# Individual Claims Reserving using Activation Patterns

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- 1. Introduction
- 2. Activation Patterns Model

- 3. Numerical application
- 4. Conclusion



- 1. Introduction
- 2. Activation Patterns Model

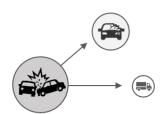
- 3. Numerical application
- 4. Conclusion

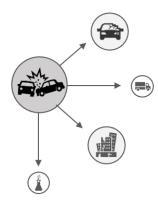
# Introduction

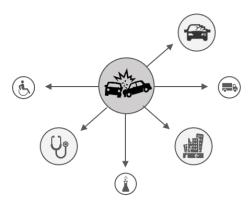


You just had a car accident...what could go wrong?









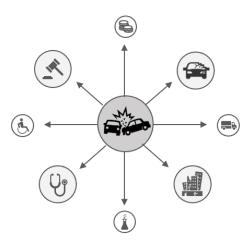




Figure 1: Typical development process of a claim.



- Examples of dependence modelling in the (granular) claims reserving litterature:
  - Zhou, X. and Zhao, X. (2010), Applying copula models to individual claim loss reserving methods, *Insurance: Mathematics* and *Economics*
  - Lopez, O. (2016), A censored copula model for micro-level claim reserving, *Insurance: Mathematics and Economics*
- Examples of correlated risks modelling in the insurance pricing litterature:
  - Frees, E. and Valdez, E. (2008), Hierarchical insurance claims modeling, *Journal of the American Statistical Association*
  - Shi, P., Feng, X. and Boucher, J.P. (2016), Multilevel modeling of insurance claims using copulas, The Annals of Applied Statistics



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### **Notation**

- $\mathbf{A}_{i,j} \in \{0,1\}^C$ : activation pattern vector of the C insurance coverages, of dimension  $1 \times C$  for claim i, i = 1, ..., n in development year j, j = 1, ..., J.  $\mathcal{V}$  is the set of the  $V = 2^C 1$  patterns possible in development year j.
- $(P_{i,j,c}|A_{i,j,c}=1) \in \{0,1\}$ : payment pattern

$$(P_{i,j,c}|A_{i,j,c}=1)= egin{cases} 1, & ext{if a payment has been made for claim } i \ & ext{and coverage } c ext{ in year } j ext{ given } A_{i,j,c}=1, \ 0, & ext{otherwise}. \end{cases}$$

- $(Y_{i,j,c}|P_{i,j,c}=1) \in \mathbb{R}^+$ : severity associated to claim i in development year j for coverage c.
  - $\tilde{Y}_{i,j,c}$ : total remaining severity of claims i for coverage c from development year j until settlement of the claim.

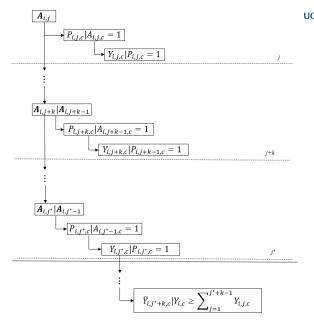


Figure 2: Summary of the activation patterns model

# Development year j

a) Activation patterns:  $\mathbf{A}_{i,j}$ 

Let  $\boldsymbol{a}_{i,j}^{\scriptscriptstyle V} \in \mathcal{V}$  be a possible realisation of  $\boldsymbol{A}_{i,j}$ .

$$P[\boldsymbol{A}_{i,j} = \boldsymbol{a}_{i,j}^{v} | \boldsymbol{x}_{i,j}, \boldsymbol{\beta}_{j,v}] = \frac{\exp(\boldsymbol{x}_{i,j}^{v} \boldsymbol{\beta}_{j,v})}{\sum_{k=1}^{V} \exp(\boldsymbol{x}_{i,j}^{v} \boldsymbol{\beta}_{j,k})}.$$

b) Payment patterns:  $P_{i,i,c}|A_{i,i,c}=1$ 

$$(P_{i,j,c}|A_{i,j,c}=1)\sim \mathsf{Bernoulli}(\pi_{j,c}(\pmb{x}_{i,j},\pmb{\gamma}_{j,c}))$$

$$\pi_{j,c}(\boldsymbol{x}_{i,j}, \boldsymbol{\gamma}_{j,c}) = \frac{\exp\left(\boldsymbol{x}_{i,j}' \boldsymbol{\gamma}_{j,c}\right)}{1 + \exp\left(\boldsymbol{x}_{i,j}' \boldsymbol{\gamma}_{j,c}\right)}$$

c) Claim severity:  $Y_{i,j,c}|P_{i,j,c}=1$ 

$$\mathsf{E}[Y_{i,j,c}|P_{i,j,c}=1]=g^{-1}(x'_{i,j}\alpha_{j,c}).$$

# **Development years** $j + k, j + k + 1, ..., j^*$ , $k \ge 1$

# Hypothesis:

• 
$$(A_{i,j+k,c}|A_{i,j+k-1,c}=1)=1$$
, for all  $k \ge 1 \iff \mathcal{V}^* \subset \mathcal{V}$ 

• Stabilization of the activation patterns after development year  $j^*$ 

a) Activation patterns:  $\mathbf{A}_{i,j+k}|\mathbf{A}_{i,j+k-1}$ 

$$\mathsf{P}[\boldsymbol{A}_{i,j+k} = \boldsymbol{a}_{i,j+k-1}^{v*} | \boldsymbol{A}_{i,j+k-1}, \boldsymbol{x}_{i,j+k}, \boldsymbol{\beta}_{j+k,v^*}]$$

$$= \begin{cases} \frac{P[\boldsymbol{A}_{i,j+k} = \boldsymbol{a}^{\vee*}_{i,j+k-1} | \boldsymbol{x'}_{i,j+k}, \boldsymbol{\beta}_{j+k}]}{\sum_{\boldsymbol{a}^{\vee*}_{i,j+k-1} \in \mathcal{V}^*} P[\boldsymbol{A}_{i,j+k} = \boldsymbol{a}^{\vee*}_{i,j+k-1} | \boldsymbol{x'}_{i,j+k}, \boldsymbol{\beta}_{j+k}]}, & \text{if } \boldsymbol{a}^{\vee*}_{i,j+k-1} \in \mathcal{V}^* \\ 0, & \text{otherwise,} \end{cases}$$

b) Payment patterns:  $P_{i,j+k,c}|A_{i,j+k,c}=1$ 

$$(P_{i,j+k,c}|A_{i,j+k,c}=1) \sim \mathsf{Bernoulli}(\pi_{j+k,c}(\pmb{x}_{i,j+k},\gamma_{j+k,c}))$$
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ight)}{1+\exp\left(\pmb{x}_{i,i+k}'\gamma_{j+k,c}
ight)}$ 

c) Claim severity:  $Y_{i,j+k,c}|P_{i,j+k,c}=1$ 

$$E[Y_{i,j+k,c}|P_{i,j+k,c}=1]=g^{-1}(\mathbf{x}'_{i,j+k}\alpha_{j+k,c})$$

When we reach development year  $j^*$ ,  $Y_{i,j^*,c}$  is the last severity calculated for claim i and coverage c such that the total severity for that claim is equal to  $Y_i = \sum_{j=1}^{j^*-1} \sum_{c=1}^{C} Y_{i,j,c} + \sum_{c=1}^{C} \widetilde{Y}_{i,j^*,c}$ .

# Development years $j^* + k$ , $k \ge 1$

When claim i has reached development year  $j^* + k$  with  $k \ge 1$ , its remaining severity for coverage c starting from year  $j^* + k$  is given by

$$Y_{i,j^*+k,c}|Y_{i,c} \ge \sum_{j=1}^{j^*+k-1} Y_{i,j,c}.$$

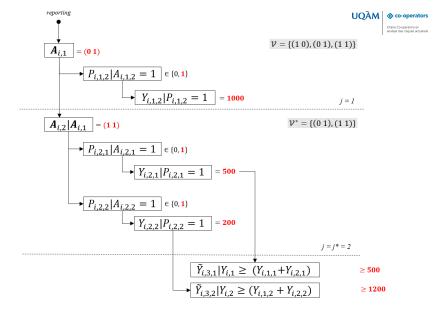


Figure 3: Illustration of the activation patterns model

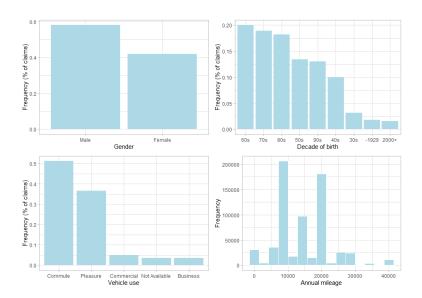


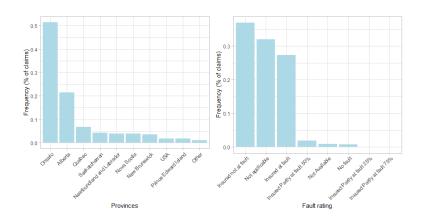
- 1. Introduction
- 2. Activation Patterns Model

- 3. Numerical application
- 4. Conclusion



# Data exploration - Risk factors







# **Data exploration - insurance coverages**

Table 1: Weight of each coverage in the portfolio

Coverage	% of claims	% of the total cost	% of the reserve
Accident Benefits	9.42	12.82	30
Bodily Injury	5.70	13.13	55
Vehicle Damage	96.39	70.44	14
Loss of Use	51.89	3.61	>1

# Data exploration - activation and payment delays

Table 2: Percentage of claims with different activation delays for the four coverages

	Activation delays			
Coverage	No delay	1 year	≥2 years	
Accident Benefits	96.65	3.18	0.11	
Bodily Injury	89.89	7.70	2.11	
Vehicle Damage	98.20	1.73	0.07	
Loss of Use	97.80	2.17	0.03	

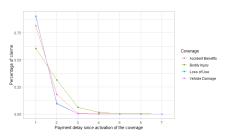


Figure 4: Payment delays per coverage

#### **Estimation**



- C = 4 insurance coverages.
- $i^* = 2$
- Activation of the coverages at any time in any given year until the 30<sup>th</sup> of December, subsequent payments are recorded on the 31<sup>st</sup> of December.
- Estimation by maximum likelihood.

Table 3: Choice of the distributions for the payment severities.

C	Madal	j = 1		j = 2+	
Coverage	Model	AIC	BIC	AIC	BIC
	Log-Normal	266,408	266,651	181,577	181,827
	Gamma	264,411	264,654	183,670	183,921
Accident Benefits	Pareto	262,903	263,146	181,281	181,532
	Generalized Beta II	261,110	261,368	181,222	181,487
	Weibull	264,101	264,344	182,545	182,796
	Log-Normal	100,523	100,735	106,985	107,214
Bodily Injury	Gamma	99,675	99,887	107,096	107,325
	Pareto	98,971	99,183	106,691	106,919
	Generalized Beta II	99,966	100,185	106,884	107,119
	Weibull	99,187	99,400	106,673	106,902
Vehicle Damage	Log-Normal	5,375,907	5,376,246	620,136	620,431
	Gamma	5,385,180	5,385,519	619,456	619,751
	Pareto	5,342,022	5,342,361	617,247	617,542
	Generalized Beta II	5,330,989	5,331,349	617,245	617,557
	Weibull	5,371,787	5,372,126	618,531	618,827
Loss of Use	Log-Normal	1,874,185	1,874,498	193,705	193,967
	Gamma	1,868,867	1,869,180	192,929	193,191
	Pareto	1,894,927	1,895,241	194,376	194,638
	Generalized Beta II	1,861,585	1,861,918	192,212	192,489
	Weibull	1,877,508	1,877,821	193,459	193,721



# Predictive distributions and model comparisons

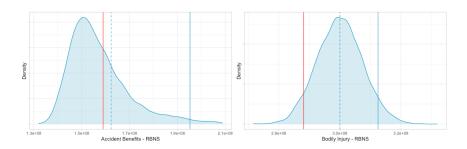


Figure 5: Simulated reserves for the Accident Benefits and Bodily Injury coverages as of 01/01/2019.



# Comparison with 3 models:

- Overdispersed Poisson Chain Ladder
- Independence model
- Individual claims reserving model proposed by K. Antonio and R. Plat (2014) [1]

Coverage	Observed	Simul.	Act. pat.	ODP	Ind.	[1]
Accident Benefits	>158.90	Mean VaR <sub>0.95</sub>	162.15 196.64	71.01 81.66	143.41 173.50	143.46 169.30
Bodily Injury	>288.17	Mean VaR <sub>0.95</sub>	300.02 312.58	177.64 204.63	278.18 290.31	-
Global reserve	>524.91	Mean VaR <sub>0.95</sub>	536.86 574.58	493.14 537.16	495.32 526.93	



- 1. Introduction
- 2. Activation Patterns Model

- 3. Numerical application
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# 4. Conclusion



- Separate modelling of activation and payments, allowing for a more complete modelling of the development of claims.
- Use of aggregate models requires larger quantities of data.
- Heavier-tailed, more conservative predictive distribution.
- More prudent predictions at the coverage-level, leading to a better understanding of the underlying dynamics of the portfolio.

#### Selected references









Frees, E., Shi, P., Valdez, E. (2009), Actuarial Applications of a Hierarchical Insurance Claims Model, ASTIN Bulletin, 39(1), 165-197.

Shi, P., Feng, X. and Boucher, J-P. (2016), Multilevel modeling of insurance claims using copulas, The Annals of Applied Statistics, 10, 834-863.