Evaluating Credit Risk Models: Methods and Issues

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Overview

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Current practice: value-at-risk models

Key question: model validation / evaluation

II. Credit Risk Modeling

General issues

Supervisory issues

III. Proposed Evaluation Methods

Statistical criteria

Current limitations

I. “Internal Models” Approach to Bank Supervision

Over the last 10 years, financial institutions have significantly increased their use of econometric models to measure and manage their risk exposures

- increased trading activities
- increased emphasis on risk-adjusted returns on capital
- advances in theoretical & empirical finance
- advances in computer power & speed

Given these developments, bank supervisors have also focused their attention on the use of such “internal models” for:

- supervisory reasons: focus on banks’ overall risk management systems

- the possibility of setting capital requirements that more accurately reflect banks’ true risk exposures

Supervisors have taken steps in using the “internal models” approach with the adoption of the Market Risk Amendment to the 1988 Basle Capital Accord

(“Compendium of Documents Produced by the Basle Committee on Banking Supervision” / Volume 2: Advanced supervisory methods / Chapter 2: Capital adequacy; http://www.bis.org/publ/index.htm)

The Market Risk Amendment

Regulatory concerns about market risk provide insight into concerns about credit risk (Hendricks & Hirtle, 1997)

Current regulatory framework (effective Jan. 1998):

- applies to commercial banks whose trading activity accounts for $>10\%$ of total assets or $>$ \$1 billion

- cover all assets in trading account (assets carried at current market value) and all FX & commodity positions wherever located

Qualitative standards for bank risk management:
(www.federalreserve.gov:80/boarddocs/SupManual/trading/trading.pdf)

- independent risk control unit; internal & external audits
- integration of methods/ models into management process
- model review: "stress-testing" and "backtesting"

Quantitative criteria & capital requirements:

- based on value-at-risk estimates from banks' models
- explicitly linked to model performance via "backtesting"

Key issue: model validation / evaluation

II. Credit Risk Modeling

Credit risk modeling dates to the 1960's; see Altman & Saunders review article in *Journal of Banking & Finance*, April 1998.

Only recently have these models gained widespread use in credit risk management, especially for loans and credits. (Creditmetrics; Credit Risk+; KMV; etc.)

However, recent proposals, such as IIF (1998) and ISDA (1998; www.isda.org/crsk0398.pdf), now argue that these models should also be used for risk-based capital requirements for loans.

General Issues in Credit Risk Modeling:

Wide variety of credit risk models, but two general categories:

default models = losses only in the case of default
multi-state models = model ratings migration; losses are incurred with both rating changes and default

Common output:
forecasted probability distribution of credit losses

Notation:

Distribution forecast is based on two components:

- multivariate distribution of losses on individual credits
- weighting vector characterizing credit holdings

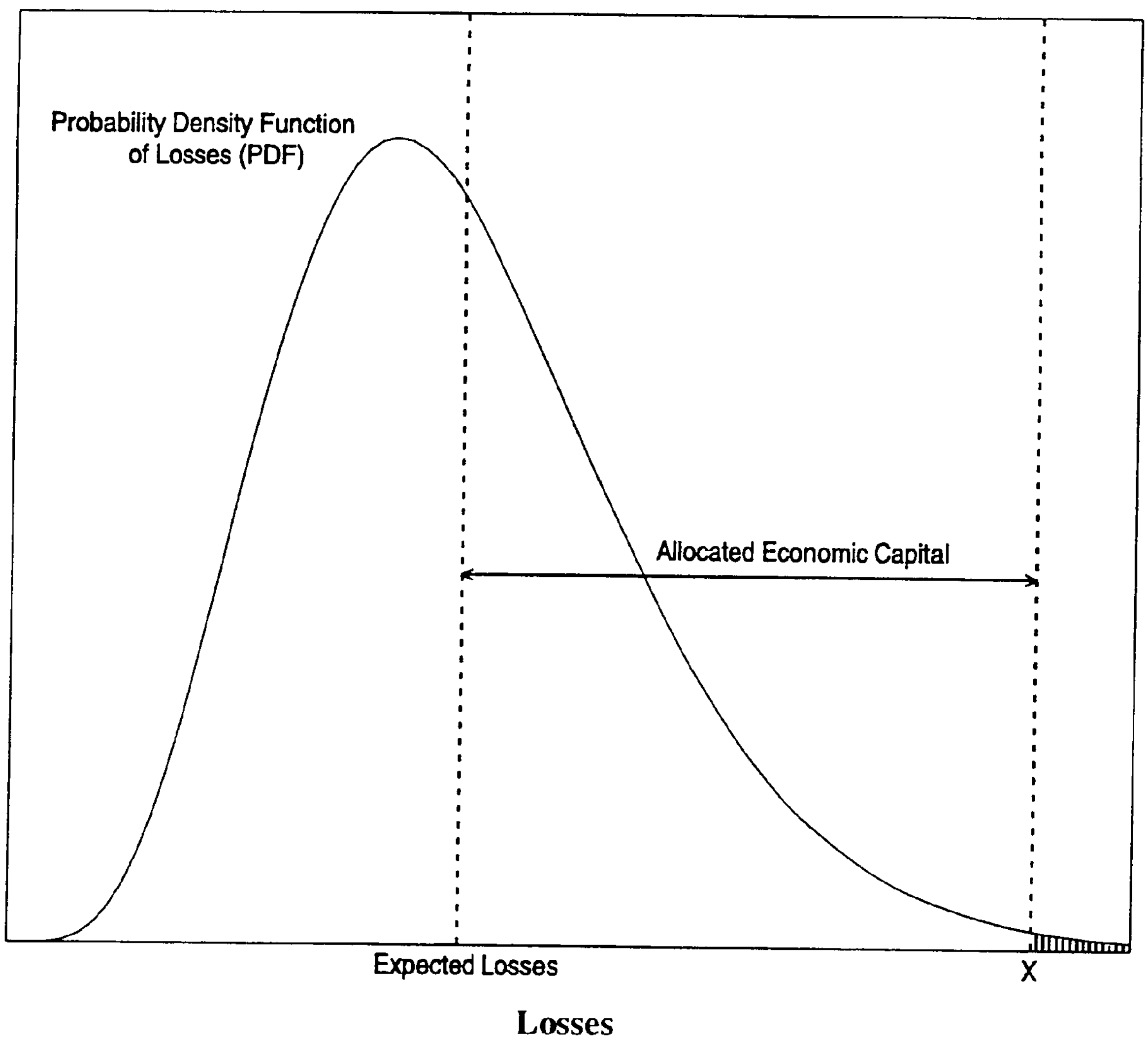
Let N = the number of credits in a bank's portfolio
A_t = an (Nx1) vector of the PDV of credits at time t
P_{bt} = $w_b{}'A_t$ is value of bank b's credit portfolio at time t

Focus on one-period-ahead forecasts; usually one year

Object of interest: $\Delta P_{bt+1} = w_b'\left(A_{t+1} - A_t\right)$

Credit risk model "m" is characterized by $\hat{F}_m\left(\Delta P_{bt+1}\right)$, the forecasted cumulative distribution function of portfolio losses based on the portfolio weights w_b and the distribution function of ΔA_{t+1}

Forecasted probability distribution function of credit portfolio losses based on portfolio weights w_b and distribution function of ΔA_{t+1}



Supervisory Issues & Concerns

(See "Credit Risk Models at Major U.S. Banking Institutions" at:
www.federalreserve.gov:80/boarddocs/press/General/1998/19980529/study.pdf)

Qualitative standards for bank risk management:

- same as before; in addition, issues of input quality:
    - credit data is less standard than financial markets
    - exposures are more difficult to calculate
    - consistent ratings of credits (Treacy & Carey, 1998)

Quantitative criteria:

- minimum capital requirements might be based on the upper $\alpha\%$ tail of the institution's credit portfolio

- issues of model validation procedures:

  choice of evaluation criteria:
  What measures to use for model validation?

  data limitations over time:
  insufficient data for out-of-sample testing;
  especially across business cycles / credit cycles

<u>Our goal</u>: To begin addressing the latter two issues

III. Proposed Evaluation Method

Using a panel data approach, we propose a simulation-based method for evaluating credit risk models that:

(a). addresses the limited amount of data available;
(b). uses criteria familiar from VaR evaluations; and
(c). permits comparison between alternative models

Intuition from time-series analysis (Granger & Huang, 1997):

If a model's out-of-sample forecasts exhibit properties of accurate forecasts, then the model can be said to be properly specified and accurate.

For panel data models, extend to cross-sectional element; if model's out-of-sample predictions exhibit certain properties, then properly specified & accurate.

We propose to create additional cross-sectional observations by creating simulated portfolios from the original set N

For each year of data, create R credit portfolios by resampling with replacement from N; thus, (T*R) observations

Generate, via model m, corresponding $\hat{F}_m\left(\Delta P_{it+1}\right)$ forecasts and evaluate with statistical criteria

Structure of simulated credit portfolio forecasts

$\hat{F}_m\left(\Delta P_{bt+1}\right)$	$\hat{F}_m\left(\Delta P_{bt+2}\right)$	$\hat{F}_m\left(\Delta P_{bt+3}\right)$
$\hat{F}_m\left(\Delta P_{1,t+1}\right)$	$\hat{F}_m\left(\Delta P_{1,t+2}\right)$	$\hat{F}_m\left(\Delta P_{1,t+3}\right)$
$\hat{F}_m\left(\Delta P_{2,t+1}\right)$	……	……
…..		
…..		
…..		
$\hat{F}_m\left(\Delta P_{R,t+1}\right)$	$\hat{F}_m\left(\Delta P_{R,t+2}\right)$	$\hat{F}_m\left(\Delta P_{R,t+3}\right)$

Proposed Statistical Criteria for a Credit Risk Model

(a). Evaluating forecasts of expected loss:

Forecast error $e_{mit+1} = L_{it+1} - \hat{\mu}_m\left(\Delta P_{it+1}\right)$

Test $H_0: \bar{e}_m = 0$ using regression techniques

(b). Evaluating forecasted critical values:

$\hat{CV}_m\left(\alpha, \Delta P_{it+1}\right)$ = upper $\alpha\%$ critical value

Similar to VaR estimates, evaluate using binomial method

Test H_0: $\alpha = \hat{\alpha}$, where $\hat{\alpha}$ = percent of exceptions

(c). Evaluating forecasted distributions:

$$q_{mt+1}\left(L_{it+1}\right) = \hat{F}_m\left(L_{it+1}\right) = \int_{-\infty}^{L_{it+1}} \hat{f}_m(x)\,dx$$

Tests of whether quantiles have specified properties:

Crnkovic & Drachman (1996): Kupier statistic
Diebold *et al.* (1998): CUSUM statistic
Berkowitz (1998): Rosenblatt-transforms

Evaluation Criteria for Multiple Models

For portfolio w_i generated via simulation, generate forecasted loss distributions from two models, denoted $\hat{F}_{1i}$ and $\hat{F}_{2i}$.

(a). Evaluating forecasts of expected loss:

Forecast errors: $\hat{e}_{1i} = L_i - \hat{\mu}_{1i}$; $\hat{e}_{2i} = L_i - \hat{\mu}_{2i}$

(i). Count method: test $H_0\text{: } E\left[e_1^2\right] = E\left[e_2^2\right]$

(ii). Sum/difference regressions

(iii). Analysis under a general cost function g(x)
Diebold & Mariano (1995):
$H_0\text{: } E\left[g\left(e_1\right)\right] = E\left[g\left(e_2\right)\right]$

(b) & (c). Evaluating forecasted critical values & distributions

Multivariate extensions of univariate tests

Bonferroni bounds test with size bounded above by k%; i.e., conduct separate tests of size k/2%

Limitations to Such Evaluations

(a). Analysis based on a limited amount of data over time must be interpreted with care.

Worst case: what if we have just one year of data?

The proposed method makes the most use of the data available, so can still evaluate model accuracy.

Yet, one-year results must be interpreted with care.

As more data becomes available, aggregate results as well as across-year results can be evaluated.

(b). Analysis tied to original set of N assets, while dynamic portfolio management is (or will be) the norm

Although presented here with a static set of assets, the method can be extended to dynamic credit exposure across years.

Conclusions

Credit risk modeling is a promising direction for bank risk
measurement and management (& bank supervision)

However, much work needs to be done to get it to the level of
acceptance enjoyed by value-at-risk modeling

Supervisory concerns for "internal models" approach:
- qualitative standards
- quantitative capital requirements

Key question for model users & supervisors:
how to evaluate the accuracy of a credit model's forecasts?

(Must have confidence in model performance)

Using a panel data approach, we propose a simulation-based
method for evaluating credit risk models that:

(a). addresses the limitations of the available data;
(b). uses criteria familiar from VaR evaluation;
(c). permits comparison between alternative models