

# f | Pandemic Scenario Modelling: *Strengthening ORSA for Uncertainty*

VSAE Actuarial Congress 2025

Presented by Finalyse

4 March 2025

A FRESH TAKE ON RISK AND VALUATION



# Introduction

## Your Presenters



**Frans Kuys**  
Principal Consultant  
[frans.kuys@finalyse.com](mailto:frans.kuys@finalyse.com)

- Qualified actuary and Financial Risk Manager
- 15+ years of experience
- Worked across a wide range of fields in the actuarial industry
- Extensive experience in the insurance & pensions sectors:
  - actuarial valuations
  - financial reporting
  - risk management
  - asset-liability modelling (ALM)



**Jayadevan Vijayan**  
Senior Consultant  
[jayadevan.vijayan@finalyse.com](mailto:jayadevan.vijayan@finalyse.com)

- Senior Consultant at Finalyse Netherlands.
- Significant experience in the life insurance & reinsurance industry across different markets.
- Experience in variety of roles in the insurance industry:
  - Actuarial modelling
  - Risk management
  - Financial reporting roles (SII, SAM, IFRS 4)
- Proficient in modelling tools such as Moody's AXIS, Python and Prophet.



# Introduction: Who we are

## Finalyse at a glance



**Consultants:**  
120+



**Office Locations:**

- Amsterdam
- Brussels
- Budapest
- Dublin
- Luxembourg
- Warsaw
- Paris



**Key Accounts:**  
120 key accounts including major European financial institutions



**Delivering projects**  
in the entire EMEA region



**Consolidated income:**  
€12,7 M

**A leading consultancy founded in 1988 and operating in EMEA**

We specialise in guiding you through valuation, risk management for banking and insurance and regulatory compliance changes.

Empowering your decision-making, we provide a unique blend of financial and technological skills for unbiased analyses and modern solutions.

With over 30 years of successful projects, our expertise, pragmatism, team spirit and fairness build lasting relationships.



1. Introduction
2. Why scenario modelling?
3. Developing a storyline
4. Estimating impact
5. Scenario Aggregation
6. Q&A





# 1 | Introduction





### Economic Impact

- Recession due to reduced economic activity from lockdowns
- Unemployment
- Supply chain disruptions

### Healthcare Impact

- Vaccine development
- Overburdened Health care system

### Insurance Impact

- Increased claims for health & life insurance
- Business interruption claims
- Change in underwriting practices & policy terms

### Personal Life Impact

- Remote work
- Social isolation during lockdown
- Education disruptions



## 2 | Why Scenario Modelling?





## Definition

*“Stress scenarios are **severe** but **plausible** hypothetical situations that can **adversely affect** the **balance sheets** and **solvency positions** of insurance undertakings.*

*Scenarios can comprise of a **single shock** or a **combination** of **market, demographic, financial and insurance specific shocks** that are expected to affect the resilience of individual undertakings and insurance sector as a whole.*

*The **main constituents** of a scenario are the **narrative** and **shocks**”*

~ Methodological Principles of Insurance Stress Testing EIOPA Guidance 2019





### Purpose

- Test the Solvency resilience of the undertaking
- Understand the economic impact of scenario on:
  - Capital Adequacy
  - Liquidity
  - Pricing
  - Business plans
  - Investment Strategy
- Identify the most affected Line of Business
- Regulatory Requirement:
  - ORSA
  - Internal Model SII SCR calculations



# 3 | Developing a Storyline





## Base Case Scenario Specification Generic Approach Overview

### 1. Analysis of historical data & other info

- Gather information of past events
- Focus on severe events
- Develop narrative on chosen event
- Base possible impact of scenario on actual impact of events
- Collect data on past events to form likelihood assessment

### 2. Narrative Definition

- Narratives for 1<sup>st</sup>, 2<sup>nd</sup> & 3<sup>rd</sup> order effects.
- Definition of timeframe of events:
  - timing
  - instantaneous or lasting?
  - repetitive or one-off?
  - combination of events?...

Consider loss mitigation actions:

- Embedded: reinsurance, policy terms (franchise, self-retention, annual aggregate, maximum liability, ...)
- Ex-post: reinsurance, government bail-outs, policy terms, ...

Analysis of Concentrations

- Geographical
- Industry
- Lines of business

### 3. Likelihood Estimation

- Estimate likelihood of Base Scenario on a forward-looking basis.
- Use Bayesian and / or frequentist approach.

### 4. Impact Estimation

- Translate scenario narratives into shocked Model Parameters.
- Several approaches can be used to estimate the impact of the scenario



## Approach & Considerations

- Historical Approach
- Forward looking approach
- Hybrid approach
- Single/Multiple Risk factor
- Combined scenario

## Factors to include in Narrative

### General

- Aim of exercise
- Time Horizon
- Date of event
- Geography

### Business

- Entities affected
- LoB's affected
- Scope ~ New Business, Renewals
- Management Actions

### Calculations

- Individual Shocks
- SCR shocks
- Loss Distribution
- Impact of reinsurance
- Likelihood





## Example of a Short Narrative

A **global** pandemic scenario with the same mortality, speed of contagion and symptoms of COVID-19. Assumed to occur in **beginning of the year** with effects manifesting over a **year**.

However, with a crucial difference:

- **Limited State support** to allow building of risks within portfolio of the business or effectiveness is **x%** in comparison to actual state support during pandemic

Consider impact of scenario on a Trade Credit insurer as an example:

- Entities: All entities as it's a global scenario
- Assets: Market shocks ( Historical | Future-looking | Hybrid )
- Liabilities: Trade credit insurance policies - increase in PD's, LGD ~100%
- Reporting delays ~ (Quarter | Half-year)
- Expenses

Impact with or without management actions can be considered:

- Change in investment strategy
- Reinsurance arrangements etc



## 4 | Estimating Impact





- Impacts could be 1<sup>st</sup> order (direct) or 2<sup>nd</sup> order impacts:
- 1<sup>st</sup> order impacts: Direct effect of scenario on claims  
E.g. Increase in health claims due to COVID impact
- 2<sup>nd</sup> order impacts: Impacts due to secondary effects of scenario  
E.g. Increase in claims due to recession as an impact of lockdowns

### Stressed claim ratio



- Impact on short term mortality rates
- Can consider permanent change in level of mortality
- Consider impact on mortality improvement
- Non-Life LoB's such as Business Interruption and Trade Credit insurance could be affected

### Asset modelling



The duration of shocks could be based on recovery scenarios, for example:

- **V** : Quick recovery (3-6 months)
- **U** : Longer economic contraction (6-9 months)
- **W** : Downturn after initial recovery
- **L** : Long term stagnation



- A scenario's impact on GDP can be assessed using research and expert judgement.
- Some examples include:
  - Using the same impact of historical scenarios
  - Adjusting impact of historical scenarios
  - Impact of scenario on productivity (e.g. how does the lockdown impact on productivity)
- A link model which links GDP to claim ratios can be developed using statistical methods e.g. regression based on business data
- We can derive the effect of scenario on the claim ratios by estimating the impact on GDP and then using the link model.



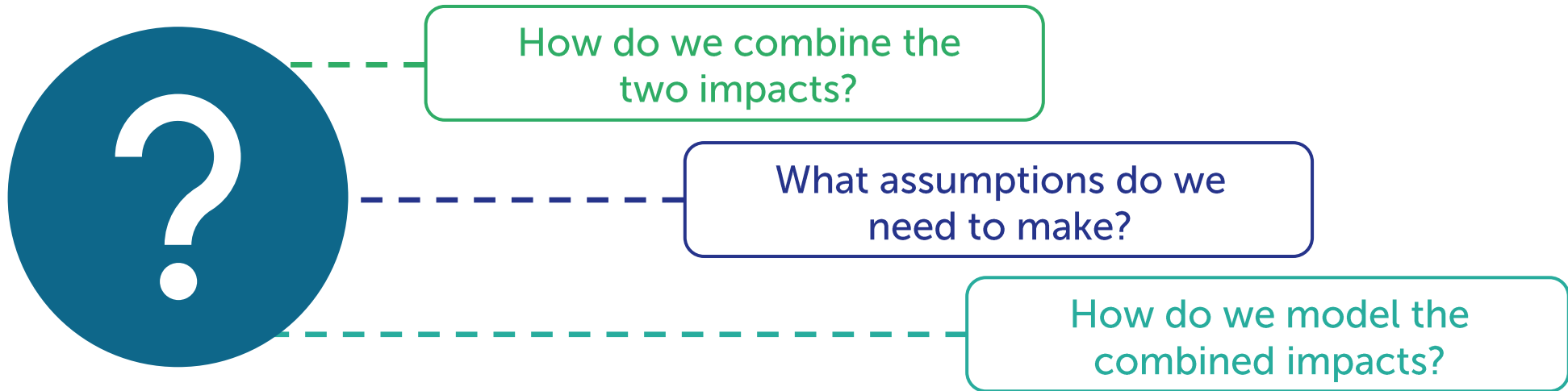


# 5 | Scenario Aggregation





- Most companies will have an existing model to estimate impacts e.g. Standard or Internal model to calculate capital requirements
- In extraordinary circumstances (e.g. during the pandemic), we may need to model the impact of pandemic related events separately.





We first define the random variables  $X$ ,  $Y_i$ , and  $Z_i$ :

- 1  $X$  is the random variable for our internal model results
- 2  $Y_i$  is the random variable for the model results for the  $i^{\text{th}}$  extraordinary circumstances
- 3  $Z_i$  is the random variable for the combined model results with the  $i^{\text{th}}$  extraordinary event

Assuming:

- $Y_i$  is a binominal distribution with parameter  $p_i$  ( $p_i$  is probability of event occurring)
- $X$  has  $n$ -possible outcomes with all the same probabilities of occurring

We can define a probability mass function: 
$$p_Z(\mathbf{z}) = \sum_{y \in \{0,1\}} p_X(x)p_Y(y)$$

- This means that the probability of both  $x$  and  $y$  occurring at the same time is equal to the probability of  $x$  occurring and  $y$  occurring.
- Since there are  $n$  possible outcomes for  $X$ , and two possible outcomes for  $Y_i$ , our range of outcomes increases to  $2n$ .



- Since the distribution of each  $Y_i$  is known, it is possible to determine the joint distributions  $Z = X + Y_i$  for  $i \in \{1, \dots, n - 1\}$  with the use of Monte Carlo simulations together with Cholesky's Decomposition.
- Assuming that there is no correlation between each  $X$  and  $Y_i$ , the correlation matrix is an  $n$ -by- $n$  identity matrix.
- We can then apply the result of Cholesky decomposition ( $R = LL^T$ ) to  $n$  standard normal simulations, we get the correlated standard normal variables for each  $X$  and  $Y_i$ .
- We can then compute the CDF for each  $X$  and  $Y_i$ . This is important when aggregating results because we can determine the quantile values for  $X$  with the CDF, and then add on the effect of  $Y_i$  if  $F(z_i) \geq p_i$  where  $z_i$  is the  $i^{th}$  simulated value for  $Y_i$ .
- (Reminder that each  $Y_i$  has a binominal distribution with parameter  $p_i$ )





## Scenario Aggregation

### Examples: Code

```
# Compute the Cholesky decomposition
L = np.linalg.cholesky(corr_matrix)
print(L)
# Generate n samples from a standard normal distribution

z = np.random.normal(size=(num_sim, num_cat+1))

# Multiply the samples by the Cholesky matrix to obtain correlated samples
corr_data = np.dot(z, L.T)

# Apply the normal CDF on the first column of corr_data
cdf_data = norm.cdf(corr_data)

quantile_values = np.quantile(data, cdf_data[:,0])
```

- $L \rightarrow$  Cholesky Factor
- $z \rightarrow$  standard normal simulations
- $cdf\_data \rightarrow$  Used to obtain the probabilities of each outcome
- $quantile\_values \rightarrow$  The first column is used because that represents the simulations for  $X_i$



## Scenario Aggregation

### Examples: Code

```
binary_values = np.zeros((num_sim, num_cat))

impact = [80000000, 7994125, 50000000, 32744742, 6793479]
event_probabilities = [0.01, 0.0651, 0.05, 0.025, 0.045]
```

```
num_cat = len(impact)
```

```
num_sim = 3000000
```

```
for i in range(num_cat):
    print(i)
    event_impact = impact[i]
    p = event_probabilities[i]
    print(event_impact)
    print(p)
```

```
# Loop through each element of the quantiles vector and apply the get_binary_variable() function
for ii in range(num_sim):
```

```
    q = cdf_data[ii, i + 1]
    if q < 1 - p:
        binary_value = 0
    else:
        binary_value = event_impact
```

```
    binary_values[ii, i] = binary_value
```

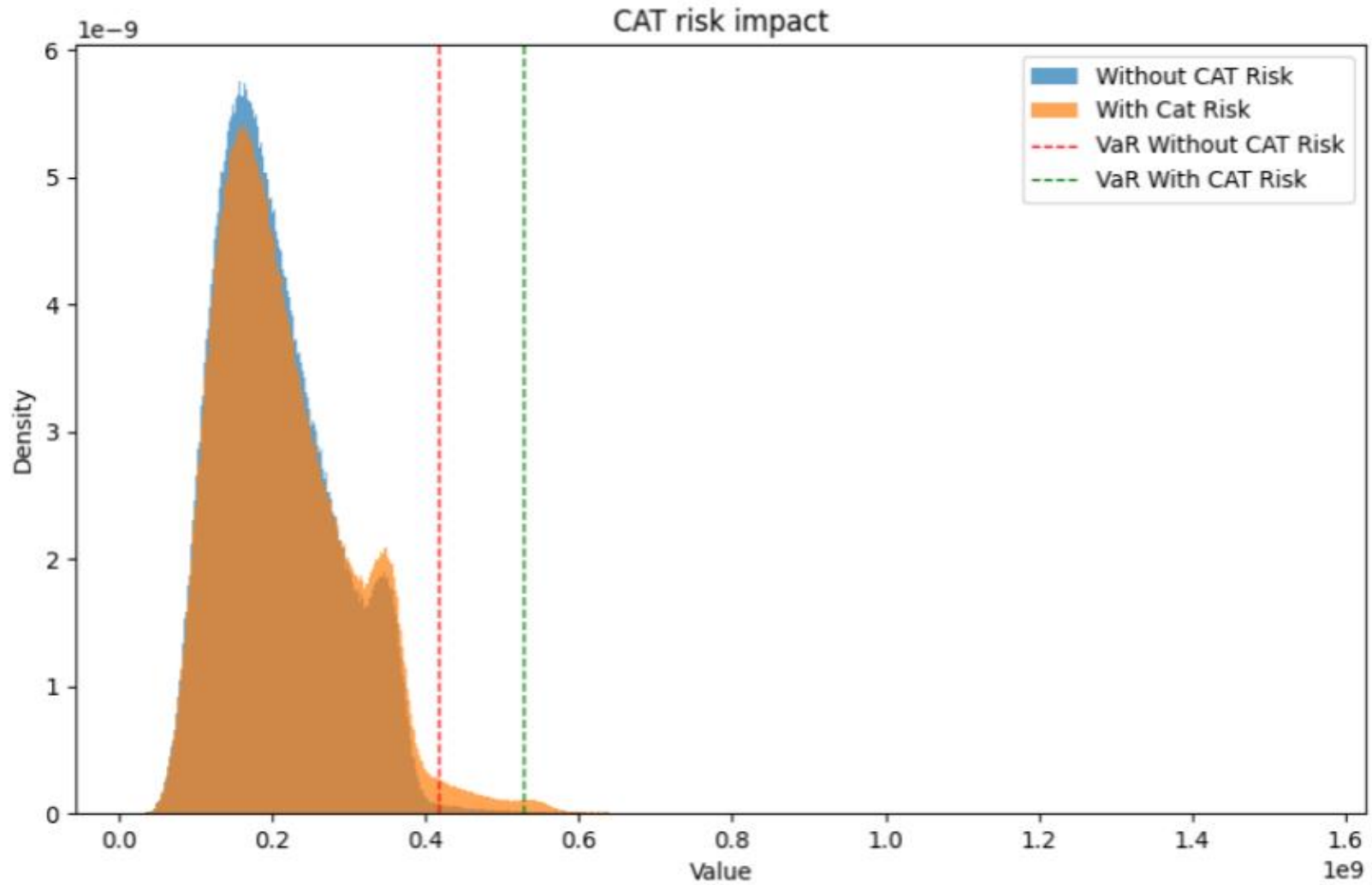
```
losses_with_CAT = np.sum(binary_values, axis=1) + quantile_values
```

- `impact` → Array of outcomes for  $Y_i$
- `event_probabilities` → Array of probabilities for  $Y_i$
- `q` →  $F(z_i)$
- `binary_value` → Since the outcomes of  $Y_i$  is 1 or 0



# Scenario Aggregation

Examples: Applying the methodology to SCR and SCR with CAT Risk





Thank you & Q&A