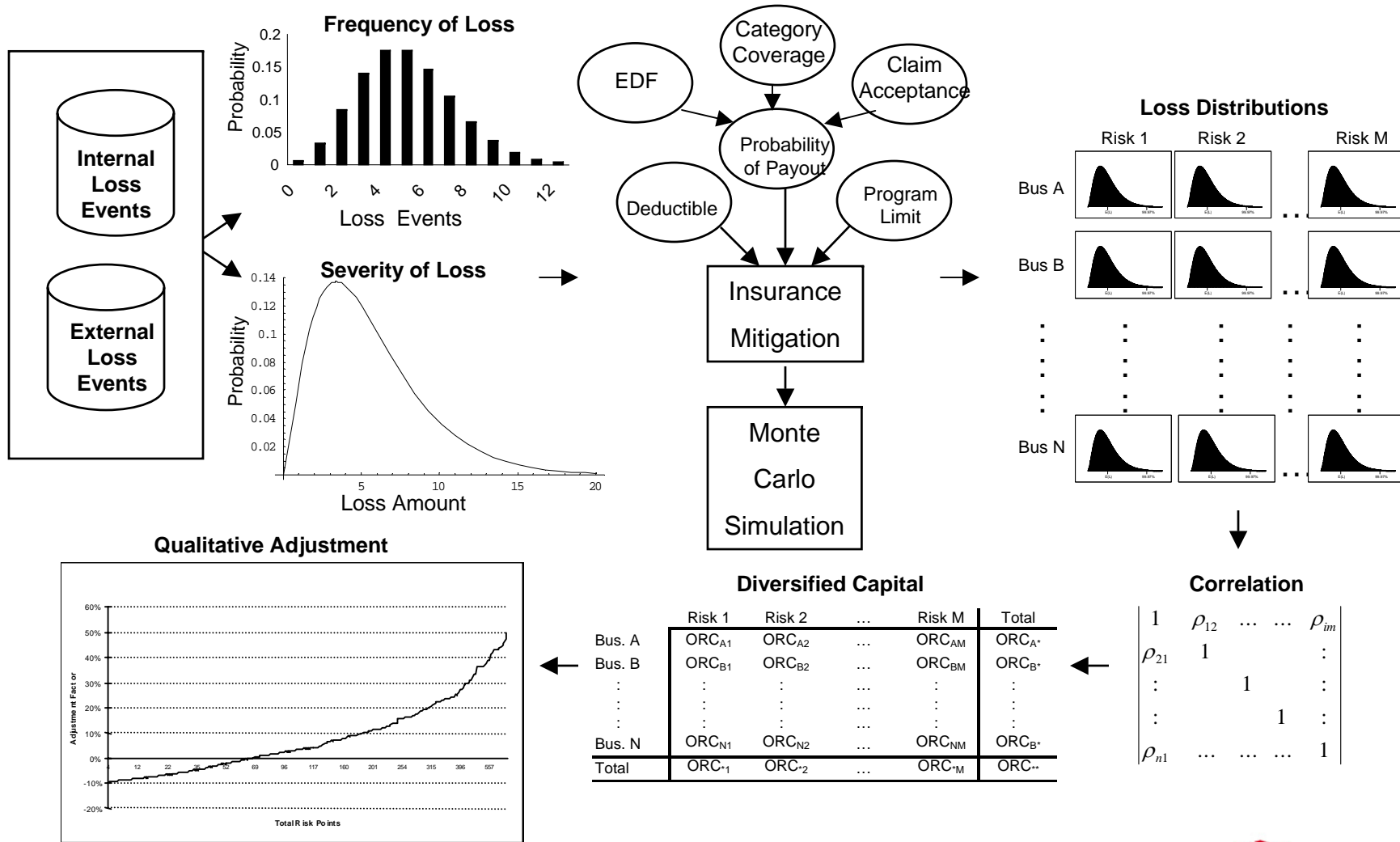


AMA Conference Federal Reserve Bank of Boston

May 20, 2005

Bank of America's AMA



Characteristics of the AMA

- Formal data policy requiring all operational losses above \$10k be reported
- External data source is ORX
- Frequency and severity distributions calculated for 28 internal business lines and 7 event categories
- Internal and external data is combined using a decision tree approach based on data sufficiency
- Insurance deductibles, program limits and payout probabilities are mapped to Basel categories and applied in the simulation process
- External parameters estimates are scaled using a relative relationship approach
- Bank level capital is determined by applying conservative correlation estimates applied to the stand alone loss distributions
- A qualitative adjustment based on line-of-business self-assessments is calibrated to a scale of -10% to +25% of capital

Limitations of Internal Data

Basel BL	Basel Loss Type							Total
	Loss Event Type 1	Loss Event Type 2	Loss Event Type 3	Loss Event Type 4	Loss Event Type 5	Loss Event Type 6	Loss Event Type 7	
Business Line 1	5	450	435	1,730	5,615	450	5	9,815
Business Line 2	1	40	2	15	85	5	5	153
Business Line 3	25	110	10	50	1,355	8,955	10	10,515
Business Line 4	3	20	5	10	5	5	5	53
Business Line 5	10	10	5	10	385	1,305	25	1,750
Business Line 6	600	3,360	55	2,060	313,685	1,084,430	9,350	1,413,540
Business Line 7	2	30	2	40	60	5	15	154
Business Line 8	5	135	1	15	55	5	5	221
Total	651	4,155	515	3,930	321,245	1,095,160	10,545	1,436,201

Illustrative

- Limitations
 - Inevitably, some cells will be sparsely populated
 - Confidence intervals around the parameter estimates may be large even for a cell with “sufficient data”
- Solutions
 - Use external data from consortia and/or public databases to determine frequency and severity distributions
 - Incorporate scenario analysis to supplement the internal/external loss event data
- This presentation will focus on approaches for combining internal and external data
- Scenario analysis is equally valid but not covered in this presentation

Approaches for Combining Internal and External Data

- Decision tree approach
 - Applies a series of binary (either/or) choices on whether to use internal or external data and the level of data aggregation
 - Decision points may depend purely on number of data points available or can use more sophisticated criteria (e.g., goodness-of-fit)
- Weighting severity parameters
 - Separately estimate parameters for internal and external data
 - Create a composite distribution by taking weighted averages of the estimated parameters
- Pooling internal and external data
 - Commingling internal, external and/or scenario derived data
 - Need to address the effect of truncation points for the various data sources
- Convolution
 - Estimate separate distributions for internal and external data and use Monte Carlo simulation to draw from each
 - Typically, losses above a threshold are selected from the external data
- Joint MLE estimation
 - Jointly estimate severity parameters from internal and external data assuming events are drawn from the same distribution
 - Most effective when the truncation point for the external data is known with certainty but methods are available for random truncation

Controlled Experiment

- Assume internal and external losses are driven from the same stochastic process
- Draw 100 pseudo random variables from a (-4,2,4) Gamma-Normal Distribution to represent the “internal” data
- From the same distribution, draw 250 numbers greater than \$25,000 to represent the “external” data
- Use maximum-likelihood estimation to separately parameterize the two samples recognizing the truncation point in the external data and assuming a Gamma-Normal Distribution
- Case 1: Let the weighted average composite distribution be a based on a simple event weighted average of the separately estimated distributions
- Case 2: Consider approaches to pooling – the first commingles the internal and external data but makes no explicit adjustment for the truncation level in the external data
- Case 3: The second pooling approach commingles the two data sets but drops internal observations below \$25,000
- Case 4: Generate a joint mle distribution by solving the following where α is the truncation point for the external data (see Baud, Frachot, Roncalli 2002):

$$\max_{\{\theta\}} \left[\sum_{i=1}^M \ln[f(\theta; x_i^I)] + \sum_{j=1}^N \ln[f(\theta; x_j^E)] - N * \ln[1 - F(\theta; \alpha)] \right]$$

Experiment Results

Weighted Average:

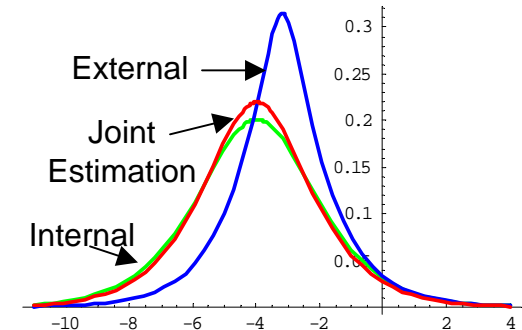
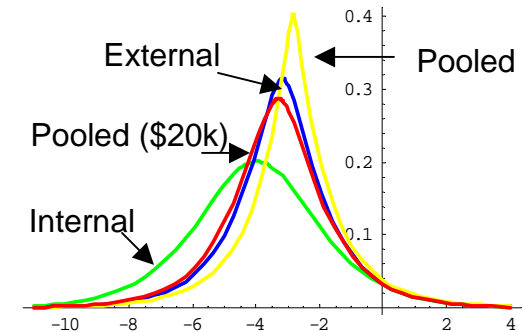
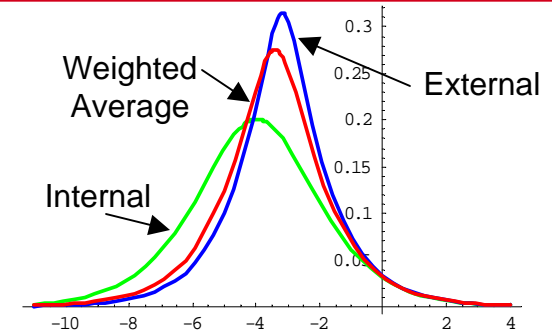
	N	Mean	Std. Dev.	Kurtosis
Internal	100	-3.9780	2.2587	4.0707
External	250	-3.1756	1.8370	6.0909
Weighted Average	350	-3.4049	1.9575	5.5137
True Distribution	n/a	-4.0000	2.0000	4.0000

Pooled Data:

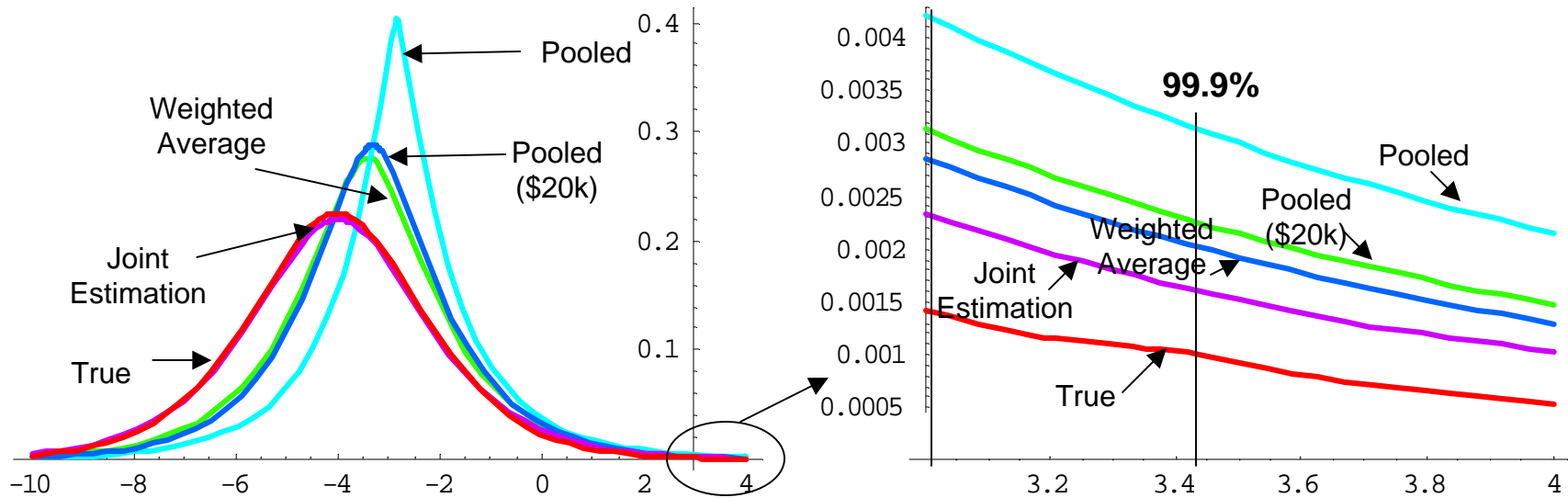
	N	Mean	Std. Dev.	Kurtosis
Internal	100	-3.9780	2.2587	4.0707
External	250	-3.1756	1.8370	6.0909
Pooled	350	-2.8402	1.8157	7.9810
Pooled (\$20k Truncated)	301	-3.2993	1.8738	5.4821
True Distribution	n/a	-4.0000	2.0000	4.0000

Joint Estimation:

	N	Mean	Std. Dev.	Kurtosis
Internal	100	-3.9780	2.2587	4.0707
External	250	-3.1756	1.8370	6.0909
Joint Estimation	350	-3.9804	2.1328	4.3241
True Distribution	n/a	-4.0000	2.0000	4.0000



Comparison of Approaches

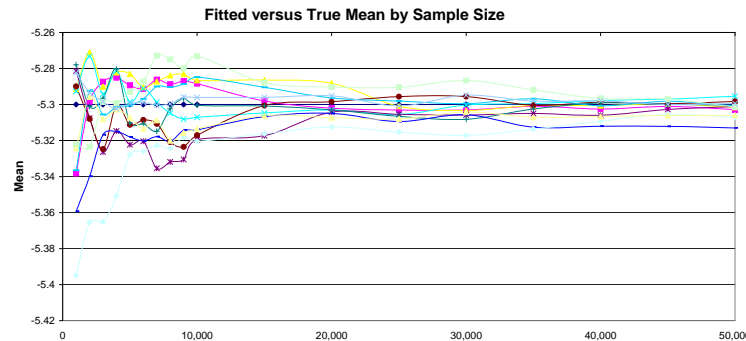


Parameter Estimate Comparison:

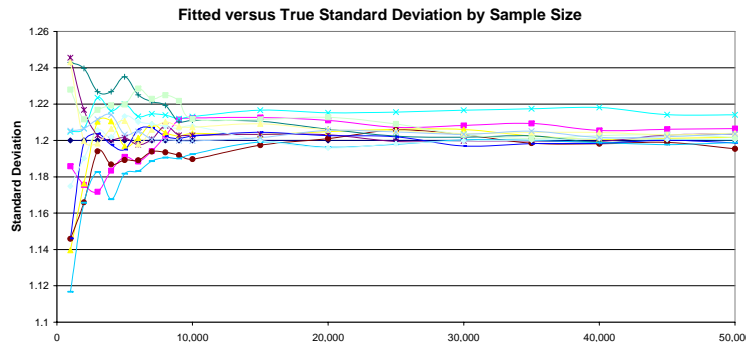
	N	μ	σ	κ
Internal	100	-3.9780	2.2587	4.0707
External	250	-3.1756	1.8370	6.0909
Weighted Average	350	-3.4049	1.9575	5.5137
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True Distribution		-4.0000	2.0000	4.0000

Convergence of MLE Estimators

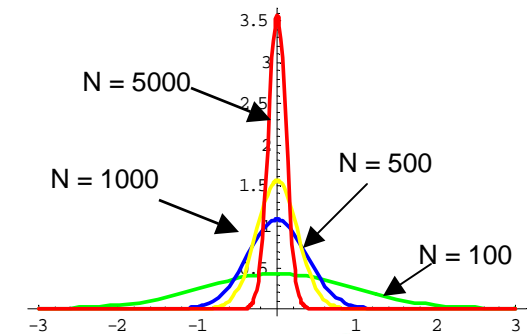
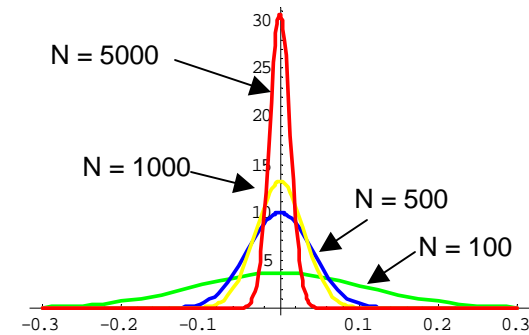
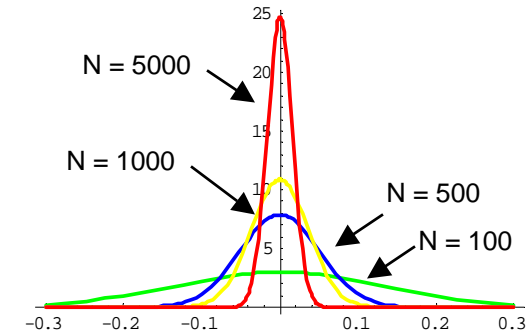
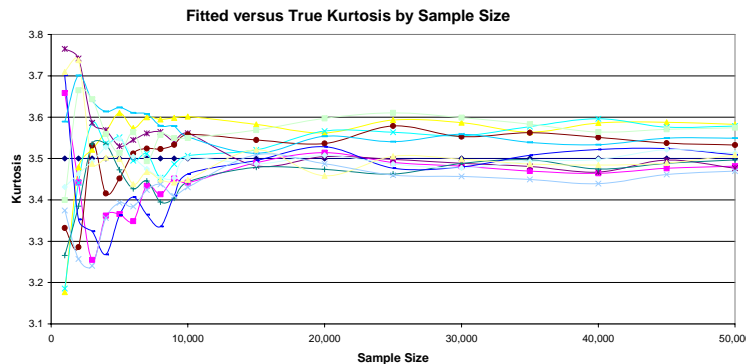
Mean: -5.3



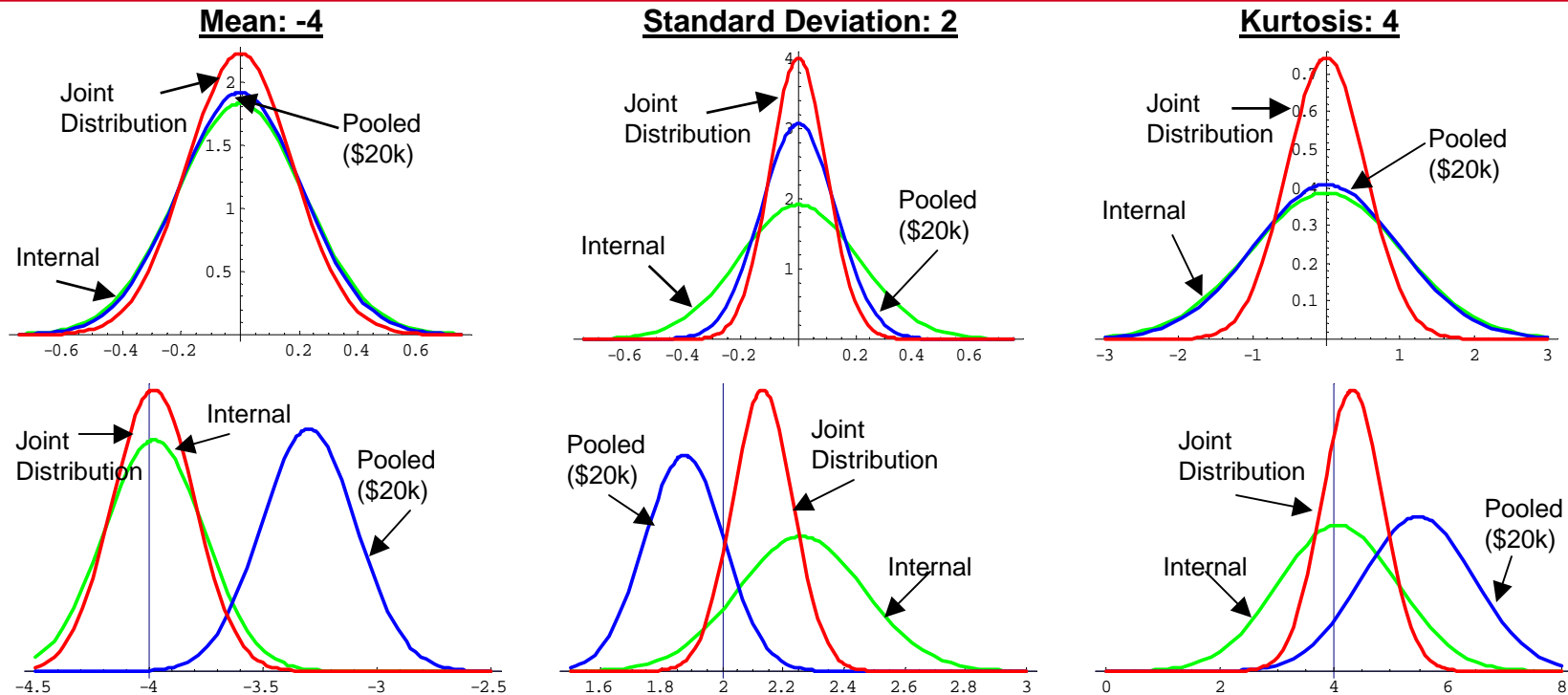
Standard Deviation: 1.2



Kurtosis: 3.5



Model Uncertainty



- Random numbers drawn from a Gamma-Normal Distribution (-4, 2, 4)
- Number of events – Internal = 100; External = 250
- Upper graphs show normalized standard errors; lower graphs show standard errors around the point estimator
- Vertical lines in lower graphs show true parameter values

Commentary/Conclusions

- MLE estimators converge on the true parameters as the sample size increases
- Likewise, confidence intervals decrease as the sample size increases
- Even with large databases, a Bank will inevitably be faced with the problem of data sufficiency
- Developing an effective method for combining internal and external data can improve the quality of/confidence in parameter estimates
- Joint MLE estimation appears to offer a promising method for improving the estimation process of combined data
- Improved confidence intervals around the estimator requires comfort with the assumption of a common stochastic process
- Even with a strong approach to combining data, scenario analysis will be an important input or validation component