

# Gaussian emergence for stochastic reserve risk modelling Ramsay Nashef

## Welcome

#### **Disclaimers**

- 1. The theory presented here has not been published or formally reviewed.
- 2. It is not necessarily a new invention.



# **Prior knowledge**

#### Required

A Brownian motion (aka Wiener process) is:

- a random process  $(W_t)$  beginning at  $W_0 = 0$
- with continuous sample paths
- and independent, Gaussian increments.

#### Optional

G(u)

0

0

u

#### A distortion function is:

- a non-decreasing function
- mapping [0,1] **onto** [0,1].

It can be interpreted as a change of probability measure, re-weighting the likelihood of different scenarios.





# What are we trying to solve?

An insurer's balance sheet includes liabilities for the expected cost of unknown future risk.

Suppose we have already modelled the potential ultimate cost of risk, calculated the expectation and reserved a best estimate liability for this risk.

Next we ask, how could this estimate of the risk develop over time?

- distribution of potential future estimates for the risk
- capital requirements over different time horizons
- future capital requirements conditional on future scenarios
- expected cost of capital required over lifetime of risk (risk margin).

 Table 1.
 Acme Inc. balance sheet as at 31/12/2024

Assets		Liabilities	
Cash	£2400	Expected c claims	ost of £2000
Inventory	£1600	Equity	£2000
Total	£4000	Total	£4000



## How should an emergence model behave?

Let *X* represent the ultimate losses from a particular risk.

Let T = [0,1] represent time.

Let  $X_t = \mathbb{E}_t[X]$  represent the expectation of X conditional on information known at time t.

#### Requirements for the random process $(X_t)$ :

- begin at mean:  $X_0 = \mathbb{E}[X]$
- end at ultimate:  $X_1 = X$
- be a martingale: if s < t, then  $\mathbb{E}[X_t|X_s] = X_s$ .







# **Standard approach**

#### **Straight-line emergence**





## New approach

#### **Gaussian emergence**





## **Gaussian emergence**

The equation for Gaussian emergence is  $F(X) = \Phi(W_1)$ , where:

- *F*() is the distribution function of the ultimate risk *X*
- $\Phi()$  is the distribution function of the standard Normal distribution
- $W_t$  is a standard Brownian motion, which we observe over time  $t \in [0,1]$ .

This results in the following:



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### **Approximate calculation with nested simulations**

$$X_t = \mathbb{E}[X|W_t] = \mathbb{E}\left[F^{-1}\left(\Phi(W_t + \mathcal{N}(0, 1-t))\right) \middle| W_t\right]$$

We can easily approximate  $X_t$  using nested simulations:

$$X_t \approx \frac{1}{M} \sum_{i=1}^M F^{-1} \left( \Phi \left( W_t + \sqrt{1-t} \Phi^{-1}(u_i) \right) \right), \text{ where } u_i \text{ are a sample of } \mathcal{U}(0,1), \text{ such as } u_i = \frac{i - \frac{1}{2}}{M}.$$

- In simulation models,  $F^{-1}()$  can be calculated by looking up values on the distribution of X.
- *M* does not need to be huge.
  - M = 100 seems enough for accuracy within about 1%.







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### **Emergence patterns (deterministic)**

The rate of emergence is controlled by adjusting the time axis, mapping real-life time into [0,1].





# **Key features**

- Regardless of the distribution of *X*, the method guarantees that *X<sub>t</sub>* begins at the mean of *X*, ends at *X*, and is a martingale.
- It's fairly efficient to approximate  $X_t$ .
- We can control the rate of emergence by controlling the rate that t moves from 0 to 1.

**Bonus feature:** If X is (Log)Normal, then  $X_t$  is naturally a (Geometric) Brownian motion:

- if  $X \sim \mathcal{N}(\mu, \sigma)$  then  $X_t = \mu + \sigma W_t$
- if  $\ln(X) \sim \mathcal{N}(\mu, \sigma)$  then  $\ln(X_t) = \mu + \sigma W_t + \frac{1}{2}(1-t)\sigma^2$ .

**Open question:** Are there analytical solutions for other special cases?



# Limitation #1 – fixed rates of risk emergence

The Gaussian emergence model is overly simplistic if you assume that a known amount of risk from the Brownian motion emerges in each time period.

This does not reflect real life, where the information about risks may emerge at unknown rates.

#### **Solution**

The emergence rate can easily be made stochastic. Instead of mapping each future time to a fixed  $t \in [0,1]$ , you use something random.

Examples: Dirichlet allocation, Poisson process.

This does not create major difficulties in stochastic simulation of the reserve process.

However, it makes some of the maths more difficult. In particular, Value-at-Risk calculations are more complicated because the amount of "emergence time" in a time period is uncertain.



# Limitation #2 – no concept of payment timing

In real-life reserve risk settings, there is usually a Paid amount which also emerges over time and acts as a lower bound for the ultimate risk. This dynamic is not present in the model.

As a result, regardless of how much emergence time has elapsed and how high a level  $X_t$  has reached, there always remains a possibility that it subsequently drops to the lowest possible value of X.



#### Challenge

It could be possible to develop a similar model based on Brownian motions for the simultaneous emergence of Paid and Incurred based, as envisaged in the graph to the left.



# Value-at-Risk and Solvency II Risk Margin

- Let  $V_{t \to h}(p)$  be the Value-at-Risk of  $X_t$  over horizon  $h \le 1 t$  at probability level p, satisfying:  $\mathbb{P}[X_{t+h} \le V_{t \to h}(p)|W_t] = p.$
- This is calculated just as easily as  $X_t$ :

$$W_{t\to h}(p) = \mathbb{E}\left[F^{-1}\left(\Phi\left(W_t + \sqrt{h} \, \Phi^{-1}(p) + \sqrt{1 - t - h} \, \Phi^{-1}(U)\right)\right) \middle| W_t\right], \qquad U \sim U(0, 1).$$

- For fixed horizon *h* and level *p*,  $V_{t \rightarrow h}(p)$  is also a martingale.
- This tells us that  $\mathbb{E}[V_{t \to h}(p)] = V_{0 \to h}(p)$ , enabling a calculation of the Solvency II Risk Margin as the <u>expected</u> discounted cost of capital:

$$\operatorname{Risk}\operatorname{Margin} \coloneqq C \sum_{i=0}^{N-1} \operatorname{DiscountFactor}_i \times \mathbb{E} \left[ V_{t_i \to (t_{i+1} - t_i)}(99.5\%) - X_{t_i} \right]$$
$$\approx C \sum_{i=0}^{N-1} \frac{\operatorname{DiscountFactor}_i}{M} \left( \sum_{k=1}^M F^{-1} \left( \Phi \left( \sqrt{t_{i+1} - t_i} \ \Phi^{-1}(99.5\%) + \sqrt{1 - (t_{i+1} - t_i)} \ \Phi^{-1}(u_k) \right) \right) - \mathbb{E}[X] \right).$$

where *C* is the assumed cost of capital and  $(t_i)$  are future calendar years mapped to [0,1]. Note that Limitation #1 suggests that this calculation is imprudent!



### **Emergence by distortion**

When we observe  $W_t$  we change our view of the likely ultimate  $W_1$ .

This is the same as re-weighting the probabilities of  $W_1$  with a distortion function  $G_t(u)$ :

- $G_t(u) \coloneqq \Phi\left(\frac{\Phi^{-1}(u) W_t}{\sqrt{1-t}}\right)$
- $G_t^{-1}(u) = \Phi\left(W_t + \sqrt{1-t} \Phi^{-1}(u)\right).$

The distortion provides an updated view of the distribution of  $W_1$  and therefore of X.

 $X_t$  is simply the **distorted expectation** of X using this distortion function:

- Expectation:  $\mathbb{E}[X] = \int xf(x)dx = \int_0^1 xdF(x) = \int_0^1 F^{-1}(u)du \qquad \approx \frac{1}{M} \Sigma_{i=1}^M F^{-1}(u_i)$
- Distorted expectation:  $\mathbb{E}_t[X] = \int_0^1 x dG_t(F(x)) = \int_0^1 F^{-1}(G_t^{-1}(u)) du \approx \frac{1}{M} \Sigma_{i=1}^M F^{-1}(G_t^{-1}(u_i)).$

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# Making X more complicated

Suppose  $X = f(X_1, X_2, ...)$  is a complicated function of a vector of multiple random variable components  $X_i$  with distribution functions  $F_i()$ , each with their own separate emergences  $W_{i;t}$  and associated distortions  $G_{i;t}()$ .

Then 
$$\mathbb{E}[X|W_{1;t_1}, W_{2;t_2}, \dots] = \mathbb{E}[f(F_1^{-1}(G_{1;t_1}^{-1}(U_1)), F_2^{-1}(G_{2;t_2}^{-1}(U_2)), \dots)|W_{1;t_1}, W_{2;t_2}, \dots].$$

The complexity of the calculation increases in line with the number of variables and the function f, but for the approximate mean calculation, M still only needs to be large enough for a decent sample average.

**Example:**  $X = X_A + 2X_B$ .

If  $X_A$  has emerged by  $t_A \in [0,1]$  and  $X_B$  by  $t_B \in [0,1]$  then:  $X_{t_A,t_B} \approx \frac{1}{M} \sum_{i=1}^M F_A^{-1} \left( G_{A;t_A}^{-1}(u_{A,i}) \right) + 2F_B^{-1} \left( G_{B;t_B}^{-1}(u_{B,i}) \right).$ 

If  $(X_i)$  are correlated, the dependency develops naturally over the course of emergence.



## Recap

- Framing of the problem:
  - We start off already having a model of the ultimate risk *X*.
  - We want to find a suitable process  $(X_t)$  representing the best estimate as risk emerges.
- Solution to use a Brownian motion  $(W_t)_{t \in [0,1]}$  as a proxy for the emergence of X.
- The key equation is  $F(X) = \Phi(W_1)$ , which equates the rank of X to the terminal rank of  $(W_t)$ , which we will observe.
- Future reserve paths can be simulated with a fairly quick approximation, outlined below:



- We can control the rate of emergence by controlling how real-life time maps into T = [0,1].
- Limitations include:
  - Deterministic emergence rates will generally understate the volatility.
    - Stochastic emergence patterns solve this but make the maths more complex.
  - There is no concept of payment timing in the model.





Expressions of individual views by members of the Institute and Faculty of Actuaries and its staff are encouraged.

The views expressed in this presentation are those of the presenter.

