Economic Response Models in LookAhead®
Introduction

Economic Response Models (ERMs) in LookAhead® provide a mathematical relationship between the dependent historical exogenous residual, and independent macroeconomic time-series. For example, the historical exogenous residuals for delinquency rates can be related to historical unemployment rates. The ERM is then used to predict future changes of the exogenous residual(s) based on actual and forecasts of the macroeconomic time-series.

A good ERM needs to:

> Show sensible correlation between historical macro-economic data and the historical exogenous residual

> Be based on macro-economic variables that directly impact consumer behavior; For example, exogenous residuals for delinquency worsen when unemployment rate increases

> Exhibit coefficients that are reasonably stable over time

This paper describes best practices for building ERMs using LookAhead®.

ERM Building Blocks

The construction of ERMs in LookAhead® uses the following building blocks:

a) Macro-economic variable(s) that directly impact consumer behavior such as Unemployment Rates, House Price Indices (HPI), and Interest Rates

b) Time-series transforms such as LogAverage and LogDiff
c) Time-series windows and lags
d) Regression models
e) Linkage models

1 Interthinx’s patented Dual-time Dynamics (DtD) technology employs a two-stage decomposition. The first stage is a nonlinear decomposition into three independent effects along the dimensions of age, calendar time and origination date. The calendar-time based effect is referred to as the exogenous effect and quantifies the change in performance relative to the maturation curve due to time-varying conditions such as seasonality, policy changes and macroeconomic effects. The exogenous curve undergoes a second stage of decomposition to separate out these factors using a linear decomposition. After subtracting seasonality and discrete impacts, the remaining exogenous residual contains macroeconomic structure and random noise.
A. MACRO-ECONOMIC VARIABLES

When modeling consumer loan portfolios, it is important to note that the macro-economic variables most useful in building ERMs are those that affect the overall financial health of the consumer on a direct basis; that is through a material effect on their income, assets, debts or expenses as illustrated in Figure 1.

While it may be tempting to perform an automated search among these candidate variables to build an ERM, it must be kept in mind that typical portfolio data often contains less than 10 years of performance, covering at most one economic cycle. Therefore, automated search among the large number of available macro-economic time-series, for those with the best correlation to portfolio performance will likely include spurious correlations. We recommend that the analysts use their knowledge, experience and intuition to sub-select a limited set of variables. ERMs with 1-3 variables can be quite effective because Dual-time Dynamics decomposition accounts for other factors driving portfolio performance independently of the economic signal. Macro-economic variables selected for ERMs should have an intuitive relationship to the exogenous residual of interest and reliable forecasts of future values. For example, to predict mortgage foreclosures, the analyst may select a short-list of variables such as HPI, Mortgage Interest Rate, and Unemployment Rate. In contrast, Consumer Sentiment measures may correlate well to consumer behavior but forecasts are not readily available.

Figure 1: Good candidates for macro-economic predictor variables
B. TRANSFORMS OF ECONOMIC VARIABLES

In time-series modeling, it is often necessary to transform one or more variables in order to find meaningful relationships over time. Transforms can also be used to normalize data ranges and facilitate more direct comparison between time-series. Transforms applied to macro-economic variables determine the shape of the response of their dependent variables. Table 1 describes the recommended transform for a selection of important macro-economic variables.

<table>
<thead>
<tr>
<th>Macro-economic Variable</th>
<th>Recommended Transform</th>
<th>Illustration (with Lag=0, Window=12)</th>
<th>Other Recommended Transforms</th>
</tr>
</thead>
<tbody>
<tr>
<td>Unemployment Rate, Interest Rate</td>
<td>LogAverage</td>
<td><img src="image.png" alt="Illustration" /></td>
<td>LogitAverage, LogDiff, LogitDiff</td>
</tr>
<tr>
<td>HPI, Financial Obligations Ratio</td>
<td>LogDiff</td>
<td><img src="image.png" alt="Illustration" /></td>
<td>LogitAverage, LogAverage, LogitDiff</td>
</tr>
</tbody>
</table>

Table 1: Examples of recommended transforms

The economic time-series can be transformed and/or time shifted relative to the exogenous residual.

The modeling of delinquency rate exogenous residuals using the unemployment rate provides a good illustration of considerations when building LookAhead® ERMs. The LogDiff transform of unemployment rate often provides the best description of the response of delinquency rate exogenous residuals to unemployment rate. However, another important criteria when building ERMs concerns the reasonability of the
forecast, and when this transform is used in future scenarios with a flat unemployment rate, after an initial perturbation, this results in the forecast exogenous residuals being 0 whether the unemployment rate is flat at a very high or a very low level, as seen in Figure 2. Therefore, care must be exercised when using this transform to ensure reasonable forecasts; in particular, use of the LogDiff transform of unemployment rate in conjunction with short windows is often undesirable.

A good ERM should exhibit sensible correlation with the historical exogenous residual. The reasonableness of the forecast should also be considered under both baseline and stressed scenarios.

Figure 2: Response to different flat unemployment rate scenarios when the LogDiff transform is used.
C. LAGS AND WINDOWS

The timing of the model response can be adjusted by user selection of windows and lags. The effect of lags and windows in ERMs is best understood by examining the response of a LogAverage transform of a dependent variable to a square pulse in the independent variable.

Figure 3 shows that the effect of increasing the lag (while holding the window constant) is to delay the response of the dependent variable to the change in the independent variable. When the lag is 0, the response is immediate. But, if the lag is set to 12 months, the response in the exogenous residual doesn’t begin until 12 months after the initial increase in the independent variable. Changing the lag affects the delay of the exogenous residual response.

![Figure 3: Lags affect the delay of the response of the LogAverage transform of the dependent variable to a square pulse in the independent variable](image)
Figure 4 shows that the effect of increasing the window (while holding the lag constant) is to increasingly spread out the response of the exogenous residual. In all these cases, the response starts at the same time (in this example immediately, since the lag is set to 0). What is important here is the spreading out of the response over time; the change in level is less important as it can be adjusted by the calibrating the ERM, as described in the next section.

While the response to the square pulse provides the clearest demonstration of the effect of windows and lags, triangular pulses are more similar to the cyclical aspects of economic data. Figures A1 to A4 in Appendix A show the response of the LogAverage transform and the LogDiff transforms to a more realistic triangular pulse. Regardless of the shape of the economic series, the effect of increasing the lag is to delay the response and the effect of increasing the window is to spread out the response over a longer time period.

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While the response to the square pulse provides the clearest demonstration of the effect of windows and lags, triangular pulses are more similar to the cyclical aspects of economic data. Figures A1 to A4 in Appendix A show the response of the LogAverage transform and the LogDiff transforms to a more realistic triangular pulse. Regardless of the shape of the economic series, the effect of increasing the lag is to delay the response and the effect of increasing the window is to spread out the response over a longer time period.
LookAhead® provides a correlation matrix that supports both positive and negative time lags, along with windowed transformations on the time series. This matrix is helpful in identifying meaningful correlations between the dependent exogenous residual and the independent macro-economic data. Figure 5 provides an illustration of the concept. Typically, it is a good idea to look for macro-economic variables that lead the portfolio by twelve months or less. But in some cases, longer lags and even small negative lags can be useful.

The use of lags and windows helps to account for the lagged/smoothed nature of the consumer response to the change in the economic environment. For example, let’s consider the impact of a spike in unemployment rate on default rates:

> Some of those who become unemployed will likely default immediately. So we should expect relatively quick response and hence relatively short lags — of the order of the time it takes to get to the stage of default being considered. (Of course if the timing of default is long, such as in some mortgage portfolios where it is on the order of 18 months, then we should expect that the lags will be correspondingly long).
> Others who become unemployed at the same time will take much longer
to default. Some individuals likely would be able to hold on for years
rather than months before defaulting, due to both the “character” of the
individual that makes them try to meet their obligations for as long as
possible, as well as the “capacity” that different individuals will have to
avoid default, based on their savings, their other debt obligations, and
unemployment benefits. It should be noted that with unemployment
benefits being extended for as much as 99 weeks post-recession (as
opposed to the traditional 26 weeks), the length of time a consumer can
hold on without defaulting in the face of unemployment has probably
become longer than before. Based on what is likely a large range of
responses, we can expect relatively long windows — on the order of many
months or a few years — for the ERMs.

D. REGRESSION MODELS

The level of the response can be adjusted in the same way as in a standard linear
regression model. Once the economic variable, transform, window and lag have
been selected, LookAhead® will automatically calculate the slope and intercept
that minimizes the error in fitting economic data to exogenous residuals.

E. LINKAGE MODELS

An optional tool when building LookAhead® ERMs is the ability to use a ‘linked’
approach to relate the exogenous residual of interest to macro-economic time-
series via other exogenous residual(s). This approach is particularly useful
when building an ERM for an exogenous residual where the dependence on
the economy is obscured by policy. For example, the economic impact on the
exogenous residual for charge-off rate is often obscured by a lender’s policy
around charge-offs. In this case, a good approach to building the ERM may
be to relate a mid-stage delinquency exogenous residual that is sensitive to
the economic environment to macro-economic time-series, and then link the
charge-off rate exogenous residual to this mid-stage delinquency exogenous
residual. Building linkage models is an advanced technique requiring care
to avoid increasing modeling error and reducing sensitivity due to the more
complicated ERM.

Linkage models are particularly useful when building ERMs for exogenous residuals
where the dependence on the economy is obscured by policy.
APPENDIX A

TRIANGULAR PULSE AND DELAY IN RESPONSE

The following four plots provide an illustration of the effect of lags and windows on the response of a LogAverage and a LogDifference transform of the dependent variable to a triangular pulse in the independent variable — as might be caused by a stylized peak in unemployment, for example.

**Figure A1:** Effect of lags on the response of the LogAverage transform to a triangular pulse in the independent variable

**Figure A2:** Effect of windows on the response of the LogAverage transform to a triangular pulse in the independent variable
Economic Response Models in LookAhead®

**Figure A3**: Effect of lags on the response of the LogDiff transform to a triangular pulse in the independent variable.

**Figure A4**: Effect of windows on the response of the LogDiff transform to a triangular pulse in the independent variable.

To discuss how Interthinx Predictive Analytics solutions can help create ERMs for your portfolios, email sales@interthinx.com or call 800-333-4510.