

# Reserve Variability

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# Session Outline

1. Convolution Equations in Loss Reserving
2. Properties of Convolutions
3. Reserve Risk = Inflation Risk + Insurance Risk
4. Duality and Transforms

# Convolution

Statistical Meaning: The sum of two independent random variables

Algebraic Meaning: A linear transformation to or from diagonals

# Sum of Two Dice

	1	2	3	4	5	6
1	2	3	4	5	6	7
2	3	4	5	6	7	8
3	4	5	6	7	8	9
4	5	6	7	8	9	10
5	6	7	8	9	10	11
6	7	8	9	10	11	12



# Convolution of Two Dice

$$\text{Prob}(7) = \sum \text{Prob}(A) \text{Prob}(7-A)$$

	1	2	3	4	5	6
1						1/36
2					1/36	
3				1/36		
4			1/36			
5		1/36				
6	1/36					

# Convolution

The sum of two independent random variables:

$$T = X + Y$$

$$P(T = t) = \int_{-\infty}^{\infty} f(x)g(t-x)dx$$

# Paid Loss Development

1.  $Ultimate(AY) = CumPaid(AY) \times LDF(age)$

2.  $Unpaid = \sum Ultimate(AY) - CumPaid(AY)$

Substitute  $age = CY - AY$  in 1, then combine 1 & 2:

$$Unpaid(CY) = \sum CumPaid(AY) (LDF(CY - AY) - 1)$$



# Traditional Methods as Convolutions

- Paid Loss Method:

$$\text{Unpaid}(\text{CY}) = \int \text{CumPaid}(\text{AY}) (\text{LDF}(\text{CY}-\text{AY}) - 1) d\text{AY}$$

- Incurred Loss Method:

$$\text{IBNR}(\text{CY}) = \int \text{CumInc}(\text{AY})(\text{LDF}(\text{CY}-\text{AY}) - 1) d\text{AY}$$

- Bornheutter-Ferguson:

$$\text{IBNR}(\text{CY}) = \int \text{ExpLoss}(\text{AY}) (1 - 1/\text{LDF}(\text{CY}-\text{AY})) d\text{AY}$$

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# Notation

We will use the symbol  $*$  to denote convolution,

i.e.  $h = f * g$  means

$$h(y) = \int_{-\infty}^{\infty} f(x)g(x - y)dx$$

# Linearity

- Commutative

$$f * g = g * f$$

- Associative

$$f * (g * h) = (f * g) * h$$

- Distributive over addition

$$f * (\alpha g + \beta h) = \alpha f * g + \beta f * h$$

# Operator Algebra

## Operator

- Identity
- Shift by  $t$
- Definite Integral
- Indefinite Integral
- Derivative

## Distribution

- Point mass at 0, or  $\delta$
- Point mass at  $t$ , or  $\delta(t)$
- 1
- $1^-$  or  $1^+$  (right or left limit)
- $d\delta/dt$ , denote  $\Delta$

# Derivative Rule

$$(f * g)' = f' * g = f * g'$$

$$(f * g) * \Delta = (f * \Delta) * g = f * (g * \Delta)$$

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# Three Factor Model

Incremental:

$$\text{IncrLoss}(AY, \text{age}) = X(AY) Y(CY) Z(\text{age})$$



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$$\textit{Ultimate}(AY) = \int_{\text{age}=0}^{\infty} X(AY) Y(CY) Z(\text{age}) d\text{age}$$

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$$\text{Ultimate}(AY) = \int_{\text{age}=0}^{\infty} X(AY) Y(CY) Z(\text{age}) d\text{age}$$

$$\text{Ultimate}(AY) = \int_{CY=AY}^{\infty} X(AY) Y(CY) Z(CY - AY) dCY$$

# Rearrange Terms

$$\text{Ultimate}(AY) = \int X(AY) Y(CY) Z(CY-AY) dCY$$

$$\text{Ultimate}(AY) = \int Y(CY) [X(AY)Z(CY-AY)]dCY$$

$$\text{Ultimate}(AY) = \text{Inflation} * \text{Insurance Risk}$$

$$\text{Unpaid}(AY,t) = \text{Inflation} * \text{Insurance Risk} * 1^+(t)$$

# Expanded Version

Reserve Risk(AY) = Inflation Risk \* Insurance Risk

Reserve Risk = Inflation Risk \*

Frequency Risk \*

Claim Intensity Risk

# Risk Theory

## **Traditional**

Frequency – Systemic

Severity - Diversifiable

## **Convolution**

Frequency – Systemic

Intensity – Diversifiable

Inflation - Systemic

# Risk Theory

## **Traditional**

Frequency – Systemic

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## **Convolution**

Frequency – Systemic

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# Transform

An operation on distributions that changes convolution to multiplication

$$T(f * g) = T(f) T(g)$$

Drawback:

Actuaries don't like "magic formulas"



# General Form

$$T(f(x)) = \int_a^b f(x)g(s)ds$$

# Familiar Transforms

## Transform

## Object Space

Limit points of sequences of smooth functions with...

MGF

... Bounded Support

Fourier Transform

... Bounded

LaPlace Transform

... Exponentially Bounded

# LaPlace vs. Fourier Transforms

Theorem:

$$\mathcal{L}(f(x)) = \mathcal{F}(e^{-\alpha x} f(x))$$

The LaPlace Transform of a distribution equals the Fourier Transform of the “de-trended” distribution

# Count – Time Duality

Duality:

An alternate formulation of a problem that preserves basic properties

Equivalence between a discrete distribution and a continuous distribution

# Poisson – Exponential Duality

## Poisson (Discrete)

Let  $N_t$  denote the number of occurrences in  $[0,t]$

## Exponential (Continuous)

The time between occurrences ( $T_1$ ) is Exponential

Let  $T_n$  denote the time of the  $n^{\text{th}}$  occurrence

$$P[N_t \geq n] = P[T_n \leq t]$$

# Geometric Distribution

The number of failures until the first success

The Geometric distribution can be used as a discrete approximation to the Exponential

For a short time interval  $t$ , define failure as no claims, The Geometric distribution will give the discrete time until a claim occurs.

$$P(\text{no claims}) = q = 1 - e^{-\lambda t}$$

# Negative Binomial

Traditional Formulation

Poisson mixed by Gamma

Alternate Formulation

N-fold convolution of Geometric Distributions

# LaPlace Transform

$$\mathcal{L}(x^n/n!) = (1/s)^n$$

The Laplace Transform maps from Poisson to Geometric



# Collective Risk Model

## Traditional Formulation

A combinatoric mix of convolutions

## Alternative Formulation

A convolution of convolutions

# Collective Risk Model

$$\text{Aggregate Loss} = \sum_{n=0}^{\infty} P(n) f(x)^{*n}$$

$$\text{Aggregate Loss} = \text{Normal} * g(x)^{*m}$$

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$$\text{Aggregate Loss} = \sum_{n=0}^{\infty} P(n) f(x)^{*n}$$

$$\text{Aggregate Loss} = \text{Normal} * g(x)^{*m}$$

$$\text{Aggregate Loss} = P(N) n \mu_x * f(x - \mu_x)^{* \mu_N}$$