

# Advancements in Implementing Operational Risk, Stress Testing and Risk Appetite for ORSA Institute of Actuaries of Japan

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  - a) Operational Risk
  - b) Risk Appetite
  - c) Stress Testing
  - d) Interest Rate Risk



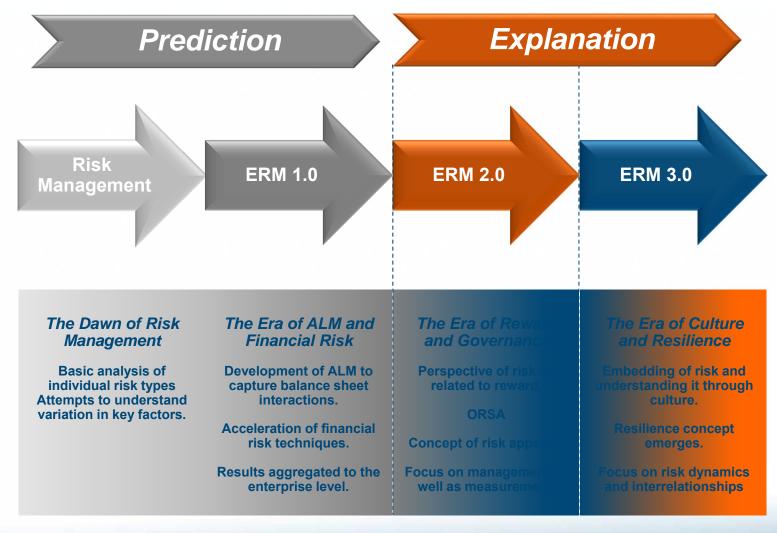
# The Evolution of ERM

### Section 1





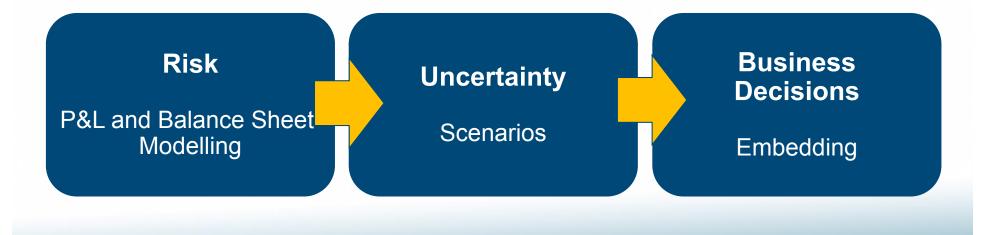
### **The Evolution of ERM**





# **ORSA Becoming a Global Standard**

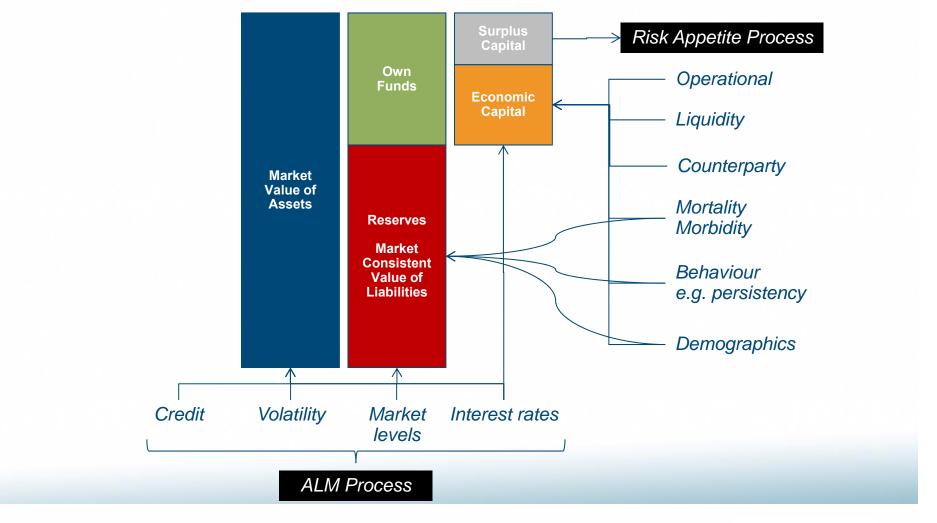
What ousiness decisions do we need to take given we are exposed to risk and uncertainty?





# **ORSA: Balance Sheet Risk Management**

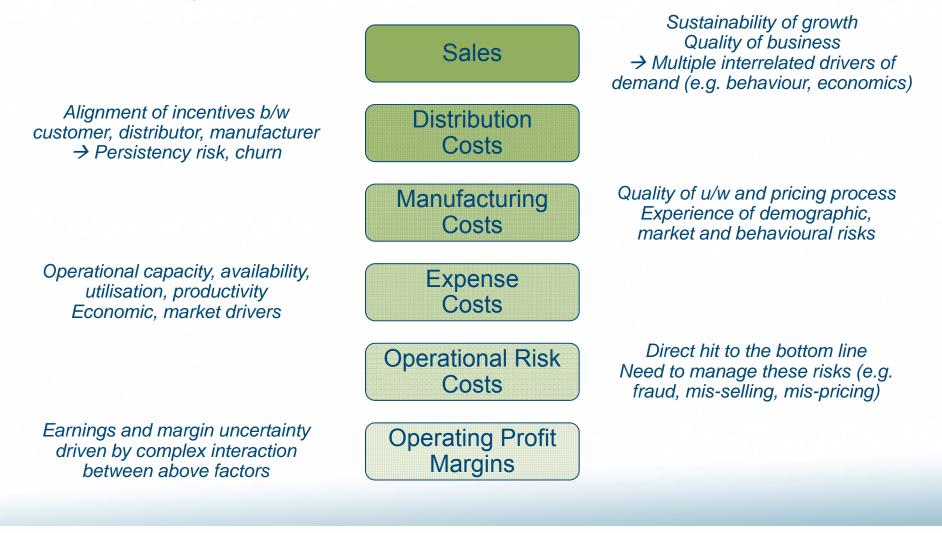
Components and Inter-relationships





# **ORSA: P&L Risk Management**

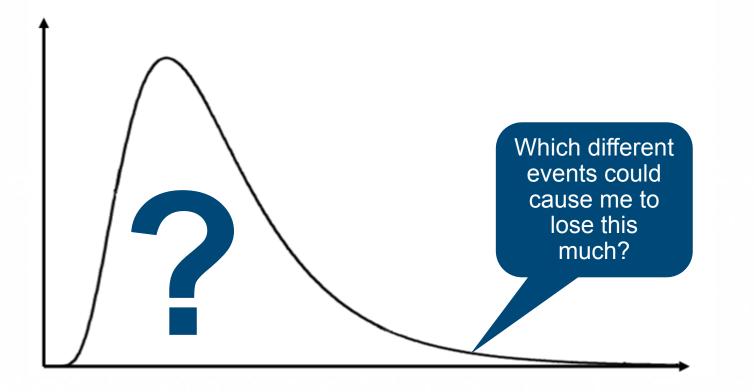
Understanding the drivers of P&L uncertainty





## **Prediction** ≠ **Explanation**

Need to move from pure statistical to causal risk frameworks





# **Complexity / Connectivity / Emergence**



WEF Global Risks Map 2013

Complex systems mean you can't understand the whole by only studying the sum of the parts.

It is the inherent and dynamic relationships between risks, causal drivers and outcomes that is key.

Simple measures of dependency such as linear correlation are typically misleading

Risks relating to complex adaptive systems exhibit emergent properties



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# **Current and Emerging Challenges**



- Risk governance
- Risk processes
- Operational risk
- ORSA pillar 2
  - Strategic / holistic risk assessment
  - Operational risk
  - Risk appetite
  - Scenario / stress testing
  - Risk interdependencies
  - Risk reporting
- Operational risk systems



- Resilience
- Risk culture
- Behavioural risks
- Emerging risk
- Reverse stress testing
- Risk dynamics and inter-relationships through systems science
- Causal light models focused on explanation, not just prediction
- Risk engagement with business
- Integration of predictive analytics



# **Technical Developments**

What you know

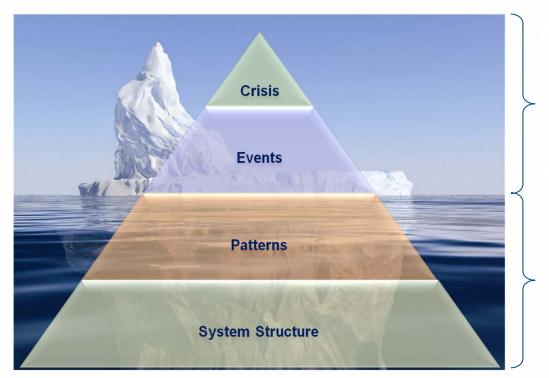
Section 2a





## **Companies are Complex Adaptive Systems**

Risk is an undesirable outcome of a complex system



#### **Traditional Risk Management Frameworks**

Statistical models, assuming constant drivers Registers assuming single characteristics Scenarios "imagined" Emerging risks by spotting events

#### Frameworks based on complex systems

Descriptions of risk profile taken holistically Scenarios derived from risk profile Models integrate all types of information Emerging risks spotted early from system

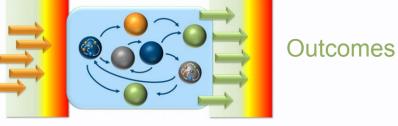
#### Risk management can be hard if looked at it through the wrong lens



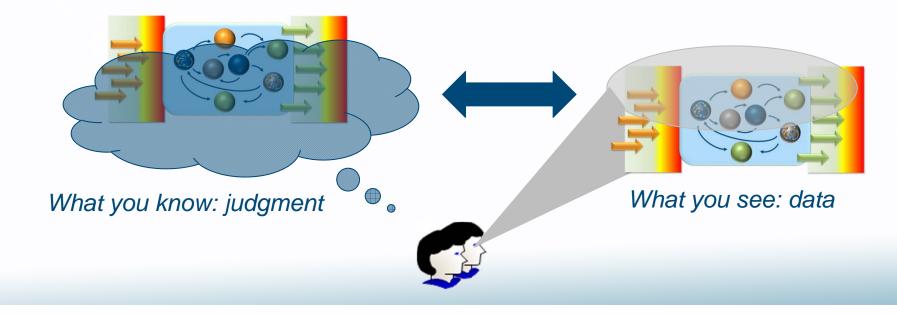
# Data is only part of the information set

interactions

Inputs

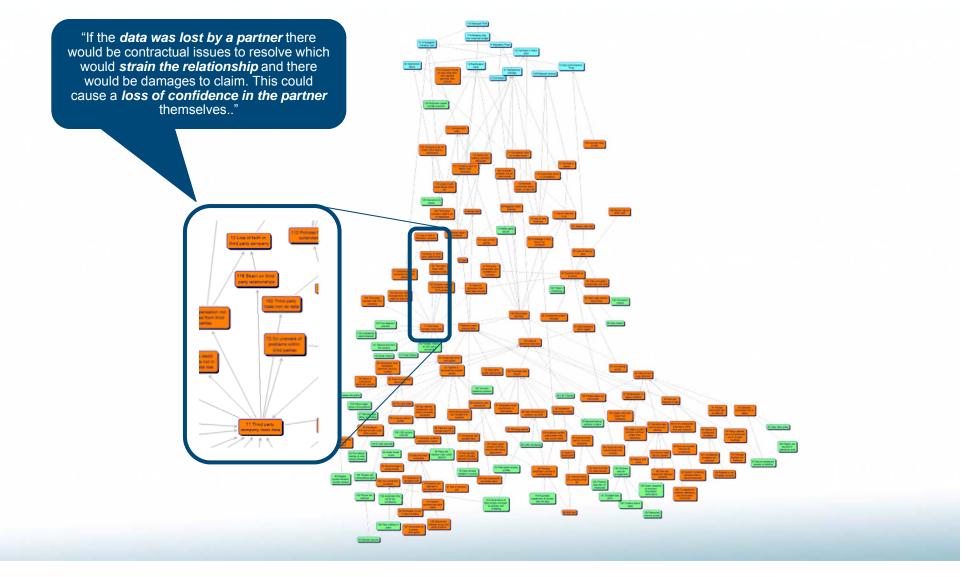


The System: information



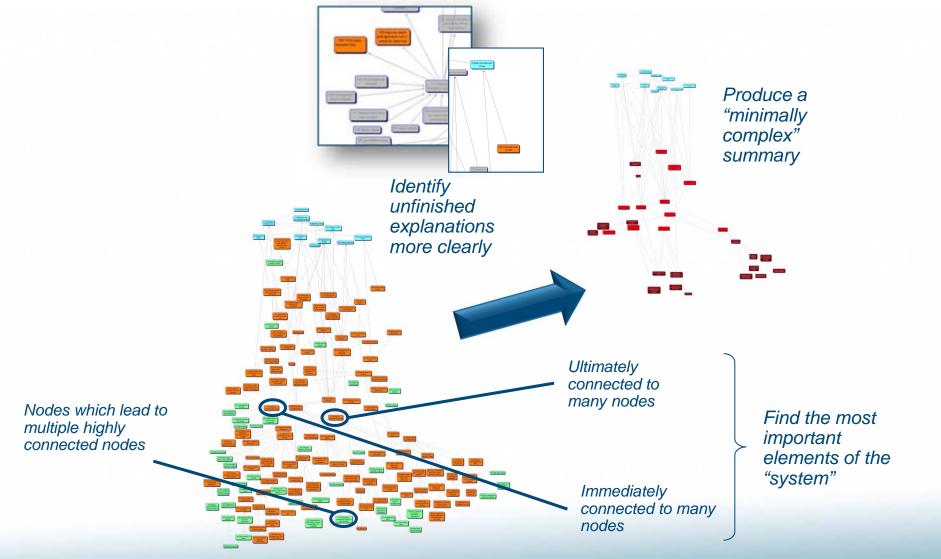


## **Describing the System**



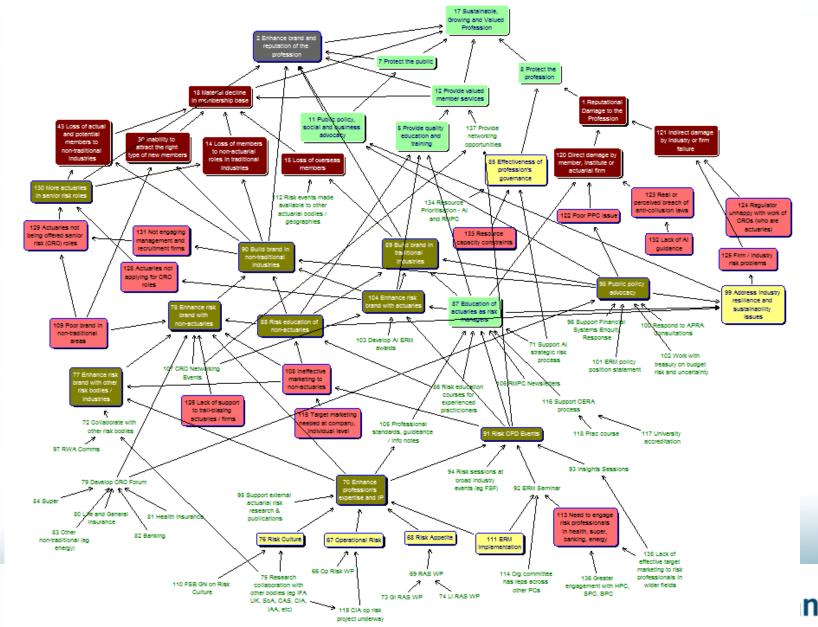


# **Cognitive Analysis**



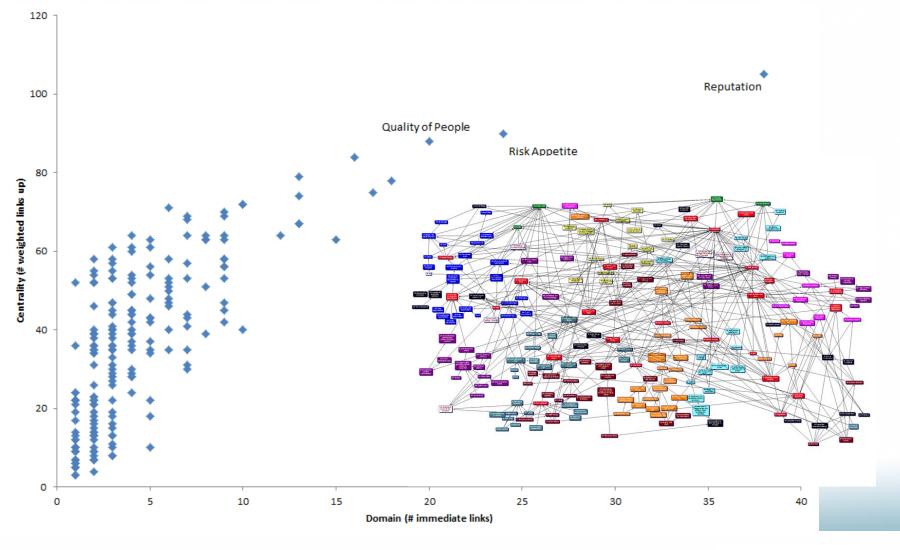


### What are the Risks to the Actuarial Profession?



16

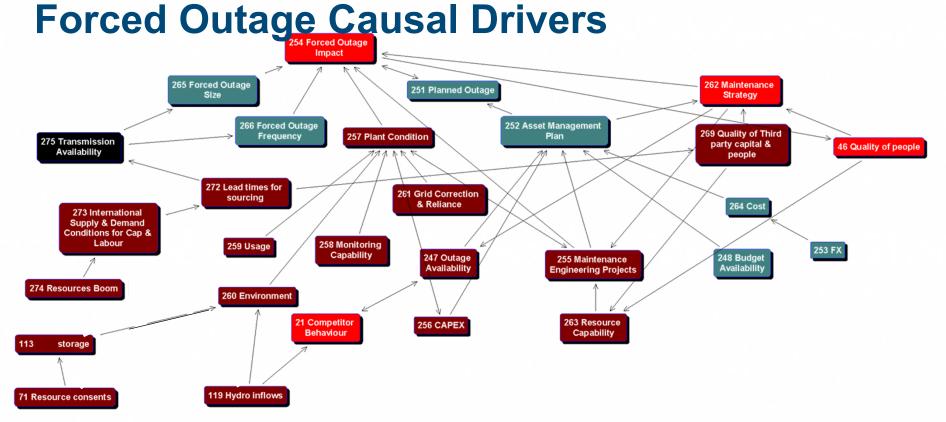
### **Relative Importance of Risk Drivers**



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# **Deriving the Full Risk Profile**



- Dominated by asset management drivers and other potent drivers
- Note multiple feedback loops: e.g. Quality of people, maintenance strategy



# **Technical Developments**

What you see

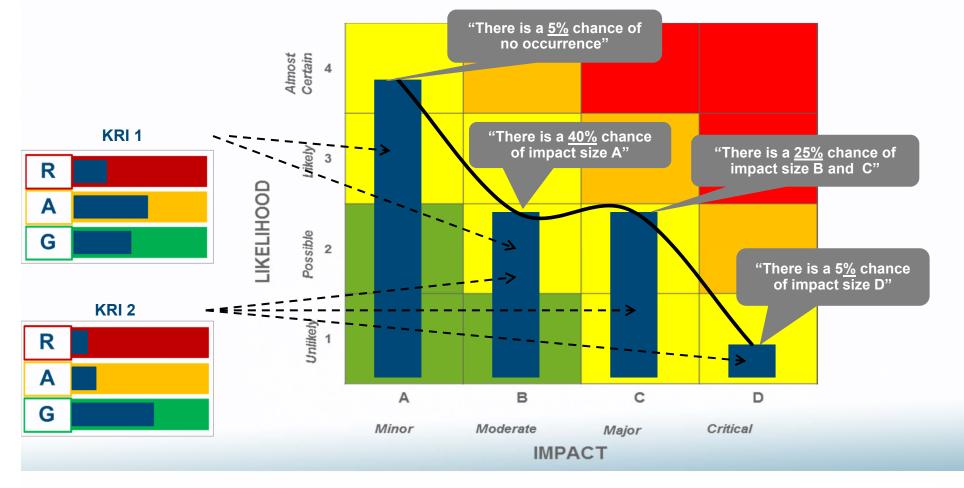
Section 2b





# **Using Data to Move Beyond Point Estimates**

What do key risk indicators (KRIs) tell us about the likelihood of each type of risk outcome?

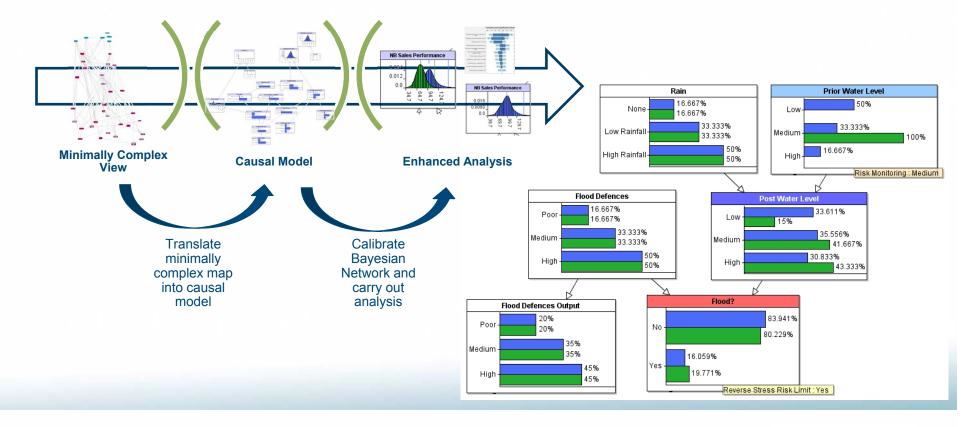




# **Causal Modelling with Bayesian Inference**

#### Prediction with Explanation

Causal modelling techniques can be used to formally demonstrate how indicators flow through to the business outcomes being studied. Framework retains the dynamic links between causes and losses so risks are viewed in context and incorrect conclusions from silo-thinking are avoided.





# **A Bayesian Approach**

- Bayesian networks are a method which can integrate dependencies directly between trigger events, risk drivers, and consequences
- Simultaneously assess all levels of outcomes (profit, capital)
- Can think of the prior as the "theory", and the evidence as "observation"
  - All scientific fields use Bayesian statistics, so why don't we!

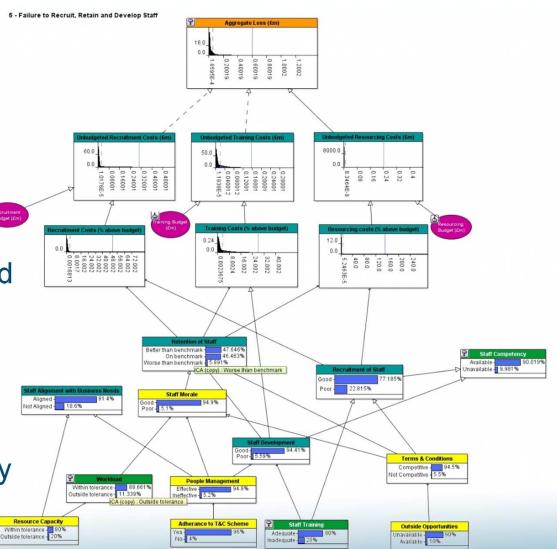
$$P(A, B) = p(A / B).p(B)$$
$$P(B, A) = p(B / A).p(A)$$
$$\therefore P(A / B) = \frac{p(B / A).p(A)}{p(B)}$$

where P(A) is the prior P(A/B) is the posterior P(B/A)/P(B) is the evidence



# What is a Causal Model?

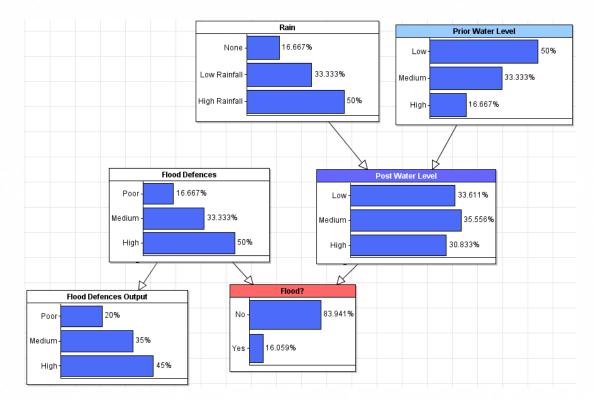
- A causal model is one which conditions outcomes directly upon a set of interrelated causal factors
- Causal factors are defined directly in terms of business language
- It captures the complex web of interrelationships and dependencies directly from the outset





# Simple BN Case Study - Flood Model

- Outcomes:
  - Prob(Flood)
- Risk indicators
  - Rain (forecast)
  - Dam levels (avg)
- Risk mitigants
  - Quality of flood defenses (measurable but uncertain)



Source: AgenaRisk



# **Risk Monitoring**

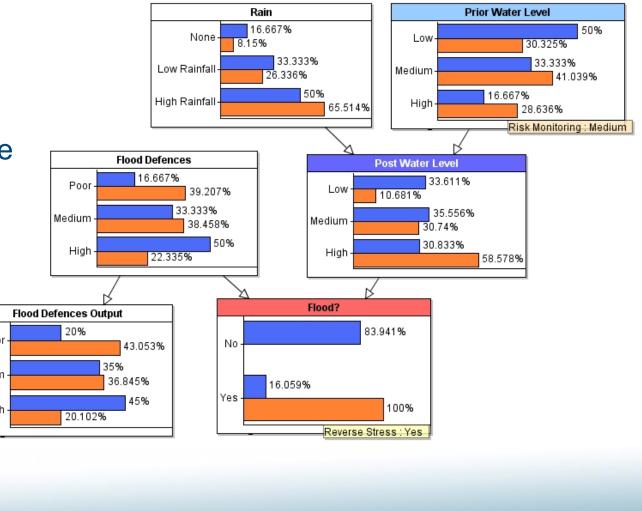
Prior water = medium Rain Prior Water Level 16.667% 50% None-Low 16.667% 33.333% 33.333% Low Rainfall-Medium 33.333% 100% 50% 16.667% Risk level changes as High Rainfall-High 50% Risk Monitoring : Medium the states of causal Flood Defences Post Water Level drivers change 16.667% 33.611% Poor Low 16.667% 15% 33.333% 35.556% Medium Medium 33.333% 41.667% 50% 30.833% High High 50% 43.333% Flood? Flood Defences Output 83.941% 20% Poor No · 20% 80.229% 35% Medium 35% 16.059% Yes 45% 19.771% High 45% Reverse Stress Risk Limit : Yes

Consistent states of other variables calculated using Bayesian inference



# **Reverse Stress Test**

- Flood = 100%
- What does the system look like?
- Bayesian inference used to resolve states of related drivers
- This is how we resolve risk appetite statements into consistent risk driver limits





# **Technical Developments**

### Relationships

Section 2c





# **Unsupervised vs Supervised Techniques**

Derivation of rules / algorithms to search data to uncover correlations and patterns Human judgment required to either structure the analysis or as an information source itself

- Decision trees
- Random forests
- Neural nets
- Nearest neighbours
- Support vector machines
- Cluster modelling
- Mutual information



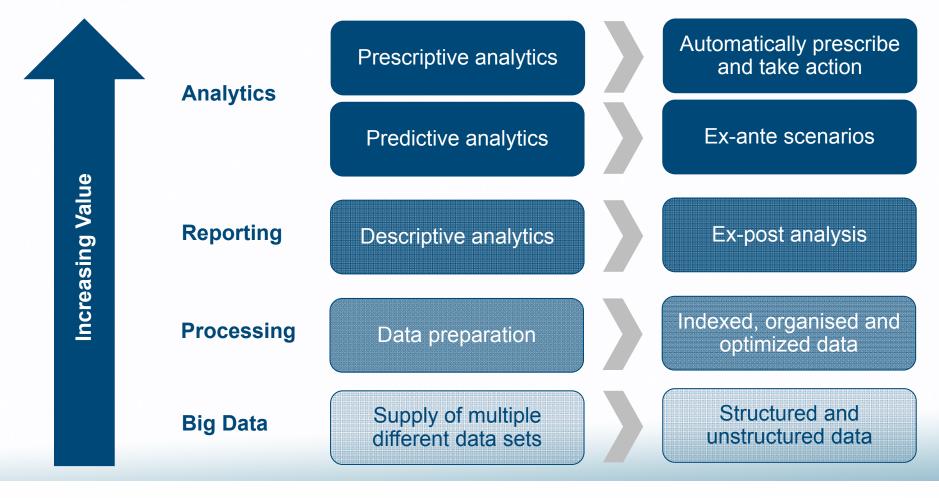
- Linear multifactor regression
- Conditional / Bayesian probability
- Non-linear copulas
- Cognitive mapping
- Bayesian networks
- Phylogenetics
- Network analysis





# **Data Analytics**

Data is a key strategic asset, but only part of the solution





# **Information Theory Shows us the Way**

Perhaps the most critical question in risk management:

"Do I have any information upon which to condition an outcome / risk driver etc. and what quality level do I place on it?"

- Information theory concepts:
  - <u>Entropy</u>: quantifies the uncertainty involved in predicting the value of a random variable
  - <u>Mutual information</u>: quantifies the amount of information in common between two random variables

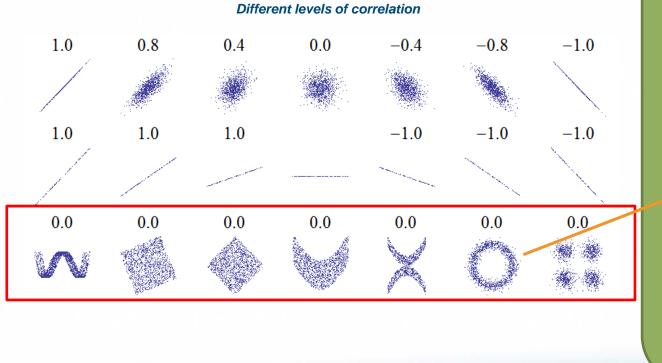
 $I(x) = -\log p(x)$ 

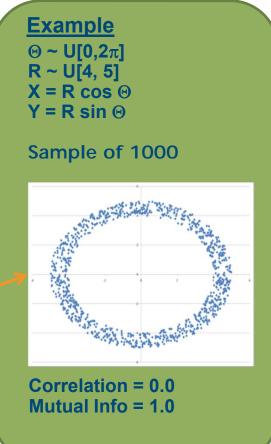
 In light of no other information, the principle of maximum entropy applies: all outcomes are equally likely



# **Connectivity – Capturing Non-Linearity**

- Typical correlation measures cannot spot non-linear dependency
- Mutual information sharing can

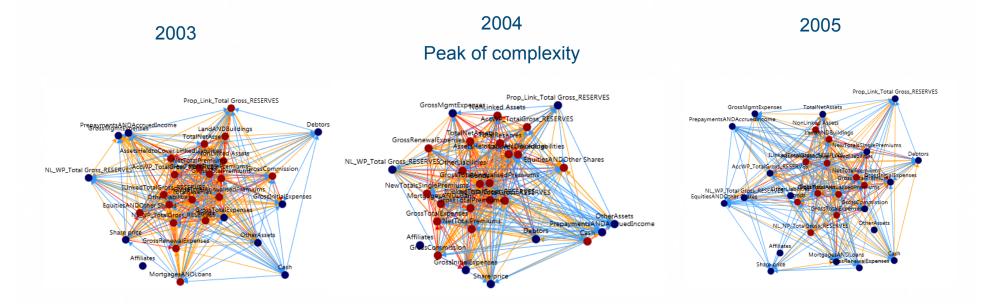






# **Assessing Network Connectivity & Complexity**

Non-linear measures of dependence are critical



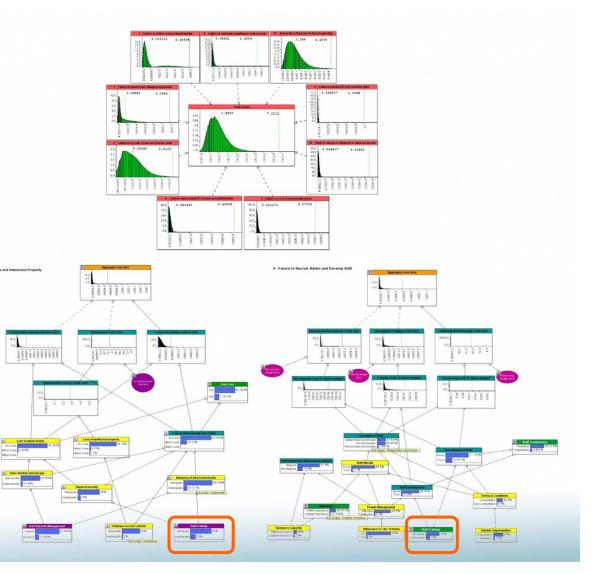
 Complexity changes significantly over the year, with several of the key drivers changing between 2003 to 2005





# **Aggregate Loss – Dependency Structure**

- A profoundly different way of aggregating risks
- Diversification at all parts of the loss distribution can now be explained by the states and interrelationships of business drivers
- No need for abstract correlations, copulas

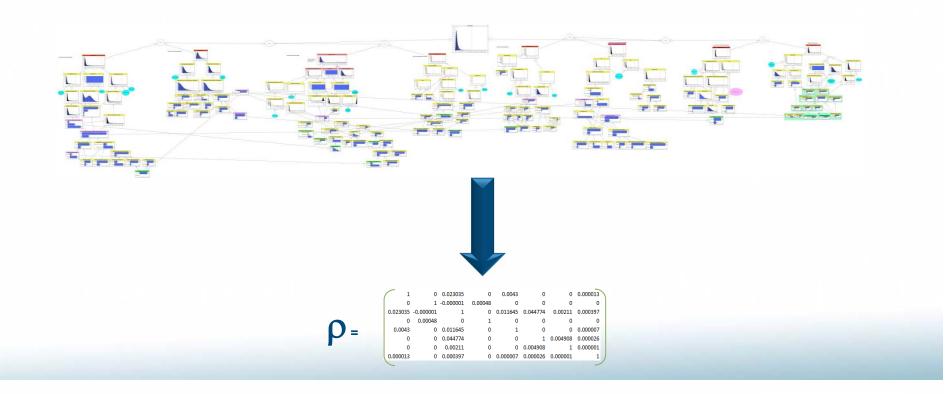




# **Correlation from Cause**

#### Validating Dependency Structures

- Correlations measure a degree of co-variation. You can determine this co-variation for complex phenomena by using causal models of their dynamic relationships.
- The models more naturally allow for an understanding of regime shifts in behaviours and allow you to meaningfully stress dependency parameters used in other models.





# **Applications** *Operational Risk*

#### Section 3a



Milliman Research Report 2013

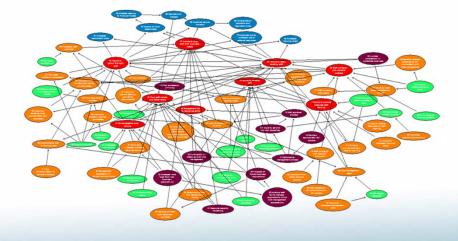




## **Risk - Failure to recruit, retain and develop staff**

Cognitive Map Analysis

- Key concepts:
  - Impacts: customer service worsens, quality of work deteriorates
  - Drivers: failure to provide adequate staff training, unmanageable work volume, failure to align staff with business needs
  - Controls: staff appraisal process, performance management process
- Map properties

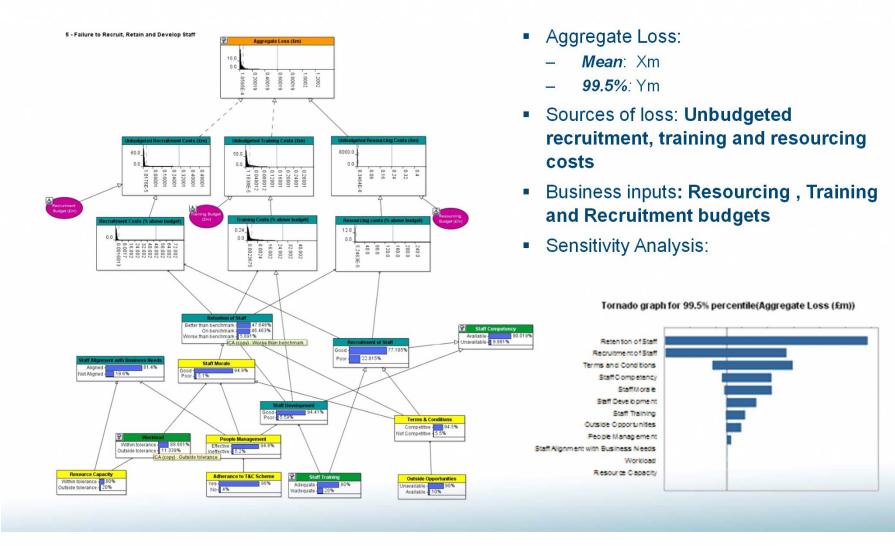


	Property	Check
	Links: Nodes ≥ 2 : 1	✓
	Hyperconnectivity	×
	Heads (% of Nodes)	3%
	"Heads" all impacts?	✓
	"Tails" (% of Nodes)	21%
	Free nodes?	×
	Loops?	✓



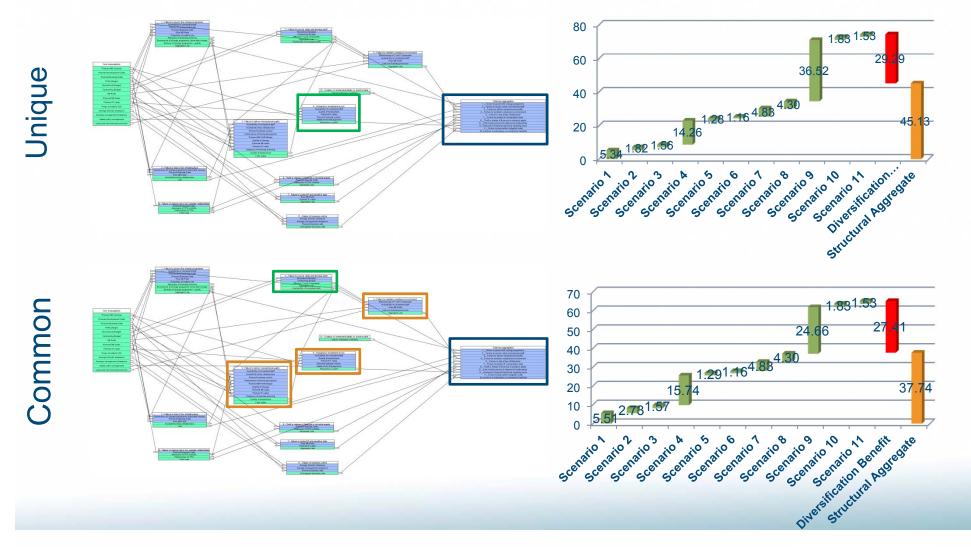
### **Risk - Failure to recruit, retain and develop staff**

Risk Quantification using a Bayesian Network





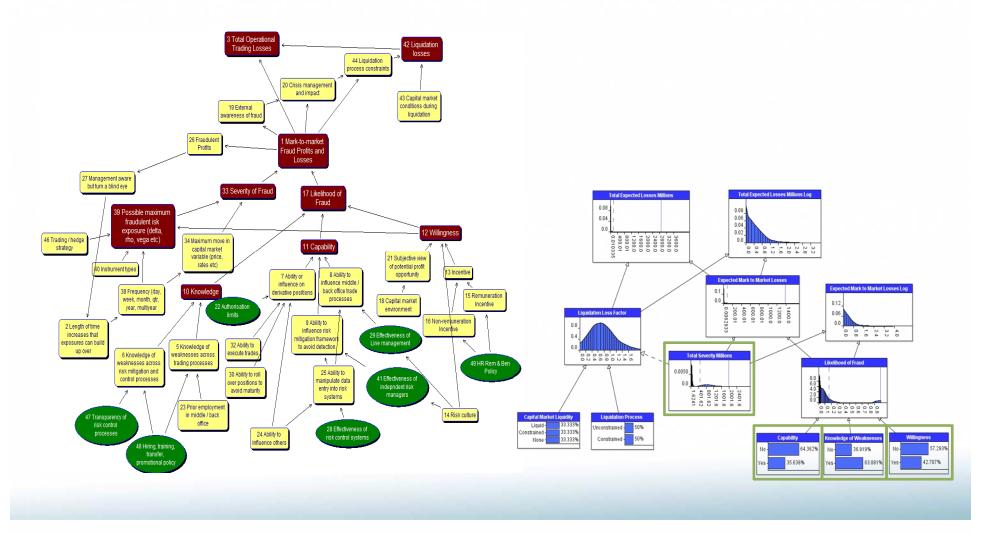
## **Operational Risk Capital**





# **Assessing Extreme Risk Events**

Rogue Trader Scenario





# **Applications**

Risk Appetite

#### Section 3b





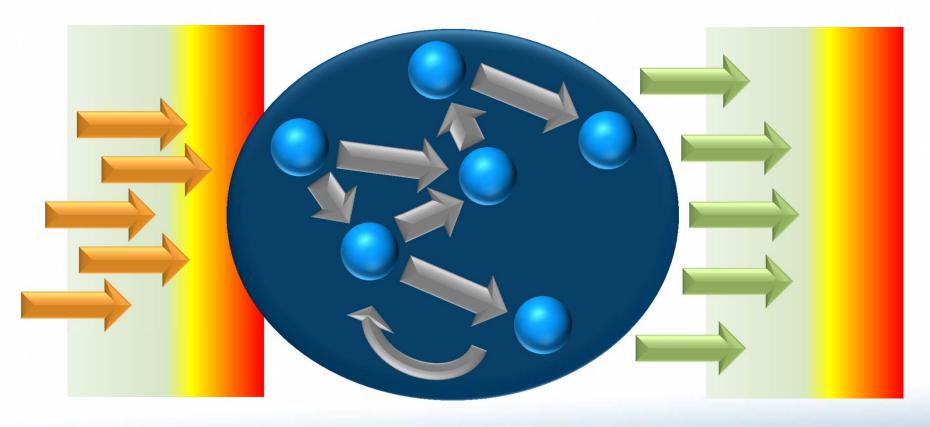
# **Primary Risk Appetite Challenge:**

Aggregating / cascading RAS thresholds  $\leftarrow \rightarrow$  risk limits

Knowing how these

...interact...

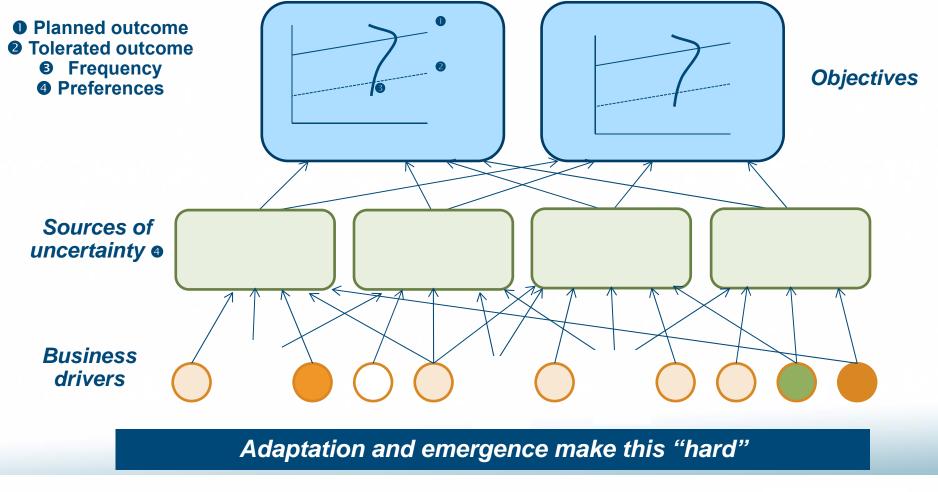
...to produce these



It is essentially a large, complex multi-objective optimisation and control challenge



# **Risk Appetite Components**

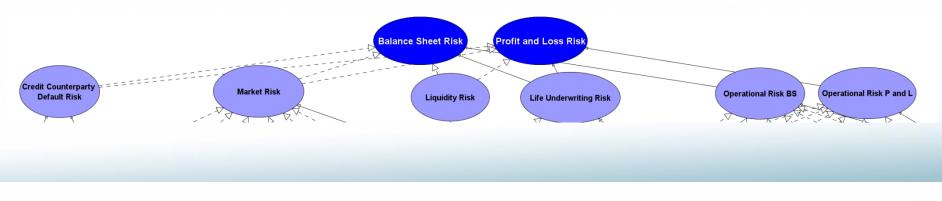




## **Business Objectives Linked to Risk Sources**

- Risk Sources:
  - Market
  - Credit Counterparty Default
  - Liquidity
  - Underwriting
  - Operational

- Contribution of risk source to overall risk set from:
  - Capital analysis
  - Profit analysis
  - Expert judgment



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# **Identify Sources of Uncertainty for Each Risk**

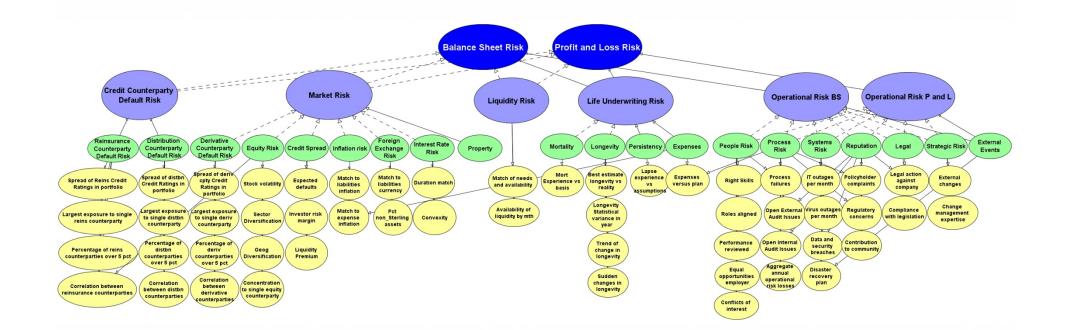
- Credit:
  - Reinsurance counterparty
  - Distribution counterparty
  - Derivative counterparty (or classified under market)

- Market:
  - Equity
  - Credit spreads
  - Inflation
  - Foreign exchange
  - Interest rate





# Model now links business objectives to sources of risk and indicators



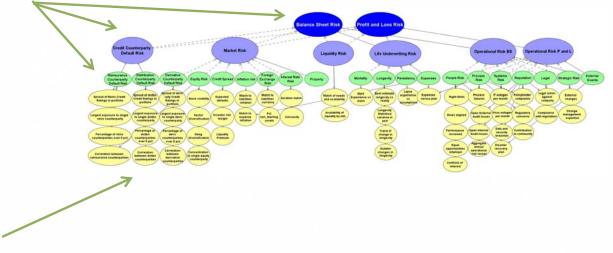
 Capture multiple influences: operational risk in particular links to more than one risk characteristic



# **Setting Risk Appetite**

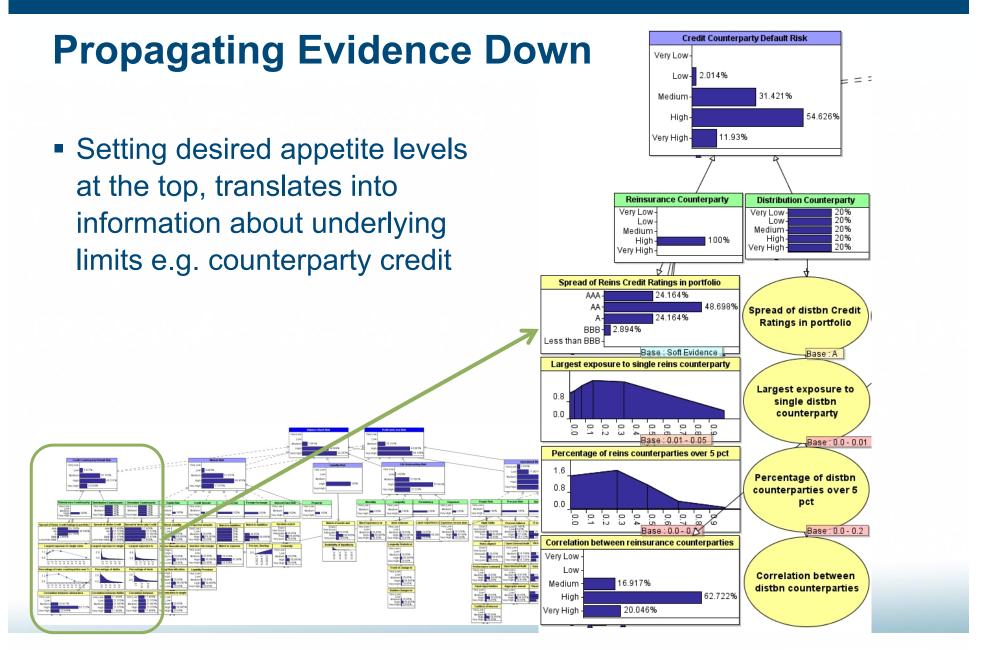
Use propagation properties of Bayesian Networks

Setting an outcome here...



...tells us what the states ought to be here

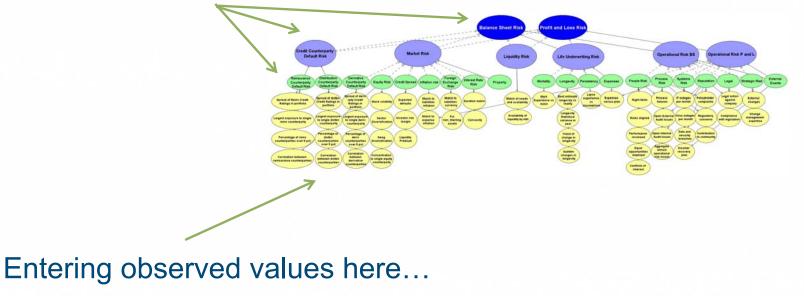




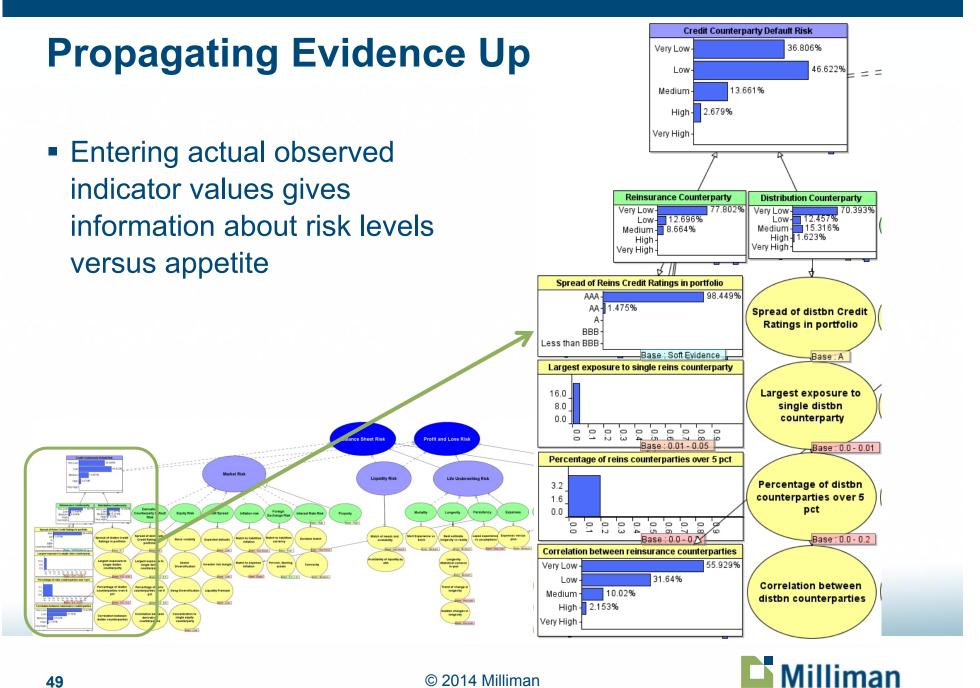


# **Monitoring Risk Levels Against Appetite**

- Use propagation properties of Bayesian Networks
- ... gives us an estimate of risk levels here







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# Applications Stress Testing

#### Section 3c



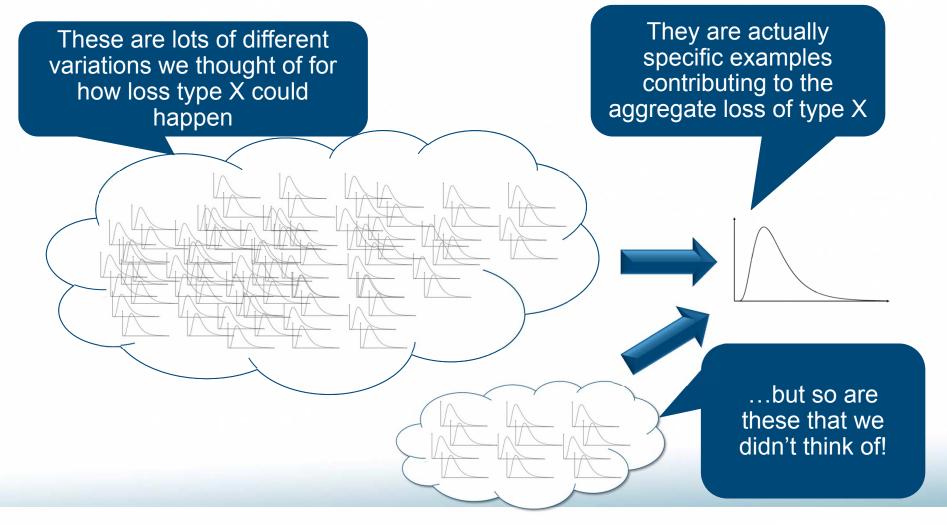
Award for "Practical Risk Management Applications" at ERM Symposium 2013





# **Stress / Scenario Testing:**

### **Overload But Incomplete**

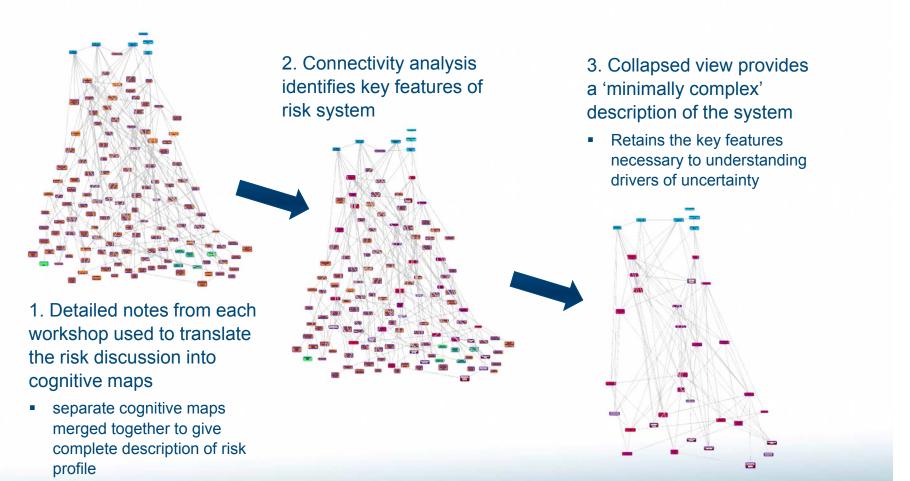




# **Codifying Business Intelligence**

Cognitive Mapping & Analysis

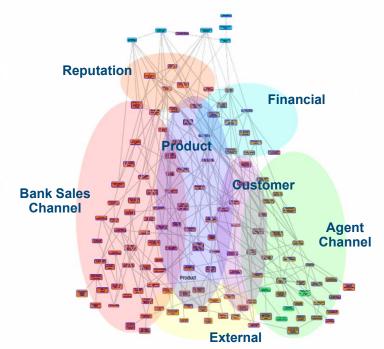






# **Identifying Critical Drivers**

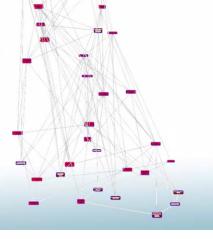
Highly connected drivers across the various silos



- Structure of the map broadly reflects the key areas discussed within the workshops
  - Financial, Agent Channel, Product, Customer, Reputation, External, Bank Sales Channel
- Visually represents the distinct risk profile of each sales channel

Cognitive analysis identified key interactions between the risk profiles



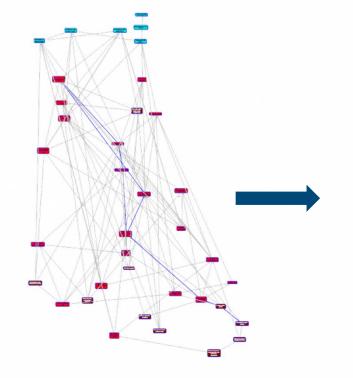




# **Qualitative Scenario Creation**

Understand full narrative of causes to consequences





1. Minimally complex view of the system studied to identify interesting pathways between concepts "The life company does not deliver effective agent training with respect to current regulation, industry best practice, and product knowledge. This leads to a gradual decline in the ability of sales agents to offer compliant advice and meet required sales standards.

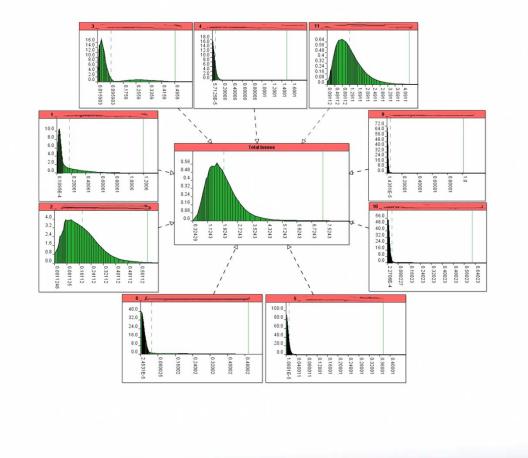
Out-of-date and incomplete sales advice leads to increased incidence of product mis-selling across the business's product offering.

A build up of customer complaints is picked up by industry press and the regulator decides to review current sales practise."

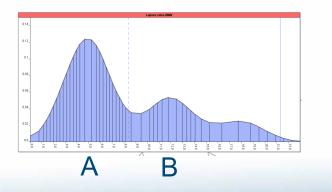
> 2. Pathways used as a framework for the scenarios, with additional context included from the full cognitive map



## **All Shapes And Sizes**



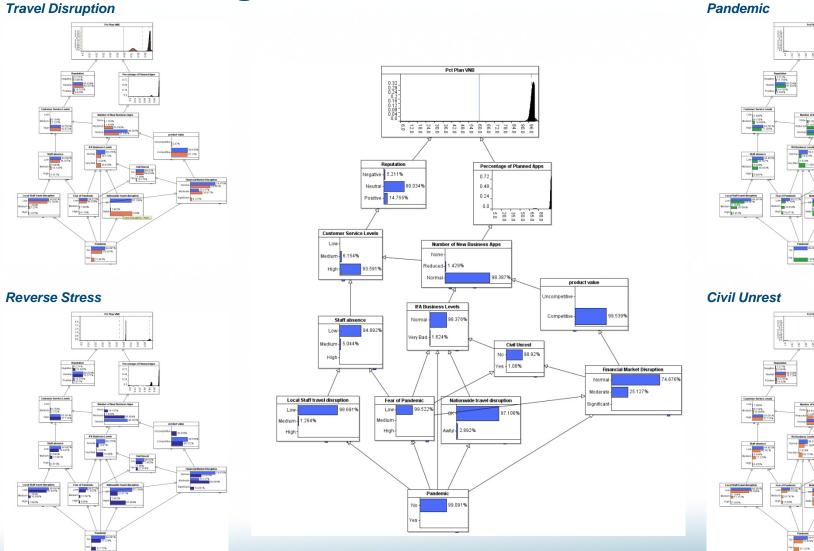
# The transition from A to B will be sudden not smooth

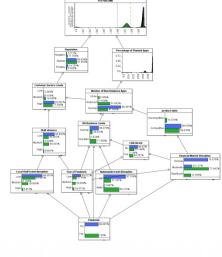


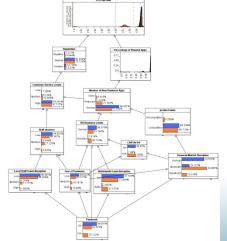


# **Recovering Scenarios**

Travel Disruption









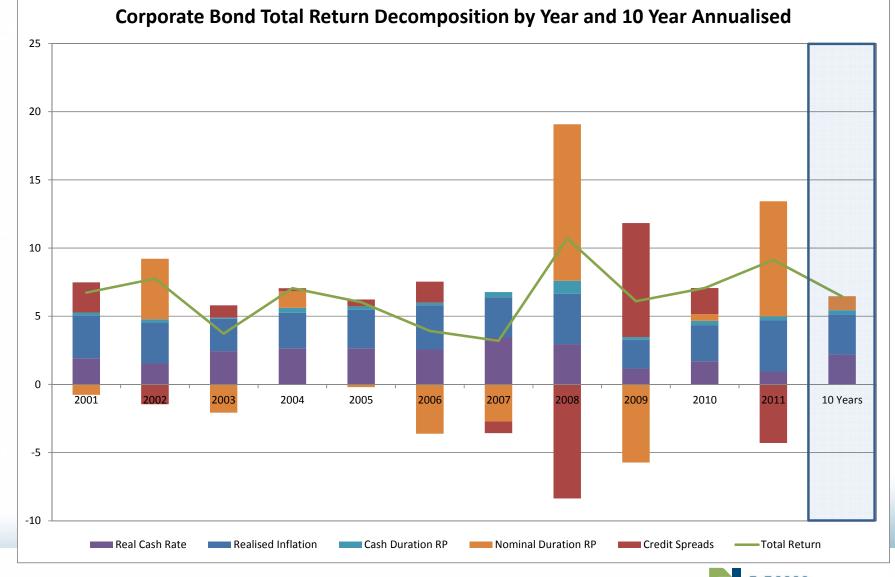
# **Applications** Interest Rate Risk

#### Section 3d



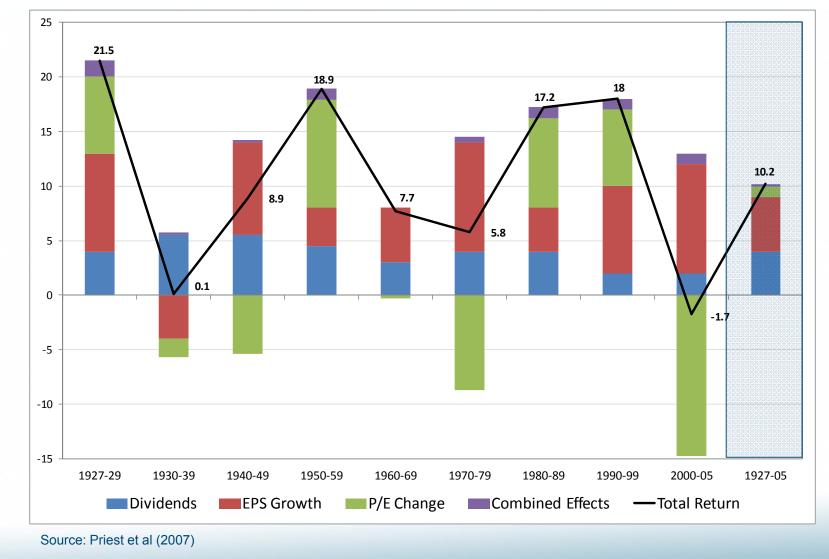


# **Causal Factor Explanation of Corporate Bonds**



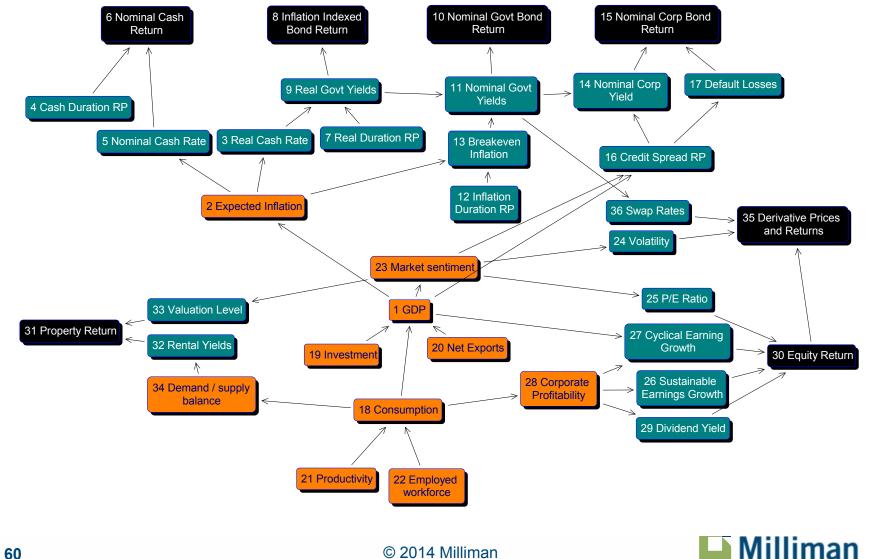


## Long Term US S&P Return Decomposition





# Eliciting the Causal System Structure to Understand Inter-relationships



# Modelling Full Dynamic Risk Factor Distributions

Breakeven Inflation Forecast Nominal Bond Yield Condition uncertainty in key 0.32 0.24 0.24 capital market variables upon 0.16 0.16 0.08 0.08 0.0 risk factors / drivers 0.0 6.0 4.0 2.0 -1.0 0.0 0 - 5.0 - 4.0 - 2.0 0 (subjective & objective) Forecast Real Bond Yield Expected Inflation Inflation Duration Risk Premium 0.48 0.24 0.8 0.32 0.12 0.4 0.16 0.0 0.0 0.0 0.5 0 0 . . 'N 'ω ່ຫ ່ອ 0 .0. <u>\_</u> 'N ω. ω. o 'N 4.5 <u>\_</u> 0.7 -0.4 0.1 ö ίση. ίσι Ö ίσι in j\_ j. i. **Current Recent Inflation Regime** 2 Discrete GDP States Inflation Uncertainty Deflationary 10% Low-Depression or Recession - 1.2% 100% Normal 85% Medium 98.8% Low, Normal or High-Inflationary High - 5% Scenario 1 : Soft Evidence



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# **Questions?**

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