



UiO : **Department of Mathematics**  
University of Oslo

## Life Insurance and Finance

Lecture 8: Thiele's differential equation

David R. Banos

**STK4500**

**1 Introduction**

**2 Transition rates vs. transition probabilities**

**3 Thiele's differential equation**

**4 Examples**

- Pure endowment
- Term insurance
- Endowment insurance
- Pension
- Premiums
- Disability insurance

# Introduction

What we have learnt so far...

- To model the **states** of the insured with a Markov chain  $X_t$ .

## What we have learnt so far...

- To model the **states** of the insured with a Markov chain  $X_t$ .
- To model **cash flows**, denoted by  $A$ , with **policy functions** according to the states of the insured.

## What we have learnt so far...

- To model the **states** of the insured with a Markov chain  $X_t$ .
- To model **cash flows**, denoted by  $A$ , with **policy functions** according to the states of the insured.
- To defined **stochastic prospective value**  $V_t^+$  and the **expected prospective value** given a state  $i$ ,  $V_i^+(t)$ .

## What we have learnt so far...

- To model the **states** of the insured with a Markov chain  $X_t$ .
- To model **cash flows**, denoted by  $A$ , with **policy functions** according to the states of the insured.
- To defined **stochastic prospective value**  $V_t^+$  and the **expected prospective value** given a state  $i$ ,  $V_i^+(t)$ .
- To include periodic premiums and determine their value by using the **actuarial equivalence principle**.

## What we have learnt so far...

- To model the **states** of the insured with a Markov chain  $X_t$ .
- To model **cash flows**, denoted by  $A$ , with **policy functions** according to the states of the insured.
- To defined **stochastic prospective value**  $V_t^+$  and the **expected prospective value** given a state  $i$ ,  $V_i^+(t)$ .
- To include periodic premiums and determine their value by using the **actuarial equivalence principle**.
- All this, under a continuous time setting and a discrete time setting.



## What we have learnt so far...

- To model the **states** of the insured with a Markov chain  $X_t$ .
- To model **cash flows**, denoted by  $A$ , with **policy functions** according to the states of the insured.
- To defined **stochastic prospective value**  $V_t^+$  and the **expected prospective value** given a state  $i$ ,  $V_i^+(t)$ .
- To include periodic premiums and determine their value by using the **actuarial equivalence principle**.
- All this, under a continuous time setting and a discrete time setting.
- Next:
  - Thiele's differential equation (continuous time setting)
  - Thiele's difference equation (discrete time setting)

# Transition rates vs. transition probabilities

Thiele's differential equation (Thiele's ODE) is:

Thiele's differential equation (Thiele's ODE) is:

- a differential equation for the quantity  $V_i^+(t)$ .

Thiele's differential equation (Thiele's ODE) is:

- a differential equation for the quantity  $V_i^+(t)$ .
- So, for each state  $i \in \mathcal{S}$  we have an equation for  $V_i^+(t)$ .

Thiele's differential equation (Thiele's ODE) is:

- a differential equation for the quantity  $V_i^+(t)$ .
- So, for each state  $i \in \mathcal{S}$  we have an equation for  $V_i^+(t)$ .
- Idea of Thiele's ODE: Start from the end of the contract  $t = T$  where you know its exact value (either 0 or some survival benefit) and work your way backwards to  $t = 0$ .

Thiele's differential equation (Thiele's ODE) is:

- a differential equation for the quantity  $V_i^+(t)$ .
- So, for each state  $i \in \mathcal{S}$  we have an equation for  $V_i^+(t)$ .
- Idea of Thiele's ODE: Start from the end of the contract  $t = T$  where you know its exact value (either 0 or some survival benefit) and work your way backwards to  $t = 0$ .
- Why bother about a differential equation for  $V_i^+(t)$  when we actually have a nice explicit formula for  $V_i^+(t)$ ?

Thiele's differential equation (Thiele's ODE) is:

- a differential equation for the quantity  $V_i^+(t)$ .
- So, for each state  $i \in \mathcal{S}$  we have an equation for  $V_i^+(t)$ .
- Idea of Thiele's ODE: Start from the end of the contract  $t = T$  where you know its exact value (either 0 or some survival benefit) and work your way backwards to  $t = 0$ .
- Why bother about a differential equation for  $V_i^+(t)$  when we actually have a nice explicit formula for  $V_i^+(t)$ ?

Look at the explicit formula for *expected prospective value*:

$$V_i^+(t) = \sum_j \int_t^\infty \frac{v(s)}{v(t)} p_{ij}(t, s) da_j(s) + \sum_{\substack{j,k \\ k \neq j}} \int_t^\infty \frac{v(s)}{v(t)} p_{ij}(t, s) \mu_{jk}(s) a_{jk}(s) ds.$$



Thiele's differential equation (Thiele's ODE) is:

- a differential equation for the quantity  $V_i^+(t)$ .
- So, for each state  $i \in \mathcal{S}$  we have an equation for  $V_i^+(t)$ .
- Idea of Thiele's ODE: Start from the end of the contract  $t = T$  where you know its exact value (either 0 or some survival benefit) and work your way backwards to  $t = 0$ .
- Why bother about a differential equation for  $V_i^+(t)$  when we actually have a nice explicit formula for  $V_i^+(t)$ ?

Look at the explicit formula for *expected prospective value*:

$$V_i^+(t) = \sum_j \int_t^\infty \frac{v(s)}{v(t)} p_{ij}(t, s) da_j(s) + \sum_{\substack{j,k \\ k \neq j}} \int_t^\infty \frac{v(s)}{v(t)} p_{ij}(t, s) \mu_{jk}(s) a_{jk}(s) ds.$$

It depends on all  $p_{ij}(t, s)$  which is tricky...

The statistician can "easily" estimate the transition rates  $\mu_{ij}$  by observing at each time how many immigrations and emigrations there are.

The statistician can "easily" estimate the transition rates  $\mu_{ij}$  by observing at each time how many immigrations and emigrations there are.

Let  $\mathcal{S} = \{1, \dots, m\}$ ,  $m$  states and we have a cohort of individuals  $X^1, \dots, X^n$  (i.e. with the same age and characteristics). Here  $X_t^k$  is the state in  $\mathcal{S}$  at time  $t$  of the individual  $k = 1, \dots, n$ .

The statistician can "easily" estimate the transition rates  $\mu_{ij}$  by observing at each time how many immigrations and emigrations there are.

Let  $\mathcal{S} = \{1, \dots, m\}$ ,  $m$  states and we have a cohort of individuals  $X^1, \dots, X^n$  (i.e. with the same age and characteristics). Here  $X_t^k$  is the state in  $\mathcal{S}$  at time  $t$  of the individual  $k = 1, \dots, n$ .

Let

$$R_i^{X^k}(h) = \int_0^h I_i^{X^k}(s) ds$$

be the time spent by individual  $k$  in state  $i$  during  $[0, h]$  and

$$N_{ij}^{X^k}(h)$$

be the number of transitions  $i \rightsquigarrow j$  on  $[0, h]$  by individual  $k$ .

$$R_i^k(h) = \int_0^h I_i^{X^k}(s) ds \quad N_{ij}^{X^k}(h)$$

Furthermore, define the total number of time spend in  $i$  and transitions  $i \rightsquigarrow j$  during  $[0, h]$  as

$$R_i(h) = \sum_{k=1}^n R_i^{X^k}(h) \quad N_{ij}(h) = \sum_{k=1}^n N_{ij}^{X^k}(h).$$

Assume that  $\mu_{ij}$  is constant and that we observe what happens on an interval  $[0, h]$ ,  $h > 0$ .

Then the MLE estimator of  $\mu_{ij}$  based on the time interval  $[0, h]$  is given by

$$\hat{\mu}_{ij} = \hat{\mu}_{ij}(h) = \frac{N_{ij}(h)}{R_i(h)}$$

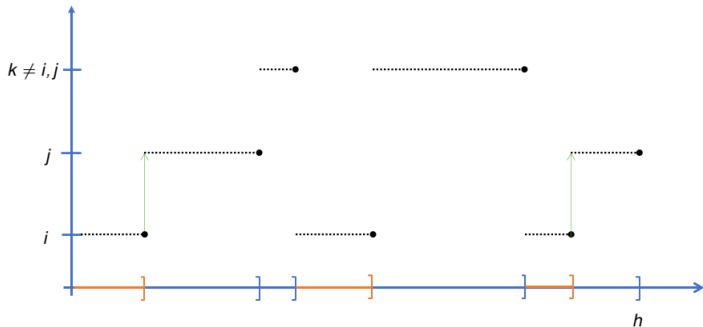


Figure: In this realization observed on  $[0, h]$  we have  $N_{ij} = 2$ . If  $h = 1$  then the orange lines account for around  $R_i \approx 0.32$ , so  $\hat{\mu}_{ij} = 2/0.32 = 6.25$ .

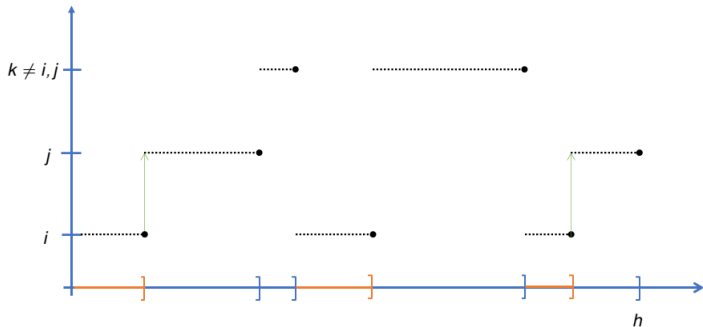


Figure: In this realization observed on  $[0, h]$  we have  $N_{ij} = 2$ . If  $h = 1$  then the orange lines account for around  $R_i \approx 0.32$ , so  $\hat{\mu}_{ij} = 2/0.32 = 6.25$ .

In general,  $\mu_{ij}$  is **not** time homogeneous. To estimate  $\mu_{ij}(t)$ ,  $t \geq 0$  one may split time into intervals where it is plausible to assume constant rates or to use a parametric family for  $\mu_{ij}(t)$ .

Recall that  $\mu_{ij}(t)h \approx p_{ij}(t, t+h)$  for small  $h$ . Hence, estimating  $\mu_{ij}(t)$  by observing what happens around  $t$  seems easier. Once we get  $\mu_{ij}$  we can obtain  $p_{ij}$  through Kolmogorov's equations.

This suggests that a formula for  $V_i^+(t)$  which is independent of  $p_{ij}(t, s)$  for arbitrary  $t, s$  would be nice.



Recall that  $\mu_{ij}(t)h \approx p_{ij}(t, t+h)$  for small  $h$ . Hence, estimating  $\mu_{ij}(t)$  by observing what happens around  $t$  seems easier. Once we get  $\mu_{ij}$  we can obtain  $p_{ij}$  through Kolmogorov's equations.

This suggests that a formula for  $V_i^+(t)$  which is independent of  $p_{ij}(t, s)$  for arbitrary  $t, s$  would be nice.

This is the point of Thiele's equations. Let's start!

# Thiele's differential equation

Recall the explicit formula for the expected prospective value, given  $X_t = i$ ,

$$V_i^+(t) = \sum_j \int_t^\infty \frac{v(s)}{v(t)} p_{ij}(t, s) da_j(s) + \sum_{\substack{j,k \\ k \neq j}} \int_t^\infty \frac{v(s)}{v(t)} p_{ij}(t, s) \mu_{jk}(s) a_{jk}(s) ds.$$

Recall the explicit formula for the expected prospective value, given  $X_t = i$ ,

$$V_i^+(t) = \sum_j \int_t^\infty \frac{v(s)}{v(t)} p_{ij}(t, s) da_j(s) + \sum_{\substack{j,k \\ k \neq j}} \int_t^\infty \frac{v(s)}{v(t)} p_{ij}(t, s) \mu_{jk}(s) a_{jk}(s) ds.$$

**From now on** we will assume that the policy function  $a_i$  is almost everywhere **differentiable** with at most, **one discontinuity** at maturity time  $T$ . This means  $da_i(s) = \dot{a}_i(s)ds$  for a.e.  $s$  and  $\Delta a_i(s) = 0$  for every  $s \in [0, T)$  and  $\Delta a_i(T) \neq 0$ .

Recall the explicit formula for the expected prospective value, given  $X_t = i$ ,

$$V_i^+(t) = \sum_j \int_t^\infty \underbrace{\frac{v(s)}{v(t)} p_{ij}(t, s)}_{=f(s)} da_j(s) + \sum_{\substack{j,k \\ k \neq j}} \int_t^\infty \frac{v(s)}{v(t)} p_{ij}(t, s) \mu_{jk}(s) a_{jk}(s) ds.$$

**From now on** we will assume that the policy function  $a_i$  is almost everywhere **differentiable** with at most, **one discontinuity** at maturity time  $T$ . This means  $da_i(s) = \dot{a}_i(s)ds$  for a.e.  $s$  and  $\Delta a_i(s) = 0$  for every  $s \in [0, T)$  and  $\Delta a_i(T) \neq 0$ .

Following the ingredients of Riemann-Stieltjes integration we have that for every function  $f$ :

$$\int_0^T f(s) da_i(s) = f(T)\Delta a_i(T) + \int_0^T f(s)\dot{a}_i(s)ds.$$

Recall the explicit formula for the expected prospective value, given  $X_t = i$ ,

$$V_i^+(t) = \sum_j \int_t^\infty \underbrace{\frac{v(s)}{v(t)} p_{ij}(t, s)}_{=f(s)} da_j(s) + \sum_{\substack{j,k \\ k \neq j}} \int_t^\infty \frac{v(s)}{v(t)} p_{ij}(t, s) \mu_{jk}(s) a_{jk}(s) ds.$$

**From now on** we will assume that the policy function  $a_i$  is almost everywhere **differentiable** with at most, **one discontinuity** at maturity time  $T$ . This means  $da_i(s) = \dot{a}_i(s)ds$  for a.e.  $s$  and  $\Delta a_i(s) = 0$  for every  $s \in [0, T)$  and  $\Delta a_i(T) \neq 0$ .

Hence, under this assumption on  $a_i$ , the expected prospective value can now be written in terms of Riemann as follows:

$$V_i^+(t) = \sum_j \frac{v(T)}{v(t)} p_{ij}(t, T) \Delta a_j(T) + \sum_j \int_t^T \frac{v(s)}{v(t)} p_{ij}(t, s) \dot{a}_j(s) ds \\ + \sum_{\substack{j,k \\ k \neq j}} \int_t^T \frac{v(s)}{v(t)} p_{ij}(t, s) \mu_{jk}(s) a_{jk}(s) ds.$$

Now, let us compactify things in the formula:

$$V_i^+(t) = \sum_j \frac{v(T)}{v(t)} p_{ij}(t, T) \Delta a_j(T) + \sum_j \int_t^T \frac{v(s)}{v(t)} p_{ij}(t, s) \dot{a}_j(s) ds \\ + \sum_{\substack{j,k \\ k \neq j}} \int_t^T \frac{v(s)}{v(t)} p_{ij}(t, s) \mu_{jk}(s) a_{jk}(s) ds.$$

Now, let us compactify things in the formula:

$$\begin{aligned}
 V_i^+(t) &= \sum_j \frac{v(T)}{v(t)} p_{ij}(t, T) \Delta a_j(T) + \sum_j \int_t^T \frac{v(s)}{v(t)} p_{ij}(t, s) \dot{a}_j(s) ds \\
 &\quad + \sum_{\substack{j,k \\ k \neq j}} \int_t^T \frac{v(s)}{v(t)} p_{ij}(t, s) \mu_{jk}(s) a_{jk}(s) ds.
 \end{aligned}$$

Observe that the integrals in  $ds$  can be put under one and the sums over  $j$  can be merged together:

$$\begin{aligned}
 V_i^+(t) &= \sum_j \frac{v(T)}{v(t)} p_{ij}(t, T) \Delta a_j(T) \\
 &\quad + \sum_j \int_t^T \frac{v(s)}{v(t)} p_{ij}(t, s) \underbrace{\left( \dot{a}_j(s) ds + \sum_{k \neq j} \mu_{jk}(s) a_{jk}(s) \right)}_{=\theta_j(s)} ds
 \end{aligned}$$



So far we have

$$V_i^+(t) = \sum_j \frac{v(T)}{v(t)} p_{ij}(t, T) \Delta a_j(T) + \sum_j \int_t^T \frac{v(s)}{v(t)} p_{ij}(t, s) \theta_j(s) ds,$$

where

$$\theta_j(s) \triangleq \dot{a}_j(s) + \sum_{k \neq j} \mu_{jk}(s) a_{jk}(s).$$

Recall Kolmogorov's backward equation:

$$\frac{d}{dt}p_{ij}(t, s) = - \sum_{k \in \mathcal{S}} \mu_{ik}(t)p_{kj}(t, s).$$

Recall Kolmogorov's backward equation:

$$\frac{d}{dt}p_{ij}(t, s) = - \sum_{k \in S} \mu_{ik}(t)p_{kj}(t, s).$$

Separate the case  $k = i$ :

$$\frac{d}{dt}p_{ij}(t, s) = -\mu_{ii}(t)p_{ij}(t, s) - \sum_{k \neq i} \mu_{ik}(t)p_{kj}(t, s).$$

Recall Kolmogorov's backward equation:

$$\frac{d}{dt} p_{ij}(t, s) = - \sum_{k \in S} \mu_{ik}(t) p_{kj}(t, s).$$

Separate the case  $k = i$ :

$$\frac{d}{dt} p_{ij}(t, s) = -\mu_{ii}(t) p_{ij}(t, s) - \sum_{k \neq i} \mu_{ik}(t) p_{kj}(t, s).$$

Now recall that the sum of  $\mu_{ik}$  over  $k$  is 0:

$$\sum_k \mu_{ik}(t) = \sum_{k \neq i} \mu_{ik}(t) + \mu_{ii}(t) = 0 \iff \mu_{ii}(t) = - \sum_{k \neq i} \mu_{ik}(t).$$

Recall Kolmogorov's backward equation:

$$\frac{d}{dt} p_{ij}(t, s) = - \sum_{k \in S} \mu_{ik}(t) p_{kj}(t, s).$$

Separate the case  $k = i$ :

$$\frac{d}{dt} p_{ij}(t, s) = -\mu_{ii}(t) p_{ij}(t, s) - \sum_{k \neq i} \mu_{ik}(t) p_{kj}(t, s).$$

Now recall that the sum of  $\mu_{ik}$  over  $k$  is 0:

$$\sum_k \mu_{ik}(t) = \sum_{k \neq i} \mu_{ik}(t) + \mu_{ii}(t) = 0 \iff \mu_{ii}(t) = - \sum_{k \neq i} \mu_{ik}(t).$$

Hence,

$$\frac{d}{dt} p_{ij}(t, s) = \sum_{k \neq i} \mu_{ik}(t) p_{ij}(t, s) - \sum_{k \neq i} \mu_{ik}(t) p_{kj}(t, s).$$

Recall Kolmogorov's backward equation:

$$\frac{d}{dt} p_{ij}(t, s) = - \sum_{k \in S} \mu_{ik}(t) p_{kj}(t, s).$$

Separate the case  $k = i$ :

$$\frac{d}{dt} p_{ij}(t, s) = -\mu_{ii}(t) p_{ij}(t, s) - \sum_{k \neq i} \mu_{ik}(t) p_{kj}(t, s).$$

Now recall that the sum of  $\mu_{ik}$  over  $k$  is 0:

$$\sum_k \mu_{ik}(t) = \sum_{k \neq i} \mu_{ik}(t) + \mu_{ii}(t) = 0 \iff \mu_{ii}(t) = - \sum_{k \neq i} \mu_{ik}(t).$$

Hence,

$$\frac{d}{dt} p_{ij}(t, s) = \sum_{k \neq i} \mu_{ik}(t) p_{ij}(t, s) - \sum_{k \neq i} \mu_{ik}(t) p_{kj}(t, s).$$

Finally, put together under the same sum:

$$\frac{d}{dt} p_{ij}(t, s) = \sum_{k \neq i} \mu_{ik}(t) (p_{ij}(t, s) - p_{kj}(t, s)).$$

Back to  $V_i^+(t)$ :

$$V_i^+(t) = \sum_j \frac{v(T)}{v(t)} p_{ij}(t, T) \Delta a_j(T) + \sum_j \int_t^T \frac{v(s)}{v(t)} p_{ij}(t, s) \theta_j(s) ds,$$

where

$$\theta_j(s) \triangleq \dot{a}_j(s) ds + \sum_{k \neq j} \mu_{jk}(s) a_{jk}(s).$$

Back to  $V_i^+(t)$ :

$$V_i^+(t) = \sum_j \frac{v(T)}{v(t)} p_{ij}(t, T) \Delta a_j(T) + \sum_j \int_t^T \frac{v(s)}{v(t)} p_{ij}(t, s) \theta_j(s) ds,$$

where

$$\theta_j(s) \triangleq \dot{a}_j(s) ds + \sum_{k \neq j} \mu_{jk}(s) a_{jk}(s).$$

Next step: pass  $v(t)$  over to the left side:

$$v(t) V_i^+(t) = \sum_j v(T) p_{ij}(t, T) \Delta a_j(T) + \sum_j \int_t^T v(s) p_{ij}(t, s) \theta_j(s) ds,$$



Back to  $V_i^+(t)$ :

$$V_i^+(t) = \sum_j \frac{v(T)}{v(t)} p_{ij}(t, T) \Delta a_j(T) + \sum_j \int_t^T \frac{v(s)}{v(t)} p_{ij}(t, s) \theta_j(s) ds,$$

where

$$\theta_j(s) \triangleq \dot{a}_j(s) ds + \sum_{k \neq j} \mu_{jk}(s) a_{jk}(s).$$

Next step: pass  $v(t)$  over to the left side:

$$v(t) V_i^+(t) = \sum_j v(T) p_{ij}(t, T) \Delta a_j(T) + \sum_j \int_t^T v(s) p_{ij}(t, s) \theta_j(s) ds,$$

Next step: differentiate both sides with respect to  $t$ .

Define the following function

$$H(t) = \int_t^T f(t, s) ds$$

for an integrable function  $f(t, \cdot)$  for every  $t$ . What is  $H'(t)$ ?

Define the following function

$$H(t) = \int_t^T f(t, s) ds$$

for an integrable function  $f(t, \cdot)$  for every  $t$ . What is  $H'(t)$ ?

Define the following bivariate function

$$F(x, y) = \int_y^T f(x, s) ds.$$

Define the following function

$$H(t) = \int_t^T f(t, s) ds$$

for an integrable function  $f(t, \cdot)$  for every  $t$ . What is  $H'(t)$ ?

Define the following bivariate function

$$F(x, y) = \int_y^T f(x, s) ds.$$

Then, clearly  $H(t) = F(t, t)$ .

Define the following function

$$H(t) = \int_t^T f(t, s) ds$$

for an integrable function  $f(t, \cdot)$  for every  $t$ . What is  $H'(t)$ ?

Define the following bivariate function

$$F(x, y) = \int_y^T f(x, s) ds.$$

Then, clearly  $H(t) = F(t, t)$ . To compute  $H'(t)$  we can use the (bivariate) chain rule:

$$H'(t) = \frac{\partial}{\partial x} F(x, y)|_{(x,y)=(t,t)} + \frac{\partial}{\partial y} F(x, y)|_{(x,y)=(t,t)}.$$

Define the following function

$$H(t) = \int_t^T f(t, s) ds$$

for an integrable function  $f(t, \cdot)$  for every  $t$ . What is  $H'(t)$ ?

Define the following bivariate function

$$F(x, y) = \int_y^T f(x, s) ds.$$

Then, clearly  $H(t) = F(t, t)$ . To compute  $H'(t)$  we can use the (bivariate) chain rule:

$$H'(t) = \frac{\partial}{\partial x} F(x, y)|_{(x,y)=(t,t)} + \frac{\partial}{\partial y} F(x, y)|_{(x,y)=(t,t)}.$$

We have

$$\frac{\partial}{\partial x} F(x, y) = \int_y^T \frac{\partial}{\partial x} f(x, s) ds, \quad \frac{\partial}{\partial y} F(x, y) = -f(x, y).$$

$$F(x, y) = \int_y^T f(x, s) ds \Rightarrow H(t) = F(t, t).$$

As a result,

$$H'(t) = \int_t^T \frac{\partial}{\partial x} f(x, s)|_{x=t} ds - f(t, t).$$

$$F(x, y) = \int_y^T f(x, s) ds \Rightarrow H(t) = F(t, t).$$

As a result,

$$H'(t) = \int_t^T \frac{\partial}{\partial x} f(x, s)|_{x=t} ds - f(t, t).$$

That is

$$H'(t) = \int_t^T \frac{d}{dt} f(t, s) ds - f(t, t).$$



$$F(x, y) = \int_y^T f(x, s) ds \Rightarrow H(t) = F(t, t).$$

As a result,

$$H'(t) = \int_t^T \frac{\partial}{\partial x} f(x, s)|_{x=t} ds - f(t, t).$$

That is

$$H'(t) = \int_t^T \frac{d}{dt} f(t, s) ds - f(t, t).$$

In the case where  $f(t, s) = v(s)p_{ij}(t, s)\theta_j(s)$  we have

$$\frac{d}{dt} \int_t^T v(s)p_{ij}(t, s)\theta_j(s) ds = \int_t^T v(s) \frac{d}{dt} p_{ij}(t, s)\theta_j(s) ds - v(t)p_{ij}(t, t)\theta_j(t).$$

Back to:

$$v(t)V_i^+(t) = \sum_j v(T)p_{ij}(t, T)\Delta a_j(T) + \sum_j \int_t^T v(s)p_{ij}(t, s)\theta_j(s)ds,$$

Back to:

$$v(t)V_i^+(t) = \sum_j v(T)p_{ij}(t, T)\Delta a_j(T) + \sum_j \int_t^T v(s)p_{ij}(t, s)\theta_j(s)ds,$$

The derivative of the right-hand side is:

$$-r(t)v(t)V_i^+(t) + v(t)\frac{d}{dt}V_i^+(t).$$

Back to:

$$v(t)V_i^+(t) = \sum_j v(T)p_{ij}(t, T)\Delta a_j(T) + \sum_j \int_t^T v(s)p_{ij}(t, s)\theta_j(s)ds,$$

The derivative of the right-hand side is:

$$-r(t)v(t)V_i^+(t) + v(t)\frac{d}{dt}V_i^+(t).$$

The derivative of the left-hand side is:

$$v(T)\sum_j \frac{d}{dt}p_{ij}(t, T)\Delta a_j(T) + \sum_j \int_t^T v(s)\frac{d}{dt}p_{ij}(t, s)\theta_j(s)ds - v(t)\underbrace{\sum_j p_{ij}(t, t)\theta_j(t)}_{=\theta_i(t)}.$$

Back to:

$$v(t)V_i^+(t) = \sum_j v(T)p_{ij}(t, T)\Delta a_j(T) + \sum_j \int_t^T v(s)p_{ij}(t, s)\theta_j(s)ds,$$

The derivative of the right-hand side is:

$$-r(t)v(t)V_i^+(t) + v(t)\frac{d}{dt}V_i^+(t).$$

The derivative of the left-hand side is:

$$v(T)\sum_j \frac{d}{dt}p_{ij}(t, T)\Delta a_j(T) + \sum_j \int_t^T v(s)\frac{d}{dt}p_{ij}(t, s)\theta_j(s)ds - v(t)\underbrace{\sum_j p_{ij}(t, t)\theta_j(t)}_{=\theta_i(t)}.$$

So far,

$$\begin{aligned} -r(t)v(t)V_i^+(t) + v(t)\frac{d}{dt}V_i^+(t) = \\ v(T)\sum_j \frac{d}{dt}p_{ij}(t, T)\Delta a_j(T) + \sum_j \int_t^T v(s)\frac{d}{dt}p_{ij}(t, s)\theta_j(s)ds - v(t)\theta_i(t). \end{aligned}$$

So far,

$$-r(t)v(t)V_i^+(t) + v(t)\frac{d}{dt}V_i^+(t) =$$
$$v(T)\sum_j \frac{d}{dt}p_{ij}(t, T)\Delta a_j(T) + \sum_j \int_t^T v(s)\frac{d}{dt}p_{ij}(t, s)\theta_j(s)ds - v(t)\theta_i(t).$$

So far,

$$-r(t)v(t)V_i^+(t) + v(t)\frac{d}{dt}V_i^+(t) = \\ v(T)\sum_j \frac{d}{dt}p_{ij}(t, T)\Delta a_j(T) + \sum_j \int_t^T v(s)\frac{d}{dt}p_{ij}(t, s)\theta_j(s)ds - v(t)\theta_i(t).$$

Recall that

$$\frac{d}{dt}p_{ij}(t, s) = \sum_{k \neq i} \mu_{ik}(t)(p_{ij}(t, s) - p_{kj}(t, s)).$$

So far,

$$-r(t)v(t)V_i^+(t) + v(t)\frac{d}{dt}V_i^+(t) =$$

$$v(T)\sum_j \frac{d}{dt}p_{ij}(t, T)\Delta a_j(T) + \sum_j \int_t^T v(s)\frac{d}{dt}p_{ij}(t, s)\theta_j(s)ds - v(t)\theta_i(t).$$

Recall that

$$\frac{d}{dt}p_{ij}(t, s) = \sum_{k \neq i} \mu_{ik}(t) (p_{ij}(t, s) - p_{kj}(t, s)).$$

Let us look at the terms with  $\frac{d}{dt}p_{ij}$ . Substituting:

$$v(T)\sum_j \sum_{k \neq i} \mu_{ik}(t) (p_{ij}(t, T) - p_{kj}(t, T))\Delta a_j(T)$$

$$+ \sum_j \int_t^T v(s)\sum_{k \neq i} \mu_{ik}(t) (p_{ij}(t, s) - p_{kj}(t, s))\theta_j(s)ds.$$



So far,

$$-r(t)v(t)V_i^+(t) + v(t)\frac{d}{dt}V_i^+(t) =$$

$$v(T)\sum_j \frac{d}{dt}p_{ij}(t, T)\Delta a_j(T) + \sum_j \int_t^T v(s)\frac{d}{dt}p_{ij}(t, s)\theta_j(s)ds - v(t)\theta_i(t).$$

Recall that

$$\frac{d}{dt}p_{ij}(t, s) = \sum_{k \neq i} \mu_{ik}(t) (p_{ij}(t, s) - p_{kj}(t, s)).$$

Let us look at the terms with  $\frac{d}{dt}p_{ij}$ . Substituting:

$$v(T)\sum_j \sum_{k \neq i} \mu_{ik}(t) (p_{ij}(t, T) - p_{kj}(t, T))\Delta a_j(T)$$

$$+ \sum_j \int_t^T v(s)\sum_{k \neq i} \mu_{ik}(t) (p_{ij}(t, s) - p_{kj}(t, s))\theta_j(s)ds.$$

Now, the sum  $\sum_{k \neq i} \mu_{ik}(t)$  can be moved completely out:

Now, the sum  $\sum_{k \neq i} \mu_{ik}(t)$  can be moved completely out:

$$\begin{aligned} & v(T) \sum_j \sum_{k \neq i} \mu_{ik}(t) (p_{ij}(t, T) - p_{kj}(t, T)) \Delta a_j(T) \\ & + \sum_j \int_t^T v(s) \sum_{k \neq i} \mu_{ik}(t) (p_{ij}(t, s) - p_{kj}(t, s)) \theta_j(s) ds. \end{aligned}$$

Now, the sum  $\sum_{k \neq i} \mu_{ik}(t)$  can be moved completely out:

$$v(T) \sum_j \sum_{k \neq i} \mu_{ik}(t) (p_{ij}(t, T) - p_{kj}(t, T)) \Delta a_j(T) \\ + \sum_j \int_t^T v(s) \sum_{k \neq i} \mu_{ik}(t) (p_{ij}(t, s) - p_{kj}(t, s)) \theta_j(s) ds.$$

Indeed,

$$\sum_{k \neq i} \mu_{ik}(t) \left[ v(T) \sum_j (p_{ij}(t, T) - p_{kj}(t, T)) \Delta a_j(T) \right. \\ \left. + \sum_j \int_t^T v(s) (p_{ij}(t, s) - p_{kj}(t, s)) \theta_j(s) ds \right].$$

Observe that we can recover the expression for  $V_i^+(t)$  and  $V_k^+(t)$ .

$$\sum_{k \neq i} \mu_{ik}(t) \left[ v(T) \sum_j (p_{ij}(t, T) - p_{kj}(t, T)) \Delta a_j(T) + \sum_j \int_t^T v(s) (p_{ij}(t, s) - p_{kj}(t, s)) \theta_j(s) ds \right].$$

Observe that we can recover the expression for  $V_i^+(t)$  and  $V_k^+(t)$ .

$$\sum_{k \neq i} \mu_{ik}(t) \left[ v(T) \sum_j (p_{ij}(t, T) - p_{kj}(t, T)) \Delta a_j(T) + \sum_j \int_t^T v(s) (p_{ij}(t, s) - p_{kj}(t, s)) \theta_j(s) ds \right].$$

Observe that we can recover the expression for  $V_i^+(t)$  and  $V_k^+(t)$ .

$$\sum_{k \neq i} \mu_{ik}(t) \left[ v(T) \sum_j (p_{ij}(t, T) - p_{kj}(t, T)) \Delta a_j(T) + \sum_j \int_t^T v(s) (p_{ij}(t, s) - p_{kj}(t, s)) \theta_j(s) ds \right].$$

Thus,

$$\sum_{k \neq i} \mu_{ik}(t) (V_i^+(t) - V_k^+(t)).$$

Observe that we can recover the expression for  $v(t)V_i^+(t)$  and  $v(t)V_k^+(t)$ .

$$\sum_{k \neq i} \mu_{ik}(t) \left[ v(T) \sum_j (p_{ij}(t, T) - p_{kj}(t, T)) \Delta a_j(T) + \sum_j \int_t^T v(s) (p_{ij}(t, s) - p_{kj}(t, s)) \theta_j(s) ds \right].$$

Thus,

$$v(t) \sum_{k \neq i} \mu_{ik}(t) (V_i^+(t) - V_k^+(t)).$$

So far,

$$-r(t)v(t)V_i^+(t) + v(t) \frac{d}{dt} V_i^+(t) = v(T) \sum_j \frac{d}{dt} p_{ij}(t, T) \Delta a_j(T) + \sum_j \int_t^T v(s) \frac{d}{dt} p_{ij}(t, s) \theta_j(s) ds - v(t) \theta_i(t).$$

Observe that we can recover the expression for  $v(t)V_i^+(t)$  and  $v(t)V_k^+(t)$ .

$$\sum_{k \neq i} \mu_{ik}(t) \left[ v(T) \sum_j (p_{ij}(t, T) - p_{kj}(t, T)) \Delta a_j(T) + \sum_j \int_t^T v(s) (p_{ij}(t, s) - p_{kj}(t, s)) \theta_j(s) ds \right].$$

Thus,

$$v(t) \sum_{k \neq i} \mu_{ik}(t) (V_i^+(t) - V_k^+(t)).$$

So far,

$$-r(t)v(t)V_i^+(t) + v(t) \frac{d}{dt} V_i^+(t) = v(t) \sum_{k \neq i} \mu_{ik}(t) (V_i^+(t) - V_k^+(t)) - v(t)\theta_i(t).$$



Observe that we can recover the expression for  $v(t)V_i^+(t)$  and  $v(t)V_k^+(t)$ .

$$\sum_{k \neq i} \mu_{ik}(t) \left[ v(T) \sum_j (p_{ij}(t, T) - p_{kj}(t, T)) \Delta a_j(T) + \sum_j \int_t^T v(s) (p_{ij}(t, s) - p_{kj}(t, s)) \theta_j(s) ds \right].$$

Thus,

$$v(t) \sum_{k \neq i} \mu_{ik}(t) (V_i^+(t) - V_k^+(t)).$$

So far,

$$-r(t)v(t)V_i^+(t) + v(t) \frac{d}{dt} V_i^+(t) = v(t) \sum_{k \neq i} \mu_{ik}(t) (V_i^+(t) - V_k^+(t)) - v(t) \theta_i(t).$$

In a summary,

$$-r(t)V_i^+(t) + \frac{d}{dt}V_i^+(t) = \sum_{k \neq i} \mu_{ik}(t) (V_i^+(t) - V_k^+(t)) - \theta_i(t).$$

In a summary,

$$-r(t)V_i^+(t) + \frac{d}{dt}V_i^+(t) = \sum_{k \neq i} \mu_{ik}(t) (V_i^+(t) - V_k^+(t)) - \theta_i(t).$$

Remember that

$$\theta_i(t) \triangleq \dot{a}_i(t) + \sum_{k \neq i} \mu_{ik}(t) a_{ik}(t).$$

In a summary,

$$-r(t)V_i^+(t) + \frac{d}{dt}V_i^+(t) = \sum_{k \neq i} \mu_{ik}(t) (V_i^+(t) - V_k^+(t)) - \theta_i(t).$$

Remember that

$$\theta_i(t) \triangleq \dot{a}_i(t) + \sum_{k \neq i} \mu_{ik}(t) a_{ik}(t).$$

Therefore,

$$\frac{d}{dt}V_i^+(t) = r(t)V_i^+(t) - \dot{a}_i(t) + \sum_{k \neq i} \mu_{ik}(t) (V_i^+(t) - V_k^+(t)) - \sum_{k \neq i} \mu_{ik}(t) a_{ik}(t).$$

Simplifying we finally get **Thiele's differential equation**:

$$\frac{d}{dt} V_i^+(t) = r(t) V_i^+(t) - \dot{a}_i(t) - \sum_{k \neq i} \mu_{ik}(t) (a_{ik}(t) + V_k^+(t) - V_i^+(t))$$

Observe that the final condition is given by

$$V_i^+(T) = \Delta a_i(T).$$

Simplifying we finally get **Thiele's differential equation**:

$$\frac{d}{dt} V_i^+(t) = r(t) V_i^+(t) - \dot{a}_i(t) - \sum_{k \neq i} \mu_{ik}(t) (a_{ik}(t) + V_k^+(t) - V_i^+(t))$$

Observe that the final condition is given by

$$V_i^+(T) = \Delta a_i(T).$$

**Remark:** The equation does not depend on transition probabilities, only rates. Thus, the equation produces  $V_i^+(t)$  from the rates  $\{\mu_{ij}(t)\}_{ij}$  without having to go through Kolmogorov's equation. In some sense, Kolmogorov's equation is already embedded into Thiele's equation.

# Examples

## Pure endowment

Thiele:

$$\frac{d}{dt} V_i^+(t) = r(t) V_i^+(t) - \dot{a}_i(t) - \sum_{k \neq i} \mu_{ik}(t) (a_{ik}(t) + V_k^+(t) - V_i^+(t)).$$



## Pure endowment

Thiele:

$$\frac{d}{dt} V_i^+(t) = r(t) V_i^+(t) - \dot{a}_i(t) - \sum_{k \neq i} \mu_{ik}(t) (a_{ik}(t) + V_k^+(t) - V_i^+(t)).$$

Only two states:  $\mathcal{S} = \{*, \dagger\}$  and  $V_{\dagger}^+ \equiv 0$ , hence we only have one function  $V_*^+(t)$ . Moreover all  $a_{ij}$  are 0. The equation reduces to:

## Pure endowment

Thiele:

$$\frac{d}{dt} V_i^+(t) = r(t) V_i^+(t) - \dot{a}_i(t) - \sum_{k \neq i} \mu_{ik}(t) (a_{ik}(t) + V_k^+(t) - V_i^+(t)).$$

Only two states:  $\mathcal{S} = \{*, \dagger\}$  and  $V_{\dagger}^+ \equiv 0$ , hence we only have one function  $V_*^+(t)$ . Moreover all  $a_{ij}$  are 0. The equation reduces to:

$$\frac{d}{dt} V_*^+(t) = r(t) V_*^+(t) - \dot{a}_*(t) - \sum_{k \neq *} \mu_{*k}(t) (V_k^+(t) - V_*^+(t)).$$

Since  $k \neq *$  means  $k = \dagger$  we have

$$\frac{d}{dt} V_*^+(t) = r(t) V_*^+(t) - \dot{a}_*(t) - \mu_{*\dagger}(t) (V_{\dagger}^+(t) - V_*^+(t)).$$

## Pure endowment

Thiele:

$$\frac{d}{dt} V_i^+(t) = r(t) V_i^+(t) - \dot{a}_i(t) - \sum_{k \neq i} \mu_{ik}(t) (a_{ik}(t) + V_k^+(t) - V_i^+(t)).$$

Only two states:  $\mathcal{S} = \{*, \dagger\}$  and  $V_{\dagger}^+ \equiv 0$ , hence we only have one function  $V_*^+(t)$ . Moreover all  $a_{ij}$  are 0. The equation reduces to:

$$\frac{d}{dt} V_*^+(t) = r(t) V_*^+(t) - \dot{a}_*(t) - \sum_{k \neq *} \mu_{*k}(t) (V_k^+(t) - V_*^+(t)).$$

Since  $k \neq *$  means  $k = \dagger$  we have

$$\frac{d}{dt} V_*^+(t) = r(t) V_*^+(t) - \dot{a}_*(t) - \mu_{*\dagger}(t) (V_{\dagger}^+(t) - V_*^+(t)).$$

Moreover,  $V_{\dagger}^+ \equiv 0$  and  $\dot{a}_*(t) = 0$  for all  $t \neq T$ . Hence,

$$\frac{d}{dt} V_*^+(t) = r(t) V_*^+(t) + \mu_{*\dagger}(t) V_*^+(t), \quad V_*^+(T) = \Delta a_*(T) = E,$$

where  $E$  is the survival benefit to be paid out at time  $T$  in case of survival.

## Term insurance

Thiele:

$$\frac{d}{dt} V_i^+(t) = r(t) V_i^+(t) - \dot{a}_i(t) - \sum_{k \neq i} \mu_{ik}(t) (a_{ik}(t) + V_k^+(t) - V_i^+(t)).$$

## Term insurance

Thiele:

$$\frac{d}{dt} V_i^+(t) = r(t) V_i^+(t) - \dot{a}_i(t) - \sum_{k \neq i} \mu_{ik}(t) (a_{ik}(t) + V_k^+(t) - V_i^+(t)).$$

Only two states:  $\mathcal{S} = \{*, \dagger\}$  and  $V_{\dagger}^+ \equiv 0$ , hence we only have one function  $V_*^+(t)$ . Moreover all  $a_i$  and  $a_{ik}$  are 0 except for  $a_{*\dagger}(t) = B$  for  $t \in [0, T]$ . The equation reduces to:

## Term insurance

Thiele:

$$\frac{d}{dt} V_i^+(t) = r(t) V_i^+(t) - \dot{a}_i(t) - \sum_{k \neq i} \mu_{ik}(t) (a_{ik}(t) + V_k^+(t) - V_i^+(t)).$$

Only two states:  $\mathcal{S} = \{*, \dagger\}$  and  $V_{\dagger}^+ \equiv 0$ , hence we only have one function  $V_*^+(t)$ . Moreover all  $a_i$  and  $a_{ik}$  are 0 except for  $a_{*\dagger}(t) = B$  for  $t \in [0, T]$ . The equation reduces to:

$$\frac{d}{dt} V_*^+(t) = r(t) V_*^+(t) - \sum_{k \neq *} \mu_{*k}(t) (a_{*k}(t) + V_k^+(t) - V_*^+(t)).$$

Since  $k \neq *$  means  $k = \dagger$  we have

$$\frac{d}{dt} V_*^+(t) = r(t) V_*^+(t) - \mu_{*\dagger}(t) (B - V_*^+(t)).$$

## Term insurance

Thiele:

$$\frac{d}{dt} V_i^+(t) = r(t) V_i^+(t) - \dot{a}_i(t) - \sum_{k \neq i} \mu_{ik}(t) (a_{ik}(t) + V_k^+(t) - V_i^+(t)).$$

Only two states:  $\mathcal{S} = \{*, \dagger\}$  and  $V_{\dagger}^+ \equiv 0$ , hence we only have one function  $V_*^+(t)$ . Moreover all  $a_i$  and  $a_{ik}$  are 0 except for  $a_{*\dagger}(t) = B$  for  $t \in [0, T]$ . The equation reduces to:

$$\frac{d}{dt} V_*^+(t) = r(t) V_*^+(t) - \sum_{k \neq *} \mu_{*k}(t) (a_{*k}(t) + V_k^+(t) - V_*^+(t)).$$

Since  $k \neq *$  means  $k = \dagger$  we have

$$\frac{d}{dt} V_*^+(t) = r(t) V_*^+(t) - \mu_{*\dagger}(t) (B - V_*^+(t)).$$

Hence,

$$\frac{d}{dt} V_*^+(t) = r(t) V_*^+(t) + (\mu_{*\dagger}(t) + B) V_*^+(t), \quad V_*^+(T) = \Delta a_*(T) = 0,$$

## Endowment insurance

Thiele:

$$\frac{d}{dt} V_i^+(t) = r(t) V_i^+(t) - \dot{a}_i(t) - \sum_{k \neq i} \mu_{ik}(t) (a_{ik}(t) + V_k^+(t) - V_i^+(t)).$$



## Endowment insurance

Thiele:

$$\frac{d}{dt} V_i^+(t) = r(t)V_i^+(t) - \dot{a}_i(t) - \sum_{k \neq i} \mu_{ik}(t) (a_{ik}(t) + V_k^+(t) - V_i^+(t)).$$

It's a combination of a pure endowment and a term insurance, hence:

$$\frac{d}{dt} V_*^+(t) = r(t)V_*^+(t) + (\mu_{*+}(t) + B)V_*^+(t), \quad V_*^+(T) = \Delta a_*(T) = E.$$

## Pension

Thiele:

$$\frac{d}{dt} V_i^+(t) = r(t) V_i^+(t) - \dot{a}_i(t) - \sum_{k \neq i} \mu_{ik}(t) (a_{ik}(t) + V_k^+(t) - V_i^+(t)).$$

## Pension

Thiele:

$$\frac{d}{dt} V_i^+(t) = r(t)V_i^+(t) - \dot{a}_i(t) - \sum_{k \neq i} \mu_{ik}(t) (a_{ik}(t) + V_k^+(t) - V_i^+(t)).$$

Two states:

$$\frac{d}{dt} V_*^+(t) = r(t)V_*^+(t) - \dot{a}_*(t) - \mu_{*\dagger}(t) (a_{*\dagger}(t) + V_{\dagger}^+(t) - V_*^+(t)).$$

## Pension

Thiele:

$$\frac{d}{dt} V_i^+(t) = r(t) V_i^+(t) - \dot{a}_i(t) - \sum_{k \neq i} \mu_{ik}(t) (a_{ik}(t) + V_k^+(t) - V_i^+(t)).$$

Two states:

$$\frac{d}{dt} V_*^+(t) = r(t) V_*^+(t) - \dot{a}_*(t) - \mu_{*\dagger}(t) (a_{*\dagger}(t) + V_{\dagger}^+(t) - V_*^+(t)).$$

In a pension we have  $\dot{a}_*(t) = P$  during the retirement time  $t \in [T_0, T)$ . Hence,

$$\frac{d}{dt} V_*^+(t) = (r(t) + \mu_{*\dagger}(t)) V_*^+(t) - P \mathbb{I}_{[T_0, T)}(t), \quad V_*^+(T) = 0.$$

## Premiums

Thiele:

$$\frac{d}{dt} V_i^+(t) = r(t)V_i^+(t) - \dot{a}_i(t) - \sum_{k \neq i} \mu_{ik}(t) (a_{ik}(t) + V_k^+(t) - V_i^+(t)).$$

Then we assume  $\dot{a}_*(t) = -\pi \mathbb{I}_{[0, T_0)}(t)$ . Hence,

$$\frac{d}{dt} V_i^+(t) = r(t)V_i^+(t) + \pi + \mu_{ik}(t)V_i^+(t), \quad V_*^+(T_0) = 0, \quad t \in [0, T_0].$$

## Disability insurance

Thiele:

$$\frac{d}{dt} V_i^+(t) = r(t) V_i^+(t) - \dot{a}_i(t) - \sum_{k \neq i} \mu_{ik}(t) (a_{ik}(t) + V_k^+(t) - V_i^+(t)).$$

## Disability insurance

Thiele:

$$\frac{d}{dt} V_i^+(t) = r(t) V_i^+(t) - \dot{a}_i(t) - \sum_{k \neq i} \mu_{ik}(t) (a_{ik}(t) + V_k^+(t) - V_i^+(t)).$$

Three states:  $\mathcal{S} = \{*, \diamond, \dagger\}$ . Hence,

$$\frac{d}{dt} V_*^+(t) = r(t) V_*^+(t) - \dot{a}_*(t) - \sum_{k \neq *} \mu_{*k}(t) (a_{*k}(t) + V_k^+(t) - V_*^+(t)),$$

$$\frac{d}{dt} V_\diamond^+(t) = r(t) V_\diamond^+(t) - \dot{a}_\diamond(t) - \sum_{k \neq \diamond} \mu_{\diamond k}(t) (a_{\diamond k}(t) + V_k^+(t) - V_\diamond^+(t)).$$

The pensions/premiums would go in  $\dot{a}_*$  and the disability pensions in  $\dot{a}_\diamond$ .

## Disability insurance

Thiele:

$$\frac{d}{dt} V_i^+(t) = r(t) V_i^+(t) - \dot{a}_i(t) - \sum_{k \neq i} \mu_{ik}(t) (a_{ik}(t) + V_k^+(t) - V_i^+(t)).$$

Three states:  $\mathcal{S} = \{*, \diamond, \dagger\}$ . Hence,

$$\begin{aligned} \frac{d}{dt} V_*^+(t) &= r(t) V_*^+(t) - \dot{a}_*(t) - \mu_{*\diamond}(t) (a_{*\diamond}(t) + V_\diamond^+(t) - V_*^+(t)) - \mu_{*\dagger}(t) (a_{*\dagger}(t) + V_\dagger^+(t) - V_*^+(t)) \\ \frac{d}{dt} V_\diamond^+(t) &= r(t) V_\diamond^+(t) - \dot{a}_\diamond(t) - \mu_{\diamond*}(t) (a_{\diamond*}(t) + V_*^+(t) - V_\diamond^+(t)) - \mu_{\diamond\dagger}(t) (a_{\diamond\dagger}(t) + V_\dagger^+(t) - V_\diamond^+(t)) \end{aligned}$$

The pensions/premiums would go in  $\dot{a}_*$  and the disability pensions in  $\dot{a}_\diamond$ .



## Disability insurance

Thiele:

$$\frac{d}{dt} V_i^+(t) = r(t) V_i^+(t) - \dot{a}_i(t) - \sum_{k \neq i} \mu_{ik}(t) (a_{ik}(t) + V_k^+(t) - V_i^+(t)).$$

Three states:  $\mathcal{S} = \{*, \diamond, \dagger\}$ . Hence,

$$\frac{d}{dt} V_*^+(t) = r(t) V_*^+(t) - \dot{a}_*(t) - \mu_{*\diamond}(t) (a_{*\diamond}(t) + V_\diamond^+(t) - V_*^+(t)) - \mu_{*\dagger}(t) (a_{*\dagger}(t) - V_*^+(t)),$$

$$\frac{d}{dt} V_\diamond^+(t) = r(t) V_\diamond^+(t) - \dot{a}_\diamond(t) - \mu_{\diamond*}(t) (a_{\diamond*}(t) + V_*^+(t) - V_\diamond^+(t)) - \mu_{\diamond\dagger}(t) (a_{\diamond\dagger}(t) - V_\diamond^+(t)).$$

The pensions/premiums would go in  $\dot{a}_*$  and the disability pensions in  $\dot{a}_\diamond$ .

UiO : **Department of Mathematics**  
University of Oslo



David R. Banos



**Life Insurance and Finance**

Lecture 8: Thiele's differential equation

