

# Operational Risk Management

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## **Casualty Actuarial Society 2001 Seminar on Understanding the Enterprise Risk Management Process**

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Samir Shah, FSA, MAAA

*Tillinghast - Towers Perrin*

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## Significant differences between Operational Risks and Financial Risks have implications on quantifying OpRisks

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- OpRisks are endogeneous - vary significantly based on a company's internal operations
  - need company-specific data
  - data must be representative of current ops environment
- OpRisks are managed by changes in process, technology, people, organization and culture - not through capital markets
  - need to model risks as a function of operational decisions
  - need to understand causal factors
- OpRisks have skewed distributions - not “random walk”
  - need to use ‘coherent risk measures’ for determining and allocating capital

OpRisk modeling must tap knowledge of experienced managers to supplement the data.

## We will cover the following three modeling methods that combine historical data and expert input

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### ■ System Dynamics Simulation

- Developed by Jay Forrester, MIT
- Used primarily in engineering sciences but becoming prominent in business simulation

### ■ Bayesian Belief Networks (BBNs)

- Based on Bayes' Rule developed by Rev. Thomas Bayes (1763)
- Used primarily in decision sciences

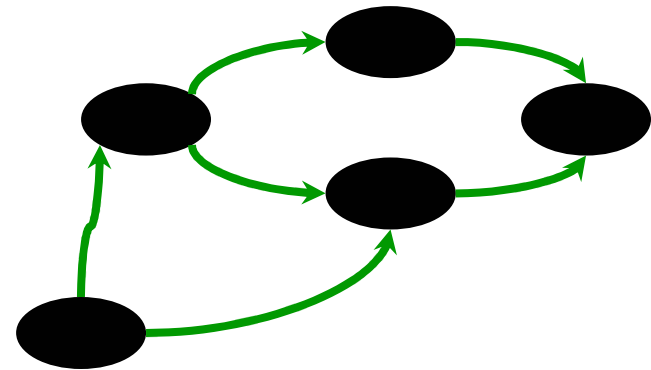
### ■ Fuzzy Logic

- Based on fuzzy set theory developed by Lotfi Zadeh
- Used primarily in engineering control systems, cognitive reasoning and artificial intelligence

## System Dynamics Simulation

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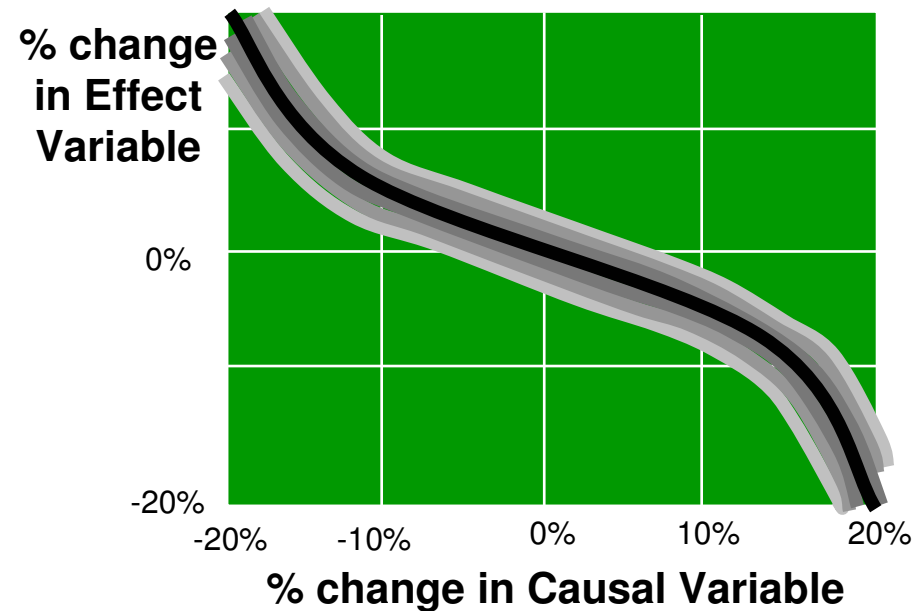
- Use expert input to develop a system map of cause-effect relationships



## System Dynamics Simulation

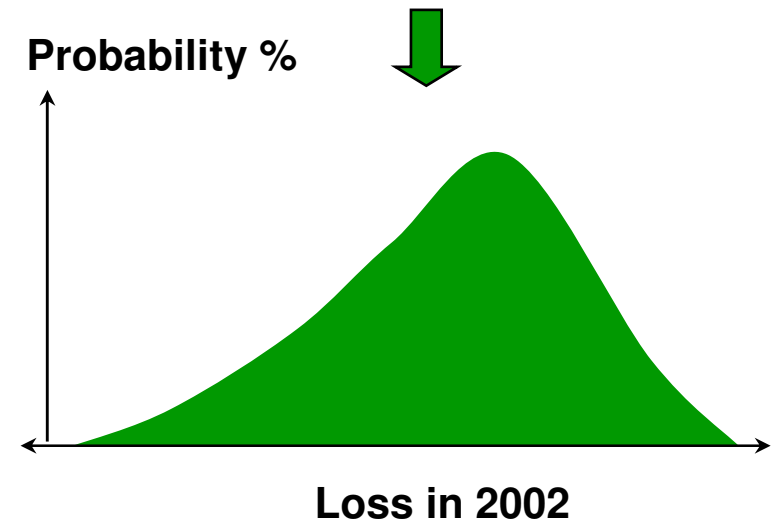
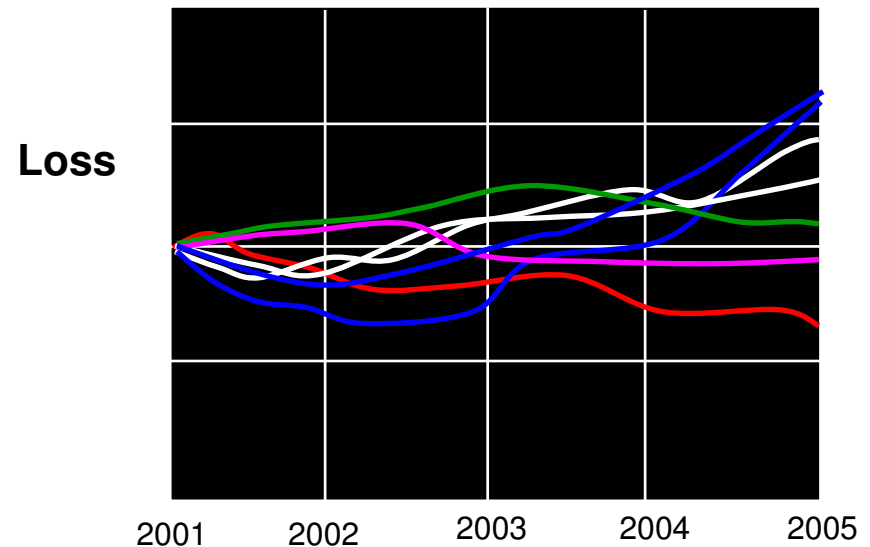
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- Use expert input to develop a system map of cause-effect relationships
- Quantify each cause-effect relationship using a combination of data and expert input
- Explicitly reflect the uncertainty of expert input as ranges around point estimates

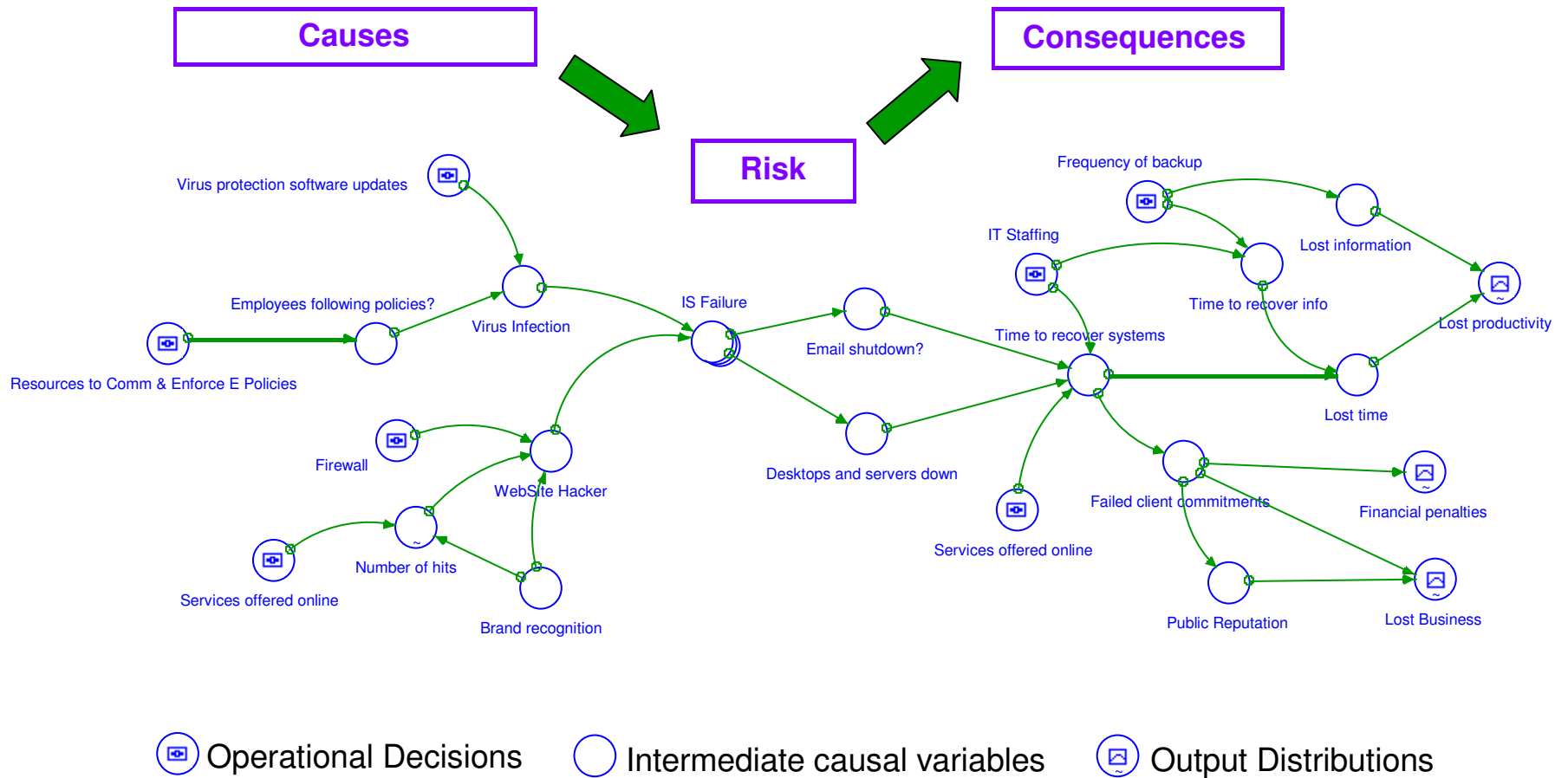


## System Dynamics Simulation

- Use expert input to develop a system map of cause-effect relationships
- Quantify each cause-effect relationship using a combination of data and expert input
- Explicitly reflect the uncertainty of expert input as ranges around point estimates
- Computer simulate the range of outcomes
- Summarize outcomes as probability distribution



# For example, here is an illustrative System Dynamics map for Information Systems Failure



# Demonstration of System Dynamics Simulation Model

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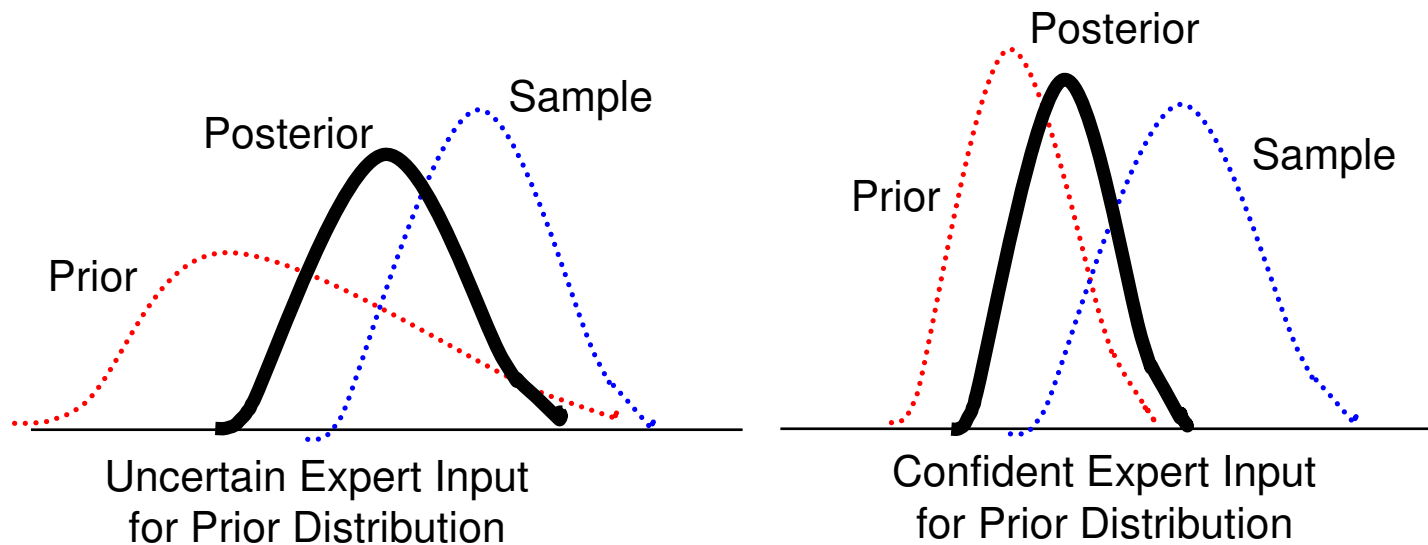


## Bayesian Belief Networks (BBNs)

- Based on Bayes' Rule:

$$\text{prob}(X|Y) = [ \text{prob}(Y|X) / \text{prob}(Y) ] * \text{prob}(X)$$

$$\boxed{\text{Posterior Density}} \propto \boxed{\text{Sample Likelihood}} * \boxed{\text{Prior Density}}$$



# Bayesian Belief Networks (BBNs)

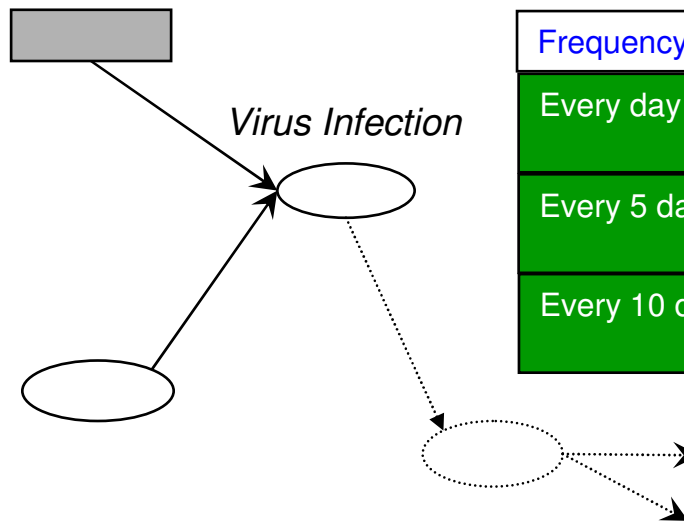
- Nodes - represent decision variables, causal variables and outputs
- Arcs - connect Nodes indicating the logical causal relationship
- Node probabilities - probabilities for various values of the Node variable, conditioned on values of its causal variables

*Frequency Of Virus Protection Updates*

Every day	0.0
Every 5 days	1.0
Every 10 days	0.0

*Employees following E-Policies?*

Yes	.25
No	.75



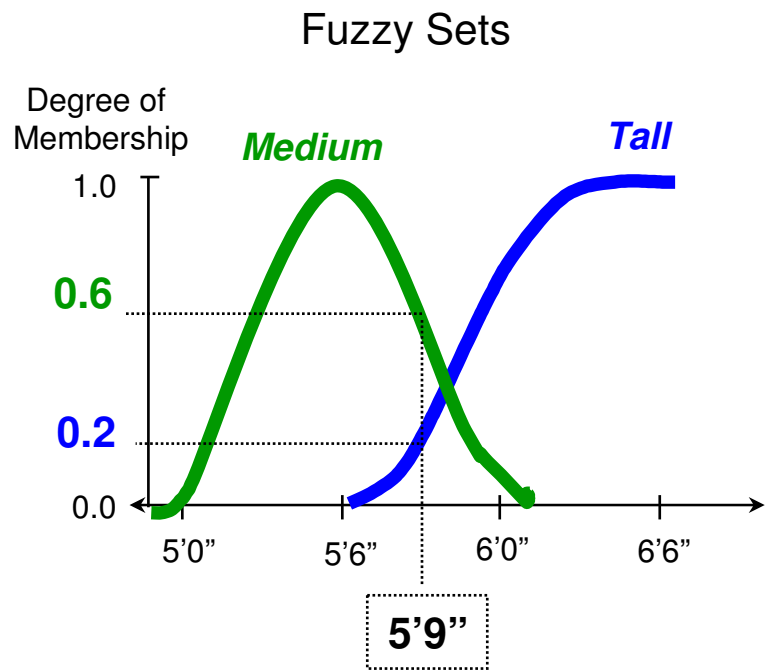
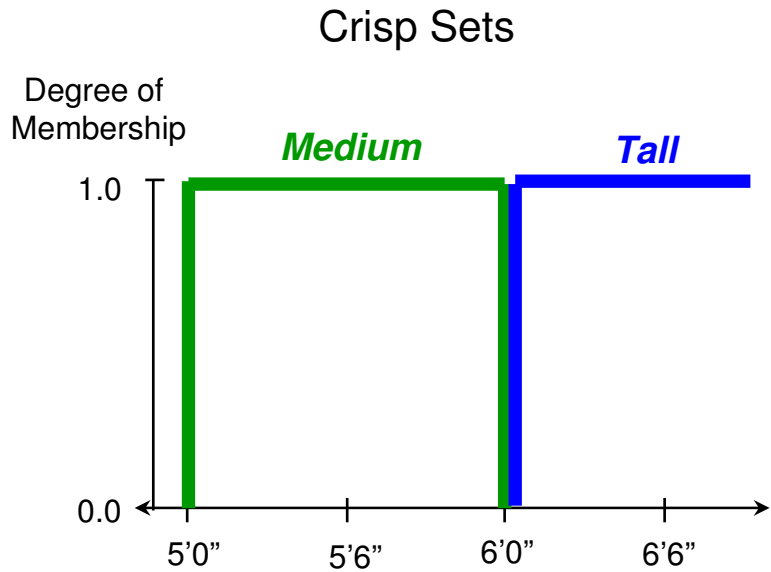
Frequency	Emp	Infection?	
		Yes	No
Every day	Yes	.01	.99
	No	.02	.98
Every 5 days	Yes	.02	.98
	No	.05	.95
Every 10 days	Yes	.05	.95
	No	.10	.90

Analytical “cousin” to System Dynamics Simulation - however, simulation offers much greater modeling flexibility

# Fuzzy Logic

- Based on fuzzy set theory
  - for non-fuzzy sets (crisp sets), an element is either a “member of the set” or is not a “member of the set”
  - for fuzzy sets, an element is a “member of the set to some degree” from 0% to 100% --- degree of truth

## Examples of Membership functions to characterize Height



# Fuzzy Logic

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- Fuzzy sets make way for the use of “linguistic variables” instead of numerical variables
  - *Tall, Medium, Low, High, ...*
- Adjectives and adverbs are used to modify the membership curves mathematically:

Adjectives/Adverbs	Membership Curve Change
<i>almost, definitely, positively</i>	Intensify contrast
<i>generally, usually</i>	Diffuse contrast
<i>neighboring, close to</i>	Approximate narrowly
<i>vicinity of</i>	Approximate broadly
<i>above, more than, below, less than</i>	Restrict a fuzzy region
<i>quite, rather, somewhat</i>	Dilute a fuzzy region
<i>very, extremely</i>	Intensify a fuzzy region
<i>about, around, near, roughly</i>	Approximate a scalar
<i>not</i>	Negation or complement

# Fuzzy Logic

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- Fuzzy set mathematics are used to combine fuzzy sets:

Fuzzy Set Operators	Meaning
Intersection: Set A $\cap$ Set B	Min. of $M_A(x)$ and $M_B(x)$
Union: Set A $\cup$ Set B	Max. of $M_A(x)$ and $M_B(x)$
Complement: $\sim$ Set A	$1 - M_A(x)$

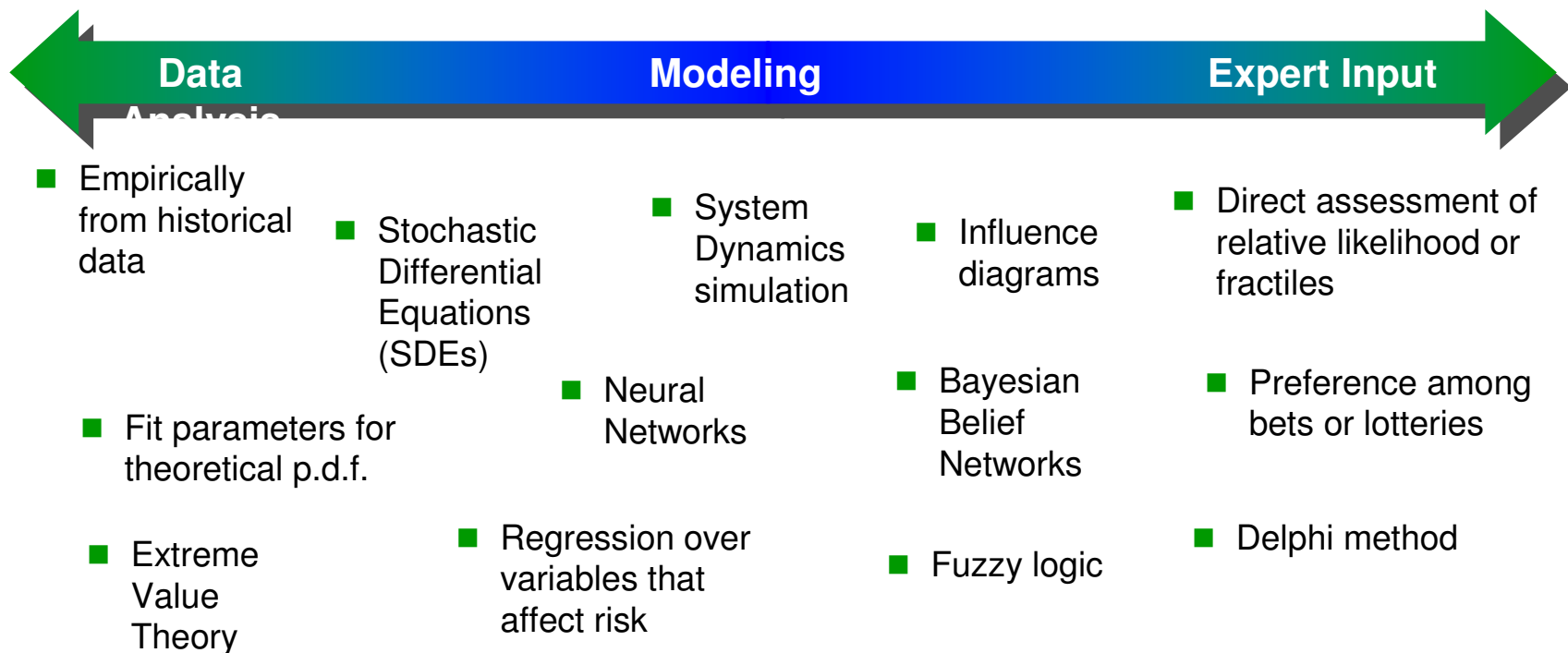
- Fuzzy rules, specified by experts, define cause-effect relationships:
  - Rule 1: If **age is YOUNG** then **risk is HIGH**
  - Rule 2: If **distance.to.work is FAR** then **risk is MODERATE**
  - Rule 3: If **accidents are above ACCEPTABLE** then **risk is EXCESSIVE**
  - Rule 4: If **dwi.convictions are above near ZERO** the **risk is UNACCEPTABLE**

# Demonstration of Fuzzy Logic Model

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## There is a continuum of methods for quantifying risks based on the relative availability of historical data vs. expert input



Each method has advantages/disadvantages over the other methods — method should be selected to suit facts and circumstances.

## There are several advantages of using modeling methods that explicitly incorporate expert input

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- Explicitly depicts cause-effect relationships
  - lends itself naturally to development of risk mitigation strategies
  - can determine how OpRisk changes based on operational decisions
- Explicitly models interaction of risks across an enterprise
  - by aggregating knowledge that is fragmented in specialized functions
- Provides organizational learning
  - ongoing use calibrates subjective beliefs with objective data
  - managers develop an intuitive understanding of the underlying dynamics of their business
- Focuses the data-gathering effort
  - sensitivity analysis identifies areas of expert input that should be supported by further data

Operational Risk Management is not just a modeling exercise  
- senior and middle management must get involved!



# Coherent Risk Measures

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## Operational risk measures for determining and allocating capital

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- Operational risks will often have skewed probability distributions - unlike “random walk” for asset risks
- Traditional risk measures used for financial risks may not be appropriate for OpRisks, for example:
  - Value-at-Risk (VaR) used in banking
  - Probability of Ruin used in insurance

## Here's an example ...

- Under a 1% probability of default, or 99% VaR, risk constraint, Companies A & B need to hold the same amount of assets, i.e., \$10,000

		<i>Probability</i>	<i>Loss</i>	<i>Required Assets</i>	<i>Shortfall</i>	<i>ECOR Ratio*</i>	
<b>Company A</b>	Scenario 1	97%	8,784	10,000	0	2.0%	
	Scenario 2	2%	10,000		10,000		0
	Scenario 3	1%	28,000		10,000		18,000
	Expected	100%	9,000		180		
<b>Company B</b>	Scenario 1	97%	8,505	10,000	0	5.0%	
	Scenario 2	2%	10,000		10,000		0
	Scenario 3	1%	55,000		10,000		45,000
	Expected	100%	9,000		450		

*\*ECOR is the Economic Cost of Ruin and is equal to the expected Shortfall.  
ECOR Ratio is the Expected Shortfall divided by Expected Loss*

- But Company B is much more risky. Its loss distribution has a “fatter tail” than the one for Company A.

## Continuing the example ...

- If we combine Company A and Company B, the new Company C appears to need **more**, not less, capital

	<i>Scenarios</i>	<i>Joint Probability</i>	<i>Loss</i>	<i>Required Assets</i>	<i>Shortfall</i>	<i>ECOR Ratio</i>
Company C	A1 x B1	94.09%	17,289	22,000	-	
	A2 x B1	1.94%	18,505	22,000	-	
	A1 x B2	1.94%	18,784	22,000	-	
	A2 x B2	0.04%	20,000	22,000	-	
	A3 x B1	0.97%	36,505	22,000	-	
	A3 x B2	0.02%	38,000	22,000	-	
	A1 x B3	0.97%	63,784	22,000	25,784	
	A1 x B3	0.02%	65,000	22,000	27,000	
	A1 x B3	0.01%	83,000	22,000	45,000	
	Expected	100.00%	18,000			260

- How can this be?

## Lessons learned from the example ...

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- Probability of ruin, VaR and other quantile measures do not properly reflect the tail of the loss distribution
- When the loss distributions are not uniform across the range of outcomes, quantile measures distort the determination of required capital for business combinations and capital allocations
- Expect this to be the case frequently for operational risks - as well as other insurance risks - which have:
  - Non-symmetrical distributions
  - “Fat-tail” distributions

## Coherent Risk Measures for Operational Risks

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- A Coherent Risk Measure\* is one which meets the following four criteria:
  - If a portfolio X does better than portfolio Y under all scenarios, then the capital for X should be less than for Y
  - Combining uncorrelated risks should never increase the capital requirement
  - Combining perfectly correlated risks should never change the capital requirement
  - If a non-risky investment of \$X is added to a risky portfolio, then the capital requirement should decrease by \$X
- Probability of Ruin and VaR are not Coherent Risk Measures because they fail the second criteria

\* Defined by Artzner, Delbaen, Eber, and Heath (1997)

## ECOR Ratio is a Coherent Risk Measure

- Using the ECOR ratio leads to intuitively correct results
  - Company B needs more capital than Company A
  - Company C needs **less** capital than Company A + Company B

	<i>At 1.0% Prob. Of Ruin or 99% VaR</i>	<i>At 1.4% ECOR Ratio</i>
	<u><i>Required Assets</i></u>	<u><i>Required Assets</i></u>
<i>Company A</i>	10,000	15,039
<i>Company B</i>	10,000	42,039
<i>Company C</i>	38,000	38,000
<i>Sum of A and B</i>	20,000	57,078
<i>Diversification Benefit (Penalty)</i>	(18,000)	19,078

## Conclusion

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- Intuitively simple and well understood measures of risk can be seriously misleading.
- For capital allocation and business combinations, use of a coherent risk measure such as the ECOR ratio, is preferable.



Samir Shah

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**Tillinghast-Towers Perrin**  
**Arlington, VA**  
**703.351.4875**  
**shahsa@towers.com**