quantrix Modeler	R	Statistica	Excel
User-defined reporting	F	F	F	F	F	F	F	F	F	F	F	F
Export to Excel	F	F	F	F	F	F(1)	F	F	F	N	F	F
Publish to Web	N	N	F	N	F(2)	F	N	F	F(4)	N	N	N
Publish to PDF/Word	N	N	F	N	F(2)	N	F	F	N	N	N	N
Publish to mobile	N	N	N	N	F(2)	F(3)	N	F	N	N	N	N

Key: F Functionality fully supported, P functionality partly supported, N functionality not supported
Notes:
(1) Requires WebFOCUS Quickdata module
(2) Requires SQL Server Reporting Services
(3) Requires WebFOCUS Mobile module
(4) HTML export and Quantrix Qloud options

Implementation

How predictive analytics solutions are deployed will depend on the business requirements of the equipment finance organization. For largely ad-hoc analyses, or those involving a single or small number of analysts, deployment on single user PCs is likely to be the most common means of implementation. With big workgroups, such as in large risk management and compliance functions, or where the application is shared between several groups of users, a server-based deployment will be more suitable. Server installations also will be required where real-time predictive analytics are implemented.

All the applications can be implemented as single user installations on PCs. Most also can be deployed in a server environment, although BusinessObjects, Crystal Ball, and KnowledgeSTUDIO do not support this option. The Professional Plus version of Quantrix Modeler is required for server deployment. The deployment options and operating platforms of the reviewed software tools are shown in **Figure 11**.

Figure 10
Process Support Capabilities

	BusinessObjects	Crystal Ball	SAS JMP Pro	SPSS Modeler	SQL Server BI Edition	WebFOCUS	KnowledgeSTUDIO	MicroStrategy	Quantrix Modeler	R	Statistica	Excel
Ad hoc investigation	F	F	F	F	F	F	F	F	F	F	F	F
Automated real-time analytics	N	N	N(1)	F(2)	N	F	F(3)	N	N	F	F	N
Support for PMML	N	N	N(1)	F	N	F	F	F	N	N	F	N

Key:F Functionality fully supported, P functionality partly supported, N functionality not supported
Notes:
(1) Available in SAS Enterprise Miner
(2) Server version
(3) StrategyBUILDER module required

For organizations not desiring in-house applications or wishing to share models securely over the Internet, there is the option of Software as a Service ("SaaS") solutions. Most SaaS providers offer a subscription model, which avoids large up-front license costs. The only predictive analytics solutions not available as SaaS options are BusinessObjects, Crystal Ball, SPSS Modeler, and Statistica.

From an operating platform perspective, all the applications evaluated are available on the later Microsoft Windows versions with a number supporting Windows Server as well. Linux versions are available for SAS, SPSS Modeler and WebFOCUS, as well as Microstrategy, R and Statistica. The Linux platform is more likely to be adopted for server deployments, although R also can be run through a Linux desktop client such as Ubuntu.

Mac users, by comparison, have very little choice with predictive analytics applications, although using a virtual machine running Windows OS to access this functionality might be a solution. None of the enterprise business intelligence suites support the MacOS platform for their predictive analytics modules, nor do most of the standalone predictive analytics applications. Only Quantrix Modeler, R, and Excel are available on Mac.

Entry costs, training and support

Software costs typically vary by the number of users, type of deployment (PC versus server), type of license (annual versus perpetual), and the functionality provided when applications are sold as a series of modules. Prices also are subject to negotiation, particularly for large corporate purchasers that may already be using major software vendors' platforms.

Licensing fee structures vary between software vendors, rendering a pricing comparison problematic. One common model is based on an initial, up-front license fee, followed by an annual renewal fee that covers ongoing support, upgrades, and bug fixes.

Some vendors, including IBM, offer the options of licensing by named or concurrent users. While the latter provides more flexibility, it is more expensive on a one-off basis. Perpetual or annual license fees represent additional payment options, although users of perpetual licenses have to purchase a support-and-upgrade

Figure 11
Deployment Options and Operating Platform Support

	BusinessObjects	Crystal Ball	SAS JMP Pro	SPSS Modeler	SQL Server BI Edition	WebFOCUS	KnowledgeSTUDIO	MicroStrategy	Quantrix Modeler	R	Statistica	Excel
Deployment												
Single user PC	F	F	F	F	F	F	F	F	F	F	F	F
Server	N	N	N	F	F	F	N	F	$F_{(4)}$	F	F	N
SaaS	N	N	N	N	$F_{(1)}$	$F_{(1)}$	$F_{(2)}$	$F_{(3)}$	F	$F_{(5)}$	N	$F_{(6)}$
Operating platform												
Windows	F	F	F	F	F	F	F	F	F	F	F	F
MacOS	N	N	F	N	N	N	N	N	F	F	N	F
Linux	N	N	N	F	N	F	N	F	N	F	N	N

Key: F Fully supported, P partly supported, N not supported
Notes:
(1) SaaS option available through third party partners
(2) KnowledgeCLOUD
(3) MicroStrategy Cloud Platform
(4) Professional Plus version only
(5) Azure Burst/Amazon AWS platforms
(6) Office Live

contract separately. Annual licenses bundle the support-and-upgrade contract for the 12-month period. SaaS pricing typically is priced on a monthly or annual per user basis.

Despite the differences in pricing structures, pricing is broadly related to functionality provided. The enterprise business intelligence suites tend to command premium prices, as they offer a wide range of functionality and generally are aimed at multi-user deployments with pricing structured for larger numbers of users. Concurrent, as opposed to named, user-license pricing also is available for each of these options at a somewhat higher cost.

Full functionality analytics solutions, such as KnowledgeSTUDIO and Statistica, are positioned between SAS Enterprise Miner, SPSS Modeler, and SQL Server from a cost perspective, with annual maintenance fees at 20% of the initial license cost. Statsoft, interestingly enough, also offers a leasing option that comprises 40% of the initial license cost over three years, and includes annual maintenance and support.

Point solutions such as Crystal Ball are less costly, as they offer a much more limited range of functionality, while R is free in its native form. Microsoft Excel invariably will be covered by most companies' corporate Microsoft licenses. All of the software providers covered in this review offer training and support for their solutions with the exception of R, which is an open-source application.

Choosing the right software solution is a critical element in successfully implementing predictive analytics. But as in all aspects of adopting predictive analytics, a formal, structured evaluation process with full involvement from all stakeholders, business and technical, as well as C-level sponsorship, is required for benefits to be properly realized.

Survey of Industry Practices

Predictive analytics can be studied extensively, and its many applications and benefits extolled, yet its impact will be minimal unless it actually is used. Key elements of this study, therefore, include perspectives on the current and prospective role of predictive analytics in the equipment leasing and finance industry, and how companies are using it to make meaningful business decisions.

Corollary aspects include not only how predictive analytics is utilized, and the tools being used, but also the willingness of equipment leasing and finance companies to incorporate predictive analytics into their decision making. To this end, a survey of selected ELFA members was conducted as to various aspects of how the industry views and uses predictive analytics.

Methodology

The criteria used to select the survey participants included company size, the market segment, and company type[4] in order to achieve a representation of companies ranging from larger, more resource rich participants to smaller ones. The mix between surveyed companies, based on net assets and industry designation, is shown in **Figure 12**.

Figure 12

Survey Participants

Net assets	Independent	Captive	Bank
> $10 billion	2	1	
$1 – 10 billion	1	1	2
< $1 billion	1	1	

Alta selected, with Foundation input, the companies to be interviewed, and designed and constructed a survey to determine the targets' perception and utilization of predictive analytics. Questions to identify trends, practices, adoption rates, new areas of implementation, and perceived business benefits of predictive analytics also were included. The questions used in the survey are attached as **Appendix Two**.

In-depth interviews, were conducted with senior level decision-makers and users of data within the targeted companies. These interviews were completed in person, by telephone, as it was felt that live interviews would yield more insights into company practices than the use of online survey technologies or formal written responses.

During these interviews the extent of the survey targets' use of predictive analytics, available tools, and their integration with enterprise software was examined. How the companies approached the use of predictive analytics within the various areas of the company was surveyed as well.

[4]Alta has retained the traditional company type designation (captive, independent, etc.) of the survey participants although some nonbank entities now are under the control of bank holding companies.

Responses

All companies interviewed indicated that they currently use predictive analytics to one degree or another, although not many had programs beyond credit decisioning. The larger players use analytics in more areas and with greater sophistication than the smaller companies. In many cases, this greater usage is a function of regulatory requirements and the leveraging of parent company capabilities.

The survey asked whether respondents would describe their company's predictive analytics efforts as ad hoc or formalized. For purposes of the question, a formalized predictive analytics program was defined as one that consolidated various predictive analytics efforts into one, although not necessarily, a centralized, organization.

Only one respondent stated that its efforts could be described as formalized, although parent companies of several respondents surveyed are known to have established predictive analytics units. Predictive analytics were more formalized in the credit risk and adjudication, collections, and delinquency management areas, reflecting the broad acceptance of this aspect of predictive analytics in the equipment finance industry.

"The increasing regulatory requirements mean that you must squeeze every cent of profit out of operations. Predictive analytics allows us to do that."

Benefits

All respondents to the survey consider the use of predictive analytics to be a competitive advantage due to the benefits it provides, as listed in **Figure 13**, among others. Cost reduction and efficiency were the benefits mentioned most often during the surveys. For instance, one respondent stated that "The increasing regulatory requirements mean that you must squeeze every cent of profit out of operations. Predictive analytics allows us to do that."

Utilization

The predictive analytics efforts of the survey respondents are best described as ad hoc, in that predictive analytics usage either is sporadic throughout the company or mostly focused in one area. Predictive analytics is formalized to a much greater degree in the credit risk function, where several companies have specific departments working on the predictive analytics aspects of credit, including adjudication and delinquency management.

Given this information, it is not surprising that the chief risk officer or chief credit officer generally has ultimate responsibility for the predictive analytics program amongst those surveyed. The credit element of the respondents' predictive analytics, consequently, is formalized and, in most cases, fairly robust. This is not the case with other aspects of predictive analytics, as all the respondents' efforts were deemed to be middling to nascent in terms of potential utilization.

None of the respondents described their overall predictive analytic activities as robust, with several categorizing these efforts as being nascent. These comments referred to the state of their current efforts, and not the level of predictive analytics adoption within the company. In this respect, banks are more likely to have more formalized and robust activities due to regulatory requirements and Basel III concerns.

Figure 13

Benefits of Predictive Analytics

Risk management	Profitability	Other benefits
Predicting future receivables performance	Reducing costs through reductions in underwriting staff and the cost of collections	Providing consistency in decision-making
Predicting risk better	Pricing more effectively	Increasing efficiency
Seeing risk more clearly	Enhancing capital allocation	Improving the customer experience from an underwriting perspective
Improving the risk rating	Improving portfolio management	Taking customers off the street for vendor partners
Standardizing industry risk parameters	Creating market differentiators	Making better decisions
Identifying risks and opportunities in the portfolio	Increasing market returns on a risk-adjusted basis	Identifying causes of certain behaviors
	Improving balance sheet management	Recognizing where to deploy sales staff
		Tightening the operating business model
		Predicting when to hire people
		Identifying where training is needed

The following activities were identified by respondents as being part of their predictive analytics program in one respect or another:

- Forecasting and planning
- Risk management
- Portfolio evaluation and management
- Credit adjudication and scorecards
- Delinquency management
- Customer cross and up-selling
- Sales performance
- Residual management
- Regulatory reporting
- Asset maintenance and selection
- Vendor performance
- Capital allocation
- Pricing

The top three areas in which the surveyed companies use predictive analytics are credit adjudication and scorecards, residual management, and portfolio evaluation and management.

The most commonly-used end user tool amongst respondents, by far, is Microsoft Excel. While readily available and easily used, respondents pointed out several negative aspects of using Excel to perform predictive analytics. Some of these negative aspects included the burden of data consolidation among applications and the internal control issues surrounding Excel.

Figure 14 lists which of the analytical tools reviewed in the Study are being used by the survey respondents. As can be seen, predictive analytical software tools rarely are utilized outside of the credit function. Very few respondents used enterprise-scale analytic platforms and only one of the companies with an ERP integrated its predictive analytics capabilities with that enterprise system.

Figure 14

Analytical Tools Used

End-user tools	Used?	Enterprise-scale platforms	Used?
Angoss KnowledgeSEEKER		IBM SPSS Modeler	
Microstrategy		SAS JMP Pro	Yes
Quantrix		SAP BusinessObjects	Yes
TIBCO Spotfire		Oracle Hyperion	Yes
Rapid Insight Analytics		Microsoft Business Intelligence	Yes
Revolution Analytics R		Information Builders WebFOCUS	
Statsoft Statistica			
Emanio Insight!			
Microsoft Excel	Yes		
Fair Isaacs	Yes		
Risk Frontier	Yes		
Oracle Crystal Ball			

Future trends

All but one of the survey respondents expect their company's use of predictive analysis to increase in the coming year. Even so, only two respondents intend to commit additional personnel to predictive analytics in the near future. One of these respondents plans on doing so because of regulatory necessity, while the other one expects to expand its capabilities. The remaining respondents plan to leverage already existing capabilities and personnel, in essence, doing more with the same resources.

Is this response the result of penny pinching, underutilization of existing resources, or a need to leverage scarce skill sets? Leveraging existing capabilities does make sense, since one of the primary benefits of predictive analytics is efficiency and cost reduction. As one interviewee put it, "One of the major reasons for using predictive analytics is to become more efficient, so why would we want to add costs to do it?" These responses indicate that predictive analytics requires more structure and formalization in order to leverage its benefits.

A key element of the survey was on general comments and trends. Comments included the need for cultural change and how, even with predictive analytics, some executives still 'trust their gut' on certain decisions rather than accepting the results of the predictive analytics. Unfortunately, there were no studies, or even anecdotal evidence, as to the ultimate efficacy of experiential versus predictive analytic decision making.

"…other than in credit adjudication, predictive analytic remains a largely untouched area…"

Several respondents provided comments about the challenges of implementing predictive analytics in their company, generally to the effect that it is one thing to have access to the data and the tools to manipulate it, but it takes people to do it. Several noted that another challenge is to make certain that the information is timely and up to date. "You can't just look at the numbers or losses and think you are okay. It needs constant attention and updated analysis to be effective."

Others commented that the real challenge is not getting the information or the tools to perform the analyses. It is, instead, overcoming company culture and executive insistence and/or focus on the role of experience in decision making. In other words, "I know what the analytics are telling me, but my experience is telling me something else." The general feeling among the respondents was that not only will changing company culture be difficult, but that many of them were not necessarily even ready to start that change.

The primary conclusion to be drawn from the survey results is that, other than in credit adjudication, predictive analytics remains a largely untouched area of equipment leasing and finance activities.

As a final note to this section of the Study, the Foundation and Alta wish to acknowledge the contributions of the following companies that graciously shared their time, experience, and opinions in the survey process, thereby making this data possible:

- Altec Capital Services
- Cisco Systems Capital Corporation
- CIT
- De Lage Landen Financial Services
- John Deere Financial
- Key Equipment Finance
- LEAF Commercial Capital, Inc.
- PHH Arval
- RBS Citizens Asset Finance

Illustrative Scenarios

This section of the study highlights and demonstrates the practical application of the elements presented so far through real world scenarios of predictive analytics processes, data utilization, risk identification, and application. The purpose of these examples, in combination with the research aspects of the study, is to deliver practical guidance to those considering a predictive analytics implementation. The scenarios consist of:

- Credit scoring with analytics
- Increasing residual profits
- Improving future financial performance

Scenario One – Credit scoring with analytics

Credit scoring represents one application of predictive analytics in risk management. The statistical evaluation of the credit scores is another way of using predictive analytics in the credit domain. This evaluation can be used to improve the finance company's credit adjudication process, and, hence, profitability, through an anticipated reduction in credit losses and write-offs. While reducing losses certainly is high on the list of benefits, the benefits of more accurate decisioning also are well worth the effort.

It is possible, using predictive analytics, to approve more transactions with the same dollar amount of losses (and even more still with the losses as a percent of the originations rate). The type of information created through predictive analytics also helps support fact-based pricing and structuring. For instance, it may be unprofitable to lend to a certain tier of applicants on standard terms; however, with a greater down payment or extra collateral to reduce the Loss Given Default ("LGD"), taking on customers like this can be made profitable.

This scenario illustrates how predictive analytics can be used to compare the predictive lift of one credit score versus another, followed by a discussion of close rate data, LGD rates, and the total economic impact of various cut-off and decisioning strategies. The scenario concludes with the pros and cons of score-based decisioning guidelines versus actual instantaneous auto-decisioning, along with auto-approving and auto-declining issues.

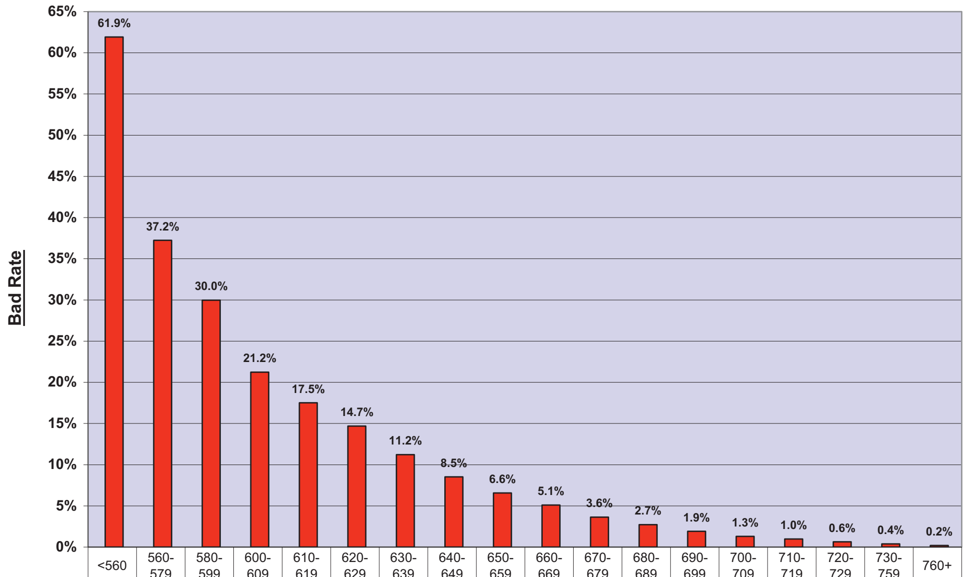
The predictive lift of credit scores

The most fundamental concept in credit score evaluation is referred to as retro analysis. In retro analysis, the decision-maker calculates a borrower's score at some prior point in time, using only information that was available at that time. An analysis is made to see whether the borrower's transaction subsequently performed well (a "good") or not (a "bad"), based on some fixed, relevant definition, such as whether the transaction was ever 91 days past due.

Transactions with similar scores at origination are then grouped together into score ranges (e.g., 680-689) and, for each range, the percentage of transactions that went bad is calculated. Low scoring ranges should show higher bad rates (almost all scores are calibrated so that higher is better, although there are a small number that work the other way).

The fundamental concept of this exercise is that the past repeats itself, and that the best measure of what one can expect in the future from a score is what it did in the past. The retro analysis is a virtual historical usage, although if the score was being used in the past, the actual score values obtained at that time can be used for this analysis. **Figure 15** illustrates the results of the retro analysis used to assess the scoring parameters in this scenario.

Figure 15
Retro Analysis Results



	<560	560-579	580-599	600-609	610-619	620-629	630-639	640-649	650-659	660-669	670-679	680-689	690-699	700-709	710-719	720-729	730-759	760+
Total Deals	329	623	1,685	2,342	4,493	7,307	11,862	17,094	23,137	29,989	37,746	43,884	40,762	28,848	17,103	9,275	8,469	527
Bad Deals	204	232	505	497	787	1,073	1,331	1,458	1,521	1,529	1,368	1,193	783	373	167	60	33	1
% Bad	61.9%	37.2%	30.0%	21.2%	17.5%	14.7%	11.2%	8.5%	6.6%	5.1%	3.6%	2.7%	1.9%	1.3%	1.0%	0.6%	0.4%	0.2%

Once the retro analysis is completed, the predictive value of the scores being analyzed should be determined. Consider, for instance, two different scores, Score A and Score B. Each score is evaluated on a retro basis, as described above, on a portfolio of 100 transactions that had a 10% bad rate. The "predictiveness" of each score is summarized in **Figure 16.**

Although both scores seem to work, Score A appears to work better. In the case of Score A, there are seven bads identified in the bottom 20% of the scored population (those scoring 600 or 610), fully 70% of all the bads in the portfolio. Score B, however, only identifies four bads in the bottom 20% of the population, only 40% of all the bads in the portfolio. Note that this still is better than random selection, which, with 20% of the population, would only identify 20% of the bads.

The differences illustrated in **Figure 16** can be seen more easily using a Lorenz Curve (also known as a Power Curve), as illustrated in **Figure 17**. The X-axis of the Lorenz Curve represents all transactions, with the lowest scoring ones at the left, and the highest scoring transactions at the right. The Y-axis is the total cumulative portion of bads identified by the score for a given cumulative portion of all the transactions.[5]

Figure 16
Score Predictiveness

Score A

Score	All Deals	Bad Deals	Bad Rate	Cumulative % of All Deals	Cumulative % of Bad Deals
600	10	4	40%	10%	40%
610	10	3	30%	20%	70%
620	10	1	10%	30%	80%
630	10	1	10%	40%	90%
640	10	0	0%	50%	90%
650	10	0	0%	60%	90%
660	10	1	10%	70%	100%
670	10	0	0%	80%	100%
680	10	0	0%	90%	100%
690	10	0	0%	100%	100%
Total	100	10	10%		

Score B

Score	All Deals	Bad Deals	Bad Rate	Cumulative % of All Deals	Cumulative % of Bad Deals
200	10	2	20%	10%	20%
210	10	2	20%	20%	40%
220	10	1	10%	30%	50%
230	10	1	10%	40%	60%
240	10	1	10%	50%	70%
250	10	1	10%	60%	80%
260	10	0	0%	70%	80%
270	10	1	10%	80%	90%
280	10	0	0%	90%	90%
290	10	1	10%	100%	100%
Total	100	10	10%		

The Lorenz Curve for a perfect score would start at the lower left-hand corner, and go almost straight up, reaching the 100% bad capture level with the bottom 10% of the population, and the line would then continue horizontally to the upper right hand corner. As can be seen, the curve for Score A is always closer to the ideal than the curve for Score B, indicating that Score A is a better performing score throughout the credit quality spectrum.

Another approach to assessing score performance is to focus on how far a score's curve is above the random diagonal; that is, towards the upper, left-hand corner. The most commonly used metrics in this regard include:

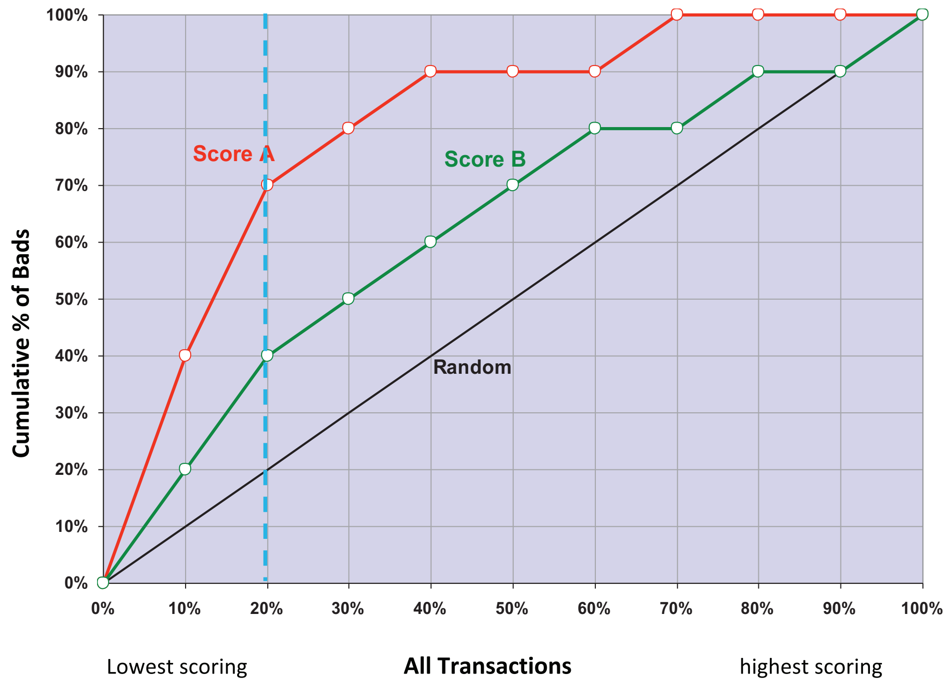
- *Accuracy ratio* – The area between the score's Lorenz Curve and the random diagonal, divided by the area between a perfect score and the random diagonal. The Accuracy Ratio, or AR, ranges from a high of 100% to a low of 0%, although technically, if a score were worse than random, the AR would be negative.

- *ROC statistic* – Quite similar to the AR, except that it is based on an ROC Curve in which the X-axis, instead of being all transactions, represents only the good transactions. A comparison between the ROC Curve and the Lorenz Curve is contained in **Figure 18**.

  While these curves are something on the order of 90% the same, it means that the curve of the perfect score on the ROC Curve goes vertically up from the lower left-hand corner to the upper right-hand corner, so there is no need for division as there is in the AR. Rather, the ROC Statistic is simply the area below the curve, with 1.000 being perfection, and 0.500 being random (it is usually quoted as a decimal with the digits). The ROC Statistic is illustrated in **Figure 19**.

[5]Note that the conventions of left versus right and up versus down referenced here are consistently used in the United States, but are sometimes done the other way in other countries.

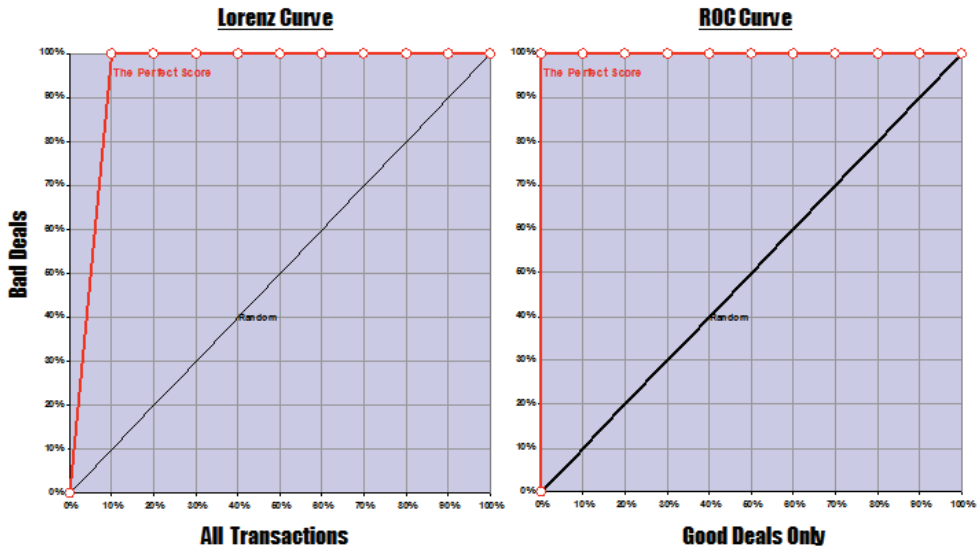
Figure 17
Lorenz Curve



- *K-S Statistic (Kolmogorov–Smirnov Statistic)* – Based on the ROC Curve, the K-S Statistic is the maximum vertical distance between the score's curve and the random diagonal. Perfect would be 100, and random is zero, although, technically, it is between zero and one, but the decimal point usually is omitted. The K-S Statistic is illustrated in **Figure 20**.

In general, these statistics are usually between a half and a quarter of the way above random toward perfection. For an ROC, 0.750 is half the way to perfect and 0.625 is a quarter of the way. The very strongest scores will be above half way, but not by much, and some scores in use will be below a quarter of perfection, but not by much. There is no absolute benchmark for what is a good predictiveness level, because many factors affect what is possible, such as quantities and types of data used, the nature of the transactions being scored, etc.

Figure 18
Lorenz and ROC Curves



Evaluating the economic impact of credit scores

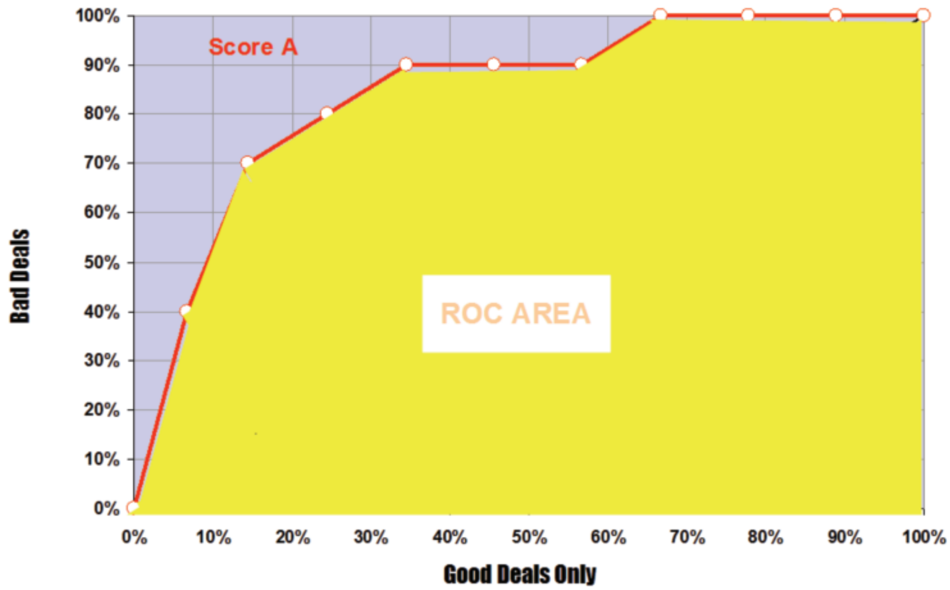
One of the questions oftentimes asked of the credit function by management is the impact of new business of ‘moving the lever’ on the credit score. The classic method for evaluating the impact of doing so is Swap Set Analysis. This analysis assesses the impact of ‘swapping’ credit approvals, i.e., approving some transactions that were previously declined, and declining others that were previously approved.

The first step is to examine the current decisioning practice by score tier of the score being evaluated, listing the number of applications, the current approval rate, the close rate, and, based on a Retro Analysis, the bad/default rate for that score tier. This information is combined with the average transaction amount and estimated LGD and then multiplied, resulting in estimated losses for each score tier. Estimated losses are then totaled for all score tiers, as are origination volumes. This process, for the company’s current decisioning process, is illustrated in **Figure 21**.

The next step is to swap out approvals in the low scoring tiers that have high default rates for more approvals in the high scoring tiers with low default rates. When evaluating the impact of the score there is no reason to approve any transactions with high default rates when there are additional lower default rate transactions that can be approved.

The most logical initial step of this analysis is originations-neutral, keeping origination levels where they are but seeing how much benefit can be had through more accurate decisioning. The ideal, of course, would be to approve all good transactions and none of the bad.

Figure 19
ROC Statistic

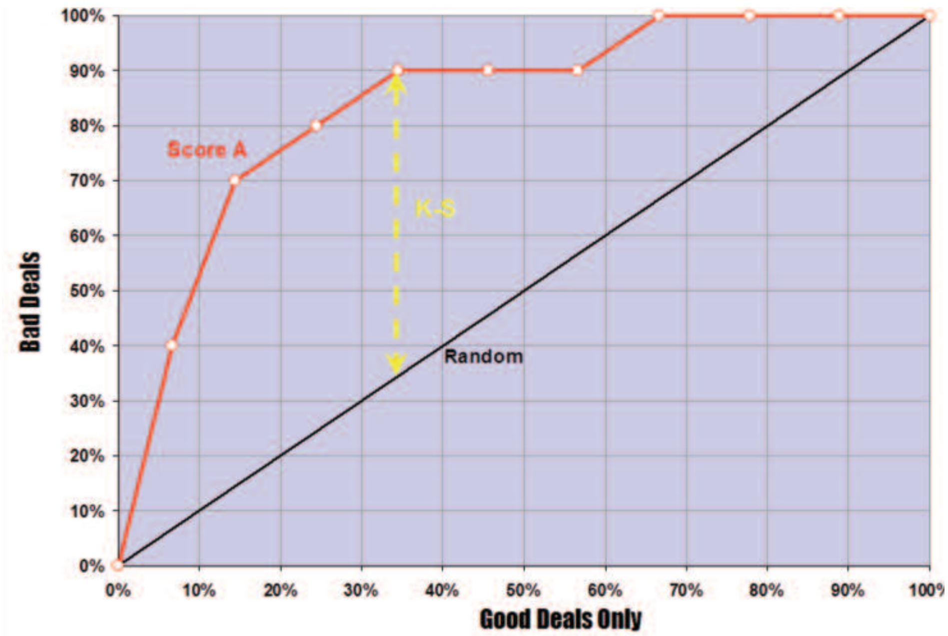


In the example in **Figure 22**, all transactions scoring 660 and above are approved, all transactions scoring 639 and below are declined, and a portion (23%) of those scoring 640-659 are approved. Total origination volume is unchanged from the steady state example in **Figure 22**, at $480 million annually, but expected losses are reduced from $4.8 million to $3.7 million, representing not only a 23.5% reduction in losses, but also a net bottom line savings of $1.1 million.

It often is said in the lending world that it takes ten or twenty good deals to make up for one bad one. If so, why would a finance company approve transactions in score tiers with 20-50% default rates, particularly since not approving these deals materially improves profitability? Using assumptions for profit margin (spread over cost of funds, less operating expenses) and term, it is possible to analyze the impact of such a change in credit decisioning. As shown in **Figure 23**, this change results in a 7.8% improvement in overall profit over the life of one year's worth of transactions.

Identifying a predictive credit score that leads to more accurate decisioning makes it possible to approve more transactions and still maintain the same dollar amount of losses (and even more still with losses as a percent of originations rate). Additional analysis, as in **Figure 24**, shows that approving essentially all applications scoring 640-659 not only maintains the estimated loss amount from the current practice scenario ($4.8 million) but also results in $29 million more in originations, which is a 6% increase.

Figure 20
K-S Statistic



This scenario is slightly more profitable than the originations-neutral, loss reduction scenario, but the two are close enough that changes in some of the assumptions, particularly margin, could change which course is the most desirable one to be taken. As has been previously noted, this type of information also can be used to support fact-based pricing and structuring.

Implementation nuts-and-bolts

Predictive scores can be a great benefit, when used in a purely informational mode, to help a credit manager make a subjective decision. They also can be quite beneficial when used in conjunction with subjective decisioning. For example, credit policies may be adopted precluding someone with credit authority from approving deals scoring below a certain level (or declining deals scoring above a certain level) without having another credit person concur. In such use, the score becomes a virtual second opinion.

Scores have an even greater impact, however, when used for auto-decisioning as costs and time are removed from the process, which is one of the benefits of predictive analytics. Auto-decisioning can be in the form of auto-approval, auto-decline, or both. As a rule, banks are more likely to auto-decline, captives to auto-approve, and independent finance companies to do both, in each case reflecting their transaction economics, although there are lenders of all types taking each of these approaches.

Figure 21
Current Credit Decisioning Practice

Application Date Range: 1/1/2010 to 12/31/2010 Loss Given Default: 30%

PayNet Score	Quality Grade	Total Apps	Declined	Approved	Booked	Current Approval Rate	Current Closing Rate	Default Rate	Projected Losses
560-589	F	13	10	3	2	25%	57%	50.0%	$41,748
590-599	F	17	11	6	4	35%	62%	44.4%	$74,218
600-619	D-	66	36	30	17	46%	55%	23.0%	$172,632
620-629	D	72	33	40	29	55%	72%	17.6%	$227,548
630-639	D+	103	48	55	30	53%	55%	16.4%	$226,185
640-659	C-	343	93	250	180	73%	72%	13.1%	$1,069,663
660-669	C+	244	45	199	138	82%	70%	8.3%	$523,586
670-679	B	345	52	293	223	85%	76%	5.4%	$550,736
680-689	B	381	32	350	276	92%	79%	4.1%	$519,729
690-699	B+	461	31	430	350	93%	81%	3.3%	$531,787
700-719	A	1,041	55	986	809	95%	82%	1.6%	$590,720
720-729	A	434	18	416	351	96%	84%	1.0%	$160,485
730-739	A+	403	12	391	335	97%	86%	0.4%	$57,064
740-799	A+	487	12	476	429	98%	90%	0.2%	$39,989
Grand Total		4,412	488	3,925	3,172	**89%**	81%		

$ Avg. Transaction Size	**$151,260**
$ Est. Annual Originations	**$479,820,198**
$ Est. Total Losses	**$4,786,089**

Before any auto-decisioning occurs, the system is run in parallel, and many people review what the prospective outcomes would be if the system were live (reviewing not just the credit decision, but the transaction, the precise entity approved, etc.). In practice, auto-decisioning always begins with a small portion of applications.

Letting the first group of deals proceed automatically, no matter how small, always is the most difficult – somewhat akin to a Normandy Beach situation. From there, however, it tends to grow rather quickly, as it becomes clear that the deals being approved or declined really should be. The positive feedback from the market and the sales team regarding 60-second decisions further supports the initiative.

There comes a point of diminishing returns, however, when a substantial portion or, perhaps, even the majority of transactions are auto-decisioned. The rate of increase slows, therefore, as borderline deals and unusual/special circumstances do exist. Consequently, almost no lender, at least in the commercial term lending market, gets very close to 100% auto-decisioning today.

Figure 22
Alternative Decisioning Strategy – No Change in Originations

Application Date Range: 1/1/2010 to 12/31/2010 Loss Given Default: 30%

PayNet Score	Quality Grade	Total Apps	Declined	Approved	Booked	New Approval Rate	Closing Rate	Default Rate	Projected Losses
560-589	F	13	13	0	0	**0%**	57%	50.0%	$0
590-599	F	17	17	0	0	**0%**	62%	44.4%	$0
600-619	D-	66	66	0	0	**0%**	55%	23.0%	$0
620-629	D	72	72	0	0	**0%**	72%	17.6%	$0
630-639	D+	103	103	0	0	**0%**	55%	16.4%	$0
640-659	C-	343	263	80	58	**23%**	72%	13.1%	$342,574
660-669	C+	244	0	244	170	**100%**	70%	8.3%	$642,088
670-679	B	345	0	345	263	**100%**	76%	5.4%	$649,297
680-689	B	381	0	381	302	**100%**	79%	4.1%	$566,915
690-699	B+	461	0	461	376	**100%**	81%	3.3%	$570,463
700-719	A	1,041	0	1,041	854	**100%**	82%	1.6%	$623,782
720-729	A	434	0	434	366	**100%**	84%	1.0%	$167,586
730-739	A+	403	0	403	346	**100%**	86%	0.4%	$58,809
740-799	A+	487	0	487	439	**100%**	90%	0.2%	$40,955
Grand Total		4,412	534	3,878	3,172	**88%**	82%		

$ Est. Annual Originations	**$479,820,198**
$ Change in Originations	**$0**
Margin (200 bps x 2 years)	**4%**
$ Change in Orig. Margin:	**$0**
% Change in Originations =	**0.0%**

$ Est. Total Losses	**$3,662,470**
$ Change in Losses	**-$1,123,619**
Total Net P&L Benefit:	**$1,123,619**
% Change in Losses =	**-23.5%**

In addition to applications scoring in the grey/borderline area, there also are applications that trigger review rules. Any auto-decisioning environment should include rules that prevent auto-decisioning in cases in which:

- There is insufficient data
- Unusual events have occurred, or unusual terms are being requested
- Negative events have occurred that, in all likelihood, would result in a very low score and no auto-approval, (e.g., a bankruptcy). While probably not necessary, these do no harm, and remove any question as to whether such auto-decisions could ever occur.

It always is easier to begin auto-decisioning with smaller transactions than with larger ones, so most lenders start small and move up over time. While some lenders focus on transaction amount, most focus on exposure amount with, perhaps, an add-on type rule allowing for a very small additional amount for a large exposure.

Figure 23

Effect of Decisioning on Profit Margin

Gross profit impact	Current approval practice	New approval strategy	$ change	% change
Profit margin (200 bps x 2 years)	$19,192,808	$19,192,808	$0	0.0%
Losses	(4,786,089)	(3,662,470)	(1,123,619)	-23.5%
Net profit (margin minus losses)	$14,406,719	$15,530,338	1,123,619	7.8%
Losses (% of originations)	1.00%	.76%		-23.5%

Figure 24

Alternative Decisioning Strategy – Hold Losses and Grow Origination

Application Date Range: 1/1/2010 to 12/31/2010 Loss Given Default: 30%

PayNet Score	Quality Grade	Total Apps	Declined	Approved	Booked	New Approval Rate	Closing Rate	Default Rate	Projected Losses
560-589	F	13	13	0	0	**0%**	57%	50.0%	$0
590-599	F	17	17	0	0	**0%**	62%	44.4%	$0
600-619	D-	66	66	0	0	**0%**	55%	23.0%	$0
620-629	D	72	72	0	0	**0%**	72%	17.6%	$0
630-639	D+	103	103	0	0	**0%**	55%	16.4%	$0
640-659	C-	343	0	343	247	**99.95%**	72%	13.1%	$1,466,193
660-669	C+	244	0	244	170	**100%**	70%	8.3%	$642,088
670-679	B	345	0	345	263	**100%**	76%	5.4%	$649,297
680-689	B	381	0	381	302	**100%**	79%	4.1%	$566,915
690-699	B+	461	0	461	376	**100%**	81%	3.3%	$570,463
700-719	A	1,041	0	1,041	854	**100%**	82%	1.6%	$623,782
720-729	A	434	0	434	366	**100%**	84%	1.0%	$167,586
730-739	A+	403	0	403	346	**100%**	86%	0.4%	$58,809
740-799	A+	487	0	487	439	**100%**	90%	0.2%	$40,955
Grand Total		4,412	271	4,141	3,361	**94%**	81%		

$ Est. Annual Originations	**$508,398,098**	**$ Est. Total Losses**	**$4,786,089**
$ Change in Originations	**$28,577,900**	**$ Change in Losses**	**$0**
Margin (200 bps x 2 years)	**4%**		
$ Change in Orig. Margin:	**$1,143,116**	**Total Net P&L Benefit:**	**$1,143,116**
% Change in Originations =	**6.0%**	**% Change in Losses =**	**0.0%**

The rationale to initiate auto-decisioning with small transactions is that the cost savings in this market are important and that there simply is more at risk with a larger transaction. Part of the issue also is whether one believes that scores can make better credit decisions than people, or perhaps more to the point, than the average credit person. Retro and Swap Set Analysis show that, at least in some markets, scores, on average, and when properly managed, do a better job.

That said, the easiest, and probably most effective method of deciding up to what amount to auto-decision, is to review the institution's recent decisions. This can be done by looking at approvals versus declines on a graph with the credit score on one axis and exposure size on the other. The data then is reviewed for patterns, e.g., below what dollar level and above what score cut-off are the company's recent decisions consistently approvals? If there is a pattern, but with a few exceptions, those specific deals are reviewed as to why they were declined, and whether, perhaps, they should have been approved.

Similarly, is there a score level below which the institution consistently declines? If there is a score cut-off below which it would be consistent to auto-decline a small application, that cut-off should at least be considered if the low scoring applicant applies for a large transaction. After all, if giving the applicant a small amount is out of the question, why seriously consider giving it a large amount?

Since the economic environment affects loan performance, credit managers do their best to factor the economy into their decisions when subjectively decisioning deals. Credit scoring faces the same issue. Essentially, all credit scores do is provide a relative measure of risk. A 700 transaction has a lower risk than a 650, but it is not clear what that means in terms of expected default rate. Some lenders look at historical, through-the-cycle default rates associated with specific score tiers, and assume they apply across the board.

This can be dangerous, as the default odds for any given score tier shift over the course of the economic cycle. During the most recent recession, for example, almost every score continued to rank-order risk, as it was built to do (700s defaulted at a lower rate than 650s). The absolute magnitude of the default rates increased for all score tiers, however, resulting in higher losses than some lenders expected. **Figure 25**, showing 18-month default rates by year of origination, is a typical example of what occurs over the course of an economic cycle.

In order to maintain a constant default rate cut-off, therefore, a lender needs to adjust score cut-offs as the economy changes. Rather than simply producing a score, some newer predictive scoring models are being designed to include macroeconomic factors and to predict a specific probability of default (e.g., 4.5%) based on the borrower's credit quality and the economy. While such models are more useful, and do not require on-going cut-off adjustments, they are significantly more difficult to build, and require much more data.

In summary, predictive analytics can be used to both develop a credit score and evaluate the performance parameters of such a score. In this way, the company is able to use predictive analytics not only to reduce the costs associated with manual credit adjudication but also to increase profitability through analyzing the results of those credit decisions.

Figure 25
Default Rates across the Economic Cycle

Score	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009
< 600	34.8%	41.8%	36.2%	28.9%	22.1%	19.7%	23.3%	29.5%	34.0%	25.8%
600-619	21.5%	18.9%	17.9%	15.5%	14.4%	16.6%	18.8%	21.5%	26.2%	23.3%
620-639	14.4%	12.2%	10.5%	10.2%	9.9%	11.2%	13.3%	15.5%	18.0%	14.6%
640-659	9.4%	7.1%	6.1%	5.8%	5.7%	6.7%	8.2%	10.2%	11.2%	8.6%
660-679	5.9%	4.2%	3.7%	3.3%	3.2%	3.9%	4.8%	6.3%	6.7%	4.2%
680-699	3.5%	2.5%	2.2%	1.9%	1.7%	2.0%	2.5%	3.4%	3.8%	2.5%
700-719	2.0%	1.6%	1.3%	1.1%	1.0%	1.0%	1.3%	1.8%	2.2%	1.4%
720+	2.0%	0.9%	0.9%	0.7%	0.6%	0.6%	0.7%	1.0%	1.3%	0.9%

Scenario Two – Increasing residual profits

Risk management is one of the categories in which companies are applying predictive analytics today. This area includes asset management, as most lessors consider it an aspect of risk management, since properly managing residual risk increases residual profits. For a lessor to effectively manage residual risk using predictive analytics, however, the causative risk factors associated with the residual value must be identified and considered in the predictive analytics process.

The approach taken in this scenario, therefore, focuses on properly defining the risks and factors that affect residuals so that the predictive analytics program may be effectively designed and deployed. The goal of doing so is to help companies migrate to a better risk model capable of leveraging the benefits of predictive analytics.

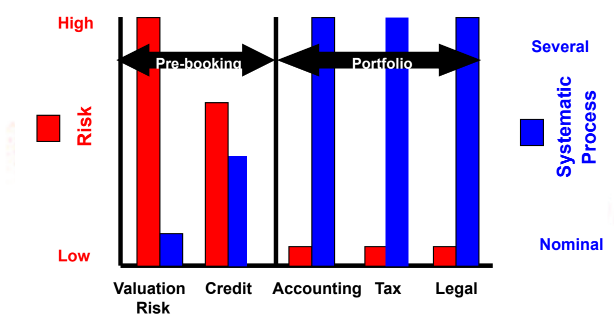
Current process

A common practice in the 1980s was for an asset manager to seek input on the residual value from several sources in the industry or commission a formal appraisal, if dictated by policy. These values were then averaged, and, most likely, a haircut applied to that average to create a residual forecast matrix that was used for pricing and risk analysis. Not much has changed 30 years later, except now this information is stored electronically rather than in a file room.

The problem with this approach is that it is static, relies heavily on historical data, particularly comparative sales, and focuses on make, model, and asset category reporting. From a broader perspective, this approach has tended to commoditize the leasing product as companies prefer to vacate the space rather than develop analytics to better correlate asset values to the true risk factors that drive them.

There is a dearth of standardized guidelines, systems, and processes in residual management. Credit underwriting, by comparison, has such standards and is supported and monitored by various agencies. The tax, accounting, and legal functions also have numerous guidelines, systems, and processes specific to them, as can be seen in **Figure 26**, even though there is very little economic risk associated with these functions. Contrarily, there are few systematic processes for valuing assets.

Figure 26
Risk Relative to Systematic Processes



One reason the risk factors of an asset may not be addressed is the organizational structure of the asset management function. For instance, some risk/valuation departments align by specialty. Although these analysts have detailed knowledge of the latest avionics, powertrain, diagnostics, technology, etc., this approach sometimes creates potential roadblocks to proper risk analysis.

Such analysts may view their industry or asset as unique, rather than recognizing the similarities of general risk factors across assets and industries. The result is that the value of the data for the identified risk variables is ignored or not leveraged. Analysts with multiple industry responsibilities have the ability to see how the risk drivers play across different assets, thereby raising their view of risk to a portfolio level.

Another challenge of assessing the residual risk in transactions is the need to support new volume and provide analytics in a condensed time frame. Past ELFA Surveys of Equipment Finance Activity show that turnaround times on transactions have been dropping over the last six to seven years.

As the pressures for a fast turnaround increase, deals may become backlogged or the analysis hurried, which in a non-systematic environment, compounds the risk. It also carries over into the portfolio, where it is further exacerbated by the inability to make remedial changes to the asset once it is on the books. This is another area in which residual management differs from other functions, as shown in **Figure 27**.

Figure 27

Differences Between Functions

	Asset valuation	Noncredit functions
Systematic processes	No	Yes
Industry standards and processes	No	Yes
Demonstrable process and audit trail	Limited	Yes
Ability to correct post-booking	No	Yes
Competitive advantage	Yes	No

For example, if a mistake is made in assigning the depreciable life of an asset for tax purposes, it can be remedied during the term of the lease. Even adverse credit events can be addressed prior to end of term with restructures or additional collateral. There are very few viable options to correct a residual during the term due to a faulty analysis, however. **Figure 28** illustrates some additional items, whether they are systematic or manual processes, and their risk attributes.

A final factor relates to the fact that the equipment leasing and finance industry currently tends to focus more on the 'number,' as opposed to the actual risk factors that drive that number. The lack of ability to properly classify and identify the appropriate risk factors has led to losses in asset values in vehicles such as SUVs, Class 8 tractors, aircraft, and construction equipment, to name but a few.

When asset losses increase, new policies are added to assure management that this will not happen again. Since these policies do not deal with the underlying risk and value drivers, however, they can create unintended consequences such as increased conservatism or the over-structuring of deals, potentially reducing the chances of winning new business.

A proposed approach

Thus far, several factors that impede proper risk management in the residual management space have been discussed. Given these impediments, the question becomes one of how to establish a foundation for utilizing predictive analytics in residual management that identifies relevant risk attributes and assigns them to various asset categories.

It is helpful to begin the discussion of how to classify asset and residual risk with an examination of the elements of risk, in general. One approach is to examine risk from an audit perspective. There are four types of risk in an audit environment:

- *Inherent risk* – the risk that the identified event will occur
- *Control risk* – the risk that the proper controls and processes are not in place to prevent the identified event from occurring
- *Detection risk* – the risk that the controls in place do not prevent the identified event from occurring
- *Audit risk* – the risk that the identified event is not detected upon audit

Figure 28

Systems and Risk Correlation

Function	Item	Systematic/Manual	Risk
Tax	Asset life	Systematic via pricing or origination software	Low risk – update/change after booking
Tax	Sales/use taxes	Systematic via software	Low risk – adjust after first invoicing if required
Accounting	Lease classification	Systematic via pricing and front end applications.	Low risk – can rebook to proper classification before period end
Legal	Lease documents	Systematic, either through origination software or review prior to being sent to the lessee	Medium/high risk – most agreements are standardized with revision management
Legal	UCC filings	Systematic via standard filing processes and ability to outsource to service providers	Low risk – standardized process and only applicable to deals in which lessee defaults or UCC is not filed on a timely basis
Credit	Credit reviews	Quasi-systematic via review of financials, key metrics/ratios, past performance, industry, and the economy	Medium/high risk – challenge is to quantify risk under various scenarios and support sales at the same time
Credit	Coverage and exposure	Manual or quasi-systematic as amortizations show coverage/exposure versus collateral position	Medium risk – pricing and amortization is systematic, but ability to review against collateral and provide "what if" analysis is not easily managed.
Credit	Additional collateral	Manual as part of underwriting to minimize exposure or increase coverage	Low/medium – determine guarantors, collateral support, cross defaults, etc.

The equipment leasing and finance company can reduce the control and detection risk levels by implementing a more systematic and robust governance process for classifying and identifying asset risk. Reducing the inherent risk in asset and residual management is more challenging. One approach is to identify, categorize, and index the proper risk factors and variables associated with the assets.

Guidance and policy, much of which has the force of law, exists to help reduce inherent risk in other equipment-finance functions. This guidance includes FASB Topics and Standards Updates, government statutes, IRS regulations, the Uniform Commercial Code, and so on. Although not as well-recognized and seldom incorporated into residual risk management practices, similar guidance also exists for the appraisal and valuation of assets.

The Uniform Standards of Professional Appraisal Practice ("USPAP") are the generally accepted standards for professional appraisal practice in North America. USPAP contains standards for all types of appraisal services, including real estate, personal property, business, and mass appraisal. The Financial Institutions Reform, Recovery and Enforcement Act of 1989 recognizes USPAP and requires that appraisers comply with it in federally-related transactions.

State appraiser certification and licensing boards, federal, state, and local agencies, appraisal services, and appraisal trade associations all require compliance with USPAP. The American Society of Appraisers ("ASA") also aligns with USPAP and provides classes and certification.

The notion that depreciation affects asset value is fairly widely accepted. Depreciation also represents the risk in the leased or financed asset. There are three types of depreciation recognized by USPAP, the ASA, appraisers and the courts. These are physical deterioration, functional obsolescence, and economic obsolescence. The following are the accepted definitions of these terms:

- *Physical deterioration* – the loss in value or usefulness of a property due to the using up or expiration of its useful life caused by wear and tear, deterioration, exposure to various elements, physical stresses, and similar factors
- *Functional obsolescence* – the loss in value or usefulness of a property caused by inefficiencies or inadequacies of the property itself, when compared to more efficient or less costly replacement property
- *Economic obsolescence (or external obsolescence)* – the loss of value of a property by factors external to the property. These may include such things as the economics of the industry, availability of financing, loss of material and/or labor sources, passage of new legislation or ordinances, increased cost of raw materials, labor, or utilities (without an offsetting increase in product price), reduced demand for the product, increased competition, inflation, or high interest rates.

These three areas of risk probably have less than twenty analytical variables associated with them. This combination, however, would create at least 80 potential scenarios to analyze when assessing the asset risk or in setting a residual. The current residual management process does not have the foundation to perform predictive analytics because historical data is not categorized or indexed by these risk factors and variables. The same holds true for institutionalized personal experience and other asset knowledge.

Properly identifying the risk factors and variables associated with an asset is vital to providing a predictive analytics foundation. As an example, consider the distressed commercial property loan portfolio of a medium-sized bank. The bank regulators were questioning why the equipment lease portfolio was not subject to the same economic risks as the commercial property (and, therefore, the same large write-down). The auditors, with good reason, were skeptical of the bank's underwriting/risk practices and, by association, its leasing company.

The portfolio manager explained to the auditors that the valuation/appraisal methodology being used simply looked at what similar property was trading for at the time. Other risk factors affecting value, such as supply and demand, were not incorporated into the valuation. The appraisal did not have a baseline to validate the supply/demand balance. The portfolio manager then illustrated this point through the example in **Figure 29**.

Figure 29

Supply and Demand Baseline

Property	A	B	C	D	E
	Annual net migration to state	% of net migration requiring office space	# of net migration requiring office space	Baseline square footage absorption per year	Number of years to absorb capacity
Class A office space	20,000 people	5%	1,000 (A x B)	100,000 (C x 100)	10 (1,000,000/C)

In this real estate example, the unoccupied square footage available was 1,000,000 square feet. Assuming an occupancy rate of 100 square feet per person, it would take 10,000 people to fill the space being analyzed. Based on the net migration of individuals into the state at the time, it would take ten years to absorb the existing office space. The portfolio manager took a baseline across the equipment leasing portfolio to show how the assets were not under the risk of the same potential write-down, thereby satisfying the auditors.

Another similar example involves vehicles. At the time, the automobile lessors were taking large residual losses, particularly with SUVs, and there was concern the equipment leasing industry would be viewed as risky and painted with a similar brush. Responses to those losses varied, but most revolved around taking more conservative residuals or shunning SUVs as an asset class, rather than addressing the underlying risks.

These responses were interesting from a risk and analytical standpoint but not unexpected from an operational perspective. In this case, the risk managers lost sight of the real risk issues, which were the functional and economic risk from assets with poor fuel and energy efficiency. **Figure 30** illustrates how the risk analysis for a vehicle differs based on only one risk variable (fuel costs), as represented by miles-per-gallon (MPG).

Mathematically, and assuming similar residual processes, vehicle Y in **Figure 30** does not have any greater residual risk than vehicle Z. Although this statement is true on its face, properly identifying the risk would have exposed the approximately three times greater residual risk associated with the fuel and energy prices of vehicle Y. This analysis indicates that vehicle Y requires more monitoring for this economic risk attribute. Incorporating variables such as this into the residual risk management foundation allows the company to leverage the power of predictive analytics.

This example illustrates the potential impact of improperly focusing on assets from a manufacturer and model perspective in lieu of the actual risk. **Figure 31** is an example of how the engineering stage risk of an asset can be classified from a functional obsolescence standpoint. If management asked the residual risk department today for a similar portfolio report based on risk classifications such as this, it is likely they would be disappointed.

Figure 30

MPG Analysis

Vehicle	A	B	C	D	E	F
	Original cost	Residual %	Residual $ (A x B)	MPG	Residual/MPG (C/D)	Increased risk from fuel/energy costs (EY/EZ)
Y	$40,000	20%	8,000	15	533	333%
Z	$20,000	20%	4,000	25	160	N/A

Note: Z could be considered a baseline policy for MPG risk

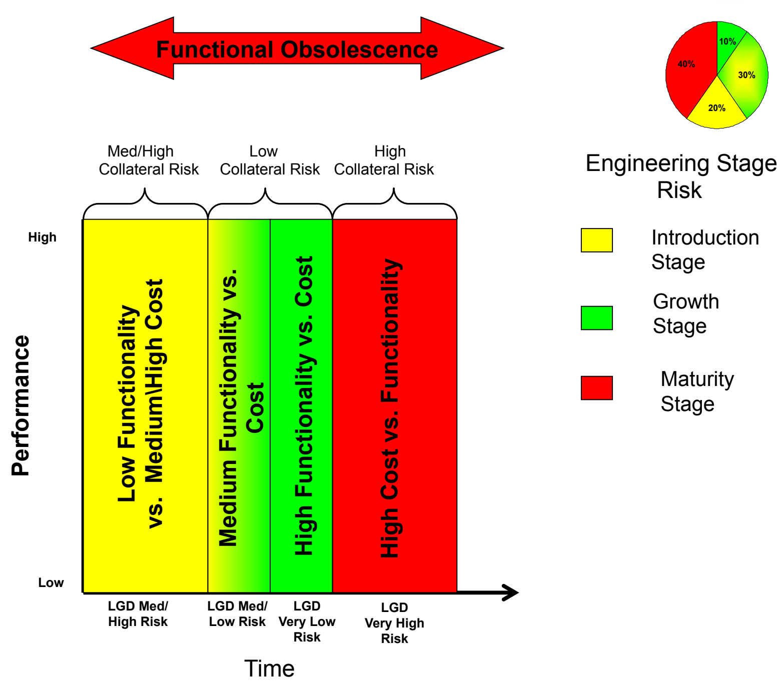
The type of information contained in **Figure 31** can be combined with predictive markers based on the likelihood of renewing the equipment, etc., to establish remarketing strategies and comply with regulatory requirements, among other things. This exercise also can be utilized to determine loss given default and properly assign reserves for the overall portfolio.

Ideally, after the risk criteria are identified for each asset, a library of, say, 20 risk attributes, with performance curves for each based on years of data, relevant factors, and correlation analysis can be developed. Then, as each asset is reviewed, the analyst can identify the applicable risk factors in the asset and find the curves that best match those risk factors.

The last example regarding risk factors relates to locomotives, or SD40-2s in particular. If the functional obsolescence risk of **Figure 31** was mapped to the portfolio these locomotives would be in the "High Collateral Risk" area. The SD40-2 locomotive also can be used to illustrate application of the three risk factors (physical, functional, and economic) to provide a foundation for analytics going forward. A methodology using these risk factors will be presented and then compared to the current processes for assessing asset risk.

In order to assess physical depreciation risk, the loss in the value of the asset from wear, tear, and the operating environment needs to be determined. The three main wear and tear components of the SD40-2 are the engine, wheel motors, and alternator. The cost at risk for these components today is a minimum of $100,000. By examining **Figure 32**, it can be seen that this amount places the physical depreciation risk as very high. Once the physical depreciation risk is identified, its elements can be monitored properly and mitigated by asset management.

Figure 31
Functional Obsolescence Analysis



The next risk factor considered in this example is functional obsolescence, or the loss in value inherent within the equipment. The value and, thus, the useful life of an asset are driven by the industry and applications of the equipment within that industry. The market for locomotives, for instance, generally is in the Class 1, regional, and short line railroads. Of those locomotives, the SD40-2, with its six axles (in lieu of the standard four) and weight, typically only is operated in volume by Class 1 railroads.

Since the SD40-2 locomotives typically are not cascaded down in high volumes to the normal secondary market of regionals and short lines, the SD40-2 has a niche application within one industry. It is this niche application that gives the SD40-2 a high risk rating, as represented in **Figure 32**.

Another risk classification within functional obsolescence is technological change. Historically, diesel electric locomotives derived tractive power from the direct utilization of DC electricity generated and then transferred to a DC-based traction motor. Introduction of the AC traction motor changed the game, however, as AC power provided increased pulling power, improved resistance to moisture, and reduced wheel slip.

Lower maintenance and lifecycle costs for AC motors also were achieved due to their lower level of complexity. As a result, locomotives began migrating to AC power from the standard DC power. DC technology was, from an engineering technology perspective, in the Maturity Stage (in red), as represented in **Figure 34**. This stage, in which there is high cost versus functionality, represents high asset risk.

The last risk area considered in this example is economic risk, or risks external to the asset, such as fuel and energy costs. **Figure 34** shows how the value will continue to decrease as SD40-2 units flood the market and lease expirations continue to introduce the dated technology into the market, thereby compounding the problem. Furthermore, since the later units coming off lease likely will have the largest cost, the losses per unit will increase. The remaining units will be scrapped and/or salvaged for components to support other applications.

Figure 32
Physical Depreciation Risk

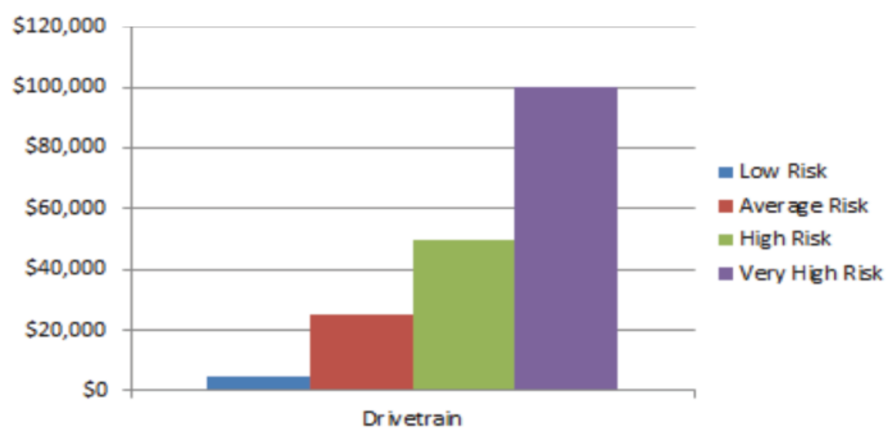
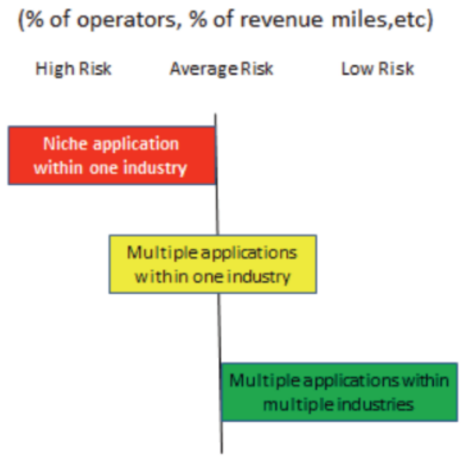
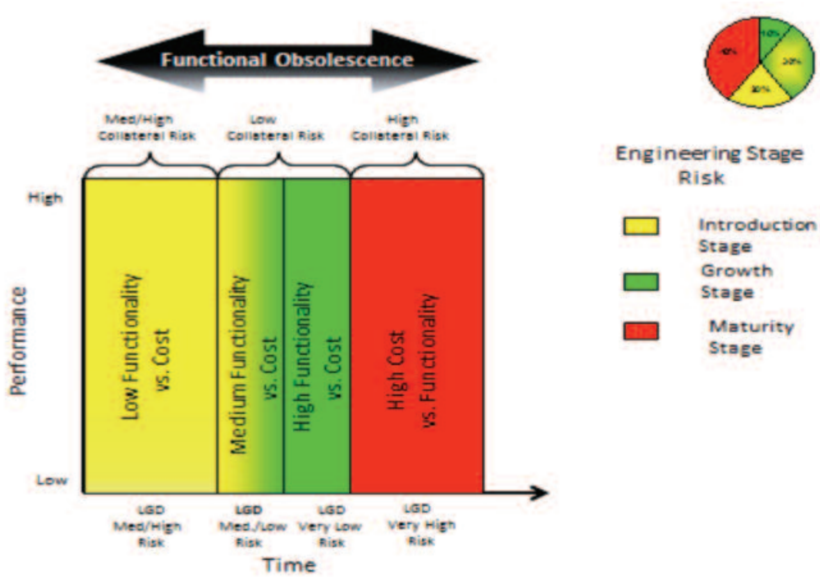


Figure 33
Market Applications



How does this risk factor approach to asset valuation compare to the historical data approach? Today, the data is gathered and a forecast is made to project value over the term, which does not align well with the risk approach previously outlined. For example, SD40-2s would trade in the market anywhere from $275,000 to $325,000. Different forecasts likely would occur for projected fair market value, therefore, based on what similar units were bringing at a like term in the market – in essence, a historical basis.

Figure 34
DC Power Functional Obsolescence

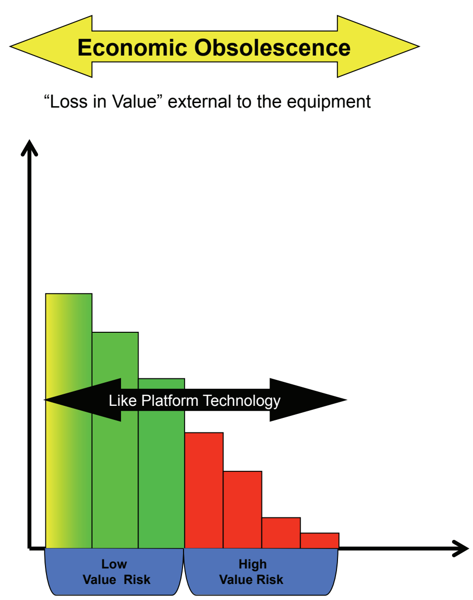


This forecast approach does not align with the risk classification process. For example, it does not recognize the impact of physical risk impact on the historical sales data, in that the $100,000 minimum cost is not qualified in the analytics. It also does not recognize the functional risk, as there is nominal or no sales data to address the six axle issue, the inability to cascade large volumes down to non-Class 1 railroads, or to show the impact of new technology (the shift from DC to AC power). Nor does the forecast approach recognize the impact of economic risk on the historical data, as historical sales data does not reflect the displaced technology impact as fleets continue to be returned and further depress the market.

Using the risk factor approach, the portfolio can be classified by risk (e.g., market applications, the engineering stage, or engineering model runoff) and monitored by a system based on the risk classification assignment. This risk classification also can be used predictively. For example, locomotives with similar attributes (six axles and non-AC technology) likely may be subject to the same effects on their value or useful life. Even the values or useful lives of other transportation assets with niche applications within their industry, or assets affected by gains in energy efficiency are likely to experience impacts similar to those in the rail industry.

The current asset management processes are not well-aligned to leverage the benefits of predictive analytics, however, as they focus on sales of similar assets, rather than the three USPAP depreciation factors. Consequently, changes must be made to those practices and how risk is perceived if predictive analytics are to be utilized effectively in this function. Perhaps the best advice regarding predictive analytics and residual management is reflected in a quote by Jack Welch, former CEO of GE, to "Change before you have to."

Figure 35
Risk Relative to Economic Obsolescence



Scenario Three – Improving future financial performance

Another reason to utilize predictive analytics in the equipment leasing and finance industry is to increase profitability and financial performance. Predictive analytics can do so by providing insights into the portfolio-level results of various decisions, including up-front pricing and back-end disposition practices. External factors such as measures of national or global economic activity also can be made part of predictive analysis.

This knowledge of how various factors and corporate decisions affect portfolio returns can be used to allocate resources or uncover hidden sources of profit (or loss). The combination of this knowledge, with constant and immediate feedback on actual performance, then can lead to possible courses of action targeting increased profitability, as measured by the applicable yields.

Practices for evaluating credit and residual risk were examined in the previous two scenarios. This scenario will incorporate credit and asset risks into a portfolio-based measure of return in order to understand and begin to predict the overall performance of a portfolio of equipment finance transactions. While a number of performance measures are certainly valid for this analysis, the focus here is on Risk-adjusted Return on Capital (RAROC), since it directly incorporates the two key variables of customer credit information and asset quality ratings.

For an analysis to result in relevant and actionable information, it must be expressed at the portfolio level. Yet, because the yield-producing units within a portfolio are transactions, actions must be implementable at the loan and lease level and at key decision points over the life of the transaction. The ultimate profitability of the portfolio depends to a great extent on how well understood and executed the firm's policies are at each of these decision points.

If management is to predict the performance of a portfolio of equipment leases and loans, it not only must identify the variables that drive portfolio performance, it also must analyze how changes in those variables affect returns. Management then must establish a link between its analysis of portfolio performance and actual business practices such as quotation, program design, marketing emphasis, and collection practices. This link has three major components:

- *Historical* – profitability analysis of completed transactions against different values for the driving variables, and comparison to how the transactions initially were priced
- *Predictive* – review of expected changes to portfolio profitability as the values for the causative variables change. These reviews may be simple what-if reviews or sophisticated stress style analyses, as both types fall under predictive analytics
- *Diagnostic* – on-going measurement of actual results against expected results along with continuous validation and refinement of data elements and predictive capabilities.

The derivation of actionable information starts with consistent and complete data on financial performance at the transaction level, which is the level that ultimately drives portfolio performance and at which many of the most important variables act. This data then must be processed and analyzed through a sufficiently sophisticated, transparent, and flexible portfolio performance model that provides results on a timely basis.

The predictive analysis model

While the predictive analytics model must focus on the financial performance of the individual leases and loans that make up the portfolio, it also should allow for grouping transactions in logical units, for example, by territory or asset type, as well as more ad hoc groupings, such as by yield or buy-out date. This flexibility will allow predictive analysis of questions such as:

- How will yields of asset class A compare to the overall portfolio or compared to asset class B if residual realization is changed?
- How will tightening credit standards affect performance in territory A as opposed to territory B, or as compared to the overall portfolio?
- How will degradation of the credit quality for a class of customers affect yield and capital requirements?

The important point is not to use a model that locks the firm into a particular form of analysis. Because predictive analytics is iterative, it will have a strong tendency to suggest further questions that may not have been anticipated at the beginning. Much of the value of a predictive model, therefore, lies in the ability to perform intelligent ad hoc analysis with it. A good predictive model also anticipates the needs of a varied set of users, including budgeting and forecasting, pricing, and portfolio management.

The model must accommodate real world outcomes, as many transactions do not play out in the real world as they were originally contracted. For example, the payments due on the 20th of the month in a 60-month transaction are unlikely to be made precisely on the 20th, or even to run the full 60 months. Events such as buy-outs or upgrades often will make the real transaction very different from what was priced. Therefore, a useful model will incorporate various transaction outcomes, both on the historical and predictive sides.

Many equipment finance companies adjust their pricing in order to win deals that they know, through experience, will play out more profitably than as originally priced. Good examples of this are office equipment that has a strong track record of going month-to-month, or contracts in which the equipment is repeatedly refreshed and the contract extended. A good analytics model should be able to express these realities in terms of yield, so that management knows, for example, that certain lines of business return, on average, 25 more basis points than originally priced.

Good portfolio analytics also should help identify the characteristics of customers with suboptimal behaviors such as those that always return the copier precisely when the lease expires. Pricing management then can use this information to consider modifying the pricing policies in an attempt to limit originating these lower-yielding deals. In all cases, it is important to express the gain or loss under these various scenarios in terms of the yields used by pricing management.

A predictive model helps develop theories about how the portfolio will perform in the future based on changes in underlying factors and variables, thereby suggesting actions to enhance performance. In practice, this includes such things as:

- Producing a forecast of the run off of the existing book of business, including forecasting how the various outcomes will affect returns
- Layering on a new business forecast, again, modeling the outcomes based on historical data, and incorporating the impact of external factors
- Comparing actual results with predicted results and determining any differences or shortfalls

Methodology

The predictive model and methodology discussed in this section was applied to a portfolio of 67 completed aircraft transactions supplied by an ELFA member company. In addition to removing company specific data, customer names, and information identifying specific aircraft, credit scores were converted from the proprietary system indicators to a simple numerical scale. The portfolio included four tax leases and 63 conditional sales contracts.

The data in the subject portfolio was reasonably rich, containing actual cash flows (dates and amounts) from the system of record, as well as information on the aircraft type, targeted returns, and buyout amounts. In a few cases, most notably the term of the original transaction, data was incomplete. A representative term of 84 months was used when the original term was unknown.

Before applying predictive analytics to the sample portfolio, a series of questions about the performance of individual completed transactions, groups of completed transactions, and, ultimately, the historical portfolio as a whole, was asked.

- What was the anticipated yield of the transaction, group, and portfolio?
- What was the actual yield on the transaction, group, and portfolio?
- What factors accounted for the differences between the priced yields and those actually realized?
- Can these factors be statistically correlated to the outcomes?

The sample portfolio of completed transactions was used to create a variety of analytic portfolios to better understand how these completed transactions perform under certain scenarios. For example, the analyst could determine when, and under what conditions, transactions were terminated early or renewed, and if there were identifiable factors or variables driving those actions.

Two portfolios were assembled for analysis from the sample portfolio data. The 'Actual' portfolio contained the cash flows and returns actually experienced. The 'As Priced' portfolio, on the other hand, represented the assumed cash flows and returns that were in place at the time of booking the deals. Although the individual transactions in this portfolio were large enough to warrant individual analysis, the ideas and principles of this analysis applied to portfolios of smaller assets, as well.

A single transaction from the portfolio was used to illustrate the method of analysis. In this transaction, an airplane was financed in July of 2003 on an 84-month conditional sales contract with a targeted, after-tax economic ROE of 15.09%. What actually happened, however, was that the lessee exercised an early buyout option after only three years.

Figure 36 contains a comparison of the economic, ROE cash flows for this transaction. These include certain portfolio-level expense assumptions, referred to as secondary expenses, which represent the cost of carrying the transaction on the portfolio, as well as the tax savings. The actual, versus as-priced, yields for the same transaction are compared in **Figure 37**.

The highlighted nominal, after-tax ROE of 15.09% is the yield that was targeted when the transaction was priced. In this case, the actual transaction results fell well short of the targeted yield. Understanding why it fell short, and what factors contributed to the shortfall, could help the company analyze how changes in these factors would impact future portfolio performance.

Examination of the actual cash flows of this deal shows that the lessee paid rents almost exactly as the transaction anticipated, and that nearly all the difference between the actual versus priced yield is the result of an early buyout. The buyout amount at 36 months is lower than the estimated 84-month residual value used to price the deal.

This shortfall suggests three areas for further investigation. First, was the residual value used for pricing correctly determined? Were the physical, functional, and economic risk factors, such as future fuel prices, properly taken into account? Second, was the early buyout quoted and executed correctly? Third, how will future buyouts impact portfolio performance?

Figure 36

Single Transaction Summary Cash Flow Comparison

Cash Flow	Actual	As priced
Asset cost	(8,616,622)	(8,616,622)
Rent	3,281,445	6,393,381
Buyout/residual	6,751,287	7,046,416
Total cash In	10,032,732	13,439,797
Pretax cash flow	1,416,110	4,823,175
Taxes paid	(495,638)	(1,688,111)
After-tax, ROA cash flow	920,472	3,135,064
Internal Interest	(864,209)	(1,419,155)
Internal Interest - taxes saved	302,473	496,704
Secondary expenses paid	(85,004)	(163,584)
Secondary expenses - taxes saved	29,751	57,254
After-tax, ROE cash flow	303,483	2,106,284

As the analysis of the transactions, segments, and portfolio continue, many other areas of investigation present themselves to the analyst, investigations that are guided by common sense and industry experience. Once valid data and modeling practices have been established, however, the analyst can apply statistical tools to help identify which factors have the greatest effect on profitability, and perform portfolio analyses to test changes in these factors.

Figure 37

Single Transaction Yield Comparison

Yield Summary	Actual		As priced	
	NPT	NAT	NPT	NAT
MISF	6.8971	4.4831	11.3384	7.3700
IRR	5.9572	3.5722	8.7001	5.6550
Economic ROE		9.8091		**15.0900**
Risk ROE (RAROC)		24.1822		25.3147
ROA		2.8515		7.8358
Average life (months)		28.5938		59.2415

Key:
NPT – Nominal pretax yield
NAT – Nominal aftertax yield
MISF – Multiple investment sinking fund

Just as in the single transactions, analysis of the portfolio shows that much more cash was anticipated in the pricing than actually was realized. Further analysis indicates that all but a few of the transactions were terminated early, with a 33.46 month, weighted-average actual term versus a presumed 84-month priced term. The yield comparisons of **Figure 38** also show that, on the whole, the actual transactions were significantly more profitable than priced, with a nearly 50 basis point premium for the NAT MISF. The economic ROE was a substantial 977 basis points better.

Given results such as these, one might be tempted to take the view in this case that the pricing and, more importantly, the early buy out policies, clearly work in practice. An examination of the returns on the individual transactions, however, shows a great deal of variation between the yields and highlights other areas requiring additional analysis. As can be seen in **Figure 39**, there is wide variability in the actual ROE between transactions. Even though all were priced to an ROE in the range of 6.92% to 31.82%, the realized ROE varies from a negative 94.51% to a positive 449.31%.

Segmentation analysis

The analyst's knowledge of the business and company practices will determine what segments to investigate before applying predictive analytics. The following discussion seeks to illustrate this by creating a series of ad-hoc segments and then drilling down into the transactions to discover the sources of the transaction performance, the preliminary outcome of which is to suggest potential causative variables that affect yields.

Since transactions were priced to an economic ROE in the subject portfolio, the first segmentation performed is actual performance against the targeted ROE. About half of the portfolio, or 33 transactions, show a realized ROE greater than 0% and less than 60%. These 33 transactions have a combined portfolio ROE of 12.43%, or 21 basis points shy of the combined ROE yield of the portfolio as it was priced.

Figure 38
Portfolio Yield Comparison

Yield Summary	Actual		As priced	
	NPT	NAT	NPT	NAT
MISF	8.4070	5.4645	7.0546	4.9678
IRR	8.2066	5.3343	6.7915	4.7209
Economic ROE		22.4060		12.6307
Risk ROE (RAROC)		22.4797		15.3352
ROA		2.8800		2.7208
Average life (months)		31.3140		76.9875

Key:
NPT – Nominal pretax yield
NAT – Nominal aftertax yield
MISF – Multiple investment sinking fund

Twelve of the remaining 34 transactions show negative ROEs, and have a combined portfolio yield of negative 3.82%. The remaining 22 transactions, those with ROEs over 60%, yielded a combined portfolio ROE of 124.85%. These ROE bands are shown in **Figure 40**.

Based on this initial segmentation, the portion with unusually poor returns can be analyzed further to identify potential predictive variables that may have affected these returns. Drilling down to view the most egregiously low ROE transactions within the 12 transactions with negative ROEs yielded the following information:

- A lease of a Cessna Citation Excel that ran for 20 months was bought out at fair market value. This suggests that the initial appraisal of the asset was overly optimistic, or that some event – perhaps excessive use or unaccounted for obsolescence – rendered the fair market value of the end-of-term asset far below expectations.

- A lease of a Cessna Citation XLS had a very poor payment history over 30 months before the asset was liquidated. The customer credit rating was a seven on a one to ten scale (where one is best), so the poor payment history was not a shock. This outcome suggests further investigation into both the accuracy of the credit scoring on the transaction and the lessee acceptability criteria in order to determine whether this was bad luck, bad pricing, or the result of a measureable variable.

Note that a similar level of analysis could be performed on segments in larger portfolios of middle or small ticket assets. This could be done by creating segments using multiple filter criteria, such as a segment of actual transactions with a poor ROE, poor payment history, and, yet, fair to good credit scores.

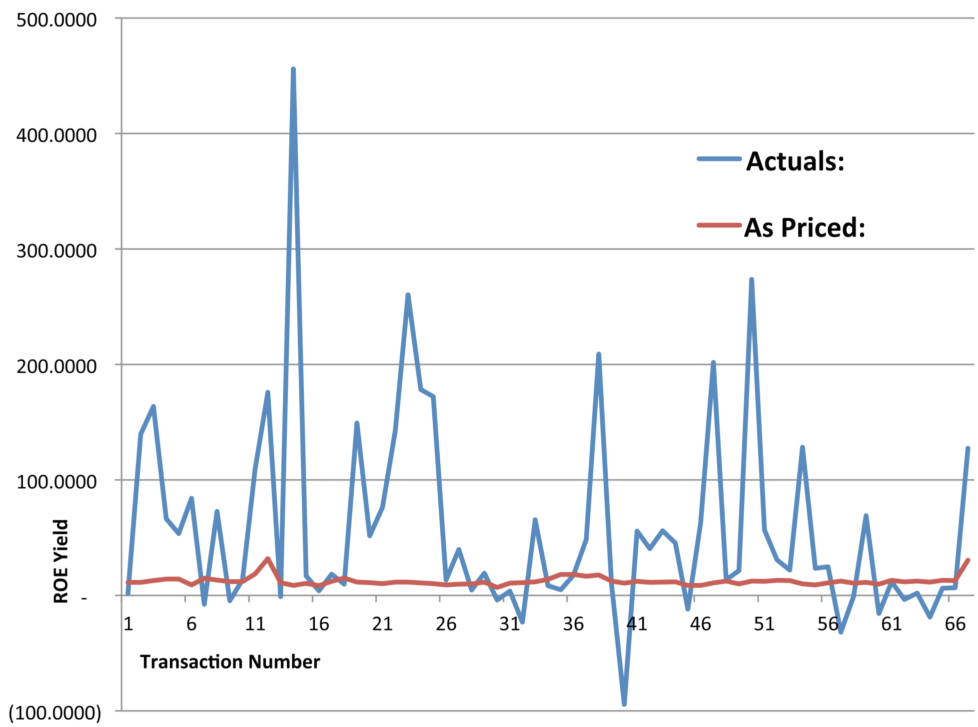
In addition to providing potential predictive data, analysis of the poor performing transactions might point out risks for which the lessor should be compensated through more favorable pricing and structuring. It also might suggest that transactions with certain characteristics should be avoided altogether.

Examination of high-yielding transactions, on the other hand, seeks to identify any traits that would allow the lessor to target similar transactions, and, if necessary, determine how much more competitive the sales team can be, given the increase in actual yields over the priced yields. An analysis of the high-yielding transactions produced the following information:

- The highest yielding transaction was a lease of a Cessna Citation Excel that ran for 30 months and, over that term, collected payments worth nearly twice the original value of the aircraft. In looking at this deal, an accounting error first must be ruled out, but if the cash flows are accurate, the analyst would want to learn more detail about this transaction.

- This lease of a Gulfstream G200 ran for only four months, after which the aircraft was purchased by the lessee for more than the original asset cost. The analyst would want to know if this is the result of a bridge financing program, or if the transaction was really intended to run longer. Given the high yield, and if it was intended to run longer, the analyst should look for predictive factors or characteristics that identify similar potential opportunities.

Figure 39
Economic ROE as Priced and Realized



Given that two of the top three most profitable transactions had very short terms, a logical question to ask is whether short term transactions are more profitable, in general, and, if so, what predictive variables might be driving these results? The average and weighted average terms are displayed, by ROE band, in **Figure 41**, as a simple first pass at assessing the effect, if any, of transaction term on ROE. Although slicing the transaction terms this way does not seem to indicate any correlation between ROE and term, it does suggest yet another avenue of investigation.

For example, further analysis indicates that both the highly profitable and unprofitable transactions tend to run shorter than the normal transactions in the subject portfolio. While the negative ROE on shorter transactions makes some sense, as deals that default or have other payment troubles typically end early, it is not clear why very profitable transactions also tend to be shorter. This finding merely raises additional questions, though, as no conclusions can be reached at this point about the relationship of actual term to profitability.

Two more ways that may prove valuable in identifying predictive factors include the relationship between manufacturer and ROE (**Figure 42**). It is clear that ROE is not consistent across manufacturers in the sample data, yet the distribution of transactions among the two major vendors and the others that make up the subject portfolio is roughly comparable.

Figure 40
Asset Funding and ROE Band

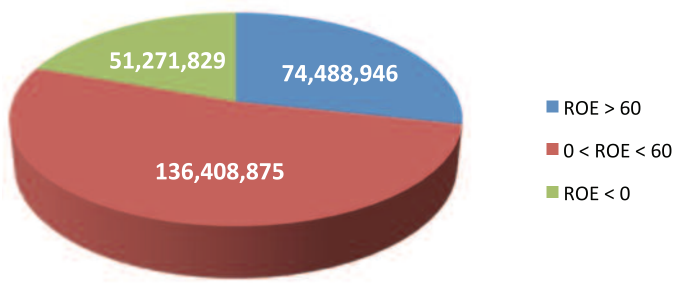


Figure 41

Average and Weighted Average Term by ROE Segment

	Average term	Average weighted term
ROE > 60	20.41	19.92
0 < ROE < 60	37.94	41.95
ROE < 0	23.25	30.55

Figure 42

Segmentation by Manufacturer and ROE Distribution

			Number of transactions in range		
	Total	Overall ROE	ROE > 60	0 < ROE < 60	ROE < 0
Gulfstream	23	30.90	8	12	3
Cessna	26	19.65	9	12	5
Other	18	15.76	5	9	4

Figure 43 shows that the variation in yield assumes a clear pattern, i.e., the better the credit score, the better the return, except in the 'Other' category. This could mean that better credits could be priced more aggressively if there is more market share to be had, or, perhaps, that the company is not being fully compensated for the risk inherent in the poorer credits.

Figure 43

Segmentation by Manufacturer and Credit Band

		Credit Score			
		1 - 2	**3 - 4**	**5 - 6**	**7 - 10**
Gulfstream	Number of transactions	0	9	7	7
	ROE	-	95.59	47.03	15.09
Cessna	Number of transactions	3	6	5	12
	ROE	289.03	57.02	43.79	14.49
Other	Number of transactions	3	3	7	5
	ROE	14.36	6.83	23.72	14.56

When using a predictive analytics model, companies will explore a wide variety of segment views into their data, and then delve further into those that promise to provide the most actionable and effective information. The process of determining which views hold most promise can be guided heuristically, using the knowledge and experience of the leasing professional, or a 'big data' approach may be taken, in which analysis is performed on all available data with the hope of uncovering previously undiscovered relationships.

A sufficiently large and rich set of data should be collected and regression statistics between the variables calculated. The statistical significance of the relationship between those variables then is established. The iterative process of establishing a data set, investigating it, taking action, and measuring the results leads to further refinement and additions to the data. This new data then is refined and added to the investigative approach, where new and different actions are taken, and new results measured.

Outcomes modeling

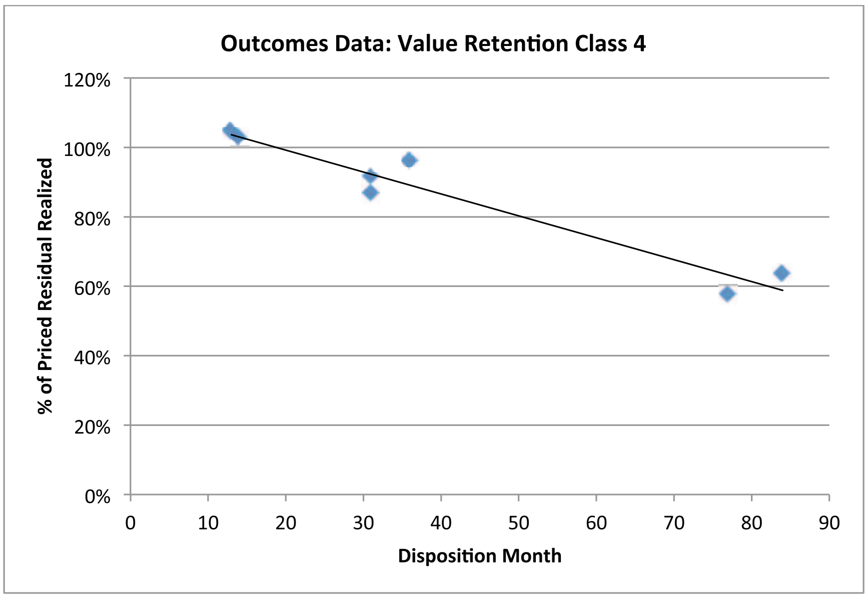
Validation of predictive analytics requires creation of portfolio forecasts that then can be compared to actual outcomes. As is evident from the preceding comparison of actual transaction performance to the original transaction pricing, the analyst must model the real world outcomes present in any real portfolio in order to create a meaningful portfolio forecast.

In the subject portfolio, there were no extensions or re-leases, as all but one of the transactions ended early. Consequently, the outcome model for forecasts based on the subject portfolio need only be concerned with early terminations. The other outcomes, which will not be discussed here, would be developed and treated very similarly, however.

A number of collateral quality factors were set for each aircraft as part of setting up the RAROC calculations. One such factor was value retention over the course of the lease. One method for creating an outcomes model is to evaluate realized disposition amounts by value retention class. **Figure 44** plots the realized disposition amount, as a percentage of original asset cost, over the number of months into the transaction when the deal was terminated, for one value retention class. The trend line represents how the value of the asset decreases over time.

An outcomes model for the value retention of class 4 transactions can be built from this information, as illustrated in **Figure 45**. The first column of **Figure 45** shows the outcomes model broken up into seven, 12-month bands. The second shows the likelihood of termination within each 12-month band, based on how many transactions out of the entire population of value retention class 4 transactions in the actual portfolio did, in fact, terminate in that timeframe. The third column smoothes the termination percentage curve, as the lumpiness in the actual data is presumed to be the result of the small number of transactions. The last column approximates the trend line numerically.

Figure 44
Basic Analysis for Outcomes Modeling of Early Termination



Using this basic method, the analyst could construct an outcomes model for each set of transactions that has materially different outcomes behaviors. Within the predictive analytics model, outcome models can be applied to forecasts and runoff in two ways:

- *Simple percentage method* – each transaction is modeled to behave like the entire class to which the outcomes model is applied. In this example, based on **Figure 45**, in month 24, 25% of each transaction would be assumed to terminate, with a disposition amount equal to 105% of the asset cost times that 25%. In month 36, another 25% would terminate, with a disposition amount equal to 96% of the asset cost times that 25%, and so on, until the last ten percent of the transaction runs the full term with a residual amount of 60% of the asset cost times ten percent.

The advantage of the simple percentage method is that, viewed from a portfolio level, it provides an accurate representation of how the forecast runs off – every month, the fragments of deals that are terminated add up to exactly the predicted attrition. However, viewed on an individual transaction basis, it does not reflect reality. Each transaction either terminates or it does not – a series of systematic partial terminations is not realistic.

Figure 45

Outcomes Model for Value Retention Class 4

Month	Termination likelihood	Rationalized	% of OEC realized
12	0.0%	0.0%	n/a
24	28.6%	25.0%	105.0%
36	28.6%	25.0%	96.0%
48	14.3%	15.0%	87.0%
60	0.0%	15.0%	78.0%
72	14.3%	10.0%	69.0%
84	14.3%	10.0%	60.0%
Total	100.0%	100.0%	

- *Stochastic method* – one stochastic model, the Monte Carlo method, rolls the dice, as it were, each month for each transaction, so that, just as in the real world, the transaction either terminates or it does not, according to the probabilities set up in the figure. The stochastic method is used for stress testing the data.

Outcomes models in some form are used by many equipment finance companies, often as a part of the treasury or forecasting functions. The outcomes modeling needs of a profitability model are similar in many respects to existing approaches, with the exception that the outcomes must be viewed at the transaction level for optimal usefulness. There are many different ways to construct useable outcomes models, ranging from very simple to extraordinarily complex. The above discussion is merely a sample approach used to illustrate the concept.

Forecasting

Once an historical analysis has been performed, a forecast is generated that embodies whatever strategies have been decided upon. In this example, it is assumed that new target pricing has been developed in response to the analysis. The analyst first investigates how this forecast looks from a cash, tax, and accounting perspective, and then performs what-if analyses to test potential scenarios. Finally, as actual data comes in, the analyst can see how well the new policies and practices are working and, if necessary, take corrective action immediately.

Figure 46 contains a simple representation of a portfolio forecast. Just as in the analysis of historical data, forecasts also need to be represented at a transaction level. The predictive analytic model converts the data in **Figure 46** into transactions. The lessor in this example hopes to book about $500 million in new aircraft lease business in 2013.

In addition to the basics economics represented in **Figure 46**, the lessor includes risk assumptions that will be used to drive the capital allocation and expense loads used in the RAROC calculations. The risk assumptions for this example include value retention, the collateral grade, and credit score and are used to generate probability of default, LGD, and equity requirements. After creating this forecast, the analyst can examine the cash, tax, and accounting implications.

What if, after reviewing the forecast, though, it was deemed that the credit quality was liable to deteriorate? By creating a segment from customers with a credit score of five, the analyst could for instance, modify those credit scores to eight. This allows the analyst to see how such credit deterioration would affect portfolio performance, as shown in **Figure 47**. Note that the MISF and IRR yields are unaffected, since they are calculated without the risk loads, but, in **Figure 48**, the economic ROE and the Risk ROE are seriously compromised.

Figure 46
2013 Forecast Summary

Type	Start	ROE target	Cost	Residual %	Term	Days between transactions	Number
TL	1/1/2013	11.26	25,000,000	100	36	90	4
CS	1/1/2013	11.26	25,000,000	100	36	45	8
CS	1/1/2013	12.91	2,250,000	105	24	30	12
CS	1/1/2013	14.22	7,000,000	85	60	90	4
CS	1/1/2013	14.25	1,000,000	65	36	90	4
CS	3/1/2013	9.17	10,000,000	70	30	90	3
CS	3/1/2013	14.96	13,000,000	80	84	90	3
CS	3/1/2013	13.29	15,000,000	80	84	90	3
TL	3/1/2013	12.05	10,000,000	50	84	90	3

Key:
TL – Tax lease
CS - Conditional sale
Start - Start date of the earliest transaction in the row
Number - Total number of new transactions as defined in the row

The deteriorating credit scores caused more capital to be allocated to the transactions, resulting in lower interest costs, but they also created a large increase in secondary expenses for higher expected losses. The net result is that the ROE yields were driven much lower. What-if analysis such as this also could encompass any combination of residual variation, fee income and expenses, borrowing costs, new business volume, or changes in the yield target.

By layering the forecast onto the current working portfolio and applying the appropriate outcomes models, the analyst creates a solid view into the financial behavior of the company's portfolios based on potential changes in the underlying variables. This ability to rapidly develop and test out profitability enhancement ideas and to monitor the results of ongoing efforts for continual improvement is the essence of predictive analytics.

Figure 47

Forecast Portfolio Yield and Forecast with Deteriorating Credit

Yield summary	Forecast		With deteriorating credit	
	NPT	NAT	NPT	NAT
MISF	6.0377	3.9245	6.0377	3.9245
IRR (PTCF)	5.1837	3.3694	5.1837	3.3694
Economic ROE		12.5135		5.8711
Risk ROE (RAROC)		31.9535		13.6592
Average life (months)		38.0348		38.0348

Figure 48

ROE Cash Flow Summary

	Forecast	With deteriorating credit
Internal interest	73,837,831	65,723,642
Internal interest - taxes saved	(25,843,241)	(23,003,275)
Secondary expenses paid	495,196	5,351,232
Secondary expenses - taxes saved	(173,319)	(1,872,931)
Net, after-tax ROE cash flow	14,251,713	16,369,512

Advanced analysis

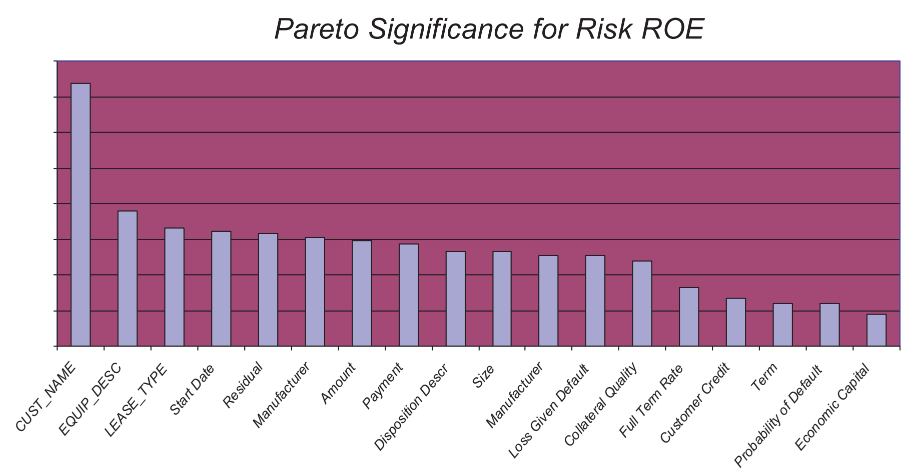
The analysis of the subject portfolio so far has identified a number of areas in which further investigation is warranted. The portfolio analysis only has scratched the surface of the kind of analysis, system design, and data collection required to apply robust predictive analytics to large, diverse portfolios, though. Additionally, the set of about 100,000 data points used to create the subject portfolio hardly qualifies as big data, and an entirely different level of insight also could be gained by including external economic factors such as GDP growth or unemployment rate in the analysis.

Nonetheless, even with these limitations, correlation analysis on the sample portfolio yields interesting results. The portfolio was subjected to a standard correlation analysis in order to produce a Pareto table showing how the data items in the individual transactions correlate to the Risk ROE, or RAROC. This Pareto chart for the entire portfolio, correlated to Risk ROE, is shown in **Figure 49**.

The labels along the X-axis are the categories of data available for analysis. The goal of this exercise is to obtain an unbiased ranking of factors that affect profitability. **Figure 49** presents the results of a naive analysis, in which no assumptions were made about what kind of relationships exist between the Risk ROE and the underlying transaction data. The factors are listed from left to right in the order of their relative effect on ROE.

- *CUST_NAME* – the highest correlation is by customer name and confirms the common knowledge that some customer relationships are more profitable than others. What is new in this example, though, is the ability to put hard return numbers on that common sense observation, to view how customer profitability changes over time, and to quickly ferret out exceptional cases in which particular customers may have transactions with wildly different yields

Figure 49
Risk ROE Correlation



- *EQUIP_DESC* – the next most significant factor is equipment description, or type of aircraft. Grouping the portfolio by aircraft type shows that 14 different types of aircraft are represented. These results match what experience suggests, i.e., leases of some assets are more profitable than others, but a level of clarity and the ability to further investigate the data has been added here.

- *LEASE_TYPE* – Common sense suggests this is not a meaningful result on a portfolio this small, given that chance could easily result in the four tax leases having considerably higher or lower yields than the average, which is what this result is saying.

Correspondingly richer results may be obtained in a larger portfolio with better information on assets, customers, and external economic factors. In a more varied portfolio, correlation analysis can also be done more effectively on a segment, since it is likely that the factors driving portfolio profitability for a railcar portfolio are different from those driving profitability on office equipment or lift trucks.

The last level of advanced statistical tools to be discussed is stochastic analysis, which includes Monte Carlo simulations. Stress tests such as these are used widely in the financial world, often due to regulatory requirements. In addition to stress testing, stochastic analysis also can be used for more active management of portfolio performance, such as evaluating the likely outcomes from entering or exiting a line of business, changing pricing policy, or purchasing a portfolio.

A first-pass stochastic model could test the portfolio against any variable or set of variables, such as those that drive the credit scoring or collateral valuation models. A representative collateral valuation model was created in the subject portfolio using factors such as aircraft size, manufacturer stability, etc., to predict how likely the asset was to retain its value over time. Based on these inputs, a formula determined the collateral quality rating, which then was used with the customer's credit rating to determine expense loads and capital requirements in the RAROC calculations.

Stochastic analysis achieves a new level of usefulness because it changes many variables across set ranges according to statistical probabilities, running thousands of cases to determine the most likely outcomes. Applying stochastic analysis, pricing management could use its collateral quality or credit rating formulas to analyze the effect of a change in fuel prices on RAROC, for instance. By establishing an expected fuel price (based on external economic data), pricing could then determine whether the expected RAROC is still within the company's expectations. A similar analysis could be used to assess the impact on profitability of expected renewal activities, or of an economic downturn.

The value of tools such as those discussed in this scenario is that they can be used to improve future profitability by assessing portfolio performance under different assumptions. They also can be used to evaluate the impact of changing those internal or external assumptions. Gaining insight into the effect of these potential outcomes allows the equipment finance company to take appropriate courses of action targeted to addressing them.

Conclusions

Equipment leasing and finance companies can no longer compete by employing only those technologies that gather, traditionally analyze, and store data. Progressive firms are already leveraging information to create competitive advantage—and this trend will continue as other members of the industry feel the pain and take steps, literally and figuratively, to get up to speed. But companies not yet using business intelligence and, particularly, predictive analytics face a double challenge: They must first collect and assemble worthwhile data. They must then determine the most effective applications for analyzing that data to produce actionable information.

Decisions must also be made regarding how data is to be segmented, the methods by which it is to be integrated, and the applications it is to be integrated into. Additional decisions concern how the data is to be analyzed and how it is to be used, as well as the frequency with which the data is to be updated and the method by which currency is to be assured.

Thus it is one thing to access big data and possess tools to manipulate it. It is quite another to bridle these assets in such a way that they produce actionable information. Doing so requires financial resources, highly specialized expertise, and time to implement new processes. Also instrumental: the intellectual horsepower to choose methodologies, manage process conversions, and create and nurture the cultural acceptance necessary to support the new approach .

Companies today are deluged with data, but predictive analytics remains a component of business intelligence that is largely untouched. The question industry executives must answer, then, is whether their firms will rise to the challenge and drive higher volumes and profits by leveraging data through predictive analytics—or whether they will procrastinate and become mired in the mud of indecision.

Appendix One
– Glossary –

Accuracy Ratio
The accuracy ratio is the area between a score's Lorenz Curve and the random diagonal, divided by the area between a perfect score and the random diagonal. The Accuracy Ratio, or AR, ranges from a high of 100% to a low of 0%.

Business intelligence
Business intelligence is the ability of an organization to take its data, convert it into knowledge, and get the right information to the right people, at the right time, via the right channel. If implemented effectively, business intelligence can show not only the big picture, but the details behind the key drivers of the business. Common functions of business intelligence technologies include reporting, analytics, data mining, process mining, complex event processing, business performance management, and benchmarking.

Economic obsolescence
Economic obsolescence is the loss of value of a property by factors external to the property, including such things as the economics of the industry, availability of financing, passage of new legislation, increased cost of raw materials, labor, or utilities (without an offsetting increase in product price), reduced demand for the product, increased competition, inflation or high interest rates, or similar factors.

Functional obsolescence
Functional obsolescence can be thought of as the loss in value or usefulness a property caused by inefficiencies or inadequacies of the property itself, when compared to a more efficient or less costly replacement property that new technology has developed.

K-S Statistic (Kolmogorov–Smirnov Statistic)
Based on the ROC Curve, the K-S Statistic is the maximum vertical distance between the score's curve and the random diagonal. Perfect would be 100, and random is zero (though technically it is between zero and one, the decimal point is usually omitted).

Lorenz Curve
A Lorenz Curve is a graphical representation of the cumulative distribution of an empirical probability distribution. As a graph, it shows the proportion of the distribution assumed by the bottom y% of the values. It is used in business modeling, such as to measure distributions such as the actual delinquency (Y%) of the X% of customers with the worst predicted risk scores.

LGD (Loss Given Default)
LGD is the likely loss on the transaction, typically expressed as a percentage of the exposure. It is transaction-specific because the losses are generally understood to be a function of key transaction characteristics such as the value of the collateral or residual.

Monte Carlo simulation
The Monte Carlo is an example of a stochastic model. When used in portfolio evaluation, multiple simulations of the performance of the portfolio are done based on the probability distributions of the individual variable being analyzed. A statistical analysis of the results then helps determine the probability that the portfolio will provide the desired performance.

Pareto chart

A Pareto chart is used to graphically summarize and display the relative importance of the differences between groups of data. It contains both bars and a line graph, where individual values are represented in descending order by bars, and the cumulative total is represented by the line. It can be constructed by segmenting the range of the data into groups, segments, bins, or categories.

Physical deterioration

Physical deterioration is the loss in value or usefulness of a property due to the using up or expiration of its useful life caused by wear and tear, deterioration, exposure to various elements, physical stresses, etc.

Predictive analytics

Predictive "analytics" is the application of statistical techniques to current and historical facts to make predictions about future events in order to enhance decision making. Predictive models exploit patterns found in data to identify risks and opportunities and capture relationships among many factors, thereby allowing assessment of the risk or opportunity associated with a particular set of conditions.

Retro analysis

Retro analysis is a concept in credit score evaluation in which the decision-maker calculates a borrower's score at some prior point in time, using only information that was available at that time. An analysis is made to see whether the borrower's transaction subsequently performed well or not, based on some fixed, relevant definition, such as whether the transaction was ever 91 days past due.

ROC Statistic

ROC Statistic is quite similar to the Accuracy Ratio, except that it is based on the ROC Curve where the x-axis, instead of being all transactions, is only the "good" transactions. The curve of the perfect score on the ROC Curve goes vertically up from the lower left-hand corner to the upper right-hand corner, so there is no need for division as there is in the Accuracy Ratio. The ROC Statistic is the area below the curve, with 1.000 being perfection, and 0.500 being random.

Stochastic modeling

Stochastic modeling is a method of financial modeling in which one or more variables within the model are random. Stochastic modeling is used to estimate the probability of outcomes within a forecast to predict what conditions might be like under different situations. The random variables are usually constrained by historical data, such as return on past leases.

Appendix Two

–Questions Asked in the Study Survey–

1. What do you consider to be the primary benefits of predictive analytics?

2. Do you consider the use of predictive analytics to be a competitive advantage:
   a. Currently?
   b. In the future?

3. Does your company currently use predictive analytics?

4. Would you describe your company's predictive analytics efforts as:
   a. Ad hoc?
   b. Formalized?

5. If formalized, who within the company has responsibility for the predictive analytics program?

6. At what level in the company is the information created from your predictive analytics efforts disseminated and used?

7. If formalized, how would you describe the state of your predictive analytics program?
   a. Nascent?
   b. Middling?
   c. Robust?

8. Which of the following elements are parts of your predictive analytics program?
   a. Forecasting and planning
   b. Risk management
   c. Portfolio evaluation and management
   d. Credit adjudication and scorecards
   e. Delinquency management
   f. Customer cross-selling and up-selling
   g. Sales performance
   h. Residual management

9. What are the top three areas in which your company uses predictive analytics?
   a. Forecasting and planning
   b. Risk management
   c. Portfolio evaluation and management
   d. Credit adjudication and scorecards
   e. Delinquency management
   f. Customer cross-selling and up-selling
   g. Sales performance
   h. Residual management

10. What end-user analytical tools do you use for predictive analytics?
    a. Angoss KnowledgeSEEKER/KnowledgeSTUDIO
    b. Microstrategy
    c. Quantrix
    d. TIBCO Spotfire
    e. Rapid Insight Analytics
    f. Revolution Analytics R
    g. Statsoft Statistica
    h. Emanio Insight!
    i. Microsoft Excel

11. Is the company's predictive analytics capability integrated with its enterprise system?

12. Does the company utilize a full-featured, enterprise-scale analytic platform?

13. If yes, which enterprise-scale analytic platform does it use?
    a. IBM SPSS
    b. SAS
    c. SAP BusinessObjects
    d. Oracle Hyperion
    e. Microsoft business intelligence
    f. Information Builders WebFOCUS

14. Will your company's use of predictive analysis in the coming year:
    a. Decrease?
    b. Remain the same?
    c. Increase?

15. Does your company plan on committing additional resources to predictive analysis in the coming year?

16. What emerging trends in the use of predictive analytics do you see:
    a. Currently?
    b. In the future?

Appendix Three

– Study Partners –

Advanced Portfolio & Application Services

Mark Belec is President of Advanced Portfolio & Application Services, based in Minnesota. He has 25 years of experience in the finance/leasing industry, during which he has taken on increasing responsibilities. He has consulted and/or worked for over 200 finance/lease clients, including PwC, Wells Fargo, Chase/Bank One, BearingPoint, Third Pillar, and IDS. Mark has testified in federal court and worked with the U.S. Treasury and Federal Bureau of Investigation on past leasing-related items.

In addition, Mark works with software companies and third party/service providers for integrating with lessors/finance companies to improve profitability, operations and residual/risk management. Mr. Belec is a past chairman of the ELFA Equipment Management Committee and has spoken at ASA, ELFA, and Alta conferences. Mr. Belec holds an Associate of Arts & Bachelor of Science degree from McPherson College and attended Scottsdale University School of Law.

The Alta Group

The Alta Group is a leading management consulting firm focusing exclusively in equipment leasing and finance. Alta professionals, who have held senior management positions at successful commercial finance companies, provide broad and deep knowledge and experience while helping clients achieve peak performance and profitability. The firm's international consultants (including The Alta Group, Canada, The Alta Group, China, Invigors/EMEA, and The Alta Group, LAR) offer years of hands-on experience in due diligence, strategic planning, mergers and acquisitions, professional development programs, and legal support services.

Clients rely on The Alta Group for keen and current insights in forming captive and vendor finance programs and in financing all types of capital assets. In addition to its unparalleled industry background and perspective, Alta creates strong survey and project deliverables on a regular basis and brings extensive experience in assignments similar to the predictive analytics project, such as in Alta's *Perfect Storms* and *Changes to Lease Accounting* engagements.

Ivory Consulting Corporation

Ivory Consulting Corporation has been the premier provider of equipment finance pricing and analysis software tools for 28 years. Ivory products include the flagship SuperTRUMP pricing software. Ivory pioneered the industry's use of sophisticated RAROC pricing models, and its newest product, Portfolio Analytics, is gaining wide industry acceptance. Founded in 1983, Ivory employs professionals who average over 10 years' experience in sophisticated lease pricing and analytics.

Joseph Moore is Director of Sales & Marketing at Ivory. Over the last 15 years, he has worked with large lessors around the world on pricing and portfolio issues. He has trained hundreds of equipment finance professionals in equipment finance pricing and has given a number of presentations at ELFA events. Mr. Moore holds a Liberal Arts degree from the Great Books program at St. John's College and an MBA in International Business and Finance from San Francisco State.

EIMEX Software and Consulting

Dr. David Eimerl blends a unique background in physics, engineering and information technology. A recognized thought leader whose understanding of the fundamental principles of nature informs and complements his computer modeling expertise, Dr. Eimerl designs and delivers customized solutions, astutely predicts and prioritizes outcomes, and helps select the appropriate course of action.

Dr. Eimerl holds a Ph.D. from Northwestern University in Theory: Sub-Nuclear Physics and Scattering, and an M.A. in Physics (summa cum laude) from Oxford University in Cambridge, England. He is an active Board member of PATCA, currently serving as Director, Treasurer, and Internet Committee Chair; and sits on the Technical Advisory Boards of Ultratech Corporation, and Reliant Corporation

PayNet, Inc.

PayNet, Inc. is the premier provider of risk management tools and market insight to the commercial credit industry, collecting real-time loan information from more than 250 leading U.S. lenders and turning it into actionable intelligence. The company's proprietary database, updated weekly, is the richest and largest collection of commercial loans and leases, encompassing more than 19 million current and historic contracts worth over a trillion dollars.

Thomas Ware is PayNet's Senior Vice President of Analytics and Product Development. He has over 25 years of experience in equipment finance and small business lending with banks, captives, and independent lessors, including as Senior Vice President, Operations & Chief Credit Officer of American Express Equipment Finance. He graduated with Distinction in Mathematical Economics from Dartmouth College and has an MBA from Harvard Business School.

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