Preparing for Basel II Modeling Requirements

Part 4: Stress Testing

by Jeffrey S. Morrison

Earlier articles in this series have focused on the development and validation of PD and LGD models. In contrast, this fourth and final article will introduce a different modeling approach that employs aggregated data to predict the impact of economic and portfolio changes on bank default losses.

The term *stress testing* describes a range of techniques used to assess the vulnerability of a portfolio to major changes in the economic environment or to exceptional but plausible events. Stress tests make risks more transparent by estimating the potential losses on a portfolio in abnormal markets. They complement the internal models and management systems used by financial institutions for capital allocation decisions.[1]

More simply, stress testing is a way to produce alternative scenarios using sensitivity analysis. Banks as well as other businesses have been using sensitivity analysis for years, even if only in an ad hoc framework. However, stress testing as referred to in the new Basel Capital Accord uses more quantitative approaches—methods where assumptions can be empirically evaluated. Stress testing should be able to link dramatic changes in the economic environment to the bank's portfolio:

> 297. A bank must have in place sound stress testing processes for use in the assessment of capital adequacy. Stress testing should involve identifying possible events or future changes in economic conditions that could have unfavorable effects on a bank's credit exposures and assessment of the bank's ability to withstand such changes.
> —New Basel Capital Accord (2001)

Unfortunately, Basel has not yet established specific guidelines on how to do this, which is not surprising given the range of issues to be covered, such as data availability, portfolio diversity, and standardization of model inputs and outputs. This article does not intend to present a survey of all possible techniques for stress testing. All such techniques have their strengths and weaknesses, depending on the bank's resources and portfolio structure. Instead, this article introduces a methodology that is practical, easy to implement, understandable, and has a statistical foundation that has been around for years. The approach can be particularly useful for the retail side of the business because of the greater number of defaults, and it could also prove beneficial on the commercial side of the house.

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Before designing any stress test approach, the first thing we want to know is what's on the test. In other words, what questions do you want answered? Some questions might include the following:

- What would happen to our risk level if we went into a deep recession?
- Would the recession affect us immediately, or would there be a delay?
- How do differences in local economies affect our risk?
- What would happen to our risk level if interest rates went up significantly?
- What impact do new accounts have on our portfolio risk level?
- If we were to enter a major recession, could we mitigate its impact by focusing on specific geographies? Would it be better to loosen lending policies in some areas while tightening them in others?
- What would be the effect of a significant increase in property values in an area?
- What would happen in the event of a significant shift in the industry composition of our portfolio?
- Is our small business portfolio more risk sensitive to changes in the economy than our middle-market accounts?
- How does the economy affect our large customers? Which industries are more sensitive?

Questions like these not only highlight the need to understand the impact of economic scenarios on your portfolio, they also point to the need to quantify strategies for mitigating potential risk.

Given the availability of data, some of these questions may be unanswerable except by judgment and intuition. However, a great deal of data from loan accounting systems is often available, making model development a distinct possibility. Therefore, a flexible stress-test approach should have dials not only to turn down the levels of such external recessionary factors as employment and income (outside the control of the bank) but also to adjust for internal factors (within the bank's control, reflecting efforts to mitigate risk).

A Different Kind of Regression

As noted in previous articles in this series, the statistical techniques recommended for PD (probability of default) and LGD (loss given default) were *regression models*. These models statistically quantify the correlation of a set of predictor variables with the default condition, or the percentage of dollars not recovered. They use account-specific characteristics at a particular moment in time to estimate account-specific predictions. In a PD model, for example, the default definition for an account is determined over a one-year time frame. If a default occurs anytime within a year, then the dependent variable gets assigned a value of 1. Otherwise, it is assigned a value of 0. No attempt is made to link variations in risk over time to explanatory factors that also change over time. From that perspective, these types of models are one dimensional—representing the characteristics of the borrower at a single snapshot in time.

Fortunately, a different type of regression model is capable of using more than one point of time. It is called *pooled cross-sectional time series regression*[2]. It works by using data that has been rolled up from the account level into broader levels of aggregation. These levels might be counties, MSAs (metropolitan statistical area), bank branches, states, industries, etc., and are generically referred to as cross-sections. Mapping account-level data into their proper cross-section or MSA before aggregation has begun is done through zip code. Data on each aggregated group is tracked over time and placed into a regression framework, where correlation estimates can be made, tested for statistical importance, and used for prediction. If MSA were the level of aggregation, then we might try to explain the MSA default rate over time as a function of the following variables from our loan account systems, also at the MSA level:

- Average LTV.
- Average age of the loan.
- Percent of loans less than one year old.
- Average risk rating or FICO score.
- Average loan size.
- Average credit limit.
- Average percentage of loans renewed.
- Average level of delinquency.
- Percent of loans with cash advances.
- Average number of loans per obligor.

However, internal data from our accounting systems is not enough. In order to capture outside influences on our portfolio, we must obtain some external data from other sources. Luckily, a number of economic service providers offer historical and forecasted data products at various levels of aggregation. Some credit bureaus even offer aggregated consumer data. There is even free information on the Internet. Therefore, we could add the following type of external information to our list of resources:

- Average home prices.
- Credit card delinquency rate—30/60/90.
- Credit card utilization.
- Average credit limit—credit cards.
- Bankruptcy rate.
- Unemployment rate.
- Number of households.
- Disposable income.
- Median household income.
- Total employment.
- GDP.
- Federal funds rate.
- Prime rate.
- 30-year fixed mortgage rate.

Model Estimation

The estimation of pooled cross-sectional time series models is a little more involved than for PD and LGD models, but it still involves relating a dependent variable to a set of explanatory variables over a historical time period. The difference is that it accounts for data across two dimensions—by cross-section and time series. In most statistical software packages like SHAZAM, LIMDEP, and SAS®, the data has to be arranged a certain way to estimate the regression. Figure 1 shows the data design in spreadsheet form for a fictitious example in which the cross-section is MSA.

For example, the cross-section called MSA #1 could represent the Atlanta MSA. As can be seen, data for the first cross-section is listed first and ordered by date, followed by the next cross-section, again ordered by date. The total number of observations in the data would be the number of cross-sections times the number of time periods. Since we are now dealing with multiple snapshots in time, we can also create variables that are lagged. For example, in Figure 1 the variable Prime Rate Lag (1) represents a one-quarter lag in the prime rate. In a regression model where the dependent variable was the MSA default rate, the inclusion of this variable would infer that today's prime rate takes one quarter for its influence to be felt in our portfolio.

The last two columns of Figure 1 represent additional indicators called dummy variables. It is standard statistical practice to use these types of variables to enhance model accuracy. Dummy variables account for differences at the MSA level that are not already captured by the other explanatory variables in the model. These variables are assigned a value of 1 if the account is a member of that particular MSA (cross-section), or

Figure 1

Pooled Cross-Section Time Series Data Structure

Cross Section	Time Period	Dependent Variable	%New Accounts	Average LTV	% SIC #67	% 60 days Deliquent	Avg Unempl Rate	Avg Household Income	Avg Bankruptcy Rate	Avg Prime Rate	Prime Rate Lag (1)	MSA #1 Dummy Variable	MSA #2 Dummy Variable
MSA #1	2001Q1	0.12%	5.00%	81.50%	10.10%	1.20%	5.12%	$56,405.54	6.30%	8.62%	-	1	0
MSA #1	2001Q2	0.13%	5.20%	83.00%	11.20%	1.33%	5.12%	$56,442.37	6.51%	7.34%	8.62%	1	0
MSA #1	2001Q3	0.14%	5.50%	87.40%	12.20%	1.22%	5.13%	$56,603.60	6.74%	6.57%	7.34%	1	0
MSA #1	2001Q4	0.22%	6.00%	84.30%	12.20%	1.54%	5.12%	$56,897.32	7.08%	5.16%	6.57%	1	0
MSA #1	2002Q1	0.22%	6.50%	88.30%	13.30%	1.44%	6.11%	$57,189.21	7.29%	4.75%	5.16%	1	0
MSA #1	2002Q2	0.28%	6.40%	79.20%	12.60%	1.65%	6.43%	$57,478.13	7.42%	4.75%	4.75%	1	0
MSA #1	2002Q3	0.24%	7.00%	85.10%	12.80%	2.11%	6.43%	$57,684.58	7.69%	4.75%	4.75%	1	0
MSA #1	2002Q4	0.21%	6.50%	85.60%	11.80%	2.01%	7.23%	$57,790.08	7.88%	4.54%	4.75%	1	0
MSA #2	2001Q1	0.34%	12.30%	65.40%	15.30%	5.33%	4.32%	$35,822.07	7.37%	8.62%	-	0	1
MSA #2	2001Q2	0.43%	13.60%	66.10%	17.40%	4.33%	4.54%	$34,066.79	7.86%	7.34%	8.62%	0	1
MSA #2	2001Q3	0.42%	14.30%	65.70%	16.70%	5.32%	5.44%	$33,519.87	8.31%	6.57%	7.34%	0	1
MSA #2	2001Q4	0.51%	12.40%	66.50%	18.20%	4.32%	5.01%	$34,272.91	8.69%	5.16%	6.57%	0	1
MSA #2	2002Q1	0.49%	14.50%	67.40%	18.30%	4.66%	5.04%	$35.031.90	8.96%	4.75%	5.16%	0	1
MSA #2	2002Q2	0.41%	15.20%	65.70%	19.50%	5.67%	5.23%	$35,773.35	9.24%	4.75%	4.75%	0	1
MSA #2	2002Q3	0.32%	16.40%	66.10%	20.20%	5.98%	5.21%	$36,014.37	9.30%	4.75%	4.75%	0	1
MSA #2	2002Q4	0.45%	17.90%	65.50%	19.50%	6.21%	5.21%	$36,201.34	9.09%	4.54%	4.75%	0	1

0 otherwise. Standard practice is to include in the regression as many dummy variables as there are cross-sections, less one.

A Stress Test Walk-Through: A Simple MSA Example

Typically, two regression models are recommended for each portfolio. One model is to predict the default rate. This may be defined simply as the loan dollars defaulted at the MSA level divided by the total outstanding dollars in that area at a particular point in time. This model, however, will not account for the condition in which the obligor draws on credit lines during difficult economic times. Therefore, a second model is needed to predict usage. For this model, usage is defined as the average outstanding balances for the MSA or cross-section at a particular point in time. Once these models are estimated, their predicted values can be multiplied together to obtain the dollar impact resulting from the stress test.

As an example, let's perform a simple stress test reflecting the impact of a substantial increase in the unemployment rate.

Step 1: Collect and aggregate historical data (two years or more) into MSAs or cross-sections. This includes internal loan accounting data and such external data as economic or credit bureau information. Be sure to add any dummy variables you created or variables with time lags.

Step 2: Define the dependent variable in each regression—(a) average default rate (b) average outstanding balances.

Step 3: Look at the correlations between each explanatory variable and the dependent variable. Explanatory variables with the higher correlations are good candidates for the regression. Check the sign of the correlation. If the correlation is negative, then there is an inverse relationship between the default rate and your explanatory variable. Does it make sense? Graph the trends associated with each variable over time.

Step 4: Pick the variables to include in the regression. Make sure the variables you put in make business sense. Be wary of using a stepwise selection feature as you may have done in your PD model. The correlations between the explanatory variables can be complex and may interfere with some automatic routines designed to reduce the number of variables in the regression. Instead, use the t-tests produced by the software to give some guidance as to which variables should remain in the model. Generally, a t-value greater than 2 (in absolute terms) is an indication that the variable has some importance. Reestimate the model with different variables and time lags until you get a model with valid t-values and coefficients with signs that make sense. If you are trying to predict the default percentage and get a negative LTV coefficient, does it make sense that MSAs with higher LTVs have a lower percentage default than MSAs with lower LTVs—all other things remaining equal? If not, go back to the drawing board. Try to get a statistic called the adjusted R-square as high as possible—all other things remaining equal. In general, the higher this value, the better the model.

Step 5: Look at the elasticities produced by the model—one for each variable. These are sensitivity measures produced by most software packages. A variable with a high elasticity (greater than 1 in absolute value) implies that small changes to that variable will result in larger changes to your dependent variable. These are the nuts and bolts of your stress test. They reflect a standardized unit of measure for the correlation structure in your model.

Step 6: Produce your stress tests:

a) Default rate model. Let's say the model produces an elasticity of +.42 for the unemployment rate. An elasticity of +.42 implies that a 1% increase in the unemployment rate will lead to a .42% increase in the default rate—all other things remaining equal. So if we look at an unemployment rate shock (stress test) of, say, 25%, then the default rate would be expected to increase by 10.5% (25 × .42).

b) Average balance model. Let's say this model produces an elasticity of +.22 for the unemployment rate variable.

Figure 2

Hypothetical Example of a Stress Test

A	B	C	D	E	F	G
		Stress	Stress	MSA #1	MSA #1	MSA #2
	Elasticity	Test %	Variable	Current	Stressed	Difference
Default Rate	0.42%	25%	Unemployment Rate	0.47%	0.52%	0.05%
Average Balance	0.22%	25%	Unemployment Rate	$235.00	$247.93	$12.93
# Accounts	-	-	-	10,000	10,000	N/A
Predicted Default Dollars	-	-	-	$11,045.00	$12,875.98	1,830.98
% Increase						
In Default $$Default						**16.58%**

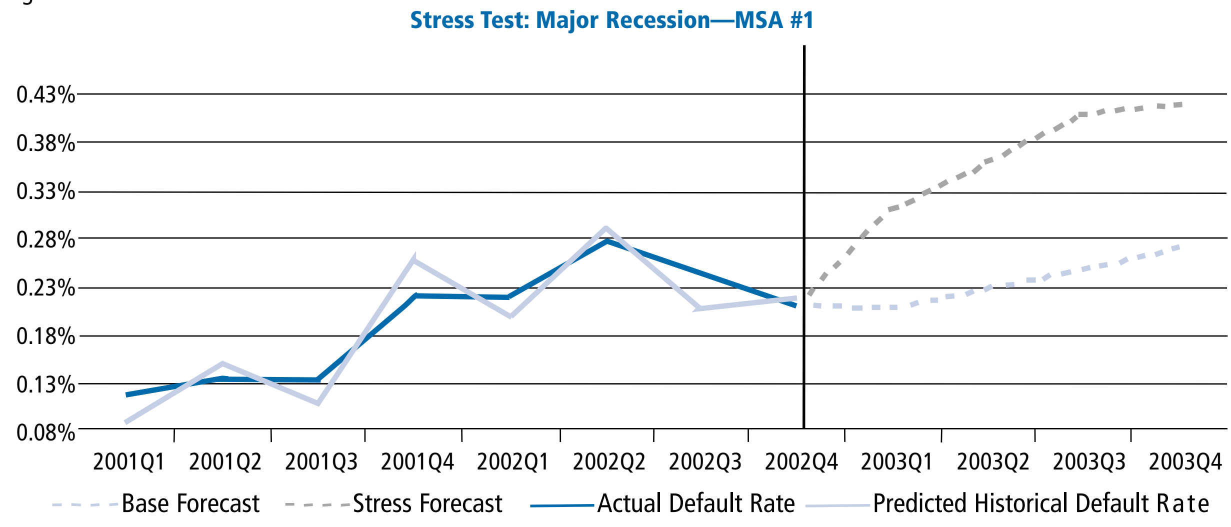
An elasticity of +.22% implies that a 1% increase in the unemployment rate will lead to a .22 percent increase in average balances—all other things remaining equal. So if we stress test the unemployment rate at 25%, then the average balance will increase by 5.5% (25 × .22).

c) Calculate percent increase in default dollars. For a particular MSA, assume there are currently 10,000 accounts with an average default rate of .47% and an average balance of $235, as shown in column E of Figure 2. The new stressed default rate is calculated to be .52% (.47 × 1.105) while the new stressed average balance is found to be $247.93 ($235 × 1.055) as shown in column F. The predicted default dollars are simply the default rate × average balance × number of accounts. By subtracting the difference between columns F and E, you get a stress test result of $1,830.98. This is 16.58% ($1,830.98 / $11,045) over what you would have seen if there had been no shock at all.

Step 7 (optional): Develop detailed stress test forecasts. The method presented in Step 6 is good to produce ballpark stress-test results. Unfortunately, these methods do not easily address the timing of the stressed event or the performance of stress tests across a combination of variables at the same time. To handle the timing and complexity of more advanced stress tests, the estimated model can be placed in an Excel spreadsheet along with any historical and forecasted data to provide a more detailed analysis. This kind of approach makes for a useful planning tool where multiple scenarios can be made quickly, based on forecasted assumptions of the explanatory variables. If you are working with an economic data provider that gives you a worst-case scenario for the economy, you already have some of your assumptions done. The remainder of the variables in your models that may have come from your loan accounting system must also be forecasted or trended over the forecast horizon.

Figure 3 shows an example of this approach, where the historical and forecasted data for the explanatory variables are applied against the regression equation. For each model, two forecasts are run. The first is the base-case forecast, in which a business-as-usual trend of the explanatory variables is made and then applied to the regression equation. Next, a stress-test forecast is done, in which new values for the explanatory variables associated with the stress test are applied to the regression equation. This could include a more complex recessionary scenario comprised of a 35% increase in the unemployment rate, a 15% decrease in income per capita, and even a 12% rise in the prime rate. Figure 3 shows a graphical illustration of such a default-rate scenario for a particular MSA. Once applied to each MSA or cross-section, the difference between the base-case forecast and the stress-test forecast can be calculated and rolled up to

Figure 3



determine the overall stress effect on the entire portfolio. The what-if capabilities of the spreadsheet can be extended to adjust the stress-test forecast for policy measures that might be taken to mitigate the impact of the recession. Assuming that a major recession is on the way, the bank could begin to simultaneously stress test loan accounting system variables in the model that could offset the expected economic shock to the default rate. For example, if the "average FICO score" is a variable in the default rate model, assumptions could be made to reflect more conservative cut-off score policies. If the "percentage of accounts 60+ days late" is also in the model, assumptions could be adjusted to reflect a more aggressive treatment of delinquent accounts. In the average balance model, assumptions could be modified to reflect the lowering of credit limits in high-risk areas to minimize exposures.

Summary

The New Basel Capital Accord requires banks to keep information on each loan from the moment it is booked for the purpose of building and validating risk-rating models. Fortunately, this data can be aggregated and supplemented in such a way as to meet another Basel requirement—stress testing. The idea behind stress testing is to ensure the bank has the necessary capital in reserve to cover unexpected events. The procedure presented in this article introduces a type of regression model that can not only be used for stress testing purposes, but also can serve as a strategic planning tool to quantify policy changes which hopefully would mitigate recessionary or other pressures on the portfolio.❒

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