

# Exam Presentation

## Life Insurance Mathematics

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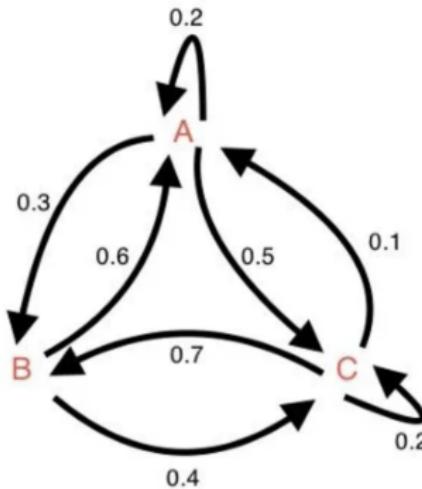
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# Task 1: Markov Model

# Markov Chains

## What is a Markov Chain?

It is a Stochastic model that describes sequence of transitions/ possible events in which the probability of each event depends only on the state attained in the previous event.



## Markow Chains

## Definition

$(X_t)_{t \in \mathbb{N}} : (\Omega, \mathcal{A}, \mathbb{P}) \rightarrow \mathcal{S} = \{1, 2, 3, \dots\}$ , is called a **Markov chain** if and only if,

$$\mathbb{P}[X_{t_{m+1}} = i_{m+1} | X_{t_1} = i_1, \dots, X_{t_m} = i_m] = \mathbb{P}[X_{t_{m+1}} = i_{m+1} | X_{t_m} = i_m]$$

for  $t_1 < t_2 < \dots < t_m < t_{m+1}$  and  $i_1, i_2, \dots, i_{m+1} \in S$ .

We say that such a stochastic process  $(X_t)_{t \in \mathbb{N}}$  has no memory.

# Markov Chains

## Chapman-Kolmogorov Theorem

Let  $p_{ij}(s, t) = P(X_t = j | X_s = i)$  be the transition probabilities of a Markov chain. Then, for any  $0 \leq s < u < t$ ,

$$p_{ij}(s, t) = \sum_k p_{ik}(s, u)p_{kj}(u, t).$$

Or written in matrix form,  $P(s, t) = P(s, u)P(u, t)$ .

Idea: What is the probability of being in state  $j$  at time  $t$ , given that at time  $s$  we are in state  $i$ ?

## Markov Chains

## Proof

$$\begin{aligned}
p_{ij}(s, t) &= \mathbb{P}[X_t = j | X_s = i] = \mathbb{P}[X_t = j \cap \bigcup_{k \in \mathcal{S}} \{X_u = k\} | X_s = i] \\
&= \sum_{k \in \mathcal{S}} \mathbb{P}[X_t = j, X_u = k | X_s = i] \\
&= \sum_{k \in \mathcal{S}} \frac{\mathbb{P}[X_t = j, X_u = k, X_s = i]}{\mathbb{P}[X_s = i]} \cdot \frac{\mathbb{P}[X_u = k, X_s = i]}{\mathbb{P}[X_u = k, X_s = i]} \\
&= \sum_{k \in \mathcal{S}} \underbrace{\mathbb{P}[X_t = j | X_u = k, X_s = i]}_{\mathbb{P}[X_t=j | X_u=k]} \mathbb{P}[X_u = k | X_s = i] \\
&= \sum_{k \in \mathcal{S}} p_{ik}(s, u) p_{kj}(u, t)
\end{aligned}$$

In the above we used  $\mathbb{P}[A \cap B | C] = \mathbb{P}[A | B \cap C] \cdot \mathbb{P}[B | C]$  as well as the Markov property as well as assuming that  $\mathbb{P}[X_u = k, X_s = i] \neq 0$ .

# Markov Model

To model a life Insurance we need three ingredients:

- a Markov chain  $(X_t)_{t \in \mathbb{N}}$
- a one-year discount factor  $v = \frac{1}{1+i}$
- contract functions  $a_i^{pre}(t)$  and  $a_{ij}^{post}(t)$

The starting point of an Markov model are the various possible conditions for an insured person, building the state space  $\mathcal{S}$ . E.g.  $\mathcal{S} = \{\text{'living'}, \text{'death'}\}$ .

# Induced Cashflow & Mathematical Reserve

A central task in life insurance is the determination of the actuarial reserve, i.e., the amount of money which has to be set aside at a given time  $t$  to be able to meet all future obligations/benefits towards each policy.

We denote by  $A_t$  the payments that are due for a policy at time  $t$ .  
 $(A_t)_{t \in \mathbb{N}}$  is a stochastic process.

$$A_t = a_{X_t}^{Pre}(t) + a_{X_{t-1}X_t}^{Post}(t)$$

where  $a_{ij}^{Post}(-1) = 0$  for all  $i,j \in \mathcal{S}$ ,  $t \in \mathbb{N}$ .

# Induced Cashflow & Mathematical Reserve

We set  $I_i(t) = \mathbb{1}_{\{X_t=i\}}$ . Then we can compute the **induced cash flows** as follows:

$$A(t) = \underbrace{\sum_{i \in S} I_i(t) \cdot a_i^{pre}(t)}_{\text{annuity}} + \underbrace{\sum_{i,j \in S} I_i(t) \cdot I_j(t+1) \cdot a_{ij}^{post}(t)}_{\text{capital/lump sum paid at time } t+1}$$

Idea:  $A(t)$  are the payments due at time  $t$  for a given policy. We can also compute the present value (PV) of  $A(t)$  which is given by:

$$\tilde{A}(t) = \sum_{i \in S} I_i(t) \cdot a_i^{pre}(t) + v \cdot \sum_{i,j \in S} I_i(t) \cdot I_j(t+1) \cdot a_{ij}^{post}(t)$$

Finally we can define the mathematical reserve at time  $t$  as:

$$V_j(t) = \mathbb{E}[\text{PV of future cash flows} | X_t = j] = \mathbb{E}\left[\sum_{\tau=0}^{\infty} v^{\tau} \tilde{A}(t+\tau) | X_t = j\right]$$

# Mathematical Reserve

We can compute the mathematical reserves with the following results:

$$\mathbb{E}[I_i(t + \tau) | X_t = j] = p_{ji}(t, t + \tau)$$

$$\mathbb{E}[I_i(t + \tau) I_k(t + \tau + 1) | X_t = j] = p_{ji}(t, t + \tau) p_{ik}(t + \tau, t + \tau + 1)$$

Hence the reserve is given as:

$$V_j(t) = \sum_{\tau=0}^{\infty} v^{\tau} \left( \sum_{i \in \mathcal{S}} a_i^{Pre}(i + \tau) p_{ji}(t, t + \tau) \right. \\ \left. + v \sum_{i,k \in \mathcal{S}} a_{ik}^{Post}(t + \tau) p_{ji}(t, t + \tau) p_{ik}(t + \tau, t + \tau + 1) \right) \quad (1)$$

Hence  $V_j(t)$  is the current value of the future actuarial reserve cash flow ( $A$ ) based on todays information, i.e.  $X_t = j$ .

# Thiele Equation

We can relate the mathematical reserves at two subsequent time points  $t$  and  $t+1$  via the following equation:

## Theorem (Thiele's difference equation)

The mathematical reserve between two subsequent periods are related by:

$$V_j(t) = a_j^{pre}(t) + \sum_{i \in S} v \cdot p_{ji}(t, t+1) \cdot (a_{ji}^{post}(t) + V_i(t+1))$$

### Remarks:

- Calculates the expected reserve directly using transition probabilities, while simulation estimates it by averaging over many random trajectories
- To solve Thiele's equation we need the boundary condition  $V_j(T) = 0$  for all  $j \in S$ .
- The Thiele equation leads to the same results as for the classical insurance model (using commutation functions)
- Forward computation of reserves is possible, too. but numerically less stable.

# Proof Thiele Equation

We start the prove by separating the above sum into  $\tau = 0$  and the rest:

Lets start with  $\tau = 0$ :

$$\begin{aligned} & \sum_{i \in S} a_i^{Pre}(t) \underbrace{p_{ji}(t, t)}_{\delta_{ij}} + v \sum_{i, k \in S} a_{ik}^{Post}(t) p_{ji}(t, t) p_{ik}(t, t+1) \\ &= a_j^{Pre}(t) + v \sum_{k \in S} a_{jk}^{Post}(t) p_{jk}(t, t+1) \end{aligned}$$

Continue with  $\tau \geq 1$  and using Chapman-Kolmogorov:

$$\begin{aligned} & \sum_{\tau \geq 1} v^\tau \left( \sum_i a_i^{Pre}(t+\tau) \cdot \underbrace{p_{ji}(t, t+\tau)}_{\sum_l p_{jl}(t,t+1)p_{li}(t+1,t+\tau)} \right. \\ & \quad \left. + \sum_{i, k} a_{ik}^{Post}(t+\tau) \cdot \underbrace{p_{ji}(t, t+\tau)}_{\sum_l p_{jl}(t,t+1)p_{li}(t+1,t+\tau)} \cdot p_{ik}(t+\tau, t+\tau+1) \right) \end{aligned}$$

# Proof Thiele Equation

By factor out terms which are independent of  $\tau$  as well as rearranging the  $\tau$ -sum ( $\tau - 1 \rightarrow \tau$ ) we get:

$$\sum_l p_{jl}(t, t+1) \cdot v \cdot \left( \sum_{\tau \geq 0} v^\tau p_{li}(t+1, t+1+\tau) \right. \\ \left[ \sum_i a_i^{Pre}(t+1+\tau) + \sum_{i,k} a_{ik}^{Post}(t+1+\tau) p_{ik}(t+1+\tau, t+\tau+1+1) \cdot v \right] \right)$$

Comparing the expression in () with equation (??) we recognize that this is just  $V_l(t+1)$ . Now combining both parts we get:

$$V_j(t) = a_j^{Pre}(t) + v \sum_{k \in S} p_{jk}(t, t+1) (a_{jk}^{Post}(t) + V_k(t+1))$$

This concludes the proof.

# How to simulate a trajectory of a discrete time, finite State space Markov Chain

To simulate a trajectory of a discrete time, finite State space Markov Chain with finite state space  $\mathcal{S} = \{1, 2, 3, \dots, n\}$  and transition probability matrix  $P = (p_{ij})$  we can use the **Inverse Transformation Method**:

- ① Start with initial state  $X_0 = i_0$
- ② At each time step  $t$ , given  $X_t = i$ 
  - Generate  $U \sim \text{Uniform}(0, 1)$
  - Find  $j$  such that  $\sum_{k=1}^{j-1} p_{ik} \leq U < \sum_{k=1}^j p_{ik}$
  - Set  $X_{t+1} = j$

This algorithm fulfills the Markov no-memory property by construction since only the current state  $X_t$  is used to determine the next state  $X_{t+1}$ .

## Simulate mathematical reserve

The expression  $V(X(\omega))[0]$  denotes the PV of future cash flows generated by  $X(\omega)$  at time  $t = t_0$  for a given trajectory of the Markov chain. Recall that the mathematical reserve is defined as

$$V_j(t) = \mathbb{E}[\text{PV of future cash flows} | X_{t_0} = j].$$

Now given  $n$  independent trajectories  $X(\omega_1), X(\omega_2), \dots, X(\omega_n)$  we know that by the **Law of Large Numbers**:

$$\lim_{n \rightarrow \infty} \frac{1}{n} \sum_{k=1}^n V(\omega_k)[0] = V(t = t_0),$$

i.e., the average of the PV of future cash flows over many independent trajectories converges to the true mathematical reserve at time  $t = t_0$  almost surely.

# Determination of cumulative Probability Density of the reserves

Let  $\{V(\omega_k)[0]\}_{k=1}^n$  be independent trajectoires. The empirical cumulative distribution function is given by:

$$F_n(v) = \frac{1}{n} \sum_{k=1}^n \mathbb{1}_{[-\infty, v]}(V(\omega_k)[0])$$

Then define the random variable  $D_n = \sup_{v \in \mathbb{R}} |F_n(v) - F(v)|$ . By the **Glivenko-Cantelli Theorem** we know that  $D_n \xrightarrow{a.s.} 0$  for  $n \rightarrow \infty$ .

Hence if we have enough samples/trajectories we can approximate the cumulative distribution function of the mathematical reserves.

Task 2 : Stopping to pay  
Premium

# Mixed Endowment Insurance

What is a mixed endowment?

- a mix of a term (temporary death) and a pure endowment insurance
- a lump sum is payable on death or reaching a certain age

Let us look at these random variables individually

- **term insurance** :  $Z_1 = v^{k+1} \mathbb{1}_{k < n}$

$$A_{x:\bar{n}}^1 = \mathbb{E}[Z_1] = \sum_{k=0}^{n-1} v^{k+1} {}_k p_x \cdot q_{x+k} = \sum_{k=0}^{n-1} v^{k+1} \cdot \frac{l_{x+k}}{l_x} \cdot \frac{d_{x+k}}{l_{x+k}}$$

$$= \sum_{k=0}^{n-1} \frac{C_{x+k}}{D_x} = \frac{M_x - M_{x+n}}{D_x}$$

- **pure endowment**:  $Z_2 = v^{k+1} \mathbb{1}_{k \geq n}$

$$A_{x:\bar{n}}^1 = \mathbb{E}[Z_2] = \sum_{k=n}^{\infty} v^n \mathbb{P}[K = k] = v^n \mathbb{P}[K \geq n] = v^n \cdot {}_n p_x = \frac{D_{x+n}}{D_x}$$

- Thus the expectation value for the mixed endowment is given by

$$A_{x:\bar{n}} = \mathbb{E}[Z] = \mathbb{E}[Z_1] + \mathbb{E}[Z_2] = \frac{M_x - M_{x+n} + D_{x+n}}{D_x}$$

# Equivalence Principle

In order to determine the premium one typically uses the Equivalence Principle

- ①  $\mathbb{E}[L] = 0$  where  $L$  denotes the loss, or equivalently,
- ② The expected value of premiums is equal to the expected value of benefits.

Remark:

- The Equivalence Principle is equivalent to the requirement of the mathematical reserve at inception to be zero.

As an example consider a termn insurance where we define the loss as

$$L = C \cdot v^{k+1} \mathbb{1}_{k < n} - \Pi \cdot \ddot{a}_{\min(k, n)}$$

By the Equivalence Pricinple we have  $\mathbb{E}[L] = 0$  which leads to

$$\Pi \cdot \ddot{a}_{x:\bar{n}} = \Pi \cdot A_{x:\bar{n}}^{-1}.$$

# Mathematical Reserves

The Mathematical Reserves  $V$  at given time  $t$  are defined as

$$V = PV(\text{future benefits}) - PV(\text{future premiums})$$

For a mixed endowment insurance with  $n$  annual premiums  $\Pi$  the mathematical reserve at time  $t$  is given by (expressed in commutation functions)

$${}_t V_x = \frac{M_{x+t} - M_{x+n} + D_{x+n} - \Pi \cdot (N_{x+t} - N_{x+n})}{D_{x+t}}$$

## 2.1 Premium for Product at Inception

- Compute the premium by means of the equivalence principle.
- For the mixes endowment with benefit  $L$  we have

$$\Pi = L \frac{A_{x:\bar{n}}}{\ddot{a}_{x:\bar{n}}} = L \left( \frac{M_x - M_{x+n} + D_{x+n}}{N_x - N_{x+n}} \right)$$

- Plugging in the values we get  $\Pi \approx 12'302.98$

## 2.2 Benefit $\tilde{L}$ after policyholder stops after one premium.

- Combining the formulas for the mixed endowment insurance  $A_{x+k:n-\bar{k}}$  and the mathematical reserve  ${}_k V_x$  we obtain the following expression for the reduced benefit using commutation functions

$${}_1 \tilde{L} = \frac{{}_k V_x}{A_{x+k:\overline{n-k}}} = {}_k V_x \cdot \frac{D_{x+k}}{M_{x+k} - M_{x+n} + D_{x+n}}$$

- Result of the python code is:  ${}_1 \tilde{L} \approx 9228.77$ .

## 2.3 Benefit Level $\tilde{L}$ as a function of the number of paid premiums

- Let  $k$  be the number of paid premiums then by the previous exercise

$${}_k \tilde{L} = \frac{{}_k V_x}{A_{x+k:n-k|}} = {}_k V_x \cdot \frac{D_{x+k}}{M_{x+k} - M_{x+n} + D_{x+n}}$$

$k$	Reserve ${}_j V_x$	Benefit Level ${}_k \tilde{L}$
1	8062.41	9228.77
2	16260.21	18375.48
3	24650.21	27498.51
4	33308.23	36670.15
5	42335.99	45980.83
6	51870.01	55545.00
7	62095.67	65509.06
8	73266.94	76062.14
9	85736.24	87450.96
10	100000.0	100000.0

## 2.4 Which equivalence principle is fulfilled for the first premium assuming only one premium is paid.

- $t = 0$  and premium  $P$
- Payout/Benefits:
  - i.) if  $t \in [0, 1)$  then  $L = 100'000$  ii.) if  $t \in [1, 10)$  then  ${}_t\tilde{L}$
- by the **Equivalence Principle**:  $\mathbb{E}(\text{premium}) = \mathbb{E}(\text{benefits})$
- the benefits are computed as

$$\begin{aligned}\mathbb{E}(\text{benefits}) &= v \cdot q_x \cdot L + v^2 \cdot {}_1\tilde{L} \cdot p_x \cdot q_{x+1} + \cdots + v^{10} \cdot {}_1\tilde{L} \cdot {}_{10}p_x \\ &= v \cdot q_x \cdot L + v \cdot p_x \cdot {}_1\tilde{L} \cdot A_{x+1:\bar{9}}\end{aligned}$$

- A short check in the jupyter notebook shows that  $\mathbb{E}(\text{premium}) = \mathbb{E}(\text{benefits})$

## 2.5 Which equivalence principle is fulfilled for the second premium assuming only one premium is paid.

- Consider  $t = 1$
- Assuming one premium is paid at  $t = 0$
- Assuming that insured person survives the first year
- Insurer is at risk to pay  $L$  if the death occurs in  $[0, 1)$
- From time  $t = 1$  on until maturity the insurer is at risk of  $_1\tilde{L}_x$
- By the Equivalence Principle  $\mathbb{E}(\text{premium}) = \mathbb{E}(\text{benefits})$
- $\mathbb{E}(\text{premium}) = {}_1V_x$

## 2.5 Which equivalence principle is fulfilled for the second premium assuming only one premium is paid.

- Similar to before we compute the benefits:

$$\begin{aligned}\mathbb{E}(\text{benefits}) &= v \cdot q_{x+1} \cdot {}_1\tilde{L} + v^2 \cdot {}_1\tilde{L} \cdot p_{x+1} \cdot q_{x+2} + \cdots + v^9 \cdot {}_1\tilde{L} \cdot {}_9p_x \\ &= {}_1\tilde{L} \cdot A_{x+1:\bar{9}|}\end{aligned}$$

- A short check in the jupyter notebook shows that  $\mathbb{E}(\text{premium}) = \mathbb{E}(\text{benefits})$  as well as the euqality is exactly the defintion for the reduced benefit  ${}_1\tilde{L}$ .

# Task 3: Disability Insurance on two lives

### 3.1

Two random variables  $X$  and  $Y$  are **stochastically independent** if and only if their joint probability distribution factorizes:

$$P(X = x, Y = y) = P(X = x) \cdot P(Y = y) \quad \forall x, y$$

Or equivalently:

$$P(Y = y | X = x) = P(Y = y) \quad \forall x, y.$$

*Intuitively:* Knowing  $X$  provides no information about  $Y$

Two random variables  $X$  and  $Y$  are **uncorrelated** if their covariance is zero:

$$\text{Cov}(X, Y) = \mathbb{E}[(X - \mathbb{E}[X])(Y - \mathbb{E}[Y])] = 0.$$

Or equivalently:

$$\mathbb{E}[XY] = \mathbb{E}[X] \cdot \mathbb{E}[Y].$$

# 3.1

## Independence $\Rightarrow$ Uncorrelated, Proof

Let  $X$  and  $Y$  be discrete and independent random variables.

$$\begin{aligned}\mathbb{E}[XY] &= \sum_x \sum_y xy \cdot P(X = x, Y = y) \\ &= \sum_x \sum_y xy \cdot P(X = x) \cdot P(Y = y) = \mathbb{E}[X] \cdot \mathbb{E}[Y].\end{aligned}$$

This concludes the proof.

## Uncorrelated $\neq$ Independence

Two variables can be uncorrelated yet still be dependent!

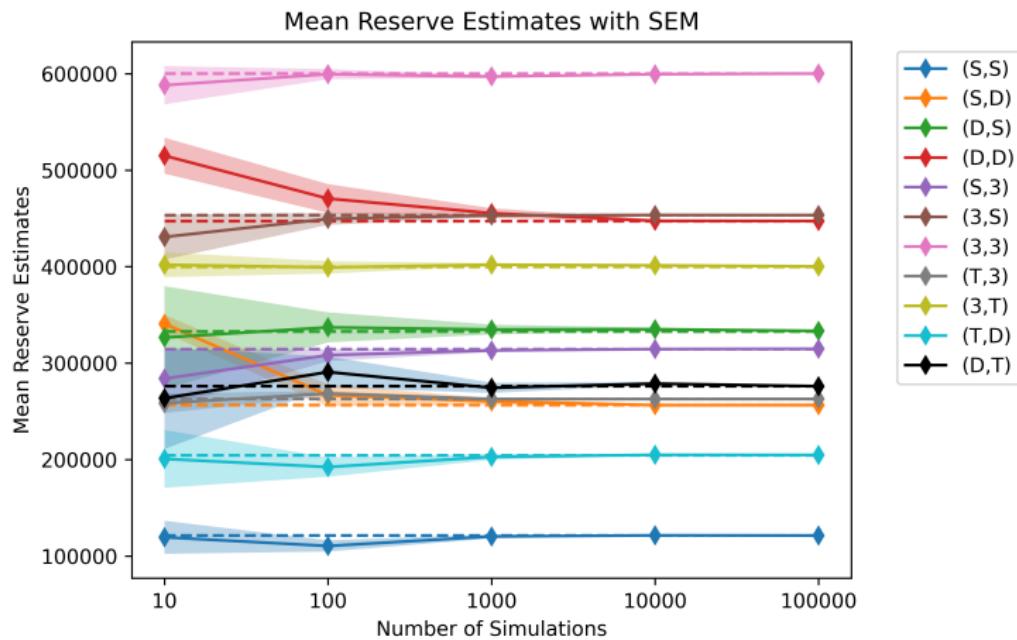
### 3.1 Counterexample: Uncorrelated but Dependent

Let  $X \sim \text{Uniform}(-1, 1)$  and  $Y = X^2$

- $\mathbb{E}[XY] = \mathbb{E}[X^3] = 0$  (by symmetry)
- $\mathbb{E}[X] = 0$  and  $\mathbb{E}[Y] = \frac{1}{3}$
- Therefore:  $\mathbb{E}[X] \cdot \mathbb{E}[Y] = 0$
- So  $\text{Cov}(X, Y) = 0 \Rightarrow \text{uncorrelated}$
- But  $Y$  is completely determined by  $X \Rightarrow \text{dependent!}$

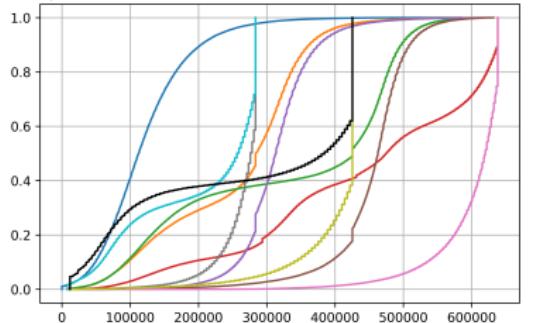
## 3.4 MC Averages Analysis

Here we show how the Monte Carlo estimates move with increasing number of simulated trajectories. We see that with increasing number of simulations the estimates converge to the true mathematical reserve (computed via Thiele's equation).



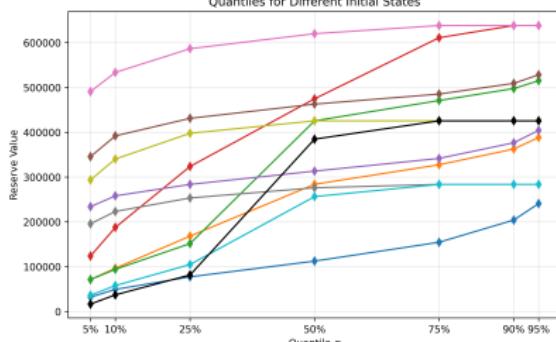
## 3.4 CDF and Quantiles for 100'000 Simulations

Empirical CDF for different initial states with 100'000 simulations



Legend:  
(S,S) (S,D) (D,S) (D,D) (S,3) (3,S) (3,3) (3,T) (T,3) (T,D)

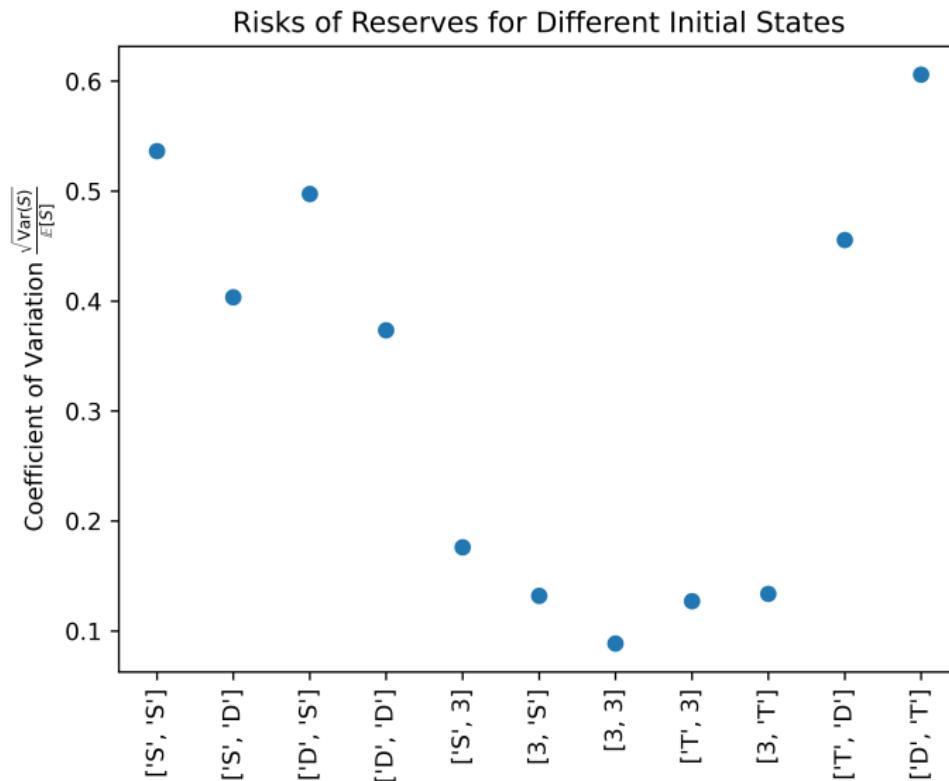
Quantiles for Different Initial States



**Figure 1:** Empirical CDF of the reserve

**Figure 2:** Quantiles of the reserve

## 3.5 coefficient of variation across different states



## 3.5 Discussion of Risk Levels of States

In order to discuss the riskiness of the states we consider two risk measures: value at risk (VaR) and the coefficient of variation (CoV):

- The **VaR** at level provides a concrete monetary amount for tail losses, making it ideal for determining how much capital to hold in reserve
- Directly answers: "How much money do we need to cover losses in 95% of scenarios?"
- The **CoV** normalizes volatility by the mean, allowing fair comparison between states with very different expected losses
- Directly answers: "Which state has the most unpredictable or volatile losses relative to its average?"
- W.r.t VaR at level 95% we conclude that the state  $(3, 3)$  and  $(D, D)$  are the most dangerous states.
- W.r.t CoV the most dangerous state is  $(D, T)$ .

## 3.5 Discussion of Risk Levels of States

Now since it is stated in the task to assume that the insurer has the adequate amount of reserves we assume that the VaR is also ready covered since this measure tells us on how much to reserve.

Hence we judge the riskiness by the CoV, which measures how much harder it is to maintain adequate reserves over time.

- The state  $(D, T)$  is the most dangerous state (has highest CoV) since the man is disabled and rather young (30y). Hence he has three possibilities: reactivate, remain disabled for extended periods.
- The diversification from having two people in similar but independent states reduces relative variability
- The state  $(3, 3)$  is the safest one (although highest annuity to be paid) since both persons are disabled and either remain disabled or die.
- So ranking the states according to their risk level (from riskiest to safest) is given by sorting the CoV in decreasing order:

$$\begin{aligned}(D, T) &> (S, S) > (D, S) > (T, D) > (S, D) > (D, D) \\ &> (S, 3) > (3, T) > (3, S) > (T, 3) > (3, 3)\end{aligned}$$

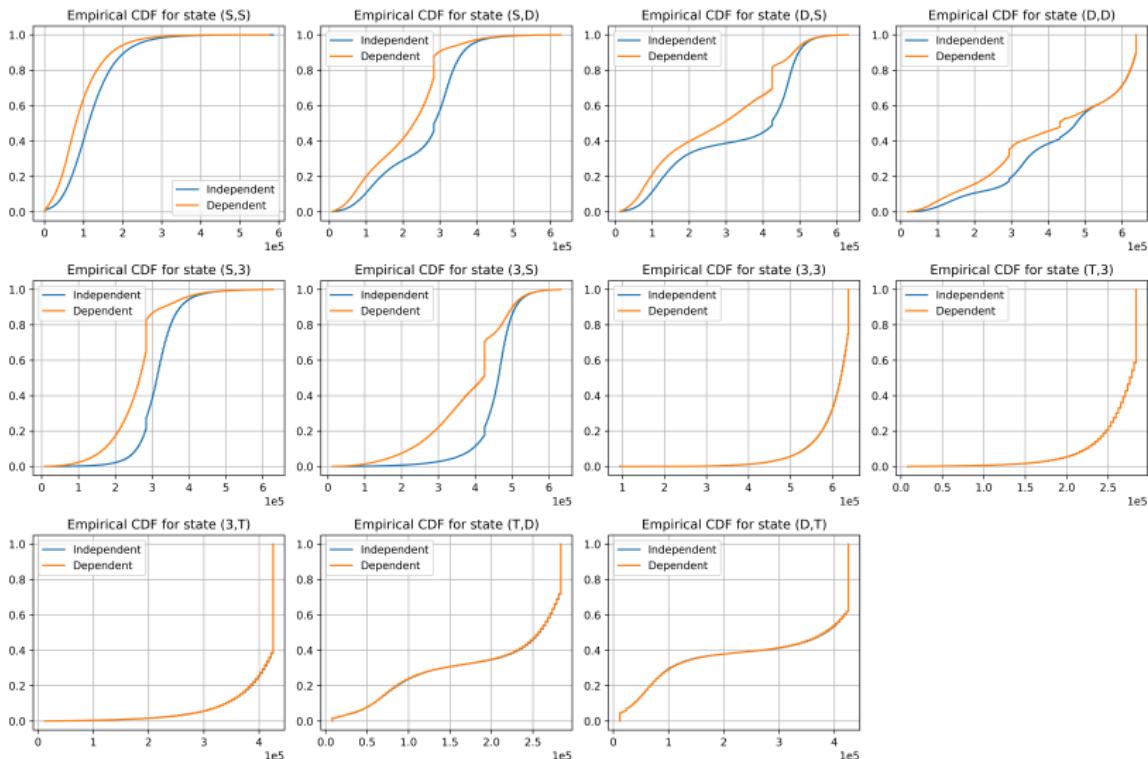
## 3.6 Dicussion of Changes in Risk when changing from independent to Dependent Random Variables

We make the random variables dependent by adapting the follwoing in the code:

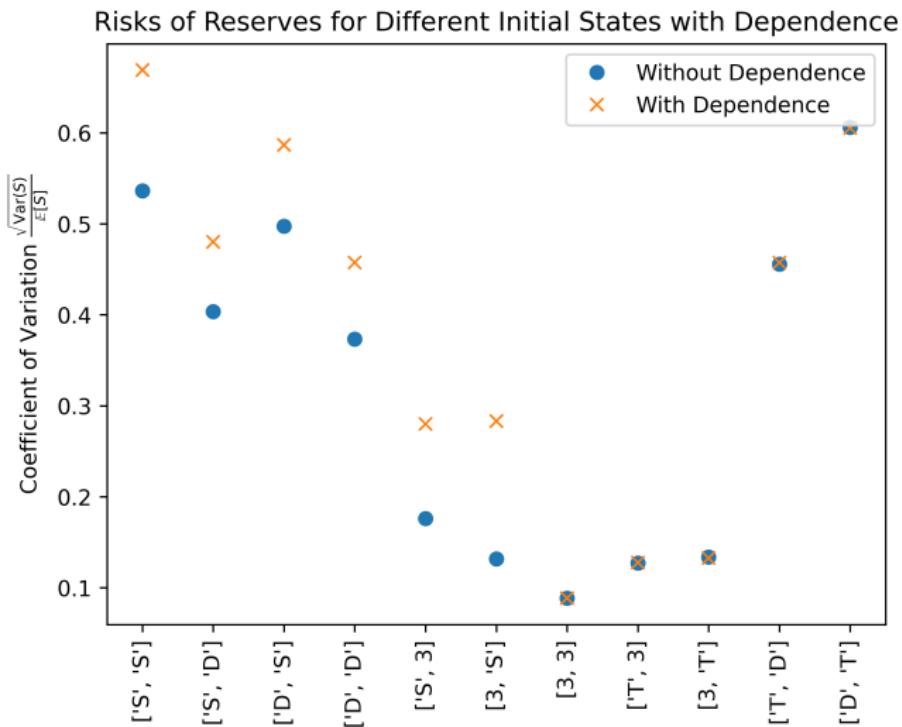
```
a.vSetLevelsMort(dMortSS = 1., dMortSD =10., dMortDD=1., dMortST=1.)  
a.vSetLevelsDis(dDisSS=1., dDisSD=1., dDisST=1.)  
a.vSetLevelsReact(dReactSD=1., dReactDD=1., dReactDT=1.)
```

This means that if one person is disabled the other one has a 10 times higher chance of dying.

# 3.6 Dicussion of Changes in Risk when changing from independent to Dependent Random Variables



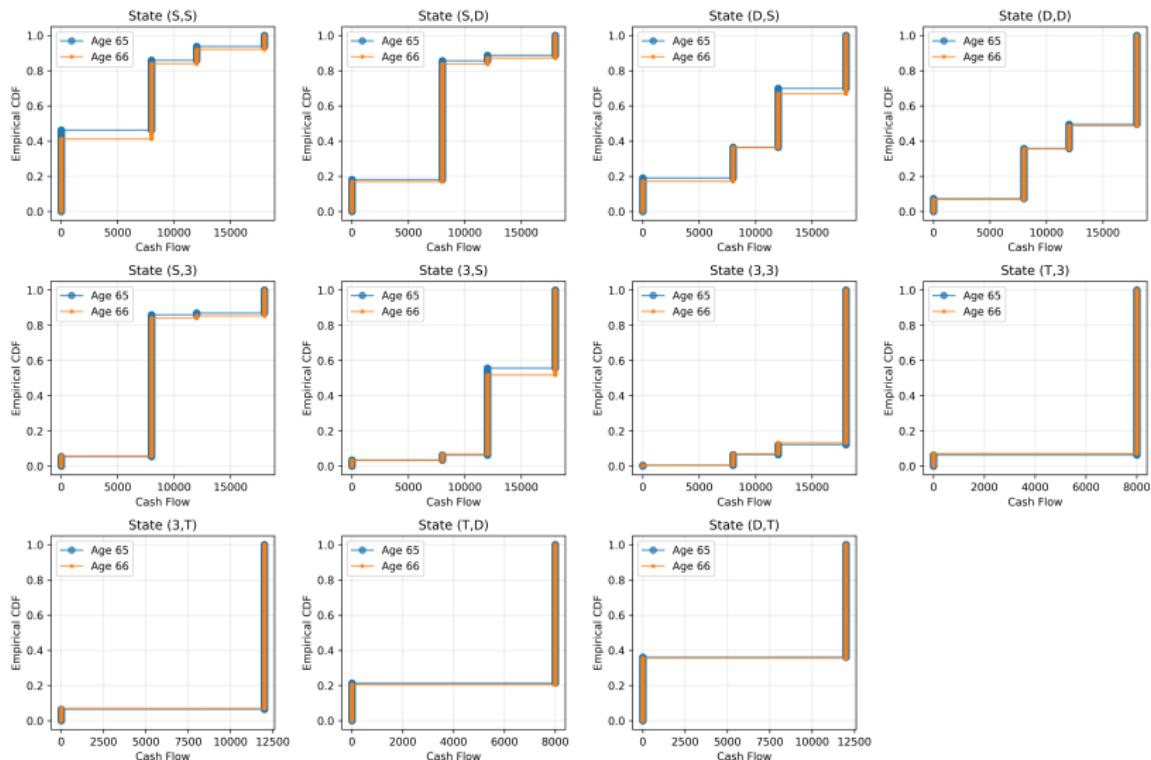
## 3.6 Dicussion of Changes in Risk when changing from independent to Dependent Random Variables



## 3.6 Dicussion of Changes in Risk when changing from independent to Dependent Random Variables

- The CDFs for the dependent case are shifted to the left compared to the independent case.
- This is intuitive since the higher chance of death leads to lower expected cash flows to be paid out by the insurer.
- Hence the VaR at level 95%

# 3.7 Cashflows CDF distribution for age 65 and 66



## 3.7 Observations

- A trend we observe over all states is that the CDF for age 66 is shifted below the CDF for age 65.
- This is intuitive since the older the person the higher the probability of death and hence the lower the expected cash flows to be paid out by the insurer.

## 3.8: 8-policy portfolio simulation

- Assuming the 8 policies are independent, we compute the total loss as the sum of the individual mathematical reserves.

$$\mathbb{E}[L] = \sum_{i=1}^8 \mathbb{E}[L_i] = 1'816'458.10$$

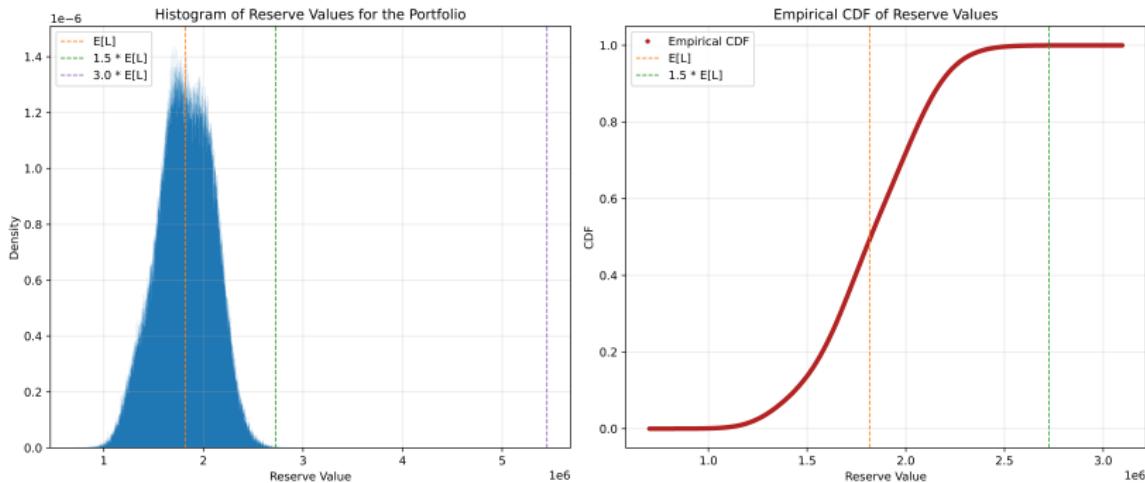
- Now we want to compute the stop loss premium  $\Pi(\beta)$  for the **deductibles**  $\beta \in \{1.5 \cdot \mathbb{E}[L], 3 \cdot \mathbb{E}[L]\}$
- The stop loss premium is defined as

$$\Pi(\beta) = \mathbb{E}[(L - \beta)_+] = \int_{\beta}^{\infty} (1 - F(x)) dx$$

- In order to create a histogram-based approximation of the cumulative distribution function  $F(x)$  we use 1'000'000 simulated portfolio losses (in total 8'000'000 simulations)

## 3.8: 8-policy portfolio simulation

Here we plot the histogram and empirical CDF of the portfolio reserves for 1'000'000 simulation runs per policy (in total 8'000'000 simulations).



The above histogram contains of  $\approx 4800$  bins of width 500.

## 3.8: 8-policy portfolio simulation

Now we shortly describe how to compute the stop loss premium  $\Pi(\beta)$  using a histogram-based approximation of the cumulative distribution function  $F(x)$ .

- Let the bins of the histogram be  $[a_1, a_2]$ ,  $[a_2, a_3]$ ,  $\dots$ ,  $[a_N, a_{N+1}]$ .
- Assume the survival function is constant on each bin:  
 $\bar{F}(x) = 1 - F(x) \approx \bar{F}_i$  where  $\bar{F}_i$  denotes the value of the survival function on bin  $i$ .
- The integral representation approximated by the Riemann sum:

$$\Pi(\beta) \approx \sum_{i: a_i \geq \beta} \bar{F}_i (a_{i+1} - a_i)$$

- Plugging in the values for  $\beta$  we get:

$$\Pi(1.5 \cdot \mathbb{E}[L]) = 8.47$$

$$\Pi(3 \cdot \mathbb{E}[L]) = 0.0$$

# Appendix

# Commutation Functions

We have the following declarations:  $I_x$  : number of living persons at age  $x$   
 $d_x = I_x - I_{x+1}$  : number of deaths between age  $x$  and  $x + 1$

$$D_x = v^x \cdot I_x, \quad N_x = \sum_{k=x}^{\infty} D_k, \quad S_x = \sum_{k=x}^{\infty} N_k$$

$$C_x = v^{x+1} \cdot d_x, \quad M_x = \sum_{k=x}^{\infty} C_k, \quad R_x = \sum_{k=x}^{\infty} M_k$$