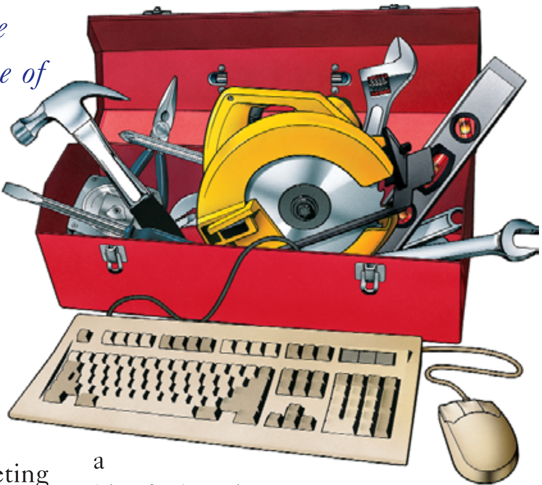
Controlling Risk Across an Enterprise: Don't Forget the Marketing Function

by Jeffrey S. Morrison and Susan Alvarez

The Basel toolbox already has proven to have more than one application. Financial institutions can make even greater use of this resource by adapting information for marketing purposes. Moving from quant to marketer may not be such a stretch in institutions using an enterprise approach to risk and *growth.*



In financial institutions, as with any business, it is a challenge to grow an existing portfolio while controlling inherent levels of risk. And, in an enterprise environment, risk can take a variety of forms. While credit risk is lenders' core risk discipline, a financial institution's profitability depends on effective control of risks across the enterprise.

Quantitative analysis plays a primary role in controlling risk, especially from the regulators' point of view. *The New Basel Capital Accord* makes this very clear:

> The overarching principle behind these requirements is that rating and risk estimation systems and processes provide for a meaningful assessment of borrower and transaction characteristics; a meaningful differentiation of risk; and reasonably accurate and consistent quantitative estimates of risk.
>
> *The New Basel Capital Accord*
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Yet quantitative analysis can make a significant contribution to business growth as well. Quantitative risk assessment simply makes good business sense. The same can be said on the marketing side of the enterprise. After all, in most organizations, the marketing function assumes the primary role of managing strategic or competitive risk. Marketing can apply the analytic techniques used by risk management to portfolio growth by identifying 1) those current customers most likely to purchase additional products and 2) those likely to turn to the competition most quickly.

Consider a bank associate who has worked in Risk Management for a number of years and has built quantitative models to bring the bank's consumer portfolios into compliance with the new Accord. This employee should be able to transfer his or her knowledge into a new marketing role within the bank. Certainly, a career shift from Risk Management to the Marketing Division would require a bit of a learning curve; however, the associate's quantitative experience will play a huge role in such areas like helping to grow the consumer credit card business, determining how better to up-sell existing customers, and developing a segmentation strategy for an existing portfolio.

Regression and other Basel II tools can be used to create marketing tools, such as a road map to a prospect list that is ranked in order of those most likely to respond to a mailing. After all, the very foundation of such a technique is based on known statistical properties and sampling distributions that help determine whether a piece of predictive information is truly "statistically significant."

Under the Basel Accord, a primary objective might be to build a

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probability of default (PD) model that predicts payment default, based on information such as loan to value (LTV), credit score, recent payment history, and time-on-books. On the recovery side, another type of regression tool might help determine the amount or percentage that could be recovered from an account if a default were to occur. When these tools are used in the context of meeting marketing objectives, they fall under the broader umbrella of *database marketing*.

Generally, database marketing is the "art and science" of targeting potential customers for a given product or service. It is an art because there is no one-size-fits-all approach that works for every company's marketing objective. It is a science because it uses a library of statistical techniques to mine the data effectively and to select those customers best suited for a particular marketing effort. Most database marketing activities seek to achieve similar objectives for the business, identifying, for example:

- Which customers to include in a direct-mail campaign to grow an existing portfolio.
- Which customers are the best candidates for up-selling or cross-selling a product or service.
- How to achieve optimal customer retention.

Developing a Response Model

As discussed in past *RMA Journal* articles, regression models are easy to develop. However, for Marketing to use them to grow a customer base requires the right kind of data. Regardless of the functional area, the business objective is the same—to quantify the differences between two populations by using historical information.

- First, conduct a random test mailing of potential prospects—perhaps tempered by a credit score. The anticipated response rate is crucial in determining the amount of test mailings. For example, if the expected response rate is 1%, then 500 responses would come from a mailing of 50,000. In the risk world, working with 500 defaults might be considered the bare minimum required to build a PD model. The same is true for marketing. Typically, at least 2,000 responders are needed for model-building and validation purposes.
- After mailings have been sent out and responses collected, this information can be combined with other data—such as demographics, income, and past credit characteristics—for regression-modeling purposes. Predictive tools of this kind are often referred to as *response models*.
- Now it is time to build the response model. Under Basel, a risk manager would be building a PD model where the default event might be determined over a one-year performance window. In marketing, the time it takes for the majority of customers to respond to a mailing determines the "performance window"—usually only one or two months. This is the primary difference between the two model-building practices—the performance window for risk is typically much longer. Other than that, a marketing manager would use the exact same model-building approach as suggested in the checklist discussed in earlier *RMA Journal* articles:

1. Define your prediction (dependent) variable. A variable with a value of 1 if the customer that was mailed responded; otherwise, a value of 0 is assigned.
2. Define the performance window. This is the time it takes for the mailing to go out and the majority of people to respond—again, usually one to two months.
3. Determine the sample size for your predictive model. If you have about 2,000 responders, split your data into 75% for building the model and 25% for validating it.
4. Attach the attributes you think might be predictive to each record if you haven't already.
5. Examine the information for unusual data points. Graph the distributions and analyze their correlations with each other and your prediction variable.
6. Account for missing data. Substitute sample averages for missing predictive attribute values, etc.

7. Use logistic regression to estimate the predictive model.
8. Examine the signs of each predictive weight produced by the regression procedure. Make sure it makes sense.
9. Calculate the predicted probabilities from your regression model on your development and validation sample and rank them from highest to lowest. The observations in the top 20% of the list are those prospects most likely to respond to your promotional campaign.
10. Score your new mailing list. This means use the algorithm from your regression model to identify your most likely prospects with a mailing that is now based upon much better marketing intelligence and contains a high degree of information content. This will give you a list, which is rank ordered from high to low—a list that should be mailed from top to bottom based on the budgetary dollars associated with the campaign.

Developing a "Look-alike" Model

Marketing budgets often do not support the expense of random test mailings resulting in a 1% response rate. Another methodology for these instances is often referred to as a *prospect* or a *look-alike* model. By using the same technique from the Basel toolbox, this model predicts the chance that a potential prospect "looks like" a customer you already have. Rather than measuring response to any upcoming promotional campaign, it reflects this thought: "If this customer were to respond to our mailing, he or she would tend to look like one of our best customers." The criteria to identify these best customers might come from an RFM analysis—an evaluation of their accounts in terms of *recency* of purchase, *frequency* of the purchasing habits, and the associated *monetary value*.

As before, information on two populations is needed.

- First, obtain a list of the "best" accounts. For a look-alike model, the prediction variable used in the regression would take on a value of 1 if that account represented a "best" account.
- Next, obtain a prospect list, randomly sampled down to about the same number of "best" accounts in the analysis.
- Append the prospect list to the best accounts list, to represent the second population of individuals who are currently not customers of the bank. For those accounts, the prediction variable would take on a value of 0.

The model-building process would be the same as for a response model in which a logistic regression is performed and the resulting algorithm is then used to score new prospects and rank-order them from high to low for the marketing campaign.

Developing Cross-Sell Opportunities

The discussion so far has dealt with getting new customers. What about those accounts that already exist? How can you sell them more products or services?

For a common banking scenario of selling more home equity loans to an existing customer base, marketers can—once again—turn to the Basel toolbox to design an effective cross-sell strategy. As before, the differences between two populations need to be established. For this scenario, the populations would be those who have a mortgage with the bank as well as a home equity loan, and those who are simply mortgage customers with no home equity product. Since the bank already has this data on both groups, a cross-sell model could be built quickly with internal data or expanded to include additional demographic data sources, which could further increase the model's predictive power.

- The prediction variable for the regression is created where the account has a value of 1 if it is both a mortgage customer and has a home equity loan.
- For those accounts with no home equity loans, the prediction variable takes on a value of 0.

The model-building process would follow the same pattern of performing a logistic regression and using the resulting algorithm to score existing accounts. The score would reflect the account's chances that it resembled or "looked like" a candidate for cross-selling the home equity product. A high score would reflect a relatively higher chance of cross-selling; a low score would mean the chances of an effective cross-sell attempt would be small.

Establishing Customer Loyalty

Because the cost of obtaining a new account is typically much larger than that for keeping existing ones, most companies are very interested in implementing some type of customer retention program. In wireless telecommunications, churn is a huge problem; marketers are constantly trying to keep their current customers from switching to a competitor for reasons other than price. In the mortgage world, a rise in loan customers who decide to pay off their remaining balance early will have a dramatic impact on the bank's financial forecasts. If the bank could anticipate early on those customers who were expected to opt for a prepayment alternative, a lender could revise the terms of the loan, making it more profitable to the bank.

In a 2004 *RMA Journal* article, another type of regression procedure called *survival analysis* was introduced to help financial institutions meet *The New Basel Capital Accord* regulatory guidelines. The focus of this tool would be on predicting the timing of payment defaults. This tool also can be used in marketing to predict time-to-prepayment for a residential mortgage portfolio where account retention is an important strategic goal.

Survival analysis uses a specialized type of regression uniquely suited for dealing with the type of data often applied in customer retention studies—censored data. Censored data implies an information gap. For example, we don't know the status of the prediction variable once it advances past a certain point in time within the study period. In the mortgage example for predicting prepayment, we could track a collection of accounts over a three- to five-year period and count how many months (or quarters) they have "survived" without paying a loan off early. Factors predicting this behavior might be loan size, credit score, LTV, loan term, interest rate, local economic conditions, indicators for a first or second mortgage, current coupon for ARMs, prepayment penalty indicators, age of the loan, and other demographic information.

As with all the other tools discussed in this article, survival analysis requires a prediction variable—in this case, the length of time an account has gone (survived) without prepayment. The output from the study can be divided into two parts:

1. The probability that the account will not prepay over a specific period of time.
2. The actual number of months (or quarters) that the account will survive—that is, not prepay.

Both predictive aspects of survival analysis can be used in marketing to proactively offer customer retention incentives before prepayment might occur, as well as provide input into portfolio models for revenue and profitability projections.

Summary

This article has highlighted just a few areas where knowledge of statistical techniques gained in support of meeting the regulatory guidelines for the new Accord can easily translate across the enterprise and into the world of marketing. Indeed, these quantitative approaches can be applied across the spectrum of enterprise risk management. The business objectives for marketing are different from those of traditional credit risk management—but of no less importance. Other advanced statistical techniques, such as CHAID, neural networks, and pooled cross-section time-series models, can easily be used by marketers to identify new prospects, develop segmentation schemes, produce greater cross-sell opportunities, or even measure the aggregate impact of a changing economic environment on a bank's retail portfolio. ❒

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