Retail Credit Risk Models: What do these models look like and how did they fare in the crisis?

A presentation for the conference on "Modeling Retail Credit Risk After the Sub-Prime Crisis"

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Disclaimer: The views expressed are my own and do not necessarily reflect the views of the Federal Reserve Bank of Philadelphia or the Federal Reserve System.

Overview

- Discuss common, well-accepted modeling techniques
- Detail the typical usage for retail credit risk models within Risk Management
- Highlight retail credit trends in the industry
- Assess the state of industry models

Common Uses of Models in Retail Credit Risk Management

- Loan Loss Reserves (ALLL)
  - Models are used to determine expected loss (EL) over the next 12-months across key risk segments.
  - Models should reflect trends observed in standard risk management reporting.
- Front-end Credit Risk Detection
  - Risk management regularly uses models to test the efficacy of new account management strategies.
  - Models might test whether the “right” population responded to a credit line increase or repricing.

Common Modeling Uses in Retail Credit Risk Management Practices (continued)

- Back-end Risk Performance
  - All account management strategies are evaluated and tracked to measure performance.
  - Scorecards can be constructed to “target” unique populations such as the likelihood that current accounts will file bankruptcy.
- Economic Capital Input
  - In creating marketing budgets for different business lines, credit risk models are needed to determine the average net present value (NPV) for a new account.
  - Basel II key A-IRB risk parameters help facilitate the calculation of RAROC metrics.
- Model Validation
  - Statistical models are primarily used to validate all scorecards in production for marketing, credit risk, collections, and financial optimization purposes.

Retail Credit Modeling Frameworks

- Scorecard Models
- Matrix Models
- Roll Rates
- Markovian Chain
- Vintage Models

Scorecard Models

- Scorecard model development is primarily used for rank-ordering purposes despite the fact that log-odds map to distinct delinquency and default rates.

- Scorecards are used as input into many modeling frameworks (such as in joint-odds), but is not commonly used for loan loss reserve estimation (i.e. not easily manipulated or understood by senior management).

- Scorecard development requires specialized staff and resources (e.g. software, hardware, and data access). Larger institutions usually build them internally while smaller institutions rely more heavily on third party vendors.

- Scores can be built for several purposes (delinquency, default, bankruptcy, attrition, profitability, solicitation response, etc.), but the power of scorecards is the ability to build them at a segment level.

- Scorecard models can capture all factors if properly calibrated (i.e. regional economic data can be appended to account files, indicator variables can proxy account strategies and other exogenous factors) and segmented.

- Macroeconomic information is rarely considered in scorecard modeling.

Scorecard Models (continued)

- Factor-based models are considered causal models of portfolio credit risk. The modeling reference data must be augmented.
- Factor-based models include the realization of both macroeconomic and segment- or borrower-specific factors.
- Factor-based credit risk models are useful for stress-testing and estimating portfolio losses conditional on economic forecast scenarios.

$$\mathrm{p}_j(Z^s) = \frac{1}{1+a_j \exp\left(b_j \sum_k B^s_{lk} Z^s_k\right)}, \text{ Segment-based Logit Model}$$

$$\mathrm{p}_j(Z) = \frac{1}{1+a_j \exp\left(b_j \sum_k B^M_{lk} Z^M_k + B^s_j Z^s_j\right)}, \text{ Factor-based Logit Model}$$

Matrix Models

- Matrix models are static in nature and capture the risk profile of the portfolio across a minimum of two dimensions. Unlike scorecards, matrix models are constructed at the segment or portfolio level.

- By combining both an external (FICO) and internal (behavioral score) scorecards one can identify exogenous factors (both systemic and idiosyncratic) impacting behavior across a particular segment such as delinquency, debt management, and over-limit.

- In particular, each scorecard takes account of *n* risk factors and summarizes credit risk into two dimensions.

- Each cell of the matrix can represent the loss rate for a group of accounts with a particular FICO and behavioral score (e.g. the estimated net loss rate for accounts with a 660 FICO and 900 behavioral score is 5.23%).

- A 12-month forecast is determined by applying the distribution of one-year historical loss rates to the current distribution of outstanding loans.

- The matrix model does not consider attrition, management strategies, and economic factors in the upcoming 12-month forecast horizon.

The joint-odds matrix works well for stable portfolio distributions.

Behavioral Score

FICO	No_score	1-849	850-899	900-924	925-949	950-959	960-969	970-979	980-984	985-989	990-992	993+
No_score	15.98%	24.38%	16.89%	8.45%	7.60%	6.84%	6.16%	5.85%	5.56%	5.28%	5.01%	4.76%
000-590	16.74%	36.57%	21.38%	10.69%	9.62%	8.66%	7.79%	7.40%	7.03%	6.68%	6.35%	6.03%
591-610	11.58%	20.41%	19.12%	9.56%	8.60%	7.74%	6.97%	6.62%	6.29%	5.98%	5.68%	5.39%
611-630	11.01%	16.29%	15.67%	7.84%	7.05%	6.35%	5.71%	5.43%	5.15%	4.90%	4.65%	4.42%
631-650	10.57%	14.20%	14.38%	7.19%	6.47%	5.82%	5.24%	4.98%	4.73%	4.49%	4.27%	4.06%
651-660	8.68%	10.22%	10.45%	**5.23%**	4.70%	4.23%	3.81%	3.62%	3.44%	3.27%	3.10%	2.95%
661-670	8.66%	8.45%	9.83%	4.92%	4.42%	3.98%	3.58%	3.40%	3.23%	3.07%	2.92%	2.77%
671-690	6.59%	7.68%	7.56%	3.78%	3.40%	3.06%	2.76%	2.62%	2.49%	2.36%	2.24%	2.13%
691-710	5.11%	5.22%	5.33%	2.67%	2.40%	2.16%	1.94%	1.85%	1.75%	1.67%	1.58%	1.50%
711-730	4.32%	3.25%	1.60%	0.80%	0.72%	0.65%	0.58%	0.55%	0.53%	0.50%	0.47%	0.45%
731-750	2.13%	0.10%	0.33%	0.16%	0.15%	0.13%	0.12%	0.11%	0.11%	0.10%	0.10%	0.09%
751+	0.59%	0.00%	0.31%	0.16%	0.14%	0.13%	0.11%	0.11%	0.10%	0.10%	0.09%	0.09%

High Risk **Low Risk**

Roll Rate Models

- Measures the percentage of accounts or dollars that "roll" from one stage of delinquency to the next.
- Individual accounts are not tracked, only the volume for a particular bucket.
- The roll rates are averages across risk segments or for the total portfolio.
- The critical roll rate is the 'net charge-off' rate since it gives you the amount of charge-off at the end of the next month (t+1).
- Roll rate models fit the retail credit business model well as call centers and collection departments are commonly aligned by stage of delinquency.
- The roll rate model do not explicitly incorporate attrition, management strategies, and exogenous factors such as the economy.

Roll Rate Model Results

Month	Current ($Bil.)	30-DPD	%	60-DPD	%	90-DPD	%	120-DPD	%	150+ DPD	%	CO	%
Feb-06	$84,273	$1,313	32.36%										
Mar-06	$83,595	$1,182	27.63%	$821	62.49%								
Apr-06	$84,849	$1,149	32.70%	$808	68.36%	$673	82.05%						
May-06	$86,122	$1,175	31.74%	$766	66.67%	$656	81.23%	$592	87.84%				
Jun-06	$87,413	$1,227	32.95%	$776	66.00%	$614	80.14%	$589	89.67%	$533	90.14%		
Jul-06	$88,725	$1,163	30.55%	$791	64.48%	$610	78.61%	$555	90.37%	$526	89.41%	$272	51.01%
Aug-06	$90,056	$1,223	32.38%	$808	69.52%	$622	78.65%	$551	90.39%	$490	88.40%	$266	50.50%
Sep-06	$91,406	$1,265	32.41%	$865	70.71%	$635	78.57%	$559	89.88%	$472	85.64%	$253	51.49%
Oct-06	$92,777	$1,304	32.54%	$848	67.00%	$664	76.84%	$564	88.72%	$480	85.78%	$244	51.60%
Nov-06	$94,169	$1,380	32.44%	$883	69.08%	$656	78.02%	$583	89.66%	$500	86.61%	$253	51.20%
Dec-06	$95,582	$1,422	32.46%	$922	68.93%	$682	77.81%	$589	89.42%	$516	86.01%	$270	51.43%

Note: The 30-DPD roll rate was determined using a 5-DPD roll rate that was omitted for presentation purposes. Figures in red are forecasts and roll rates were determined by using a rolling 3-month average.

Markov Chain Models

- A sequence of random variables is said to form a Markov chain if each time an account is in some initial state *I* and there is a fixed probability that it will next be in another state *J*.

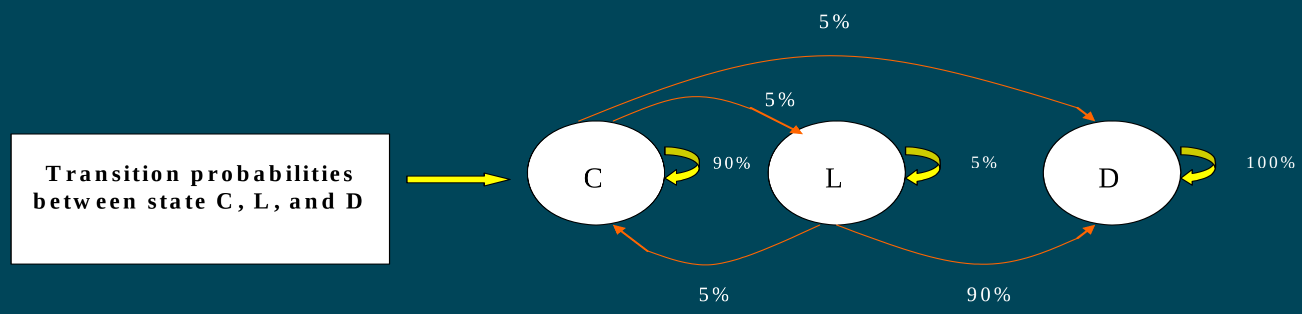
- Markov chain models can account for all probabilities within delinquency stages, not just those that move sequentially from one stage of delinquency to the next.

- Rules must be used to limit the dimensions of the Markov chain. For example, an account can only be current (c), delinquent (L), and default (D).

- Transition probabilities are averaged across risk segments or the total portfolio.

- Markov chain models can account for attrition and some account management strategies, but still ignore economic factors.

Markov Chain Process



The transition probabilities can be characterized by an array and a transition matrix:

		Initial State		
		C	**L**	**D**
Next State	**C**	90%	5%	0%
	L	5%	5%	0%
	D	5%	90%	100%

Transition Matrix

$$P = \begin{pmatrix} 90\% & 5\% & 0\% \\ 5\% & 5\% & 0\% \\ 5\% & 90\% & 100\% \end{pmatrix}$$

Markov Chain Process (continued)

Forecasts for accounts in each state then can be easily computed:

For the t+2 forecast, use t+1 account distribution.

10,000 accounts in C <u>this month (t)</u>.

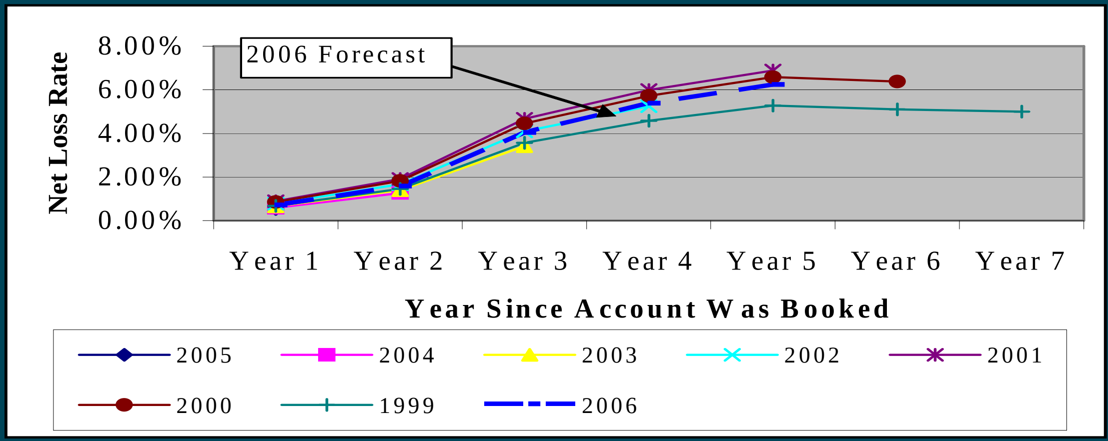
$$\begin{pmatrix} 90\% & 5\% & 0\% \\ 5\% & 5\% & 0\% \\ 5\% & 90\% & 100\% \end{pmatrix} * \begin{pmatrix} 10{,}000 \\ 0 \\ 0 \end{pmatrix} = \begin{pmatrix} 9{,}000 \\ 500 \\ 500 \end{pmatrix} \Rightarrow \begin{pmatrix} 90\% & 5\% & 0\% \\ 5\% & 5\% & 0\% \\ 5\% & 90\% & 100\% \end{pmatrix} * \begin{pmatrix} 9{,}000 \\ 500 \\ 500 \end{pmatrix} = \begin{pmatrix} 8{,}125 \\ 475 \\ 1{,}400 \end{pmatrix}$$

9,000 accounts in C, 500 in L, and 500 in D <u>next month (t+1)</u>.

Vintage Models

- Vintage models segment the portfolio by either the year (YOB) or month that an account is booked (MOB).
- Once the vintage criteria is determined, the loss performance of the segment is tracked over time.
- Vintage models can be further segmented to reflect more granular levels of risk such as delinquent/non-delinquent and bankrupt/non-bankrupt populations.
- Annual loss rates and month-on-book losses usually provide fewer data points so exponential smoothing techniques (weighted averages) are useful.
- Vintage models can account for management strategies and exogenous factors by optimally adjusting parameters within the exponential smoothing algorithm.
- Forecasts for the next YOB could simply reflect the previous YOB performance with downward or upward adjustments based on the credit quality of new loans.

Vintage models easily incorporate management judgment and work well in NPV models.



	Year Since Account was Booked							
		Year 1	Year 2	Year 3	Year 4	Year 5	Year 6	Year 7
Account Booked	1999	0.68%	1.46%	3.57%	4.58%	5.27%	5.10%	5.00%
	2000	0.85%	1.82%	4.46%	5.72%	6.59%	6.38%	
	2001	0.89%	1.90%	4.67%	5.99%	6.89%		
	2002	0.78%	1.67%	4.09%	5.25%			
	2003	0.65%	1.39%	3.41%				
	2004	0.59%	1.26%					
	2005	0.54%						
	2006	0.71%	1.58%	4.04%	5.38%	6.25%		

$Y_{t+1} = (\sum_{i,j=1}^{n} \theta_i \; Y_{t-j})/n$, where θ_i is the smoothing parameter.

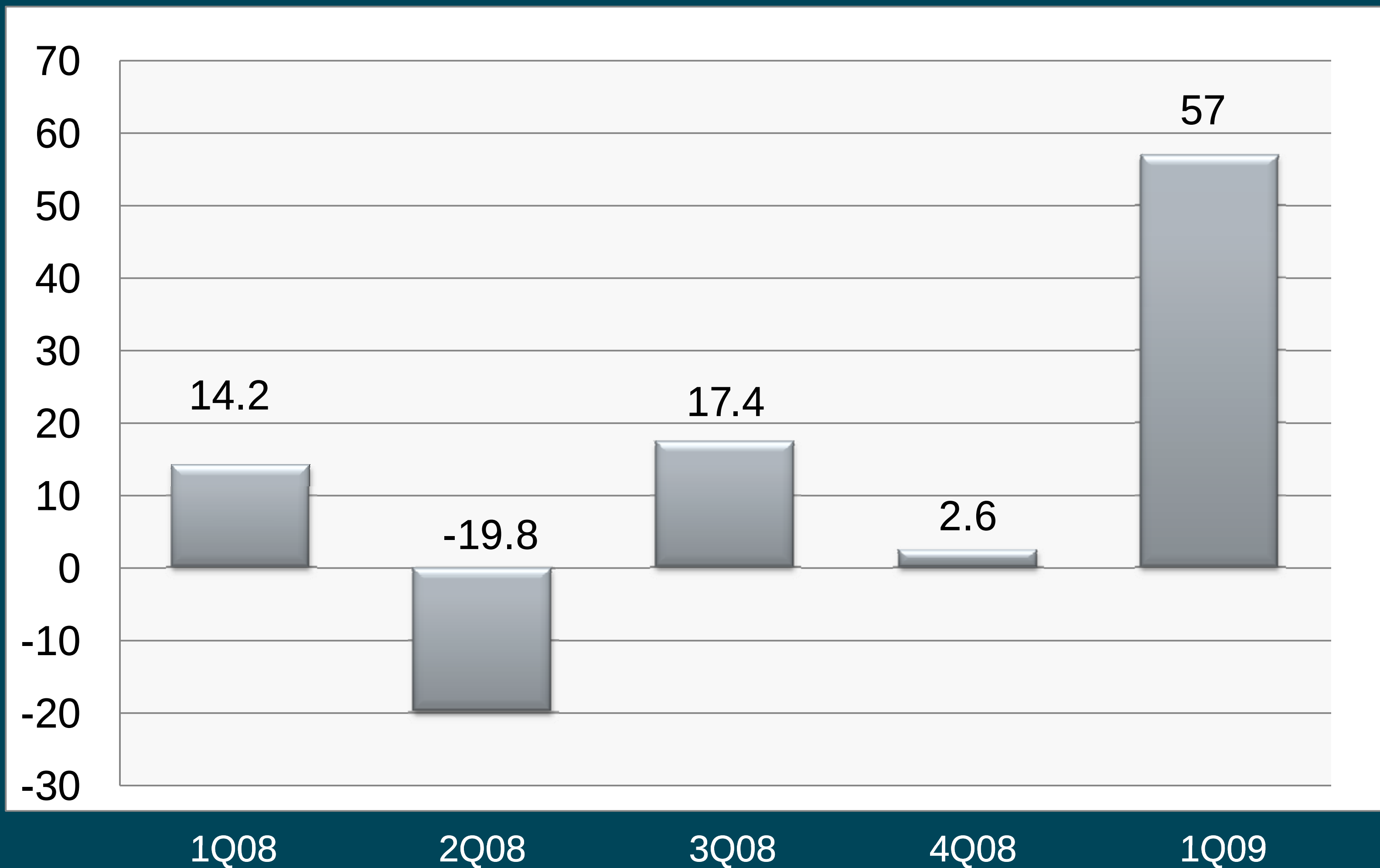
How did these models fare in the crisis?

- Retail credit conditions worsened rapidly in 2007.
- Weakness in credit card, residential mortgages, and HELOCs
- Reserve coverage falls to the lowest level since 1993
- Difficulty with asset valuation
- Ongoing liquidity challenges
- Portfolio losses & write-downs
- Earnings are under pressure

Loan Loss Reserve Needs Less Actual Allowance - All Loans

Regional US Banking Firm

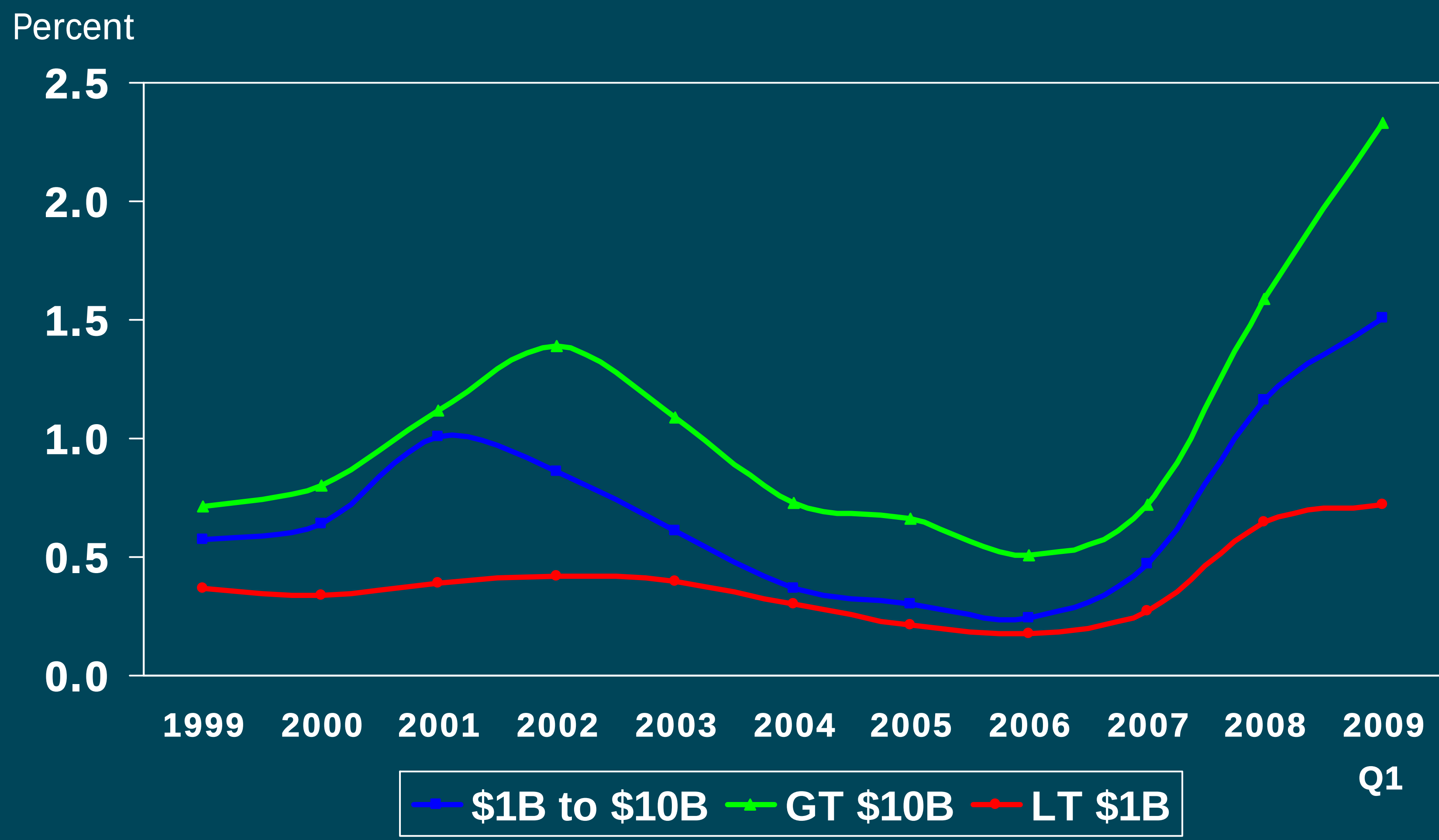
Million$



Source: Bank MIS

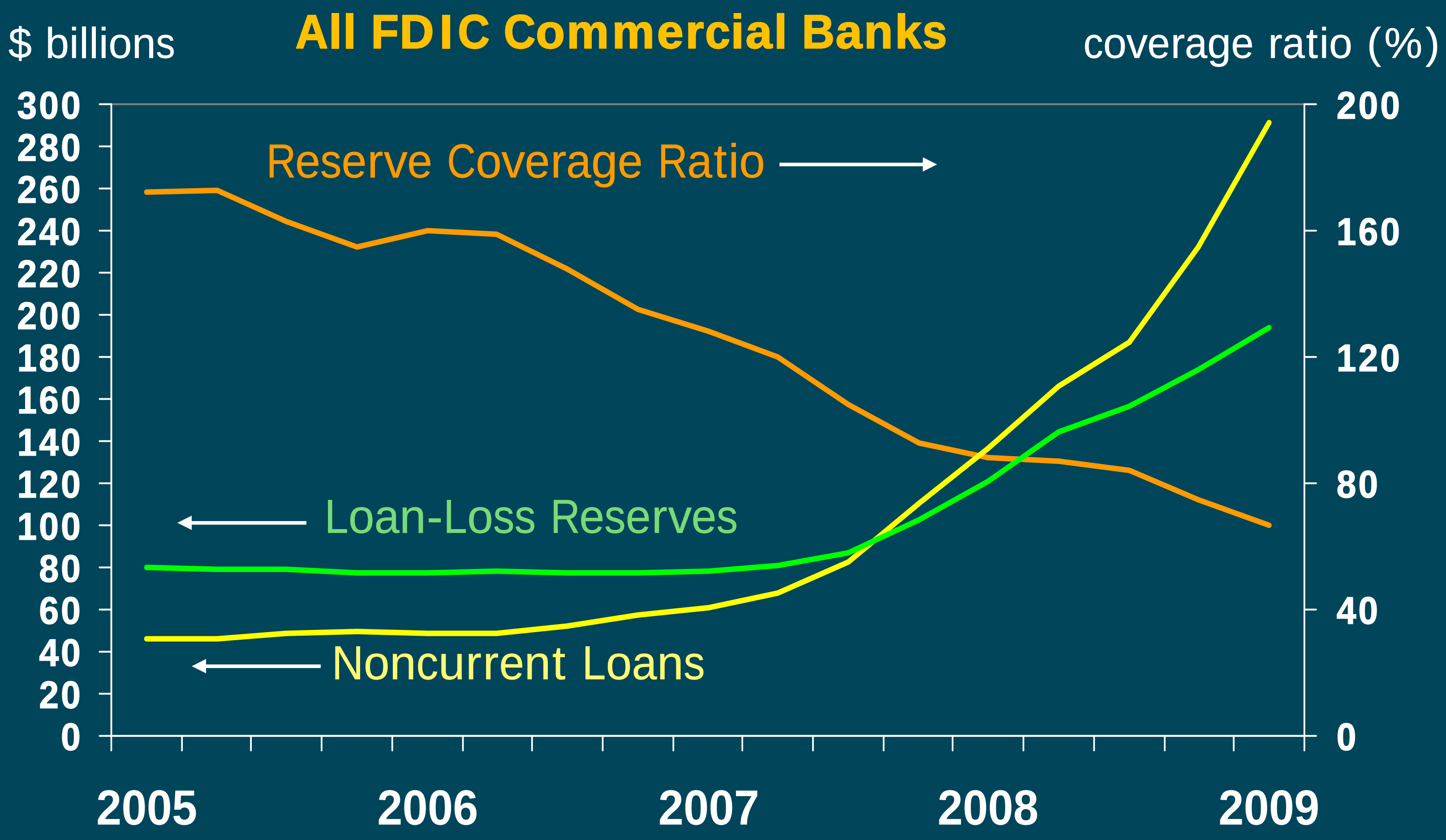
Net Charge Offs to Average Loans

All Insured Commercial Banks by Size Class



Source: Call Report

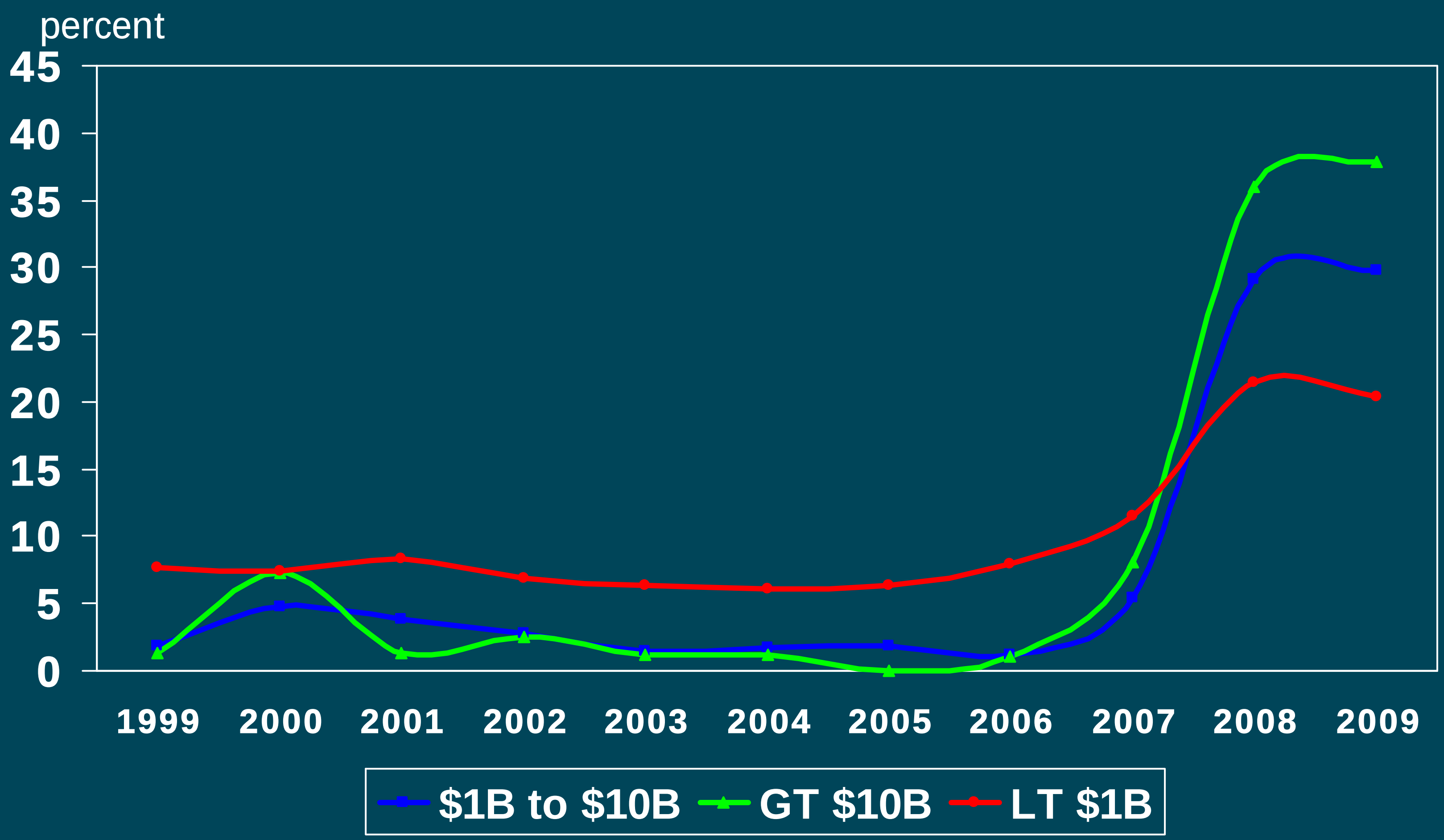
Loan Loss Reserve Fails to Keep Pace with Deteriorating Loan Quality



Source: FDIC

Percent of Banks Losing Money

All Insured Commercial Banks - by Size Class



Source: Call Report

Conclusions

- Banking firms need to better incorporate economic variables into credit risk models.
- Most bank models need sufficient enhancement which would suggest greater rigor, but not at the cost of predictive accuracy.
- Banking firms strengthen modeling efforts by benchmarking existing models.
- Stress testing and model validation should become standard practice for banks and a common regulatory responsibility for supervisors.