Applications of a Spatial Analysis System to ERM Losses Management

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Presented at the:
2013 Enterprise Risk Management Symposium
April 22-24, 2013

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Abstract

This paper provides a description of a system using statistical spatial methods for measuring, analysis, and managing ERM losses. An example of its application to a delinquency rate in a residential mortgage portfolio analysis demonstrates how this methodology can help decrease a company's exposure in high-risk areas and increase exposure in low-risk areas.

1. Introduction

The Casualty Actuarial Society (2003) classified enterprise risk management (ERM) risks in the following four groups: (1) hazard risks (liability tort, property damage, and natural catastrophe), (2) financial risks (pricing risk, asset risk, currency risk, liquidity risk), (3) operational risk (customer satisfaction, product failure, integrity, reputational risk), and (4) strategic risks (competition, social trend, capital availability).

A spatial analysis methodology suggested in this paper addresses the key responsibilities any ERM analyst faces: (a) evaluating the risks, (b) developing a distributional analysis that allows comparing the risk measures from different locations to each other and/or to some portfolio benchmark, and (c) suggesting a set of preventive policies that can be applied to locations having risk measures that significantly deviate from the benchmark.

One of the conventional ways to measure any risk is a prevalence rate, which is the amount of losses related to the risk accidents over the total amount in a relevant portfolio. An alternative option of calculating loss rates is to use the ratio of a number of risk events to the total number of events in a portfolio. For example, an operational loss rate associated with fraudulent transactions can be estimated as a ratio of fraudulent transaction losses (or alternatively, a number of fraudulent transactions) over the portfolio overall transaction volume (or total number of portfolio transactions).

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2. Methodology

A spatial analysis system is based on building funnel plots at several meaningful levels. A risk-level funnel plot originates from the normal approximation for a sampling distribution of a ratio (Anderson et al. 2005). A single funnel plot is a chart combining observed sample rates in areas with a line connecting confidence intervals for the population rates, which are estimated for all possible sample sizes at the same confidence level. The funnel plots have proven to be an effective and statistically valid tool for comparing the rates in small samples and often used in epidemiology for monitoring outbreaks of the contagious diseases (Dover 2010).

In the banking industry the funnel plots can be applied to the borrowers' default rates (i.e., 30-, 60-, and 90-day delinquency rates) in consumer credit portfolios and aimed at detection of areas with either significantly high or low deviation of the observed delinquency rates from the expected delinquency rate given a portfolio size. In practice, a risk analyst faces two issues: (1) comparing the default rates from the areas with different portfolio sizes (also called loan volumes) and (2) monitoring concentration of defaults in the neighboring areas.

The application of the funnel plots is straightforward in consumer credit portfolios, since these portfolios are quite homogeneous. These portfolios usually consist of standardized loan products sold to many borrowers that are relatively identical in their wealth. In contrast, application of the method to commercial portfolios comes with strong reservations. Commercial portfolios are more heterogeneous and more concentrated, since they often consist of the loans that are customized and sold to businesses of different size, specialization, and areas of operation.

2.1. Algorithm for Application of the Methodology

The suggested approach consists of six key elements and is designed to aggregate and effectively present information on loss rates:

1. Analyzing an overall portfolio area and dividing it into smaller geographic units with relatively homogeneous portfolios of sufficient size. Following a statistical rule of thumb, it is recommended to have at least 30 objects (e.g., borrowers or transactions) in the unit portfolio.

2. Constructing four funnel plots at 80 and 90 percent confidence levels by estimating the approximate confidence intervals (Anderson et al. 2005) for the benchmark loss rate $(\hat{p})$ for all observed sample sizes (n_i):

$$\hat{p} = \frac{1}{K}\sum_{i=1}^{K}\frac{D_i}{n_i}$$

$$I_{[0;1]}\left(\hat{p} \pm Z_{(1-\alpha/2)}\sqrt{\frac{\hat{p}(1-\hat{p})}{n}}\right) \quad (1.1)$$

$$n \in [\min(n_i), \max(n_i)]$$

where

$\hat{p}$ is a benchmark loss rate, which is usually an overall portfolio loss rate estimated by an average rate in all areas of interest. However, a target value that is the same for all geographic units could be an alternative option for the benchmark loss rate.

D_i is the number of loss events in all areas of interest i, i = 1, …, K.

$Z_{(1-\alpha/2)}$ is a value of the cumulative normal distribution that corresponds to $(1 \quad \alpha/2)\%$ probability. In 80 and 90 percent confidence intervals α equals 20 and 10 percent, correspondingly.

$I_{[0;1]}$ is an indicator function that limits the approximate confidence interval boundaries within a meaningful range.

3. Develop the funnel the plots by exhibiting all loss rates and their confidence intervals on the *y* axis and all potential unit sizes (n_i) on the *x* axis. A reference line is drawn on this chart to show an overall portfolio loss rate. The funnel plots will outline the boundaries of five risk groups: (1) an extremely high-risk group containing geographic units with their default rates above the 95 percent funnel plot zone, (2) a moderately high-risk group with the units having the default rates in the 90–95 percent zone, (3) a normal risk group containing the geographic units with default rates in the 10–90 percent zone, (4) a moderately low-risk group combining the units having their default rates in the 5–10 percent zone, and (5) an extremely low-risk group with the geographic units' default rates in the 0–5 percent zone.

4. Transferring the classification information onto geographic maps and assigning signal colors corresponding to the units in specific risk groups.

5. Analysis of the loss rates mapping, focused on (1) clustering of the units of the same or close risk groups and (2) consistency of their classification over the last three to five time periods.

6. Suggesting an effective policy for the units' portfolios that has loss rates significantly different from the overall portfolio benchmark.

2.2. Application of Signaling Colors in Mapping Observations and Suggested Policy for Risk Groups

Table 1 suggests the signal colors and policies that can be applied to the units' portfolios that are consistently classified in the risk category for several time periods in a row. The policies are developed for a retail loan portfolio as an example.

Table 1

An Application of Signal Colors and Suggested Policies

Risk Category	Statistic Confidence Interval Boundaries Outlined by the Funnel Plots	Color	Suggested Policy for a Retail Loan Portfolio
Extremely high	95% and higher	Red	Emergency intervention: stop lending in the area, investigation of the situation
Moderately high	90–95%	Pink	Toughening the credit policy: higher credit limits and minimum payment amounts, higher customer risk score requirements
Normal risk	10–90%	Green	No change in credit policy, keep monitoring
Moderately low	5–10%	Light blue	Applying a mild expansion credit policy: lower credit limits, lower payment amounts, lower customer risk score requirements
Extremely low	5% and lower	Blue	Applying an aggressive expansion credit policy: significantly lower credit limits, lower payment amounts, lower customer risk score requirements

3. Application of the Methodology to RML Delinquency Rates

To demonstrate the capabilities of the suggested approach, we have applied a 90-day delinquency rate to a conventional residential mortgage loan (RML) portfolio. For this purpose, the delinquency rate and portfolio sizes are randomly generated for the United States (i= 1,…, 52 entities) with the following assumptions for the distribution of the variables:

90-day delinquency rate$_i$ ~*Beta* (α = 0.98, β = 97.02)

Loan volume$_i$ ~10 × *Negative Binomial* (p = 0.05, k = 2)

The results produced by the approach for one of the simulations are summarized in Figures 1 and 2 and Tables 2 and 3.[1]

[1] This application is developed and realized using SAS statistical software. The corresponding SAS code will be provided by the author on request.

Chart 1. Funnel plot for 90-day delinquency rate in RML portfolio

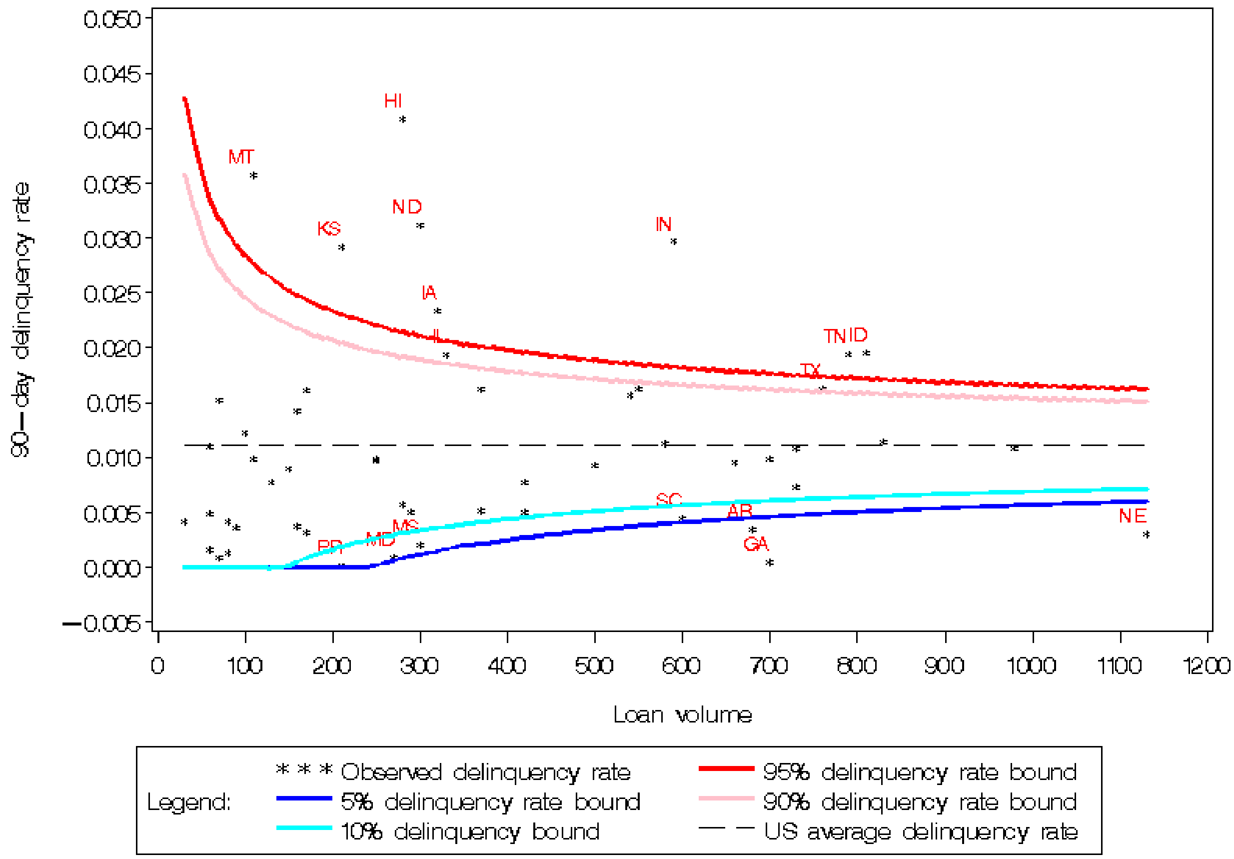


Table 2

Portfolios with High Delinquency Rate

State Name Abbreviation	State Name	Loan Volume	Observed Delinquency Rate	90% Delinquency Rate Bound
ID	Idaho	810	0.01957	0.01586
TN	Tennessee	790	0.01944	0.01592
TX	Texas	760	0.01632	0.01602
IN	Indiana	590	0.02970	0.01668
IL	Illinois	330	0.01934	0.01854
IA	Iowa	320	0.02340	0.01866

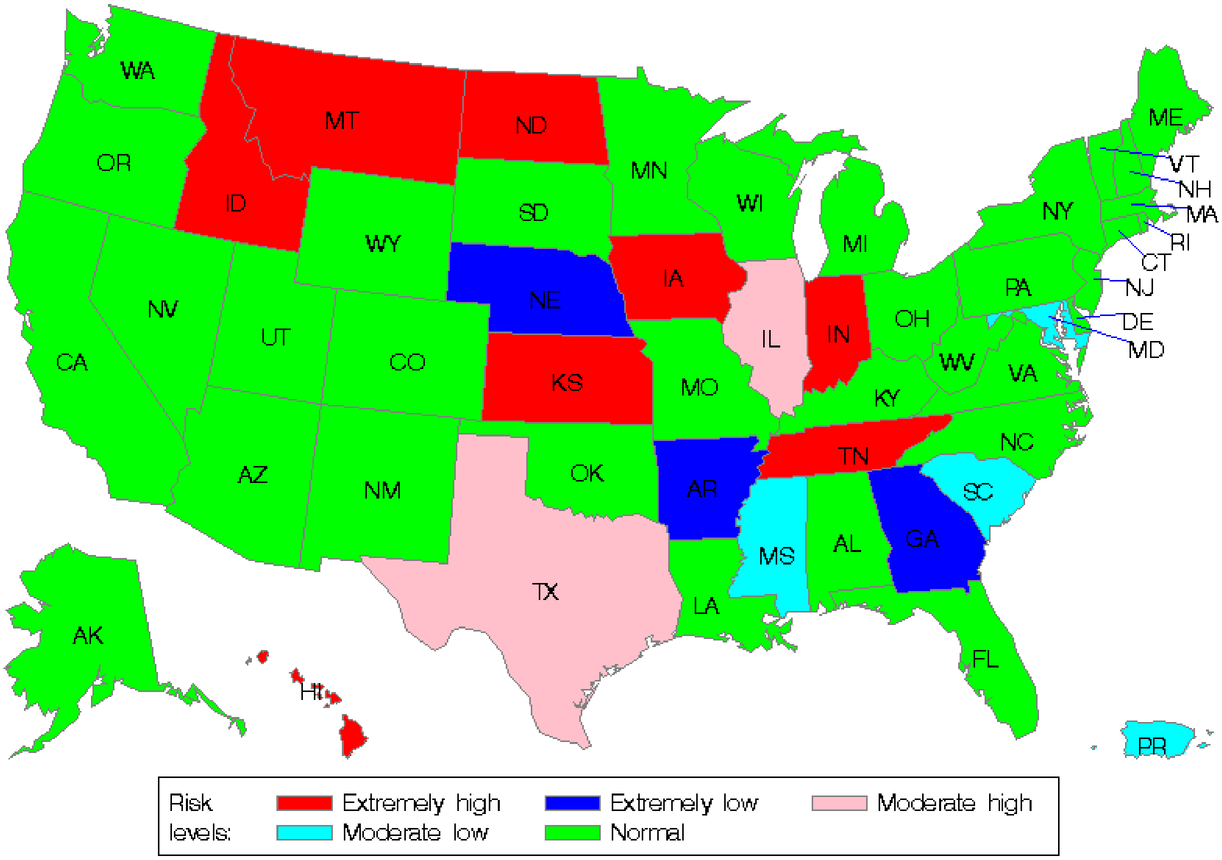
State Name Abbreviation	State Name	Loan Volume	Observed Delinquency Rate	90% Delinquency Rate Bound
ND	North Dakota	300	0.03114	0.01890
HI	Hawaii	280	0.04087	0.01918
KS	Kansas	210	0.02918	0.02042
MT	Montana	110	0.03572	0.02396

Table 3

Portfolios with Low Delinquency Rate

State Name Abbreviation	State Name	Loan Volume	Observed Delinquency Rate	10% Delinquency Bound
NE	Nebraska	1130	0.00303	0.00714
GA	Georgia	700	0.00045	0.00606
AR	Arkansas	680	0.00346	0.00598
SC	South Carolina	600	0.00446	0.00565
MS	Mississippi	300	0.00200	0.00338
MD	Maryland	270	0.00086	0.00296
PR	Puerto Rico	210	0.00014	0.00186

Chart 2. The states classification by 90—day delinquency rate in RML portfolios



Analyzing the portfolio units' loss rates and their development in risk categories over several consecutive periods, an analyst will be able to recommend changes in credit policy to limit the company's credit exposure in high-risk areas and boost the company's exposure in low-risk areas. Thus, application of this spatial methodology in practice should help decrease the company's losses and boost profits.

References

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