MTPL CLAIMS UNCERTAINTY IN THE CHAIN LADDER METHOD

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Abstract: Technical reserves, especially claims reserves are an important issue in a non-life insurance company. Under Albanian law reporting is done every quarter as well as the company's financial statements. The value of technical reserves affects directly the company's technical result.

There are several methods for estimations the technical claims reserves. Initially, most of these methods began as deterministic algorithms. Over time actuaries began developing and analyzing stochastic models that justify these algorithms. These stochastic models enable analysis and quantification of the uncertainty of forecasting responsibilities for outstanding claims. Some of the models used are: The Poisson model, the over-dispersed Poisson model, Gamma model, Negative binomial model, and the Log-normal model. Parametric models such Wright's model and Bootstrap are also used. General linear models constitute a flexible class of stochastic models and are available in the analysis of future payments.

Chain ladder model developed by Mack is the more prevalent model. This model is based on the triangle of development of incurred or paid claims and it is free distribution and also it does not require additional information. Based on the model of Mack, there are also developed other models easily applicable. Different methods yield different results, often similar to each other, but also different between them. These results are influenced by the available data. From the application made, it reached the conclusion that the data are often uncertain.

The technical claims reserves, as all technical reserves directly affecting profit loss statement, as well as the technical balance of the company, it is required as fair evaluation of them. Results of application of stochastic methods are highly dependent on the reliability and accuracy of data. The actuary seeing the progress and history of claims in a portfolio, the market where are developed claims payments over the years, the values of outstanding claims, claims in process court, which values estimates is more appropriate to establish technical reserves. Also the insurance company must hold sufficient assets to cover technical reserves. The value of assets covering technical provisions must at all times be not less than the gross amount of technical reserves.

Stochastic methods of reserves estimation discussed in this paper serve to assess the technical provisions of outstanding claims, as well as forecast cash payment of claims in the coming years.

Keywords: stochastic methods**,** chain ladder model, uncertainty of data.

1. CHAIN LADDER METHOD

The chain-ladder technique uses cumulative data, and derives a set of `development factors' or `link ratios'. To a large extent, it is irrelevant whether incremental or cumulative data are used when considering claims reserving in a stochastic context, and it is easier for he explanations here to use incremental. In order to keep the exposition as straightforward as possible, and without loss of generality, we assume that the data consist of a triangle of incremental claims. This is the simplest shape of data that can be obtained, and it is often the case that data from early origin years are considered fully run-off or that other parts of the triangle are missing. Using a triangle avoids us having to introduce complicated notation to confront with all possible situations. Thus, we assume that we have the following set of incremental claims data: $C_{ij}: i=1,\dots,n;\ j=1,\dots,n-i+1$

The suffix i refers to the row, and could indicate accident year or underwriting year. The suffix j refers to the column, and indicates the delay, assumed also to be measured in years or quarterlies. The cumulative claims are defined by:

$$D_{ij} = \sum_{k=1}^{j} C_{ik}$$

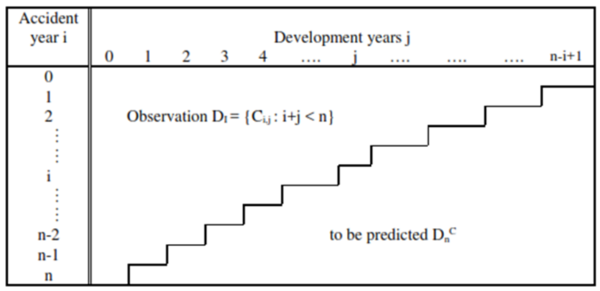
The chain-ladder technique estimates the development factors as:

$$\hat{f}_j = \frac{\sum_{i=1}^{n-j+1} D_{ij}}{\sum_{i=1}^{n-j+1} D_{i,j-1}}$$

These are then applied to the latest cumulative claims in each row $D_{i,n-i+1}$ to produce forecasts of future values of cumulative claims:

$$\widehat{D}_{i,n-i+2} = D_{i,n-i+1}\hat{f}_{n-i+2}$$
$$\widehat{D}_{i,k} = \widehat{D}_{i,k-1}\hat{f}_k \quad k=n-i+3,\ n-i+4,\dots,n$$

The chain-ladder technique, in its simplest form, consists of a way of obtaining forecasts of ultimate claims only. Here `ultimate' is interpreted as the latest delay year so far observed, and does not include any tail factors. From a statistical viewpoint, given a point estimate, the natural next step is to develop estimates of the likely variability in the outcome so that assessments can be made, for example, of whether extra reserves should be held for prudence, over and above the predicted values. In this respect, the measure of variability commonly used is the prediction error, defined as the standard deviation of the distribution of possible reserve outcomes. It is also desirable to take account of other factors, such as the possibility of unforeseen events occurring which might increase the uncertainty, but which are difficult to model. The first step to obtaining the prediction error is to formulate an underlying statistical model making assumptions about the data. If the aim is to provide a stochastic model which is analogous to the chain-ladder technique, then an obvious first requirement is that the predicted values should be the same as those of the chain-ladder technique. There are two ways in which this has been attempted: specifying distributions for the data; or just specifying the first two moments.



2. VARIABILITY OF THE CHAIN LADDER METHOD

C_{ik} denote the accumulated total claims amount of accident year i, $1 \le i \le n$, paid or incurred up to development year k, $1 \le k \le n$. The values of C_{ik} for $i + k \le n + 1$ are known and we want to estimate the values of C_{ik} for $i + k > n + 1$, in particular the ultimate claims amount C_{in} for each accident year i=2,….,n. Then

$$R_i = C_{in} - C_{i,n+1-i}$$

is the outstanding claims reserve of accident year i, as $C_{i,n+1-i}$ has alredy been paid or incurred up to now.
The chain ladder method consist of estimating the ultimate claims by

$$C_{in} = C_{i,n+1-i} \cdot f_{n+1-i} \cdot \dots \cdot f_{n-1} \qquad 2 \le i \le n \qquad (1)$$

where

$$f_k = \sum_{j=1}^{n-k} C_{j,k+1} \Big/ \sum_{j=1}^{n-k} C_{j,k} \qquad 1 \le k \le n-1 \qquad (2)$$

are called age-to-age factors.
This manner of projecting the known claims amount $C_{i,n+1-i}$ to the ultimate claims amount C_{in} uses for all accident yeras $i \ge n + 1 - k$ the same factor f_k for the increase of the claims amount from the development year k to k+1, although the observed individual development factors $C_{i,k+1}/C_{ik}$ of the accident year $i \le n - k$ are uasually different from one another and from f_k. And the end of the development year k we have consider $C_{i,k+1}$ and C_{in} as random variables whereas the realizations $C_{i1}, \dots, C_{ik}$ are known to us and therefore no longer random variables but scalars. For the purposes of analysis every C_{ik} can be a random variable or scalar depending on the development year at the end of whether C_{ik} belongs to the known part $i + k \le n + 1$ of run-off triangle or not. When taking expected values or variances we therefore must always also state the development year at the end of which we imagine to be. The chain ladder method assumes the existence of accident year independent factors $f_1, \dots, f_{n-1}$ such that, given the development $C_{i1}, \dots, C_{ik}$, the realization of $C_{i,k+1}$ is close to $C_{ik} f_k$, the latter being the expected value of $C_{i,k+1}$

$$E\left(C_{i,k+1} \middle| C_{i1}, \dots, C_{ik}\right) = C_{ik} f_k \qquad 1 \le i \le n; 1 \le k \le n-1 \qquad (3)$$

This formula is a conditional expected value. These equations constitute an assumption which is not imposed by us but rather implicitly underlies the chain ladder method. This is based on two aspects of the basic chain ladder equations (1): one is the fact that (1) uses the same age to age factors f_k for different accident years $i = n + 1 - k, \dots, n$. Therefore equations (3) also postulate age to age parameters f_k which are the same for all accident years. The other is the fact that (1) uses only the most recent observed value $C_{i,n+1-i}$ as basis for the projection to ultimate ignoring on the one hand all amounts $C_{i1},\ldots,C_{i,n-1}$ observed earlier and on the other hand the fact that $C_{i,n+1-i}$ could substantially deviate from its expected value. It be also possible to project to ultimate the amounts $C_{i1},\ldots,C_{i,n-1}$ of the earlier development years with the help of age to age factors $f_1,\ldots,f_{n-1}$, and to combine all these projected amounts together with $C_{i,n+1-i}\cdot f_{n+1-i}\cdot\ldots\cdot f_{n-1}$ into a common estimator C_{in}. It would also be possible to use the values $C_{j,n+1-i}$ of earlier accident years $j<i$ as additional estimators for $E(C_{i,n+1-i})$ by translating them into accident year i with help of measure of volume for each accident year. We can rewrite (3) into the form

$$E\left(C_{i,k+1}\middle|C_{i1},\ldots,C_{ik}\right)=f_k$$

because C_{ik} is a scalar under the condition that we know $C_{i1},\ldots,C_{ik}$. This form of (3) shows that the expected value of the individual development factor $C_{i,k+1}/C_{ik}$ equalto f_k irrespective of the prior development $C_{ik}/C_{i,k-1}$. The subsequent development factors $C_{ik}/C_{i,k-1}$ and $C_{i,k+1}/C_{ik}$ are uncorrelated. This means that after a rather high value of $C_{ik}/C_{i,k-1}$ the expected size of the next development factors $C_{i,k+1}/C_{ik}$ is the same as after a rather low value of $C_{ik}/C_{i,k-1}$. For this reason we should not apply the chain ladder method to a business where we usually observe a rather small increase $C_{i,k+1}/C_{ik}$ if $C_{ik}/C_{i,k-1}$ is higher than in most other accident years.

2.1 Analysis of age-to-age factors

$$\mathrm{f_k}=\frac{\sum_{j=1}^{n-k}\mathrm{C_{j,k+1}}}{\sum_{j=1}^{n-k}\mathrm{C_{jk}}}=\sum_{j=1}^{n-k}\frac{\mathrm{C_{jk}}}{\sum_{j=1}^{n-k}\mathrm{C_{jk}}}\cdot\frac{\mathrm{C_{j,k+1}}}{\mathrm{C_{jk}}}$$

$C_{j,k+1}/C_{jk}$, $1\le j\le n-k$, is un unbiased estimator of f_k because

$$\mathrm{D(C_{j,k+1}/C_{jk}|C_{j1},\ldots,C_{jk})=\alpha_k^2/C_{jk}}$$

$$D\left(C_{j,k+1}\middle|C_{j1},\ldots,C_{jk}\right)=C_{jk}\alpha_k^2\qquad 1\le j\le n,\quad 1\le k\le n-1\tag{5}$$

with constant $\alpha_k^2,\ 1\le k\le n-1$.

2.2 Measuring the variability of the ultimate claims

$$C_{in}=C_{i,n+1-i}\cdot f_{n+1-i}\cdot\ldots\cdot f_{n-1}$$

$$E\left(\tilde{C}_{in}\right)=E(C_{in}),\ \text{for}\ 2\le i\le n.$$

$$mse(C_{in})=E((C_{in}-\tilde{C}_{in})^2|D)$$

where $D=\{C_{ik}|i+k\le n+1\}$ are the observed values.

$$mse(C_{in})=D(C_{in}|D)+(E(C_{in}|D)-C_{in})^2$$

$$\widetilde{R_i}=\widetilde{C_{in}}-C_{i,n+1-i}$$

$$R_i=C_{in}-C_{i,n+1-i}$$

$$mse\ (R_i)=E\left(\left(\widetilde{R_i}-R_i\right)^2\middle|D\right)=E((\tilde{C}_{in}-C_{in})^2|D)=mse(C_{in})$$

$$s.e.\left(\tilde{R}_i\right)=s.e.\left(\tilde{C}_{in}\right)$$

$$\left(s.e.\left(\tilde{C}_{in}\right)\right)^2=\tilde{C}_{in}^2\sum_{k=n+1-i}^{n-1}\frac{\tilde{\alpha}_k^2}{\tilde{f}_k^2}\left(\frac{1}{\tilde{C}_{ik}}+\frac{1}{\sum_{j=1}^{n-k}C_{jk}}\right)\tag{6}$$

$$\tilde{\alpha}_k^2=\frac{1}{n-k-1}\sum_{j=1}^{n-k}C_{jk}\left(\frac{C_{j,k+1}}{C_{jk}}-\widetilde{f_k}\right)^2\qquad 1\le k\le n-2\tag{7}$$

$$\tilde{C}_{ik}=C_{i,n+1-i}\cdot\tilde{f}_{n+1-i}\cdot\ldots\ldots\tilde{f}_{k-1},\qquad k>n+1-i$$

3. UNCERTAINTY IN THE METHOD

The most important portfolio of the general insurance in Albania is Motor Third Party Liability, MTPL. It constitutes more than 65% of all premiums. Hence the reserves estimation for claims deriving from these policies is the main issue for non-life actuaries. The data used in this paper are from one of the non-life company in the Albanian market. For the triangles we consider the quarterly data, domestic third party liability paid and incurred claims from 2014 to 2019. Based on the incurred and paid calculation, the results, triangle reserve, standard error amounts and percentage standard errors are presented in the table below:

	Incurred			Paid			
Accident Quarter	**Triangle Reserve**	**Standard Error Amount**	**Standard Error %**	**Accident Quarter**	**Triangle Reserve**	**Standard Error Amount**	**Standard Error %**
2014 Q1	0	0	0.00%	2014 Q1	0	0	0.00%
2014 Q2	2,905	4,613	158.78%	2014 Q2	15,513	85,392	550.47%
2014 Q3	4,579	5,785	126.35%	2014 Q3	34,427	84,227	244.65%
2014 Q4	165,546	362,767	219.13%	2014 Q4	59,716	140,550	235.36%
2015 Q1	402,805	601,625	149.36%	2015 Q1	189,474	241,720	127.57%
2015 Q2	438,479	214,116	48.83%	2015 Q2	141,342	148,622	105.15%
2015 Q3	1,322,580	2,045,104	154.63%	2015 Q3	307,721	907,633	294.95%
2015 Q4	3,164,828	4,384,856	138.55%	2015 Q4	579,175	1,113,485	192.25%
2016 Q1	2,258,760	3,822,733	169.24%	2016 Q1	377,760	813,211	215.27%
2016 Q2	3,655,975	4,904,925	134.16%	2016 Q2	498,341	922,421	185.10%
2016 Q3	5,854,392	4,135,893	70.65%	2016 Q3	864,313	1,151,162	133.19%
2016 Q4	3,619,212	1,736,570	47.98%	2016 Q4	1,467,909	1,603,577	109.24%
2017 Q1	9,082,175	8,514,913	93.75%	2017 Q1	1,367,399	1,417,111	103.64%
2017 Q2	9,008,542	8,227,772	91.33%	2017 Q2	1,858,305	1,763,219	94.88%
2017 Q3	7,385,068	2,064,035	27.95%	2017 Q3	2,877,405	2,226,550	77.38%
2017 Q4	4,402,683	2,135,849	48.51%	2017 Q4	3,056,971	2,333,451	76.33%
2018 Q1	12,303,818	10,613,287	86.26%	2018 Q1	3,582,702	2,583,403	72.11%
2018 Q2	22,275,992	15,261,367	68.51%	2018 Q2	6,063,577	3,724,198	61.42%
2018 Q3	16,710,065	12,184,902	72.92%	2018 Q3	7,424,092	4,129,506	55.62%
2018 Q4	26,018,919	6,383,698	24.53%	2018 Q4	14,969,307	7,188,752	48.02%
2019 Q1	14,797,319	5,232,173	35.36%	2019 Q1	28,170,278	10,249,286	36.38%
2019 Q2	46,798,203	25,899,833	55.34%	2019 Q2	24,456,445	9,793,739	40.05%
2019 Q3	12,147,382	7,204,591	59.31%	2019 Q3	35,414,205	12,157,190	34.33%
2019 Q4	9,659,101	2,582,722	26.74%	2019 Q4	18,658,027	9,221,751	49.43%
Total	**211,479,329**	**128,524,129**	**60.77%**	**Total**	**152,434,402**	**74,000,157**	**48.55%**

The three assumptions of the chain ladder method are:

- $E(C_{i,k+1} | C_{i1}, \ldots, C_{ik}) = C_{ik} f_k$
- variables $\{C_{i1}, \ldots \ldots, C_{in}\}$ and $\{C_{j1}, \ldots \ldots, C_{jn}\}$ of different accident year $i \neq j$ are independent
- $D(C_{j,k+1} | C_{j1}, \ldots, C_{jk}) = C_{jk} \alpha_k^2$

$$\sum_{i=1}^{n-k} \left(C_{i,n+1} - C_{ik} f_k\right)^2 = minimum$$

Cumulative paid triangle, quarterlies from 2014 to 2019

Accident Quarter	**1 (3m)**	**2 (6m)**	**3 (9m)**	**4 (12m)**	**5 (15m)**	**6 (18m)**	**7 (21m)**	**8 (24m)**	**9 (27m)**	**10 (30m)**	**11 (33m)**	**12 (36m)**	**13 (39m)**	**14 (42m)**	**15 (45m)**	**16 (48m)**	**17 (51m)**	**18 (54m)**	**19 (57m)**	**20 (60m)**	**21 (63m)**	**22 (66m)**	**23 (69m)**	**24 (72m)**
2014 Q1	3,316,900	6,508,783	6,557,783	7,585,026	9,617,107	15,587,107	17,987,107	18,079,107	18,079,107	18,079,107	18,079,107	18,079,107	18,079,107	18,079,107	18,079,107	19,504,107	19,504,107	19,504,107	19,504,107	19,636,107	19,636,107	19,768,107	19,768,107	19,768,107
2014 Q2	3,214,939	6,866,628	7,345,703	11,687,703	14,487,703	14,487,703	23,927,703	27,027,703	27,779,259	27,779,259	27,779,259	27,779,259	27,779,259	27,779,259	27,779,259	27,779,259	27,779,259	27,779,259	27,779,259	27,779,259	27,779,259	27,779,259	27,779,259	
2014 Q3	5,276,015	9,841,315	9,919,315	13,288,315	16,125,315	19,205,315	19,205,315	19,205,315	19,283,315	19,283,315	19,283,315	19,283,315	20,174,341	27,276,438	27,276,438	27,276,438	27,276,438	27,276,438	27,276,438	27,276,438	27,276,438	27,276,438		
2014 Q4	6,555,188	11,820,388	12,967,388	16,961,733	19,727,022	19,739,022	20,570,355	27,445,385	27,445,385	27,445,385	27,507,385	27,507,385	27,507,385	27,555,385	27,555,385	27,750,385	27,750,385	27,750,385	27,750,385	27,750,385	27,750,385			
2015 Q1	10,118,350	15,553,350	18,269,750	23,534,950	25,810,950	28,644,550	40,111,851	43,535,108	43,913,108	45,721,053	53,982,971	54,714,533	55,664,533	55,664,533	55,670,817	55,670,817	57,750,817	57,750,817	57,750,817	57,750,817				
2015 Q2	3,575,356	8,674,585	9,734,885	9,943,885	10,987,590	21,122,864	21,128,864	25,128,864	25,187,464	28,098,512	28,455,272	28,455,272	28,455,272	28,455,272	28,455,272	28,455,272	28,455,272	28,455,272	29,952,030					
2015 Q3	7,913,952	15,063,348	16,234,648	19,444,026	22,588,993	29,375,993	30,955,993	33,177,499	34,788,899	37,681,830	37,717,830	40,562,335	40,568,614	40,995,886	44,050,009	44,100,009	44,100,009	46,920,009						
2015 Q4	7,366,624	15,316,574	16,217,674	22,415,195	34,729,946	39,913,919	44,354,894	44,462,894	53,852,614	62,712,614	62,925,548	62,925,548	63,961,935	64,211,935	64,716,735	64,716,735	64,914,735							
2016 Q1	8,239,731	15,953,091	20,646,001	22,161,070	24,446,785	29,089,203	31,239,203	32,799,203	36,252,203	36,622,513	36,622,513	36,622,513	36,772,513	37,399,692	38,721,192	38,721,192								
2016 Q2	7,067,558	16,817,546	18,268,225	19,313,534	19,807,194	24,366,640	30,861,299	36,379,299	36,379,299	44,230,299	44,236,512	44,236,512	44,236,512	47,266,512	47,266,512									
2016 Q3	8,622,936	16,049,991	16,789,890	20,835,200	22,034,175	47,339,275	50,381,051	51,224,818	53,471,097	53,701,097	53,707,361	53,707,361	53,707,361	53,707,361										
2016 Q4	6,511,123	15,227,877	20,351,627	22,884,077	28,706,186	33,736,788	40,529,865	41,266,197	50,552,901	50,559,119	50,559,119	53,274,279	53,735,823											
2017 Q1	5,715,990	9,474,246	16,406,478	18,982,458	19,014,128	23,772,344	24,465,143	24,471,302	24,471,302	25,192,302	25,192,302	41,074,476												
2017 Q2	7,303,150	16,015,984	18,750,255	21,031,300	26,856,456	28,260,993	32,413,452	34,715,452	39,178,252	39,207,769	39,207,769													
2017 Q3	7,903,068	16,012,112	21,746,355	30,993,065	34,397,574	51,249,398	55,340,741	55,340,741	57,201,094	58,830,356														
2017 Q4	4,240,097	14,177,494	16,981,732	26,234,267	38,453,187	38,503,187	41,612,087	41,612,087	41,760,035															
2018 Q1	7,021,044	14,281,747	17,282,932	26,274,214	27,059,974	28,189,193	32,021,205	33,310,869																
2018 Q2	7,164,444	18,746,601	21,039,520	25,044,520	28,230,640	37,951,635	37,998,410																	
2018 Q3	5,543,291	16,072,527	17,883,153	19,864,498	21,000,863	28,180,214																		
2018 Q4	5,742,551	16,159,783	19,843,416	26,190,549	30,308,140																			
2019 Q1	5,520,738	16,191,982	26,428,570	38,597,569																				
2019 Q2	5,368,037	14,303,001	20,499,629																					
2019 Q3	8,669,164	22,168,637																						
2019 Q4	4,004,980																							

The solution is:

$$f_{k0} = \sum_{i1=}^{n-k} C_{ik} C_{i,k+1} \Big/ \sum_{i=1}^{n-k} C_{ik}^2$$

Development factors from 2014 to 2019

Development Factors	**1 (3m)**	**2 (6m)**	**3 (9m)**	**4 (12m)**	**5 (15m)**	**6 (18m)**	**7 (21m)**	**8 (24m)**	**9 (27m)**	**10 (30m)**	**11 (33m)**	**12 (36m)**	**13 (39m)**	**14 (42m)**	**15 (45m)**	**16 (48m)**	**17 (51m)**	**18 (54m)**	**19 (57m)**	**20 (60m)**	**21 (63m)**	**22 (66m)**	**23 (69m)**	**24 (72m)**
2014 Q1	1.96	1.01	1.16	1.27	1.62	1.15	1.01	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.08	1.00	1.00	1.00	1.01	1.00	1.01	1.00	1.00	
2014 Q2	2.14	1.07	1.59	1.24	1.00	1.65	1.13	1.03	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00		
2014 Q3	1.87	1.01	1.34	1.21	1.19	1.00	1.00	1.00	1.00	1.00	1.00	1.05	1.35	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00			
2014 Q4	1.80	1.10	1.31	1.16	1.00	1.04	1.33	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.01	1.00	1.00	1.00	1.00	1.00				
2015 Q1	1.54	1.17	1.29	1.10	1.11	1.40	1.09	1.01	1.04	1.18	1.01	1.02	1.00	1.00	1.00	1.04	1.00	1.00	1.00					
2015 Q2	2.43	1.12	1.02	1.10	1.92	1.00	1.19	1.00	1.12	1.01	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.05						
2015 Q3	1.90	1.08	1.20	1.16	1.30	1.05	1.07	1.05	1.08	1.00	1.08	1.00	1.01	1.07	1.00	1.00	1.06							
2015 Q4	2.08	1.06	1.38	1.55	1.15	1.11	1.00	1.21	1.16	1.00	1.00	1.02	1.00	1.01	1.00	1.00								
2016 Q1	1.94	1.29	1.07	1.10	1.19	1.07	1.05	1.11	1.01	1.00	1.00	1.00	1.02	1.04	1.00									
2016 Q2	2.38	1.09	1.06	1.03	1.23	1.27	1.18	1.00	1.22	1.00	1.00	1.00	1.07	1.00										
2016 Q3	1.86	1.05	1.24	1.06	2.15	1.06	1.02	1.04	1.00	1.00	1.00	1.00	1.00											
2016 Q4	2.34	1.34	1.12	1.25	1.18	1.20	1.02	1.23	1.00	1.00	1.05	1.01												
2017 Q1	1.66	1.73	1.16	1.00	1.25	1.03	1.00	1.00	1.03	1.00	1.63													
2017 Q2	2.19	1.17	1.12	1.28	1.05	1.15	1.07	1.13	1.00	1.00														
2017 Q3	2.03	1.36	1.43	1.11	1.49	1.08	1.00	1.03	1.03															
2017 Q4	3.34	1.20	1.54	1.47	1.00	1.08	1.00	1.00																
2018 Q1	2.03	1.21	1.52	1.03	1.04	1.14	1.04																	
2018 Q2	2.62	1.12	1.19	1.13	1.34	1.00																		
2018 Q3	2.90	1.11	1.11	1.06	1.34																			
2018 Q4	2.81	1.23	1.32	1.16																				
2019 Q1	2.93	1.63	1.46																					
2019 Q2	2.66	1.43																						
2019 Q3	2.5572																							
2019 Q4																								

4. CONCLUSIONS

The chain ladder method operates under the assumption that patterns in claims activities in the past will continue to be seen in the future. In order for this assumption to hold, data from past loss experiences must be accurate. The main reason of use of this method is its simplicity and the fact that it is distribution free. This does not mean that under this method there are no statistical assumptions. Chain ladder algorithm has many implications. These implications allow it to measure the variability of chain ladder reserves estimate. Comparing the standard errors of our data, the best estimate of claims reserves is the calculation based on the paid claims triangle, since his standard error is smaller than the calculation based on incurred claims triangle.

REFERENCES

England, P., & Verrall, R. (1999). Analytic and Bootstrap estimates of prediction error in claims reserving. Insurance: Mathematics and Economics 25, 281-293

Gerigk, E. (2004) The Mack-Method and Analysis of Variability, 2004 Institute of Actuaries of Australia

Mack, T. (1997) Measuring the variability of chain–ladder reserve estimates. In: Claims Reserving Manual, vol. 2. London: Institute of Actuaries.

Perna, C., & Sibillo, M. (2014). Mathematical and Statistical Methods for Actuarial Sciences and Finance, Springer

Quarg, G., & Mack, T. (2008). Munich Chain Ladder: A Reserving Method that Reduces the Gap between IBNR Projections Based on Paid Losses and IBNR Projections Based on Incurred Losses. In: CAS, Volume 2, Issue 2, pp. 266 -299

Verrall, R., Nielsen J.P., & Jessen, A. (2010). Prediction of RBNS and IBNR claims using claim amounts and claim counts, ASTIN Bulletin, 40(2), 871-887

Wüthrich, M.V., & Merz, M. (2008). Stochastic Claims Reserving Methods in Insurance, Wiley

Wüthrich, M.V., & Merz, M. (2013). Financial Modeling, Actuarial Valuation and Solvency in Insurance, Springer