

A Bayesian State-Space Model of Loss Development

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Thanks to Jon Evans for comments.

Outline of the Presentation

- Dimensions of Loss Development
- Loss Development as a Time Series Problem
- Modeling Loss Development in State Space
- Bayesian Model of Loss Development
- Application (1): Automobile Insurance
- Application (2): The AFG Data Set
- Application (3): Tail Estimation in NCCI Ratemaking (Test Phase)
- Conclusion

Dimensions of Loss Development

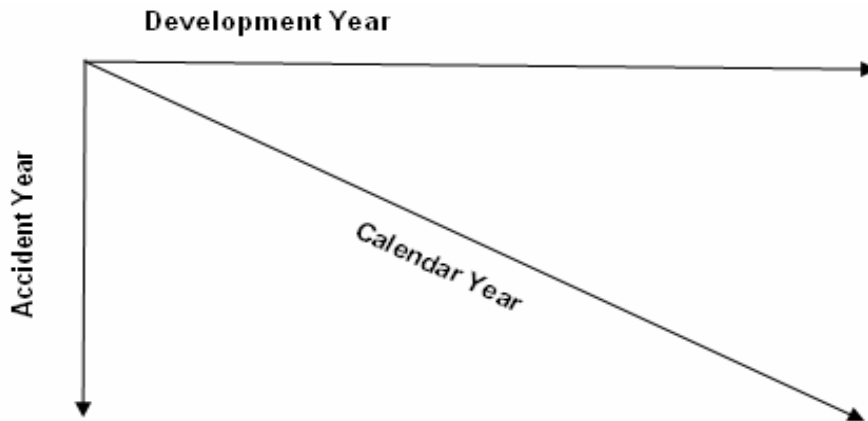
- Estimating the runoff triangle (“squaring the triangle”)—shaded yellow
- Estimating the tail—shaded pink
- Forecasting future accident (policy/injury) years—shaded aquamarine

	Development Year								
Accident Year	1	2	3	4	5	6	7	8	9
1	x	x	x	x	x				
2	x	x	x	x					
3	x	x	x						
4	x	x							
5	x								
6									
7									

x: observed value

Loss Development as a Time Series Problem

- Time permeates loss development
 - All data are observed on the time axis, at low (annual) frequency
 - There is development time
 - There is calendar year time
 - There is accident (policy/injury) year time



Modeling Loss Development in State Space

- The state-space framework is a powerful tool for modeling time series

$$X_{t+1} \sim N(X_t, \sigma^2)$$

- The future value of a variable, X_{t+1} , is distributed around its current value, X_t , with an innovation variance σ^2
- Such a random walk specification is suitable for *describing* low-frequency time processes (of which there are three in loss triangles), even if the variables in question do not follow random walks
 - For meaningful *extrapolation*, the variable in question must indeed follow a random walk

Bayesian Model of Loss Development

- The model is written in state space
- The model is estimated using the Metropolis-Hastings algorithm
 - The posterior distributions are arrived at by means of Markov-Chain Monte-Carlo (MCMC) simulation
- The model employs conjugate priors
 - Posteriors and priors are of the same family of distributions
- The model allows for arbitrarily close fitting to the observed incremental and cumulative payments
 - The researcher is able to control the degree of measurement noise
- All anti-log transformations are carried out “draw by draw” (instead of on the expected value)
 - There is no issue with bias adjustment

Bayesian Model of Loss Development

- State-space models consist of measurement equations and transition equations
 - Measurement equations fit the model to the observations
 - Here, there are two measurement equations, which form a hierarchy (as the second measurement equation employs the predicted values of the first measurement equation)
 - Transition equations describe the trajectories (path in time) of the state variables (which are the variables that adopt a new value [state] in each period)
 - There are three transition equations, one for each of the three mentioned processes

Bayesian Model of Loss Development

- Measurement equations
 - The (natural) logarithms of the incremental payments are assumed independently and identically normally distributed (first measurement equation)

$$y_{i,j} \sim \mathbf{N}(b_{i,j}, \sigma_y^2), i = 1, \dots, N, j = 1, \dots, N + 1 - i$$

- What follows are the predicted values that result from the first measurement equation:

$$\hat{y}_{i,j} \sim \mathbf{N}(b_{i,j}, \sigma_y^2), i, j = 1, \dots, N$$

- These predicted values feed into the second measurement equation

Bayesian Model of Loss Development

- Measurement equations, *cont'd*
 - The series of the cumulative sum of errors between the *predicted* log incremental payments and the actual log incremental payments for any given accident year are multivariate normal (second measurement equation)

$$\hat{m}_{i,j} = \log \left(\sum_{k=1}^j \exp(\hat{y}_{i,k}) \right), \quad i, j = 1, \dots, N$$

$$\hat{\mathbf{m}}_i' - \mathbf{z}_i' \sim \mathbf{N}(\mathbf{0}, \Sigma), \quad i = 1, \dots, N$$

- This second measurement equation makes use of the “cusum chart technique,” which is used in engineering for process control
- As the model develops the incremental payments for a given accident year, the cusum chart technique ensures that the cumulative sum of errors stays close to zero

Bayesian Model of Loss Development

- Transition equations
 - There are three time processes, that is, three (logarithmic) rates of growth, to be modeled

- Exposure growth

$$\eta_{i,1} \sim N(\eta_{i-1,1}, \sigma_{\eta}^2) , i = 3, \dots, N$$

- Growth in development ("Decay")

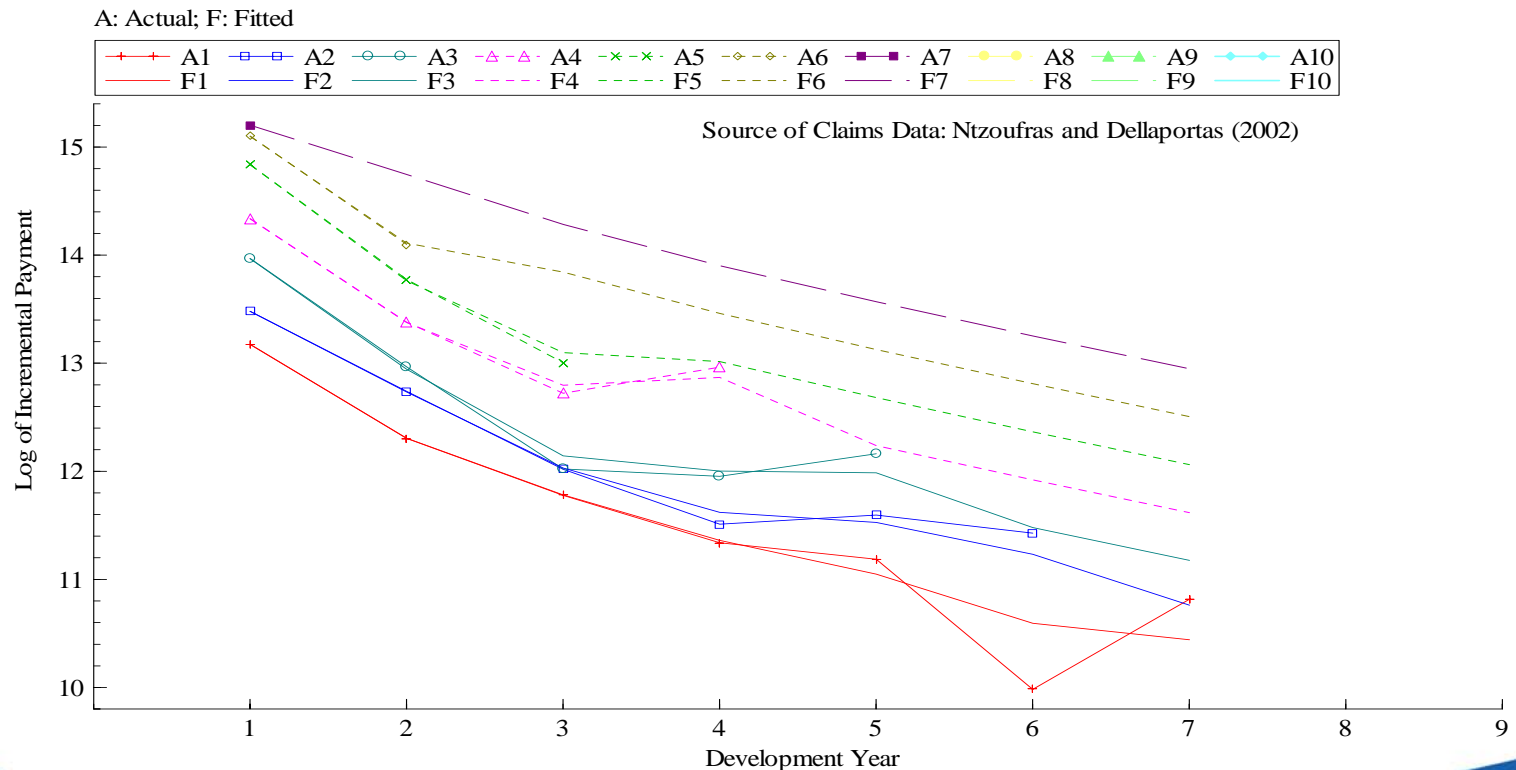
$$\delta_j \sim N(\delta_{j-1}, \sigma_{\delta}^2) , j = 3, \dots, N$$

- Calendar year effect

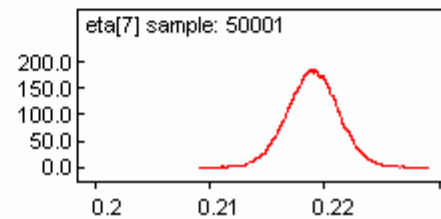
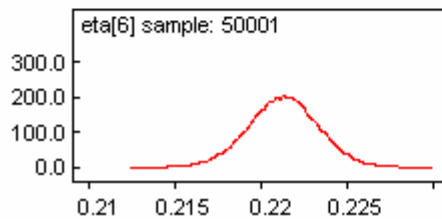
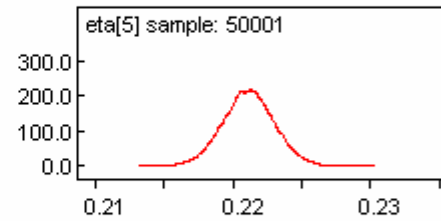
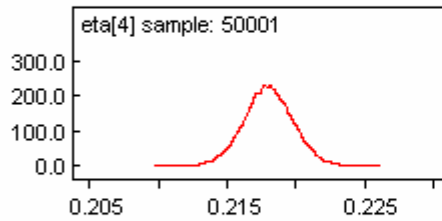
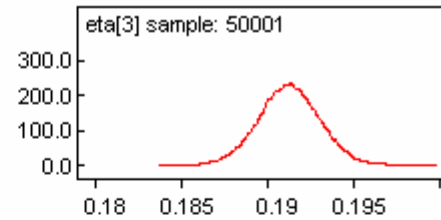
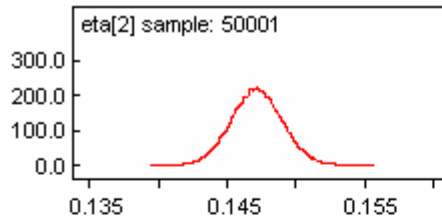
$$\kappa_{i+j} \sim N(\kappa_{i+j-1}, \sigma_{\kappa}^2) , i + j = 4, \dots, N + 1$$

Application (1): Automobile Insurance

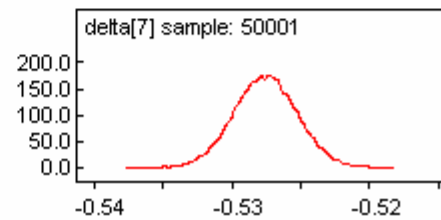
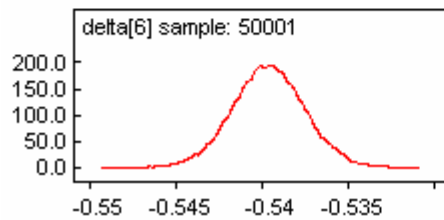
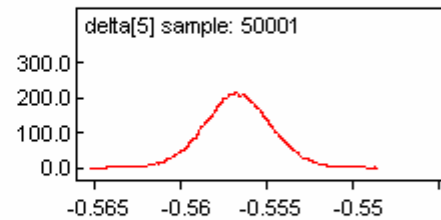
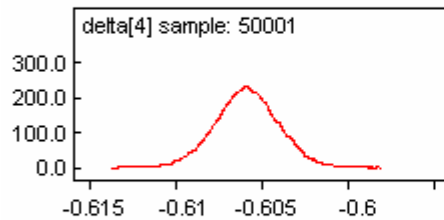
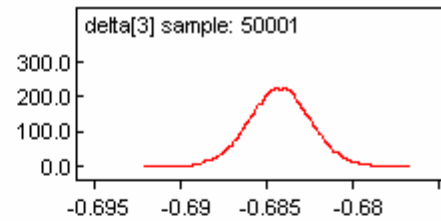
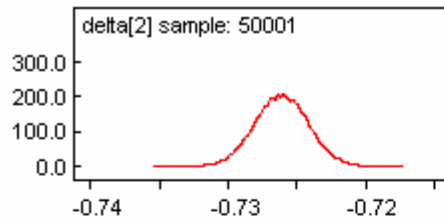
- There is in the public domain an automobile insurance claims data set from Greece that has been analyzed repeatedly in professional journals



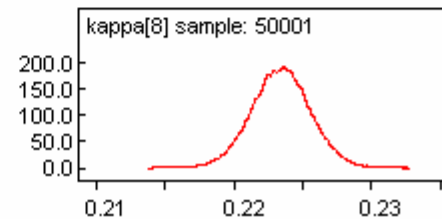
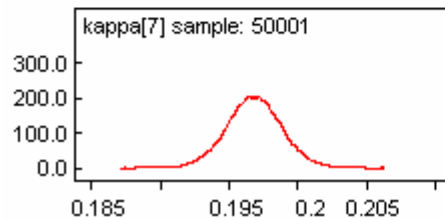
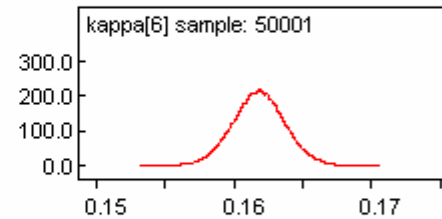
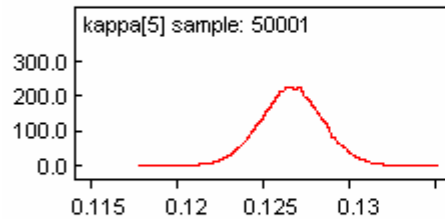
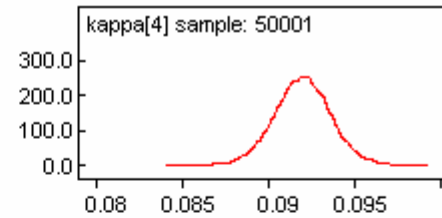
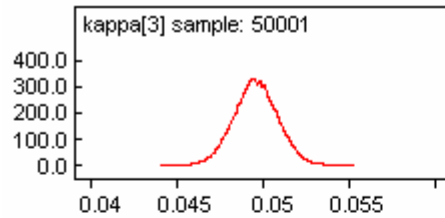
Application (1): Automobile Insurance



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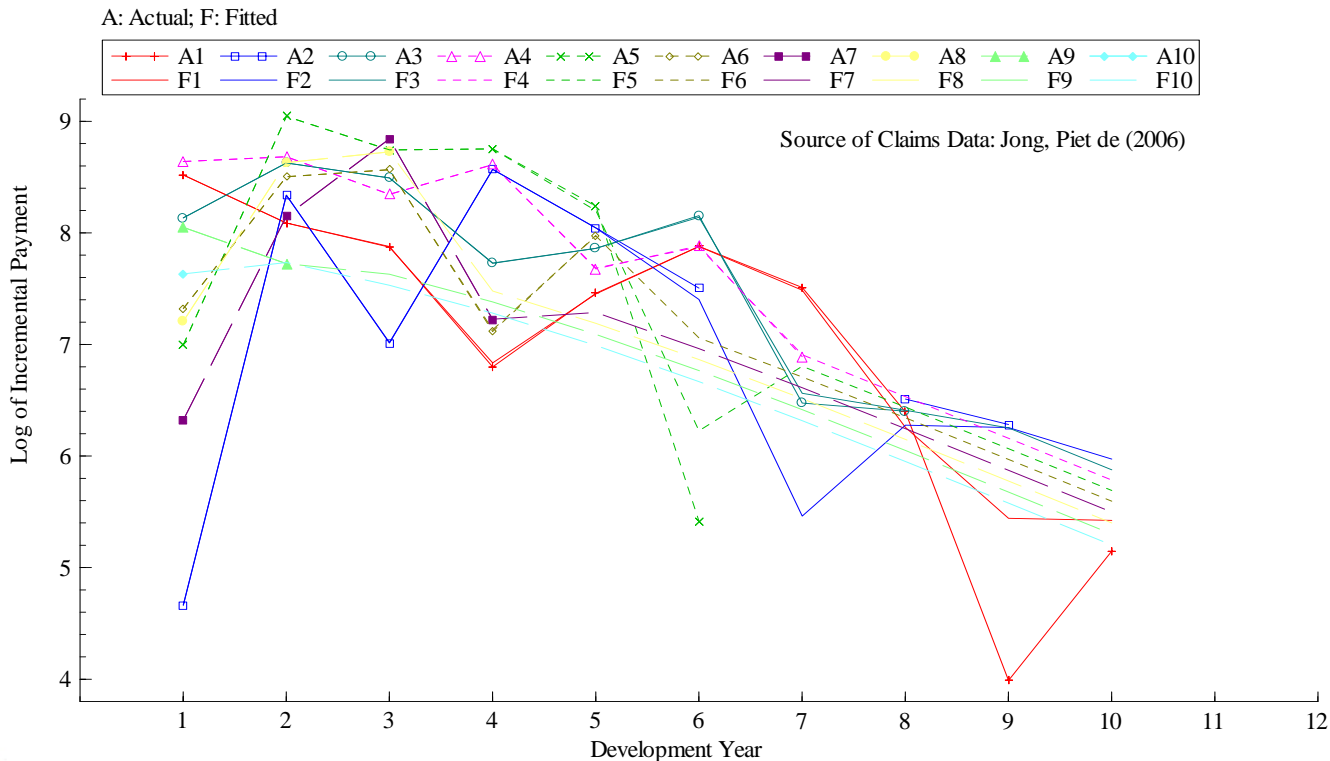


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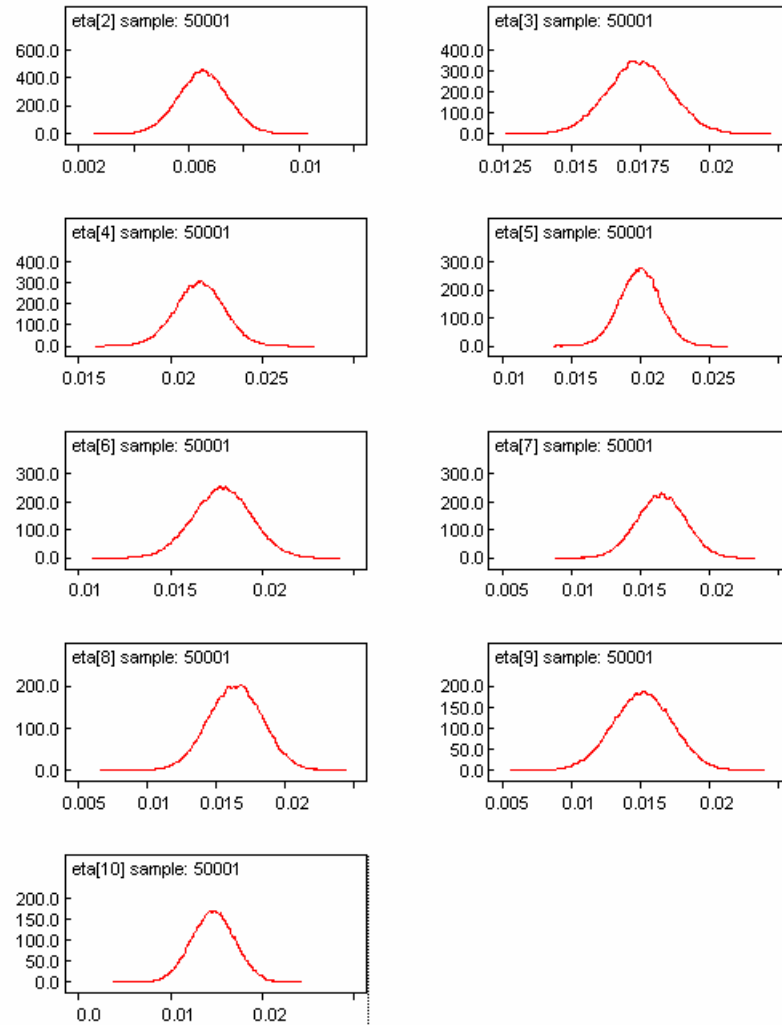


Application (2): The AFG Data Set

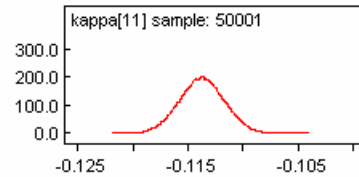
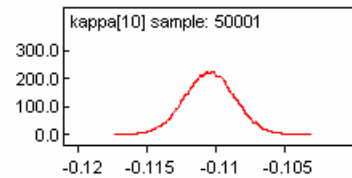
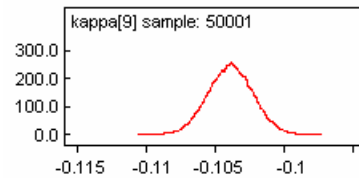
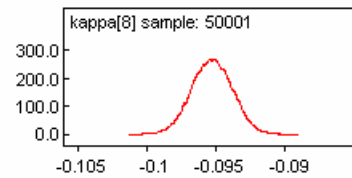
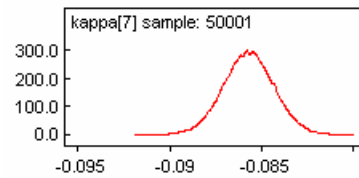
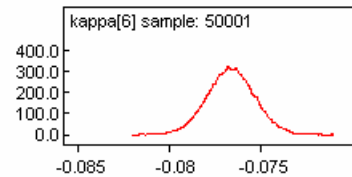
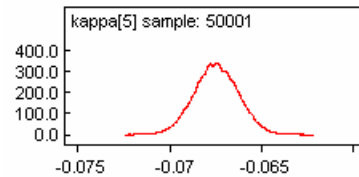
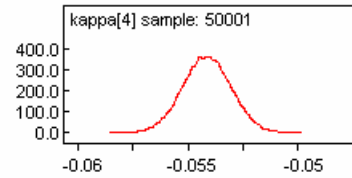
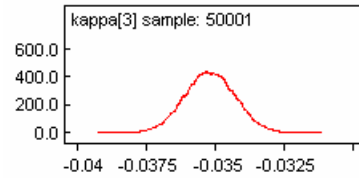
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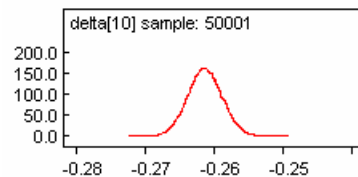
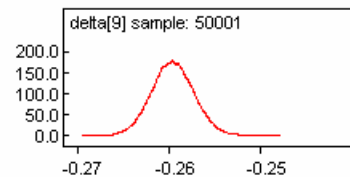
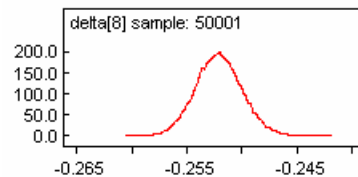
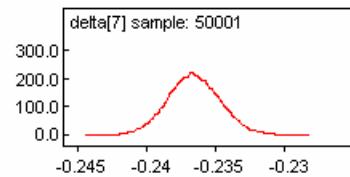
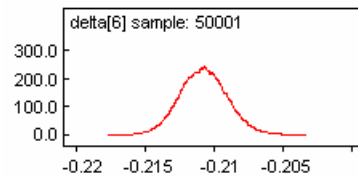
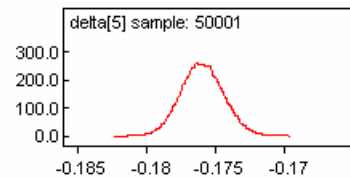
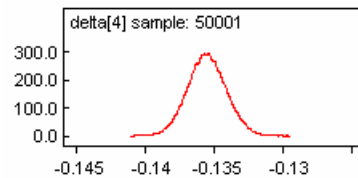
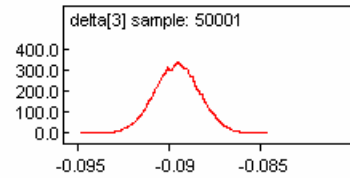
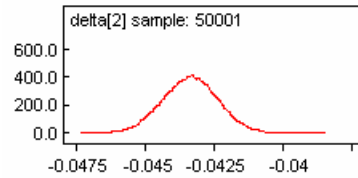
Application (2): The AFG Data Set



Application (2): The AFG Data Set



Application (2): The AFG Data Set



Application (3): Tail Estimation in NCCI Ratemaking (Test Phase)

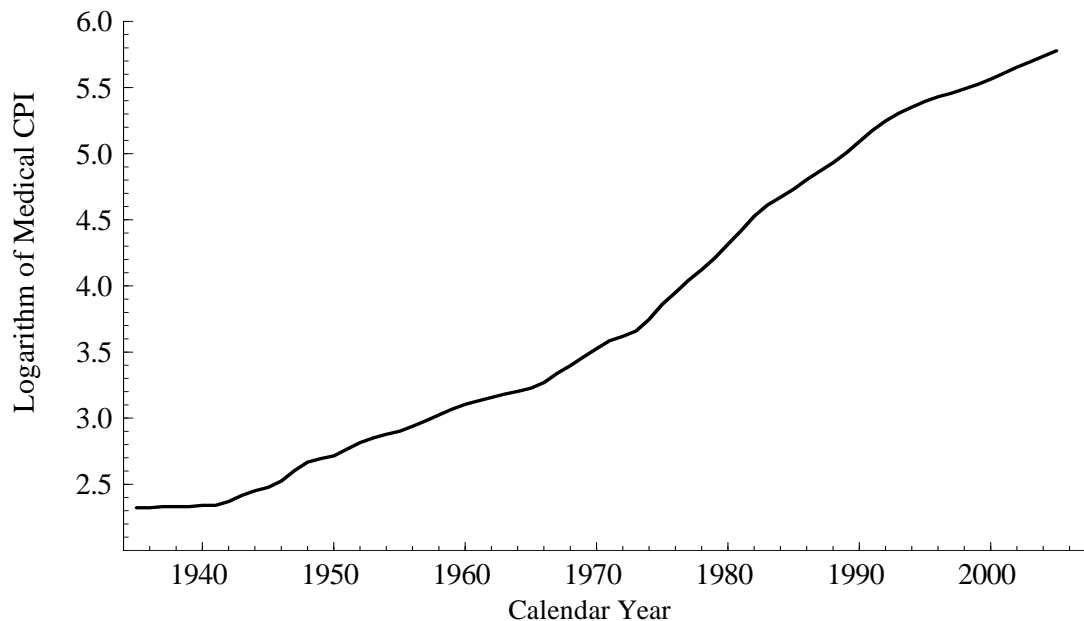
- For tail estimation, it is critical not to fit too closely to the observed incremental payments but instead allow for an appropriate degree of measurement noise
 - Overfitting shifts measurement noise to the state variables η , δ , and κ , which, via the *final states* of δ and κ , bears on the tail factor
 - The term *final state* refers to the estimated value of the state variable at the end of the time axis of the respective trajectory
 - Note that the final state of η (rate of exposure growth) is irrelevant to the tail factor

Application (3): Tail Estimation in NCCI Ratemaking (Test Phase)

- Further, for tail estimation, it is necessary to extrapolate the final estimates of κ (calendar effect)
 - In workers' compensation, the calendar effect (the rate of benefits inflation) is in the neighborhood of the respective official rate of inflation
 - For indemnity, this rate of inflation is the average weekly wage
 - For medical, this rate of inflation is the Medical Care component of the CPI (Consumer Price Index)
 - There are also one-off effects in κ , as caused by regulatory reforms
 - To the extent that there are no one-off effects, the calendar year effect follows a random walk
 - In this case, the forecast for any future value of κ is the final state

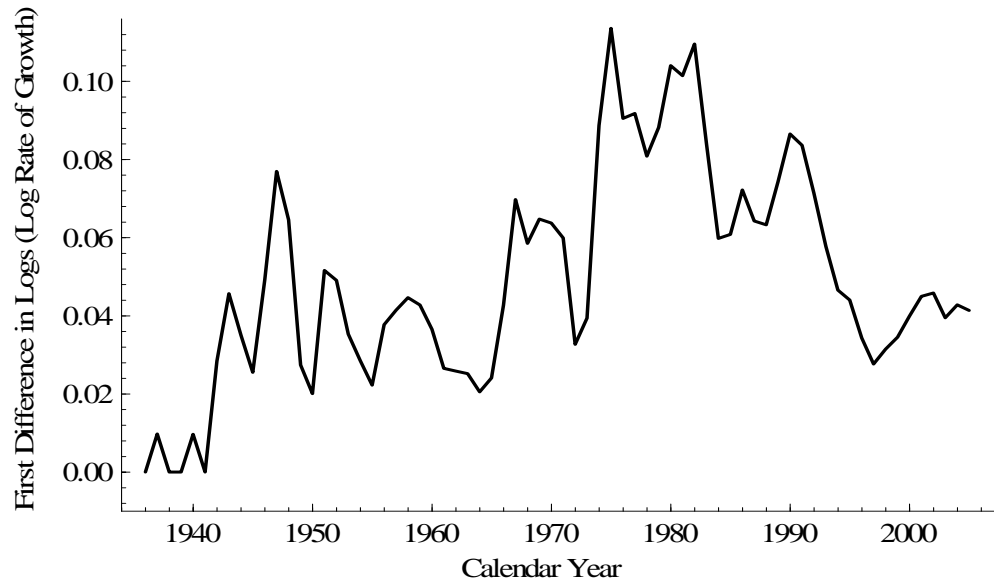
Application (3): Tail Estimation in NCCI Ratemaking (Test Phase)

- To demonstrate the random walk property of the calendar year effect, let us look at the Medical Care component of the CPI ("Medical CPI")



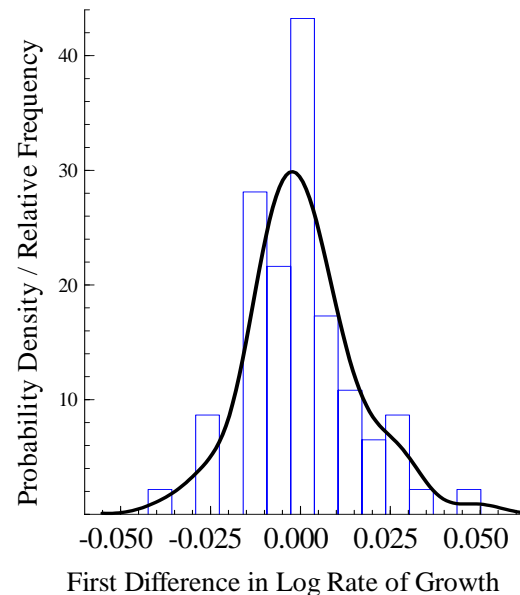
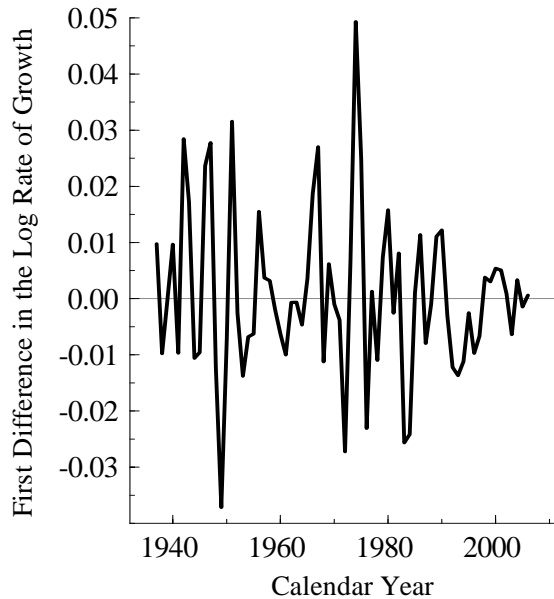
Application (3): Tail Estimation in NCCI Ratemaking (Test Phase)

- Take the first difference of the log Medical CPI
 - This series follows a random walk
 - All innovations (changes to the series) are independent draws from the normal distribution—independence implies that these innovations are permanent



Application (3): Tail Estimation in NCCI Ratemaking (Test Phase)

- Take the first difference of the first difference (the “second difference”) of the log Medical CPI
 - This series is stationary (of constant expected value) and normal, and centers on zero (mean: 0.0006)



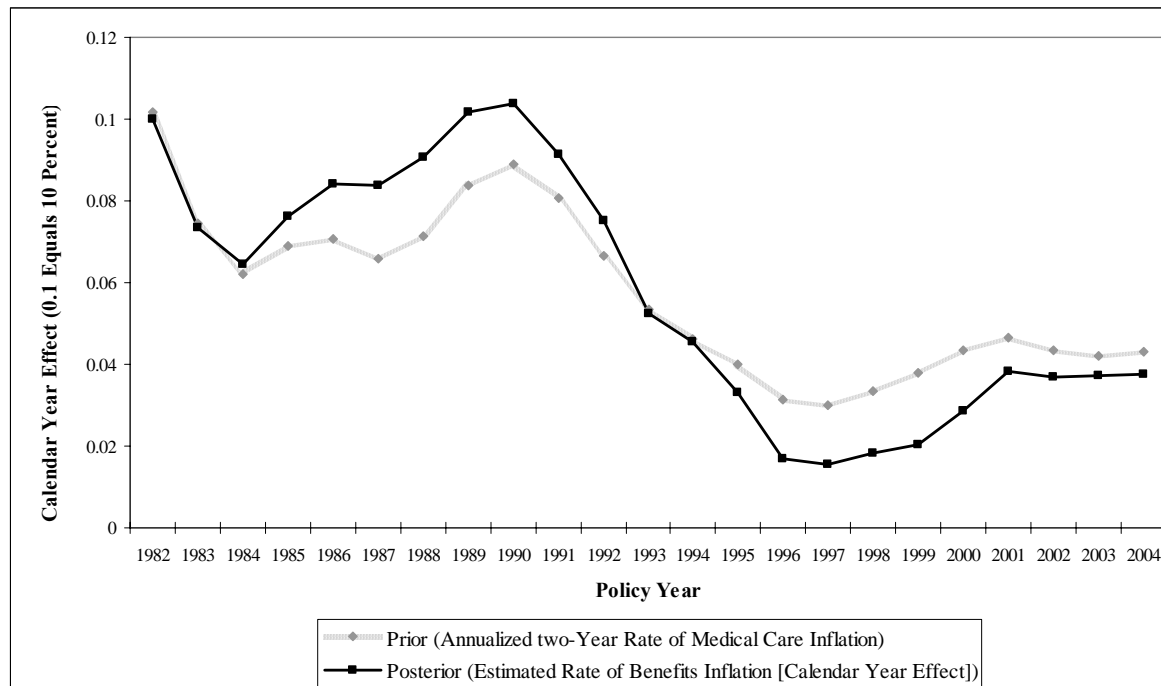
Application (3): Tail Estimation in NCCI Ratemaking (Test Phase)

- Further, for tail estimation, it is necessary to extrapolate the final estimates of δ (the rate of “decay” in development)
 - In workers’ compensation, this rate of decay will eventually approach the rate of mortality
 - Note that the rate of decay, δ , is inflation-adjusted
 - It is straightforward to build mortality information into the loss development model
- Finally, because in workers’ compensation the calendar effect can be expected to be in the neighborhood of the rate of average weekly wage and medical care inflation, respectively, the respective official rate of inflation may substitute for the random walk:

$$\kappa_{i+j} \sim N(\pi_{i+j}, \sigma_{\kappa}^2), \quad i + j = 3, \dots, N + 1$$

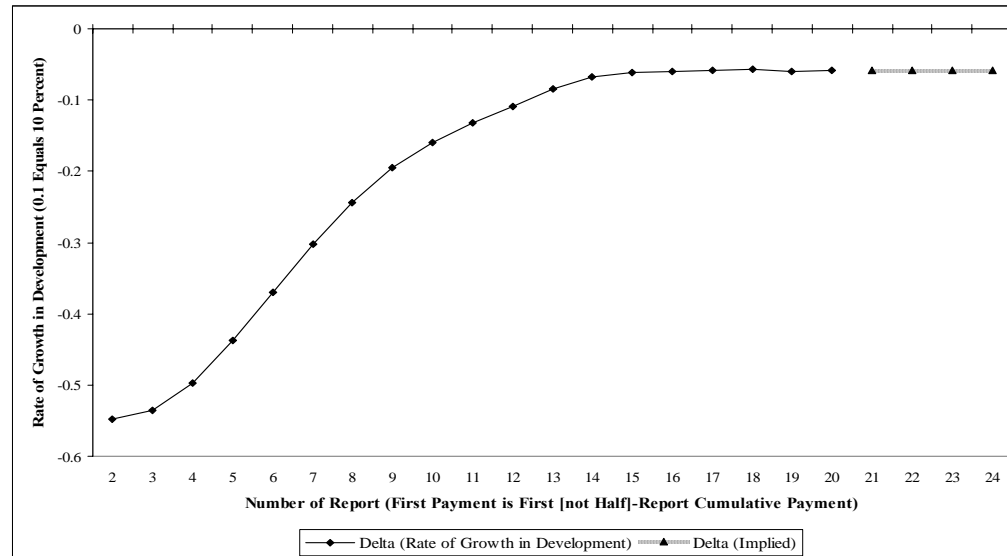
Application (3): Tail Estimation in NCCI Ratemaking (Test Phase)

- The calendar year effect for medical of the given anonymous state
 - The gray line indicates the prior, which is the official, published rate of Medical CPI



Application (3): Tail Estimation in NCCI Ratemaking (Test Phase)

- The decay in development for medical of the given anonymous state
 - Shown are only the development years for which data are available
 - Mortality information factors in beyond the data points shown here



Conclusion

- At NCCI, there is available for research and ratemaking purposes a state-of-the-art statistical model of loss development
 - The model makes use of recent statistical advances such as state-space modeling and the Metropolis-Hastings algorithm
- The loss development model meets tomorrow's standards of actuarial practice
 - The exposure draft "Property/Casualty Unpaid Claim and Claim Adjustment Expense Estimates" by the Actuarial Standards Board from February 2006 emphasizes the probabilistic nature of stated developed losses
 - Because the model is Bayesian, it offers a complete characterization of the underlying probability distribution