

A man in a white shirt and blue tie stands with his left hand on his hip and his right hand holding a glowing, golden sphere. The background is a soft-focus collage of digital and data-related elements, including binary code (0s and 1s), various symbols like '@', '#', and 'z', a globe, and a bar chart. The overall color palette is dominated by blues, greens, and yellows, creating a futuristic and data-driven atmosphere.

An Integrated Framework for Measuring and Managing Operational Risk

Ali Samad-Khan

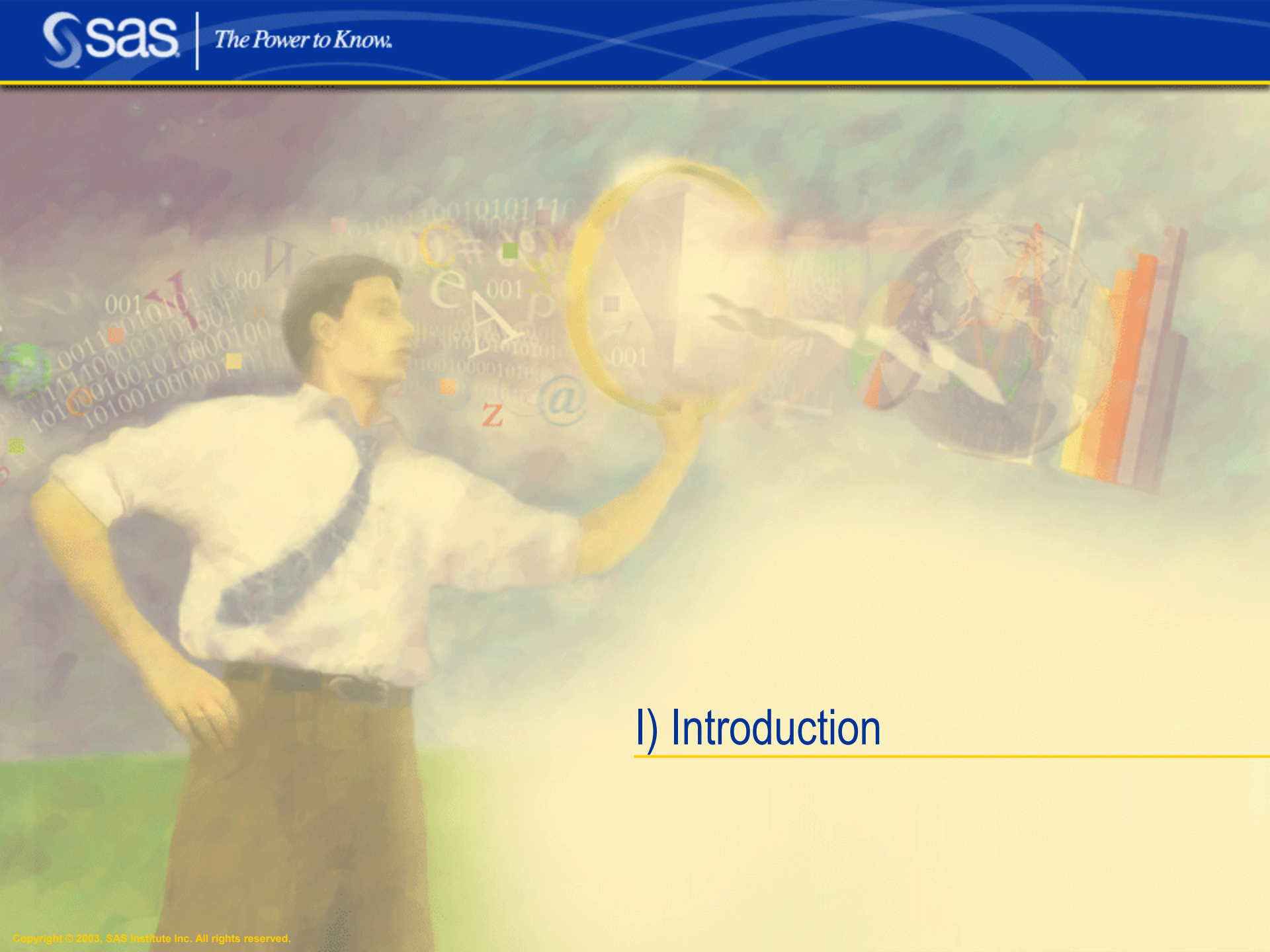
Head of Global Operational Risk Strategy

ERM Symposium, Chicago

April 27, 2004

Agenda

- I Introduction
- II A Viable AMA Framework
- III Data Issues
- IV Quantification Issues
- V Issues with CSA and Indicators



I) Introduction

What are the goals and objectives of an integrated operational risk measurement - management program?

- Identify and Define the full spectrum of operational risks
- Measure/Assess the magnitude of these risks
- Determine how well these risks are being managed and controlled
- Learn which factors drive change in risks and controls
- Optimize risk-control relationship

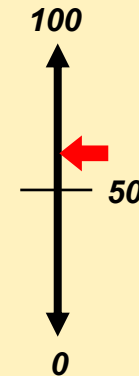
At the most fundamental level managing operational risk involves understanding ones risks and how well they are being controlled

RISKS



Measured in terms of
Financial Exposure

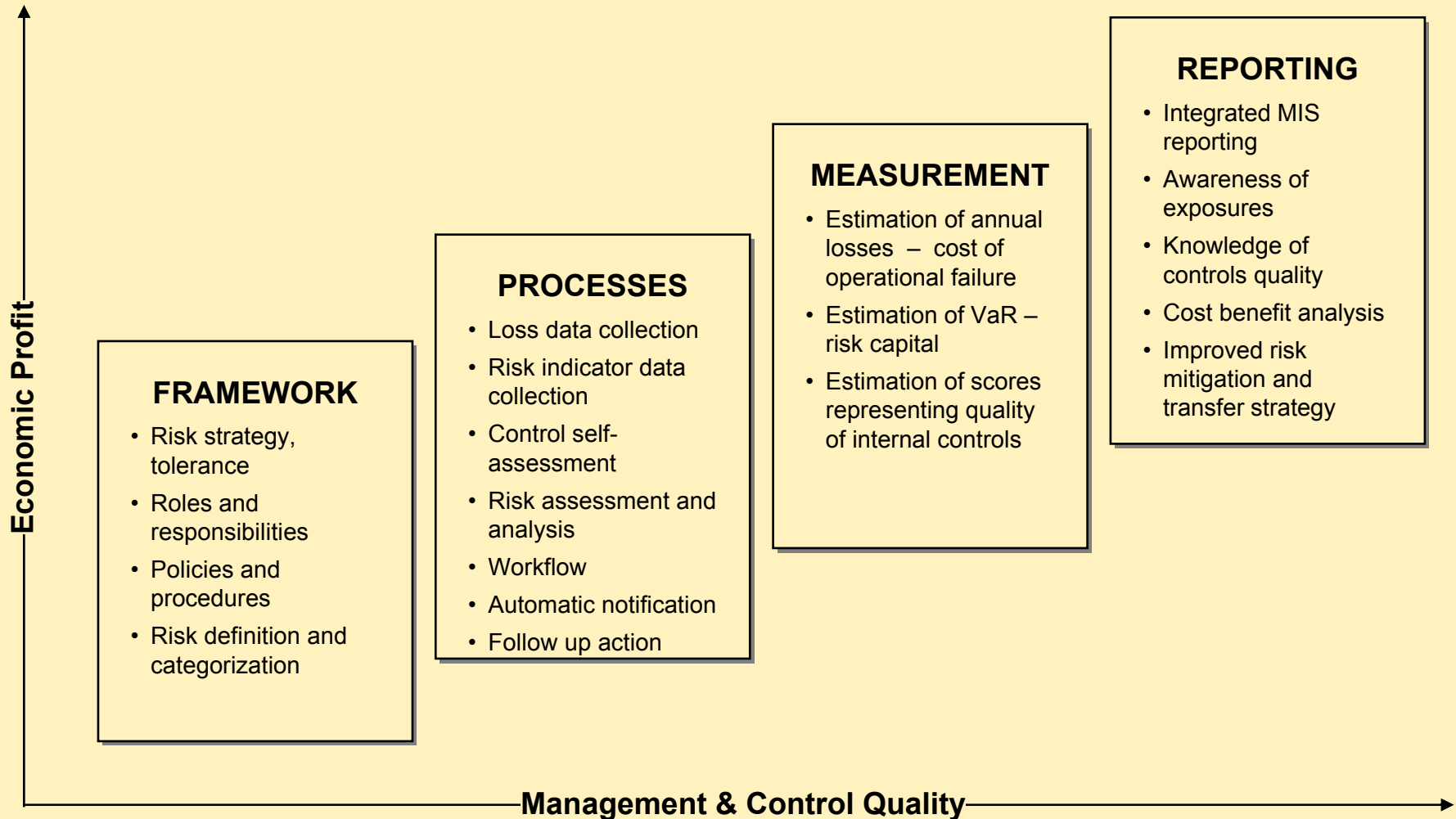
CONTROLS



Measured in terms of
Quality of Control Scores

Controls are Optimized Through Cost Benefit Analysis

There are four fundamental steps to managing operational risk, with each step leading to improvements in management & control quality and greater economic profit



What does operational risk include?

Transaction

Execution

Settlement

Technological

Inadequate Supervision

Information

Key Man

Lack of Resources

Reputation

Relationship

Theft

Criminal

Insufficient Training

People

Fraud

Rogue Trader

Compliance

Legal/Regulatory

Fiduciary

Physical Assets

Poor Management

Fixed Cost Structures

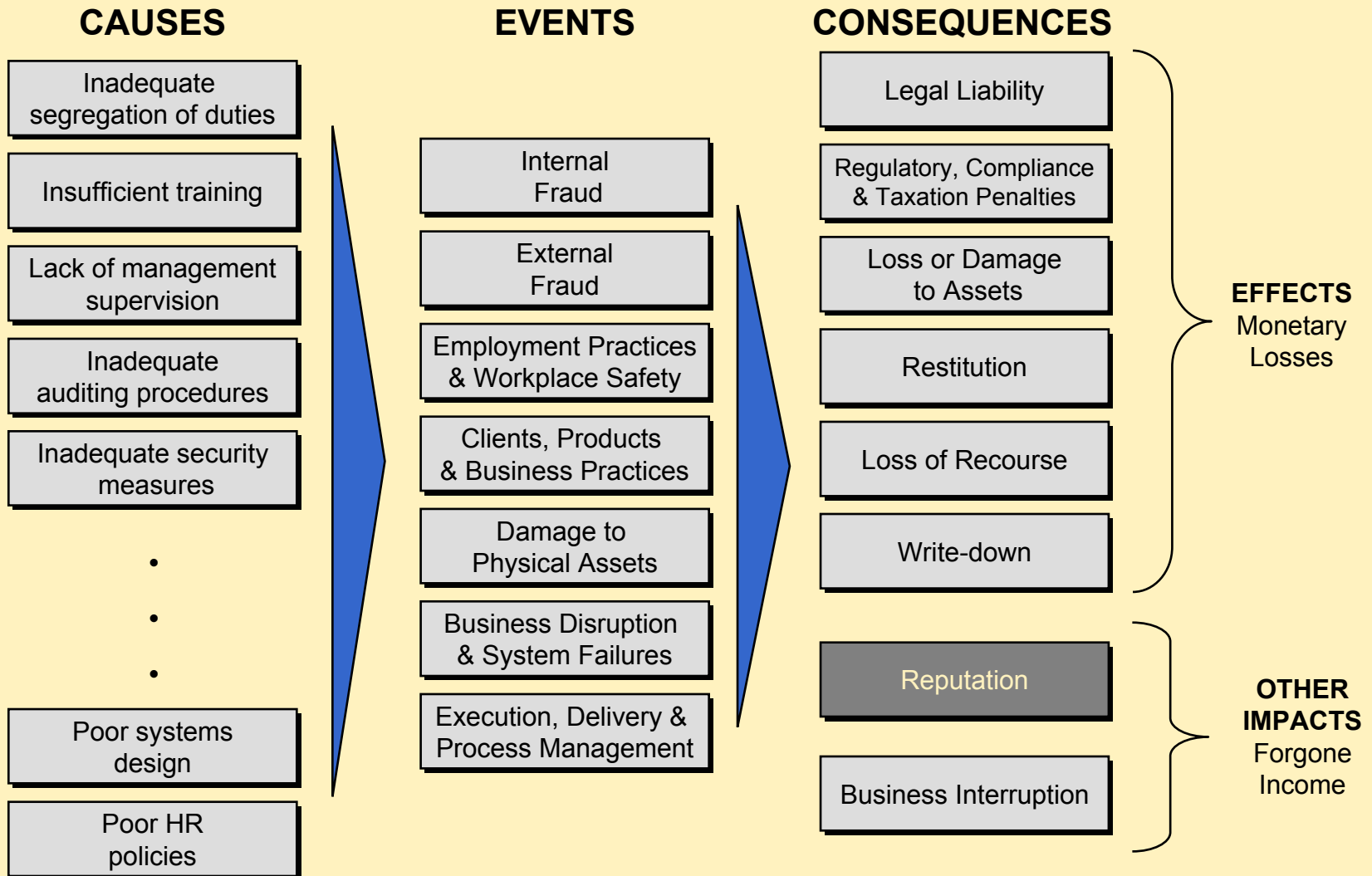
Customer

Business

Business Interruption

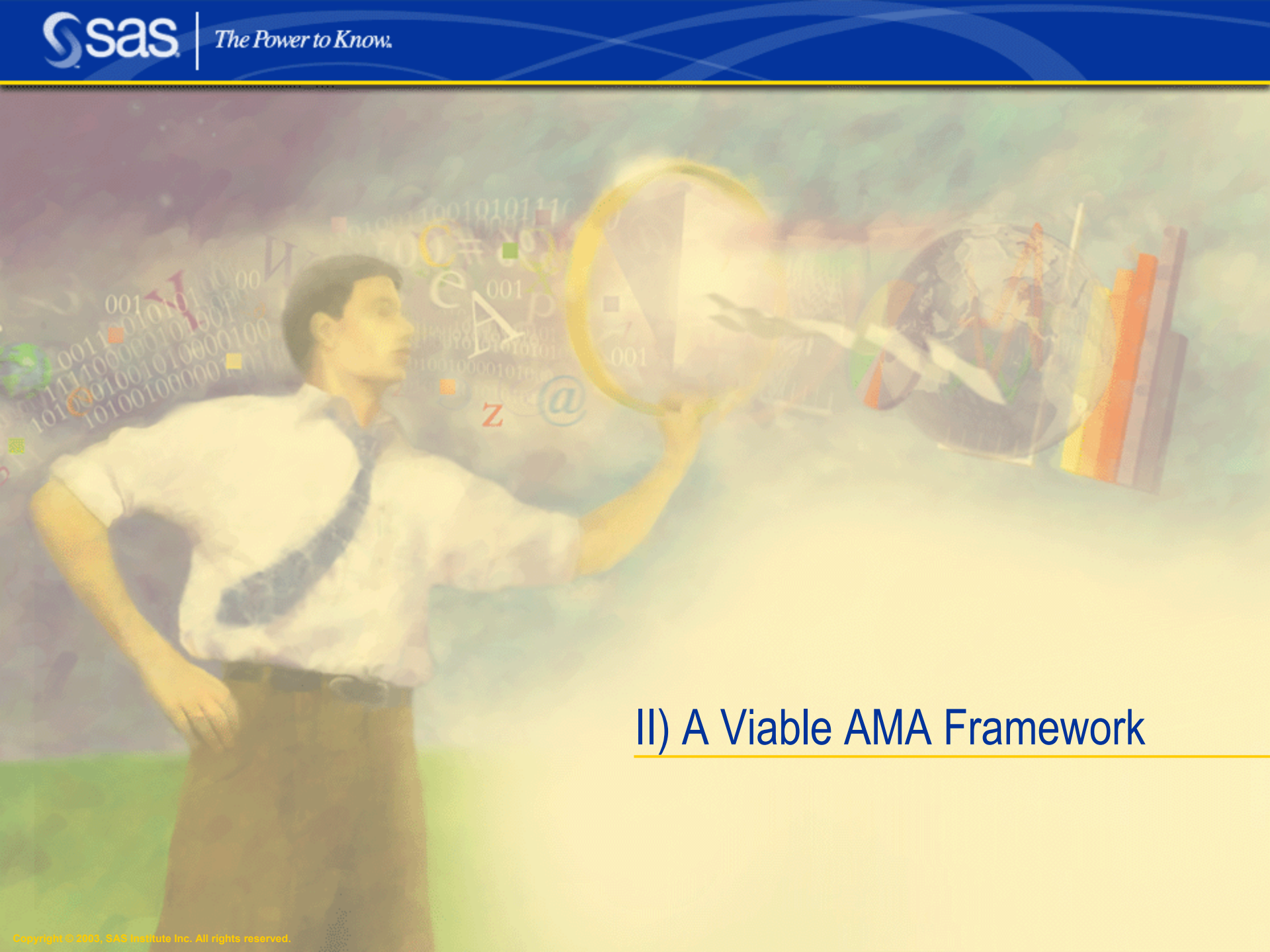
Strategic

The universe of operational risks spans causes, events and consequences



Placing loss data within a Business Line/Risk matrix helps reveal the risk profile of each business

		INTERNAL FRAUD	EXTERNAL FRAUD	EMPLOYMENT PRACTICES & WORKPLACE SAFETY	CLIENTS, PRODUCTS & BUSINESS PRACTICES	DAMAGE TO PHYSICAL ASSETS	EXECUTION, DELIVERY & PROCESS MANAGEMENT	BUSINESS DISRUPTION AND SYSTEM FAILURES	TOTAL
Corporate Finance	Number	362	123	25	36	33	150	2	731
	Mean	35,459	52,056	3,456	56,890	56,734	1,246	89,678	44,215
	Standard Deviation	5,694	8,975	3,845	7,890	3,456	245	23,543	6,976
Trading & Sales	Number	50	4	35	50	46	210	3	398
	Mean	53,189	78,084	5,184	85,335	85,101	1,869	134,517	66,322
	Standard Deviation	8,541	13,463	5,768	11,835	5,184	368	35,315	10,464
Retail Banking	Number	45	4	32	45	42	189	3	360
	Mean	47,870	70,276	4,666	76,802	76,591	1,682	121,065	59,690
	Standard Deviation	7,687	12,116	5,191	10,652	4,666	331	31,783	9,417
Commercial Banking	Number	41	3	28	41	37	170	2	322
	Mean	43,083	63,248	4,199	69,121	68,932	1,514	108,959	53,721
	Standard Deviation	6,918	10,905	4,672	9,586	4,199	298	28,605	8,476
Payment & Settlements	Number	37	3	26	37	34	153	2	292
	Mean	38,774	56,923	3,779	62,209	62,039	1,363	98,063	48,349
	Standard Deviation	6,226	9,814	4,205	8,628	3,779	268	25,744	7,628
Agency Services	Number	44	4	31	44	40	184	2	349
	Mean	46,529	68,308	4,535	74,651	74,446	1,635	117,675	58,018
	Standard Deviation	7,472	11,777	5,045	10,353	4,535	321	30,893	9,154
Asset Management	Number	40	3	28	40	36	165	2	314
	Mean	41,876	61,477	4,081	67,186	67,002	1,472	105,908	52,217
	Standard Deviation	6,725	10,599	4,541	9,318	4,081	289	27,804	8,238
Retail Brokerage	Number	48	4	33	48	44	198	3	378
	Mean	50,252	73,773	4,898	80,623	80,402	1,766	127,090	62,660
	Standard Deviation	8069	12719	5449	11182	4898	347	33365	9886
Insurance	Number	43	4	30	43	39	179	2	340
	Mean	45,226	66,395	4,408	72,561	72,362	1,589	114,381	56,394
	Standard Deviation	7,262	11,447	4,904	10,063	4,408	312	30,028	8,897
Total	Number	710	152	268	384	351	1,598	21	3,484
	Mean	45,653	67,021	4,450	73,245	73,044	1,604	115,459	56,926
	Standard Deviation	7,331	11,555	4,950	10,158	4,450	315	30,311	8,981



II) A Viable AMA Framework

Using internal and external loss data can calculate Value at Risk

INDIVIDUAL LOSS EVENTS

RISK MATRIX FOR LOSS DATA

LOSS DISTRIBUTIONS

VAR CALCULATION

TOTAL LOSS DISTRIBUTION



74,712,345
74,603,709
74,457,745
74,345,957
74,344,576

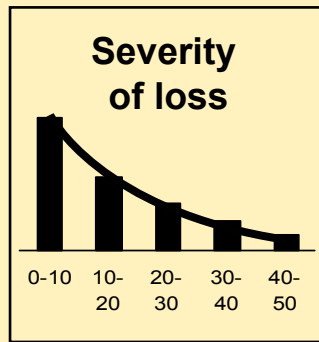
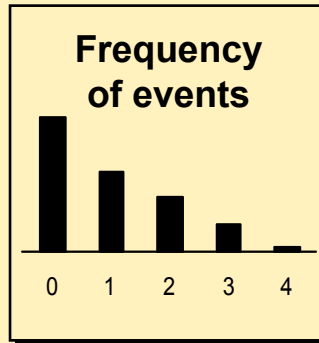
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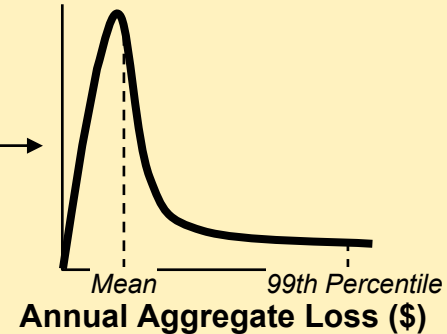
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167,245
142,456
123,345
113,342
94,458

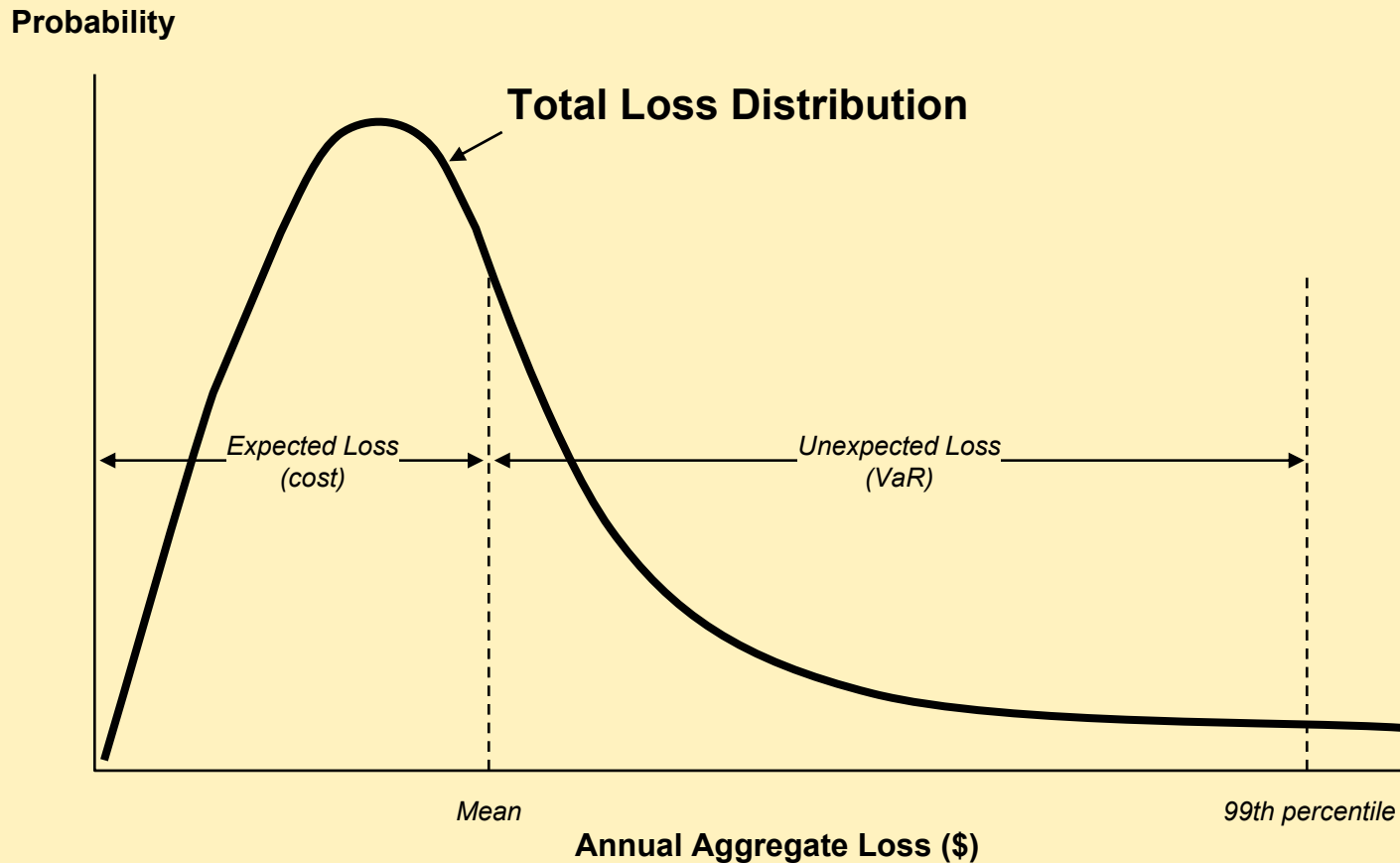
		INTERNAL EVENTS	EXTERNAL EVENTS	EMPLOYMENT INVESTORS & POLICYHOLDERS	CLIENTS PRODUCERS & BROKERS	DAMAGE TO PROPERTY & PUBLIC	SECURITY BREACHS & OPERATIONAL MANAGEMENT	BUSINESS REPUTATION & FINANCIAL	TOTAL
Corporate Events	Number	10	10	10	10	10	10	10	10
	Mean	10,000	10,000	10,000	10,000	10,000	10,000	10,000	10,000
Trading & Sales	Number	10	10	10	10	10	10	10	10
	Mean	10,000	10,000	10,000	10,000	10,000	10,000	10,000	10,000
Underwriting	Number	10	10	10	10	10	10	10	10
	Mean	10,000	10,000	10,000	10,000	10,000	10,000	10,000	10,000
Commercial Activity	Number	10	10	10	10	10	10	10	10
	Mean	10,000	10,000	10,000	10,000	10,000	10,000	10,000	10,000
Regulatory & Substantives	Number	10	10	10	10	10	10	10	10
	Mean	10,000	10,000	10,000	10,000	10,000	10,000	10,000	10,000
Agency Services	Number	10	10	10	10	10	10	10	10
	Mean	10,000	10,000	10,000	10,000	10,000	10,000	10,000	10,000
Other Management	Number	10	10	10	10	10	10	10	10
	Mean	10,000	10,000	10,000	10,000	10,000	10,000	10,000	10,000
Other Brokerage	Number	10	10	10	10	10	10	10	10
	Mean	10,000	10,000	10,000	10,000	10,000	10,000	10,000	10,000
Other	Number	10	10	10	10	10	10	10	10
	Mean	10,000	10,000	10,000	10,000	10,000	10,000	10,000	10,000
Total	Number	10	10	10	10	10	10	10	10
	Mean	10,000	10,000	10,000	10,000	10,000	10,000	10,000	10,000



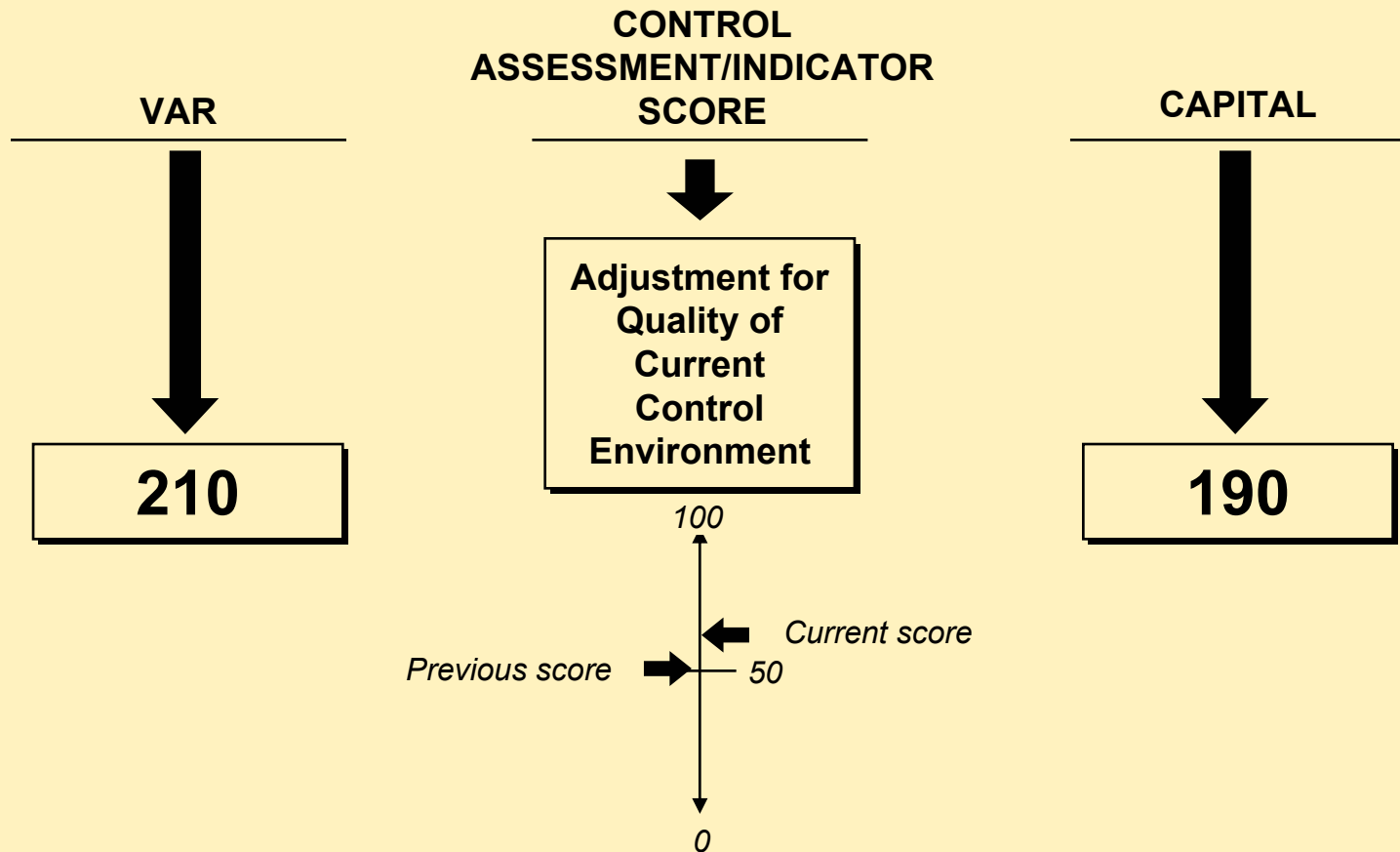
VaR Calculator
e.g.,
Monte Carlo
Simulation
Engine



Definitions: The expected loss is the mean annual aggregate loss and unexpected loss represents the volatility above this mean at a specified confidence level



Composite control assessment/indicator scores can be used to modify capital figures

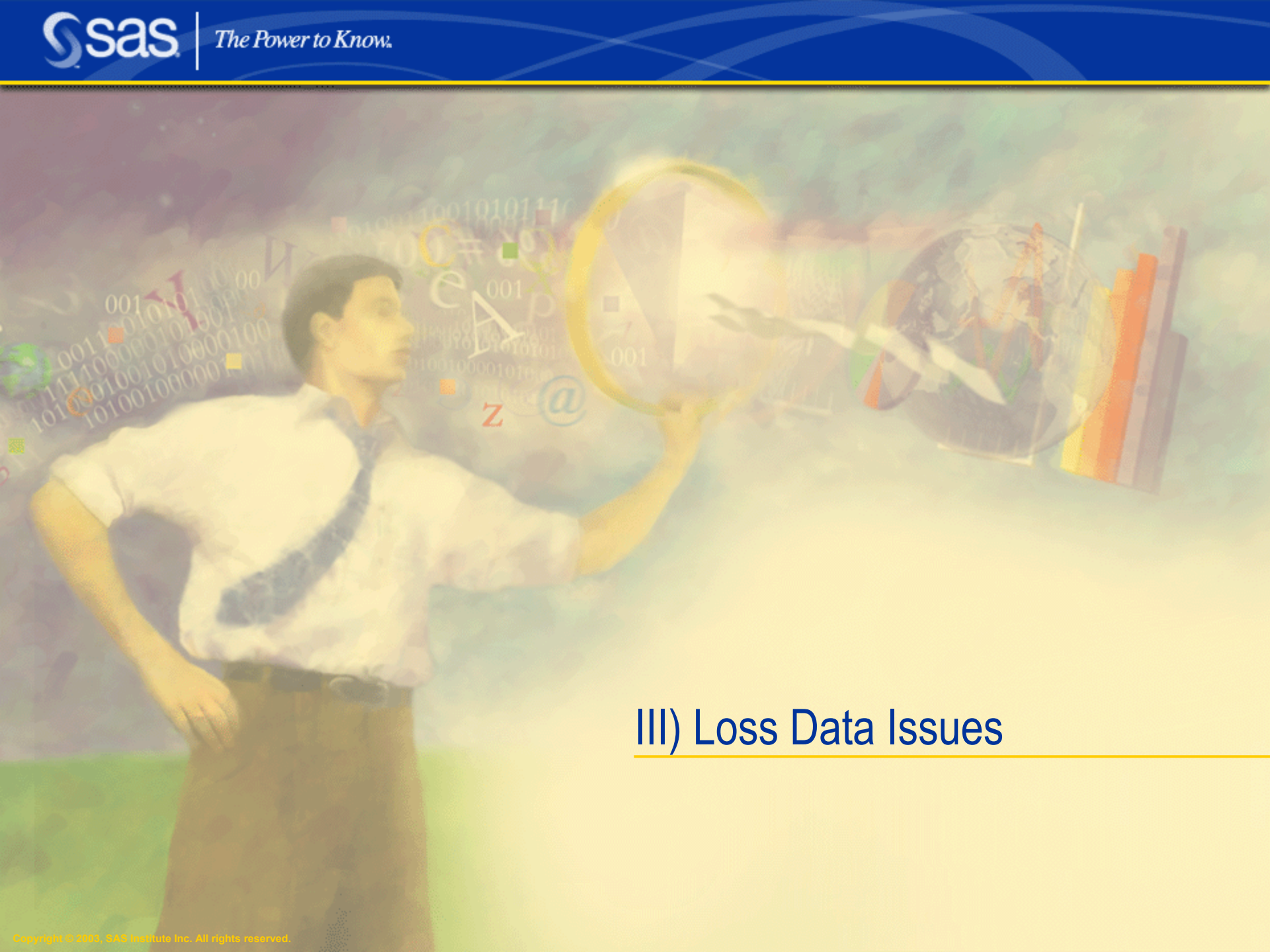


Linking capital to changes in the quality of internal controls provides an incentive for desired behavioral change

Adjustments to capital take place at the cell level, based on the change in composite control scores

RISK MATRIX FOR CAPITAL

		INTERNAL FRAUD	EXTERNAL FRAUD	EMPLOYMENT PRACTICES & WORKPLACE SAFETY	CLIENTS, PRODUCTS & BUSINESS PRACTICES	DAMAGE TO PHYSICAL ASSETS	EXECUTION, DELIVERY & PROCESS MANAGEMENT	BUSINESS DISRUPTION AND SYSTEM FAILURES	TOTAL
Corporate Finance	Previous VaR	21,000,000	36,000,000	62,000,000	75,000,000	124,000,000	86,000,000	36,000,000	362,000,000
	Prev/Current Score	50 55	60 58	75 71	61 61	45 55	50 52	50 55	50 55
	Final Capital	19,000,000	35,000,000	65,000,000	75,000,000	104,000,000	83,000,000	32,000,000	326,000,000



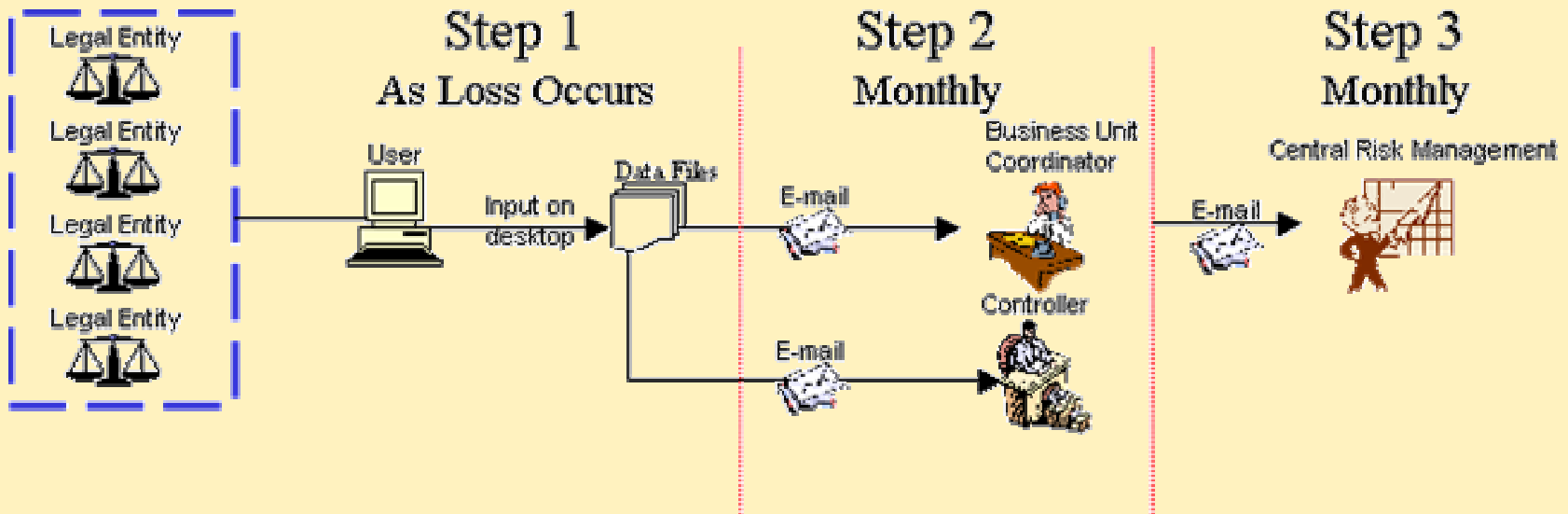
III) Loss Data Issues

Three sources of loss data may be considered

- **Internal Data** – data drawn directly from the entity whose risk is being measured; this is the most relevant data set, but such data is generally insufficient for most modeling and statistical analysis purposes because of the small sample size
- **External Pooled Data** – public and non-public data drawn from a loss data sharing consortium; this data is less relevant than internal data, but offers larger sample allowing for more accurate modeling/statistical analysis
- **External Public Data** – data drawn from public sources; less relevant than internal data, contains a larger set of “tail events,” but subject to numerous biases – so cannot be used directly for modeling.

While one would expect that consortium data will eventually prove to be more useful than external public data, this will only be true if these initiatives reach critical mass and the data is honestly reported and consistently categorized

A formal process for collecting loss event data must be implemented



Loss data needs to be adjusted for inflation and scaled for size

Inflation adjustment:

\$10 million loss in 1990 = \$12.4 million loss in 2001

Scale Adjustment:

\$10 million loss when a \$2 billion (revenue) bank = \$13.2 million loss when a \$6 billion bank¹

$$ScaledLoss = L_{DB} \left(\frac{R_{cur}}{R_{pre}} \right)^n$$

L_{DB} = Actual Loss experienced by bank

R_{cur} = Current Revenue of bank

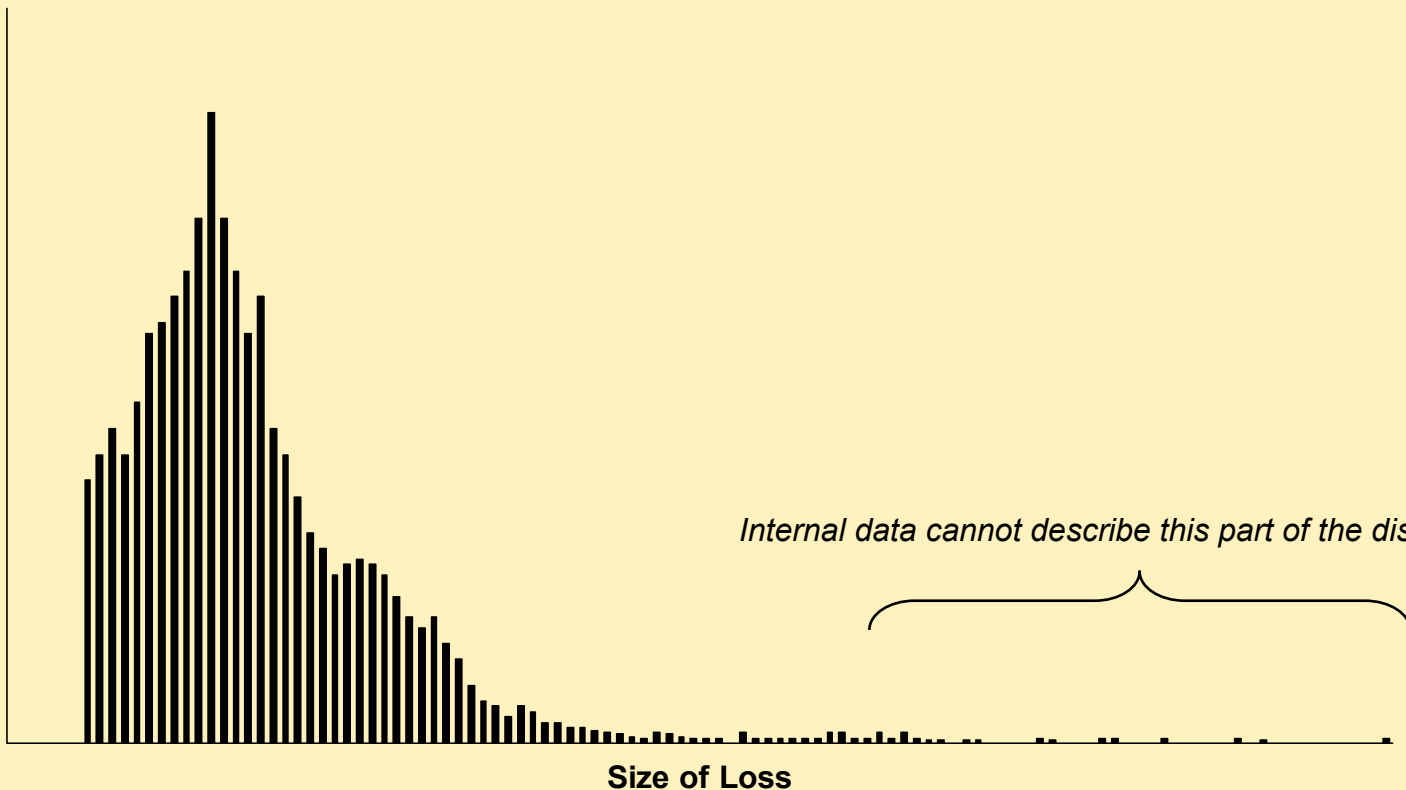
R_{pre} = Previous Revenue of bank

n = Scaling co-efficient determined by regression analysis

³Shih, J., A. Samad-Khan and P. Medapa, "Is the Size of an Operational Loss Related to Firm Size," *Operational Risk* (January 2000)

Internal data generally does not contain a sufficient number of the tail events to accurately describe that part of the distribution, therefore one needs to supplement internal data with external data

Number of Events



There are several data issues to address in modeling operational value at risk

- Internal data is the most relevant source of information for measuring operation risk, but it is generally insufficient
- Internal and external data come from fundamentally different distributions and therefore cannot be merged directly
- All operational loss data is collected above a threshold level, making it difficult to estimate parameters for modeling
- Operational loss data are not well represented by traditional two parameter severity distributions, such as the Lognormal or Weibull. Kurtosis (in log terms) ranges from 3-7.
- External data comes from so many diverse institutions, with differing sizes, cultures, risk appetites, control structures, procedures and business mixes that very little of this loss data can be relevant to a given institution

How can external data be relevant to my bank?

- **Size Bias** – Larger institutions (and businesses) are likely to experience more losses than smaller institutions. These institutions are also likely to suffer larger losses.
- **Control Bias** – Institutions with weak controls are more likely to be represented in the database because they experience more losses. These institutions are also likely to suffer more large losses than well controlled institutions.
- **Institutional Culture Bias** – More aggressive institutions (and businesses) are likely to experience more losses than less aggressive institutions. These institutions are also likely to suffer larger losses.
- **Infrastructure/Technology Bias** – Less technologically advanced institutions (and businesses) are likely to experience more losses than more advanced institutions. These institutions are also likely to suffer larger technology losses.
- **Media Bias** – Large losses more likely to be reported than small losses.
- **Legal Environment Bias** – The legal system in certain countries may lead to more frequent and/or larger losses.

The only severity information one can obtain from external public data is relative information (model transferability) – assuming the biases are consistent across all categories

**EXTERNAL
EVENT RISK MATRIX
SEVERITY PARAMETERS IN LOG TERMS**

		INTERNAL FRAUD	EXTERNAL FRAUD	EXECUTION, DELIVERY & PROCESS MANAGEMENT
Corporate Finance	Number	362	123	150
	Mean	9	6	6
	Standard Deviation	6	4	2

**EXTERNAL
EVENT RISK MATRIX
SEVERITY PARAMETERS IN RELATIVE TERMS**

		INTERNAL FRAUD	EXTERNAL FRAUD	EXECUTION, DELIVERY & PROCESS MANAGEMENT
Corporate Finance	Number	362	123	150
	Mean	1.5	1	1
	Standard Deviation	3	2	1

Using the pivot cell and relative parameter ratios from external data we can estimate severity parameter for all cells in a business line

INITIAL INTERNAL EVENT RISK MATRIX

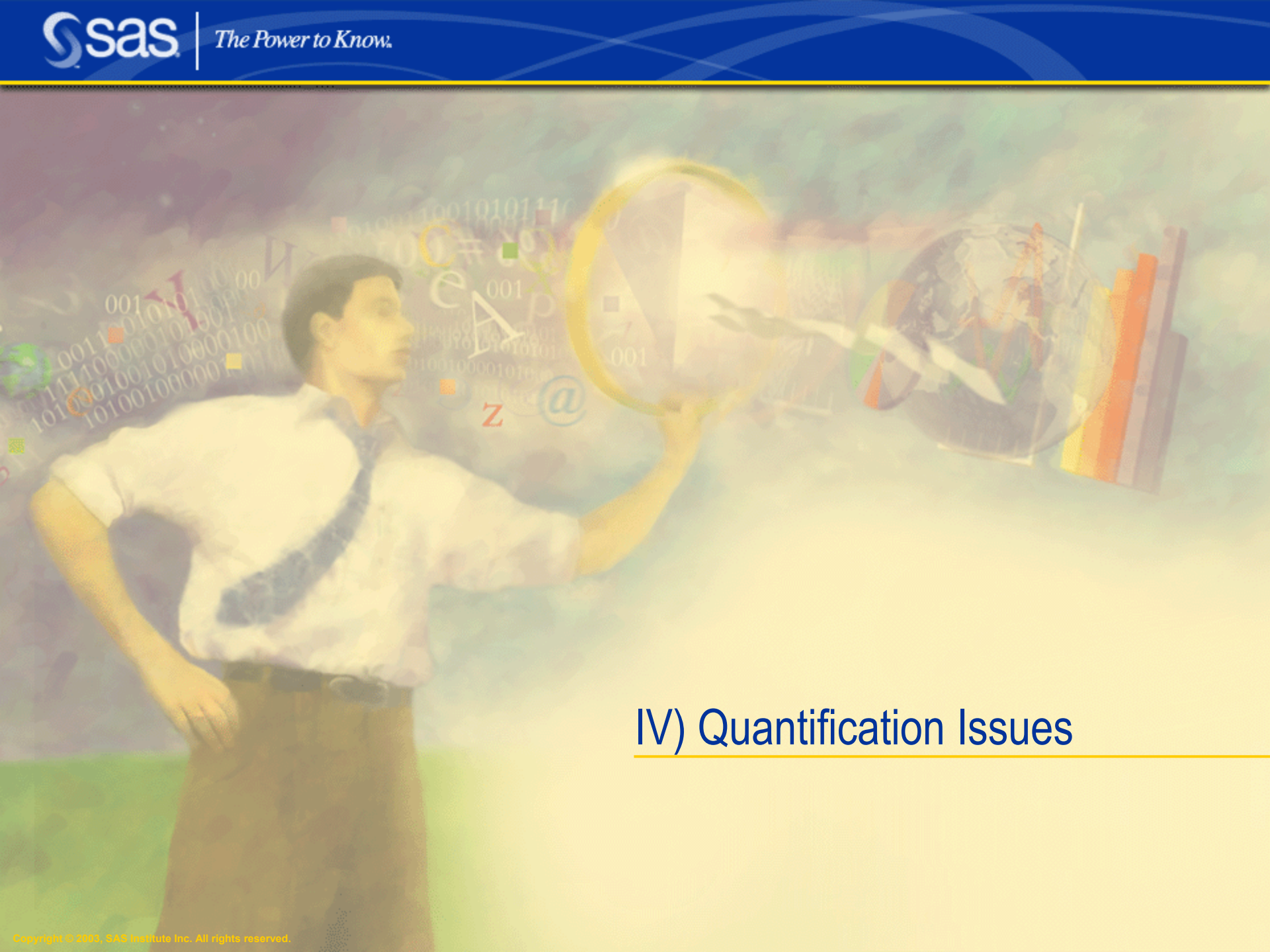
		INTERNAL FRAUD	EXTERNAL FRAUD	EMPLOYMENT PRACTICES & WORKPLACE SAFETY	CLIENTS, PRODUCTS & BUSINESS PRACTICES	DAMAGE TO PHYSICAL ASSETS	EXECUTION, DELIVERY & PROCESS MANAGEMENT	BUSINESS DISRUPTION AND SYSTEM FAILURES	TOTAL
Corporate Finance	Number						234		
	Mean						3		
	Standard Deviation						2		

PARAMETER RATIOS FROM EXTERNAL EVENT RISK MATRIX

		INTERNAL FRAUD	EXTERNAL FRAUD	EMPLOYMENT PRACTICES & WORKPLACE SAFETY	CLIENTS, PRODUCTS & BUSINESS PRACTICES	DAMAGE TO PHYSICAL ASSETS	EXECUTION, DELIVERY & PROCESS MANAGEMENT	BUSINESS DISRUPTION AND SYSTEM FAILURES	TOTAL
Corporate Finance	Number								
	Mean	1.5	1				1		
	Standard Deviation	3	2				1		

FINAL INTERNAL EVENT RISK MATRIX

		INTERNAL FRAUD	EXTERNAL FRAUD	EMPLOYMENT PRACTICES & WORKPLACE SAFETY	CLIENTS, PRODUCTS & BUSINESS PRACTICES	DAMAGE TO PHYSICAL ASSETS	EXECUTION, DELIVERY & PROCESS MANAGEMENT	BUSINESS DISRUPTION AND SYSTEM FAILURES	TOTAL
Corporate Finance	Number						234		
	Mean	4.5	3				3		
	Standard Deviation	6	4				2		



IV) Quantification Issues

Determining the most appropriate severity distribution

Severity has been observed to have a Kurtosis (in log terms) in the range of 3-7. This suggests that using a log normal distribution would understate VAR, whereas using a Weibull distribution would overstate VAR.

Distribution fitting through MLE – *Maximum Likelihood Estimation*: A process for directly estimating the density function which maximizes the likelihood (probability) of fitting the empirical data across the entire range of losses:

Lognormal-Gamma

Lognormal

Burr

Generalized Pareto

Weibull

Exponential

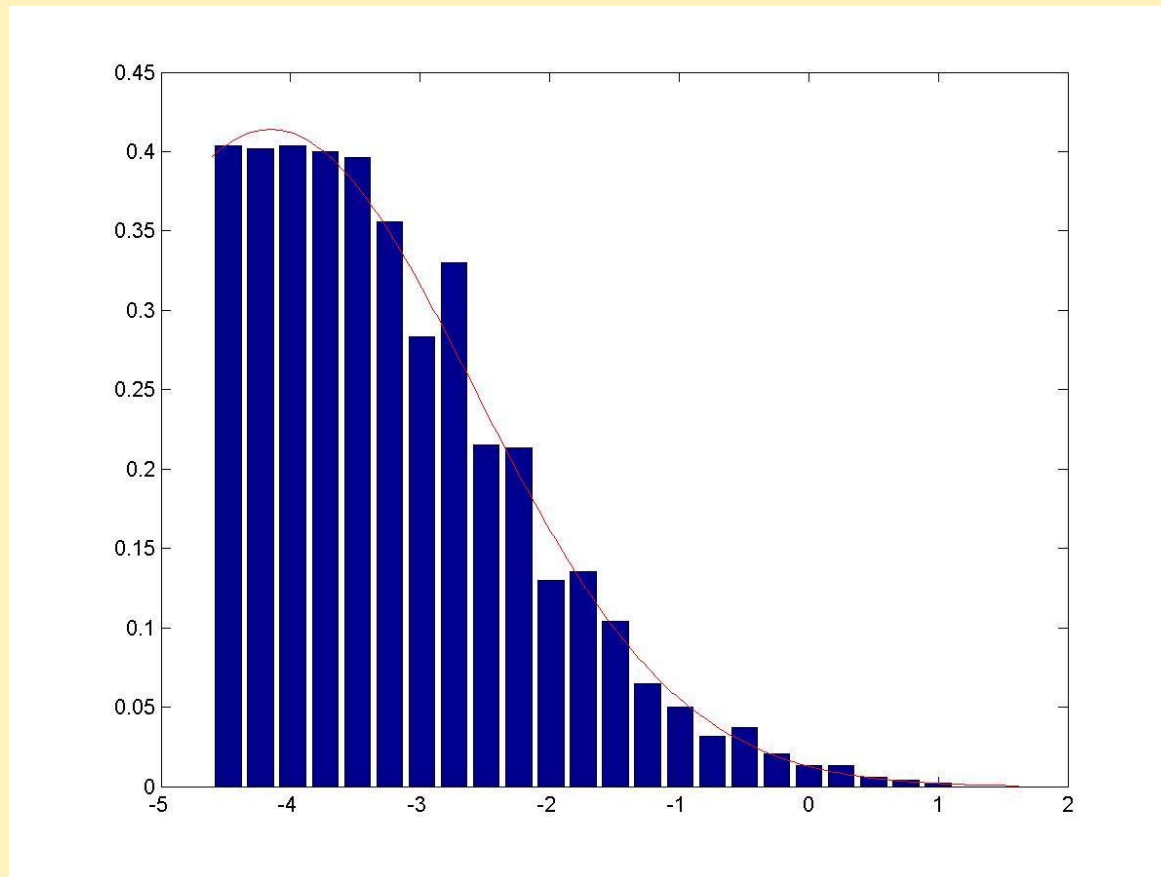
Several “goodness of fit” tests have been designed to help determine which theoretical distribution best represents the empirical data

PARAMETERS	Lognormal	Lognormal Gamma	Burr	GPD	Weibull
α	-4.320	-4.253	2.018	0.029	0.005
β	1.870	1.618	0.046	-0.678	0.183
γ		3.326	0.832		
TEST					
Anderson Darling	0.465	0.255	0.331	0.432	2.949
Kalmogorov-Smirnov	0.034	0.016	0.029	0.045	0.284
Chi Squared	18.341	11.114	14.318	19.467	228.345

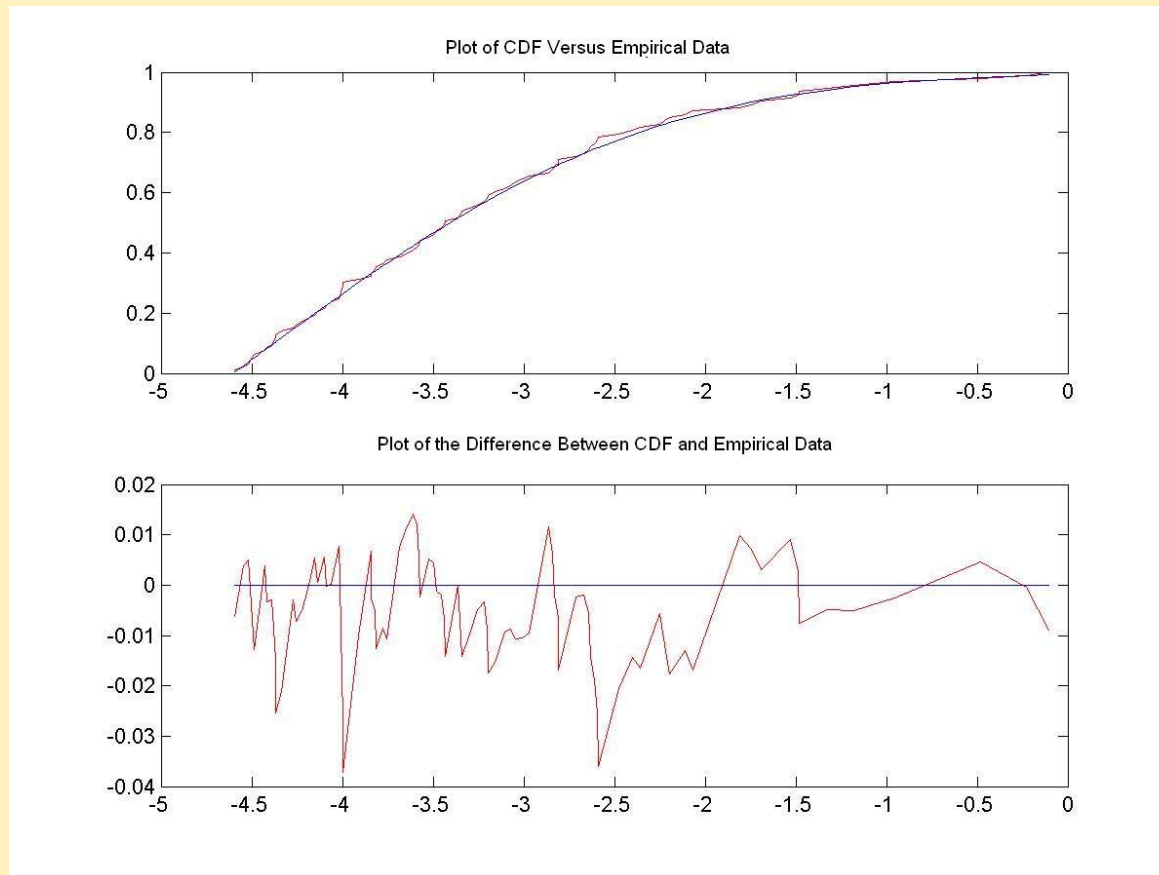
KS @ 20% Significance 0.0312

Losses represented in log terms (millions)

Goodness of fit results can also be viewed in graphical format (PDF vs Empirical Histogram)



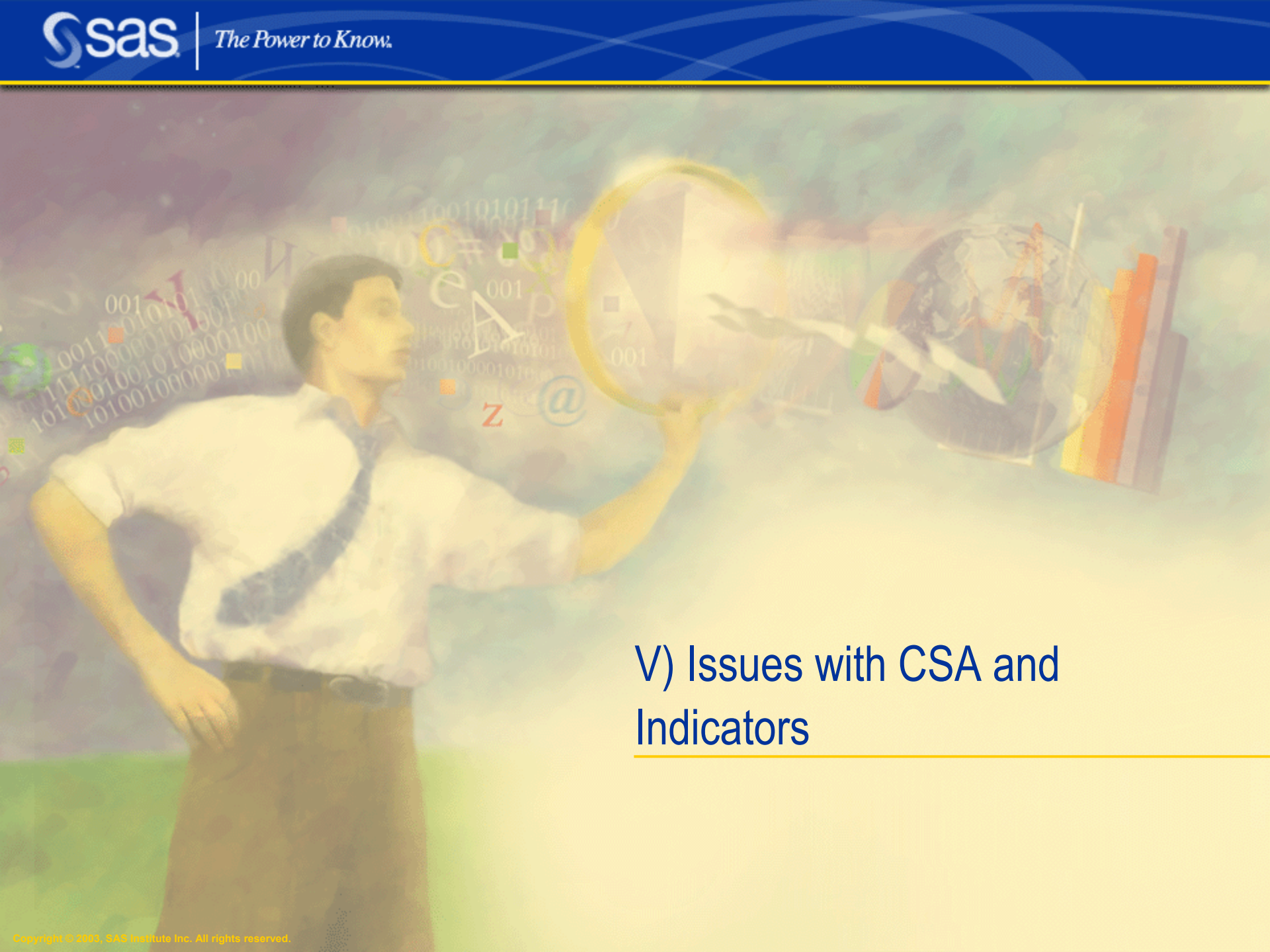
Goodness of fit results can also be viewed in graphical format (CDF and CDF Differences)



VaR results can be calculated at different confidence levels

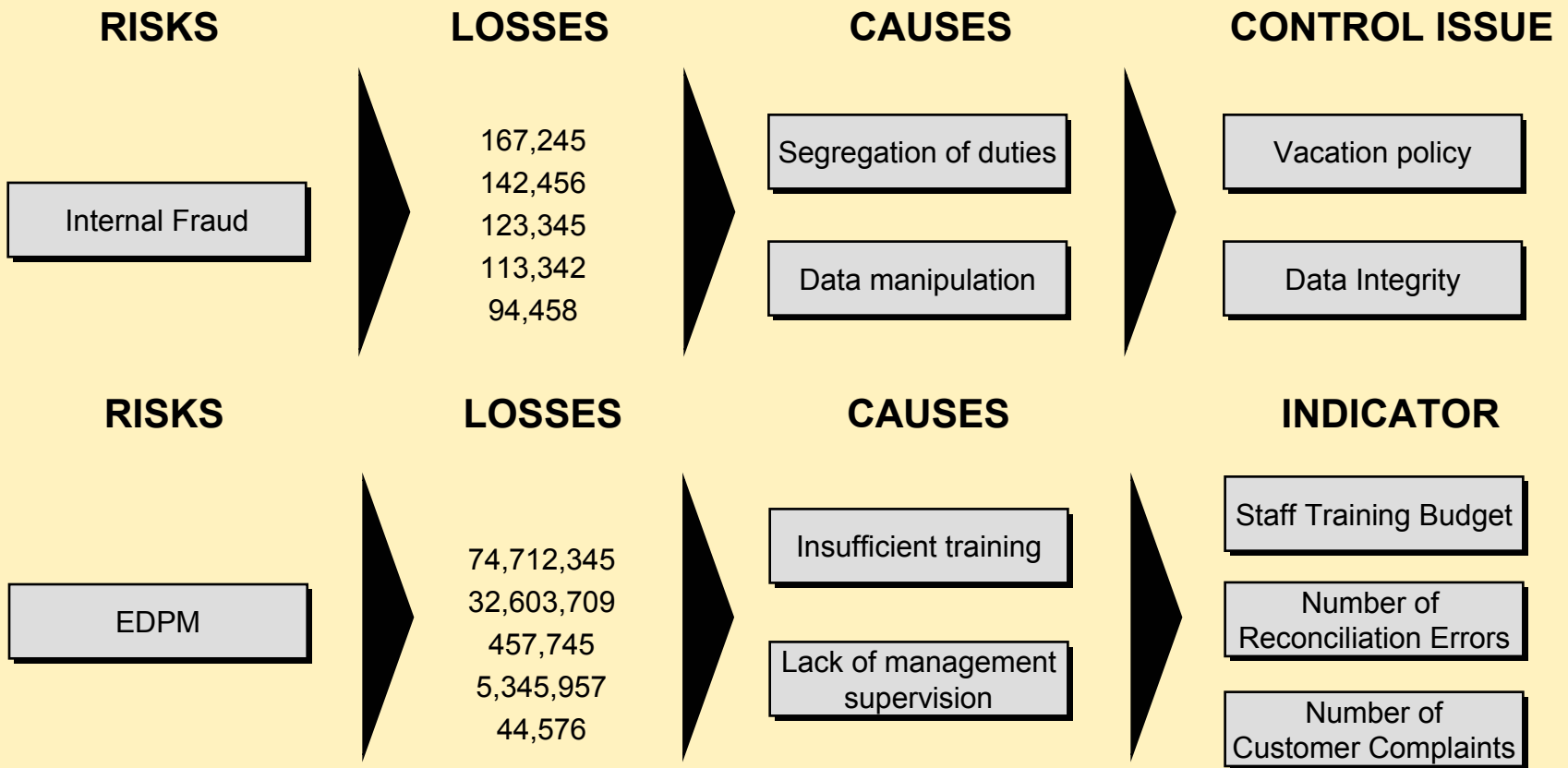
Illustrative

Percentile	Lognormal	Lognormal Gamma	Burr	GPD	Weibull
99.97	324.5	759.8	1,440.8	3,193.8	12,345.0
99.95	112.5	178.2	248.6	524.4	4,356.7
99.9	78.9	108.0	135.3	205.7	1,706.9
99.5	14.7	16.8	18.0	25.8	83.8
99	8.8	9.2	9.5	8.2	26.5
95	1.9	2.1	2.0	1.7	3.0



V) Issues with CSA and Indicators

Identifying relevant control issues and indicators requires a disciplined process that begins with identifying losses and their underlying causes



Risks are manifested in losses

A control assessment scorecard system must be relevant, consistent and objective

- **Relevance** - The control issues must be relevant to a business line and risk
- **Answer choices** - The answer choices should be consistent
- **Weighting** - The control issues must be weighted according to relevance
- **Scale** - All scores must be converted to a consistent scale, e.g., 0 to 100
- **Normalization** - The process for normalizing scores must be theoretically valid
- **Transparency** - The process must be transparent to allow for buy in and to identify opportunities for improvement
- **Validation** - Responses must be validated to avoid “gaming” the system

SAS OpRisk Monitor

- Home
- Loss Data
- Business Structure
- Financial Data
- Users and Roles
- Help

Assessment Questionnaire

- Save
- Stop Editing This Questionnaire
- Cancel
- View History

Business Line

- Asset Management Group
- Commercial Banking Group
- Global Trading and Sales
- International Investment Banking Group
- Private Banking Group

Validation Workflow

Originator	
oprisk, ,	
Stage 2	
joel, , joel@sas.com	
Stage 1	

Questions

1. To what extent is access to office premises restricted to authorized personnel?	<input type="radio"/> 1 <input type="radio"/> 2 <input type="radio"/> 3	<input type="radio"/> 4 <input type="radio"/> 5 <input type="radio"/> 6	<input type="radio"/> 7 <input type="radio"/> 8 <input type="radio"/> 9
	No key cards or identification badges have been issued. No formal security measures have been implemented.	Access to premises is controlled at one point of entry. Identification badges or key cards are required for entry.	Access to premises is controlled at two points of entry - at the building level and floor level; all employees are required to present key card/identification badges at both entry points.
Answer Justification <div style="border: 1px solid gray; height: 40px; width: 100%;"></div>			

Single-Period Report - Microsoft Internet Explorer

File Edit View Favorites Tools Help

Address: http://localhost:9191/monitor/AggregateScoreViewer.do?handle=10036%7C&businessLineID=&riskCategoryID=-1%7C&type=csa&assessmentProject=-1%7C

SAS OpRisk Monitor *The Power to Know.*

Home Loss Data Control Self Assessment Key Risk Indicators Business Structure Financial Data Users and Roles Help

Single-Period Report

Done

Business Line

- Internal Business Lines
 - Consumer Banking Division
 - Investment Banking Group
 - Processing & Servicing

Event Risk Category

- Internal Event Risk Categories
 - Business Disruption and System Failures
 - Clients, Products & Business Practices
 - Damage to Physical Assets
 - Employee Practices and Workplace Safety

Reporting Period: 2004 Quarter 1

Aggregation Matrix	Business Disruption and System Failures	Clients, Products & Business Practices	Damage to Physical Assets	Employee Practices and Workplace Safety	Execution, Delivery & Process Management	External Fraud	Internal Fraud
Consumer Banking Division	100% 78%	61%	61%	21%	73%	61%	63%
Investment Banking Group	100% 51%	86%	48%	50%	50%	50%	40%
Processing & Servicing	100% 78%	85%	73%	85%	66%	74%	78%

Local intranet

SAS OpRisk Monitor

Home | Loss Data | Control Self Assessment | Key Risk Indicators | Business Structure | Financial Data | Users and Roles | Help

Control Self Assessment Time Series Plot

Done

Business Line

List of Questions

- Internal Business Lines
 - Asset Management Group
 - Commercial Banking Group
 - Global Trading and Sales
 - International Investment Banking Group
 - Private Banking Group
 - Retail Banking Group
 - Worldwide Insurance Services

- Sample CSA Assessment Issue
- Vacation Policy
 - Product Knowledge ✓
 - Date Integrity

Date Criteria

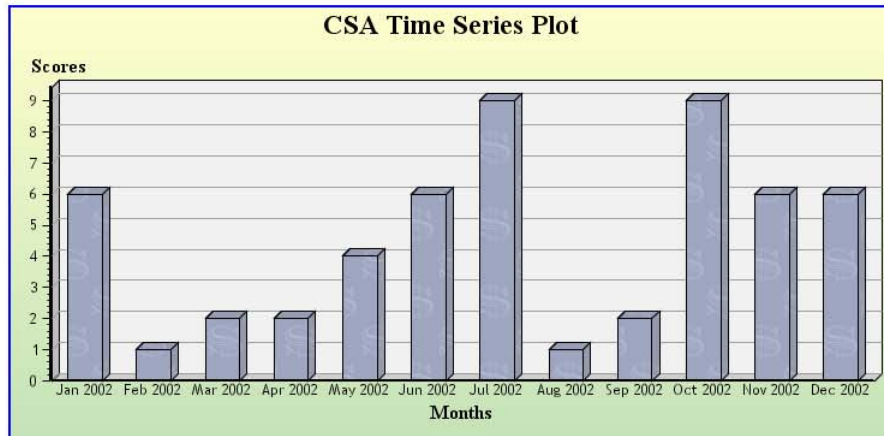
Roll-up Criteria

Starting Date *

Ending Date *

Average Min Max

Product Knowledge



Risk indicators must be validated through empirical analysis

Issue	Indicator	Description
Systems	System Downtime	Number of minutes per month system is offline
Data Quality	Processing Errors	% of transactions with errors
Scale	Employees	Number of Employees
Scale	Transactions	Number of Transactions
Level of Employee Knowledge	Employee Experience	Average months of experience per employee

$$Y_t = \alpha_t + \beta_{1_t} X_{1_t} + \dots + \beta_{n_t} X_{n_t} + \varepsilon_t$$

In order for an indicator to be a true risk indicator, there must be empirical evidence (from econometric analysis) supporting a relationship between the indicator and loss frequency or loss severity

SAS OpRisk Monitor

- Home
- Loss Data
- Control Self Assessment
- Key Risk Indicators
- Business Structure
- Financial Data
- Users and Roles
- Help

Key Risk Indicator Time Series Plot

Done

Business Line

List of Indicators

Internal Business Lines

- Asset Management Group
 - Global Term Investments (GTI)
 - Institutional Asset Management (IAM)
 - Investment Counsel Group (ICG)
 - Investment Management (AIM)
 - Mutual Funds Group Services (MFGS)
 - Test

Sample KRI Indicator Group

- Transaction Processing Errors
- [No. of Customer Complaints](#) ✓
- [No. of Help Desk Calls](#)
- [Cumulative System Downtime](#)

Date Criteria

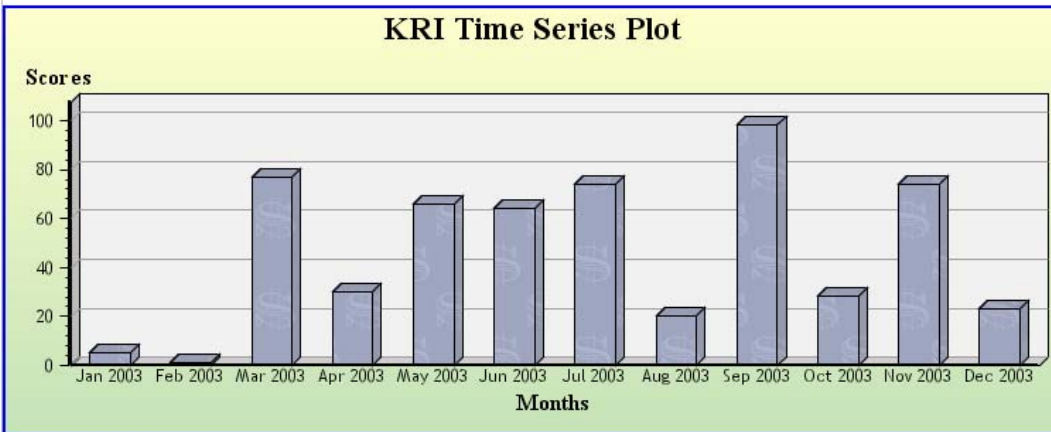
Roll-up Criteria

Starting Date *

Ending Date *

Average Min Max

No. of Customer Complaints



Biographical Information

Ali Samad-Khan is Head of Global Operational Risk Strategy at SAS, Inc. (New York, NY) He has seven years experience in operational risk measurement and management and approximately twenty years of professional experience. His areas of expertise include: establishing an operational risk department, internal loss database design and implementation, loss event data collection and reporting; data quality assessment, data sufficiency, risk indicator identification, risk and control self assessment, scenario analysis, causal/predictive modeling, advanced VaR measurement techniques and economic capital allocation.

Mr. Samad-Khan has presented his ideas on operational risk measurement and management at seminars and on an individual basis to a large number of major banking institutions around the world. His significant practical experience in this field comes from managing the implementation of more than ten operational risk measurement and management projects at leading institutions in North America, Europe and Australia.

Immediately prior to joining SAS Mr. Samad-Khan was CEO of OpRisk Analytics. (SAS acquired OpRisk Analytics in June of 2003.) Before that he was with PricewaterhouseCoopers (PwC) in New York, where he headed the Operational Risk Group within the Financial Risk Management Practice. Prior to joining PwC he worked in the Operational Risk Management Department at Bankers Trust. He has also worked at the Federal Reserve Bank of New York and the World Bank.

Mr. Samad-Khan holds a B.A. in Quantitative Economics from Stanford University and an M.B.A. in Finance from Yale University.

Articles include: *“Is the Size of an Operational Loss Related to Firm Size,”* with Jimmy Shih and Pat Medapa, Operational Risk, January 2000; *“Measuring and Managing Operational Risk,”* with David Gittleson, Global Trading, Fourth Quarter, 1998.

Working papers include: *“How to Categorize Operational Losses – Applying Principals as Opposed to Rules.”* March 2002 and *“Categorization Analysis,”* January 2003.



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