Migration Analysis: Combining Approaches for Better Results

by Mike A. Shearer and Robert Christensen

The recipe for the best migration analysis model combines average-loss-rate (ALR) and Markov models. This article describes the strengths and shortcomings of base-period ALR, and Markov models and suggests a possible solution for finding the best migration analysis model.

Lenders increasingly use migration analysis to measure historical default and loss rates, primarily in commercial portfolios, by risk rating. KPMG’s Sixth Annual Survey of Bank Credit Risk Management Practices revealed that 51% of all bank respondents use migration analysis. Of those banks with assets greater than $10 billion, 70% report using migration analysis. However, there are, perhaps, as many different twists on migration methodology as there are institutions using migration analysis.

In the past, migration analysis models were developed solely to derive loss factors necessary to support the reserving process. As the need for relevant and timely information intensifies in the current competitive environment, however, management seeks more responsive, flexible, and more accurate models.

Many leading institutions also recognize the value of migration analysis in supporting a number of relatively new risk management objectives. For example, output from migration models is used to support capital allocation, risk-based pricing, and portfolio management models. Migration models can help to evaluate the effectiveness of risk-rating systems, or align risk ratings with third party rating systems, such as Standard & Poor’s or Moody’s. And, when constructed properly, migration models can help to provide valuable information about trends in the portfolio and facilitate "what-if" loss forecasting under different scenarios.

Many Variations on the Theme

So which methodology is the best for migration analysis? That depends on the institution’s objectives and intended application of information. Different techniques may produce similar results in steady-state conditions. However, clear differences emerge as credit cycles are introduced. No single methodology is best under all circumstances. The most robust and flexible approach capitalizes on the strengths of multiple techniques to provide better information for making informed judgments.

To better explain this concept, it is necessary first to establish a foundation for comparison of different methodologies. While there are many variations on the theme, migration models generally fall into one of three categories: base-period (BP) models, average-loss-rate (ALR) models and Markov models.

Base-period models. One of the most common migration modeling methodologies, particularly among institutions with less than $5 billion in assets, is the BP model. Reasons for its popularity include conceptual simplicity, relatively simple mathematics, and relative ease of data capture and analysis.
Migration Analysis

BP models track losses over a defined measurement period and then match them with the risk rating of the loans at the beginning of the measurement, or base, period. For example, assume the measurement period is eight quarters and a loan was in the “pass” category at the beginning of the period. If that loan experienced loss any time over the measurement period, the loss would be attributed to the pass rating. The loss would go into the numerator, along with any other losses over the measurement period that began in the pass category. The denominator would be the sum of the balances of all loans that in pass during the base period. The resulting fraction would be treated as the loss rate for the pass category, and would be used for making forecasts and establishing reserves (Figure 1). While the mathematics are relatively straightforward, there is an obvious problem in the logic: The loss is being attributed only to the pass rating even though the loan may well have subsequently passed through other ratings prior to experiencing the loss. If, for example, the loan was rated “doubtful” just prior to experiencing loss, it could be two years before the BP model attributes the loss to the doubtful rating. Therein lies the greatest weakness in the BP model. It can significantly lag credit cycles (Figure 2). The model also fails to account adequately for loans that enter or leave the portfolio during the measurement period.

Markov models. At the other end of the complexity spectrum is the Markov model. Markov models measure the transitions of loans through transitional states into an absorbing state over defined step values (Figure 3). The result is a transition matrix showing the probability, on average, of a loan in any risk rating migrating to another rating or into the absorbing state. The absorbing state can be either default or loss. While loss is relatively straightforward, default can be defined any number of ways. Not all institutions use the same definition of default for modeling purposes. However, nonaccrual tends to be the most common definition.

In constructing Markov models, it is important to address some underlying principles:

- The institution must consider whether it will measure transi-
tions of counterparties or facilities. Practices vary from one institution to another depending, to a large extent, on grading practices. Some institutions rate the counterparty, others rate the facility, and others rate both.

- There are assumptions that define Markov mathematics. For the Markov process to truly apply, the probability of a loan moving from one rating to another would have to be:
  - Independent of its prior rating history.
  - Constant over time.
  - The same for all loans in a given category regardless of loan characteristics.
  - Independent of the movement of any other loan.

Few would argue that these conditions describe a typical loan portfolio. While the Markov assumptions can generally be addressed, care must be taken in designing the methodology so as not to inadvertently introduce errors. This is particularly true when credit cycles are introduced. It is also important to recognize that small errors can easily be compounded into much larger errors.

For example, a three-year default rate derived from a one-quarter average transition rate may not look like an observed three-year default rate. The longer the time step, the less reliance on the Markov assumptions and the more likely the assumptions are to be sound. On the other hand, because there is typically so little default experience at the upper end of the pass rating scale, the institution may have no choice but to rely on shorter time steps to impute default rates for these ratings.

It is also important to consider the institution’s objectives before designing the model. A Markov model that calculates expected default frequencies at the counterparty level may be beneficial, if not necessary, to support capital allocation, risk-based pricing, and portfolio management models. This is particularly true if the institution wants to align its approach with third parties to better leverage off published default data. However, the Markov model may not be the best solution for deriving loss rates at the facility level to support reserving. There is a clear trade-off between the increased effort and added complexity to build a Markov model for this purpose and the benefits.

**Average-loss-rate model.** The ALR model lies somewhere in the middle of the complexity spectrum. The ALR model can be thought of as a “rolling” BP model. That is, the ALR model attributes a loss in the measurement period to every risk rating the loan passed through before experiencing loss. For example, with eight quarters of data, the model can observe seven different observations of “one-quarter-later” loss rates. Losses that occurred in the most recent quarter can be measured against balances in the prior quarter.

**Figure 3**

**Markov Transition Example**

![Markov Transition Example Diagram](image-url)
Losses that occurred seven quarters ago can be measured relative to balances eight quarters ago. Both of these observations will contribute to a weighted average one-period loss rate. Two-period, three-period, four-period, and so on loss rates can be derived in the same fashion. These period-later loss rates can be summed to arrive at a cumulative ALR for each risk rating. The result is a table that shows the observed cumulative loss rates for each risk rating (Figure 4). An institution that reserves for one year’s coverage for pass and “special mention” loans might look only to the fourth column on the table, the “four-quarters-later” (cumulative) loss rate. In reserving for the effective lives of “substandard” and doubtful loans, the institution would look to the point on the table at which the cumulative ALR tends to flatten out, that is, the point at which there is little to no marginal increase in the cumulative average loss rate in the subsequent columns. For pricing purposes for pass loans, however, the institution will also want to look to the point at which the loss rates flatten out. While the ALR model also relies to some extent on the assumptions of the Markov model, it does not rely on these assumptions to the same degree. In part, this is because the ALR model makes a much more direct connection between losses and balances in deriving loss rates. As a result, there are many advantages to the ALR approach relative to the BP or Markov approach for measuring historical loss rates. The ALR model:
- Is relatively easy to understand.
- Is much more responsive than the BP model to credit cycles.
- Produces reliable results without the added complexity associated with overcoming the limiting conditions of the Markov model.
- Provides useful information about the effective lives of substandard and doubtful loans.
- Implicitly measures exposure on unfunded commitments.

The main limitation of the ALR model is that it can project loss rates only as far into the future as historical data allow. For example, with 12 quarters of historical data, the model can project loss rates only 11 quarters into the future. While this is generally more than adequate for reserving purposes, it may not be sufficient for pricing analysis. There also may be times when the institution wants to evaluate longer-term measurements (for example, five years) based on trends in more recent periods (for example, the past two years). This requires the ability to generate a five-year equivalent loss curve from only two years of historical data. The ALR model, by itself, cannot do this.

**Leveraging Off the Strengths of Multiple Techniques**

Perhaps the best solution combines the ALR and Markov methodologies to leverage off the strengths of each. It also recognizes the benefits of different approaches for meeting different objectives. The ALR methodology typically serves as the foundation upon which the loss rates are derived. It can be used to produce reliable measurements of historical losses with relative simplicity, and is very responsive to changing credit cycles. The Markov model also can be used to generate expected default frequencies at the counterparty level to support capital allocation, risk-based pricing, and portfolio management models. And simple rating transition information can be useful in understanding trends in the portfolio. In essence, both models can coexist in a single environment.

Finally, the Markov methodology can be integrated into the ALR model to develop loss transition

### Example Cumulative Average Loss Rate Summary Table

<table>
<thead>
<tr>
<th>Grade</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
<th>10</th>
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<td>Special Mention</td>
<td>0.04%</td>
<td>0.33%</td>
<td>0.75%</td>
<td>1.23%</td>
<td>1.54%</td>
<td>1.75%</td>
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<td>2.09%</td>
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<td>2.36%</td>
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<tr>
<td>Substandard</td>
<td>0.64%</td>
<td>1.76%</td>
<td>3.16%</td>
<td>4.21%</td>
<td>4.65%</td>
<td>4.84%</td>
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<tr>
<td>Doubtful</td>
<td>4.78%</td>
<td>8.93%</td>
<td>12.20%</td>
<td>13.79%</td>
<td>14.32%</td>
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rates, when necessary, to extend the ALR forecasting capability further into the future than the historical data might otherwise allow. The idea is to use a Markov transition matrix to forecast balances, say, at two-year intervals into the future so that the ALR model can be applied to a succession of starting points. This can be particularly useful in forecasting in the early stages of a credit cycle when loans are transitioning to lower ratings but losses have yet to show up in the numerator for the ALR calculations (Figure 5). The result is a much more robust measurement and forecasting capability. If the solution is constructed properly, assumptions can be varied to shift emphasis back and forth between ALR and Markov for forecasting purposes. The institution also can evaluate the effect of short-term shifts in credit quality at an early stage in the credit cycle relative to longer-term observations over several cycles.

In any modeling framework, it also is important to consider the volatility of loss. Establishing reserves based solely upon average loss experience can leave the institution significantly under-reserved, particularly in the face of adverse trends or increased loss volatility. Simply adding measures of volatility to the analysis can significantly increase the confidence in the reserves by accounting for unexpected losses.

**Conclusion**

Ultimately, establishing an appropriate allowance for loan and lease loss is both art and science. Migration analysis is an important tool to help management make more informed decisions. When faced with changing credit quality, no single modeling methodology is sufficient. BP models, while easy to construct, can seriously lag credit cycles, leading management to erroneous conclusions about future loss expectancy. ALR and Markov models are far superior to BP models. However, neither model alone represents a “best” solution. The best solution capitalizes on the strengths of the ALR and Markov models in an integrated fashion to meet multiple objectives. Also, it is worth remembering that historical analysis is simply the starting point; the larger analytical framework must support modeling of future outcomes under various scenarios.

For more information on this approach to migration analysis, call (801) 237-1462 or -1469.