

Bank of America.



***Bank of America Corporation
Risk Capital & Portfolio Analysis***

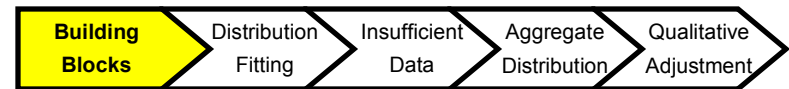
**Implementing a Comprehensive LDA
Leading Edge Issues in Operational Risk Measurement
May 29, 2003**

Discussion Items

- Status of the LDA at Bank of America
- Data Collection & Categorization
- Loss Distribution Fitting Process
- Scenario Approach
- Mixing Internal & External Data
- Integration of Insurance
- Qualitative Adjustments
- Correlation
- Concluding Comments

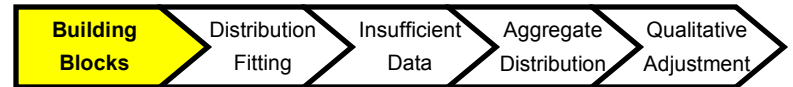
LDA at Bank of America is a Work in Progress

- Compiled database of loss events covering major operational risk categories
- Categorized events using PwC scheme
- Developed statistical modeling process using actual loss experience
- Reviewed preliminary model with key audiences and regulators
- Completed update of data through Q4 2002
- Developing scenario based approach for technology and unauthorized activities
- Modify models to reflect Basel categorization scheme when finalized for US implementation
- Develop reporting framework to create transparency and facilitate vetting process
- Communicate internally beginning June 2003 for education and feedback
- Run new approach in parallel with existing approach Q3 and Q4 2003
- Intend to implement approach in 2004

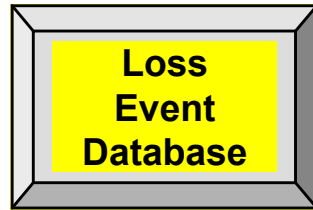


Advantages of the Actuarial Approach

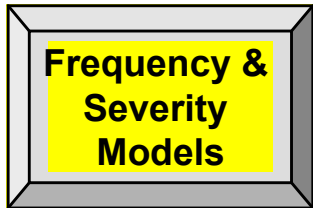
- Capital requirements are based on direct loss experience and qualitative assessment of the control environment
- The approach allows operational risk measurement to be handled in a way that is consistent with accepted market and credit risk methodologies
- Linking the capital charge to actual experience and self assessment scores encourages appropriate behavior
- Classification and measurement of risk exposure by causal factor provides the basis for more effective risk management feedback and control
- Insurance programs and other types of risk mitigation programs can be incorporated



Components of the Loss Distribution Approach



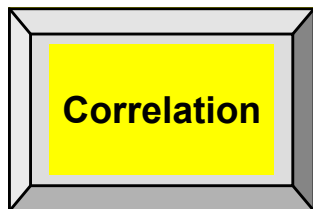
- A database of internal and external losses resulting from failed processes, people, systems and external events sorted by causal category



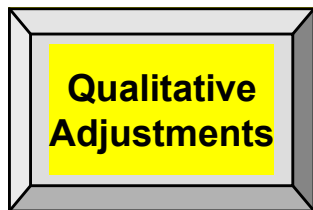
- Statistical models of the likelihood of loss events and the range of probable loss amounts for each category and business



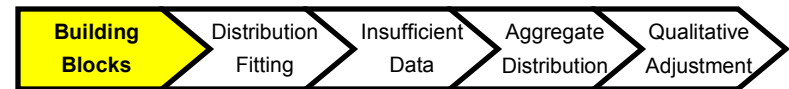
- Aggregation of frequency distributions, severity distributions and insurance overlay into an operational loss distribution



- Inter-relationship between losses falling into different causal categories and business units

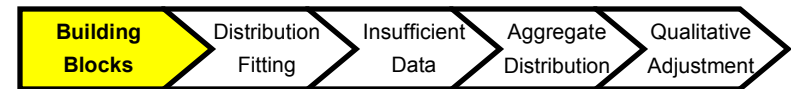


- Adjustments to take into account the state of current controls and forward looking assessment of the risk environment



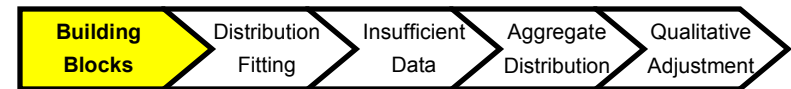
Loss Event Database

- Our definition of operational risk matches Basel CP3:
 - “Operational risk is defined as the risk of loss resulting from inadequate or failed internal processes, people and systems or from external events”
- Categorization into event types is currently based on scheme developed by PwC
- Conducted more than 50 interviews with managers throughout the organization
- Identified more than 20 sources of data, the most important of which are
 - Litigation Management System - tracks legal cases brought by and against the bank
 - Corporate Security - database includes events related to criminal activity perpetrated against the bank
 - Insurance Databases - capture fiduciary, property, general liability and workers compensation events (whether claim is made or not)
 - Liability Risk Management - repository for losses related to check fraud, teller policy and procedural errors, etc.
- Data from the various sources was consolidated into a central loss database and mapped into consistent set of definitions



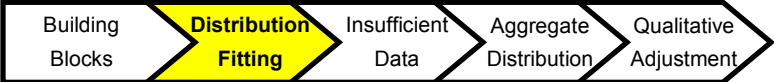
Loss Data Categorization

- The data is categorized according to a hierarchical causal category scheme developed by PwC (with the ability to map these to the Basel categories):
 - Criminal - Loss arising from criminal/fraudulent actions (internal or external)
 - Human Resources - Loss arising from management's errors of judgment involving the firm's employees
 - Management Process - Loss arising from management's failure to perform specified duties or exercising poor/bad judgment
 - Sales Practices - Losses due to inappropriate dealings with customers
 - Technology - Loss due to failure/inadequacy of internal hardware/software
 - Transaction Processing - Losses from processing failure, poor documentation and erroneous data entry
 - Unauthorized Activities - Losses arising from the unauthorized trading, overstepping authority, and concealment of positions
 - Disasters/External Environment/Vendors & Suppliers - Losses due to natural catastrophes, changes in legislative/regulatory factors, and actions of vendors/suppliers



Loss Event Descriptive Detail

- Descriptions of events are included in the database for transparency and root cause analysis
- The financial impact is further broken down by effect:
 - Asset Write-Down
 - Restitution Loss
 - Legal Loss
 - Penalty
 - Recourse Loss
 - Financial Write-Down
- Other data fields include
 - Date of first occurrence
 - Date of settlement
 - Date of first detection
 - Business Unit
 - Date of last occurrence
 - Cost Center



Loss Distribution Approach Model

Loss Events for Category

Operational Loss Event Entry Form

Business Unit: [] Risk Category: []

Sub Business Unit: [] Sub Risk Category: []

Description of Loss Event: []

Legal Liability: \$0 First Occurrence: []

Penalties: \$0 Last Occurrence: []

Loss to Assets: \$0 Date of Detection: []

Loss of Recourse: \$0 Date of Settlement: []

Restitution: \$0

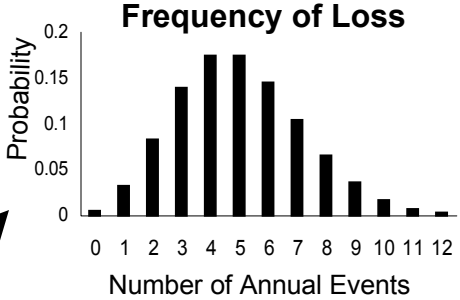
Write Down: \$0

Recovery: \$0

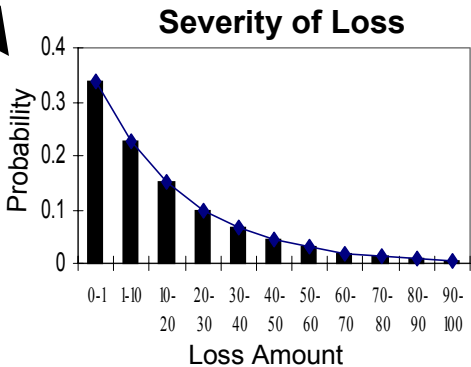
Net loss: \$0

Buttons: Save Event, New Event, Delete Event, Exit

Reference ID: [] Initials: [] Entry Date: []



- Frequency Distributions
 - Frequency of loss follows a Poisson distribution
 - Standard for the insurance industry

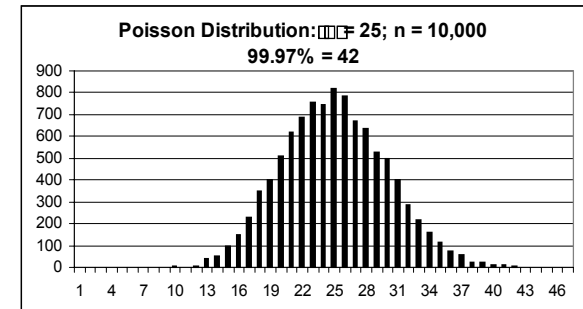
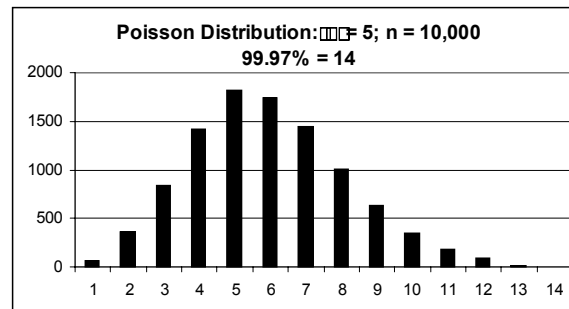
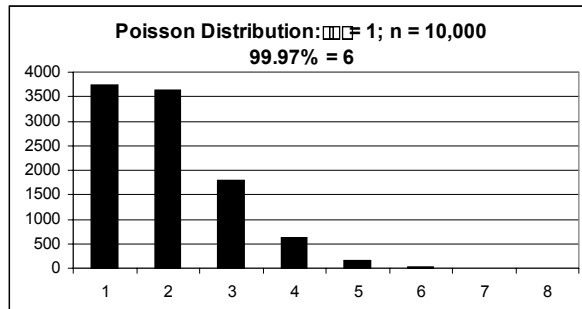


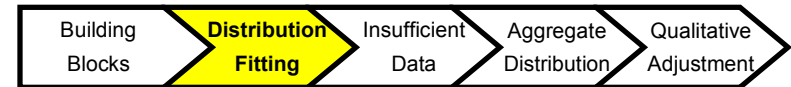
- Severity Distributions
 - Fitted internal loss data
 - Scaled and fitted external loss data
 - Scenario analysis



Frequency Distribution

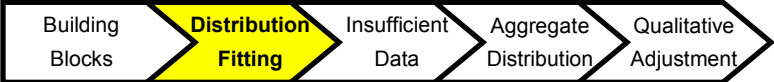
- As is common in the insurance industry, event frequency is assumed to follow a Poisson process with mean and variance = λ
- When sufficient data exists, the expected frequency of events is the average number of losses experienced per year after adjusting for trend
- When internal data is not adequate, loss frequency is estimated from external data for peer institutions
- External loss frequencies are scaled by revenue to account for differences in firm size





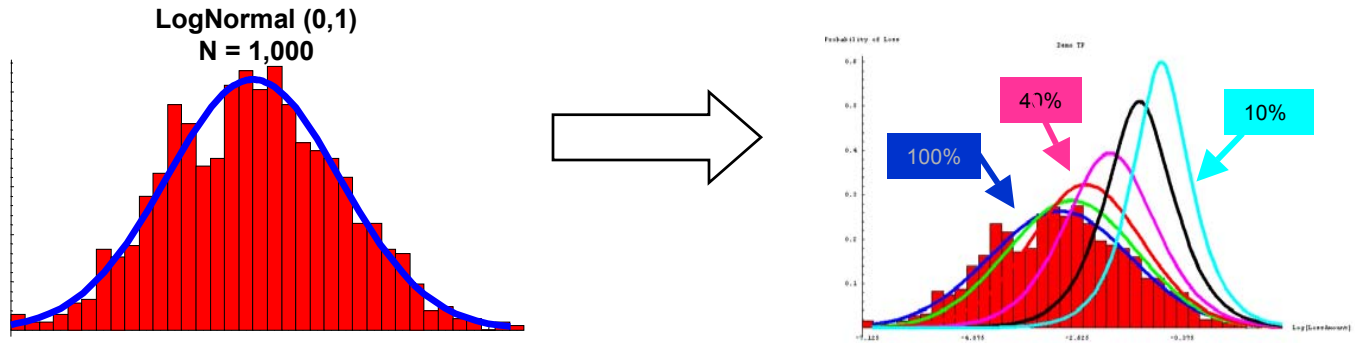
Fitting Severity Distributions

- It is commonly accepted that operational losses are appropriately characterized by heavy-tailed distributions
- Loss data is fit using three distributions: LogNormal, LogLogistic and a combined Gamma-LogNormal
- The LogNormal is a specialized case of the Gamma-LogNormal occurring when the kurtosis equals 3
- Because many small losses are not captured in the database, histograms of the data are checked visually to determine if the data is truncated
- Parameters for truncated distributions are determined using maximum likelihood estimation
- In the event that the exact truncation level is indeterminate (due to changing management objectives, multiple data sources, etc) parameter estimates at various truncation points are compared

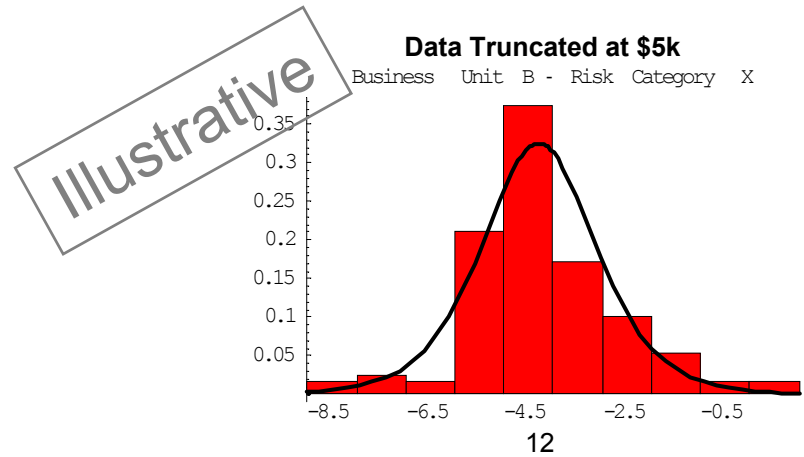


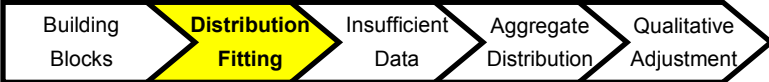
Fitting Severity Distributions - Truncation Points

- Typically data capture below a business defined threshold is incomplete
- This bias requires truncated distributions be fit to the data
- Choice of truncation point can have a dramatic impact on the values of fitted parameters
- Each distribution fit to an empirical loss data set will give a different representation of the underlying risk profile



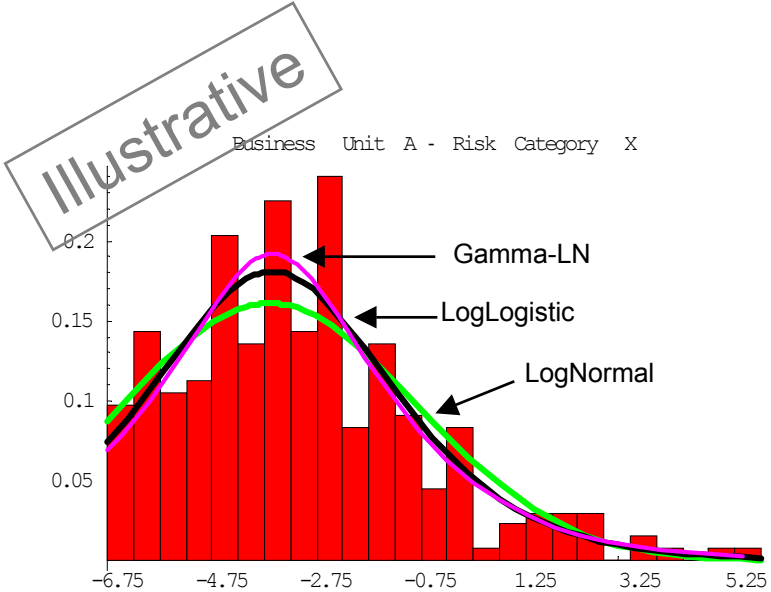
- When uncertain about the data collection threshold, visual inspection of the histogram is critical





Model Choice - Goodness of Fit Statistics

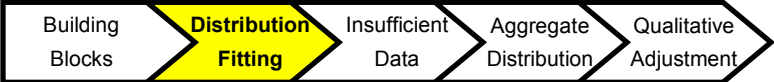
- Model choice is made based on goodness of fit statistics and reasonability of the tail loss at 99.97% confidence level



	LogNormal	LogLogistic	Gamma-LN
Mean	-3.8940	-3.8462	-3.8428
Standard Deviation	2.8069	1.5412	2.8744
Kurtosis	3.0000	N/A	4.7965
Maximum Likelihood Function	-584	-581	-580
Kolmogorov-Smirnov	0.056	0.032	0.027
Anderson-Darling	1.048	0.364	0.286
Cramer-von Mises	0.233	0.124	0.113
Required K-S Level	0.066	0.066	0.066
Is K-S Significant?	Y	Y	Y
Average of 3 Largest Losses in External Database			\$500 Million
Maximum Internal Loss			\$170 Million
Are Extreme Loss Quantiles Reasonable?			Yes

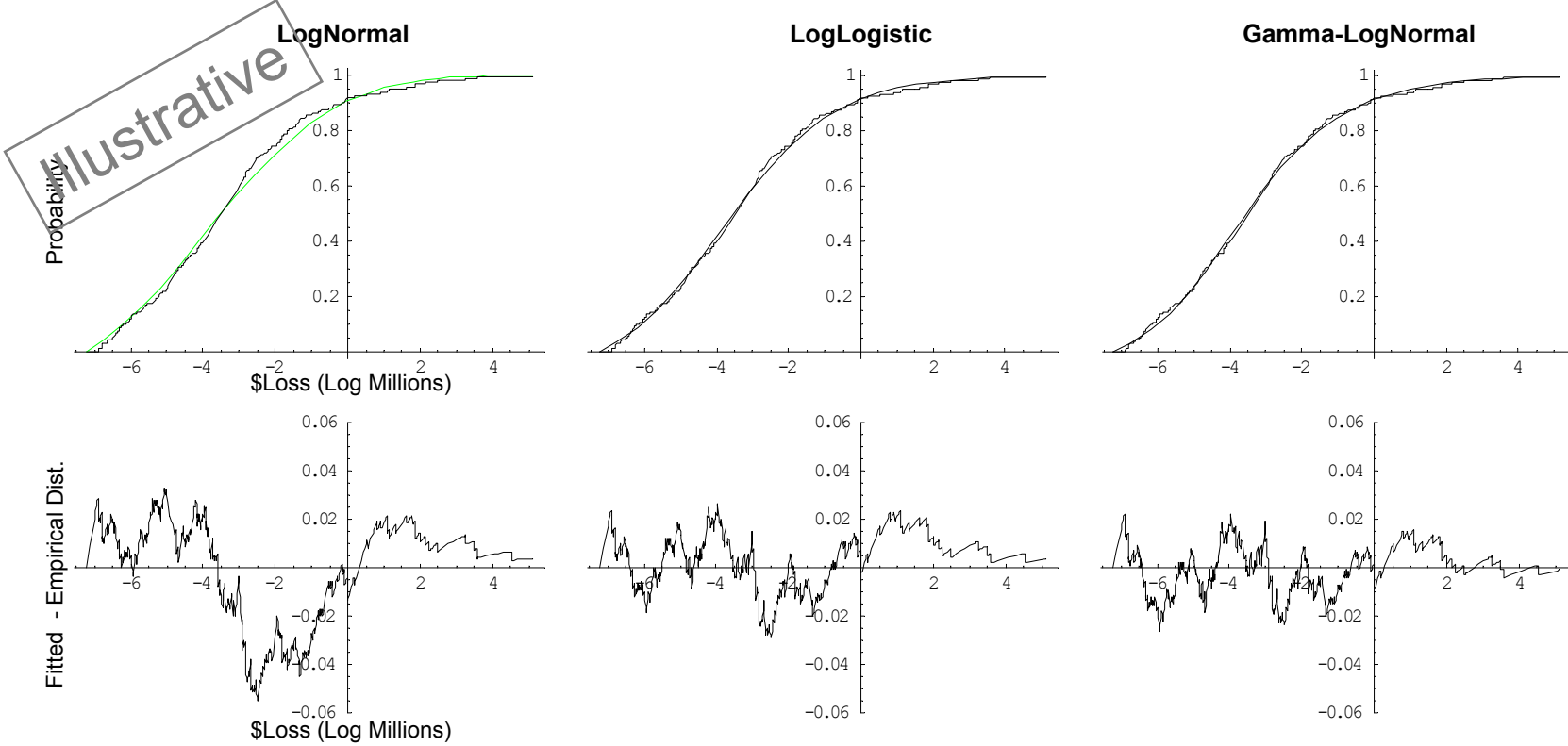
	Loss Severity for Given Percentiles						
	50%	75%	90%	95%	99%	99.9%	99.97%
LogNormal	5,609	47,769	328,780	1,043,260	9,103,890	103,232,000	305,673,000
LogLogistic	4,851	38,847	313,260	1,298,100	30,035,200	2,446,820,000	24,211,500,000
Gamma-LogNormal	5,500	46,333	315,662	995,490	8,588,340	96,205,100	283,392,000
Empirical Data	5,566	51,327	264,113	986,214	9,516,635	N/A	N/A





Model Choice - Percentile Comparisons

- Informal model validation consisting of plotting the difference between empirical and fitted distributions can be visually compelling



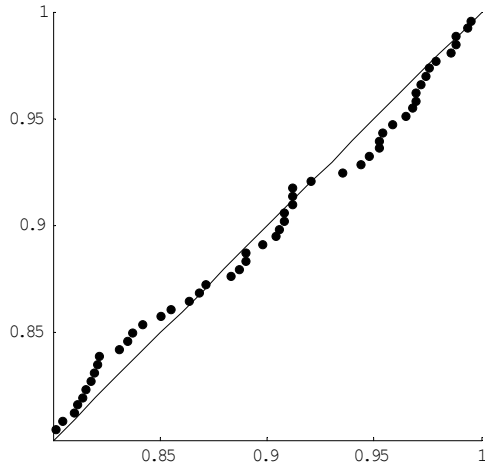
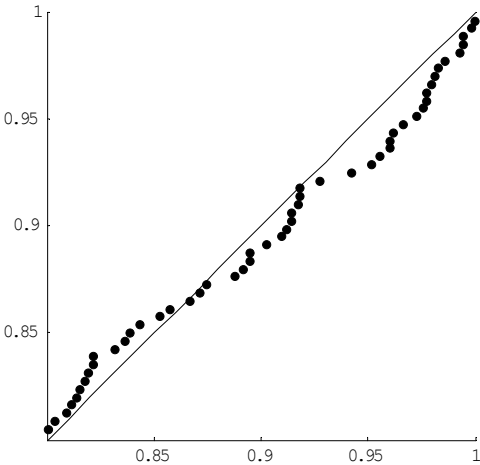
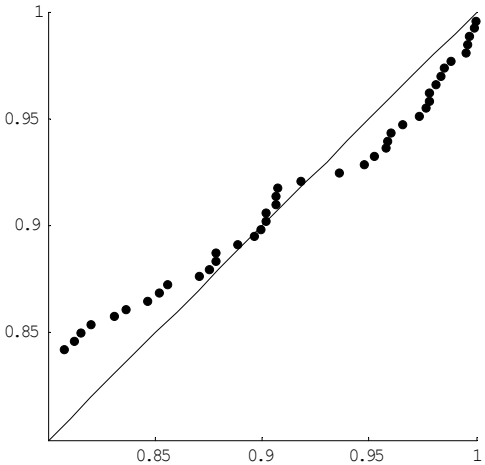
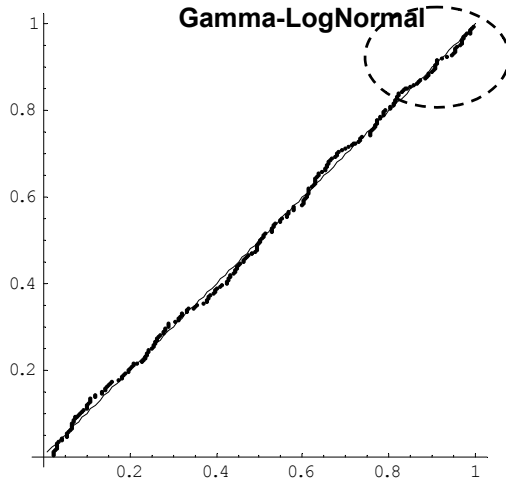
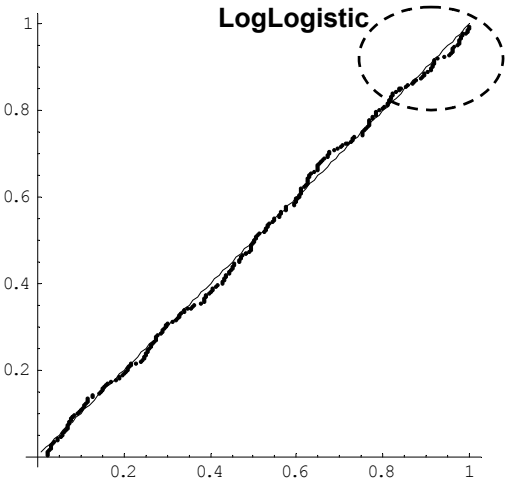
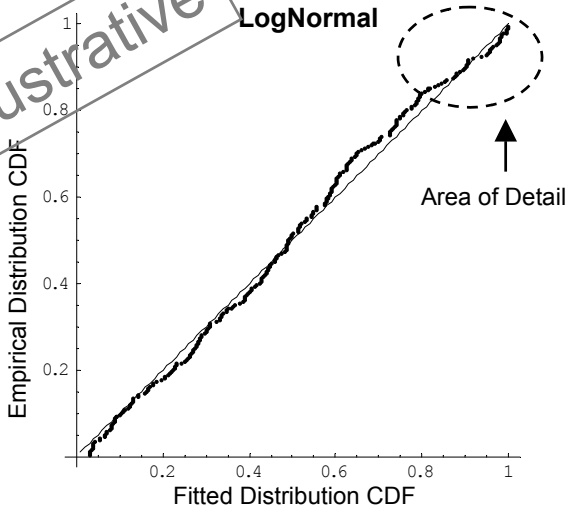
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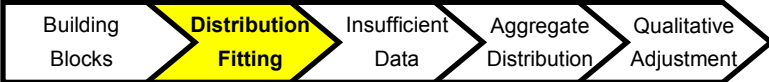


Model Choice - QQ-Plot

➤ Another informal way to gauge goodness-of-fit is the QQ-Plot with emphasis on the tail of the distribution

Illustrative





Internal Data is Generally Not Sufficient to Fit Distributions for All Cells

Illustrative

Business Unit		Criminal	Management Process	Transaction Processing	Human Resources	Sales Practices	Unauthorized Activities	Technology
Business A	Frequency Mean, SD, Log Kurtosis	100 746.5, 9804.0, 6.1	80 95.7, 3832.2, 4.7	75 118.2, 834.0, 5.1	100 81.8, 436.7, 4.9	5 661.1, 7249.0, 3.2	20 85.7, 650.1, 3.0	
Business B	Frequency Mean, SD, Log Kurtosis	75 1550.8, 20977.9, 11.8	50 658.1, 4504.5, 3.0	100 3.4, 26.7, 3.0	25 18.8, 77.9, 3.0			
Business C	Frequency Mean, SD, Log Kurtosis	25 6.4, 6.0, 3.0	15 33.2, 296.0, 3.0	100 8.9, 664.6, 3.0	20 27.1, 534.1, 4.2			
Business D	Frequency Mean, SD, Log Kurtosis	100 104.6, 177.5, 3.0	30 5.0, 260.5, 3.0	15 13.0, 51.2, 3.0	75 36.7, 245.3, 5.4	10 317.7, 4727.6, 4.7		
Business E	Frequency Mean, SD, Log Kurtosis	15 293.1, 4326.0, 3.0	10 13.5, 32.6, 3.2	5 14.3, 34.6, 3.0	10 12.1, 119.7, 3.0			
Business F	Frequency Mean, SD, Log Kurtosis		5 52.9, 181.7, 3.0					
Business G	Frequency Mean, SD, Log Kurtosis	50 3.8, 23.8, 3.0	20 25.3, 178.5, 3.0	5 43.6, 208.4, 3.0	50 24.1, 97.8, 3.4			
Business H	Frequency Mean, SD, Log Kurtosis	25 159.1, 9311.9, 3.0	50 854.0, 9868.2, 3.0	5 24.4, 448.0, 6.0	25 63.8, 593.7, 4.9	5 3061.0, 28890.5, 4.7		
Business I	Frequency Mean, SD, Log Kurtosis	10 1014.8, 13089.3, 3.0						
Business J	Frequency Mean, SD, Log Kurtosis		10 106.7, 3281.2, 5.4					
Business K	Frequency Mean, SD, Log Kurtosis		5 1047.5, 11917.8, 3.0	25 229.4, 1341.1, 3				
Business L	Frequency Mean, SD, Log Kurtosis	5 3085.2, 21613.3, 3.0			5 27.8, 299.7, 3.0			
Business M	Frequency Mean, SD, Log Kurtosis	5 223.9, 15027.8, 3.0		5 101.4, 443.1, 3.0				
Business N	Frequency Mean, SD, Log Kurtosis	50 270.9, 261.7, 3.0	50 28.2, 102.7, 3.0	15 33.8, 359.1, 3.7	15 8.1, 148.6, 3.0			
Business O	Frequency Mean, SD, Log Kurtosis		5 51.0, 486.7, 3.0		5 13.5, 374.1, 5.6	N/A N/A		

Alternatives include using industry data and/or scenario analysis





Industry Loss Distributions

- The methodology for using external data must take into account certain biases
 - High Truncation Level - minimum loss in the external database is \$1 million
 - Data Capture Bias - only the largest losses make the public record
 - Controls Bias - poorly controlled firms will have more reported losses than well controlled firms

- Key aspects of our implementation are:
 - Public data is scaled to take account of difference in firm size using a weighted least squares regression approach
 - Scaled external data is assumed to be distributed as gamma-normal and distribution parameters are estimated based on this assumption
 - Distribution parameters are scaled for differences in controls and reporting biases by relative relationship analysis



Scaling External Data - Loss Severity

- Public data events are contributed by firms of vastly different sizes
- Scaling of the data is done in order to control for this
- The hypothesized relationship between loss amount and firm size is as follows (See; Shih, Samad-Khan and Medapa (*Operational Risk*, January 2000))

:
$$L = R^\alpha F(\theta)$$

Where: L = actual loss in millions of dollars

R = business segment gross revenue in millions of dollars

α = scaling factor

θ = vector of unexplained variables

Taking the logarithm and dividing both sides by $\ln(R)$ gives:

$$y = \alpha + \beta x + \varepsilon$$

Where: $y = \ln(L)/\ln(R)$

$x = 1/\ln(R)$

$\beta = E[\ln F(\theta)]$

$\varepsilon = [\ln F(\theta) - \beta]/\ln(R)$

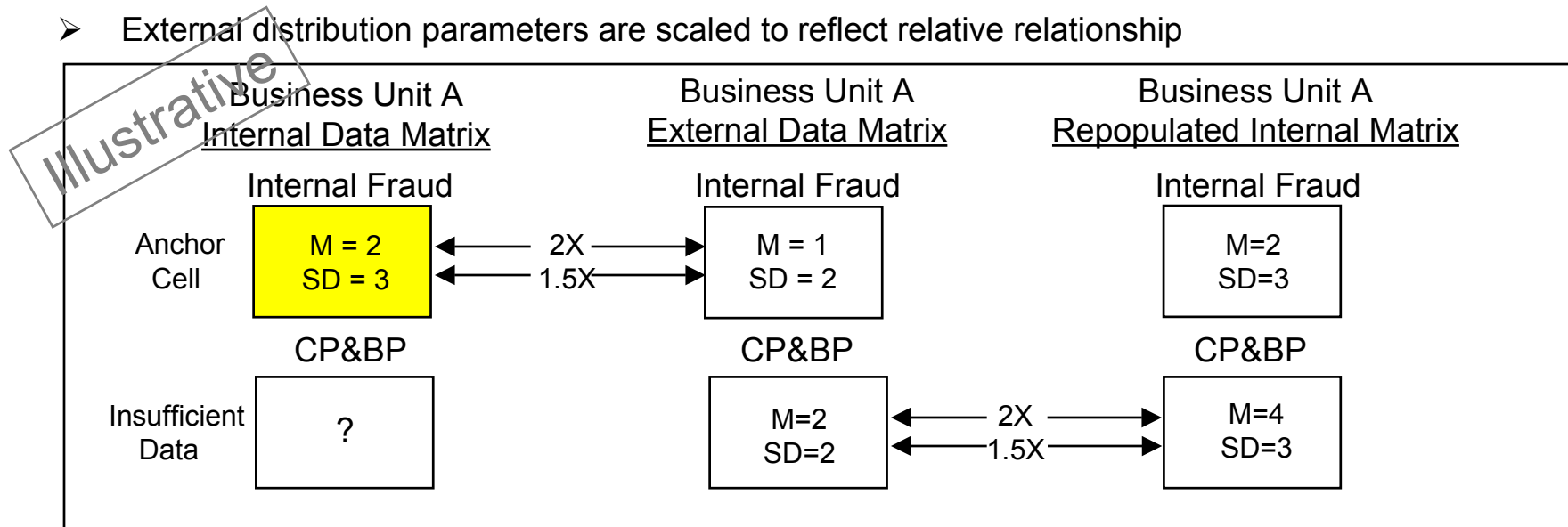
The results of the regression are presented below:

Weighted Least Squares Regression Results					
Parameter	Coefficients	Standard Error	t Statistic	Regression Statistics	
□	-0.018	0.007	-2.621	R - Square	0.84
□	2.320	0.023	99.469	Adjusted R-Square	0.84



Simple Approach to Relative Relationships

- Choose anchor cells for each business where the internal data is sufficient and fits are reliable
- The ratio of mean and standard deviations between internal and external data are determined for each anchor cell
- External distribution parameters are scaled to reflect relative relationship



- The scaling process adjusts for truncation, reporting and control bias while retaining firm specific information
- Another approach involves simultaneously optimizing across the entire matrix of fitted internal and corresponding external parameters
- Alternatively, some application of credibility theory can be used



Scenario Analysis - Alternative 1

- Frequency of technology failures are tracked consistently, by severity code, but financial consequences are rarely quantified

Illustrative

Average Annual Technology Related Events

Segment	Severity 1	Severity 2	Severity 3	Total
Business Segment 1	50	100	200	350
Business Segment 2	225	1,000	1,500	2,725
Business Segment 3	50	100	150	300
Business Segment 4	25	50	150	225
Business Segment 5	150	250	500	900
Total	500	1,500	2,500	4,500

- Scenario analysis is used to determine severity parameters to associate with frequency data
 - Severity code is directionally indicative of loss severity
 - Loss severity distribution must be assumed
 - Expert judgement is used to set mean and extreme loss amounts for each severity category

Illustrative

Assumptions

	Severity 1	Severity 2	Severity 3
Average Loss	\$50,000	\$10,000	\$1,000
99% Loss	\$5,000,000	\$1,000,000	\$100,000

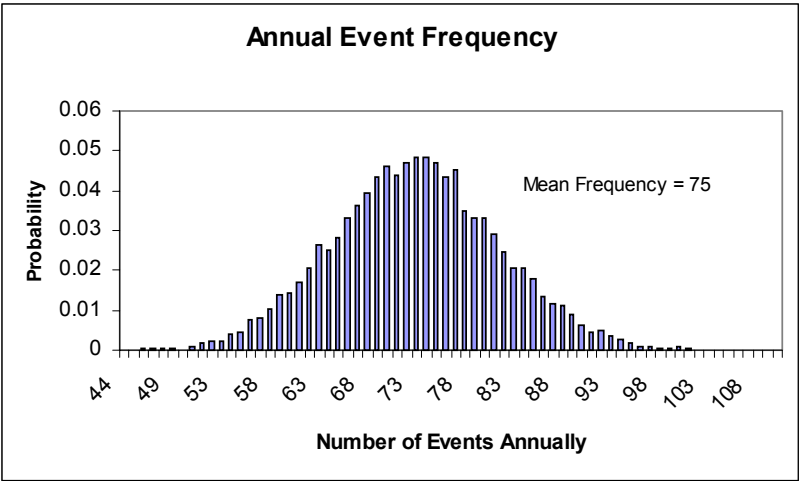
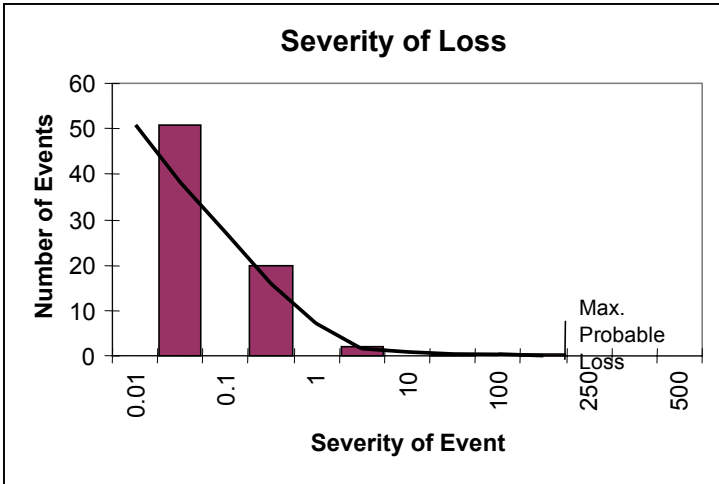


Scenario Analysis - Alternative 2

- Expert judgement is used to determine frequency of loss for pre-defined severity ranges resulting in a more fully defined loss distribution - distribution doesn't have to be assumed

Illustrative

Event Type	Estimated Annual Number of Events						Max. Single Event	Total Frequency
	< \$10K	\$10K – \$100K	\$100K – \$1MM	\$1M – \$10MM	\$10M – \$100MM	> \$100MM		
Category X	50	18	4	2.5	.4	.1	250	75



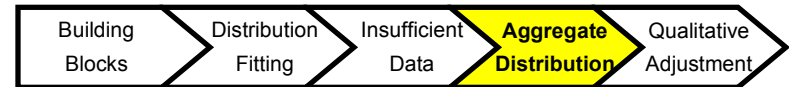


Scenario analysis and external data allow complete specification of the model

Illustrative

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Business F	Frequency Mean, SD, Log Kurtosis	2 1708.3, 11004.9, 4.3	5 52.9, 181.7, 3.0	1 357.5, 969.5, 3.4	2 441.9, 1398.6, 3.8	1 2696.2, 10347.6, 3.8	2 2186.8, 4141.7, 3.8	5 121.3, 653.6, 3.0
Business G	Frequency Mean, SD, Log Kurtosis	50 3.8, 23.8, 3.0	20 25.3, 178.5, 3.0	5 43.6, 208.4, 3.0	50 24.1, 97.8, 3.4	1 1462.5, 7776.6, 4.0	2 300.3, 1306.3, 4.3	5 121.3, 653.6, 3.0
Business H	Frequency Mean, SD, Log Kurtosis	25 159.1, 9311.9, 3.0	50 854.0, 9868.2, 3.0	5 24.4, 448.0, 6.0	25 63.8, 593.7, 4.9	5 3061.0, 28890.5, 4.7	2 1613.3, 7743.6, 4.2	10 263.9, 1302.5, 3.0
Business I	Frequency Mean, SD, Log Kurtosis	10 1014.8, 13089.3, 3.0	2 8556.2, 20.547, 3.9	1 3519.0, 4771.8, 2.9	2 3916.4, 5569.2, 3.4	1 12812.2, 26.995.9, 8.4	1 5549.2, 7730.3, 3.5	5 234.7, 1093.4, 3.0
Business J	Frequency Mean, SD, Log Kurtosis	3 10347.4, 27626.2, 3.5	10 106.7, 3281.2, 5.4	2 3510.4, 4761.8, 2.9	1 3935.1, 5615.3, 3.4	1 6519.4, 8866.8, 8.4	1 11794.9, 36297.1, 3.5	5 234.7, 1093.4, 3.0
Business K	Frequency Mean, SD, Log Kurtosis	3 10176.6, 27526.1, 3.5	5 1047.5, 11917.8, 3.0	25 229.4, 1341.1, 3	3 4431.2, 8188.4, 3.4	2 6604.1, 8957.4, 8.4	1 11781.2, 36569.6, 3.5	10 234.7, 1093.4, 3.0
Business L	Frequency Mean, SD, Log Kurtosis	5 3085.2, 21613.3, 3.0	2 4814.1, 12385.2, 3.3	3 3515.3, 4783.6, 2.9	5 27.8, 299.7, 3.0	1 5752.2, 8000.0, 4.4	1 9687.3, 22683.7, 3.6	10 234.7, 1093.4, 3.0
Business M	Frequency Mean, SD, Log Kurtosis	5 223.9, 15027.8, 3.0	2 1315.6, 4401.1, 3.9	5 101.4, 443.1, 3.0	3 435.9, 1327.3, 3.8	0.5 1235.9, 3035.1, 4.0	0.5 2184.1, 4076.5, 3.8	20 88.1, 507.0, 3.0
Business N	Frequency Mean, SD, Log Kurtosis	50 270.9, 261.7, 3.0	50 28.2, 102.7, 3.0	15 33.8, 359.1, 3.7	15 8.1, 148.6, 3.0	0.5 30.9, 559.5, 4.0	0.5 2150.9, 3997.9, 3.8	20 121.3, 653.6, 3.0
Business O	Frequency Mean, SD, Log Kurtosis	1 10166.1, 27163.6, 3.5	5 51.0, 486.7, 3.0	1 3503.8, 4732.3, 2.9	5 13.5, 374.1, 5.6	N/A N/A	0.5 11714.4, 36059.2, 3.5	20 121.3, 653.6, 3.0



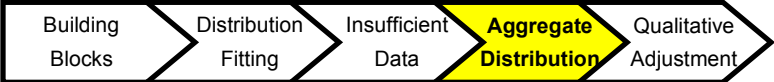


Integrating Insurance Coverage

- The bank is insured against many types of Operational Risk including (list not comprehensive):
 - Errors & Omissions for Professional Services
 - Property Damages
 - Crime (Fidelity, Premises, Computer, Forgery, In Transit)
 - Directors & Officers Liability
 - Employment Practices Liability
- Policies are mapped to loss event categories but do not cover the categories exhaustively
- Not all claims are accepted by insurance providers
- Counterparty risk is determined using PDs associated with each insurance provider

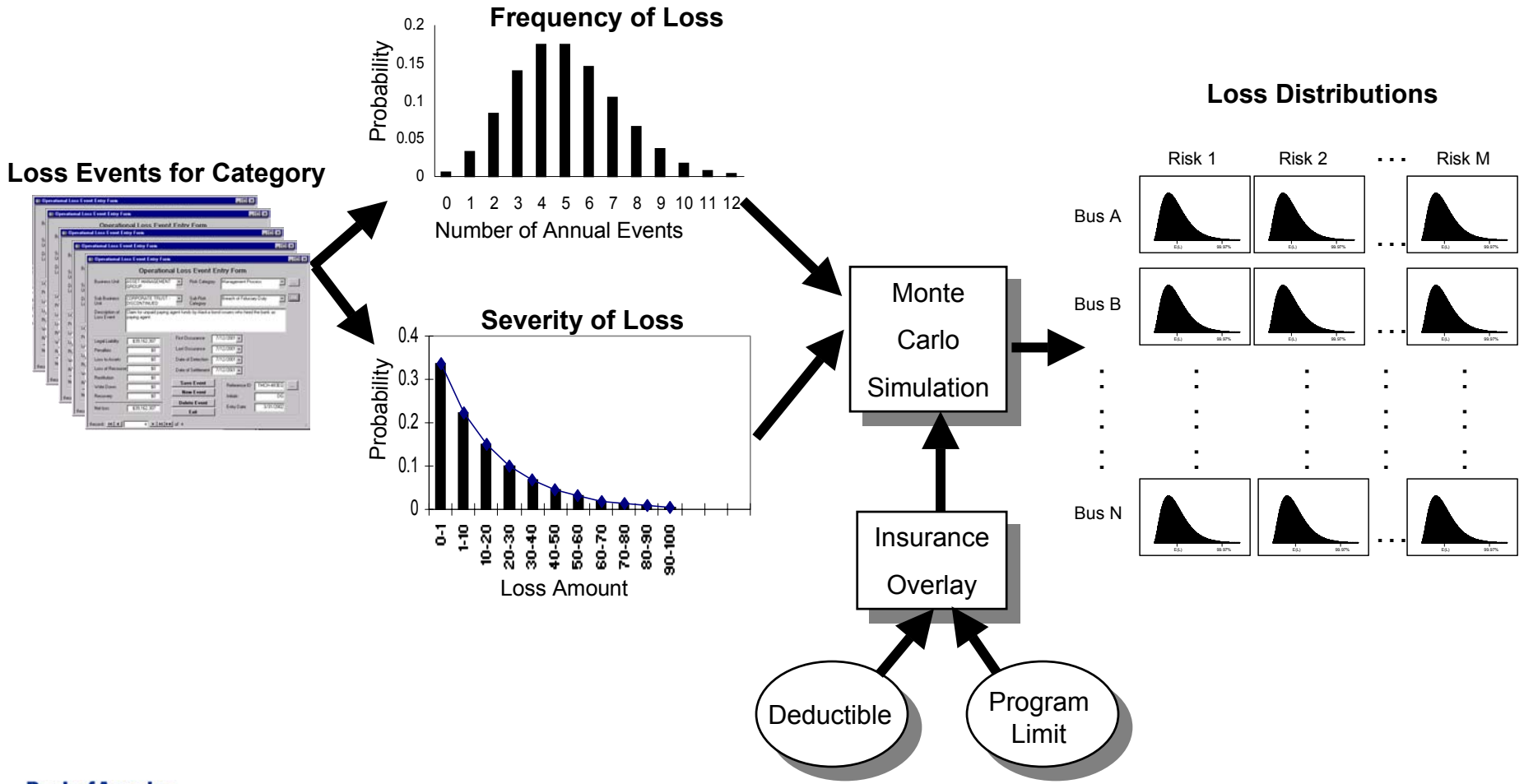
Probability of Insurance Payout

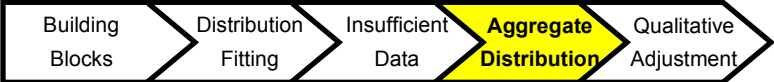
	Criminal	Management Process	Sales Practices	Unauthorized Activities	Transaction Processing	Human Resources	Disasters/ External
Deductible (\$ MM)	50	100	No Coverage	100	50	50	10
Limit (\$MM)	300	300		500	300	300	750
Probability of Coverage	80%	25%		20%	10%	90%	80%
Probability of Claim Acceptance	75%	75%		75%	75%	75%	75%
Probability of Insurer Default	0.84%	0.70%		0.70%	0.70%	0.60%	0.80%
Probability of Payout	59%	19%	0%	15%	7%	67%	60%



Calculating Operational Risk Capital

- Monte Carlo simulation generates aggregate loss distributions for each risk category and business ('n' categories x 'm' businesses)



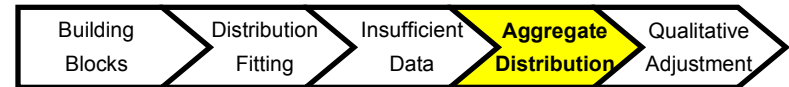


Expected Loss & Operational Risk Capital are Computed Separately for Each Category

Illustrative

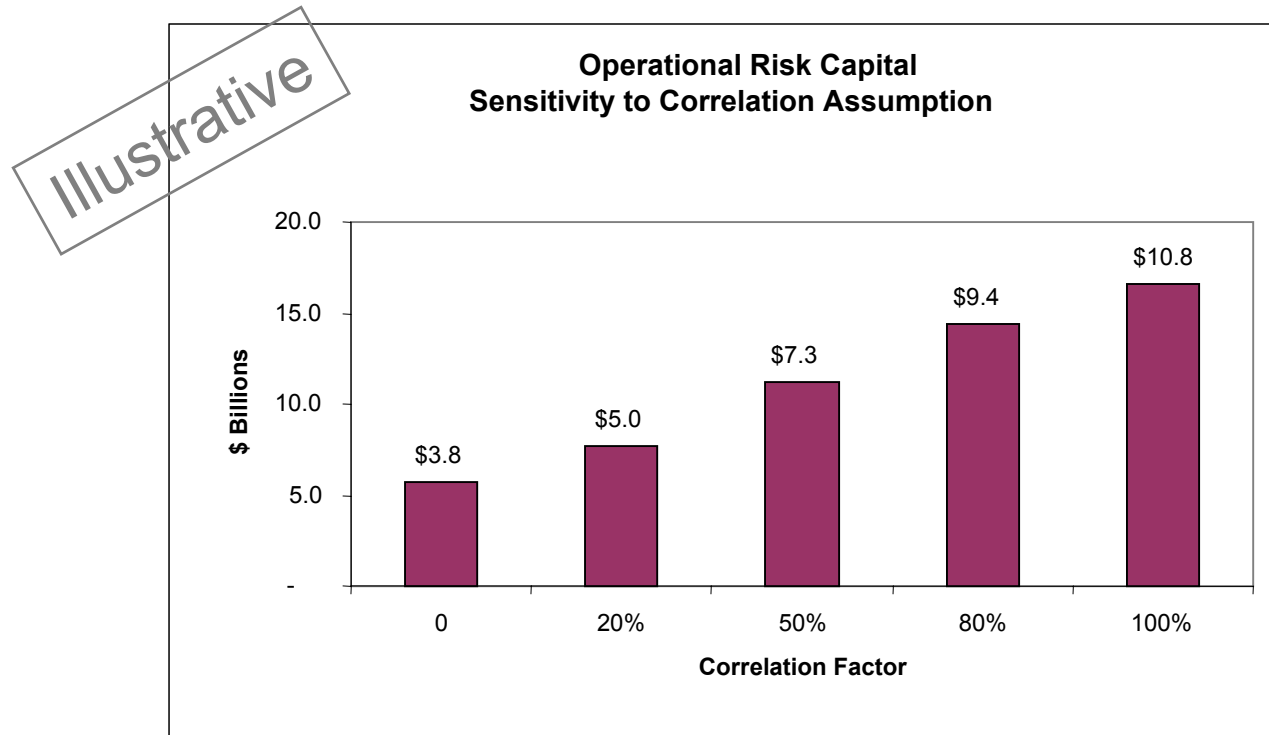
Business Unit		Criminal	Management Process	Transaction Processing	Human Resources	Sales Practices	Unauthorized Activities	Technology	External Disasters/Vendors	Undiversified Total
Business A	E(L)	90	10	10	50	5	5	50	15	235
	OpRisk Capital	750	600	75	100	250	30	100	125	2,030
Business B	E(L)	70	50	5	0	0	0	25	-	151
	OpRisk Capital	650	250	10	10	20	45	45	-	1,030
Business C	E(L)	40	1	10	1	0	0	10	-	63
	OpRisk Capital	55	25	150	25	25	20	30	-	330
Business D	E(L)	5	3	0	5	5	0	5	-	24
	OpRisk Capital	15	30	5	30	250	25	10	-	365
Business E	E(L)	5	1	0	0	0	0	5	-	11
	OpRisk Capital	200	5	5	2	25	30	10	-	277
Business F	E(L)	0	0	0	0	1	0	0	-	1
	OpRisk Capital	50	5	5	10	100	25	1	-	196
Business G	E(L)	4	0	0	5	0	0	0	-	10
	OpRisk Capital	10	10	10	10	50	5	1	-	97
Business H	E(L)	5	10	0	3	5	0	5	-	28
	OpRisk Capital	500	300	30	40	951	40	70	-	1,930
Business I	E(L)	5	3	0	0	2	0	1	-	12
	OpRisk Capital	250	150	35	40	170	35	35	-	715
Business J	E(L)	1	1	0	0	2	1	1	-	6
	OpRisk Capital	200	100	40	50	75	250	50	-	765
Business K	E(L)	1	3	0	5	2	1	5	-	17
	OpRisk Capital	250	450	75	75	60	225	50	-	1,185
Business L	E(L)	5	1	0	0	0	0	5	-	12
	OpRisk Capital	400	150	50	40	45	100	50	-	835
Business M	E(L)	1	0	0	1	0	0	5	-	8
	OpRisk Capital	180	30	10	25	25	35	50	-	355
Business N	E(L)	10	3	0	1	0	0	2	-	16
	OpRisk Capital	25	15	15	40	1	30	5	-	132
Business O	E(L)	1	0	0	0	-	1	3	-	5
	OpRisk Capital	180	25	45	50	-	250	10	-	560
Undiversified Total	E(L)	243	86	27	73	22	12	122	15	600
	OpRisk Capital	3,715	2,145	560	546	2,047	1,145	517	125	10,800





Diversification Effects

- Diversification must be considered to avoid over estimating capital requirements
- The value for correlation between loss events is determined qualitatively
- Correlation is clearly less than 100% - the worst case scenario will not occur simultaneously for every causal type and business unit
- However, assuming independence may be too generous (particularly for technology)

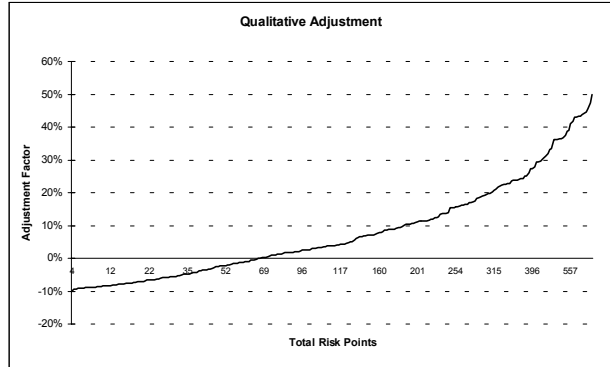
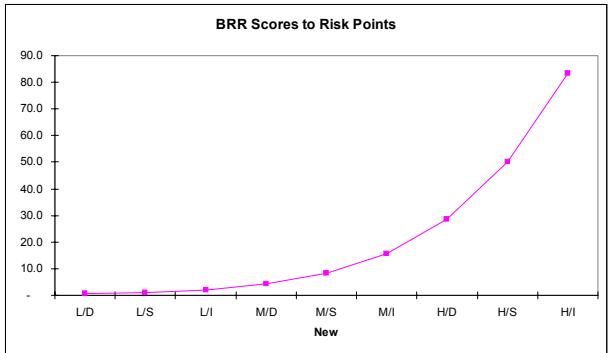
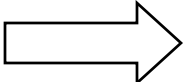


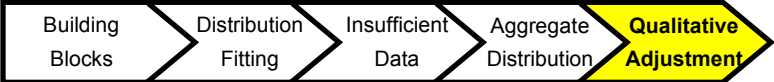
Qualitative Adjustment

- Qualitative adjustments to the LDA results should reflect current rather than historical operating environment
- Self assessment ratings are translated into risk points using an exponential function
- Translation of ratings to risk points is a policy variable and may be changed to meet risk management objectives

Illustrative

Self Assessment Rating (Residual Risk/Direction of Residual Risk)	Risk Points
Low / Decreasing	0.5
Low / Stable	1.0
Low / Increasing	2.0
Medium / Decreasing	4.0
Medium / Stable	8.0
Medium / Increasing	16.0
High / Decreasing	29.0
High / Stable	50.0
High / Increasing	83.0

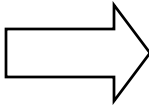
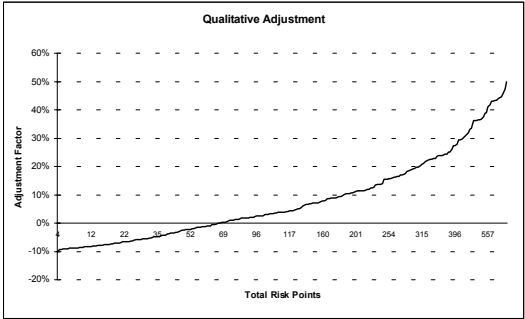
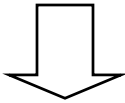




Application of the Qualitative Adjustment

Illustrative

Operational Risk Factors								
	Reputation	People	Processing	Technology	Legal	Regulatory	Execution	External Factors
Inherent Risk	L	L	H	M	M	M	M	H
Quality of Processes & Controls	L	M	M	M	M	M	M	L
Residual Risk	L	M	H	M	M	M	M	M
Direction of Residual Risk	S	S	S	S	S	I	S	S
Overall Self-Assessment	L/S	M/S	H/S	M/S	M/S	M/I	M/S	M/S
Risk Points	1	8	50	8	8	16	8	8
Total Risk Points =								107



Qualitative Adjustment Factor
+4%

Concluding Comments

- Compiling loss event database was time consuming but feasible
- Significant progress developing fitting process for internal data, goodness of fit measures, and selection criteria for LDA models
- Use of external data and/or scenario analysis is unavoidable necessitating a hybrid approach
- Methodology for utilizing external data continues to evolve
- Early stages of scenario analysis - evaluation of where to apply the approach next
- Calibration of qualitative adjustments remains a work in progress