BHG FINANCIAL

RMSG | RISK MANAGEMENT SOLUTIONS GROUP

Simple Excel Strategies for Community Banks to Show CECL Reserves Are 'Reasonable and Supportable'

Prepared by Thomas Doran, Ph.D., Dallas Munkus, and Dan Richard

Overview and Problem Statement

Microsoft Excel has become one of the most essential and widely used computer programs in the world, averaging as many as 1.2 billion monthly users worldwide. In fact, financial institutions, particularly commercial banks, have been using Excel to perform complex data analysis at scale for decades. This includes CECL exercises required through the FASB ASC Subtopic 326-20. A common discussion point related to CECL exercises involves the terms "Reasonable" and "Supportable." These are two parts of forward-looking information that management is required to consider in ACL.

On the following pages, BHG Financial and RMSG experts specializing in credit risk, CECL, and portfolio management models break down simple Excel strategies community banks can use to evaluate portfolios against the macroeconomic environment, create estimates of charge off rates, use basic regression capabilities and scatter plots, and project future losses with macroeconomic variables.

Loss estimates have several decision points. Just a few include:

Should data be segmented according to product type, vintage, geography, or another variable?

Are loan-level or portfolio-level estimates appropriate?

To which macroeconomic factor(s) do loan losses correlate?

How much weight should be given to the most recent quarters versus the worst quarters?

Acronyms Defined

ACL: Allowance for Credit Losses
ASC: Accounting Standards Codification
CECL: Current Expected Credit Loss
FASB: Financial Accounting Standards Board
RMSG: Risk Management Solutions Group

FASB ASC Topic 326 applies to all banks, savings associations, credit unions, and financial institution holding companies (collectively, institutions), regardless of size, that file regulatory reports for which the reporting requirements conform to U.S. generally accepted accounting principles. fdic.gov/regulations/laws/rules/5000-5500.html

What is reasonable for one product type may not be supportable for another. For example, segmentation based on product may work well for one bank but be entirely inappropriate for another bank of similar size and product offerings. Clear, concise, prescribed directions on how to show that ACL reserves are reasonable and supportable are difficult to come by, if offered from anyone. So, how can banks support reasonable estimates?

The clearest manner to support any estimate is with robust exercises and models showing a well-thought-out application of statistical and economic theory to extensive data. The largest banks have decades of data spanning several products, geographic footprints, and industries. This complexity and scale are overkill for many community banks, but they are still held accountable to support assumptions are reasonable.

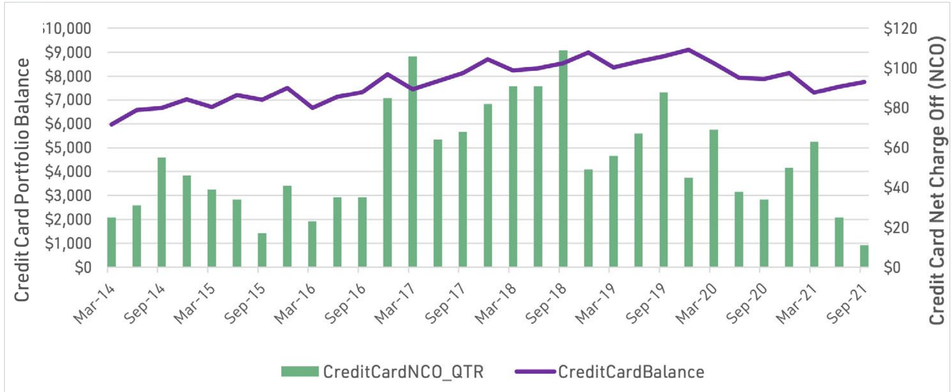
One part of CECL forecasting exercises often includes evaluating a portfolio against the macroeconomic environment. Macroeconomic variables can be used to project future losses under varying scenarios.

Large banks have data and tools to identify underlying relationships between their portfolios and the macroeconomic environment. So, what can you do if you have limited data and resources? Where do you start?

Data Introduction and Basic Charge Off Measures

In the examples below, BHG Financial and RMSG leverage data from the Federal Financial Institutions Examination Council Central Data Repository's Public Data Distribution. This includes the credit card loss data from 2014Q1 to 2021Q3 (31 quarters) from a single, sample entity (Example_Bank) that grew from $819 million to $1.2 billion in assets in that time frame.

Figure 1: Growth of Example_Bank Credit Card Portfolio and Net Charge Off ($1,000s)



Sources: The Federal Financial Institutions Examination Council Central Data Repository's Public Data Distribution, BHG Financial research.

We will step through analytic techniques and methods to cope with abnormalities along the way to estimate the relationship between Example_Bank's credit card portfolio and the macroeconomic environment. Excel comparisons are made to credit card charge off rates from banks with $1 billion to $10 billion in assets (Large_Peers) and banks with $250 million to $1 billion in assets (Small_Peers). Data for Small_Peers and Large_Peers are available for a much longer time frame: 2004Q1 to 2022Q1.

Figure 1 provides the change of Example_Bank's credit card portfolio over time. Three concerns clearly come from Figure 1 that many community banks may share for some or all of their segments:

1) Example_Bank's limited data will make a robust correlation to the macroeconomic environment difficult because it does not have many observations.

2) Example_Bank's history does not include a full cycle. Ideally, the history would include the Great Recession from the 2008-2010 era to capture the effects of downturn and growth conditions.

3) Roughly a quarter of Example_Bank's credit card history includes the COVID-19 pandemic, whose effects are still playing out and not clearly understood.

The concerns can be reasonably addressed with data techniques to support a correlation to the macroeconomic environment. Simple descriptive statistics and graphics of the data can help guide analysis. Figure 2 and Figure 3 provide comparisons of the three subjects' charge off rates. Figure 2 shows that the mean and median charge off rates for Example_Bank are lower than those of the two peer groups by over 250 basis points (BPS).

Figure 2: Comparison Descriptive Data of Charge Off Rates (2014Q1 – 2021Q3)

	Minimum	P25	Mean	Median	Std Dev	P75	Maximum
Large_Peers	3.16%	3.75%	5.66%	5.55%	1.82%	7.35%	8.34%
Small_Peers	2.59%	4.43%	5.42%	5.72%	1.27%	6.30%	7.93%
Example_Bank	0.57%	1.91%	2.79%	2.54%	1.26%	3.53%	5.69%

Sources: The Federal Financial Institutions Examination Council Central Data Repository's Public Data Distribution, BHG Financial research.

Visual Comparisons and Correlations

A little further investigation with use of a simple Excel graph over time helps identify conditions to further understand the consistency of difference between the charge off rates of each group. Figure 3 shows the comparison using trend lines to help visualize consistency between the three comparison group members. All three clearly move directionally together, which is expected. Large_Peers and Small_Peers change position over the horizon in June 2017, but Example_Bank maintains a consistently lower charge off rate than both of them. This indicates the lower mean and median values shown in Figure 2 should be expected to hold over time and are reasonable to consider consistent.

Figure 3 gives clear, visual support that the three group members have a correlation. A quick Pearson correlation analysis in Excel shows Example_Bank is 42% correlated with Large_Peers and 51% correlated with Small_Peers, based on the 31 available observations. The correlations may not be strong, but they certainly are not weak. Using Large_Peers and Small_Peers as proxies for Example_Bank's relation to the macroeconomic environment is reasonable since a full credit cycle of data are available for Large_Peers and Small_Peers.

Macroeconomic Benchmarking Analysis

Unemployment is always a good starting variable when evaluating the effects of the greater macroeconomic environment on loss expectations. Theory clearly confirms an expectation for default and loss to increase as the unemployment rate increases. Figure 4 shows the relationship of the national unemployment rate and charge off rates for Large_Peers and Small_Peers over a 15-year horizon (60 quarters), including a full credit cycle with the Great Recession and recovery periods.

Figure 3: Charge Off Rate Comparison over Time

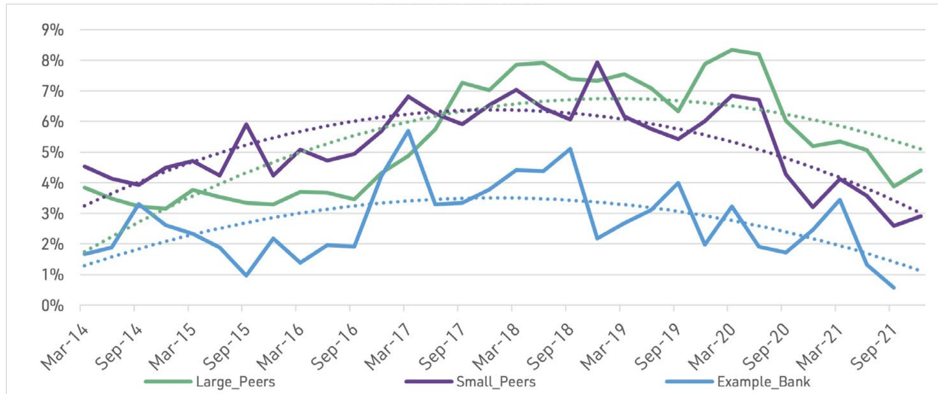
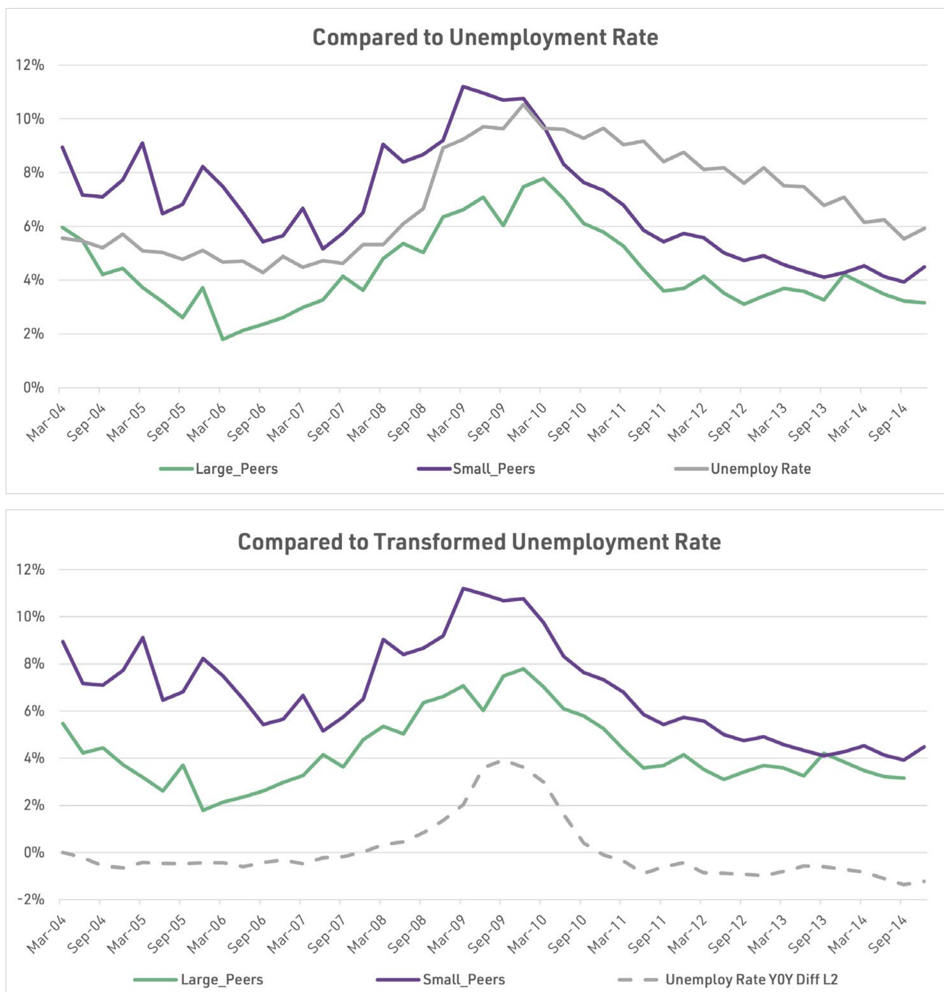


Figure 4: Charge Off Rate Compared to Unemployment Rate and Transformed Unemployment Rate



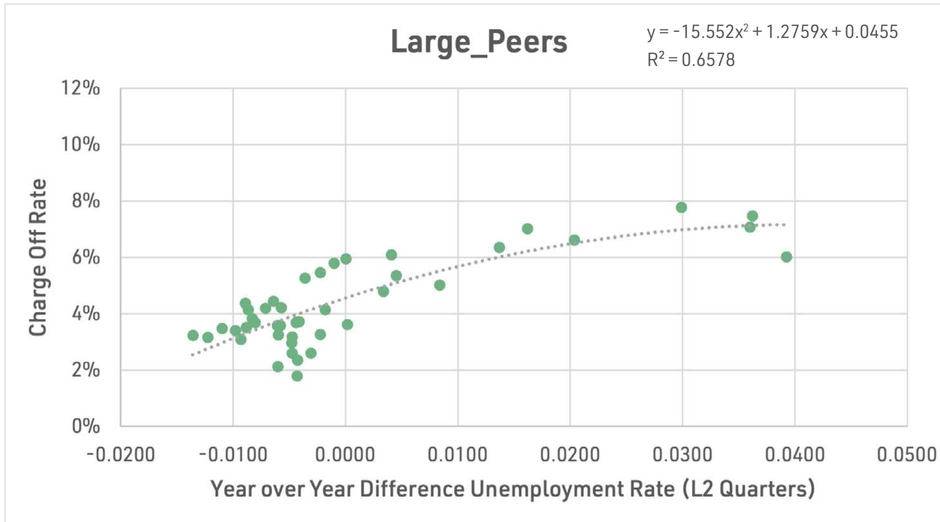
Sources: The Federal Financial Institutions Examination Council Central Data Repository's Public Data Distribution, fred.stlouisfed.org, BHG Financial research.

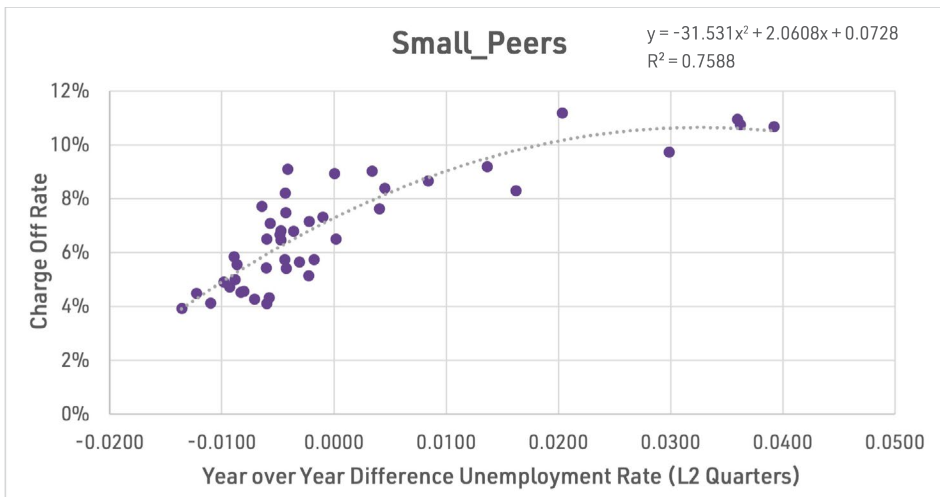
The raw unemployment rate in the top panel shows a general trend with charge off. However, the better relationship is often captured with a variable transformation, such as quarter-over-quarter difference. In this case, the year-over-year difference lagged two quarters (YoY Diff L2, in other words, the September 2008 observation of unemployment is the difference in Unemployment Rate from March 2008 to March 2007, the annual difference from two quarters prior) visually captures the relationship of charge off for both Large_Peers and Small_Peers, shown in the lower panel.

Excel includes basic regression capabilities with use of scatter plots. Figure 5 provides ordinary least squares (OLS) regression coefficients using the Scatterplot Trendline function in Excel. The regression functions are based on the data shown in Figure 4 and can be used to predict the charge off rate in the remaining period after 2014Q1 where Example_Bank results are available.

The estimates use a second-order polynomial as part of the regression. When applicable, this helps identify points at which charge off rates should be expected to change more rapidly, or inflection points. Using Small_Peers as an example, the charge off rate would not be expected to change much moving from an unemployment increase of 3.5% to an increase of 2.5% (a decrease in the increase) in this case. A larger rate of change should be expected in the 1% decrease to 2% increase range. The models are still both ordinary least square (OLS) linear models that could go beyond the 0-100% boundary. This can be accommodated with the use of caps and floors in the estimates.

Figure 5: Regression of Unemployment and Charge Off Rates: Large_Peers versus Small_Peers





Sources: The Federal Financial Institutions Examination Council Central Data Repository's Public Data Distribution, fred.stlouisfed.org, BHG Financial research.

Backtesting and Forecasting

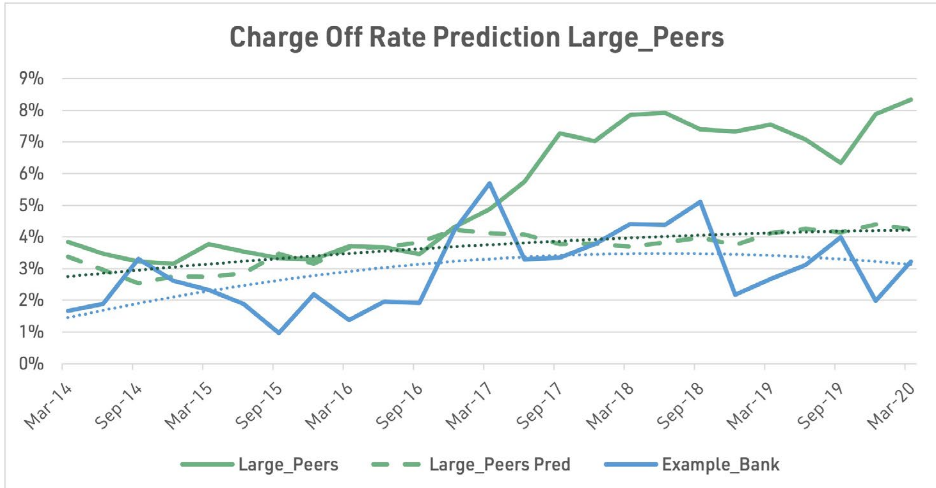
Plugging in the transformed unemployment rates from the bottom of Figure 4 to the formulas in Figure 5 creates estimates of charge off rates for Large_Peers and Small_Peers but can also be used to predict loss rates for Example_Bank.

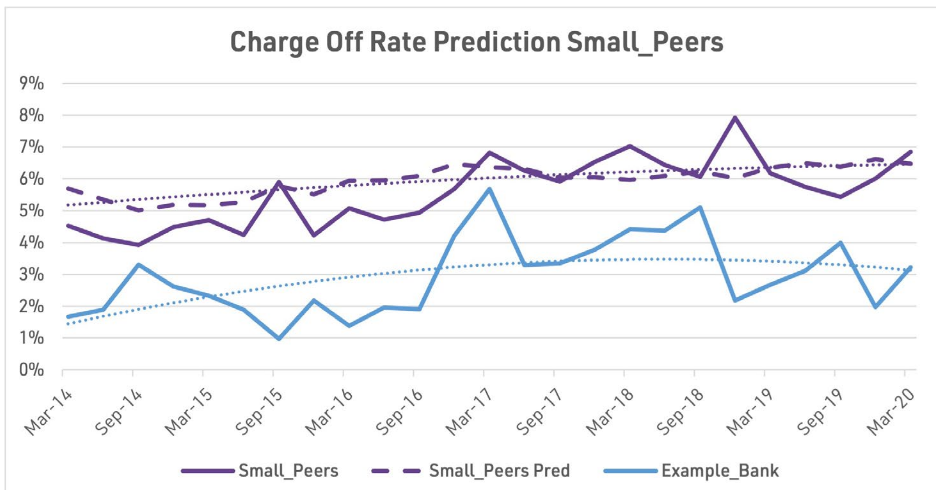
Figure 6 serves as a backtest by comparing the predicted Large_Peers and Small_Peers charge offs to the actual charge offs for Large_Peers, Small_Peers, and Example_Bank from 2014Q1 up to the COVID-19 pandemic.

Note, both estimates tend to overestimate the Example_Bank actual charge offs. The Large_Peers regression function fits well for Example_Bank, while the Small_Peers regression function consistently tends to overestimate Example_Bank by roughly 200 to 300 BPS. This establishes a reasonable range for expectations and management adjustments.

Figure 7 clarifies the reasonable range for estimates using the estimates from Figure 6 in a single graph. Trend line (dotted lines) comparisons of the predicted values to the Example_Bank actual values clearly support that the use of the Small_Peers as a forecast is reasonable, with a potential downward adjustment of roughly 200 BPS. The range can be used to understand and support conservative estimates from baseline (Large_Peers) estimates.

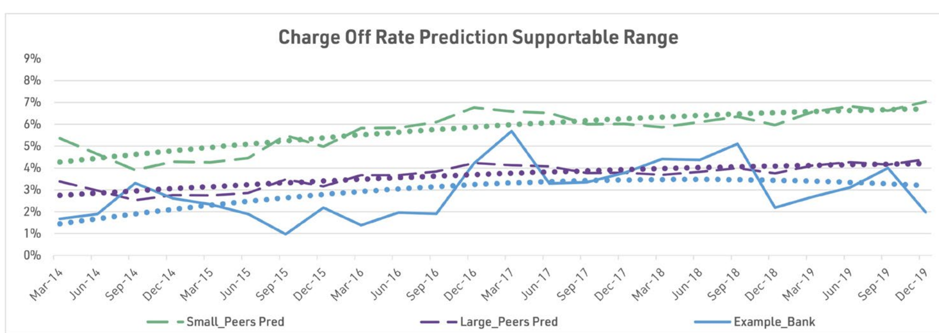
Figure 6: Charge Off Rate Predictions: Large_Peers versus Small_Peers





Sources: The Federal Financial Institutions Examination Council Central Data Repository's Public Data Distribution, fred.stlouisfed.org, BHG Financial research.

Figure 7: Charge Off Rate Prediction Supportable Range



Sources: The Federal Financial Institutions Examination Council Central Data Repository's Public Data Distribution, fred.stlouisfed.org, BHG Financial research.

Summary and Takeaways

The exercise above makes use of best practices when resources are limited:

Establish a peer group for comparison.

A peer group gives guidance. The peer group in this case is based on the product, credit cards. It also gives opportunity to establish proxies to compensate for data limitations. Other peer groups could be based on geography, industry, or other appropriate consideration.

Segmentation adds robustness, to a point.

Structuring data to allow for granular comparison gives opportunity for insight. In this case, the peer group is broken out according to size. The segmented analysis helps create a more accurate estimate than had one peer group been used. Over segmentation can reduce the robustness of quantitative estimates depending on the limitation of the data.

Simple statistics and graphics can help initiate and confirm expectations.

Review of mean, median, and other statistics can establish initial comparisons for further investigation. The graphics used here help show consistency of the differences.

Simple statistics and graphics are more universally understood to support reasoning. More sophisticated quantitative analysis is helpful for detail but can often be interpreted incorrectly if not presented in proper context. Graphics can support both simple and more sophisticated quantitative analysis.

Excel is a viable resource for less complex portfolios to provide simple and more sophisticated analysis for those with an understanding of the data and how to manipulate it.

Accept that actual loss experience from one period to the next will vary around your estimate. The key is for the difference to be within a justifiable range.

This exercise clearly establishes a quantitative range for loss expectation. The COVID-19 pandemic created conditions where expectations based on past results may or may not hold. Inclusion of the Great Recession in the analysis data as a proxy for COVID-19 helps establish a range of expectations under unprecedented circumstances. Management's role in the forecast is to consider current conditions and adjust expectations accordingly. For example, the number of loans included in the Paycheck Protection Program should be a consideration for making an adjustment.

Unemployment is used in this scenario. Household debt, consumer expenditures, interest rates, and other macroeconomic factors could be used to further develop a reasonable charge off rate range for consideration of the current inflation condition.

Another best practice is preparing a document for a regulatory audience to communicate fulfillment of the reasonable and supportable requirements. This document could include graphics as demonstrated above, the thought process that went into creating them, the reasoning behind the results, and the conclusions you reached that influenced or justified your CECL reserve.

About RMSG Analytic Consulting

Risk Management Solutions Group (RMSG) is a subsidiary of BHG Financial, the source of the most innovative financial solutions available on the market today and the creator of the largest community bank network in the country. RMSG partners with financial institutions to help them meet their regulatory and compliance needs and offers services to help strengthen their internal processes to control risk. Our team has decades of experience with extensive knowledge of the model development, model validation, and loss reserve landscapes.

RMSG's team includes data scientists experienced in building and defending models at lenders and national credit bureaus, Ph.D. economists versed in CECL and model validation for household names, and former regulators for the CFPB, OCC, and FDIC. This combination provides a unique, holistic ecosystem to help community banks validate and test their CECL models.

For more information, email analytics@riskmsg.com.

About the Authors

Thomas Doran, Ph.D.

Tom is responsible for the Model Risk Management program at BHG Financial encompassing model validation and model governance. His expertise includes credit risk, DFAST, CCAR, CECL, and portfolio management models.

Prior to joining BHG, Tom spent 10 years at Truist Financial where he developed many of the model development and model validation standards. While there, he built and reviewed many of the wholesale, retail, and consumer models used for regulatory submission and business management.

Tom earned his Ph.D. in Economics from Auburn University, his MBA from the University of Detroit, and his Bachelor's Degree in Business Administration from Hope College.

Dallas Munkus

Dallas leads the Analytic Consulting function at RMSG and is responsible for business development and delivering impactful client engagements. He brings more than 20 years of analytics and consulting experience, including custom and off-the-shelf credit scores, credit and alternative data, decision optimization, loss forecasting, customer retention, collections, staff forecasting and incentives, reporting, data management, and process engineering.

Dallas earned his Master's Degree in Applied Statistics and Bachelor's Degree in Computer Science from Kennesaw State University.

Dan Richard

Dan leads the BHG Financial Predictive Analytics program where he is responsible for statistical models that power decision-making in loan originations and portfolio management. Dan has more than 15 years of experience working in model research, development, validation, analytic consulting, and thought leadership for credit risk, credit marketing, and fraud. Prior to joining BHG, Dan held positions with TransUnion, Equifax, FactorTrust, and Scoring Solutions.

Dan earned his Master's Degree in Statistics and Bachelor's Degree in Industrial Engineering from Georgia Tech.

RMSG | RISK MANAGEMENT SOLUTIONS GROUP

RMSG is a wholly owned subsidiary of BHG Financial.
To learn more about RMSG visit www.riskmsg.com