# A BALANCED APPROACH TO FORECASTING CREDIT RISK

By Jeffrey S. Morrison

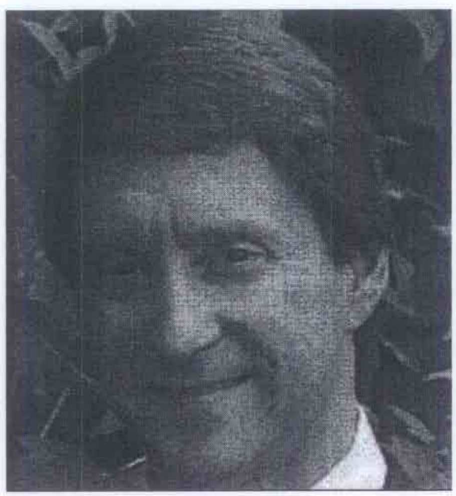
*In a recessarionay environment, management is under more pressure than ever to determine stress test loss reserves and risk forecasts under a variety of conditions ... a model with generic credit variables provides better information about charge-offs ... because of the changing market dynamics, it is dangerous to rely too much on in-house credit information.*

Understanding credit behavior at the aggregate portfolio level is becoming increasingly important, as financial institutions have extended a substantial amount of consumer credit under the assumption of strong economic growth. Now the economy is looming at the brink of recession, and management is under pressure to stress test loss reserves and to determine risk forecasts under a variety of conditions. For example, what would happen to charge-offs if income and employment were to decrease in the Southeast over the next six months? Would the knowledge of general credit trends in a recessionary environment yield greater insight into the future or is traditional economic data alone good enough? The purpose of this article is to examine the necessity of using both economic and credit information in modeling a single firm's charge-off rates for forecasting, as well as for estimating reasonable and legitimate elasticities. Now more than ever, a proper modeling approach to forecasting is needed to best understand potential losses and to prepare contingency plans. This article is a follow-up to an earlier article in the Journal of Business Forecasting entitled: *How to Stress Test your Credit Portfolio.* In that article, we recommended the development of a geo-based recessionary planning system to forecast a company's geographic charge-off rate and credit usage (average balances) through the use of a technique called Pooled Cross-Sectional Time-Series Regression. Such a planning system would require two types of data: (1). Internal factors and (2) External factors.

## THE REQUIREMENTS

First, a set of master files of "internal factors " at some level of geography is needed to reflect policies or directives under the control of management. Examples might include the average credit score in an area, the average account age, the percent of revolving accounts (accounts having a line of credit with a term loan), and delinquency measures. Since a credit score is the key risk management tool, we would expect this variable's influence on charge-offs (loans that are written off) to be high and relatively elastic. Depending on marketing and credit strategies, we might expect newer accounts to be relatively riskier, implying that as the percentage of new accounts increases, so does the level of charge-offs. Typically, revolving accounts are riskier than their installment counterparts – implying a positive relationship with charge-offs. Finally, although not all charge-off accounts go through the traditional 30/60/90/120 day delinquency cycle, the percentage of accounts that are in some way delinquent should be positively linked to the level of charge-offs.

The second requirement for a geo-based planning system is using externally based economic and credit trends. Trends like income and employment as well as industry wide movements of delinquencies such as credit usage and debt burden are outside a single company's control. In periods of economic prosperity, other things remaining equal, we would expect increases in income and employment to increase the consumer's ability to repay credit card debt and therefore drive corporate charge-off rates down. Likewise, in a recessionary environment, we would expect decreases in income and employment to exert an upward pressure on delinquencies and charge-offs as local area jobs are eliminated and equity markets



## JEFFREY S. MORRISON

**Mr. Morrison is currently Vice-President of Modeling at SunTrust Bank. He has over 20 years of analytic experience in telecommunications, natural gas distribution and consumer credit. He has spoken at numerous conferences in the areas of quantitative analysis, econometric forecasting, and new product planning. He has widely published.**

and other investment opportunities erode.

## ECONOMIC CYCLE AND CREDIT MARKETS

All things have not remained the same over the last ten years. Graph 2 shows the relationship between risk and the national unemployment rate. During the 1990-91 recession, the charge-off and delinquency rate increased with the unemployment rate. As the economy moved out of the recession, both rates began to drop, as one would expect. People could find jobs easier, investments opportunities improved, and the consumer was able to improve their payment status through the end of 1994. However, in 1995 (Graph 1) the market began to change. Given the continued improvement in the economy and the new lower charge-off rates, banks began to expand the availability of credit. More accounts were opened, pre-approved credit card offers grew, and financial institutions were willing to take advantage of a growing economy – even if it meant targeting accounts within the sub-prime market. As a result, both delinquency and charge-offs began to rise even though the economy's health continued to grow. (See Graph 2). However, these sub-prime accounts could impose a higher level of risk during a recession if the institution targeted customers who might not have the necessary funds to draw from if unemployment levels rose.

However, by mid-1997, financial institutions begun to aggressively combat the growing problem of risk emerging from the new lending policies under a healthy economy. Lenders focused on tightening score cutoffs, reducing credit limits where necessary, and scrutinizing new account acquisitions. As a result, delinquencies began to level off and charge-off rates decreased. Then came seemingly recessionary movements in the economic environment. By mid-1999, the decline in the unemployment rate (Graph 2) began to taper off as signs of a possible economic slowdown emerged. Equity markets began losing their momentum. As the year 2000 ensued, the credit market followed as charge-off rates edged upward to 2.5 %.

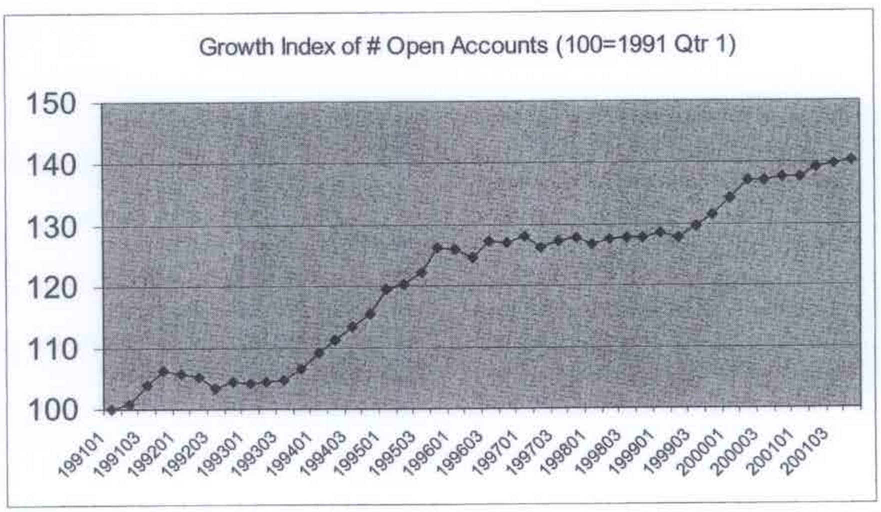
**TABLE 1**
**MEAN ABSOLUTE PERCENT ERROR (MAPE) OF MODELS WITH AND WITHOUT GENERIC CREDIT VARIABLES**
**(One-Year Ahead Forecasts)**

| One Year Ahead Credit variables | MAPE With Ex-Post Period (Full Model) | MAPE With No Credit Variables | Percent Difference |
|---|---|---|---|
| Qtr 1 | 12.90 | 14.46 | **12%** |
| Qtr 2 | 13.30 | 15.32 | **15%** |
| Qtr 3 | 17.00 | 20.85 | **23%** |
| Qtr 4 | 29.40 | 43.00 | **46%** |
| **Overall** | **18.15** | **23.41** | **29%** |
| # Ex-post Forecasts | 924.00 | 924.00 | |

## CHALLENGES FOR COMPANY SPECIFIC FORECASTS

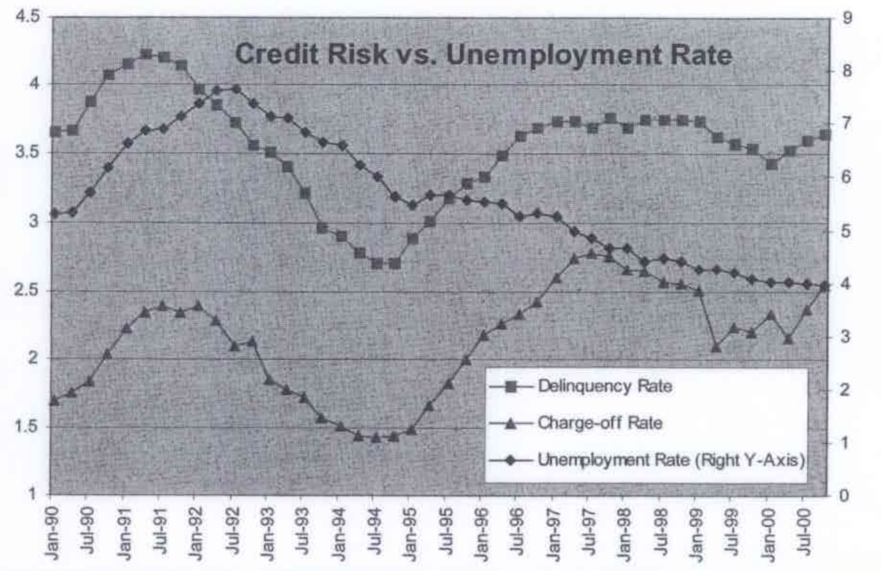
Individual companies wishing to statistically forecast credit losses tailored to their own management's strategy and portfolio of accounts faced some important challenges. As we have seen, the relationship between credit and the economy should be observed over a time period long enough to realize true market dynamics. Because most companies tend not to keep data for ten years, attempts at modeling a single firm's portfolio with their own data end up using a relatively short time horizon – maybe three years or less. Under this scenario, one could inadvertently estimate a model that produces erroneous results. For example, if during that historical timeframe both the unemployment and charge-off rates moved opposite to one another, then the model might show a negative relationship between the two – something we know is rather counter intuitive. That result, referred to as a specification bias in the statistical literature, is a problem related to the omission of important information, yielding an oversimplification of the more complex interactions within the market. Finally, using data only from a single firm

**GRAPH 1**
**U.S. GROWTH OF OPEN ACCOUNTS:**
**1991 QUARTER 1 – 2001 QUARTER 4**



to predict future credit trends makes analysis exceptionally vulnerable to company specific anomalies such as the impact of mergers, acquisitions, and new or young products.

**GRAPH 2**
**U.S. CHARGE-OFF RATE AND THE ECONOMY**




## A CASE STUDY

Even if a model happens to estimate a correct relationship (sign) between the unemployment and charge-off rates, the model's robustness regarding forecasting accuracy can be less than desirable. The following is an example of a Pooled Cross-Section Time Series customized model developed to forecast charge-off rates by MSA for a large financial institution. Some of the variables from the full (balanced) model were:

1. Average Credit Score (Internal)
2. Company Specific Delinquency Rate (Internal)
3. Company Specific Average Age of the Accounts (Internal)
4. Generic 60-120 Day Delinquency Rate (External Credit) [+]
5. Generic Bank Card Utilization (External Credit) [+]
6. Income per Employed Person (External Economic) [-]
7. Employment per Adult Population (External Economic) [-]

(Note: The signs of first three variables depend primarily on the marketing and competitive strategies the company follows. The signs of the last four variables are likely to be what are shown above at the end of each variable.)

The bracket to the right of each variable represents the sign of the coefficient estimated by the model. These relationships were derived using quarterly data over three years across 231 MSAs by a Generalized Least Squares (GLS) statistical procedure called Heteroscedastic & Time-Wise Autocorrelation Regression. Most of the explanatory variables were lagged either one or two quarters. As expected, the two generic credit variables were found to have positive signs, indicating that as overall credit conditions worsen across the U.S., the firm's own charge-off rate eventually increase. On the other hand, the MSA level economic variables – income per employment and employment per adult were found to be inversely related to the company's charge-off rate. In other words, as income and employment go down, the corporation eventually experiences increased charge-offs – something you would expect if the economy were to go into a recession.

In order to observe the value of including generic credit trend data in a model, we developed a series of ex-post forecasts. First, we dropped the credit variables from the original model and re-estimated the equation, holding out the last year of data. Then 924 ex-post forecasts were developed (231 MSAs × 4 quarters) and compared with actual historical data. As expected, both models showed some over-predictions and some under-predictions. Next, we calculated the Mean Absolute Percent Error (MAPE) – perhaps the favored measure of forecast accuracy in the literature. The same ex-post procedure was developed for the full (balanced) model, which included the generic credit variables. The results show that the forecast accuracy decreased with a model with "no generic credit variable." The percent difference between the two was seen to increase with the length of the forecast horizon. For a 1 year out forecast, the difference in accuracy was almost 50%.

In addition to the reduced accuracy related to the point forecasts, dropping the credit variables in the model resulted in changes in the elasticities of economic variables up to 40%. This finding in itself is a reason for concern if the model is going to be used for contingency planning where estimates of elasticities play an important role.

## SUMMARY

Forecasting company specific charge-off rates is a difficult process because of practical limitations on data retention and the complex dynamics associated with the credit market. Furthermore, relying too heavily on internal data to estimate future credit trends could prove problematic, given the large amount of portfolio acquisitions, mergers, and consolidations experienced by many companies over the last five years. Under the circumstances, the best way to deal with this problem is to incorporate generic credit variables in a model. The data on generic credit variables are available from the three major credit bureaus. ■