



Society of Actuaries in Ireland

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**Intro to Markov Chains Monte Carlo  
and Excess of Loss Pricing**

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Thursday 27 June 2019

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# Disclaimer

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**The views expressed in this presentation are those of the presenter(s) and not necessarily those of the Society of Actuaries in Ireland or their employers.**

# Motivation

*“I was just guessing  
numbers and figures”*

*Chris Martin,  
The Scientist*



# Key Ideas

1. Parameter Uncertainty matters...
2. ...and it matters more for reinsurance
3. Stop using excel!

# Who am I?

- ▶ Chris Gibney
- ▶ Pricing/Capital Actuary
- ▶ Lloyds
- ▶ Insurance/Reinsurance/  
Retrocession
- ▶ Most lines of business

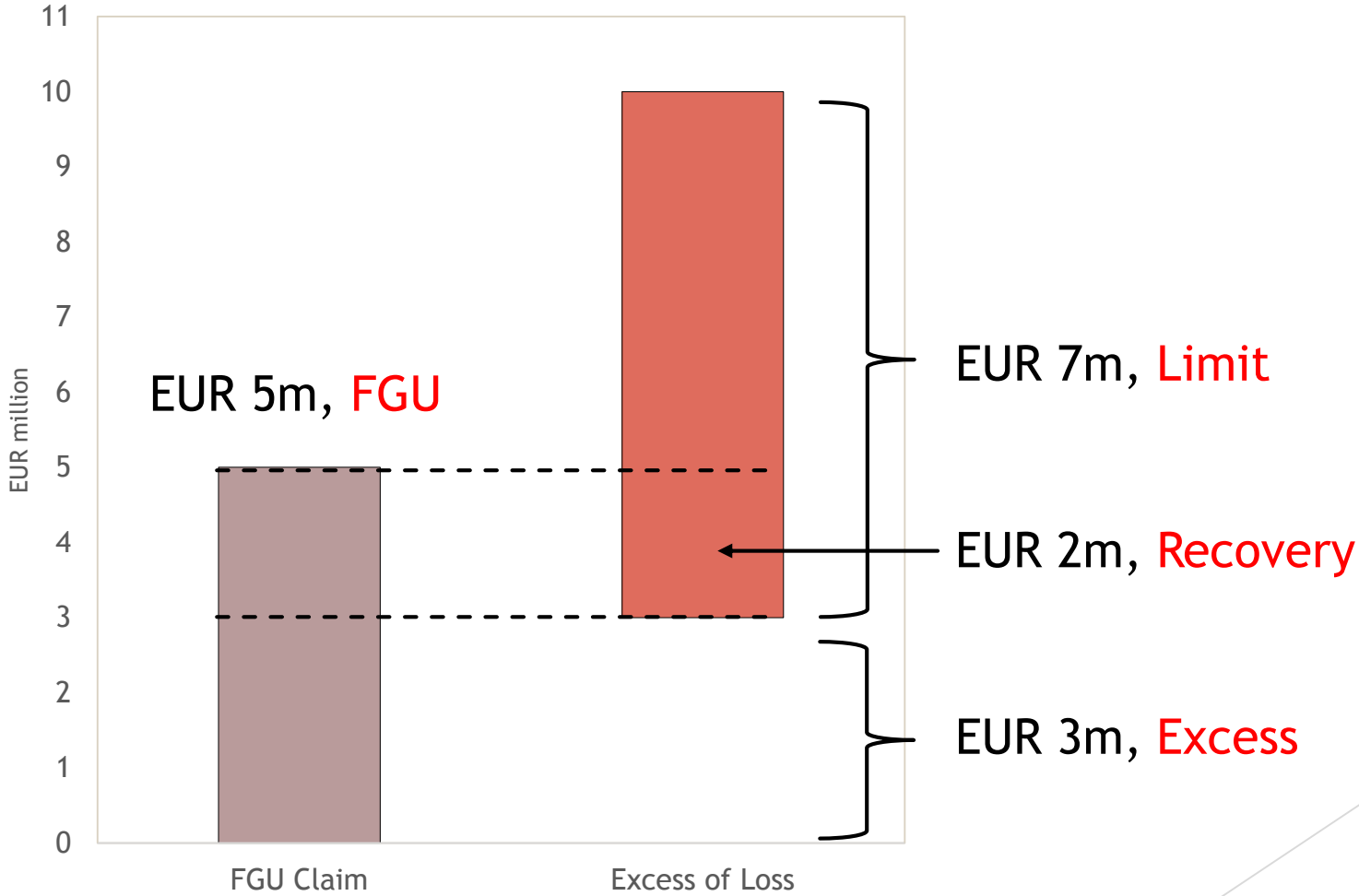


# Reinsurance

- ▶ Who works in reinsurance on a day to day basis?
- ▶ What is excess of loss reinsurance?

# Reinsurance

## Excess of Loss Reinsurance



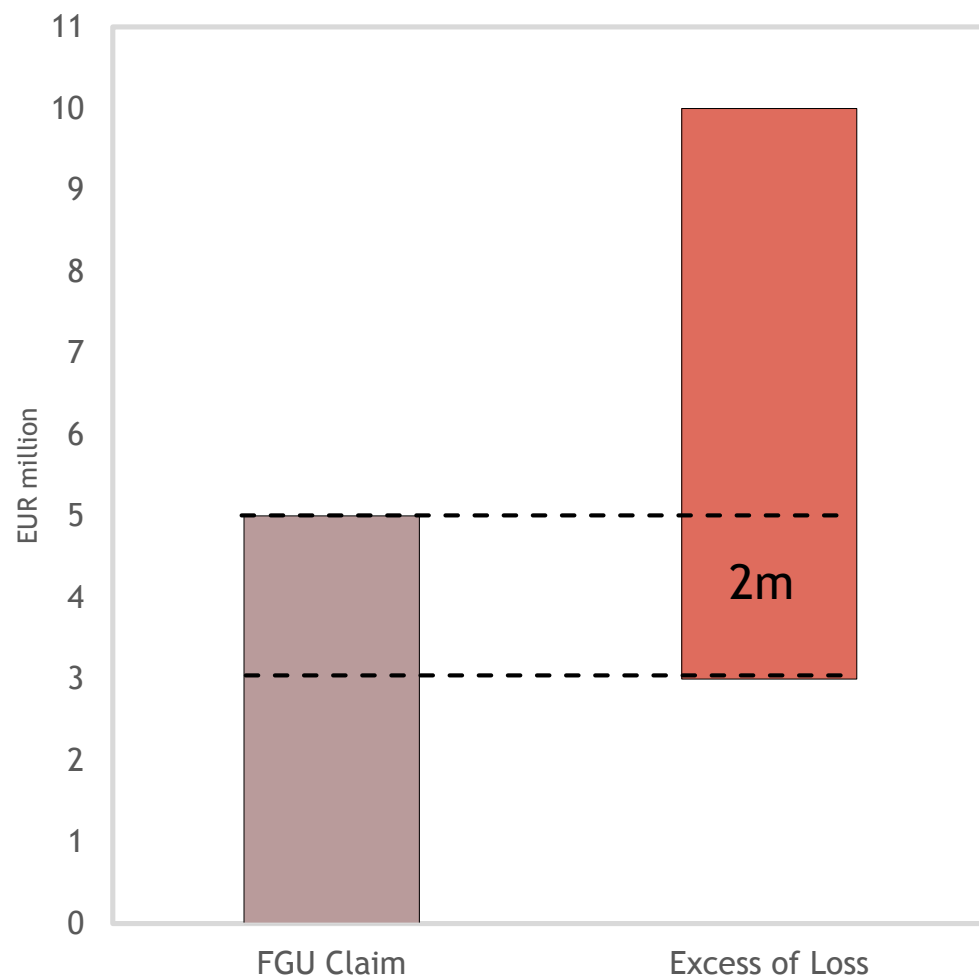
# Reinsurance

- ▶ Reinsurance is **non linear**
- ▶ **Gearing effect**



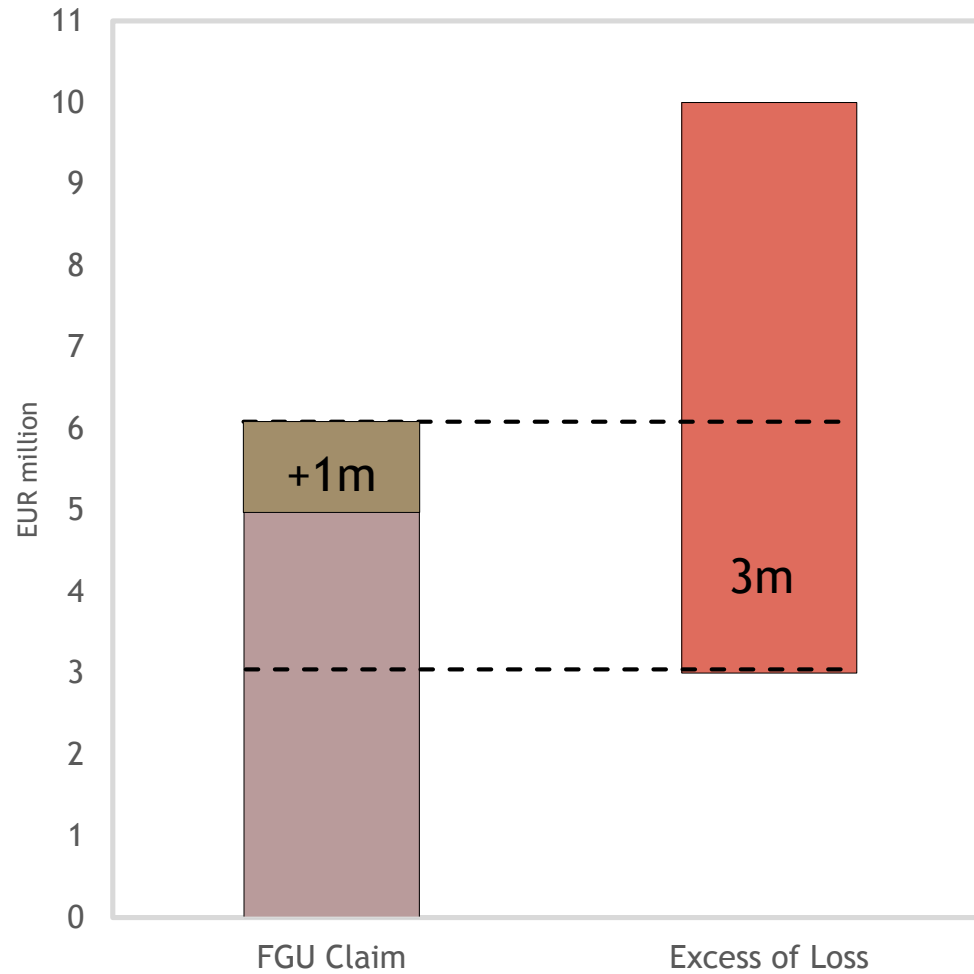
# Reinsurance

## Excess of Loss Reinsurance



# Reinsurance

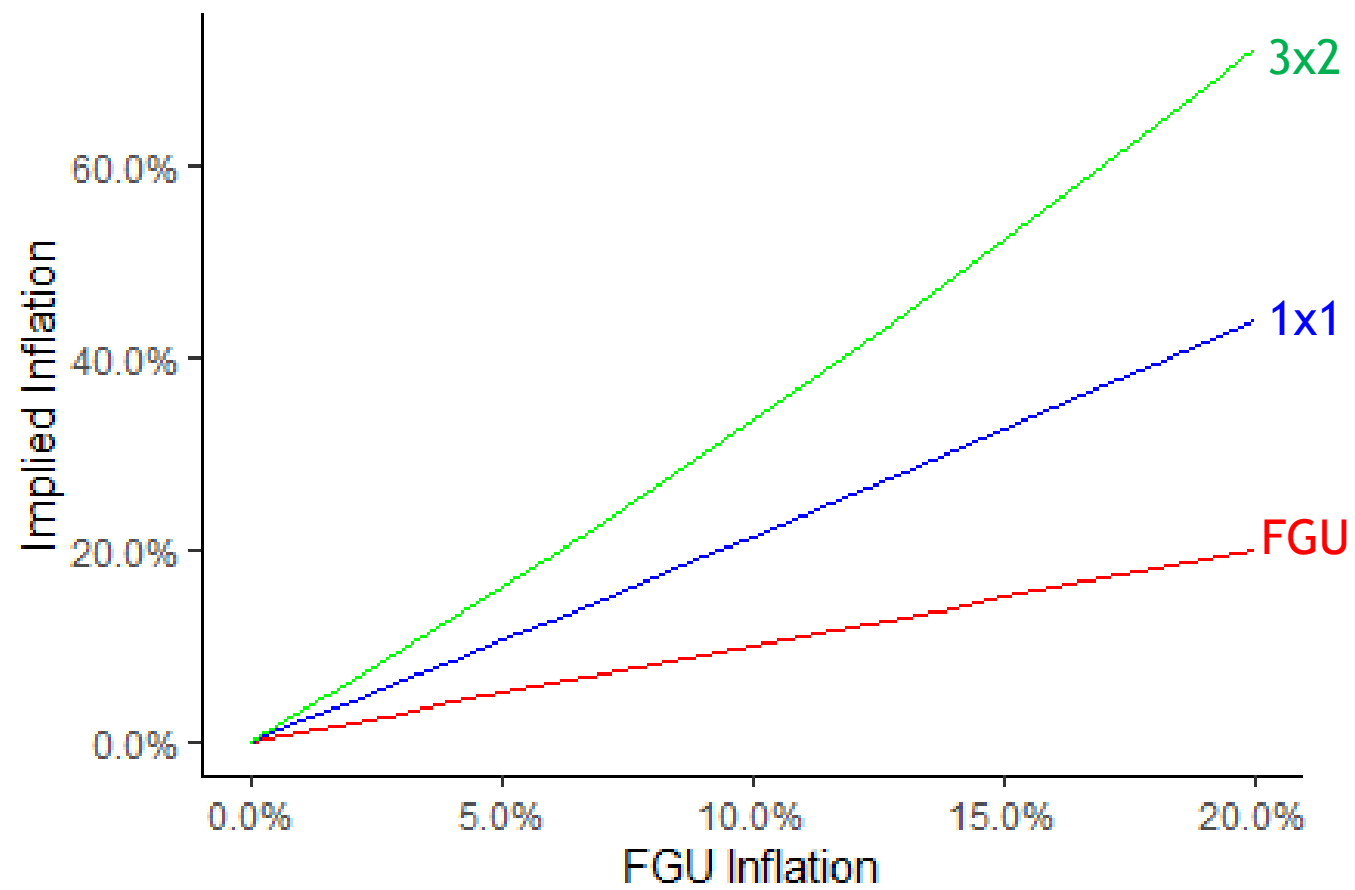
Excess of Loss Reinsurance



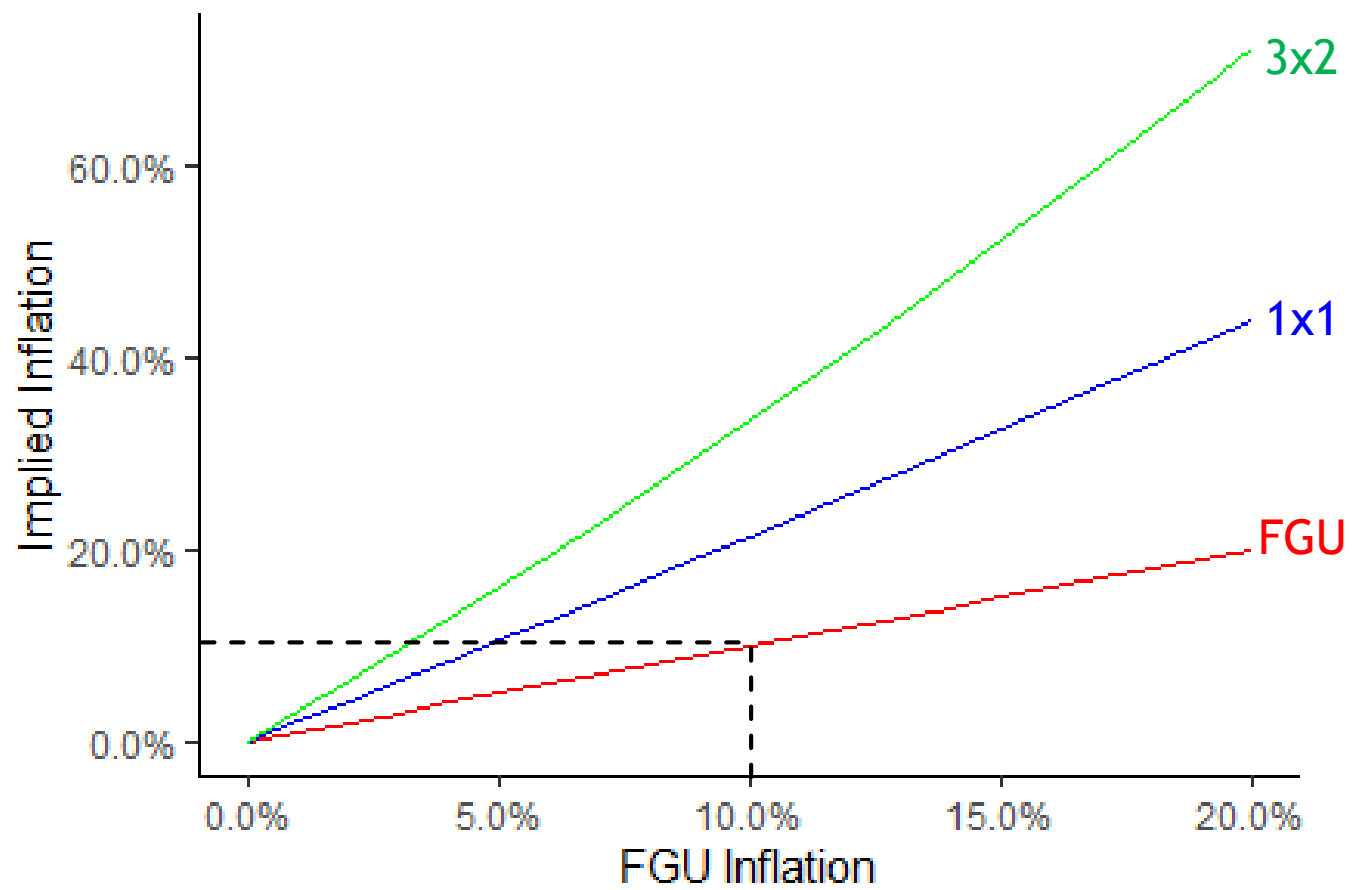
**FGU +1m (+20%)**

**RI Loss +1m (+50%)**

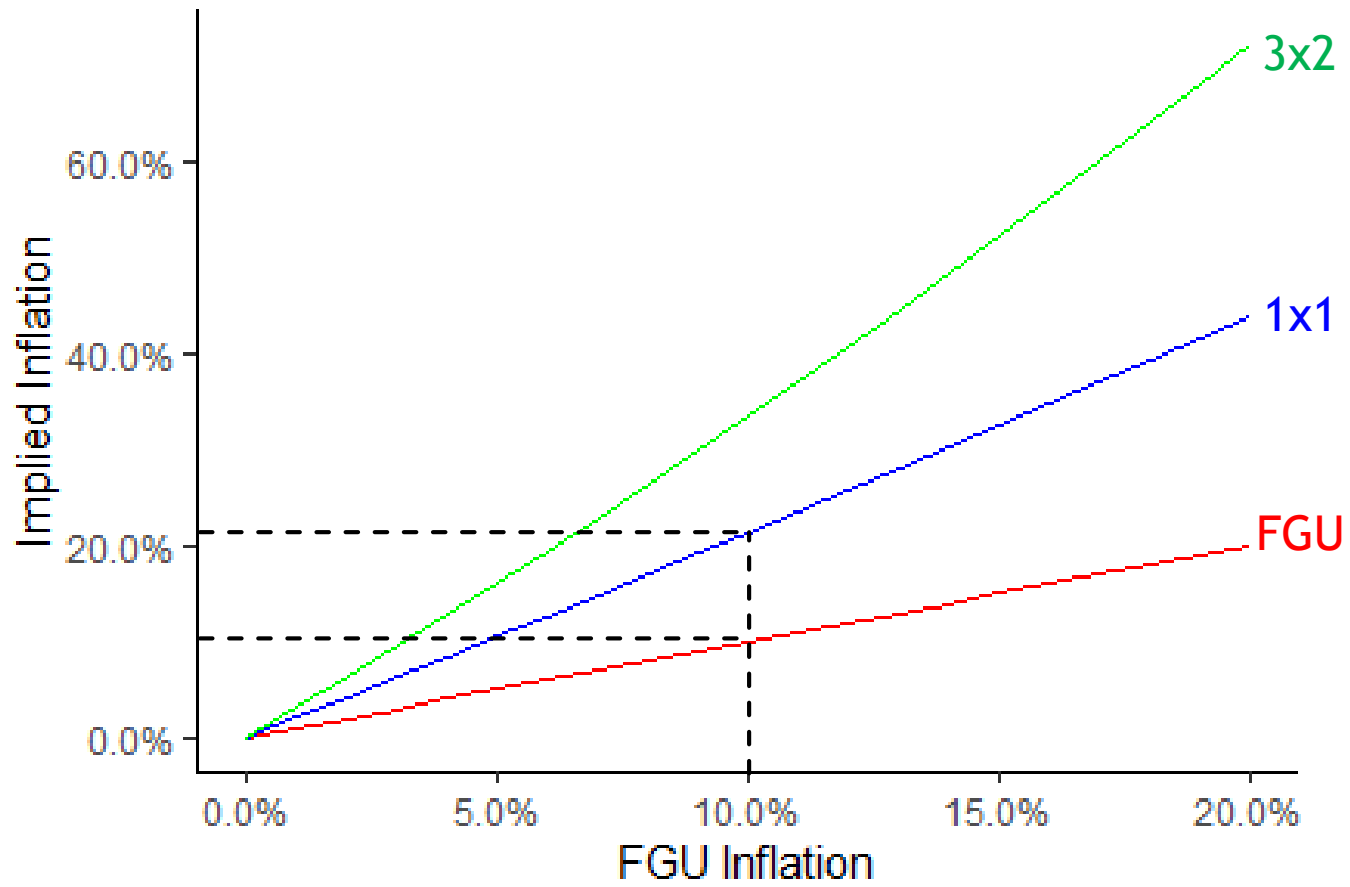
# Gearing Effect



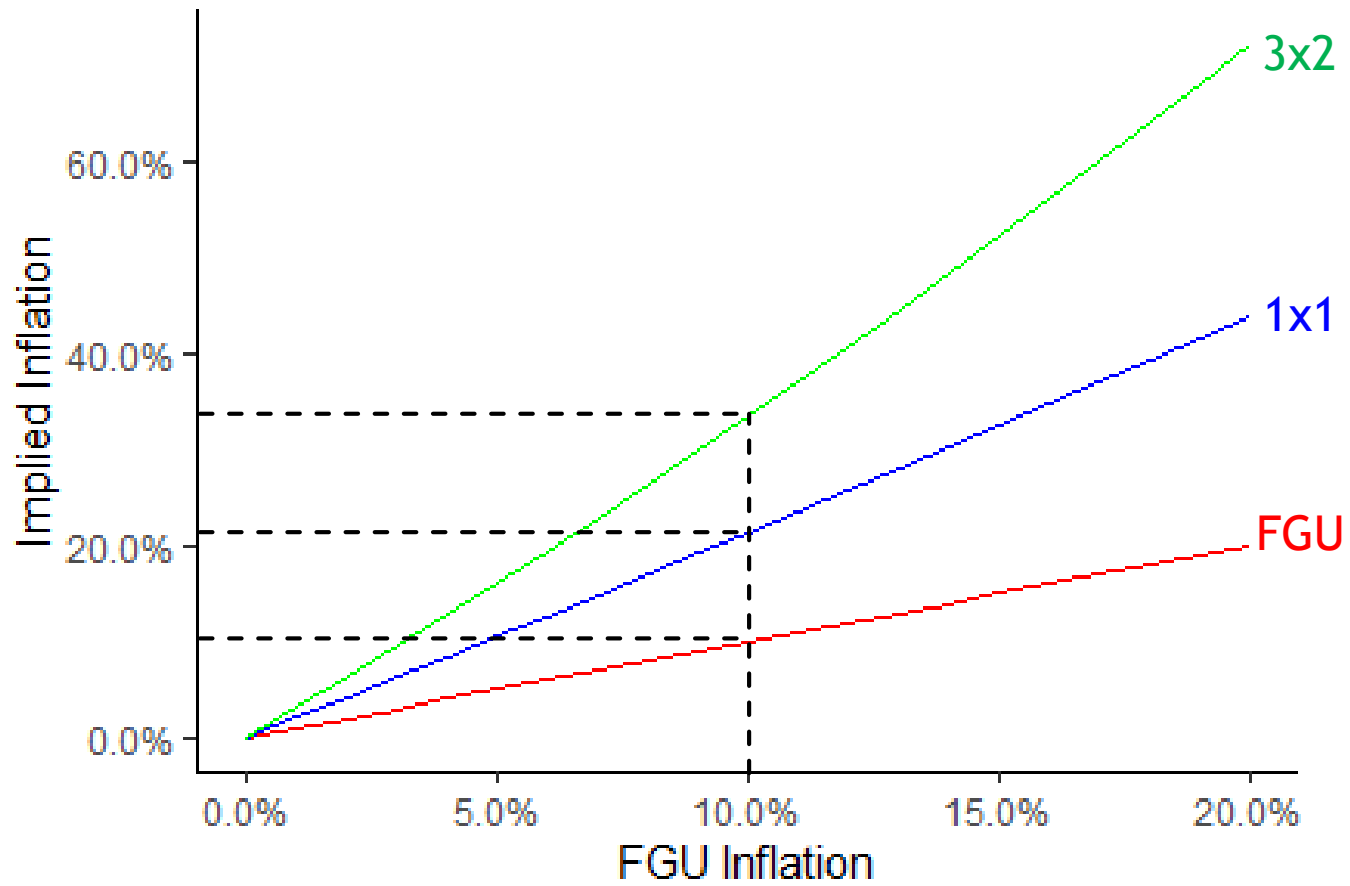
# Gearing Effect



# Gearing Effect



# Gearing Effect



Graph made in R  
Code on SAI website

# Parameter Error

- ▶ Its important to get your parameters *right*...
- ▶ ...Small error in parameters = big error in RI loss cost!

# Bayes vs Frequentist

▶  $X = \text{Claim Severity}$

▶ Frequentist

▶  $X \sim \text{LogN}(\mu, \sigma)$

▶ Bayes

▶  $X \mid \mu, \sigma \sim \text{LogN}(\mu, \sigma)$

▶  $\mu \sim ???$

▶  $\sigma \sim ???$



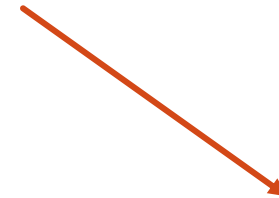
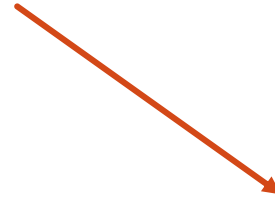
# Bayes vs Frequentist



# Bayes Formula

Likelihood

Prior



►  $P(\text{Parameter} | \text{Data}) = \frac{P(\text{Data} | \text{Parameter}) \times P(\text{Parameter})}{P(\text{Data})}$



Posterier



Evidence

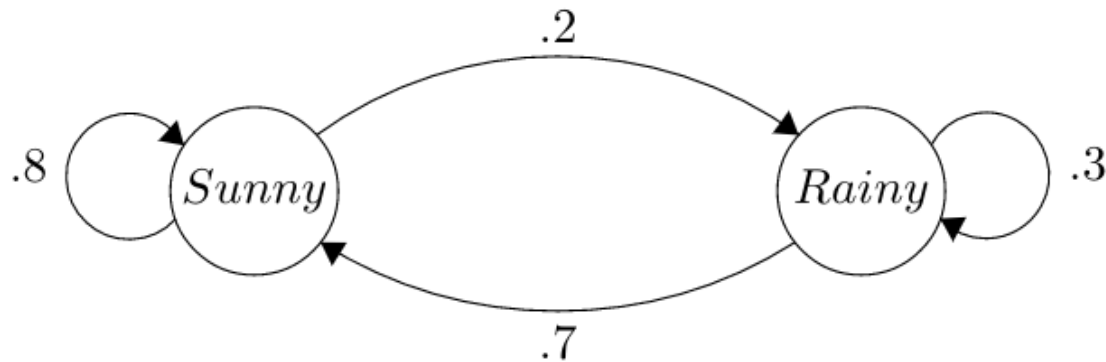
# Bayes Formula

- ▶  $P(\textit{Parameter} \mid \textit{Data}) = \frac{P(\textit{Data} \mid \textit{Parameter}) \times P(\textit{Parameter})}{P(\textit{Data})}$
- ▶  $P(\textit{Parameter} \mid \textit{Data}) \propto P(\textit{Data} \mid \textit{Parameter}) \times P(\textit{Parameter})$

# Markov Chain Monte Carlo

## ▶ Markov Chain

- ▶ Stochastic Process
- ▶ What happens next **only depends on the current state**
- ▶ Equilibrium distribution (**Ergodic Theorem**)



# Markov Chain Monte Carlo

- ▶ Monte Carlo
  - ▶ A luxury holiday spot in southern France
  - ▶ Or a lab at Los Alamos in California
- ▶ Calculate expected values using simulation



# Metropolis Algorithm

- ▶  $X = \text{Claim Severity}$
- ▶ Model:
  - ▶  $X | \mu \sim \text{LogN}(\mu, \sigma)$
  - ▶  $\mu \sim f(\theta)$
- ▶ We want to find  $P(\mu | X)$
- ▶ So how does the algorithm work?



# Metropolis Algorithm

## ► English:

1. Start with some initial value
2. Propose an alternative
3. Determine which is a better fit
4. If the proposal is a better fit, accept it
5. If the proposal is a better fit, accept it with a certain probability

# Metropolis Algorithm

Maths:

1. Start with an initial value  $\mu_{current}$
2. Propose an alternative,  $\mu_{proposal}$
3. Figure out which is a better fit:
  - ▶  $probability_{current} \propto P(X | \mu_{current}, \sigma) \times P(\mu_{current} | \theta)$
  - ▶  $probability_{proposal} \propto P(X | \mu_{proposal}, \sigma) \times P(\mu_{proposal} | \theta)$
4. IF  $probability_{proposal} > probability_{current}$ 
  - ▶  $\mu_{current} = \mu_{proposal}$
5. ELSE
  - ▶ Set Acceptance Probability =  $\frac{probability_{proposal}}{probability_{current}}$

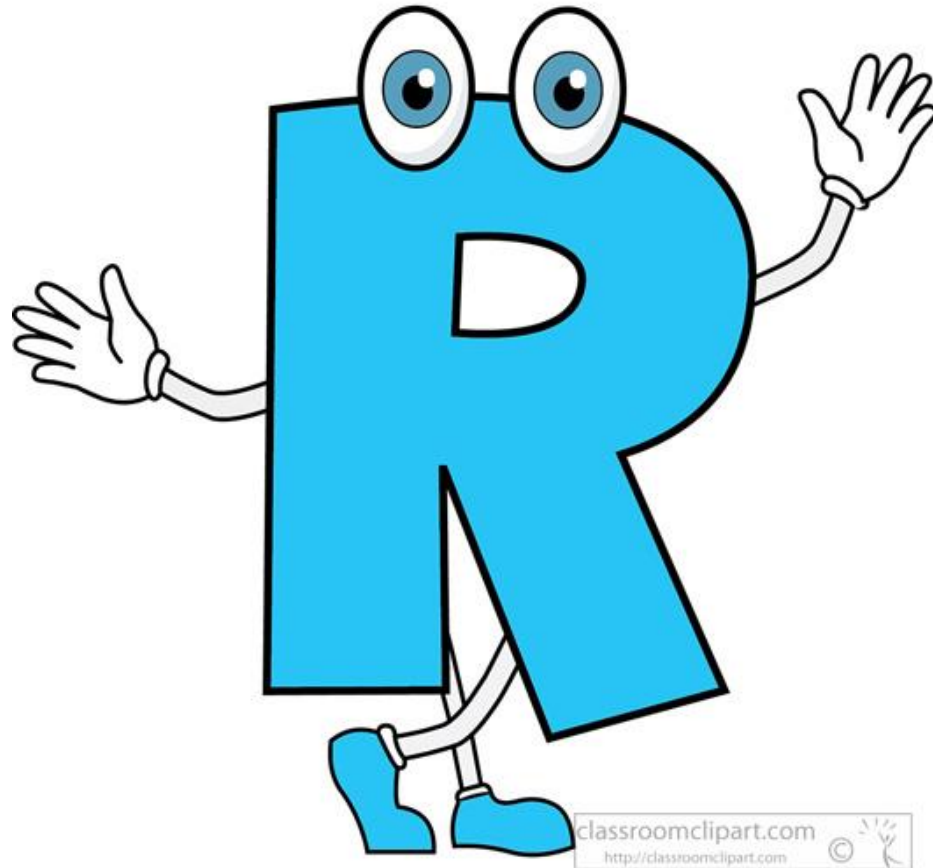


# Metropolis Algorithm

- ▶ How to come up with a proposal?
- ▶  $\mu_{proposal} \sim N(\mu_{current}, s)$
- ▶  $s = \text{proposal width}$ , algorithm parameter
- ▶ Markov Chain
- ▶ Symmetric distribution
- ▶ Ergodic theorem

# Metropolis Algorithm

► In R

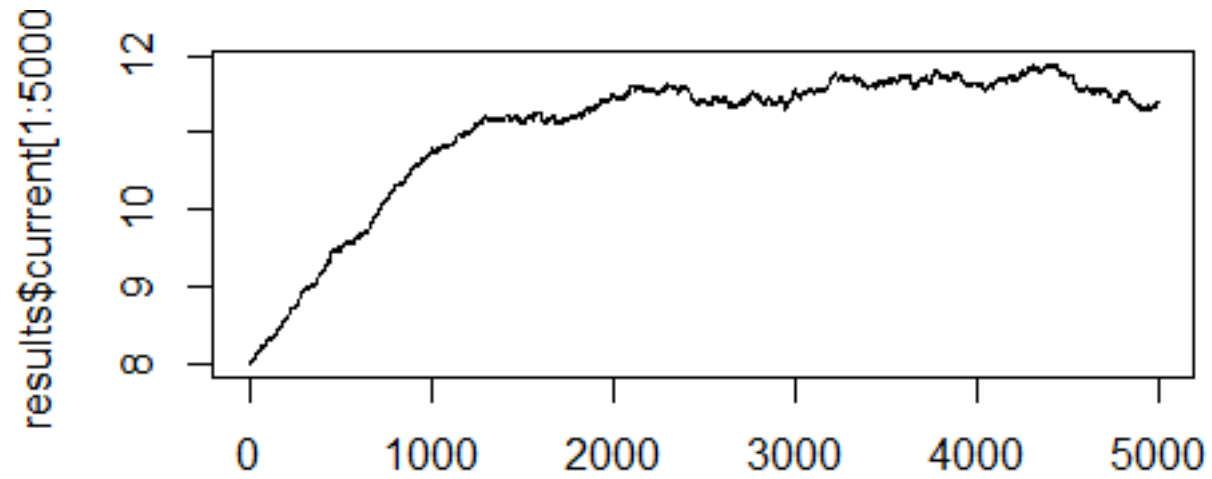
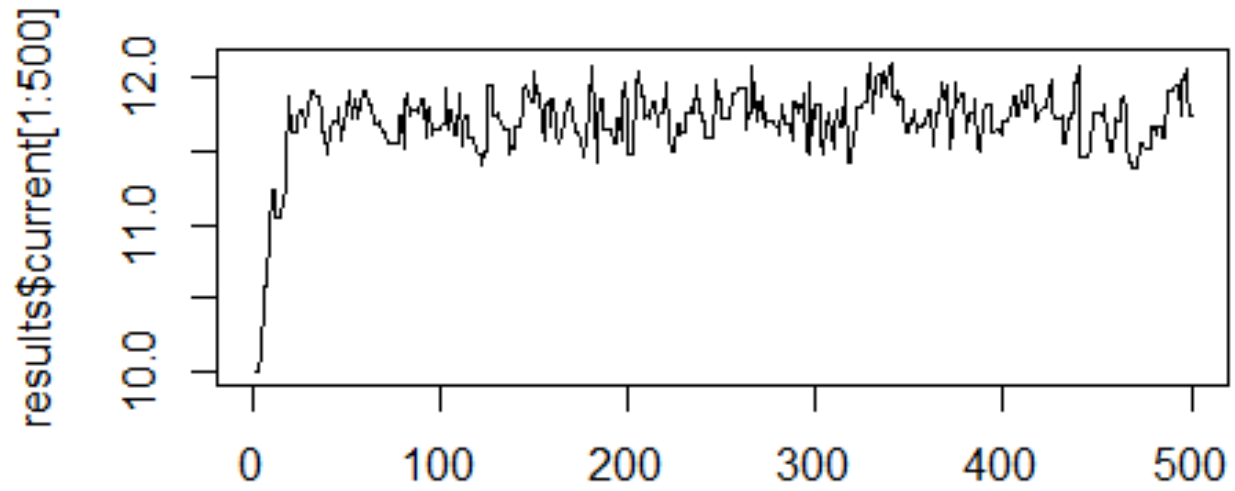


# Prior

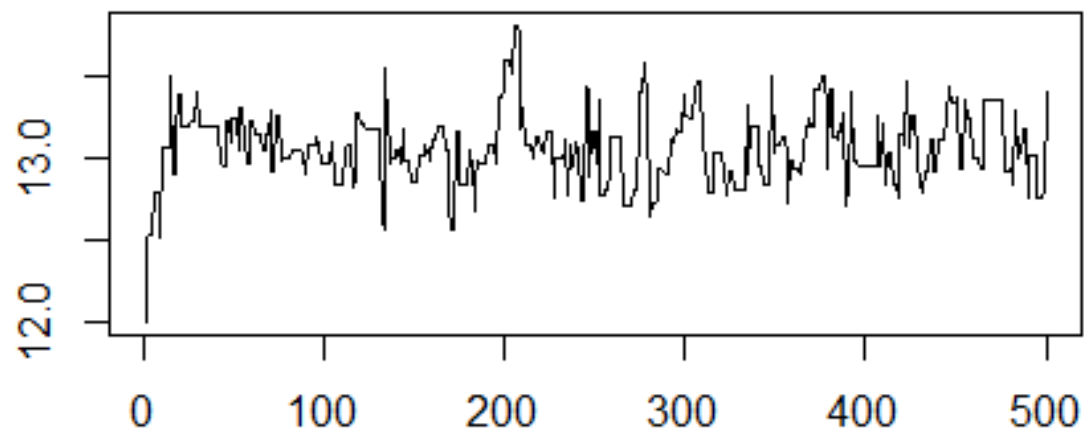
▶ It's a spectrum

▶  $probability_{proposal} \propto P(X | \mu_{proposal}, \sigma) \times P(\mu_{proposal} | \theta)$

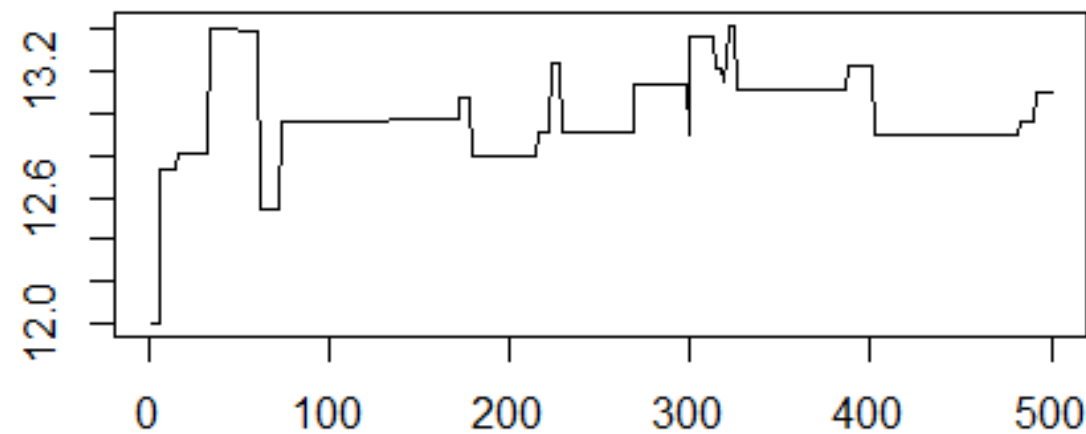
# Burn in



# Proposal Width

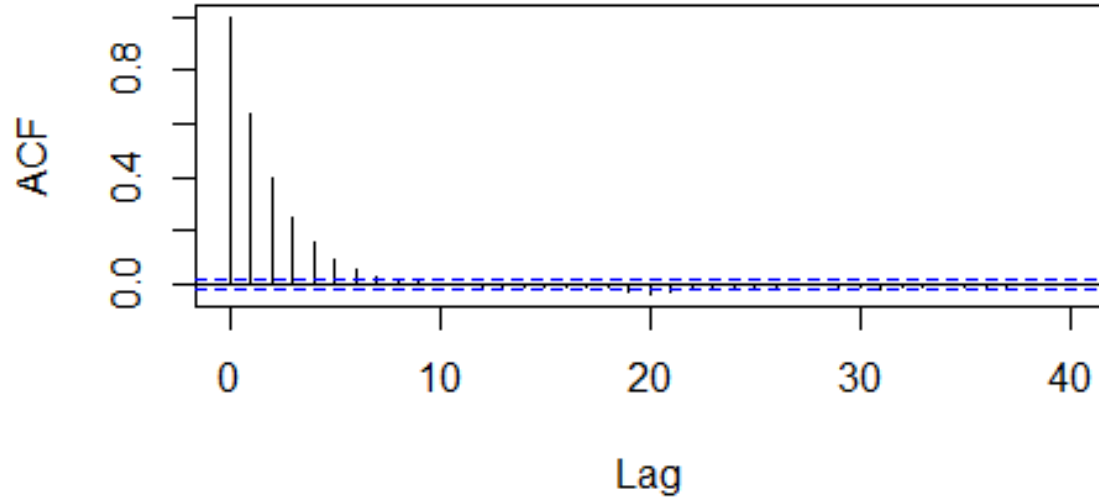


Proposal Width 0.5

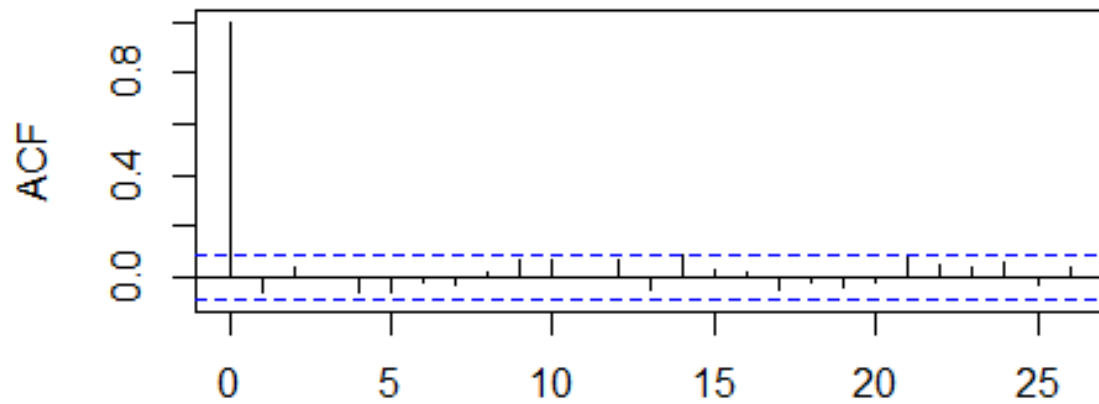


Proposal Width 5.0

# Auto Correlation



Using all simulations



Using every 20<sup>th</sup> simulation

Efficient?

# Conclusion

- ▶ MCMC is... a tool
  - ▶ I like it coz I like Bayes
  - ▶ I like it coz its easy to implement
  - ▶ I like it coz it lets me incorporate benchmark/prior
- ▶ ...but MCMC is just a tool





## Conclusion

- ▶ We have just scratched the surface...
- ▶ ...if you like it, let the SAI know!
- ▶ ...and if you didn't like it ...
- ▶ Code on website



# Questions

