

PredicTri: Rethinking Reserving with Explainable AI

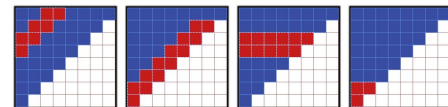
Co-founders:

Yulia Yulish-Nechay, Chief Actuary and Product Strategy

Ben Zickel, CTO

*Provides the explainable models you need, not the models you have.
Learns Directly from Data. No assumptions. Data in, results out.*

PredicTri



Why we built PredicTri

- Reserve reviews are slow and depend heavily on expert judgment
- Current models require many assumptions and manual inputs that shape the results
- PredicTri replaces guesswork with automation, transparency and robust models
- PredicTri allows actuaries focus on interpretation, not calibration



A new way to model reserves

- No need to choose or tune models: PredicTri automatically selects the best-performing one for your data
- Reserve reviews become faster, more consistent, and more reliable
- Results are driven purely by the data
- Every outcome is explained, so you always understand why the model behaves as it does

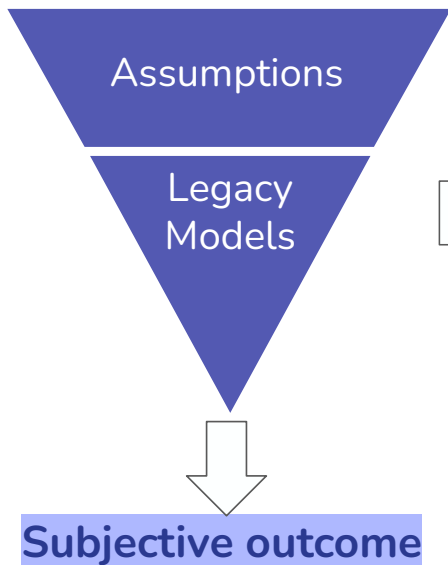
Data in. Results out. Full explainability.



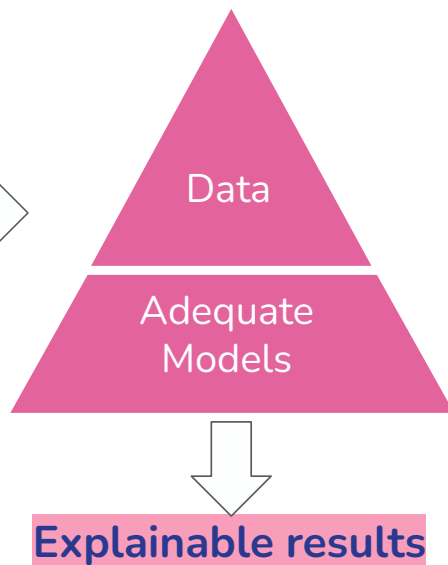
How PredicTri Transforms Actuarial Modeling

PredicTri replaces assumptions and manual levers with automation, transparency, and explainable results.

Traditional approach

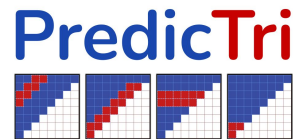


PredicTri



PredicTri provides the explainable models you need, not the models you have.

No assumptions. Data in, results out.



PredicTri: AI-powered actuarial modeling tool

- Co-founded by experienced actuaries and data scientists
- Combines actuarial methods with advanced ML
- Focuses on aggregate triangle reserving using Bayesian machine learning
- Eliminates manual assumptions: models evolve from data, ensuring consistent and reproducible results
- Acts as a transparent second-opinion framework, enhancing confidence in results without replacing existing models

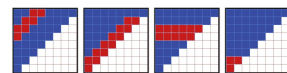


Market Verification: Industry Endorsements

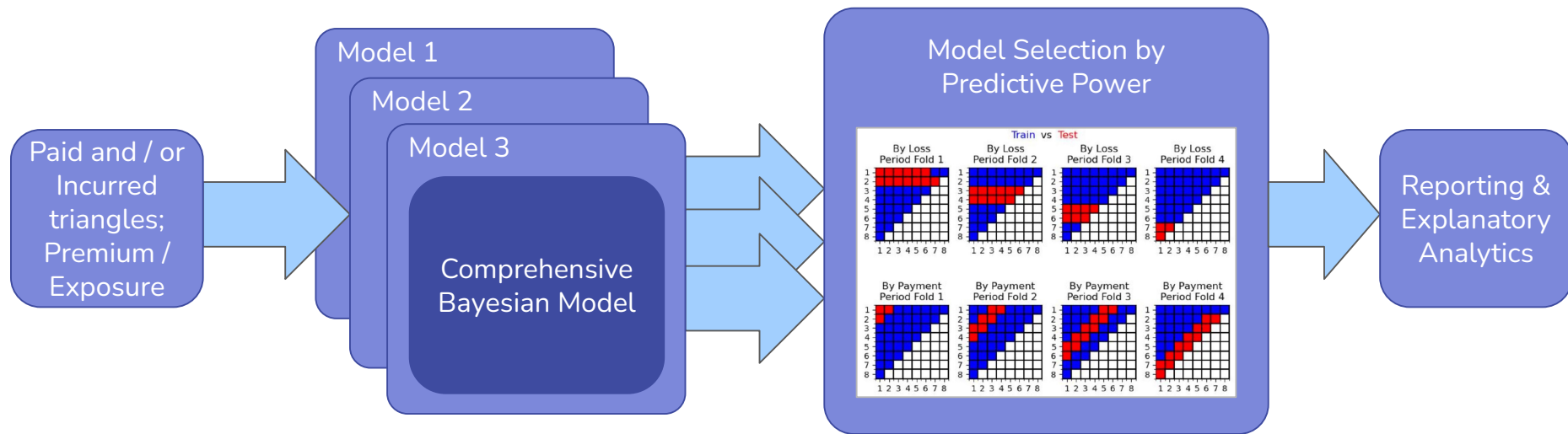
Recognized by senior industry professionals across roles:

- Operational validation: Head of Operations, global insurer: *“Exactly what should be replacing the old process.”*
- Chief actuary: *“Something new, unlike anything that exists today... Reserve estimate feeds directly into the financial statements.”*
- Data science: *“Checking if the percentiles follow a uniform distribution is a great way to validate estimates.”*
- Consulting (Global): *“We want the 95th percentile, not just expected value.”*
- Consulting (Middle East & EU): *“Strong client demand for a quick, explainable solution that mirrors familiar results while modernizing reserving practice”*
- Regulatory validation: *“The model provides full predictive distributions that support date-driven oversight... It also brings transparency... I’d like to see proof through cases where the actuary and model disagree.”*

PredicTri

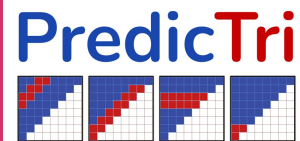


PredicTri: How does it work?



The comprehensive Bayesian model automatically evaluates 16 models, selecting the most adequate structure for each dataset.

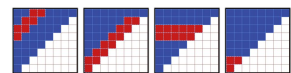
This workflow is modular and can integrate with existing actuarial tools.



Our Secret Sauce

- Building an actuarial model is one thing. Making it actually *run and learn* is another
- Even small changes to standard models often make existing software break or stop converging
- We've developed our own method that makes complex models work reliably and converge even in complex portfolios.
- It took us years of fine-tuning to ensure our models not only run but deliver stable, explainable and automated results

PredicTri



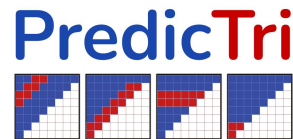
Thank you for following so far

If you'd like to pause here, you already know the essence:

In PredicTri no assumptions and manual levers are needed. Instead of requiring complex user inputs and relying on legacy models, PredicTri ranks and explains outputs of models that you can trust.

Next >>>

The next part covers the **technical foundation** of PredicTri: model structure, validation, and examples of how it works in practice.



Benchmarking Against Arius Data

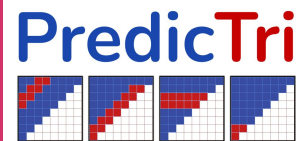
- We benchmark against the publicly available Arius sample dataset: paid and incurred triangles with corresponding premium values.
- Full dataset and report extracts are included in the Appendix.
- Purpose: to allow direct, transparent comparison of PredicTri results with a widely recognized tool.
- This ensures transparency, reproducibility, and unbiased comparison.
- Data is illustrative only, not affiliated with or endorsed by Arius.

Arius sample dataset → PredicTri workflow → Comparison results



PredicTri Results Output

- Ultimate values: calculated for all 16 model configurations. In the Appendix we show detailed examples at selected percentiles (50th and 95th).
- PredicTri highlights how each model differs from standard Chain Ladder, and explains the source of that difference.
- Development patterns (cashflows): full rectangle outputs are available for every model. Illustrative selected percentiles are included in the Appendix.
- Detailed output for full distributions: generated for each model. Representative example is provided in the Appendix.



Bayesian Model Features

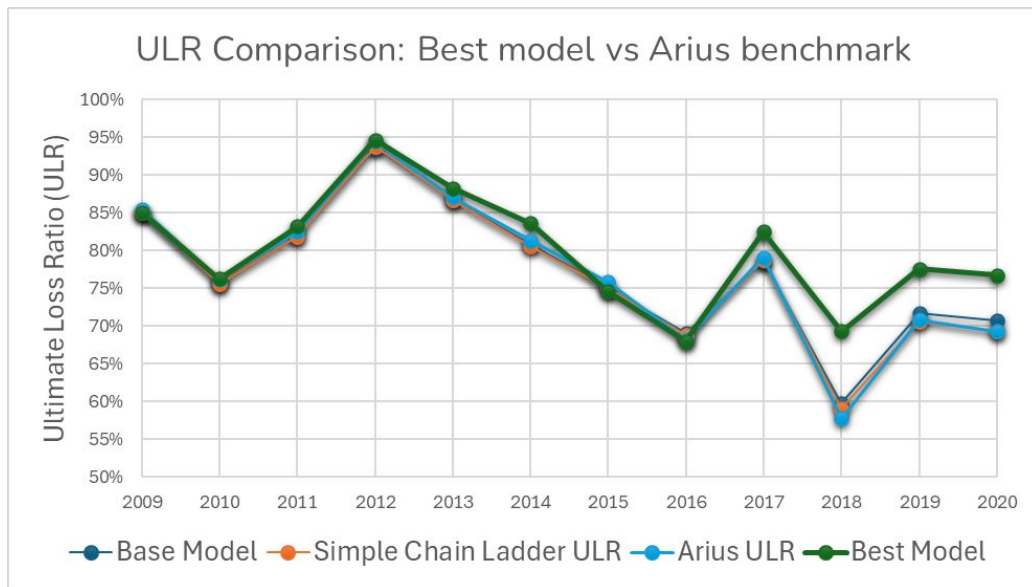
Model feature	State
JOINT* factor	Included / Not included
Evolution factor (horizontal trend)	Cumulative / Non Cumulative
Inflation factor (diagonal trend)	Included / Not included
Residuals type	Cumulative / Non Cumulative

Each factor can be toggled on or off, creating 16 transparent model variants to identify the most adequate structure for your data.

All factors are evaluated automatically. Users can review and compare their impact.

(*) Joint modeling enables the simultaneous use of both paid and incurred models.

Model comparison

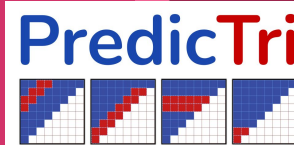


Period	Simple Chain Ladder	Arius	Base Model	Best Model
2009	85%	86%	85%	85%
2010	76%	76%	76%	76%
2011	82%	83%	82%	83%
2012	94%	94%	94%	95%
2013	87%	87%	87%	88%
2014	81%	81%	81%	84%
2015	75%	76%	75%	75%
2016	69%	68%	69%	68%
2017	79%	79%	79%	83%
2018	59%	58%	60%	69%
2019	71%	71%	72%	78%
2020	69%	69%	71%	77%

Our **base model** aligns with standard CL. The **best model** in this case adds Joint + Residuals factors. The difference is transparent and explainable

In addition, PredicTri provides confidence ranges that support management and regulatory decision-making.

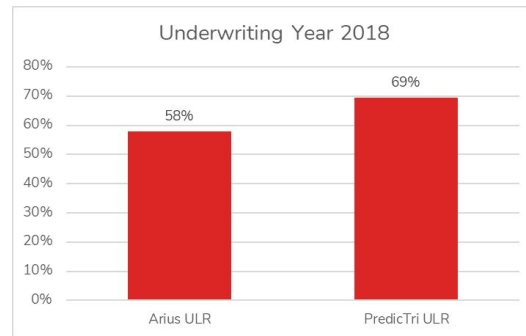
ULR: Ultimate Loss Ratio



Why UY 2018 is so high in our projection?

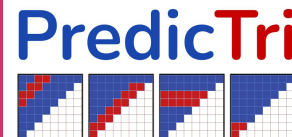
- The 69% ultimate for 2018 is driven by the insights from the Non-Cumulative Residuals model.
- Let's look at the “Loss Ratio Standard Deviation” / “Loss Ratio Average” ratio across the columns:

UY	LR development											
2009	53%	56%	55%	69%	69%	77%	80%	82%	83%	85%	85%	85%
2010	44%	46%	50%	58%	62%	70%	73%	74%	75%	76%	76%	
2011	42%	54%	57%	63%	72%	74%	76%	80%	81%	82%		
2012	50%	59%	64%	74%	77%	83%	87%	89%	92%			
2013	46%	50%	54%	64%	69%	79%	83%	84%				
2014	44%	52%	57%	62%	71%	74%	76%					
2015	35%	44%	51%	56%	63%	68%						
2016	34%	42%	49%	51%	57%							
2017	44%	48%	55%	60%								
2018	31%	37%	40%									
2019	36%	43%										
2020	36%											
LR average	41%	48%	53%	62%	68%	75%	79%	82%	83%	81%	81%	
LR stdev	7%	7%	6%	7%	6%	5%	5%	5%	7%	4%	7%	
LR stdev / LR average	16%	14%	12%	11%	9%	7%	7%	7%	9%	6%	8%	



The chart shows an 11.5% difference in the ultimate, driven by improved model accuracy.

- The ratio decreases with development, unlike in a Cumulative Residuals scenario (Chain Ladder assumption) where uncertainty increases.
- Early deviations don't predict the ultimate reliably.
- The Non-Cumulative Residuals model therefore gives a more reliable projection.



Model Validation and Scoring by Predictive Power

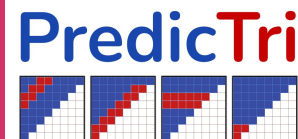
model	fold 0	fold 1	fold 2	fold 3	fold 4	fold 5	fold 6	fold 7	Total	Rank
JOINT_E0000001_R1000001	0.94	0.48	0.99	0.87	1.06	0.94	1.04	1.06	7.38	1
JOINT_E0000001_R0100001	0.93	0.48	1.12	0.79	1.04	1.02	1.04	1.02	7.44	2
JOINT_E0100001_R1000001	0.84	0.54	0.97	0.87	1.10	0.96	1.15	1.10	7.52	3
JOINT_E0100001_R0100001	0.94	0.56	1.18	0.76	1.07	1.07	1.11	1.09	7.77	4
JOINT_E0000001_I0100001_R1000001	0.90	0.48	0.98	0.98	1.16	1.09	1.07	1.18	7.85	5
JOINT_E0000001_I0100001_R0100001	0.94	0.48	1.13	0.89	1.12	1.10	1.17	1.09	7.92	6
JOINT_E0100001_I0100001_R1000001	0.89	0.46	0.99	0.95	1.21	1.12	1.18	1.19	7.98	7
JOINT_E0100001_I0100001_R0100001	6.69	0.59	1.07	0.98	1.11	1.11	1.02	1.19	13.75	8

Model validation and selection are based on predictive power, measured through cross-validation adapted for Bayesian models.

Multiple folds (diagonal, row-top, row-bottom, etc.) test robustness across development patterns:

- fold 7: uses 70% diagonals from the left (similar to a standard actuarial validation),
- fold 6: uses 70% rows from the top,
-
- fold 0: uses 70% rows from the bottom.

This data-driven validation enhances financial rigor and credibility in reserve estimates.

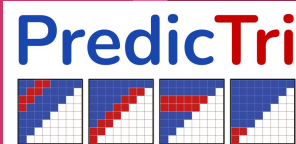


Model Transparency: Explanatory factors

How do we understand the difference between the best model's result and traditional Chain Ladder (CL) techniques?

- Transparency is quantified using Shapley values and the Explanatory Factors Matrix, which shows the contribution of each model feature to the final result relative to the base* method (E0000001_R0100001).
- Explainability builds trust as users can see how data-driven factors influence each projection.

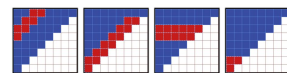
(*) The base method resembles a stochastic Chain Ladder approach, where the final loss reflects relationships between columns and random noise, similar to standard actuarial calculations.



Model Transparency: Explanatory factors, example

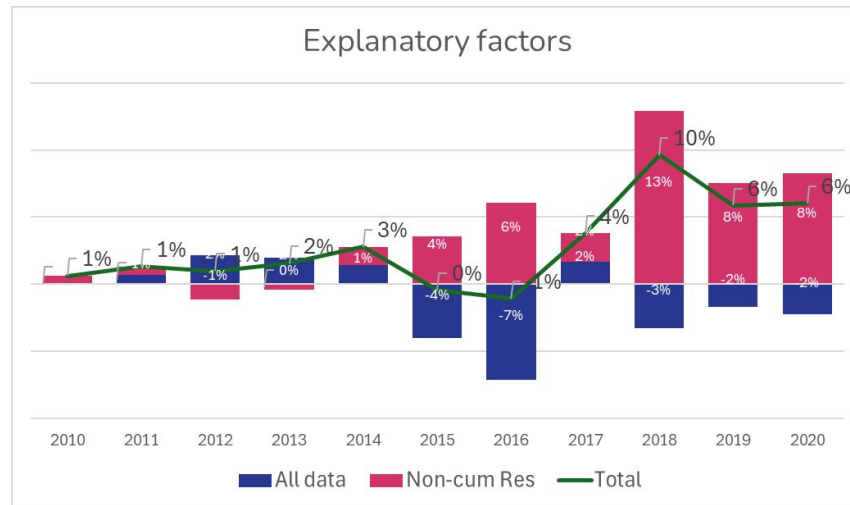
- For example, the selected (best) model is **JOINT_E0000001_R1000001**. This means that the **Non-cumulative Residuals (R1000001)** factor, and the **JOINT** factor are added to the base result.
- The 7th scored model is **JOINT_E0100001_I0100001_R1000001**. Here **Non-cumulative Residuals (R1000001)**, **JOINT** factor, **Cumulative Evolution** factor (**E0100001**) and **Inflation** factor (**I0100001**) are added to the base result.

PredicTri



Explanatory factors matrix, JOINT_E0000001_R1000001

Period	Total	All data	Non-cum Res
2009	0.0%	0.0%	0.0%
2010	0.6%	0.1%	0.6%
2011	1.3%	0.7%	0.6%
2012	1.0%	2.1%	-1.1%
2013	1.6%	2.0%	-0.4%
2014	2.8%	1.4%	1.3%
2015	-0.5%	-4.0%	3.6%
2016	-1.1%	-7.1%	6.1%
2017	3.8%	1.7%	2.1%
2018	9.6%	-3.3%	12.9%
2019	5.9%	-1.7%	7.6%
2020	6.0%	-2.2%	8.3%



For example, in 2018, the base ULR is 59%. It is then adjusted by adding the Joint (All data) factor of -3.3% and the Non-Cumulative Residuals factor of 12.9%: $58.9\% - 3.3\% + 12.9\% = 68.5\%$.

Key driver here: Non-Cumulative Residuals → +12.9% uplift.

The matrix provides a transparent quantitative justification for reserve recommendations.

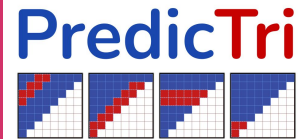
Additional explanatory factors matrix example is provided in the Appendix.



Model Development Factors, Best model (JOINT_E0000001_R1000001), Percentile 50

Period	0	1	2	3	4	5	6	7	8	9	10
2009	1.06	0.98	1.24	1.01	1.10	1.05	1.02	1.02	1.02	1.01	1.00
2010	1.07	1.07	1.16	1.07	1.14	1.03	1.01	1.02	1.01	1.00	1.01
2011	1.29	1.06	1.11	1.14	1.03	1.03	1.05	1.01	1.01	1.01	1.01
2012	1.19	1.09	1.14	1.05	1.08	1.05	1.01	1.04	1.01	1.01	1.01
2013	1.08	1.08	1.19	1.08	1.14	1.05	1.01	1.02	1.02	1.01	1.01
2014	1.19	1.08	1.10	1.14	1.04	1.03	1.03	1.03	1.02	1.01	1.01
2015	1.25	1.16	1.10	1.13	1.08	1.04	1.02	1.02	1.01	1.00	1.00
2016	1.21	1.17	1.06	1.12	1.09	1.04	1.02	1.02	1.01	1.00	0.99
2017	1.08	1.14	1.09	1.10	1.09	1.05	1.03	1.03	1.02	1.01	1.01
2018	1.21	1.08	1.18	1.12	1.11	1.06	1.04	1.03	1.02	1.01	1.01
2019	1.19	1.10	1.15	1.11	1.10	1.05	1.03	1.03	1.02	1.01	1.01
2020	1.19	1.11	1.15	1.11	1.10	1.05	1.03	1.03	1.02	1.01	1.01
Arius average factors	1.13	1.09	1.12	1.07	1.04	1.02	1.02	1.01	1.00	1.00	1.00

Blue = PredicTri projection (selected model, selected percentile).



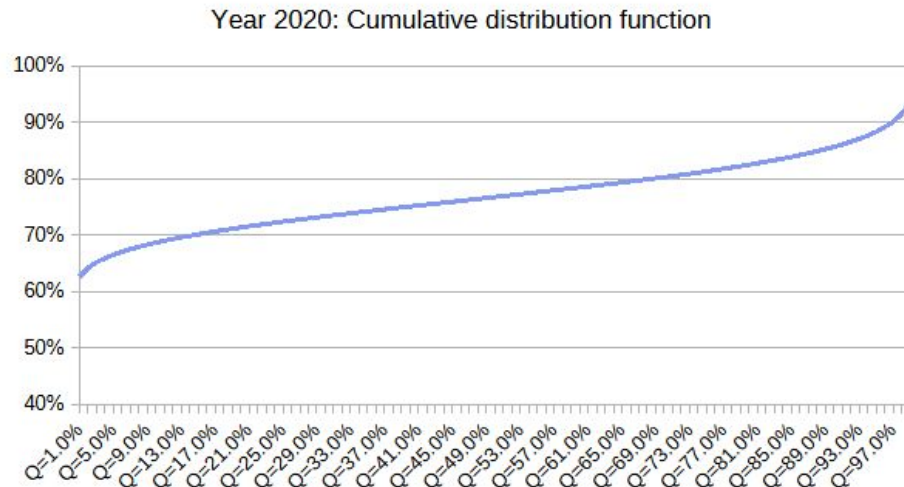
Confidence intervals example

Period	[25%:75%]		[5%:95%]	
2009	0.0%	0.0%	0.0%	0.0%
2010	-1.5%	1.5%	-3.6%	3.8%
2011	-2.1%	2.2%	-5.1%	5.5%
2012	-2.9%	2.9%	-6.9%	7.3%
2013	-3.0%	3.1%	-7.1%	7.7%
2014	-3.0%	3.1%	-7.2%	7.8%
2015	-2.9%	3.0%	-6.8%	7.5%
2016	-2.9%	3.0%	-6.8%	7.5%
2017	-3.9%	4.1%	-9.1%	10.2%
2018	-3.8%	3.9%	-8.8%	10.0%
2019	-4.3%	4.5%	-10.1%	11.4%
2020	-4.4%	4.6%	-10.2%	11.6%

Values shown are the difference from percentile 50% for the confidence intervals of [25:75]% and [5:95]% of the results distribution.

These insights enable clear, data-supported reserve decisions.

Full distribution output example



Full distributions clarify best-estimate and conservative scenarios, quantify tail risk, and support pricing and capital decisions.

Complete distribution available for every year and every model; here shown for best model JOINT_E0000001_R1000001.

Collaboration Opportunities

- Real-world pilots with insurers, reinsurers, and consultants
- Joint research on transparency and AI in actuarial modeling
- Early-access feedback shaping future product releases

What do you think?



Appendix. Technical Details and Data Sources

- Arius example data
- Arius Results
- Model output example: ultimate value, 16 models
- Model output example: development pattern for a selected model
- Full results distribution for selected model
- Explanatory factors matrix, JOINT_E0100001_I0100001_R1000001

Arius example data

- [Arius Sample Reports](#)
- Page 21:

Paid data

ANY Company, Inc.
Coverage XYZ
Paid Loss - Cumulative
Data Evaluated at 12/31/2020

Exhibit 3
Sheet 4

Accident Year	12	24	36	48	60	72	84	96	108	120	132	144
2009	223,229	1,323,605	3,181,380	6,032,736	7,650,309	9,599,951	10,616,029	11,275,591	11,840,601	12,249,863	12,525,442	12,726,242
2010	264,103	1,148,042	2,720,426	4,978,871	6,924,957	8,770,854	9,468,115	10,057,065	10,613,331	10,866,831	11,093,059	
2011	222,318	1,817,062	3,425,452	5,623,790	7,438,214	8,573,847	9,684,699	10,586,337	10,977,176	11,431,603		
2012	349,943	2,029,964	4,027,259	6,049,865	7,889,304	9,841,435	11,055,884	11,939,494	12,719,770			
2013	331,520	1,548,090	3,441,359	6,047,121	7,776,535	9,807,536	10,815,348	11,553,737				
2014	175,483	1,577,806	3,082,559	5,388,036	7,916,762	9,417,157	10,733,146					
2015	143,119	1,734,198	3,428,734	5,302,386	7,229,055	8,629,581						
2016	200,219	1,688,379	3,532,462	4,772,821	6,365,073							
2017	711,805	2,072,115	4,333,300	6,377,809								
2018	300,723	1,427,729	2,818,101									
2019	408,212	1,856,999										
2020	244,743											

Losses include ALAE;
CAT losses are excluded from above and are analyzed separately

- Page 25:

Incurred data

ANY Company, Inc.
Coverage XYZ
Incurred Loss - Cumulative
Data Evaluated at 12/31/2020

Exhibit 3
Sheet 8

Accident Year	12	24	36	48	60	72	84	96	108	120	132	144
2009	8,259,083	8,748,291	8,538,045	10,612,492	10,733,776	11,847,468	12,446,769	12,723,121	12,918,051	13,118,314	13,205,043	13,173,842
2010	6,654,966	7,108,181	7,629,687	8,838,216	9,463,351	10,776,534	11,106,560	11,252,743	11,472,813	11,613,184	11,589,441	
2011	6,176,972	7,937,583	8,408,045	9,301,156	10,595,207	10,895,271	11,187,973	11,799,692	11,922,276	12,063,803		
2012	7,342,193	8,759,647	9,537,058	10,896,902	11,415,336	12,300,797	12,927,816	13,121,249	13,695,663			
2013	7,009,272	7,546,391	8,131,674	9,713,907	10,449,222	11,963,085	12,580,022	12,669,190				
2014	7,015,825	8,339,332	9,032,949	9,939,182	11,357,375	11,791,961	12,172,858					
2015	5,796,870	7,222,753	8,391,693	9,213,393	10,454,239	11,280,995						
2016	5,806,901	7,011,670	8,200,249	8,687,486	9,699,435							
2017	7,639,758	8,288,398	9,464,581	10,334,102								
2018	5,218,974	6,316,732	6,826,828									
2019	6,247,168	7,437,611										
2020	6,332,875											

Losses include ALAE;
CAT losses are excluded from above and are analyzed separately

Disclaimer: We utilize publicly available Arius data and analysis purely for illustrative purposes. Our framework and results are not affiliated with or endorsed by Arius. This dataset was chosen because it is easily accessible to anyone, enabling a direct comparison, ensuring transparency and unbiased data selection.

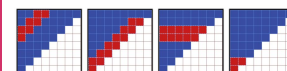
Arius Results, page 22

Ultimate Loss Based on Incurred Loss Development Data Evaluated at 12/31/2020

Accident Year	Age (months)	Cumulative Incurred Loss	Selected Development Factors	Cumulative Development Factors	Ultimate Loss (2) x (4)
—	(1)	(2)	(3)	(4)	(5)
2009	144	\$ 13,173,842	1.005	1.005	\$ 13,239,711
2010	132	11,589,441	1.000	1.005	11,647,388
2011	120	12,063,803	1.003	1.008	12,160,494
2012	108	13,695,663	1.013	1.021	13,984,904
2013	96	12,669,190	1.020	1.042	13,195,488
2014	84	12,172,858	1.025	1.068	12,995,501
2015	72	11,280,995	1.043	1.114	12,562,872
2016	60	9,699,435	1.065	1.186	11,503,701
2017	48	10,334,102	1.118	1.326	13,698,857
2018	36	6,826,828	1.090	1.445	9,864,090
2019	24	7,437,611	1.130	1.633	12,143,671
2020	12	6,332,875	1.168	1.906	12,072,605
Total		\$ 127,276,643			\$ 149,069,283

(3),(4): Exhibit 3, Sheet 6

PredicTri



Model output example: ultimate value, 16 models

Percentile 50%:

Period	Exposure	E0000001_R 0100001	E0000001_R 1000001	E0000001_I0 100001_R01 00001	E0000001_I0 100001_R10 00001	E0100001_R 0100001	E0100001_R 1000001	E0100001_I0 100001_R01 00001	E0100001_I0 100001_R10 00001	JOINT_E000 0001_R0100 001	JOINT_E000 0001_R1000 001	JOINT_E00000 01_I0100001_ R0100001	JOINT_E0000 001_I0100001 R1000001	JOINT_E010 0001_R0100 001	JOINT_E010 0001_R1000 001	JOINT_E010 0001_I01000 01_R0100001	JOINT_E010 0001_I01000 01_R1000001
2009	15,483,728	13,173,839	13,173,839	13,173,839	13,173,839	13,173,839	13,173,839	13,173,839	13,173,839	13,173,839	13,173,839	13,173,839	13,173,839	13,173,839	13,173,839	13,173,839	13,173,839
2010	15,289,024	11,562,689	11,704,055	11,575,601	11,724,391	11,561,217	11,780,024	11,565,241	11,812,524	11,624,472	11,658,113	11,616,531	11,580,892	11,623,883	11,660,503	11,618,229	11,799,613
2011	14,733,743	12,067,482	12,183,416	12,078,225	12,332,928	12,059,721	12,311,364	12,069,747	12,343,010	12,186,606	12,261,181	12,173,786	12,090,916	12,181,294	12,260,913	12,173,748	12,246,569
2012	14,806,193	13,871,669	13,513,909	13,886,931	13,786,940	13,865,359	13,616,926	13,878,475	13,668,734	13,998,935	14,016,489	13,969,624	13,594,797	13,983,786	13,977,678	13,974,207	13,381,316
2013	15,144,409	13,128,742	12,941,125	13,140,753	12,905,199	13,121,913	13,055,364	13,131,788	13,124,111	13,303,233	13,366,402	13,258,495	12,979,273	13,294,259	13,334,776	13,261,017	12,937,117
2014	15,983,341	12,922,445	13,167,376	12,940,439	13,209,974	12,927,933	13,199,824	12,937,340	13,283,418	13,186,641	13,366,031	13,135,342	13,120,744	13,170,666	13,420,540	13,123,992	13,055,830
2015	16,562,773	12,426,479	13,335,650	12,445,228	12,774,506	12,433,013	12,931,257	12,441,929	13,132,210	12,079,799	12,349,189	12,084,550	12,499,351	12,078,894	12,351,632	12,090,147	12,916,199
2016	16,869,248	11,643,070	13,158,057	11,664,944	12,242,282	11,662,001	12,508,573	11,651,455	12,734,504	10,930,570	11,463,058	10,908,950	12,053,130	10,936,955	11,393,245	10,918,945	12,608,441
2017	17,313,176	13,629,300	14,148,009	13,639,942	13,351,034	13,638,031	13,045,351	13,623,558	13,165,646	14,065,494	14,285,813	13,948,819	13,335,365	14,052,293	13,634,456	13,978,586	12,999,298
2018	17,076,964	10,192,654	12,831,121	10,223,991	11,174,037	10,207,087	11,664,324	10,211,267	11,887,538	10,070,446	11,834,931	10,068,492	11,813,475	10,070,230	11,593,668	10,083,404	11,995,266
2019	17,148,188	12,294,710	13,768,594	12,337,020	12,220,624	12,323,511	12,150,521	12,317,607	12,246,099	12,182,181	13,299,469	12,170,951	12,399,030	12,149,733	12,508,194	12,182,056	12,271,351
2020	17,427,566	12,321,535	13,992,716	12,375,146	12,251,920	12,329,900	12,349,943	12,335,484	12,425,077	12,165,637	13,370,391	12,243,577	12,428,589	12,155,243	12,615,716	12,188,678	12,443,270

Percentile 95%:

Period	Exposure	E0000001_R 0100001	E0000001_R 1000001	E0000001_I0 100001_R01 00001	E0000001_I0 100001_R10 00001	E0100001_R 0100001	E0100001_R 1000001	E0100001_I0 100001_R01 00001	E0100001_I0 100001_R10 00001	JOINT_E000 0001_R0100 001	JOINT_E000 0001_R1000 001	JOINT_E00000 01_I0100001_ R0100001	JOINT_E0000 001_I0100001 R1000001	JOINT_E010 0001_R0100 001	JOINT_E010 0001_R1000 001	JOINT_E010 0001_I01000 01_R0100001	JOINT_E010 0001_I01000 01_R1000001
2009	15,483,728	13,173,839	13,173,839	13,173,839	13,173,839	13,173,839	13,173,839	13,173,839	13,173,839	13,173,839	13,173,839	13,173,839	13,173,839	13,173,839	13,173,839	13,173,839	13,173,839
2010	15,289,024	12,204,054	12,986,989	12,234,357	13,408,406	12,217,650	13,615,619	12,216,751	13,501,467	12,287,876	12,571,407	12,256,479	12,740,109	12,292,670	12,562,693	12,265,665	13,513,070
2011	14,733,743	12,908,447	13,785,535	12,942,796	14,383,131	12,940,045	14,569,111	12,930,186	14,382,282	13,144,220	13,573,039	13,093,160	13,550,616	13,165,103	13,562,607	13,099,136	14,393,175
2012	14,806,193	15,001,281	15,523,313	15,040,365	16,189,981	15,041,912	16,374,199	15,029,858	16,143,901	15,296,052	15,758,706	15,216,127	15,405,345	15,315,784	15,747,071	15,248,106	15,939,489
2013	15,144,409	14,372,205	14,967,161	14,402,821	15,290,505	14,416,144	15,778,436	14,414,915	15,619,812	14,704,051	15,253,046	14,612,570	14,828,219	14,739,011	15,225,153	14,632,198	15,559,261
2014	15,983,341	14,273,987	15,314,733	14,305,640	15,623,417	14,324,934	16,030,187	14,318,385	15,920,055	14,704,503	15,377,513	14,589,363	15,120,602	14,697,820	15,457,245	14,610,938	15,826,083
2015	16,562,773	13,887,640	15,650,248	13,934,741	15,274,294	13,933,455	15,815,954	13,954,777	15,831,923	13,557,179	14,359,385	13,518,175	14,552,904	13,593,245	14,364,184	13,547,049	15,724,004
2016	16,869,248	13,618,725	15,532,579	13,626,273	14,763,408	13,626,947	15,446,689	13,611,114	15,488,083	12,468,263	13,527,025	12,444,081	14,180,325	12,522,858	13,464,594	12,490,875	15,398,105
2017	17,313,176	16,465,116	16,783,620	16,499,594	16,007,248	16,498,319	16,111,196	16,450,326	16,099,028	16,640,506	17,146,712	16,492,716	15,916,110	16,655,695	16,402,829	16,532,840	15,996,858
2018	17,076,964	12,875,889	15,380,056	12,943,308	13,802,983	12,898,527	14,753,802	12,891,835	14,751,978	12,633,228	14,571,776	12,444,891	14,281,557	12,581,241	14,296,062	12,491,131	14,898,448
2019	17,148,188	15,893,356	16,505,745	15,945,382	15,072,144	15,921,293	15,411,143	15,909,241	15,427,037	15,680,056	16,500,266	15,388,201	15,165,407	15,634,682	15,579,146	15,457,206	15,409,043
2020	17,427,566	16,559,954	16,876,712	16,616,567	15,688,892	16,589,363	16,105,160	16,606,058	16,153,982	16,019,654	16,638,905	15,832,239	15,491,901	15,988,399	15,906,345	15,770,651	15,930,754

Model output example: development pattern for a selected model

Percentile 50%:

Period	Exposure	Age 1 Loss	Age 2 Loss	Age 3 Loss	Age 4 Loss	Age 5 Loss	Age 6 Loss	Age 7 Loss	Age 8 Loss	Age 9 Loss	Age 10 Loss	Age 11 Loss	Age 12 Loss
2009	15,483,728	8,259,087	8,748,294	8,538,048	10,612,485	10,733,773	11,847,464	12,446,765	12,723,110	12,918,048	13,118,325	13,205,033	13,173,839
2010	15,289,024	6,654,964	7,108,183	7,629,685	8,838,215	9,463,348	10,776,524	11,106,569	11,252,739	11,472,819	11,613,195	11,589,452	11,658,113
2011	14,733,743	6,176,975	7,937,582	8,408,043	9,301,150	10,595,213	10,895,280	11,187,979	11,799,699	11,922,270	12,063,795	12,164,902	12,261,181
2012	14,806,193	7,342,191	8,759,648	9,537,061	10,896,901	11,415,347	12,300,794	12,927,809	13,121,253	13,695,673	13,847,413	13,923,301	14,016,489
2013	15,144,409	7,009,269	7,546,393	8,131,677	9,713,909	10,449,230	11,963,089	12,580,015	12,669,181	12,954,146	13,150,838	13,255,231	13,366,402
2014	15,983,341	7,015,823	8,339,334	9,032,953	9,939,186	11,357,382	11,791,960	12,172,869	12,498,567	12,835,737	13,065,324	13,211,838	13,366,031
2015	16,562,773	5,796,868	7,222,752	8,391,693	9,213,396	10,454,233	11,280,998	11,745,654	12,020,980	12,267,614	12,384,093	12,383,607	12,349,189
2016	16,869,248	5,806,899	7,011,669	8,200,247	8,687,486	9,699,431	10,580,916	11,028,030	11,282,588	11,495,825	11,587,001	11,542,051	11,463,058
2017	17,313,176	7,639,762	8,288,400	9,464,575	10,334,093	11,350,491	12,419,411	12,997,324	13,376,440	13,756,192	14,003,610	14,141,987	14,285,813
2018	17,076,964	5,218,975	6,316,731	6,826,830	8,070,723	9,051,729	10,016,839	10,581,295	10,977,207	11,347,514	11,591,827	11,725,678	11,834,931
2019	17,148,188	6,247,171	7,437,613	8,195,451	9,402,561	10,413,084	11,441,381	12,018,201	12,403,595	12,776,376	13,032,878	13,171,853	13,299,469
2020	17,427,566	6,332,872	7,537,560	8,359,766	9,614,820	10,627,159	11,654,462	12,214,643	12,583,197	12,933,855	13,159,185	13,270,909	13,370,391

Percentile 95%:

Period	Exposure	Age 1 Loss	Age 2 Loss	Age 3 Loss	Age 4 Loss	Age 5 Loss	Age 6 Loss	Age 7 Loss	Age 8 Loss	Age 9 Loss	Age 10 Loss	Age 11 Loss	Age 12 Loss
2009	15,483,728	8,259,087	8,748,294	8,538,048	10,612,485	10,733,773	11,847,464	12,446,765	12,723,110	12,918,048	13,118,325	13,205,033	13,173,839
2010	15,289,024	6,654,964	7,108,183	7,629,685	8,838,215	9,463,348	10,776,524	11,106,569	11,252,739	11,472,819	11,613,195	11,589,452	12,232,185
2011	14,733,743	6,176,975	7,937,582	8,408,043	9,301,150	10,595,213	10,895,280	11,187,979	11,799,699	11,922,270	12,063,795	12,927,274	13,072,802
2012	14,806,193	7,342,191	8,759,648	9,537,061	10,896,901	11,415,347	12,300,794	12,927,809	13,121,253	13,695,673	14,730,722	15,031,206	15,098,762
2013	15,144,409	7,009,269	7,546,393	8,131,677	9,713,909	10,449,230	11,963,089	12,580,015	12,669,181	13,772,717	14,224,871	14,452,366	14,530,157
2014	15,983,341	7,015,823	8,339,334	9,032,953	9,939,186	11,357,382	11,791,960	12,172,869	13,261,592	13,878,452	14,270,314	14,500,589	14,616,761
2015	16,562,773	5,796,868	7,222,752	8,391,693	9,213,396	10,454,233	11,280,998	12,476,531	13,011,750	13,427,382	13,633,350	13,681,304	13,586,760
2016	16,869,248	5,806,899	7,011,669	8,200,247	8,687,486	9,699,431	11,345,502	12,020,360	12,429,810	12,753,560	12,893,260	12,849,596	12,727,438
2017	17,313,176	7,639,762	8,288,400	9,464,575	10,334,093	12,160,606	13,625,113	14,392,347	14,888,418	15,378,469	15,702,297	15,905,246	16,043,226
2018	17,076,964	5,218,975	6,316,731	6,826,830	8,701,193	9,987,177	11,233,432	11,947,210	12,434,441	12,895,126	13,211,346	13,396,776	13,534,294
2019	17,148,188	6,247,171	7,437,613	8,700,763	10,295,414	11,586,137	12,897,185	13,603,228	14,092,062	14,560,311	14,895,693	15,091,199	15,261,665
2020	17,427,566	6,332,872	8,063,106	9,087,775	10,672,193	11,943,057	13,226,277	13,913,386	14,353,119	14,792,576	15,094,051	15,254,459	15,387,274

Full results distribution for selected model

Period	Exposure	Q=0.1%	Q=0.2%	Q=0.3%	Q=0.4%	Q=0.5%	Q=0.6%	Q=0.7%	Q=0.8%	Q=0.9%	Q=1.0%	Q=2.0%	Q=3.0%	Q=4.0%
2009	15,483,728	13,173,839	13,173,839	13,173,839	13,173,839	13,173,839	13,173,839	13,173,839	13,173,839	13,173,839	13,173,839	13,173,839	13,173,839	13,173,839
2010	15,289,024	9,846,090	9,962,789	10,038,770	10,103,024	10,151,938	10,187,393	10,219,848	10,251,814	10,279,407	10,303,324	10,474,645	10,586,160	10,673,950
2011	14,733,743	9,694,821	9,855,580	9,960,040	10,031,023	10,088,983	10,134,534	10,187,184	10,224,771	10,265,558	10,295,310	10,507,396	10,645,639	10,753,002
2012	14,806,193	10,286,363	10,495,131	10,614,587	10,686,318	10,751,196	10,805,113	10,844,491	10,880,652	10,916,496	10,947,693	11,210,778	11,366,015	11,487,807
2013	15,144,409	9,810,635	10,029,153	10,133,443	10,224,805	10,292,551	10,350,381	10,403,166	10,447,635	10,494,932	10,527,499	10,793,841	10,952,701	11,074,731
2014	15,983,341	9,940,253	10,131,986	10,263,737	10,360,187	10,434,436	10,497,572	10,556,859	10,603,863	10,642,480	10,678,626	10,942,401	11,114,304	11,235,326
2015	16,562,773	9,868,301	10,045,823	10,170,360	10,249,446	10,320,572	10,377,857	10,426,139	10,475,456	10,513,207	10,548,906	10,806,481	10,970,019	11,103,861
2016	16,869,248	9,455,093	9,658,220	9,786,817	9,887,129	9,965,727	10,020,106	10,074,359	10,118,552	10,164,469	10,202,818	10,460,827	10,637,093	10,755,845
2017	17,313,176	9,609,445	9,819,200	9,936,320	10,025,061	10,092,197	10,151,657	10,219,697	10,276,450	10,322,176	10,359,398	10,641,854	10,812,015	10,946,257
2018	17,076,964	8,861,064	9,038,918	9,154,035	9,254,241	9,316,430	9,369,131	9,421,742	9,469,893	9,509,990	9,550,658	9,802,462	9,977,057	10,101,948
2019	17,148,188	9,024,854	9,223,059	9,333,199	9,418,864	9,497,072	9,567,563	9,620,230	9,660,483	9,704,027	9,740,945	10,006,147	10,182,977	10,321,668
2020	17,427,566	9,090,287	9,291,232	9,441,617	9,554,927	9,638,662	9,715,222	9,775,399	9,821,234	9,859,540	9,898,448	10,184,007	10,362,230	10,499,897

Explanatory factors matrix, JOINT_E0100001_I0100001_R1000001

Period	Total	All data	Non-cum Res	Cum Evolution	Inflation
2009	0.0%	0.0%	0.0%	0.0%	0.0%
2010	1.5%	0.0%	0.9%	0.4%	0.2%
2011	1.2%	0.1%	0.8%	0.3%	0.0%
2012	-3.3%	0.3%	-2.1%	-0.4%	-1.1%
2013	-1.3%	0.6%	-1.1%	0.1%	-0.9%
2014	0.8%	0.6%	1.0%	0.0%	-0.7%
2015	3.0%	-2.3%	3.9%	0.6%	0.8%
2016	5.7%	-3.8%	7.0%	0.7%	1.8%
2017	-3.6%	1.3%	-1.7%	-1.4%	-1.8%
2018	10.6%	-0.4%	11.1%	-0.1%	-0.1%
2019	-0.1%	-0.3%	2.9%	-1.3%	-1.4%
2020	0.7%	-0.5%	3.6%	-1.1%	-1.4%

The most influential factor in this case is the Non-Cumulative Residuals. This typically occurs in complex portfolios with volatile experience.

