LookAhead™ and Mortgage Risk Model™
Model Validation Study

This Study is designed to provide users of Strategic Analytics’ LookAhead™ or Mortgage Risk Model™ with a roadmap for a robust model validation process.

1. Model Description
   LookAhead software and the Mortgage Risk Model leverage the core technology of Dual-Time Dynamics (DtD) to analyze the real-time environment for forecasting portfolio behavior, simulating portfolio response to a range of economic scenarios, and designing management strategies to adapt to changing conditions.

2. Inputs, Data, and Assumptions
   The Models require specific formatting of all input files. If the format is not met, the data will not load. Data formats are provided in the form of Excel template files and configuration documentation. Minimum data requirements for the Models are a combination of the length of the time history and the number of vintages observed. In general, the analysis works best when more than 18 vintages and 18 months of performance data are available. Strategic Analytics highly recommends using all data available.

   Using monthly vintages rather than annual or quarterly is a simple way to increase the number of vintages. DtD accuracy tends to improve with more finely grained vintages, as long as the event rate modeled does not become too infrequent for reliable analysis. There is a practical limit of approximately twelve user-defined segments, depending on the Model configuration and version deployed.

   Input and data validation is beyond the scope of responsibility for Strategic Analytics however, the Models do provide tables and plotting capabilities for visualization of input data, models produced, and forecast results.

3. Is the Model Appropriate?
   LookAhead provides modeling for a wide range of retail lending products including Installment, Line of Credit, Basel II, Student Loans, and Revenue. Mortgage Risk Model provides modeling for residential mortgage products including first liens and home equity. Within each of these products, the Models provide different modeling techniques to accurately model data with different characteristics. The responsibility of choosing the correct product/configuration type and modeling technique is placed upon the software user.
4. **Processing Components, Mathematics, Theory, and Logic**

The Models are based on DtD a process refined by Dr. Joe Breeden, President of SA, and published extensively for peer review. This technique uses nonlinear decomposition to analyze vintage level data on both the calendar date and age time scales.

Mathematically, the model for a given performance rate, \( r(v,a,t) \), with dependence upon vintage \( v \), month-on-books \( a \), and calendar date \( t \) is:

**Equation 1**

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\begin{align*}
\hat{r}(v, a, t) &= \hat{e}^{f_m(a)} \cdot \hat{e}^{f_Q(v)} \cdot \hat{e}^{f_g(t)} \cdot \varepsilon_{v, a, t}
\end{align*}
\]

- **Maturation** - \( e^{f_m(a)} \) captures product lifecycle effects as a function of age of the account.
- **Vintage Quality** - \( e^{f_Q(v)} \) measures credit quality issues due to changes in underwriting and is often captured by credit scores.
- **Exogenous** - \( e^{f_g(t)} \) captures calendar time shocks to the vintages, such as seasonality, macroeconomic effects, and certain policy and regulatory changes.
- **Residual error** is \( \varepsilon_{v,a,t} \).

5. **Historical, In-Sample Model Validation Methods**

The core assumptions of DtD decomposition are that (1) the maturation and exogenous functions apply to all vintages, and (2) the maturation function does not change with time. To test the first assumption, a user can employ the Alternating Vintage Test. The second assumption is tested using the Old Vintage/New Vintage test. The Bootstrap Test answers whether the DtD estimator for maturation, exogenous, and quality is unbiased. The Cross-Term Test shows that the model is complete.

**ALTERNATING VINTAGE TEST**

This test divides the vintages of one segment into two sub segments of “evens” and “odds”. By alternating, users can analyze the same data range of a segment as observed by two independent sets of vintages. Once the data sets have been created, decomposition is performed independently on the two subsamples and the maturation and exogenous curves between the samples and the original are compared. Since each sample has different vintages, if a normalization approach, then each data set is normalized internally and the levels of the maturation curves and the zero points of the exogenous curves may differ. For this reason, users should not be concerned with the scaling and offset differences, but rather with the shapes of the curves (Figure 1).
Figure 1 – A comparison of the maturation curves obtained from a full data set to those obtained from only the odd or even vintages. This example shows the one month delinquency account rates on a UK mortgage portfolio.

Success or failure of the test is usually clear by inspection however, statistical tests measuring the failure of the hypothesis that the curves are identical are available. In our experience at Strategic Analytics with hundreds of portfolios tested over a decade, the Alternating Vintage Test has never failed the visual inspection – odd/even curves are always within the error bars of each other and the full curve.

Alternating Vintage - Preparing the Data
To prepare data for the Alternating Vintage test, simply open the segment files and separate the odd and even vintages by date. Monthly vintages will produce the best results. When the odd/even segments are created, they must be saved with a new Segment Name (on the Segment Data worksheet) and a new file name which reflect odd or even dates. Since non-contributing vintages do not affect the model results, the user can decide whether to include them in either segment or remove them.

The following three images (Figs. 2, 3, 4) show the changes to be made from the original segment to create an odd vintage segment. Repeat these steps to create the even vintage segment.
Figure 2 – Changes to Segment Data worksheet to create the odd vintage segment.

Figure 3 – Changes to Originations Data worksheet to create the odd vintage segment.
Alternating Vintage - Running the Test

To run the Alternating Vintage Test, load the original, odd, and even vintage segments simultaneously. If the original analysis includes segment grouping, make sure there are odd and even vintages for each segment included in the grouping and group them as described in the following paragraph.

Segment A and Segment B are grouped together for maturation curves under group M1, the Alternate Vintage Test segments would be Segment A_Odd, Segment A_Even, Segment B_Odd, and Segment B_Even. Segment A_Odd and Segment B_Odd would be grouped as M1_Odd. Segment A_Even and Segment B_Even would be grouped as M1_Even. Exogenous grouping would be done similarly.
Once the segments are loaded in LookAhead, open the Maturation Data Table and create segment plots for each variable showing the original, odd, and even segments. Click on the line for the original segment to select it and click the “Add Error Bars” button on the plot. This will create a plot similar to Figure 1 above. Repeat this for each variable in the Exogenous Data table and create plots showing the original, odd, and even segments’ exogenous curves.

OLD VINTAGE/NEW VINTAGE TEST
The use of decomposition assumes that the maturation function is stable far enough into the future to be useful and that the exogenous function can be used to create stable correlations to external factors such as macroeconomic data. The only method available to test this assumption is to determine if the maturation and exogenous functions have been stable historically.

The Old Vintage/New Vintage Test requires the user to split the available vintages into two subsets based on origination date. Each subset is then decomposed separately in order to determine if the segment is stable through time relative to the DtD variable.

Old Vintage/New Vintage Test - Preparing the Data
To prepare the data simply count the vintages and split the segment files in the middle. Non-contributing vintages are not included in the number of vintages. Save the files under new file names and change the Segment Name on the Segment Data worksheet.

Old Vintage/New Vintage Test – Running the Test
Load the full, old vintage and new vintage segments simultaneously and export the maturation and exogenous curves for each DtD variable. The maturation curves and exogenous curves should overlay each other within the error bars of the full segment.

BOOTSTRAP TEST
The Alternating Vintage Test is a form of a Bootstrap Test using a unique sampling method but the goal of the Bootstrap Test is different. The estimation process for decomposition is highly nonlinear and generally not amenable to a closed form solution. By comparing the maturation curve from the full data set with the median of the distribution of the subsets at each month-on-book value, the user can verify that the estimation algorithm is unbiased.

Bootstrap Test - Preparing the Data
The steps to create the data for the Bootstrap Test are similar to the Alternating Vintage Test but more segments are created. Strategic Analytics highly recommends automating this procedure with Excel macros or programs outside of Excel. The best results are found when creating a minimum of 10 segments with a random sample of at least 50% of the original vintages.

**Bootstrap Test – Running the Test**

To conduct a Bootstrap Test, a random sample with replacement is taken from the vintages of the original data set to create many subsets. For example, random subsets containing 50% of the original vintages can be created and decomposed. By repeating this many times, a distribution of maturation curves can be obtained. There will be variations in the levels of the curves because the vintages do not all have the same quality, but users can allow this to form part of the distribution rather than worrying about renormalization (Figure 5).

![Figure 5](image)

**Figure 5** – The thick line maturation curve from the analysis of US auto 5-year term loans with 95% confidence intervals. The other lines correspond to points along the distributions formed from 100 random subsets, each containing 50% of the original vintages.

**TESTING FOR CROSS-TERMS**

The equation for determining a given performance rate using decomposition assumes that maturation, exogenous, and quality functions are mutually independent. No terms are included that are a functions of $at$ or $tv$. Intuitively, cross-terms would be situations where macroeconomic impacts worsened only for the younger accounts or only for riskier vintages. Such cross-terms seem plausible, so users should test for their existence.

Unfortunately, adding cross-terms to the decomposition model makes a complex situation worse. The simplest solution is to leverage published work on spatial correlation.\(^2\) Although not traditional spatial

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dimensions, the two time dimensions date and months-on-books, define a space suitable for applying these methods. If the user finds significant correlations in the model residuals across the age-time space, then residual structure exists within the data suggestive of cross-terms.

In practice, if evidence for cross-term structure is found, the simplest solution is usually to increase the segmentation.

6. **Scenario Based Forecasting Validation**

The effectiveness of using the historically-learned model components in scenario based forecasting must also be validated. Users should not assume that a model that performs well over a forecast horizon of a few months will perform well in the long run. Conversely, a model that performs poorly in the short-term may not perform badly in the long-term. The user should use the forecast horizon for testing that matches the desired forecast horizon in production.

**IDEAL SCENARIO VALIDATION**

The basic technique for validating a forecast model is an out-of-sample test – train a model on in-sample data, create a forecast over a forecast horizon, and measure the accuracy of the forecast. This approach requires modification for validating the Models’ scenario-based forecasting.

Some model components learned from the historical data, such as maturation and quality functions, can be assumed to carry forward as a fundamental part of the forecast, but the past environment cannot be assumed to be the future environment. To create a forecast, the Models require a scenario for the environment, so the user’s forecast cannot be any better than the scenario input.

The best approach to measuring the accuracy of the Models’ out-of-sample performance is to eliminate errors due to the scenario. During the in-sample period, the user can expect to learn the maturation function, quality of existing vintages, and seasonality, but not the marketing plan, either in volume or quality of new bookings. These are given as scenarios. The same holds true for the future environment. Having the environment provided as a scenario eliminates this component from the forecast error.

Once the forecast has been made, the error relative to actuals can be measured and the user can define the uncertainty in a forecast given the correct scenario.

**Ideal Scenario Validation - Preparing the Data**

To prepare a segment data file for the ideal scenario validation, the user should first decide the length of the out-of-sample test. For a 12-month out-of-sample test period, the user should have a minimum of four years of data for the in-sample training after the removal of the most recent history. The examples below assume a 12-month out-of-sample test is desired.
**Ideal Scenario Validation – Running the Test**

Load the full segment in the Model and create a project using the “No Forecast” option. When the full segment is loaded in the Model, open the Accounts and/or Balance tables and export the table data. Save this file in Excel under a name indicating it is the full segment’s results. Next, export a Portfolio Scenario File and save it - indicating it is from the full segment.

![Figure 7 – Load full segment and select the “No Forecast” option in the New Project Wizard.](image)

Start a new project in LookAhead loading the full segment again. At the top of the Step 5 of 6 in the New Project Wizard, set the Forecast End Date to the last historical date of the full segment. Also in Step 5 of 6 in the New Project Wizard, click the Advanced button and use the Date Filter and Vintage Filter to remove the most recent historical data (Figure 8). The End Date in the Date Filter and Vintage Filter must be the same. Click OK to close the Advanced Project Setting.
In Step 5 of 6 in the New Project Wizard, click Next to finish processing the segment data.

When processing is completed, export a portfolio scenario file and name it to indicate it is from the shortened segment. Leave this project with the shortened segment running.
Open both the full portfolio scenario and the shortened portfolio scenario. Copy the last 12 months of originations data from the full scenario to the shortened scenario file (Figure 9).

Figure 9 – Copy Originations data from the full scenario file into the shortened scenario file.
Figure 10 – Copy the entire Exogenous Residual column from the full scenario to the shortened scenario file.

Next, copy the entire Exogenous Residuals column from the full scenario to the shortened scenario file (Figure 10).
Save the shortened scenario file and import this into LookAhead using the “Suture” scenario import option (Figure 11).

![Image of LookAhead software interface](image)

**Figure 11 – Import the shortened scenario file and select the “Import Scenario and Suture” option.**

Export the same Accounts and Balances data previously exported from the full scenario saving them to indicate they are from the shortened segment. Compare actual data from the full segment to the forecast data from the shortened segment.

**FORECAST VARIANCE ANALYSIS**

Assessing model error with an Ideal Scenario Validation is useful for creating confidence intervals about a forecast. However, to diagnose exactly where a model is failing, a Forecast Variance Analysis is required. To perform this analysis the user trains a model on an in-sample data set and saves the model components. Retrain the model incorporating the out-of-sample data and save those components. One model component at a time, substitute the out-of-sample re-estimate into the in-sample model. With each substitution, the forecast is rerun until the model is finally an in-sample model across the entire data set and the remaining error is the in-sample residual.

In the Models all model parameters and assumptions are archived with every forecast. The Forecast Variance Contribution Reports are automated in the Models in the Contribution Report feature in the
plot toolbar (Figure 12). Steps to create an automated or manual Forecast Variance Contribution report can be found in the User’s Manual.

![Figure 12](image-url)

**Figure 12** – Automated Contribution Reports from plot toolbar.

7. **Forecast Diagnostics**
Explanation is just as important as validation. Several methods exist to help us gain confidence in a forecast.

**SEGMENT COMPARISONS**
The simplest test is cross-segment comparisons. Although one generally segments the portfolio to separate dynamically distinct pools of consumers, some patterns should emerge across segments. The point of segment comparison is to confirm intuition. In some cases, the intuition will be that the results should be the same, such as comparing maturation functions across geography, ex. a 30-year prime fixed mortgage should produce the same shape curve regardless of geographic region.
FORECAST CONTRIBUTION REPORTS
To explain the impact of the scenario embedded within the forecast the Forecast Variance Report previously explained separated forecast errors into components by comparing actual to a previous scenario. The same approach can be used to compare the scenario components of a forecast to what would happen if nothing changed in the past (see Figure 11) using the Forecast Contribution Reports automated in the Models (Figure 12). Steps to create an automated or manual Forecast Contribution Report are in the User’s Manual.

Figure 13 – The forecast contribution report shows which vintages were contributing the most to the 2009 forecast. This portfolio was shut down by 2008 and assumed no new originations in 2009.

HISTORIC CONTRIBUTION REPORTS
The analysis for a forecast contribution report can also be performed on recent history. Historical data is decomposed and forecasted again using default scenario components, flat quality assumption, etc. The Models successively replace each of the model components with actual scenario components. The differences describe what caused last year’s losses.

The Models provide automated solutions for Historic Contribution reports and Forecast Contribution reports which can be selected from the tool bar on line, segment, or vintage plots (Figure 12). Steps for an automated or manual Historic Contribution Report can be found in the User’s Manual.

8. Validating Econometric Models
Due to the short length of economic time series, the validation of stress test models is very difficult. Creating robust correlations is more of an art than a science. Given that there is not enough data to build a purely data-driven model, most practitioners and regulators will validate macroeconomic factors of a stress test model with a “smell test”. Are the variables typical? Are the transforms reasonable?
Does the stress test model produce plausible portfolio results out-of-sample when given plausible scenarios?

The most quantitative validation is to compare across geographies. Within a country, the user can try to build a model on a subset of regions, provinces, states, or cities and see if the same model applies equally well to other areas. The regional variations are generally much smaller than the long-term economic cycles. Those small variations allow for a validation test, but it is a weak one.

The best method is to validate all other model components as described previously. The final step of bringing in macroeconomic data will only allow validation if the user has access to decades’ worth of performance data rather than the standard five to seven years that is generally available.

9. Tracking Model Users Actions within the Models
Because the Models support multiple user actions in creating a forecast, there is a feature to record all user adjustments in the scenario creation - the scenario record feature. In addition, comments can be added by the user during scenario creation or from the Scenario Menu to explain the logic behind choices made. These comments can be added to the scenario file during export so that others may review the choices. In addition the Exogenous Events log can be used as a corporate memory of significant business events noted on the Exogenous curve and the magnitude of the impact of these events.

10. Vetting Dual-Time-Dynamics
Dual-Time-Dynamics and the Models have been used to analyze lending portfolios since 1999. The technology and analysis results have been published and have successfully undergone extensive peer reviews both in the US and internationally including numerous presentations to regulatory bodies such as the US Federal Reserve, FDIC, OCC, OSFI (Canada), FSA (UK), and APRA (Australia).
11. The following is a list of published papers by Dr. Joe Breeden. All papers can be found on the Strategic Analytics web site (http://www.strategicanalytics.com/articles.php).


