

Economic capital is the capital sufficient to absorb loss with a certain level of confidence. Thus, it is the common denominator of all risks and often is referred to as the “currency” of enterprise risk management. This three-part series explores current issues associated with economic capital and loss reserving. Part 2 will discuss how to attribute economic capital back to the business lines, and Part 3 will look at how institutions can get started in specifying inputs to their economic capital models.

Part 1:

Taking Account of the Economic Cycle in ALLL

Banks are under increasing pressure from the accounting profession and securities regulators to make loan-loss reserving more transparent and objective. Accounting accurately for the effect of the economic cycle will be an important part of any improvements.

by Shahram Elghanayan

History shows that the ups and downs of the economic cycle are a powerful driver of risk and loss in bank credit portfolios. In turn, bank reserves and charge-offs—the mechanisms through which banks make expected and realized credit losses transparent to investors and regulators—are cyclical to a significant degree. This is apparent in Figure 1, which tracks industry Allowance for Loan and Lease Losses (ALLL) and charge-off rates over the last quarter century, through the marked economic downturns of the early 1990s and the millennial stock market boom and bust. During this time peri-

od, as each economic cycle worsened—evidenced by higher charge-offs—banks tended to reserve more, and vice versa.

BancWare ERisk’s research suggests that a typical regional bank’s ALLL might fluctuate by some 25-30% purely from cyclical business conditions, once we set aside other factors, such as changes caused by growth in the portfolio or underwriting policy. The strength of the cyclical effect is partly a function of accounting and regulatory rules, which say that a bank’s ALLL should reflect management’s judgment of the current credit quality of the loan portfolio after taking into account relevant external factors, such as the business environment.

Historically, however, the rules also have allowed considerable latitude for management judgment in setting ALLL. This has led to a suspicion among investors that banks sometimes use their ALLL as a way of smoothing bank earnings, rather than as a disciplined way of reflecting changes in the credit quality of their portfolios.

What Kind of Model?

The degree of latitude carries a challenge for banks: Can they establish an objective relationship between the behavior of macroeconomic variables today and that of future bank charge-offs? If so, banks can use macroeconomic modeling to improve and support management judgments about an appro-

Figure 1

ALLL Adjusted for Business Cycles Through Management Judgment

National ALLL and Net Charge-offs as Percent of Loans (FDIC data)

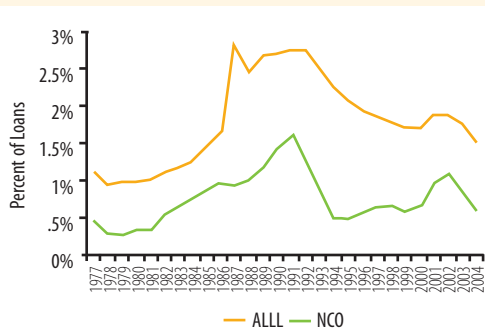
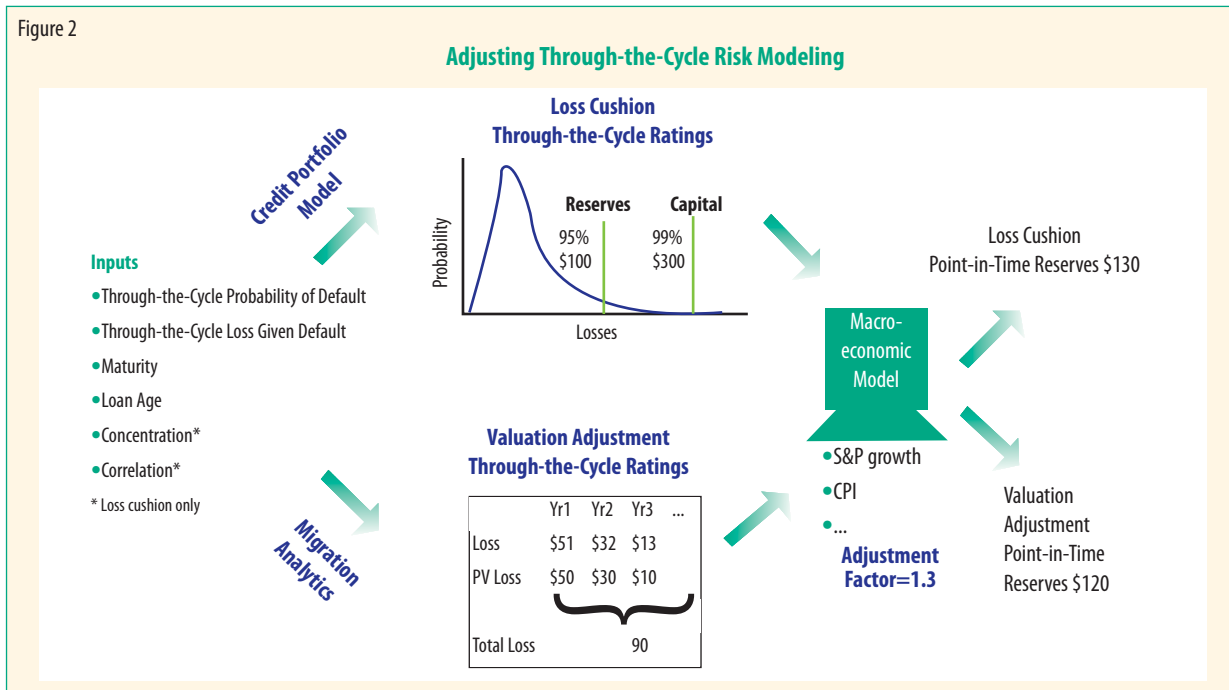


Figure 2



appropriate size for their ALLL at particular points in the economic cycle. Specifically, they can adjust their through-the-cycle estimates of loss, which are used for various risk-based applications, to point-in-time estimates of loss, a requirement for ALLL numbers. (See Figure 2 and the sidebar for an example.)

To appropriately develop a macroeconomic forecasting tool, two fundamentals must be in place:

1. Banks must understand that the loss behavior of credit portfolios driven by the ups and downs of a regional economy often cannot be modeled using superregional (e.g., national) macroeconomic data. Banks often are tempted to apply national data because it is easier to build or buy sophisticated models of national macroeconomic variables. But it doesn't matter how accurate these models are at a superregional level if

they introduce fundamental inaccuracies to loss forecasting in regional bank portfolios. We can see why this is important in Figure 3, which shows how out of kilter some regional and superregional economies can become. In this case, we can see that the regional bankruptcy rate is

much more volatile than the superregional rate, and that on occasion the rates move in quite different directions. Banks also should base their modeling on their own historical charge-off data, wherever enough of this data is available (substituting regional charge-off data as necessary).

Figure 3

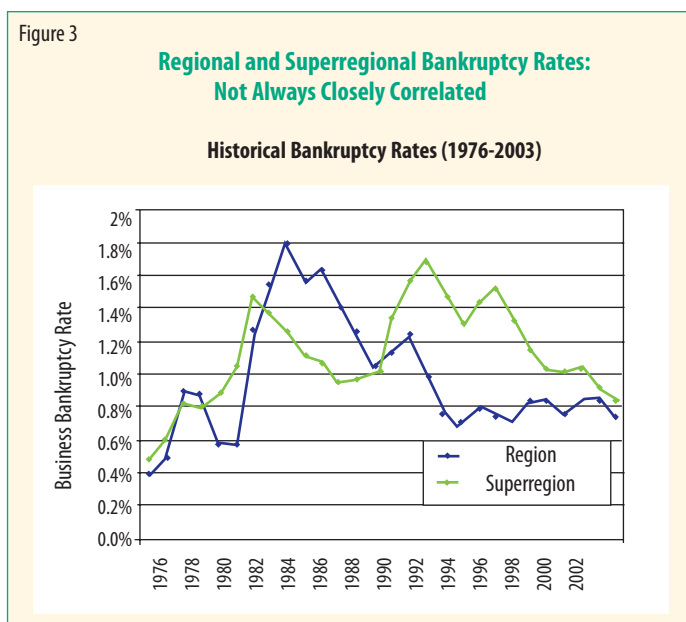
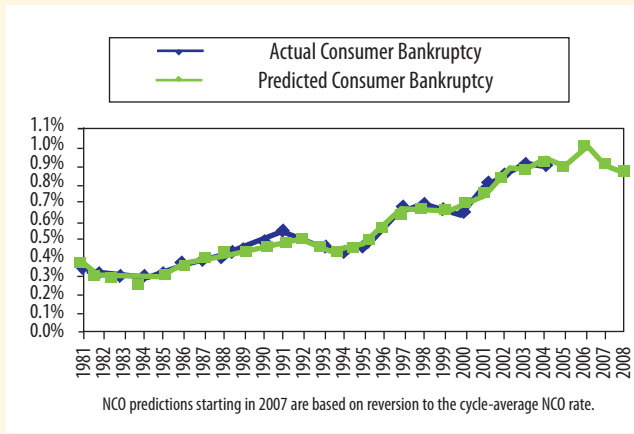


Figure 4

Consumer Macroeconomic Model

Prediction into the Future



2. The other fundamental involves the degree of segmentation. Banks must create separate macroeconomic models for disparate portfolios, such as commercial and industrial (C&I), commercial real estate, consumer, and mortgage. It's a mistake, for example, to imagine that the charge-off rate in a consumer portfolio will have the same relationship to macroeconom-

ic variables as the charge-off rate in a mortgage portfolio.

The consumer portfolio example. While macroeconomic models need to be customized, they should not be excessively complicated. The point is to make each model as simple as possible while maximizing its predictive power. In BancWare ERisk's experience, the net charge-offs in most credit portfolios can be forecast using something between

five and 10 carefully selected macroeconomic variables. For example, in the case of consumer portfolios, plausible macroeconomic variables might include 10 or so items, such as:

- Ratio of household debt service to income.
- Unemployment rate.
- Consumer bankruptcy rate.
- Consumer price index.
- Retail sales.

Statistical techniques, such as multivariable or logistical regression analysis, can be applied to each of these variables to discover which has the strongest relationship to changes in the historical charge-off rate of the relevant portfolio. Once the correct input variables and their weights within the model are established, the macroeconomic model can be used to predict future charge-off rates.

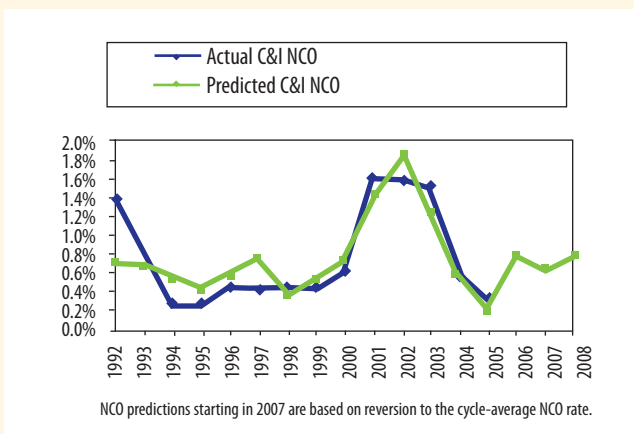
In Figure 4, we can see how one such consumer portfolio model (green line) performed over time in predicting a bank's actual net charge-off rate (blue line). The actual and predicted (modeled) charge-off rates in the graphs are based on a case study, and we can see that the relationship between the rates is very close. In this case, the model has been used to predict loss rates as far out as 2008.

Figure 4 also demonstrates one of the complications of modeling consumer portfolios. While consumer charge-off rates do exhibit cyclicity, there is an underlying upward trend that blurs the ups and downs of each cycle. Historically, this trend has been driven by such fundamental factors as changes in bankruptcy regulations and increased access to credit across a widening spectrum of consumers.

Figure 5

C&I Macroeconomic Model

Prediction into the Future



Banks need to account for this trend in their modeling approach in order to appropriately isolate the cyclical ups and downs of consumer losses.

Commercial and real-estate-linked loans. We can see a much clearer cycle emerging in Figure 5, which shows the realized charge-off rate for one bank's C&I portfolio, compared to the C&I charge-off rate predicted through macroeconomic modeling.

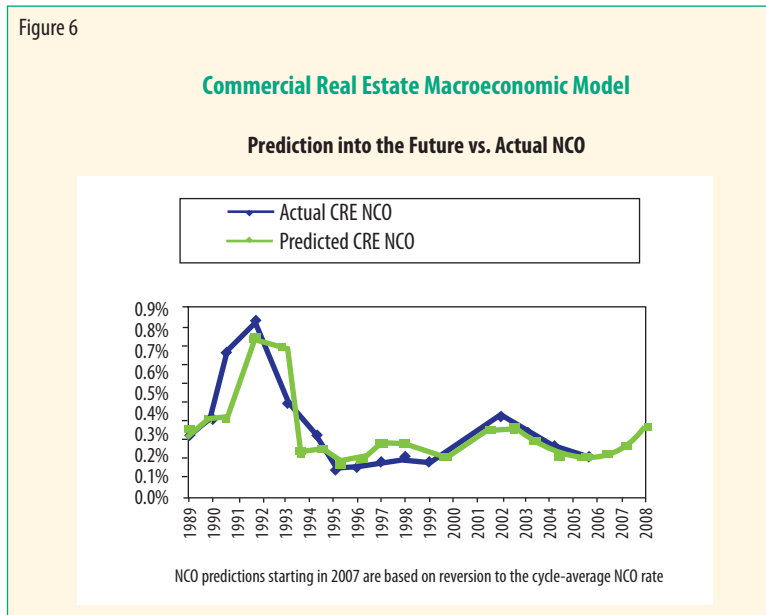
We can see that the C&I model is quite accurate in predicting charge-off rates but that the volatility of charge-off rates in C&I lending leads to a bit of over- or under-reaction whenever there are sharp changes in the rate.

For C&I and other portfolios, the trickiest part of the modeling process is ensuring that, as well as selecting the right macroeconomic variables, the bank:

- Correctly weights the variables within the model.
- Captures any complex relationships between variables in the models (e.g., a deterioration in two variables can sometimes be a particularly powerful predictor of a rise in charge-off rates).
- Captures the complex relationship between a single variable and charge-off rates (e.g., a variable may have a meaningful impact on charge-offs when it deteriorates but not as meaningful an impact when it improves).

The last point can be very important. For example, one of the macroeconomic variables for the commercial real estate model, as displayed in Figure 6, is an index of regional real estate prices. However, analysis showed that

Figure 6



real estate prices gain predictive power for commercial real estate charge-off rates only when prices fall below a given threshold value: The precise way in which this and other variables contribute to model outcomes must therefore be handled with care.

Although the macroeconomic forecasting of C&I and commercial real estate portfolio loss rates is tricky, it is important that banks come to grips with it. The size of C&I and commercial real estate portfolios at most regional banks, combined with their loss rate volatility, means they are critical contributors to cycle-induced credit losses.

Banks also need to build a set of models for different time horizons, e.g., over one and two years. This is so that different adjustments can be made to expected losses in future years on loans and other commitments with more than a one-year life span (e.g., the macroeconomic adjustment of the charge-off rate for the first year of a two-year loan will be different from that for the second year).

Testing and Implementing

Banks that adopt macroeconomic forecasting of loss rates need to do so in a robust manner. The first challenge is to backtest the predictive power of the model. For example, banks can gauge how well the model captures the relationship between macroeconomic variables and charge-off rates by applying the model to macroeconomic data from a similar region and seeing how well the model predicts that region's charge-off rates. Alternatively, the bank can run the model using "out of sample" data for particular years—data that was set aside and not used to build the original model—to test whether the model accurately predicts the bank's record of charge-offs for those years.

The second challenge is to look closely at the relationship between the bank's charge-off history and its ALLL. Charge-offs are much more volatile than ALLL, so the results of any approach that begins by modeling charge-offs must be "dampened" to make sure the bank ends up

with an adjustment that is relevant to its ALLL number.

Finally, once a model is in place, most banks will want to produce “shadow” ALLL numbers for a few quarters so that they can compare numbers from the new and old ALLL calculation processes and gain comfort that any differences are in line with the intuition of senior management.

Improved ALLL and Risk Management

As we’ve seen, macroeconomic variables can help adjust ALLL and make it more accurate for any one point in the economic cycle. This is an urgent problem in U.S. banking. Institutions with a poor

record of accuracy in their reserving, and those that cannot explain clearly why their ALLL is trending up or down, will increasingly pay a penalty in oversight costs and a depressed share price.

However, macroeconomic modeling serves many other purposes as well. For example, once a robust link has been forged between macroeconomic variables and expected loss rates, the bank can develop early warning systems that will alert management to expected changes in loss and risk levels—and ALLL volatility—into the future. Also, once the relationship between particular macroeconomic variables and loss

rates is clear, senior managers can stress-test their portfolios for exposure to dramatic, unexpected shifts in each macroeconomic risk factor. For example, the bank might want to explore how its consumer portfolios would respond to a doubling of the regional debt-to-income ratio.

Banks that invest now in macroeconomic modeling to improve their ALLL will find that they can apply their new understanding to all sorts of strategic, capital, and risk management decisions in the future. □

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How to Adjust Through-the-Cycle Risk Modeling to Improve ALLL Calculations

This article has discussed in broad terms how banks can use macroeconomic modeling to improve and support management judgments about an appropriate size for their ALLL at particular points in the economic cycle. Here is an example of how banks can use the output of the macroeconomic model to adjust their through-the-cycle estimates of reserves to produce point-in-time reserve estimates.

Credit risk inputs can help calculate a more objective ALLL through one of two methods: Loss Cushion and Valuation Adjustment. Inputs for both methods are through-the-cycle estimates of key risk factors comprising probability of default (PD), loss given default (LGD), maturity, and loan age. The Loss Cushion method also accounts for concentration and correlation effects because it employs a credit portfolio model that can incorporate these risk drivers.

In the *Loss Cushion* method, ALLL serves as a “first absorber” against losses. To calculate ALLL, a bank must use a credit portfolio model to create a loss distribution for a one-year time horizon. ALLL is then determined in a way that is similar to economic capital but uses a less stringent solvency standard. For example, if economic capital were based on a 99th percentile or higher solvency standard, ALLL calculations might be based on the 95th percentile. The solvency standard selected should reflect the bank’s degree of conservatism in setting its ALLL; for example, holding ALLL based on the 95th percentile would protect the bank against losses that might be expected once every 20 years. (Because the Loss Cushion method incorporates the tail events in the loss distribution, it tends to produce a relatively conservative measure of ALLL.)

The *Valuation Adjustment* method uses loss migration analytics to determine losses inherent in the portfolio on a hold-to-maturity basis. The calculation of the bank’s inherent losses in future years is based on the current portfolio’s through-the-cycle PD and LGD as well as portfolio migration patterns, loan maturity, and loan age characteristics. The net present value of inherent losses in future years is calculated for each loan and summed to reveal the bank’s expected losses on a hold-to-maturity basis for the current portfolio.

Since both methods use through-the-cycle estimates of PD and LGD, the resulting ALLL number is a through-the-cycle measure and needs to be adjusted for the current point in time. This is where the discussion in the preceding article begins: *Banks can use a macroeconomic model to understand where they are in the cycle and to predict loss rates in future years based on current macroeconomic variables.* The result allows the bank to come up with a measure of loss rates in future years as a ratio (or multiple) of the cycle-average loss rate. This factor is then applied to the through-the-cycle ALLL to come up with a point-in-time ALLL. As shown in Figure 2, a macroeconomic factor of 1.3—which indicates that we are in a 30% worse part of the economic cycle than average—would be applied to the bank’s through-the-cycle reserve estimates of \$100 (loss cushion) and \$90 (valuation adjustment) to arrive at point-in-time reserve estimates of \$130 and \$120, respectively.