A Proven Approach to Stress Testing Consumer Loan Portfolios
Portfolio Stress Testing in the United States

*Portfolio stress testing is receiving unprecedented attention in the US.*

*In February 2009, federal banking agencies created a stress test using two economic scenarios — one based on a consensus forecast by professionals; the other based on severe but plausible economic conditions for macro variables such as GDP, unemployment and home prices.*

**WHY DO A STRESS TEST?**

The purpose of the stress test was to assess the amount of capital required for large financial institutions to remain viable within the adverse scenario. Under the Federal Reserve Supervisory Capital Assessment Program (SCAP), the top 19 US bank holding companies (BHCs) were required to stress test their portfolios and report capital adequacy. Results were made public to enable markets to draw their own conclusions about each BHC’s robustness. As regulation evolves, the list of financial services companies required to submit results from stress testing continues to grow.

**WHO NEEDS A STRESS TEST?**

The stress testing process was formalized in the Federal Reserve’s annual Comprehensive Capital Analysis and Review (CCAR), which made forward-looking stress tests a requirement of regulatory capital planning under the Dodd-Frank legislation in 2010. Regulatory guidance in 2012 indicates that regulatory stress testing requirements will extend beyond large BHCs to include small and mid-sized banks with assets below $10 billion. Although advanced financial institutions have used stress testing for years to estimate a range of possible outcomes due to uncertain events, the industry has not defined a standard approach to stress testing. There is even a wide variation in modeling approaches across portfolios within banks. Many banks are accustomed to using stress testing to estimate Value-at-Risk (VaR) in trading portfolios and interest rate risks as part of asset and liability management (ALM). The nuances of consumer lending portfolios pose challenges in developing stress tests that focus external stress due to economic factors on the aspects of portfolio performance that are driven by economic factors. From a regulatory perspective, supervision of stress testing is relatively new and the requirements continue to evolve based on experience. The Federal Reserve continues to develop its own internal models, using various portfolio-specific modeling approaches across different consumer lending products.
WHAT MAKES AN EFFECTIVE STRESS TEST?

In the face of changing regulatory requirements or a bank’s own internal pressures, stress testing tools need to be transparent, robust, and adaptive. This document describes how Interthinx Predictive Analytics’ approach to stress testing retail-lending portfolios satisfies each of these requirements by providing a consistent credit-risk modeling framework across consumer lending and small business portfolios worldwide. Moreover, the Interthinx approach to stress testing leads naturally to estimating capital requirements in a way that avoids the problems that can result from errors in attributing portfolio effects. The approach is ideal for banks facing new regulations or smaller institutions seeking to implement best practices to manage their financial health.

Key Challenges in Retail Portfolio Stress Testing

Until recently, stress testing in retail loan portfolios was unsophisticated, usually done simply by estimating the effects of a 10% rise in delinquency. However, simplistic approaches make it difficult to discern specifically what creates change in portfolio performance, therefore making it difficult to formulate plans of action to mitigate portfolio stress risks. Some portfolio losses are expected and should be priced into the terms of credit. Others may be caused by unforeseen changes in the economic environment and this is where stress testing is typically focused.

Retail portfolios are driven by a nonlinear interaction of factors on different time scales. New loans behave differently than seasoned loans. Loans that originated at different points in time may exhibit different credit risks due to changes in origination policy or selection effects in the marketplace. Borrowers are impacted by seasonal factors, policy changes, and economic conditions that occur during the time they hold their loan. Although the credit risk for individual loans can be estimated by updating credit scores, they do not account for the nonlinear aspects of performance that will affect loans and the portfolio over time. In addition, complexities arising from combining individual loans in the portfolio can lead to errors in the estimation of overall potential losses, thereby skewing capital requirements.

WHAT MEASUREMENTS SHOULD BE USED?

The ideal stress testing approach should measure the factors driving portfolio performance and forecast future results based on user-specified scenarios, supporting both internal and regulatory scenarios for economic conditions. Instead of assuming relationships with predefined economic and originations
factors, it should create a model for each portfolio by quantifying portfolio dynamics along the dimensions of age, time, and originations to create signals that can be explained with outside data such as economic factors. This would enable models to adapt to changing conditions and changing forecast assumptions. This type of approach would allow the economic factors to be applied to the models independently from originations strategies as well as seasonal and policy-driven factors; focusing the economic forecast only on the economic component of portfolio performance.

At a high level, portfolio drivers can be described as maturation (age-based), exogenous (time-based), and origination quality (based on origination date). Because each of these factors is dependent on time, quantifying each factor’s impact can be challenging. However, measurement of the factors is essential to focusing portfolio stress on areas outside of management’s direct control and avoiding the double counting – or other incorrect distributions of risks – that can arise in models that fail to control for interaction. Quantifying these factors provides transparency into the modeling process so that managers can see why performance changes. This transparency facilitates scenario-based forecasting with targeted application of economic stress in a way that supports strategic planning for risk mitigation.

This type of methodology has been proven by Interthinx Predictive Analytics solutions to be robust across a decade of changing economic conditions. It has spanned retail lending and small business portfolios in more than 25 countries, providing a uniform modeling approach across products and regions.
Interthinx Predictive Analytics methodology is the ideal way to help banks with portfolio stress testing

Of the factors driving portfolio performance, the economy is among the most difficult to quantify. Because movements in economic factors tend to be slow and cyclical, they can be confused with changes in portfolio growth, portfolio seasoning, and even other economic factors. Furthermore, it is difficult to reliably forecast what the economy will look like in the future. However, with the right modeling approach, the effects of loan seasoning, marketing plans, underwriting criteria, policy changes and seasonal impacts are relatively straightforward to quantify and forecast. In addition to quantifying specific factors driving performance, the separation of portfolio dynamics allows factors to freely vary in the model without creating unreasonable conditions. In the context of stress testing, separation ensures that economic scenarios only apply to economic performance factors.

THE INTERTHINX PREDICTIVE ANALYTICS APPROACH

By separating the economic drivers of portfolio performance from other factors so that economic stress can be focused in the right place for forecasting, there are no assumptions about which economic variables drive the portfolio until the economic component in portfolio performance is measured empirically over time. Other modeling approaches may struggle with the nonlinear aspects of retail portfolio performance over time and as a result, inadvertently stress more than economic conditions in their forecasts. Interthinx uses a portfolio modeling approach specifically designed to isolate the components of portfolio performance.

Portfolios are characterized based on the states a loan can occupy from the time it is opened to the time it is closed. For example, a loan may be current, delinquent, or charged-off – with the charge-off state being a terminal state that closes the loan. The movement between states is measured by rates of change over time. Roll rates and probability of default are two common ways of describing the rate of change in loan states over time.

MEASURING PORTFOLIO FACTORS

Using its patented Dual-time Dynamics (DtD) technology, Interthinx Predictive Analytics employs a two-stage decomposition of historical portfolio performance from rates of change in delinquency, default and other variables. The first stage, illustrated in the top section of Figure 1 is a nonlinear decomposition along the aforementioned dimensions of age, origination date and calendar time. Each of these three measures is independent of the other. The age-based signal is referred to as maturation or lifecycle. It quantifies the natural performance of loans as they
mature, independent of factors due to the environment and the date of origination. The signal based on origination date is referred to as origination quality and it quantifies the relative change in performance due to changes in underwriting criteria or market selection. Historic credit growth cycles show clear changes in quality of originations as previously conservative lenders move down-market to grow their portfolios. Origination Quality is measured for each group of accounts that originated on a particular date. The time-based environment signal is described as the exogenous curve and it quantifies the relative change in performance due to time-varying conditions such as seasonality, policy changes and macroeconomic effects. This signal contains economic information but there is other time-varying information such as seasonality and policy changes that must be cleaned away before introducing economic data into the model. This is done using the second-stage linear decomposition of the exogenous curve.

...Dual-time Dynamics (DtD) technology employs a two-stage decomposition of historical portfolio performance from rates of change in delinquency, default and other variables.

Figure 1: Dual-time Dynamics (DtD) decomposition from vintage performance data for a 60 Days Past Due rate. Stage one performs a nonlinear decomposition along the dimensions of age, origination date, and calendar time. Stage two performs a linear decomposition on the time-varying (exogenous) signal to measure effects due to seasonality, policy changes, and trending due to economic conditions.

The bottom section of Figure 1 illustrates the separation of factors in the exogenous curve using a simple linear decomposition. After subtracting seasonality and discrete impacts – due to policy changes or other one-time events – what is left is a residual
time series (shown in the lower right of Figure 1). The residual contains macroeconomic structure and random noise. Macroeconomic data is used to model the residual and this provides a solid foundation for stress testing the portfolio using macroeconomic scenarios because confounding information has been captured in other components via the DtD decomposition.

INCORPORATING ECONOMIC DATA

Ideally, a portfolio will have multiple economic cycles to use in modeling economic impacts. However, this is rarely seen in practice today. It has been observed that by removing the confounding information through DtD decomposition, combined with best practices in selecting economic variables, it is possible to create useful economic models even when the history is relatively short. When working within the DtD framework, three or fewer economic variables are typically sufficient to model economic impacts to portfolios, resulting in simpler models.

Retail lending models are best suited to using macroeconomic variables that directly impact consumer spending behavior. The following variables from US Federal Reserve guidance are good candidates:

1. Real Disposable Income Growth
2. Unemployment Rate
3. Mortgage Rate or 10-year Treasury Yield
4. House Price Index

Figure 2: An illustration of correlation between two time series. The exogenous residual for the Balance 60 DPD Rate (black line) is compared to a log difference transformation of the US Home Price Index (HPI) lagged by six months (blue line). Over most of the comparison period, the series move in opposite directions, resulting in a negative correlation of -0.777.
Changes in exogenous residuals are often offset in time relative to changes in macroeconomic variables. For example, credit card portfolios often lead economic indicators while other portfolios tend to lag economic indicators. Therefore, it is important to evaluate correlations at various time-leading and time-lagging relationships between macroeconomic data and exogenous residuals. Figure 2 illustrates the changes over time in an exogenous residual lagging changes in the US Home Price Index by six months. A correlation matrix that supports positive and negative time lags, along with windowed transformations on the time series is helpful in identifying meaningful correlations between macroeconomic data and exogenous residuals. Figure 3 provides an illustration of the concept. Typically, it is a good idea to look for economic variables that lead the portfolio by twelve months or less, or lag the portfolio by six months or less.

Once a suitable correlation is identified, a simple regression model can be used to calibrate changes in the exogenous residual to changes in the economic series. Multiple economic series can be used to model a single exogenous residual using multivariate regression or ensemble univariate models.
CREATING A PORTFOLIO FORECAST

In order to create a portfolio forecast using economic data, an economic forecast is applied to the exogenous model to produce a forecast for the exogenous residual. The exogenous residual is then added to seasonal factors and any future policy changes to define the total exogenous curve forecast. Figure 4 provides an illustration of an exogenous curve forecast using three different economic scenarios.

![60 DPD Balance Rate Exogenous Curve](image)

Figure 4: Exogenous curve forecasts for a 60 DPD Balance Rate driven by three different macroeconomic scenarios: Default (steady-state), Strengthening (showing reduced delinquency), and Weakening (showing increased delinquency).

Each exogenous curve forecast is subsequently combined with maturation and originations quality to create forecasts for the rates of change in delinquency, default and other essential variables in the portfolio. Finally, these rates are used to determine the inventory of accounts and balances in various states on a monthly basis over the forecast horizon. Figure 5 illustrates three different forecasts for 60 DPD Balance nationally and in California. These forecasts are based on exogenous curve forecasts like those illustrated in Figure 4, combined with the maturation and vintage quality characteristics measured in stage one of the decomposition. In this example and usually when stressing the economy, maturation and vintage quality measures do not change across forecasts. Note that the impact of the economic component is directed specifically to the portfolio attributes related to the economy. This prevents spurious correlation with portfolio growth, for example, from artificially influencing the forecast.
FORECASTING THE PORTFOLIO WITH ECONOMIC DATA

Economic forecasts are simple time series inputs to the forecasting model. Using the Interthinx scenario-based forecasting paradigm, applying multiple economic forecasts is as simple as loading a set of Excel files and collecting the forecasts. A range of scenarios can be run one at a time or as a batch to tabulate a range of possible outcomes for the portfolio.

The two-stage decomposition separates portfolios drivers and provides a clear place for applying macroeconomic stresses. Although the economy is by far the most common area to stress, it is reasonable to stress future policy changes and even marketing plans when there is uncertainty in the forecasts. The separation of portfolio factors inherent in the Interthinx approach makes it straightforward to stress test these non-economic factors as well.

Interthinx Predictive Analytics provides seamless support for loss forecasting, stress testing and capital planning by utilizing a componentized, scenario-based forecasting paradigm that scales from a handful of scenarios for loss forecasting and stress testing to hundreds of thousands of scenarios for capital planning. The underlying methodology is consistent throughout the process and models do not require calibration to individual scenarios. In addition, Interthinx provides a consistent methodology across retail lending and small business products worldwide, enabling reuse of scenarios and simplifying the comparison of results.
CONCLUSION

Stress testing requires careful application of portfolio stressors to provide meaningful results. Practitioners and their managers should be mindful of the following three points when using stress testing models:

1. Understand the structure used by models to represent portfolios. Models have strengths and weaknesses that determine their fitness for different applications.
2. Stress forecasts by targeting the stress to the correct model components. Economic stress should be applied to economic components, for example.
3. Creating a range of forecasts by varying explicit assumptions provides a basis for taking action in managing the portfolio.

To discuss how Interthinx Predictive Analytics solutions can help with your portfolio stress testing, email sales@interthinx.com or call 800-333-4510.