# THE PREDICTION ERROR OF THE CHAIN LADDER METHOD APPLIED TO CORRELATED RUN-OFF TRIANGLES

BY

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### Abstract

It is shown how the distribution-free method of Mack (1993) can be extended in order to estimate the prediction error of the Chain Ladder method for a portfolio of several correlated run-off triangles.

### Keywords

Chain Ladder, Prediction Error, Correlation of Run-offs, Segmented Portfolio.

# 1. INTRODUCTION

In Mack (1993), a distribution-free method was developed in order to estimate the prediction error of Chain Ladder reserve estimates. For claims reserving purposes, an insurance company usually subdivides its portfolio into several subportfolios such that the development behavior of each subportfolio can be assumed to be homogeneous. Then, for each subportfolio, the Chain Ladder method can be applied in order to estimate the appropriate claims reserves and their prediction error.

But what is finally needed, are the claims reserves for the whole portfolio of the insurance company and their prediction error. Whereas the estimates of the claims reserves of each subportfolio can simply be added together in order to arrive at an estimate for the claims reserves of the whole portfolio, this is only the case for the prediction variances if the subportfolios can be assumed to be independent. But in long tail business, the development of different subportfolios is influenced to a substantial degree by the development behavior of bodily injury claims (medical and nursing costs). Even after correcting the data for the claims inflation, further direct and indirect sources for correlations between run-offs of a portfolio exist (see e.g. Houltram (2003)). Therefore, subportfolios in general can not be assumed to be independent. Then, the question arises how the prediction error of the aggregated portfolio can be arrived at.

In this situation, applying the Chain Ladder method to the overall triangle and taking the prediction error from this calculation is not a good solution

ASTIN BULLETIN, Vol. 34, No. 2, 2004, pp. 399-423

because already the reserve estimates obtained in this way will not be identical to the aggregation of the reserve estimates of the individual subportfolios, see e.g. Ajne (1994). Moreover, the aggregation of run-off triangles with different development patterns is like mixing apples and oranges and will normally lead to invalid results.

Therefore in this paper, a new, more sensible approach is developed. We assume that the correlation between two run-off triangles finds its manifestation in a fixed correlation coefficient between the individual development factors of the two corresponding development periods of the triangles. This correlation coefficient may depend on the development period, but not on the accident year. This assumption fits very well to the basic assumption behind the Chain Ladder method that the individual development factors of each development period fluctuate randomly around a fixed, but unknown age-to-age factor.

In actuarial practice, this approach enables the actuary to set up a range and a prudential margin for the reserves of the whole portfolio as required e.g. by several national accounting standards. The reserving bounds described in this paper are solely based on stochastic assumptions and on the observed data and not on assumed correlations between lines of business – as often done – which do not refer to the peculiarities of the underlying portfolio.

Due to the increasing importance of stochastic methods in claims reserving the prediction error of the reserves of a portfolio was subject of several publications, recently. In none of these papers, the author is aware of, the correlation between segments is defined such rigorously as it is done here. In Brehm (2002) for example, the correlation of the reserve distributions of the segments is simply set equal to the correlation of the separated calendar period inflation parameter estimate. Furthermore, Brehm does not use the Chain Ladder method for the ultimate projection.

In our approach the prediction error for the reserve estimate of a portfolio of correlated segments is based on a stochastic model. In a simulation based approach, Kirschner (2002) extended the bootstrapping technique for estimating the reserve variability of a single segment to a whole portfolio. This technique produces samples of the portfolio, but it is not clear what statistical properties these samples have actually and which correlations of the original segments are grasped in the samples at all. Aside, the bootstrapping technique assumes independent increments in the segments which does not fit with the Chain Ladder assumptions.

The paper is organized as follows: Section 2.1 gives the basic notations and repeats the recursive formulae for the prediction error of a single accident year for one triangle. From this, the prediction error of the total claims amount of all accident years is derived in section 2.2. In section 3, a second run-off triangle is introduced as well as the decisive assumption on the correlation between both triangles. In section 4, the recursive formulae for the prediction error of the sum of the two triangles are derived. In section 5, a numerical example is given including the derivation of a range for the best estimate of the portfolio reserve. In the final section 6, some remarks regarding the impact of claims inflation on the correlation of run-offs are made and properties of a simplified model are presented.

#### 2. The prediction error for one run-off triangle

#### 2.1. The prediction error of the ultimate claims amount of one accident year

Let  $C_{ik} > 0$  be the cumulative claims amount of accident year  $i, 1 \le i \le n$ , after k years of development,  $1 \le k \le n$ , for a certain subportfolio. The amounts  $C_{ik}$  with  $i + k \le n + 1$  are observable and we are interested in predicting the amounts  $C_{in}$  for i = 2, 3, ..., n. The Chain Ladder method does this recursively by

$$\hat{C}_{ik} = \hat{C}_{i,k-1} \cdot \hat{f}_k \tag{1}$$

with starting value  $\hat{C}_{i,n+1-i} = C_{i,n+1-i}$  and age-to-age factor

$$\hat{f}_{k} = \frac{\sum_{i=1}^{n+1-k} C_{ik}}{C_{<, k-1}} = \sum_{i=1}^{n+1-k} \frac{C_{i, k-1}}{C_{<, k-1}} \cdot F_{ik}$$
(2)

which is a weighted average of individual development factors

$$F_{ik} := \frac{C_{ik}}{C_{i,k-1}}$$
 with  $C_{<, k-1} := \sum_{i=1}^{n+1-k} C_{i,k-1}$ .

In the following we consider numerous conditional expectation values and variances. To avoid there lengthy expressions we introduce some notation. The condition " $T_k$ " means that all variables  $\{C_{ij} | 1 \le i \le n, 1 \le j \le k, i+j \le n+1\}$  of the run-off triangle up to and including development year *k* are given. Especially, the condition " $T_n$ " indicates that the whole triangle is given. Furthermore, we use  $T_{ik}$  when the variables  $\{C_{ij} | 1 \le j \le k\}$  are given.

On the basis of the stochastic assumptions (see Mack (1993) and (1999), where the further results of this section can be found, too)

$$\mathbf{E}\left(F_{ik}\big|T_{i,k-1}\right) = f_k,\tag{3}$$

$$\operatorname{Var}\left(F_{ik}\left|T_{i,k-1}\right) = \frac{\sigma_{k}^{2}}{C_{i,k-1}},$$
(4)

for all  $1 \le i \le n$  and  $2 \le k \le n$  where  $f_k$  and  $\sigma_k^2$  are unknown parameters, the estimation procedure (1) and (2) can be shown to be reasonable and conditionally unbiased, i.e.  $E(\hat{f}_k | T_{k-1}) = f_k$  and  $E(\hat{C}_{in} | T_{n+1-i}) = C_{i,n+1-i}f_{n+2-i} \cdot \ldots \cdot f_n = E(C_{in} | T_{n+1-i})$ , if the accident years are independent. The assumptions (3) and (4) together with the assumption of the independence of the accident years are the basis for all considerations in this paper and are used without mentioning explicitly each time.

The prediction error mse( $\hat{C}_{in}$ ) for the ultimate claims amount of an accident year is defined as

$$\operatorname{mse}(\hat{C}_{in}) := \operatorname{E}((C_{in} - \hat{C}_{in})^2 | T_n)$$

because for reserving purposes only the future variability given the observable data is of interest. This can be written in the form

$$mse(\hat{C}_{in}) = Var(C_{in}|T_{n+1-i}) + (E(\hat{C}_{in}|T_{n+1-i}) - \hat{C}_{in})^{2}$$

which for estimation purposes is approximated by

$$\operatorname{mse}(\hat{C}_{in}) \approx \operatorname{Var}(C_{in}|T_{n+1-i}) + \operatorname{Var}(\hat{C}_{in}|T_{n+1-i}).$$
(5)

In (5)  $\operatorname{Var}(C_{in}|T_{n+1-i})$  is called the random error and  $\operatorname{Var}(\hat{C}_{in}|T_{n+1-i})$  the estimation error. To keep the notation as simple as possible we omit from now on the conditions in the expectations. So, whenever for i + k > n + 1 expectations like  $\operatorname{E}(C_{ik})$ ,  $\operatorname{E}(\hat{C}_{ik})$  and variances like  $\operatorname{Var}(C_{ik})$  or  $\operatorname{Var}(\hat{C}_{ik})$  are considered, in the strict sense  $\operatorname{E}(C_{ik}|T_{n+1-i})$ ,  $\operatorname{E}(\hat{C}_{ik}|T_{n+1-i})$ ,  $\operatorname{Var}(C_{ik}|T_{n+1-i})$  and  $\operatorname{Var}(\hat{C}_{ik}|T_{n+1-i})$  are meant. The exact formulations of the following derivations can be found in Mack (1993).

Now, we deduce recursions for the random error and for the estimation error. For this purpose, the equations (3) and (4) are used in the form

$$E(C_{ik} | T_{i,k-1}) = C_{i,k-1} f_k,$$
  
Var $(C_{ik} | T_{i,k-1}) = C_{i,k-1} \sigma_k^2$ 

Then we have for i + k > n + 1

$$Var(C_{ik}) = E(Var(C_{ik} | T_{i,k-1})) + Var(E(C_{ik} | T_{i,k-1}))$$
  
=  $E(C_{i,k-1})\sigma_k^2 + Var(C_{i,k-1})f_k^2.$ 

This yields for the estimator  $\widehat{\operatorname{Var}}(C_{in})$  of the random error  $\operatorname{Var}(C_{in})$  of the ultimate claims amount the recursion

$$\widehat{\operatorname{Var}}(C_{ik}) = \widehat{\operatorname{Var}}(C_{i,k-1}) \cdot \widehat{f}_k^2 + \widehat{C}_{i,k-1} \widehat{\sigma}_k^2$$
(6)

with the starting value

$$\operatorname{Var}(C_{i,n+1-i}) = 0$$

as  $C_{i,n+1-i}$  is already known. An unbiased estimator of  $\hat{\sigma}_k^2$  is given by

$$\hat{\sigma}_k^2 = \frac{1}{n-k} \sum_{i=1}^{n+1-k} C_{i,k-1} (F_{ik} - \hat{f}_k)^2.$$
(7)

Similarly,  $\hat{C}_{ik} = \hat{C}_{i,k-1}\hat{f}_k$  yields

$$Var(\hat{C}_{ik}) = E(Var(\hat{C}_{i,k-1}\hat{f}_k | T_{k-1})) + Var(E(\hat{C}_{i,k-1}\hat{f}_k | T_{k-1}))$$
  
=  $E(\hat{C}_{i,k-1}^2 Var(\hat{f}_k | T_{k-1})) + Var(\hat{C}_{i,k-1})f_k^2.$ 

From this the following recursion for the estimator  $\widehat{\operatorname{Var}}(\hat{C}_{in})$  of the estimation error  $\operatorname{Var}(\hat{C}_{in})$  of the ultimate claims estimate  $\hat{C}_{in}$  can be deduced:

$$\widehat{\operatorname{Var}}(\widehat{C}_{ik}) = \widehat{\operatorname{Var}}(\widehat{C}_{i,k-1})\widehat{f}_k^2 + \widehat{C}_{i,k-1}^2 \cdot \frac{\widehat{\sigma}_k^2}{C_{<,k-1}}$$
(8)

because

$$\operatorname{Var}(\hat{f}_{k} | T_{k-1}) = \frac{\sigma_{k}^{2}}{C_{<, k-1}}.$$
(9)

The starting value for this recursion is

$$\widehat{\operatorname{Var}}(\widehat{C}_{i,n+1-i}) = 0$$

because  $\hat{C}_{i,n+1-i}$  is already observed. This yields the joint recursion for the estimate of the prediction error:

$$\widehat{\text{mse}}(\hat{C}_{ik}) = \widehat{\text{mse}}(\hat{C}_{i,k-1}) \cdot \hat{f}_k^2 + \hat{C}_{i,k-1}^2 \left( \frac{\hat{\sigma}_k^2}{\hat{C}_{i,k-1}} + \frac{\hat{\sigma}_k^2}{\hat{C}_{<,k-1}} \right).$$
(10)

# 2.2. The prediction error of the total ultimate claims amount of one run-off triangle

Annual reports of insurance companies usually disclose estimates only for reserves and claims amounts for all accident years together. To estimate a range of those aggregated amounts, we have to consider the estimation error and prediction error for all accident years together.

 $C_{1n}$  is already known and no estimate is necessary. Therefore the first accident year adds nothing to the random error and the estimation error for the whole run-off. Taking this into account, the prediction error  $mse(\sum_{i=2}^{n} \hat{C}_{in})$  for all accident years is defined as

$$\operatorname{mse}\left(\sum_{i=2}^{n} \hat{C}_{in}\right) := \operatorname{E}\left(\left(\sum_{i=2}^{n} (C_{in} - \hat{C}_{in})\right)^{2} \middle| T_{n}\right).$$

We have (Mack (1993))

$$mse\left(\sum_{i=2}^{n}\hat{C}_{in}\right) = Var\left(\sum_{i=2}^{n}C_{in} \mid T_{n}\right) + \left(\sum_{i=2}^{n}\left(E\left(\hat{C}_{in} \mid T_{n+1-i}\right) - \hat{C}_{in}\right)\right)^{2}\right)$$
$$= Var\left(\sum_{i=2}^{n}C_{in} \mid T_{n}\right) + \sum_{i=2}^{n}\left(E\left(\hat{C}_{in} \mid T_{n+1-i}\right) - \hat{C}_{in}\right)^{2}\right)$$
$$+ 2\sum_{2 \le i < j \le n}\left(E\left(\hat{C}_{in} \mid T_{n+1-i}\right) - \hat{C}_{in}\right)\left(E\left(\hat{C}_{jn} \mid T_{n+1-j}\right) - \hat{C}_{jn}\right)\right)$$

$$\approx \operatorname{Var}\left(\sum_{i=2}^{n} C_{in} \middle| T_{n}\right) + \sum_{i=2}^{n} \operatorname{Var}\left(\hat{C}_{in} \middle| T_{n+1-i}\right)$$
$$+ 2 \sum_{2 \le i < j \le n} \operatorname{Cov}\left(\hat{C}_{in}, \hat{C}_{jn} \middle| T_{n+1-i}\right)$$

The random error of the total ultimate loss amount is  $\operatorname{Var}(\sum_{i=2}^{n} C_{in} | T_n)$ . The estimation error  $\operatorname{Var}(\sum_{i=2}^{n} \hat{C}_{in})$  of the ultimate claims amount of all accident years together is

$$\operatorname{Var}\left(\sum_{i=2}^{n} \hat{C}_{in}\right) := \sum_{i=2}^{n} \operatorname{Var}\left(\hat{C}_{in} \big| T_{n+1-i}\right) + \sum_{2 \le i < j \le n} 2 \operatorname{Cov}\left(\hat{C}_{in}, \hat{C}_{jn} \big| T_{n+1-i}\right).$$
(11)

It is important to note, that  $\operatorname{Var}(\sum_{i=1}^{n} \hat{C}_{in})$  is only a notation for the right-handside in (11) and that it is not a variance since the right-hand-side of the definition (11) can not be rewritten as one single conditional variance due to the different conditions of the variances and covariances in the sum. This yields the following approximation for mse $(\sum_{i=1}^{n} \hat{C}_{in})$  (which is analogous to (5)):

$$\operatorname{mse}\left(\sum_{i=1}^{n}\hat{C}_{in}\right)\approx\operatorname{Var}\left(\sum_{i=1}^{n}C_{in}\right|T_{n}\right)+\operatorname{Var}\left(\sum_{i=1}^{n}\hat{C}_{in}\right).$$

Again, we omit the condition for simplicity. The random error  $\operatorname{Var}(\sum_{i=2}^{n} C_{in})$  fulfills due to the independence of the accident years (which here implies that the variables  $C_{in}$ , i = 1, ..., n are conditionally uncorrelated, Mack (2002), p. 255) the equation

$$\operatorname{Var}\left(\sum_{i=2}^{n} C_{in}\right) = \sum_{i=2}^{n} \operatorname{Var}(C_{in}).$$
(12)

Of course (12) can be generalized to

$$\operatorname{Var}\left(\sum_{i=n+2-k}^{n} C_{ik}\right) = \sum_{i=n+2-k}^{n} \operatorname{Var}\left(C_{ik}\right).$$
(13)

(13) and the recursion (6) for the random error of one accident year yield the recursion

$$\widehat{\operatorname{Var}}\left(\sum_{i=n+2-k}^{n} C_{ik}\right) = \widehat{\operatorname{Var}}\left(\sum_{i=n+3-k}^{n} C_{i,k-1}\right)\widehat{f}_{k}^{2} + \widehat{C}_{\geq,k-1}\widehat{\sigma}_{k}^{2},$$

with

$$\hat{C}_{\geq,k-1} := \sum_{i=n+2-k}^{n} \hat{C}_{i,k-1}.$$
(14)

Note,  $\hat{C}_{\geq,k-1}$  is the sum of the estimated claims amounts of development period k-1 plus the known amount  $C_{n+2-k,k-1}$  of the actual calendar year. This recursion starts with k = 2 since for the first development year all claims amounts  $C_{i1}$ ,  $1 \le i \le n$ , are already known. Here and in the following we use the convention that an empty summation is equal to 0.

For the estimation error  $\operatorname{Var}(\sum_{i=2}^{n} \hat{C}_{in})$  such a simple relation as (12) does not hold since all correlations between the ultimate claims amount estimates of different accident years have to be considered. A recursion for  $\widehat{\operatorname{Cov}}(\hat{C}_{in}, \hat{C}_{jn})$ can be achieved by (with k > n + 1 - i and i < j)

$$Cov(\hat{C}_{ik}, \hat{C}_{jk}) = E(Cov(\hat{C}_{i,k-1}\hat{f}_k, \hat{C}_{j,k-1}\hat{f}_k | T_{k-1})) + + Cov(E(\hat{C}_{i,k-1}\hat{f}_k | T_{k-1}), E(\hat{C}_{j,k-1}\hat{f}_k | T_{k-1})) = E(\hat{C}_{i,k-1}\hat{C}_{j,k-1}Var(\hat{f}_k | T_{k-1})) + Cov(\hat{C}_{i,k-1}, \hat{C}_{j,k-1})f_k^2$$
(15)

and using (9)

$$\widehat{\text{Cov}}(\hat{C}_{ik},\hat{C}_{jk}) = \widehat{\text{Cov}}(\hat{C}_{i,k-1},\hat{C}_{j,k-1})\hat{f}_k^2 + \hat{C}_{i,k-1}\hat{C}_{j,k-1}\frac{\hat{\sigma}_k^2}{C_{<,k-1}}$$
(16)

starting with  $\widehat{\text{Cov}}(\widehat{C}_{i,n+1-i}, \widehat{C}_{j,n+1-i}) = 0$  since i < j and  $C_{i,n+1-i}$  is known. (16) and (8) yield the following recursion for the estimation error:

$$\widehat{\operatorname{Var}}\left(\sum_{i=n+2-k}^{n} \hat{C}_{ik}\right) = \widehat{\operatorname{Var}}\left(\sum_{i=n+3-k}^{n} \hat{C}_{i,k-1}\right) \hat{f}_{k}^{2} + (\hat{C}_{\geq,k-1})^{2} \frac{\hat{\sigma}_{k}^{2}}{C_{<,k-1}}.$$

For the same reason as before, this recursion starts with k = 2.

The recursions for the random error  $\operatorname{Var}(\sum_{i=2}^{n} C_{in})$  and the estimation error  $\operatorname{Var}(\sum_{i=2}^{n} \hat{C}_{in})$  yield the recursion for the prediction error  $\operatorname{mse}(\sum_{i=2}^{n} C_{in})$  of the total claims amounts for all accident years:

$$\widehat{\mathrm{mse}}\left(\sum_{i=n+2-k}^{n} \widehat{C}_{ik}\right) = \widehat{\mathrm{mse}}\left(\sum_{i=n+3-k}^{n} \widehat{C}_{i,k-1}\right) \widehat{f}_{k}^{2} + \left(\widehat{C}_{\geq,k-1}\right)^{2} \left(\frac{\widehat{\sigma}_{k}^{2}}{\widehat{C}_{\geq,k-1}} + \frac{\widehat{\sigma}_{k}^{2}}{C_{<,k-1}}\right).$$
(17)

The recursion starts with k = 2. Using (4) and (9) it can be shown that (17) is the same recursion as the one already given in Mack (1999) for the prediction error. Structure of recursion (17) is the same as in (10). The only difference between the two recursions are the estimated claims amounts  $\hat{C}_{\geq,k-1}$  instead of the claims amount  $\hat{C}_{i,k-1}$  for one accident year in (10). The prediction error mse $(\sum_{i=1}^{n} \hat{C}_{in})$  gives the mean squared deviation between

The prediction error mse $(\sum_{i=1}^{n} \hat{C}_{in})$  gives the mean squared deviation between the estimated ultimate claims amount  $\sum_{i=1}^{n} \hat{C}_{in}$  and the true ultimate claims amount  $\sum_{i=1}^{n} C_{in}$ . The estimation error Var $(\sum_{i=1}^{n} \hat{C}_{in})$  gives the mean squared deviation between the estimated ultimate claims amount  $\sum_{i=1}^{n} \hat{C}_{in}$  and the expected ultimate claims amount  $E(\sum_{i=1}^{n} C_{in}) = E(\sum_{i=1}^{n} \hat{C}_{in})$ . Whereas the prediction error has to be used for the variability loading for a loss portfolio transfer, it is the estimation error which has to be used when assessing a confidence interval (range) around  $\sum_{i=1}^{n} \hat{C}_{in}$  for the best estimate  $E(\sum_{i=1}^{n} C_{in})$  of  $\sum_{i=1}^{n} C_{in}$ .

# 3. A Chain ladder-type model for the correlation between two run-off triangles

Now assume we have another subportfolio with cumulative run-off data  $\{D_{ik}\}$  in addition to the data  $\{C_{ik}\}$  of section 2. Considering that, we modify the condition " $T_{i,k-1}$ ". In the following " $T_{i,k-1}$ " means, both sets of observable variables  $\{C_{ij} | 1 \le j \le k-1\}$  and  $\{D_{ij} | 1 \le j \le k-1\}$  are given. Moreover, we assume (3), (4), to hold for this " $T_{i,k-1}$ ".

Note, in this case (3) and (4) with the " $T_{i,k-1}$ " as introduced in Section 2.1 still hold, being just a consequence of the new assumption, i.e. we have by using the notation  $C_{k-1}$  for the set  $\{C_{ij} | 1 \le j \le k-1\}$  and  $D_{k-1}$  for  $\{D_{ij} | 1 \le j \le k-1\}$ 

$$E(F_{ik} | C_{k-1}) = E(E(F_{ik} | C_{k-1}, D_{k-1}) | C_{k-1}) = f_k,$$
(18)  

$$Var(F_{ik} | C_{k-1}) = E(Var(F_{ik} | C_{k-1}, D_{k-1}) | C_{k-1}) + Var(E(F_{ik} | C_{k-1}, D_{k-1}) | C_{k-1}) = \frac{\hat{\sigma}_k^2}{C_{i,k-1}}.$$
(19)

Aside, (18) and (19) justify actuarial practice using the Chain Ladder method for a subportfolio without considering in addition the observables of all other segments of the portfolio.

For the subportfolio with cumulative run-off data  $\{D_{ik}\}$  we denote with  $g_k$  and  $\tau_k^2$  its Chain-Ladder parameters corresponding to  $f_k$  and  $\sigma_k^2$ , respectively. The stochastic assumptions are

$$E(G_{ik}|T_{i,k-1}) = g_k$$
 (20)

$$\operatorname{Var}(G_{ik} | T_{i,k-1}) = \frac{\tau_k^2}{D_{i,k-1}}.$$
(21)

Again, the accident years i = 1, ..., n are assumed to be independent.

We have the following estimators

$$\hat{g}_{k} = \frac{\sum_{i=1}^{n+1-k} D_{ik}}{D_{<, k-1}}$$
(22)

$$\hat{\tau}_k^2 = \frac{1}{n-k} \sum_{i=1}^{n-k+1} D_{i,k-1} (G_{ik} - \hat{g}_k)^2$$
(23)

with

$$G_{ik} := rac{D_{ik}}{D_{i, k-1}},$$
  
 $D_{<,k-1} := \sum_{i=1}^{n+1-k} D_{i, k-1}$ 

For each of the data sets  $\{C_{ik}\}$  and  $\{D_{ik}\}$  the stochastic model for the Chain Ladder consists of an own submodel for each development period  $k, 2 \le k \le n$ . In order to arrive at formulae for expectation and variance of the ultimate claims  $D_{in}$  in terms of the observable amounts  $\{D_{ik}, i + k \le n + 1\}$ , the submodels are simply chained together.

Therefore it seems natural to restrict any assumptions regarding the correlation between the arrays  $\{C_{ik}, 1 \le i, k \le n\}$  and  $\{D_{ik}, 1 \le i, k \le n\}$  to each of the pairwise corresponding development years  $k, 2 \le k \le n$ , if we want to stay within the chain ladder world. In this sense, the natural generalization of (4) and (21) is the assumption

$$\operatorname{Cov}(F_{ik}, G_{ik} | T_{i, k-1}) = \frac{\rho_k}{\sqrt{C_{i, k-1} D_{i, k-1}}}$$
(24)

which is equivalent to assuming that the correlation coefficient between the individual development factors  $F_{ik}$  and  $G_{ik}$ 

$$\operatorname{Corr}(F_{ik}, G_{ik} | T_{i, k-1}) := \frac{\operatorname{Cov}(F_{ik}, G_{ik} | T_{i, k-1})}{\sqrt{\operatorname{Var}(F_{ik} | T_{i, k-1}) \cdot \operatorname{Var}(G_{ik} | T_{i, k-1})}} = \frac{\rho_k}{\sigma_k \tau_k}$$

is constant for k fixed.

Of course, different accident years of the portfolio consisting of the run-off data sets  $\{C_{ik}\}$  and  $\{D_{ik}\}$  are assumed to be independent. Then we have

$$\operatorname{Cov}(C_{ik}, D_{jk} | T_{k-1}) = 0 \text{ for } i \neq j,$$

since

$$E(C_{ik} \cdot D_{jk} | T_{k-1}) = E(E(C_{ik} \cdot D_{jk} | T_{k-1}, T_{ik}) | T_{k-1})$$
  
=  $E(C_{ik} E(D_{jk} | T_{k-1}, T_{ik}) | T_{k-1})$   
=  $E(C_{ik} | T_{k-1}) E(D_{jk} | T_{k-1}).$  (25)

(25) also holds for  $F_{ik}$  and  $G_{jk}$  instead of  $C_{ik}$  and  $D_{jk}$ . This shows

$$\operatorname{Cov}(F_{ik}, G_{ik} | T_{k-1}) = 0$$
 for  $i \neq j$ .

In analogy of the estimation of  $\sigma_k^2$  and  $\tau_k^2$ , the new parameter  $\rho_k$  can be estimated by

$$\hat{\rho}_{k} = \frac{1}{n-k-1+w_{k}^{2}} \sum_{i=1}^{n+1-k} \sqrt{C_{i,k-1}D_{i,k-1}} \left(F_{ik} - \hat{f}_{k}\right) \left(G_{ik} - \hat{g}_{k}\right)$$
(26)

with

$$w_k^2 := \frac{\left(\sum_{i=1}^{n+1-k} \sqrt{C_{i,k-1} D_{i,k-1}}\right)^2}{C_{<,k-1} \cdot D_{<,k-1}}.$$

The factor  $\frac{1}{n-k-1+w_k^2}$  instead of  $\frac{1}{n-k}$  as for  $\hat{\sigma}_k^2$  and  $\hat{\tau}_k^2$  ensures that the estimator  $\hat{\rho}_k$  for  $\rho_k$  is unbiased. Note, that  $w_k^2$  is positive and  $\leq 1$  (Cauchy-Schwarz inequality).

# 4. Estimation of the prediction error of the sum of two run-off triangles

First of all, we have to define the prediction error  $mse(\hat{C}_{in} + \hat{D}_{in})$  for the ultimate claims amount of an accident year of the portfolio. It is defined analogously as for one run-off:

$$\operatorname{mse}(\hat{C}_{in} + \hat{D}_{in}) := \operatorname{E}((C_{in} + D_{in} - (\hat{C}_{in} + \hat{D}_{in}))^2 | T_n).$$

This can be approximated by

$$\operatorname{mse}(\hat{C}_{in} + \hat{D}_{in}) \approx \operatorname{Var}(C_{in} + D_{in} | T_{n+1-i}) + \operatorname{Var}(\hat{C}_{in} + \hat{D}_{in} | T_{n+1-i}).$$

Here,  $\operatorname{Var}(C_{in} + D_{in} | T_{n+1-i})$  is the random error and  $\operatorname{Var}(\hat{C}_{in} + \hat{D}_{in} | T_{n+1-i})$  is the estimation error. Again, we omit these conditions in the following.

Based on the assumption (24) which can be rewritten as

$$\operatorname{Cov}(C_{ik}, D_{ik} | T_{i,k-1}) = \sqrt{C_{i,k-1}} D_{i,k-1} \rho_k,$$

we now can calculate the random error  $Var(C_{in} + D_{in})$  and the estimation error  $Var(\hat{C}_{in} + \hat{D}_{in})$  of the combined triangle  $\{C_{ik} + D_{ik} | i + k \le n + 1\}$ . We have

$$\operatorname{Var}(C_{in} + D_{in}) = \operatorname{Var}(C_{in}) + 2\operatorname{Cov}(C_{in}, D_{in}) + \operatorname{Var}(D_{in})$$

and therefore, in addition to the recursions considered before, we need only a recursion for  $Cov(C_{in}, D_{in})$ , too. From

$$Cov(C_{ik}, D_{ik}) = E(Cov(C_{ik}, D_{ik} | T_{i,k-1})) + Cov(E(C_{ik} | T_{i,k-1}), E(D_{ik} | T_{i,k-1})) = E(\sqrt{C_{i,k-1}D_{i,k-1}})\rho_k + Cov(C_{i,k-1}, D_{i,k-1})f_kg_k$$

we deduce the recursion (for i + k > n + 1)

$$\widehat{\operatorname{Cov}}(C_{ik}, D_{ik}) = \widehat{\operatorname{Cov}}(C_{i,k-1}, D_{i,k-1})\widehat{f}_k\widehat{g}_k + \sqrt{\widehat{C}_{i,k-1}, \widehat{D}_{i,k-1}}\widehat{\rho}_k$$
(27)

for the estimated covariance between  $C_{ik}$  and  $D_{ik}$ . The starting value is

$$Cov(C_{i,n+1-i}, D_{i,n+1-i}) = 0$$

as both variables have already been observed. Similarly, for the estimation error we have

$$\operatorname{Var}(\hat{C}_{in} + \hat{D}_{in}) = \operatorname{Var}(\hat{C}_{in}) + 2\operatorname{Cov}(\hat{C}_{in}, \hat{D}_{in}) + \operatorname{Var}(\hat{D}_{in})$$

and

$$Cov(\hat{C}_{ik}, \hat{D}_{ik}) = E(Cov(\hat{C}_{i,k-1}\hat{f}_k, \hat{D}_{i,k-1}\hat{g}_k | T_{k-1})) + Cov(E(\hat{C}_{i,k-1}\hat{f}_k | T_{k-1}), E(\hat{D}_{i,k-1}\hat{g}_k | T_{k-1})) = E(\hat{C}_{i,k-1}\hat{D}_{i,k-1}Cov(\hat{f}_k, \hat{g}_k | T_{k-1})) + Cov(\hat{C}_{i,k-1}, \hat{D}_{i,k-1})f_kg_k$$

as well as

$$\operatorname{Cov}(\hat{f}_{k}, \hat{g}_{k} | T_{k-1}) = \operatorname{Cov}\left(\sum_{j=1}^{n+1-k} \frac{C_{j,k-1}}{C_{<,k-1}} F_{jk}, \sum_{j=1}^{n+1-k} \frac{D_{j,k-1}}{D_{<,k-1}} G_{jk} | T_{k-1}\right)$$
$$= \sum_{j=1}^{n+1-k} \frac{C_{j,k-1}}{C_{<,k-1}} \frac{D_{j,k-1}}{D_{<,k-1}} \operatorname{Cov}(F_{jk}, G_{jk} | T_{k-1})$$
$$= \sum_{j=1}^{n+1-k} \frac{\sqrt{C_{j,k-1}} D_{j,k-1}}{C_{<,k-1} D_{<,k-1}} \rho_{k}$$
(28)

Taken together, we have the recursion

$$\widehat{\text{Cov}}(\widehat{C}_{ik}, \widehat{D}_{ik}) = \widehat{\text{Cov}}(\widehat{C}_{i,k-1}, \widehat{D}_{i,k-1}) \cdot \widehat{f}_k \widehat{g}_k 
+ \frac{\widehat{C}_{i,k-1} \widehat{D}_{i,k-1}}{C_{<,k-1}} \widehat{\rho}_k \sum_{j=1}^{n+1-k} \sqrt{C_{j,k-1} D_{j,k-1}}$$
(29)

with starting value

$$\widehat{\operatorname{Cov}}(\widehat{C}_{i,n+1-i},\widehat{D}_{i,n+1-i})=0.$$

This completes the derivation of formulae for the random error, for the estimation error and taken together for the prediction error for the ultimate claims amount of one accident year in a portfolio consisting of two correlated subportfolios.

For actuarial evaluation of the liabilities of a whole portfolio and their potential adverse development the errors of the ultimate claims amount for all accident years of the portfolio are important quantities. The prediction error of the total ultimate claims amount  $\sum_{i=2}^{n} (\hat{C}_{in} + \hat{D}_{in})$  is

$$\begin{split} \operatorname{mse} & \left( \sum_{i=2}^{n} \left( \hat{C}_{in} + \hat{D}_{in} \right) \right) := \operatorname{E} \left( \left( \sum_{i=2}^{n} \left( C_{in} + D_{in} - \left( \hat{C}_{in} + \hat{D}_{in} \right) \right) \right)^{2} \middle| T_{n} \right) \\ &= \operatorname{Var} \left( \sum_{i=2}^{n} \left( C_{in} + D_{in} \right) \middle| T_{n} \right) \\ &+ \left( \sum_{i=2}^{n} \left( \operatorname{E} \left( \hat{C}_{in} + \hat{D}_{in} \middle| T_{n+1-i} \right) - \left( \hat{C}_{in} + \hat{D}_{in} \right) \right) \right)^{2} \\ &= \operatorname{Var} \left( \sum_{i=2}^{n} \left( C_{in} + D_{in} \right) \middle| T_{n} \right) \\ &+ \left( \sum_{i=2}^{n} \left( \operatorname{E} \left( \hat{C}_{in} \middle| T_{n+1-i} \right) - \hat{C}_{in} \right) + \sum_{i=2}^{n} \left( \operatorname{E} \left( \hat{D}_{in} \middle| T_{n+1-i} \right) - \hat{D}_{in} \right) \right)^{2} \\ &\approx \operatorname{Var} \left( \sum_{i=2}^{n} \left( C_{in} + D_{in} \right) \middle| T_{n} \right) \\ &+ \operatorname{Var} \left( \sum_{i=2}^{n} \hat{C}_{in} \right) + \operatorname{Var} \left( \sum_{i=2}^{n} \hat{D}_{in} \right) + \sum_{1 \le i, j \le n} 2 \operatorname{Cov} \left( \hat{C}_{in}, \hat{D}_{jn} \middle| T_{n+1-min(i,j)} \right), \end{split}$$

where min(i, j) denotes the Minimum of *i* and *j*. The first term is the random error, the last three together are the estimation error. Note, here we used the notation  $Var(\sum_{i=2}^{n} \hat{C}_{in})$  and  $Var(\sum_{i=2}^{n} \hat{D}_{in})$  as introduced in section 2.2.

The random error  $\operatorname{Var}\left(\sum_{i=2}^{n} (\hat{C}_{in} + \hat{D}_{in})\right)$  – omitting conditions – can be written as

$$\operatorname{Var}\left(\sum_{i=2}^{n} (C_{in} + D_{in})\right)$$
  
= 
$$\operatorname{Var}\left(\sum_{i=2}^{n} C_{in}\right) + 2\operatorname{Cov}\left(\sum_{i=2}^{n} C_{in}, \sum_{i=2}^{n} D_{in}\right) + \operatorname{Var}\left(\sum_{i=2}^{n} D_{in}\right)$$

For the random errors  $\operatorname{Var}\left(\sum_{i=2}^{n} C_{in}\right)$  and  $\operatorname{Var}\left(\sum_{i=2}^{n} D_{in}\right)$  we have already derived recursions in section 2. Therefore, only a recursion for the covariance of  $\sum_{i=2}^{n} C_{in}$  and  $\sum_{i=2}^{n} D_{in}$  is needed. Due to the independence of the accident years – which implies that the variables  $C_{in}$  and  $D_{jn}$  with  $i, j = 1, ..., n, i \neq j$  are conditionally uncorrelated – we have

$$\operatorname{Cov}\left(\sum_{i=2}^{n} C_{in}, \sum_{i=2}^{n} D_{in}\right) = \sum_{i=2}^{n} \operatorname{Cov}(C_{in}, D_{in}).$$

Using the recursions for  $Cov(C_{ik}, D_{ik})$ ,  $2 \le i \le n$  yields the recursion

$$\widehat{\text{Cov}}\left(\sum_{i=n+2-k}^{n} C_{ik}, \sum_{i=n+2-k}^{n} D_{ik}\right)$$

$$= \widehat{\text{Cov}}\left(\sum_{i=n+3-k}^{n} C_{i,k-1}, \sum_{i=n+3-k}^{n} D_{i,k-1}\right) \widehat{f}_{k} \widehat{g}_{k} + \widehat{\rho}_{k} \sum_{i=n+2-k}^{n} \sqrt{\widehat{C}_{i,k-1}, \widehat{D}_{i,k-1}}$$
(30)

starting with k = 2 since for the first development year all  $C_{i1}$  and  $D_{i1}$  are known.

For the covariances  $\text{Cov}(\hat{C}_{in}, \hat{D}_{jn})$  in the estimation error we proceed as in (15) and for (27). This leads to the recursion

$$\widehat{\text{Cov}}(\widehat{C}_{ik}, \widehat{D}_{jk}) = \widehat{\text{Cov}}(\widehat{C}_{i,k-1}, \widehat{D}_{j,k-1}) \widehat{f}_k \widehat{g}_k + \frac{C_{i,k-1}D_{j,k-1}}{C_{<,k-1} \cdot D_{<,k-1}} \widehat{\rho}_k \sum_{m=1}^{n+1-k} \sqrt{C_{m,k-1} \cdot D_{m,k-1}}$$
(31)

with starting value k = n + 1 - min(i, j). Recursion (29) is a special case of (31). The recursion for  $\sum_{i,j} Cov(\hat{C}_{in}, \hat{D}_{jn})$  is then

$$\sum_{i,j=n+2-k}^{n} \widehat{\text{Cov}}(\hat{C}_{ik}, \hat{D}_{jk}) = \sum_{i,j=n+3-k}^{n} \widehat{\text{Cov}}(\hat{C}_{i,k-1}, \hat{D}_{j,k-1}) \hat{f}_{k} \hat{g}_{k} + \hat{C}_{\geq,k-1} \hat{D}_{\geq,k-1} \hat{\rho}_{k} \frac{\sum_{i=1}^{n+1-k} \sqrt{C_{i,k-1} \cdot D_{i,k-1}}}{C_{<,k-1} \cdot D_{<,k-1}}$$
(32)

starting with k = 2 (cf. definition of  $\hat{C}_{\geq,k-1}$  in (14)). This recursion completes the derivation of the recursions for the estimation error and the prediction error for the ultimate claims amounts estimates of the sum of two correlated subportfolios. The extension to more than two subportfolios is obvious.

# 5. NUMERICAL EXAMPLE

In our numerical example we use data published by the Reinsurance Association of America (RAA) in their historical loss development study (RAA (2001)). Cumulative incurred losses  $\{C_{ik}\}$  of General Liability (GL) reinsurance business are given in Table 1. Table 2 contains the corresponding data  $\{D_{ik}\}$  for Auto Liability (AL) reinsurance business. For details see RAA (2001). For a demonstration of our approach with these runoffs we assume that the claims development comprised in each of these triangles is homogeneous so that we can limit our analysis to the two given triangles and we have not to perform any analysis of subtriangles. Moreover, we assume for simplicity that the development stops after the fourteenth year for both run-offs. Therefore we dispense with any extrapolation beyond the fourteenth development year.

	14	549.589													
	13	547.696	562.795												
	12	540.873	563.571	602.710											
	11	537.301	560.844	601.296	784.632										
	10	539.039	556.671	590.985	782.084	768.373									
	6	527.978	555.792	588.342	758.036	768.638	811.100								
OFF	8	520.309	551.437	577.425	757.440	752.434	793.603	896.728							
3ILITY RUN-0	7	513.660	532.615	559.475	736.304	742.110	768.358	873.526	1.022.241						
JENERAL LIAI	6	475.778	503.358	544.769	687.139	721.696	726.813	827.979	962.825	1.019.303					
0	5	433.265	458.791	503.999	621.738	641.332	654.652	741.226	857.859	934.103	1.141.750				
	4	349.524	383.349	425.029	547.288	561.691	560.958	620.030	755.978	769.017	955.335	1.174.196			
	3	254.512	272.936	319.204	407.318	448.530	416.882	466.214	553.702	575.441	722.336	809.926	1.032.684		
	2	163.152	153.344	170.048	273.183	278.329	245.587	285.507	313.144	343.218	459.416	436.958	528.080	772.971	
	-	59.966	49.685	51.914	84.937	98.921	71.708	92.350	95.731	97.518	173.686	139.821	154.965	196.124	204.325
	AY/DY	1987	1988	1989	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000

TABLE 1

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						AUTO LIA	BILITY RUN-	OFF						
AY/DY	1	2	3	4	S	6	7	8	6	10	11	12	13	14
1987	114.423	247.961	312.982	344.340	371.479	371.102	380.991	385.468	385.152	392.260	391.225	391.328	391.537	391.428
1988	152.296	305.175	376.613	418.299	440.308	465.623	473.584	478.427	478.314	479.907	480.755	485.138	483.974	
1989	144.325	307.244	413.609	464.041	519.265	527.216	535.450	536.859	538.920	539.589	539.765	540.742		
1990	145.904	307.636	387.094	433.736	463.120	478.931	482.529	488.056	485.572	486.034	485.016			
1991	170.333	341.501	434.102	470.329	482.201	500.961	504.141	507.679	508.627	507.752				
1992	189.643	361.123	446.857	508.083	526.562	540.118	547.641	549.605	549.693					
1993	179.022	396.224	497.304	553.487	581.849	611.640	622.884	635.452						
1994	205.908	416.047	520.444	565.721	600.609	630.802	648.365							
1995	210.951	426.429	525.047	587.893	640.328	663.152								
1996	213.426	509.222	649.433	731.692	790.901									
1997	249.508	580.010	722.136	844.159										
1998	258.425	686.012	915.109											
1999	368.762	900.006												
2000	394.997													

TABLE 2

DY	2	e	4	S	6	7	8	6	10	11	12	13	14
$\hat{f}_k$	3,235	1,720	1,354	1,179	1,106	1,055	1,026	1,014	1,012	1,006	1,005	1,005	1,003
$\hat{s}_k^2$	17.642,53	7.027,84	1.432,51	685,21	144,32	209,99	50,81	52,03	136,96	43,45	2,66	54,03	2,66
$\hat{g}_k$	2,226	1,269	1,120	1,067	1,035	1,017	1,010	1,000	1,004	0,999	1,004	0,999	1,000
$\hat{\tau}_k^2$	11.104,38	607,07	321,80	363,48	156,37	30,81	20,41	4,52	26,45	1,95	10,31	1,86	0,34
$\hat{W}_k^2$	0,988	0,995	0,995	0,996	0,996	0,996	0,996	0,995	0,995	0,994	0,998	0,998	1,000
$\hat{ ho}_k$	3.434,41	1.022,71	463,29	222,82	73,14	36,25	-5,53	12,30	20,26	6,33	-0,02	10,04	I
$\hat{ ho}_k/(\hat{s}_k\hat{ au}_k)$	0,245	0,495	0,682	0,446	0,487	0,451	-0,172	0,802	0,337	0,687	-0,004	1,001	I

TABLE 3 Development factors and parameter estimates

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# CHRISTIAN BRAUN

The Chain-Ladder method yields the development factors  $\hat{f}_k$  (for the GL run-off) and  $\hat{g}_k$  (for AL run-off) and the parameter estimates  $\hat{\sigma}_k$  (GL run-off) and  $\hat{\tau}_k$  (AL run-off) as given in Table 3. The parameters  $\sigma_{14}$  and  $\tau_{14}$  which can not be estimated via (7) and (23) since there is only one individual development factor in each run-off for the fourteenth development year, are selected as

$$\hat{\sigma}_{14}^2 = min(\hat{\sigma}_{13}^4 / \hat{\sigma}_{12}^2, \hat{\sigma}_{12}^2)$$

(see Mack (1993)) and  $\hat{\tau}_{14}^2$  analogous. The parameters  $w_k^2$  in the row 5 of Table 3 show that  $w_k^2$  is approximately 1 for all development years in this example i.e. we have  $\frac{1}{n-k-1+w_k^2} \approx \frac{1}{n-k}$ . Rows 6 and 7 of Table 3 contain the estimate for  $\rho_k$ and for the correlation coefficient  $\rho_k/(\sigma_k\tau_k)$ . For development years 8 and 12  $\hat{\rho}_k$ is negative. This should not be overstated since the estimate of the covariance parameter  $\rho_k$  is based here only on seven and three observations, respectively and has no substantial contribution to the total errors due to the small  $\rho_k$  in the later development periods.  $\rho_k$  decays rapidly with respect to k, as it is usually the case for  $\sigma_k^2$  and  $\tau_k^2$  (and also for  $f_k$  and  $g_k$ ). Row 7 shows  $\rho_k/(\sigma_k\tau_k)$  which gives the correlation coefficient of the individual development factors. It can be seen, that it is quite stable in the first seven development years.

Table 4 shows for each accident year *i* the estimated reserve  $\hat{C}_{in} - C_{i,n+1-i}$  for GL run-off and the estimated reserve  $\hat{D}_{in} - D_{i,n+1-i}$  for AL run-off and the sum of these two reserves ("Portfolio"). In the last column of Table 4 the estimated reserve is given when aggregating first both data triangles to one single triangle

Accident Year	GL run-off (A)	AL run-off (B)	Portfolio (A)+(B)	Overall Calculation
1987	0	0	0	0
1988	1.945	-135	1.810	1.988
1989	5.394	-740	4.655	5.117
1990	10.616	1.211	11.827	11.083
1991	15.220	992	16.212	15.344
1992	25.988	3.132	29.120	28.010
1993	42.133	3.661	45.793	44.553
1994	75.959	10.045	86.004	81.339
1995	135.599	21.567	157.165	149.553
1996	289.659	54.642	344.301	329.840
1997	561.237	118.575	679.812	644.927
1998	1.033.307	254.151	1.287.458	1.230.370
1999	1.887.590	565.448	2.453.038	2.331.408
2000	2.070.616	1.031.063	3.101.679	3.080.525
All years	6.155.261	2.063.612	8.218.874	7.954.058

# TABLE 4

ESTIMATED IBNR RESERVES

and then estimating the reserve with the Chain-Ladder method. This (nonsense) calculation is only done for comparison purposes and is denoted "overall calculation" in the following and in the tables. The example shows that the overall calculation leads to another result which can be considered as unusable here since run-offs with different development patterns were added together. The reserve is about 265 Mio. lower than the one by separate calculation of the GL and AL reserves. To evaluate this difference we have to consider the variability in our estimates.

Tables 5-7 show the square roots of the random error, the estimation error and the prediction error, respectively for GL run-off in column 1 and AL runoff in column 2. The column "Portfolio" of these tables shows the corresponding figures for the whole portfolio consisting of the GL and AL subportfolios, computed with our method as described in section 4 taking into account the correlation between the individual development factors. Column 3a gives the implied average coefficient of correlation, i.e. the solution  $\rho(X, Y)$  of the equation

$$\operatorname{Var}(X+Y) = \operatorname{Var}(X) + \operatorname{Var}(Y) + 2\rho(X,Y) / \operatorname{Var}(X) \operatorname{Var}(Y)$$
(33)

where X and Y are the reserves of the GL and AL run-off, and Var(X), Var(Y)and Var(X+Y) are the squares of corresponding errors from columns (1)-(3). Columns 4 to 6 show the results of the calculation (33) but assuming a positive correlation of +1, no correlation and a negative correlation –1 between the corresponding individual development factors of all columns of the GL and AL run-off. In column 7 the roots of the errors are given for the overall calculation. The errors for the reserve for "Portfolio" of each accident year and all accident years together are between the ones assuming no correlation and a correlation equal to 1. Note that, the overall calculation yields for the accident year 1988 and 1989 errors which are larger than the corresponding error of the portfolio under the assumption of a complete positive correlation between both run-offs. This is a further hint that the overall calculation is not suited for the estimation of portfolio reserves and its range.

As discussed in subsection 2.2 we have to use the prediction error when assessing a range for the reserve of the portfolio. Assuming a log-normal distribution for the reserve a range for the reserve of all accident years of the portfolio can be calculated. For this, the mean of the distribution is set equal to the estimated reserve (see table 4) and the variance equal to the prediction error (see table 7 for the square root of the prediction error). Using the interval containing 90% probability around the mean with 45% probability on each side as range for the reserve, leads to a lower bound of 7.459.480 and an upper bound of 9.157.228. This range can be interpreted as follows. Under our model assumptions and the distribution assumption for the portfolio reserve the reserve which is finally needed for the complete development of the accident years 1987 to 2000 of the portfolio, is with 90% probability in this range. Of course, this ultimately necessary amount is not known until these accident years of the portfolio are fully developed, while this range can be computed by now.

When assessing a range for the best estimate of the reserve instead of the reserve itself, we have to use the estimation error instead of the prediction

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SQUARE ROOT OF RANDOM ERROR

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Overall	Calculation (7)	0	2.536	7.551	8.453	10.435	16.665	19.610	21.971	28.869	40.512	62.871	98.979	174.416	304.289	375.000
elation	Corr. = -1 (6)	0	820	4.775	4.403	6.276	9.454	11.228	12.911	17.297	17.215	25.558	45.504	124.521	143.713	195.809
ed Portfolio Corr	Corr. = 0 (5)	0	1.289	5.966	7.292	9.384	14.977	17.464	20.567	26.692	35.016	55.553	85.456	178.936	286.149	356.872
Assume	Corr. = 1 (4)	0	1.628	6.956	9.325	11.693	18.954	21.997	26.064	33.552	46.432	74.290	111.959	220.297	378.298	465.161
Implied	Portfolio Corr. (3a)		0,000	0,899	0,369	0,425	0,370	0,426	0,289	0,345	0,365	0,408	0,518	0,475	0,294	0,340
Doutfalio	(3)	0	1.289	6.863	8.102	10.428	16.561	19.522	22.296	29.240	39.561	63.867	100.074	199.643	316.077	397.054
AI run-off	(2)	0	404	1.091	2.461	2.708	4.750	5.384	6.577	8.127	14.609	24.366	33.227	47.888	117.293	134.676
fl run-off	(1)	0	1.224	5.866	6.864	8.984	14.204	16.613	19.488	25.425	31.823	49.924	78.731	172.409	261.006	330.485
Accident	Year	1987	1988	1989	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	All years

Overall	Calculation (7)	0	2.677	6.119	7.055	7.834	10.490	12.538	14.328	16.799	23.310	33.519	50.392	87.217	127.127	304.841
elation	Corr. = -1 (6)	0	792	3.502	4.330	4.948	6.330	7.455	9.282	10.985	12.841	17.754	26.870	63.585	61.604	179.249
ed Portfolio Corr	Corr. $= 0$ (5)	0	1.320	4.533	6.088	6.872	9.308	11.019	13.339	15.686	21.015	30.814	45.332	90.352	119.229	285.911
Assume	Corr. = 1 (4)	0	1.690	5.370	7.441	8.364	11.542	13.685	16.422	19.272	26.802	39.797	58.206	110.832	156.959	362.437
Implied	Portfolio Corr. (3a)		-0,000	0,805	0,428	0,457	0,402	0,433	0,354	0,373	0,366	0,390	0,478	0,462	0,307	0,398
Doutfalia	(3)	0	1.320	5.217	6.701	7.591	10.265	12.246	14.506	17.113	23.300	34.597	51.888	100.331	131.984	318.600
	(2)	0	449	934	1.556	1.708	2.606	3.115	3.570	4.144	6.980	11.021	15.668	23.624	47.678	91.594
GI Off	(1)	0	1.241	4.436	5.885	6.656	8.936	10.570	12.852	15.129	19.822	28.775	42.538	87.209	109.281	270.843
A condent	Year	1987	1988	1989	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	All years

TABLE 6 SQUARE ROOT OF ESTIMATION ERROR CHRISTIAN BRAUN

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SQUARE ROOT OF PREDICTION ERROR

Port	-off Port
(3)	(3)
0	0 0
1.845	04 1.845
8.621	36 8.621
10.514	12 10.514
12.898	02 12.898
19.484	18 19.484
23.045	21 23.045
26.600	83 26.600
33.880	23 33.880
45.913	91 45.913
72.636	42 72.636
112.727	36 112.727
223.436	98 223.436
342.526	13 342.526
509.075	72 509.075

error. Assuming also a log-normal distribution for the best estimate of the reserve, but with mean and standard deviation according to table 4 and 6 a reasonable range for the best estimate for all accident years of our portfolio consisting of the GL and the AL runoff can be calculated. The mean is equal to the estimated reserve and the variance equal to the estimation error. We use the interval containing 50% probability around the mean with 25% probability on each side as range. This is a fair compromise between a non-informative 99%-range and the straight point estimate which would not contain the true expected reserve with 100% probability. This 50%-range leads to a lower bound of 8.008.292 and an upper bound of 8.438.171. Within this range, each amount can be taken as best estimate. This range for the best estimate of the reserve is much smaller than the range for the reserve itself as given above. The reserve estimate of the overall calculation (see table 4) is outside the range for the best estimate, since it is below the lower bound. This shows again that the overall calculation is not reasonable.

## 6. FINAL REMARKS

Correlations between run-off triangles are often attributed to the claims inflation affecting all or most of the segments of a portfolio in a similar way. For this reason, it may seem obvious to derive the correlation between the reserves from the correlation between the estimated inflation rates in the run-offs. But, since the inflation affects the diagonals in the run-offs, the basic Chain Ladder model assumption of independence of the accident years is violated. Therefore, calculating reserve ranges by using calendar year based correlations (Brehm (2002)) in conjunction with reserves estimated with the Chain Ladder method is inadvisable. In principle, all calendar year based dependencies should be removed from the run-offs, before the reserves are calculated with the Chain Ladder method. Since the inflation influences mainly payments and less incurred figures, applying the Chain Ladder method can be done for incurred run-offs with less problems.

Furthermore, the inflation rate of a calendar year does not affect the accident years of a run-off in the same way, since the payments are for different types of claims due to their different development periods. For instance, considering a fixed calendar year in a general liability portfolio, in earlier development years mainly property damages are paid while for later development years payments of bodily injury claims dominate. Thus, a run-off does not have a uniform calendar year inflation rate for all accident years, from which the correlation of the run-off triangles could be meaningful derived.

Our approach comes up with an individual correlation coefficient  $\rho_k/(\sigma_k \tau_k)$  for each development period k. In contrast to this, some other approaches express the correlation between two run-offs by a single number, e.g. by a single overall correlation coefficient. If one likes to do this with our approach – even though it is not in line with the stochastic Chain-Ladder model which consists of own parameters  $f_k$ ,  $\sigma_k$  for each development period k,  $2 \le k \le n$  – one can simply set in the basic assumption (24) for the covariance in section 3

 $\rho_k = \psi \sigma_k \tau_k$  with  $\sigma_k$  and  $\tau_k$  as before and – now by using data from all development periods – estimate  $\psi$  by the weighted average of  $\hat{\rho}_k / (\hat{\sigma}_k \hat{\tau}_k)$ , i.e.

$$\hat{\psi} = \frac{1}{\sum_{k=2}^{n-1} v_k} \sum_{k=2}^{n-1} v_k \frac{\hat{\rho}_k}{\hat{\sigma}_k \hat{\tau}_k}$$

with  $v_k := n - k - 1 + w_k^2$  and  $\hat{\rho}_k$ ,  $\hat{\sigma}_k$  and  $\hat{\tau}_k$  as given in sections 2 and 3. This simplified model implies a constant correlation coefficient  $\psi$  for all development years, i.e.

$$\operatorname{Corr}(F_{ik}, G_{ik} | T_{i,k-1}) = \psi \tag{34}$$

and using (9) and (28) yields

$$\operatorname{Corr}(\hat{f}_{k}, \hat{g}_{k} | T_{i,k-1}) = \psi \sum_{j=1}^{n+1-k} \frac{\sqrt{C_{j,k-1}D_{j,k-1}}}{\sqrt{C_{<,k-1}D_{<,k-1}}}.$$

The last equation shows that the correlation of  $\hat{f}_k$  and  $\hat{g}_k$  depends on the development period k even though  $\hat{f}_k$  and  $\hat{g}_k$  are weighted averages of individual development factors  $F_{ik}$  and  $G_{ik}$  (see (2)) whose correlation (34) is independent of k.

For the rest of this section we consider the case of a non-negative  $\psi$ . It results from the Cauchy-Schwarz inequality

$$\operatorname{Corr}(f_k, \hat{g}_k | T_{i,k-1}) \leq \psi.$$

Set  $\hat{\rho}_k = \hat{\psi} \hat{\sigma}_k \hat{\tau}_k$  in the covariance estimates (27), (29), (30) and (32) of section 4. Using

$$\widehat{\operatorname{Corr}}(C_{in}, D_{in}) := \frac{\widehat{\operatorname{Cov}}(C_{in}, D_{in})}{\sqrt{\widehat{\operatorname{Var}}(C_{in})\widehat{\operatorname{Var}}(D_{in})}}$$
(35)

as an estimate for the correlation of the ultimate claims amounts  $C_{in}$  and  $D_{in}$ it can be shown via the explicit formulas for  $\widehat{\text{Cov}}(C_{in}, D_{in})$ ,  $\widehat{\text{Var}}(C_{in})$  (cf. Mack (2002), p. 252) and  $\widehat{\text{Var}}(D_{in})$  instead of the recursive formulas (6) and (27) that

$$\widehat{\operatorname{Corr}}(C_{in}, D_{in}) \le \widehat{\psi}.$$
(36)

Defining the correlation estimates  $\widehat{\operatorname{Corr}}(\hat{C}_{in}, \hat{D}_{in}), \widehat{\operatorname{Corr}}(\sum_{i=2}^{n} C_{in}, \sum_{i=2}^{n} D_{in})$  and  $\widehat{\operatorname{Corr}}(\sum_{i=2}^{n} \hat{C}_{in}, \sum_{i=2}^{n} \hat{D}_{in})$  analogously to (35), it can also be shown

$$\widehat{\operatorname{Corr}}(\widehat{C}_{in},\widehat{D}_{in}) \le \widehat{\psi},\tag{37}$$

$$\widehat{\operatorname{Corr}}\left(\sum_{i=2}^{n} C_{in}, \sum_{i=2}^{n} D_{in}\right) \leq \widehat{\psi},$$
(38)

$$\widehat{\operatorname{Corr}}\left(\sum_{i=2}^{n} \hat{C}_{in}, \sum_{i=2}^{n} \hat{D}_{in}\right) \leq \hat{\psi}.$$
(39)

The estimated correlations (36) and (37) depend on the accident year *i* and the correlations (36)-(39) are different in general, but uniformly bounded by  $\hat{\psi}$ . (37) shows, the correlation of the developments of run-offs is underestimated by using the correlation of the ultimate estimates.

It can be easily seen by using the definition (33) and the identity

$$Var(X + Y) = Var(X) + 2Cov(X, Y) + Var(Y)$$

that the correlation estimates on the left hand side of the inequalities (36)-(39) are the implied coefficient of correlations for the considered random variables, e.g.

$$\operatorname{Corr}(C_{in}, D_{in}) = \rho(C_{in}, D_{in}).$$

Furthermore, calculating the implied coefficient of correlation  $\rho(\hat{C}_{in}, \hat{D}_{in})$  for the prediction error mse $(\hat{C}_{in} + \hat{D}_{in})$  it can also be shown that it is different from  $\hat{\psi}$  generally and

$$\rho(\hat{C}_{in}, \hat{D}_{in}) \leq \hat{\psi}$$

indicating that our estimated correlation coefficient  $\hat{\psi}$  is at least as high as the implied average one. This holds not only for each accident year *i*, but also for all accident years together. To summarize, the implied coefficient of correlation underestimates the correlation of the run-offs, independent of whether it is calculated for the random error, the estimation error or the prediction error and whether it is calculated for a single accident year or for all accident years together.

### ACKNOWLEDGEMENTS

The author would like to thank Dr. Thomas Mack for valuable comments and suggestions to improve the manuscript and Dr. Gerhard Quarg for clarifying discussions regarding conditional expectations.

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https://doi.org/10.2143/AST.34.2.505150 Published online by Cambridge University Press

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