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IBNR Reserve Estimation Using Chain-Ladder and Bootstrap Chain-Ladder Methods

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Abstract

The Incurred But Not Reported (IBNR) claims reserve is a crucial component in maintaining the financial stability of insurance companies. However, traditional deterministic approaches such as the Chain-Ladder method provide point estimates based on historical claim development patterns but do not capture the uncertainty inherent in future claim outcomes. As claim data often exhibit variability across development periods, stochastic approaches are required to quantify this uncertainty and improve the reliability of reserve estimates. Among various stochastic reserving methods, the bootstrap approach is particularly suitable due to its simplicity and direct compatibility with the traditional Chain-Ladder framework. However, empirical applications of bootstrap-based reserving methods in Indonesian motor vehicle insurance remain limited. This study addresses this gap by applying the Bootstrap Chain-Ladder method as a stochastic extension and comparing its performance with the conventional deterministic approach. Using semiannual motor vehicle claim data from PT Asuransi XYZ over the period 2019–2023, the deterministic Chain-Ladder method produced an IBNR estimate of Rp 40.17 billion, while the Bootstrap Chain-Ladder resulted in an estimate of Rp 40.94 billion, reflecting the incorporation of variability in the estimation process. Although the deterministic approach achieved slightly lower prediction errors, as measured by Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE), the bootstrap method generated a more conservative estimate and provided additional insight into reserve uncertainty. These findings suggest that integrating stochastic elements into traditional reserving frameworks enhances financial prudence while maintaining practical applicability in the general insurance industry.

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1. INTRODUCTION

The sustainability of the insurance industry plays a significant role in a country's economic growth through its dual function as a risk bearer and institutional investor. (Dawd & Benlagha, 2023) observed that during 2009–2020, insurance development in 16 OECD countries had a positive impact on economic growth to a certain degree, producing a non-linear relationship. Insurance penetration, reflected in the ratio of insurance premiums to GDP, is widely recognized as an indicator of a country's insurance sector development. In 2023, global insurance premiums accounted for 7% of world GDP, whereas Indonesia recorded only 1.3%, the lowest among Emerging Asian economies (Swiss Re Institute., 2024) General insurance penetration in Indonesia was recorded at 0.6%, lower than life insurance at 0.8%, and both remain far below the global averages of 4.2% and 2.9%, respectively. This suggests that the domestic general insurance industry retains considerable potential for growth (AAUI, 2005).

The Indonesian General Insurance Association (Asosiasi Asuransi Umum Indonesia, AAUI) reported that the motor vehicle business line ranked among the top three in premium revenue, with a claim ratio of 36.1% in 2023. Gross premium demonstrated consistent growth over the period 2020–2023, although the number of claims paid fluctuated year-to-year, ranging from –15.9% to 10.25%.

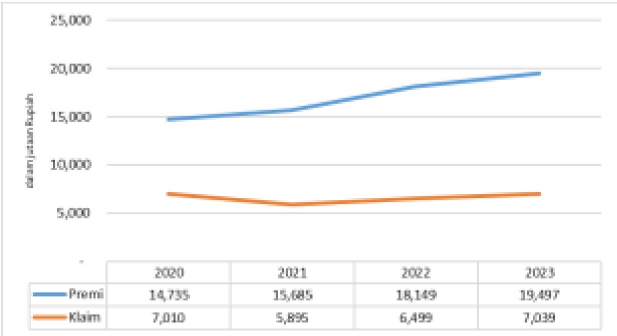

Figure 1. Premiums and Claims, Motor Vehicle Business Line, 2020-2023 (in Millions of Rupiah)
Source: The Indonesian General Insurance Association (2023)

Observed variation in the claims experience suggests uncertainty in claim outcomes, supporting the use of reserving methods that move beyond deterministic point estimates (Peremans, Segaert, Van Aelst, & Verdonck, 2023). From a regulatory perspective, insurance companies in Indonesia are required to establish technical reserves, one of which is the Incurred But Not Reported (IBNR) claims reserve (Otoritas Jasa Keuangan, 2017). The IBNR reserve reflects claims that have occurred prior to the valuation date but have not yet been reported (Bornhuetter & Ferguson, 1972). Accurate estimation of technical reserves is crucial (Klugman, Panjer, & Willmot, 2019). Underestimation may lead to overstated profits and potential failures in claim settlement, thereby weakening financial stability and public confidence.

The chain-ladder method is a classic approach commonly used in estimating IBNR claim reserves in the insurance industry (Mack, 1993). This technique assumes a stable pattern of claims development from year to year, enabling projections through the calculation of loss development factors (LDFs) derived deterministically from historical data (Brown, 1993). Deterministic models produce consistent estimates without incorporating random elements, in contrast to stochastic approaches that account for data variability (Wuthrich & Merz, 2008).

Recent work has expanded the actuarial literature through new stochastic and hybrid reserving models. For instance, Steinmetz and Jentsch (2024) showed that the Mack bootstrap chain-ladder correctly mimicked the dominant process uncertainty and, although it does not capture estimation uncertainty, still provided a more meaningful representation of reserve risk than deterministic chain-ladder methods, which do not quantify uncertainty. Based on an empirical analysis of 30 publicly available run-off triangles, Pittarello, Hiabu, and Villegas (2025) found that incorporating period and cohort effects within a stochastic extension of the chain-ladder often improved empirical fit relative to the classical age-only formulation, highlighting limitations of a purely deterministic view. Vanegas et al. (2025) showed that modeling claims as realizations of a stochastic sampling process via inverse probability weighting could materially affect reserve estimates relative to deterministic Chain-Ladder, while preserving a Chain-Ladder structure compatible with practitioner and regulatory constraints. Meanwhile, empirical applications such as Brati and Braimllari (2023) showed that bootstrap methods generate predictive distributions and enable the estimation of risk measures such as Value at Risk, providing additional insight beyond deterministic Chain-Ladder. Alternative data-driven reserving strategies, such as machine-learning-based selection of reserving methods (Andersson, 2023), further showed that chain-ladder performance varies across datasets and may not be optimal in all settings.

PT Asuransi XYZ's motor vehicle claims data for 2019–2023 showed a nonlinear LDF pattern, indicating potential instability and variability in claim development across periods.

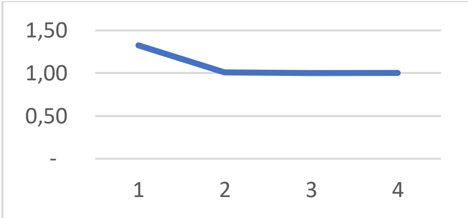

Figure 2. LDF Motor Vehicle Claim AXYZ, 2019-2023
Source: AXYZ (2023)

In practice, claims data often fluctuate across development periods, making stochastic approaches such as the bootstrap method particularly relevant. England and Verrall (1999) adapted the bootstrap framework to the chain-ladder setting by resampling residuals, following the general residual bootstrapping principle outlined by Efron and Tibshirani (1993). England (2001) refined this framework by introducing simulation to reflect process variability. This approach is regarded as both practical and effective in improving the accuracy and transparency in reserve estimation.

Despite growing international evidence, empirical applications of bootstrap-based Chain-Ladder methods in Indonesian motor vehicle insurance remain limited. As a result, stochastic reserving approaches that capture variability in IBNR estimates are underexplored. This gap is notable because deterministic projections produce only point estimates, limiting insight into reserve variability and the need for provisions for adverse deviation (Mack, 1993). Incorporating stochastic elements helps illustrate how reserve estimates may vary under alternative claim development scenarios.

Based on this background, the present study applies the bootstrap chain-ladder method to estimate the IBNR claims reserve of PT Asuransi XYZ. The discussion covers the estimation of loss development factors (LDFs) using bootstrapping, reserve estimation with the bootstrap-based chain-ladder method, and a comparison with the conventional deterministic Chain-Ladder method.

2. METHODS

This study used motor vehicle insurance claims data from PT Asuransi XYZ. Prediction accuracy was assessed by comparing in-sample and out-sample data over the observation period. The in-sample data consisted of paid motor vehicle claims from January 2019 to December 2023, and were used to project subsequent reserves. The out-of-sample data consisted of realized claims paid in the following period, and served as the benchmark for evaluating the projections (Björkwall, Hössjer, & Ohlsson, 2009).

To provide a structured overview of the analytical process, this study employed a conceptual framework that summarizes the flow from input data to reserve estimation and evaluation. As illustrated in Figure 3, the analysis began with the construction of a claims development triangle from motor vehicle claims data. The triangle was then used as the basis for estimating loss development factors (LDFs) and IBNR reserves using two approaches: the deterministic Chain-Ladder method and the Bootstrap Chain-Ladder method as its stochastic extension. The results obtained from both approaches were subsequently compared using prediction accuracy measures, namely Mean Absolute Error

(MAE) and Root Mean Squared Error (RMSE) (Willmott & Matsuura, 2005). Table 1 presents the research variables used in this study.

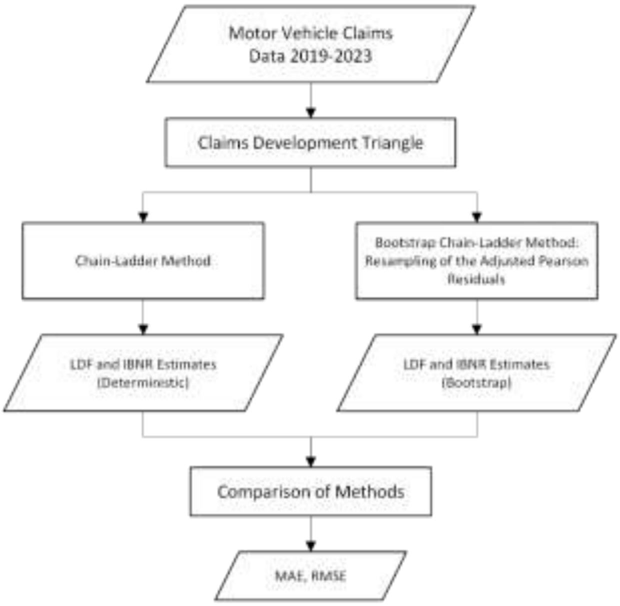

Figure 3. Conceptual Framework
Source: Development by Reseacher (2025)

Table 1. Reasearch Variables

No.	Variable	Definition	Notation
1	Incremental Claim	Claims data organized by accident year and development period.	$X_{i,j}$
2	Cumulative Claim	Claims data aggregated by accident year and development period.	$C_{i,j}$
3	Cumulative Claim (back-fitted)	Cumulative claims data derived via backward recursion.	$\widehat{m}_{ij}$
4	Cumulative Claim (resampled)	Cumulative claims data generated through bootstrap resampling.	$\hat{C}_{ij}$
5	Premium	Payments made by policyholders.	P
6	Loss Period	The period in which claims occur.	i
7	Development	The time lag between the loss period and settlement period.	j
8	Paid-to-date	Total claims paid up to the valuation date.	$C_{i,j}$
9	Loss development factor	Factor indicating claim pattern between development periods.	$\widehat{f}_J$
10	Estimated Ultimate Claim	Estimated total paid and outstanding claims for an accident period.	$C_{i,J}$
11	IBNR	Portion of claims that have occurred but have not yet been reported.	$R_{i,j}$

Source: Development by Researcher (2025)

The initial step in estimating IBNR claim reserves using the chain-ladder method involves constructing a triangle of incremental claims development. At this stage, the observed claims data($\mathcal{D}_I$) are grouped by accident period (i), while the number of semesters elapsed from the accident date to the claim payment date is designated as the development period (j). Table 2 presents the incremental claims development triangle for AXYZ motor vehicle insurance over annual periods.

Table 2. Annual Incremental Claims Development Triangle, AXYZ Motor Vehicle Insurance, 2019–2023 2019–2023 (in million Rupiah)

Incremental Claim Development Triangle					
Loss Year	**Development**				
	0	**1**	**2**	**3**	**4**
2019	67,643	20,232	1,396	115	155
2020	54,701	16,314	416	119	
2021	45,511	13,975	291		
2022	60,562	28,455			
2023	93,050				

In accident year 2021 and development period 1, the total incremental claims amounted to Rp 13.974.861.097. This value represented claims paid by the company during January–December 2022 for claims that occurred in January–December 2021. The cumulative claims development triangle was constructed by aggregating incremental claims across development periods for each accident year, as presented in Table 3

Table 3. Annual Cumulative Claims Development Triangle, AXYZ Motor Vehicle Insurance, 2019–2023 (in million Rupiah)

Cumulative Claim Development Triangle					
Loss Year	**Development**				
	0	**1**	**2**	**3**	**4**
2019	67,643	87,875	89,271	89,386	89,542
2020	54,701	71,014	71,430	71,549	
2021	45,511	59,486	59,777		
2022	60,562	89,017			
2023	93,050				

In accident year 2019 and development period 4, the total cumulative claims reached Rp 89,541,698,608. These claims arose during 2019 and were paid by the company from the accident period through the end of development period 4, which concluded at the end of 2023.

The observed claims ($\mathcal{D}_I$) were then organized into a claims development triangle to estimate the outstanding claims data ($\mathcal{D}_I^c$). This estimation required the calculation of development ratios between successive development periods, from which age-to-age factors were derived. The resulting loss development factors (LDFs) were used to project ultimate claims and estimate IBNR reserves under the deterministic Chain-Ladder approach.

Table 4. Annual Age-to-Age Factors, AXYZ Motor Vehicle Insurance, 2019–2023

Age-to-Age Factors				
Loss Year	**Development**			
	0-1	**1-2**	**2-3**	**3-4**
2019	1.2991	1.0159	1.0013	1.0017
2020	1.2982	1.0059	1.0017	
2021	1.3071	1.0049		
2022	1.4698			
2023				
Average LDF	**1.3436**	**1.0089**	**1.0015**	**1.0017**

The age-to-age factor for accident year 2019 and development period 0 to 1 was 1.2991. This factor was obtained by dividing Rp 87.875.240.796 by Rp 67.642.788.608, which reflects the claims development pattern from period 0 to 1 for claims incurred in

2019. The loss development factor (LDF) from one development period to the next across all accident years was then determined using both a deterministic approach and a stochastic approach based on the bootstrap technique.

The initial step in constructing the loss development factor with the bootstrap approach, as described by England & Verrall (1999), was to assemble the back-fitted cumulative claims triangle. This step was implemented through the backwards recursion method, which involved performing reverse calculations on the available cumulative claims data up to the valuation period. The objective of this step was to reconstruct the historical claims data based on the development pattern obtained from the chain-ladder model. The incremental claims triangle was then derived from the back-fitted data by calculating the differences between cumulative claims values in two successive development periods. This process yielded estimates of claims paid in each development period, which formed the basis for residual analysis and subsequent simulation procedures.

The next stage involved calculating the unscaled Pearson residuals $\left(r_{\mathrm{ij}}^{(P)}\right)$, which represent the differences between observed claims and model estimates for each cell in the claims triangle. Once the unscaled Pearson residuals were obtained, the Pearson scale parameter was calculated to measure the overall dispersion or variability of the residuals relative to the model structure. The residuals were then adjusted to ensure consistency with the number of observations and the model's degrees of freedom.

The next step was to perform resampling of the adjusted Pearson residuals. Bootstrapping is a resampling-based statistical technique that involves repeatedly drawing samples with replacement from the original data in order to compute statistics such as means or regression coefficients for each resample (James, Witten, Hastie, & Tibshirani, 2021). Figure 4 illustrates the resampling process of the adjusted Pearson residuals, applied at development period 7.

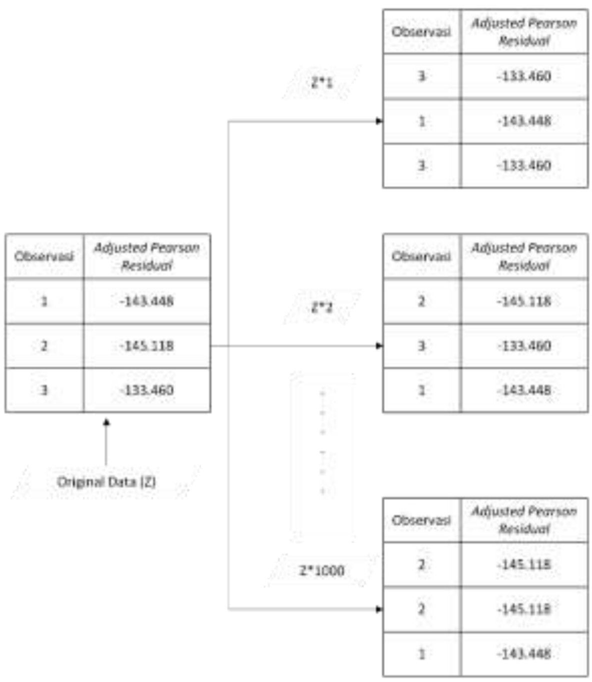

Figure 4. Bootstrap on Adjusted Pearson Residuals, n = 3 Observations

In this study, resampling was performed randomly with replacement to generate new sets of residual values, which were then used to simulate claims data. The adjusted Pearson residuals were resampled using 1,000 bootstrap iterations for each development period, from period 0 through period 7. This number of iterations is commonly considered sufficient to generate a stable resampled scenario reflecting potential variability in claim development (Efron & Tibshirani, 1993). All computations were performed using Microsoft Excel. Outlier identification revealed several claim values exceeding the upper threshold.

However, no explicit outlier treatment was applied, as these values were considered part of the natural variability of claim development (England & Verrall, 2002) and were therefore retained in the analysis.

Following resampling, an incremental claims triangle was reconstructed from the bootstrap data. In the final step, the Chain-Ladder method was applied to the bootstrap cumulative claims triangle to estimate ultimate claims and derive IBNR reserve estimates.

3. RESULTS AND DISCUSSION

This section presents statistical data on motor vehicle claims paid by PT Asuransi XYZ during the period 2019–2023. A summary of premium and claims data by reporting year is provided in Table 5.

Table 5. Gross Premiums and Claims, AXYZ Motor Vehicle Insurance, 2019–2023 (in million Rupiah)

Reporting Year	Policy Count	Premium	Claim Frequency	Claim
2019	12,949	229,329	25,387	85,837
2020	8,349	185,903	21,355	69,195
2021	7,636	225,242	19,662	59,205
2022	8,528	422,538	20,219	77,485
2023	18,440	489,266	33,977	115,325

Motor vehicle insurance claim payments at PT Asuransi XYZ generally increased over the period 2019–2023. However, both premiums and claims declined in 2020 and 2021, which can be attributed to reduced mobility during the COVID-19 pandemic, leading to lower vehicle usage and fewer reported claims.

The claims data presented in Table 5 were subsequently arranged into a semiannual cumulative claims development triangle, as shown in Table 6.

Table 6. Semiannual Cumulative Claims Development Triangle, AXYZ Motor Vehicle Insurance, 2019–2023 (in million Rupiah)

Loss Range	Development									
	-	1	2	3	4	5	6	7	8	9
2019 S1	19,589	41,672	43,579	43,777	43,777	44,078	44,080	44,112	44,193	44,200
2019 S2	25,971	42,271	44,098	44,377	45,193	45,235	45,274	45,333	45,342	
2020 S1	23,353	36,142	37,732	37,951	38,061	38,084	38,120	38,129		
2020 S2	18,558	31,571	33,063	33,190	33,346	33,414	33,420			
2021 S1	16,360	29,019	30,271	30,503	30,617	30,618				
2021 S2	16,492	27,735	28,982	29,151	29,159					
2022 S1	17,389	34,005	35,871	36,254						
2022 S2	26,557	49,118	52,763							
2023 S1	24,314	57,036								
2023 S2	36,015									

The observed claims data ($\mathcal{D}_I$) were structured into a development triangle to estimate outstanding claims ($\mathcal{D}_I^c$) based on development ratios across periods. Table 7 summarizes the age-to-age factors for semiannual development periods, which serve as the basis for projecting future claims.

Table 7. Semiannual Age-to-Age Factors, AXYZ Motor Vehicle Insurance, 2019–2023

Age-to-Age Factors

Loss Range	Development								
	0-1	1-2	2-3	3-4	4-5	5-6	6-7	7-8	8-9
2019 S1	2.1273	1.0458	1.0046	1.0000	1.0069	1.0000	1.0007	1.0018	1
2019 S2	1.6276	1.0432	1.0063	1.0184	1.0009	1.0009	1.0013	1.0002	
2020 S1	1.5477	1.0440	1.0058	1.0029	1.0006	1.0009	1.0002		
2020 S2	1.7011	1.0473	1.0038	1.0047	1.0020	1.0002			
2021 S1	1.7738	1.0432	1.0077	1.0037	1.0000				
2021 S2	1.6817	1.0450	1.0058	1.0003					
2022 S1	1.9556	1.0549	1.0107						
2022 S2	1.8495	1.0742							
2023 S1	2.3458								
2023 S2									
Average LDF	1.8456	1.0497	1.0064	1.0050	1.0021	1.0005	1.0008	1.00102	1

The deterministic loss development factors (LDFs), calculated by averaging development ratios across accident periods, are presented in Table 8 and were used to estimate IBNR reserves under the Chain-Ladder approach.

Table 8. Semiannual Deterministic LDFs, AXYZ Motor Vehicle Insurance, 2019–2023

Loss Range	Development								
	0-1	1-2	2-3	3-4	4-5	5-6	6-7	7-8	8-9
Average LDF	1.8456	1.0497	1.0064	1.0050	1.0021	1.0005	1.0008	1.00102	1

For the stochastic approach, the bootstrap procedure began with the construction of a back-fitted cumulative claims development triangle using backward recursion, as shown in Table 9. Table 9 presents the reconstructed cumulative claims values based on the development pattern implied by the deterministic Chain-Ladder model. These back-fitted values represent model-consistent estimates of historical claims and serve as the baseline for residual calculation, ensuring that subsequent resampling reflects deviations from the fitted model rather than the original data scale.

Table 9. Semiannual Back-Fitted Cumulative Claims Development Triangle, AXYZ Motor Vehicle Insurance, 2019–2023 (in million Rupiah)

Loss Range	Development									
	0	1	2	3	4	5	6	7	8	9
2019 S1	22,457	41,445	43,504	43,782	44,001	44,093	44,115	44,149	44,193	44,200
2019 S2	23,037	42,516	44,628	44,913	45,138	45,232	45,255	45,290	45,342	
2020 S1	19,372	35,753	37,529	37,769	37,957	38,037	38,056	38,129		
2020 S2	16,980	31,337	32,894	33,104	33,270	33,339	33,420			
2021 S1	15,556	28,709	30,136	30,328	30,480	30,618				
2021 S2	14,815	27,342	28,700	28,883	29,159					
2022 S1	18,420	33,995	35,684	36,254						
2022 S2	26,807	49,474	52,763							
2023 S1	28,978	57,036								
2023 S2	36,015									

As an illustration, applying equation (2.15), the claim data $\widehat{m}_{2019\ S1,7}$ are reconstructed using the development factor from period 7 to period 9.

$$\widehat{m}_{2019\ S1,9} = \widehat{m}_{2019\ S1,7}\, f_7 f_8$$

$$\widehat{m}_{2019\ S1,7} = \frac{\widehat{m}_{2019,9}}{f_7 f_8} = \frac{44.199.700.735}{(\ 1,0010 \times\ 1.0001\ )} = 44.148.568.732$$

The incremental claims triangle was then derived from the back-fitted data, and adjusted Pearson residuals were calculated and resampled to generate alternative realizations of claim development. The resulting resampled residuals are presented in Table 10. Table 10 illustrates the variability introduced through the bootstrap process, where residual values are randomly drawn with replacement across development periods. These resampled residuals capture deviations from the expected claims pattern and are subsequently used to reconstruct simulated claims triangles, thereby introducing stochastic variation into the estimation process.

Table 10. Resampled Pearson Residuals Triangle, AXYZ Motor Vehicle Insurance, 2019–2023

Loss Range	Development									
	0	1	2	3	4	5	6	7	8	9
2019 S1	1,195	-1,432	-1,070	-1,867	-8	120	-1,659	-2,008	5,452	-
2019 S2	1,292	-1,614	-1,130	-1,877	-155	-309	-1,391	-2,178	(6,066)	
2020 S1	1,129	-1,547	-779	-1,793	-145	-261	-1,195	-2,375		
2020 S2	1,086	-1,054	-925	-1,852	-387	-410	-1,681			
2021 S1	1,033	-753	-1,101	-1,727	-395	-790				
2021 S2	1,342	-1,188	-899	-1,748	534					
2022 S1	1,490	-1,297	-993	-1,722						
2022 S2	1,491	-1,949	-1,023							
2023 S1	1,011	-1,313								
2023 S2	1,631									

Based on the simulated data, bootstrap loss development factors (LDFs) were estimated and are presented in Table 11.

Table 11. Semiannual Bootstrap LDFs, AXYZ Motor Vehicle Insurance, 2019–2023

Loss Range	Development								
	0-1	1-2	2-3	3-4	4-5	5-6	6-7	7-8	8-9
Average LDF	1.84323	1.05059	1.00694	1.00575	1.00248	1.00076	1.00078	1.00102	1.00014

Table 12 summarizes the IBNR estimates obtained using both the deterministic Chain-Ladder method and the Bootstrap Chain-Ladder method.

Table 11. Summary of IBNR Estimates, AXYZ Motor Vehicle Insurance

Loss Range	IBNR CL	IBNR Bootstrap CL	EUC CL	EUC Bootstrap CL	Actual EUC, Periode 2024 S1	MAE CL	MAE Bootstrap CL	RMSE CL	RMSE Bootstrap CL
2019 S2	6	6	45,348	45,167	91,792	46,444	46,626	2,157,050,396	2,173,937,425
2020 S1	44	44	38,168	38,036	44,582	6,414	6,546	41,143,804	42,847,137
2020 S2	64	65	33,446	33,375	38,618	5,172	5,243	26,750,505	27,486,779
2021 S1	74	83	30,633	30,604	39,135	8,502	8,531	72,276,391	72,780,265
2021 S2	132	151	29,220	29,214	33,441	4,221	4,227	17,817,298	17,869,829
2022 S1	346	397	36,435	36,421	105,994	69,558	69,573	4,838,374,311	4,840,409,379
2022 S2	844	947	53,099	53,020	68,197	15,098	15,177	227,942,027	230,350,909
2023 S1	3,791	3,960	59,870	59,871	68,276	8,407	8,405	70,673,160	70,650,546
2023 S2	34,871	35,282	66,467	66,954	77,395	10,928	10,441	119,412,843	109,016,592
Total	**40,172**	**40,937**	**392,687**	**392,661**	**567,430**	**174,744**	**174,769**	**7,571,440,734**	**7,585,348,861**
n						**9**	**9**	**9**	**9**
Metrik						**19,416**	**19,419**	**29,005**	**29,031**

IBNR reserve estimates obtained using the Chain-Ladder and Bootstrap Chain-Ladder methods were derived by projecting the claims triangle using the respective LDFs. These reserves represent claims that have occurred but have not yet been reported and must be recognized as company liabilities. The results showed that both methods produced broadly comparable IBNR estimates. The bootstrap-based estimate was slightly higher than the deterministic estimate, indicating that the incorporation of stochastic variation leads to a more conservative reserve indication. This difference reflects the sensitivity of reserve estimates to variability in claim development, even when the underlying data exhibit relatively stable patterns.

The bootstrap implementation adopted in this study produces a stochastic estimate derived from a resampled claims development scenario, rather than a full predictive distribution based on repeated simulations. As such, summary statistics such as standard deviation and confidence intervals are not explicitly reported. Future research may extend this approach by performing repeated bootstrap simulations to derive distributional measures such as confidence intervals and percentile-based risk metrics. Nevertheless, the approach provides valuable insight by illustrating the potential variation in reserve estimates under alternative claim development paths. These findings are consistent with England and Verrall (1999), who demonstrated that bootstrap methods enhance the interpretation of reserve risk within the Chain-Ladder framework by introducing stochastic variation into the estimation process.

4. CONCLUSION

This study examined the estimation of Incurred But Not Reported (IBNR) reserves at PT Asuransi XYZ, with a focus on incorporating variability in claim development. Traditional deterministic approaches may overlook fluctuations across development periods, potentially leading to reserve inadequacy and increased reliance on investment income to meet claim obligations. To address this, the Bootstrap Chain-Ladder method was applied by resampling adjusted Pearson residuals to reconstruct the claims development process and introduce stochastic variation into reserve estimation. The results indicate that deterministic loss development factors (LDFs), obtained by averaging age-to-age factors across accident periods, produce stable point estimates, while the bootstrap approach incorporates variability through resampling. For the motor vehicle portfolio over 2019–2023, the estimated IBNR reserve amounted to Rp 40,172,292,736 under the deterministic approach and Rp 40,936,541,921 under the bootstrap approach. Evaluation using Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) shows that the deterministic Chain-Ladder method achieved slightly lower prediction errors, whereas the bootstrap approach produced a more conservative estimate by reflecting variability in claim development. These findings have several managerial and industry implications. For PT

Asuransi XYZ, incorporating stochastic elements into reserving practices provides a more prudent basis for determining technical reserves and enhances preparedness for adverse claim development. From a policy perspective, the results support the gradual adoption of stochastic reserving approaches within the Indonesian general insurance industry, particularly as a complement to deterministic methods, to strengthen reserve adequacy and financial resilience under uncertain claim environments.

This study is subject to several limitations. First, the bootstrap implementation generates a single stochastic estimate rather than a full predictive distribution, limiting the ability to quantify reserve uncertainty through measures such as confidence intervals or percentile-based risk metrics. Second, the analysis is based on a single line of business and a relatively short observation period (2019–2023), which may constrain the generalizability of the findings. Future research may extend this work by performing repeated bootstrap simulations to derive distributional measures of reserve risk, applying the methodology to broader datasets and additional lines of business, and comparing alternative stochastic reserving frameworks to further enhance the assessment of claim variability and reserve adequacy.

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