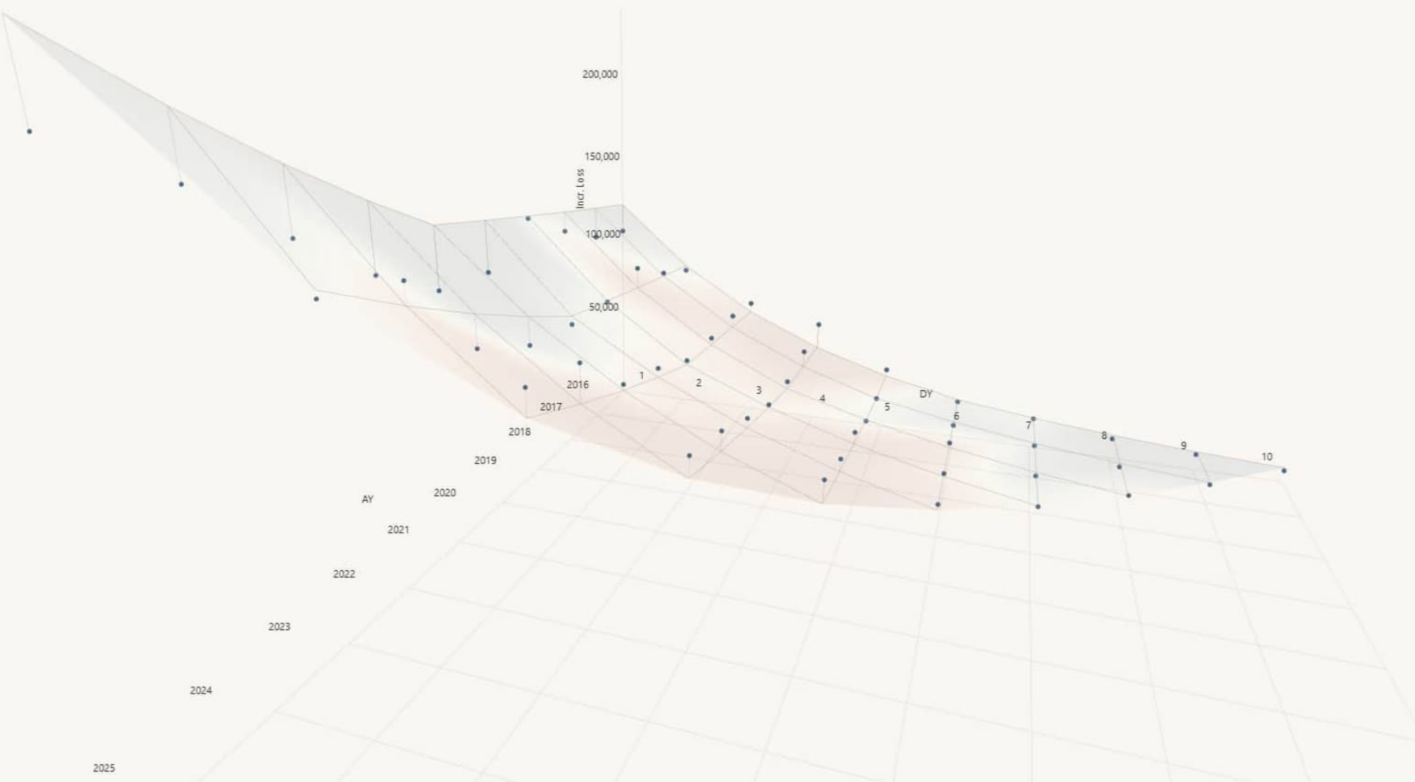
Conceptualizing Statistically Based Stochastic Trend Reserving Models



Jim Bedford, FCAS, MAAA
Bedford Actuarial Advisory, LLC

One of the many benefits of including statistically based models in the reserving process is that they reflect the fact that the observed losses are just one outcome of a complex stochastic claim process.

Deterministic methods do not reflect this and are fit to both the signal and the noise in the data. Statistical approaches separate the signal from the noise, reducing overfitting and providing more predictive estimates.

Understanding these models conceptually and how different assumptions affect our estimates can be tricky for someone new to them. Because of that, I have put together this short deck to help visualize these models.

This example uses sample data and the GLM framework with a Gamma variance function, one of many options built into the BASR software.

1. Paid Loss Triangle — Cumulative

AY	1	2	3	4	5	6	7	8	9	10
2016	107,757	194,085	263,322	323,633	360,382	382,601	400,244	412,032	421,067	427,540
2017	112,292	206,762	279,820	336,405	370,457	394,680	413,504	426,989	437,678	
2018	123,923	230,981	303,643	357,130	394,444	426,030	446,528	463,879		
2019	138,552	238,265	312,222	368,698	416,995	450,949	475,501			
2020	120,993	221,268	305,491	371,486	424,623	463,515				
2021	122,929	226,310	317,831	395,106	458,047					
2022	139,729	255,035	370,032	455,045						
2023	162,470	314,388	435,116							
2024	186,539	343,471								
2025	205,205									

2. Age-to-Age Factors

AY	1-2	2-3	3-4	4-5	5-6	6-7	7-8	8-9	9-10	10-Ult
2016	1.801	1.357	1.229	1.114	1.062	1.046	1.029	1.022	1.015	
2017	1.841	1.353	1.202	1.101	1.065	1.048	1.033	1.025		
2018	1.864	1.315	1.176	1.104	1.080	1.048	1.039			
2019	1.720	1.310	1.181	1.131	1.081	1.054				
2020	1.829	1.381	1.216	1.143	1.092					
2021	1.841	1.404	1.243	1.159						
2022	1.825	1.451	1.230							
2023	1.935	1.384								
2024	1.841									

3. LDF Selection

Method	1-2	2-3	3-4	4-5	5-6	6-7	7-8	8-9	9-10	Tail
All-Year Volume-Weighted	1.836	1.371	1.211	1.127	1.077	1.049	1.034	1.024	1.015	—
All-Year Simple Average	1.833	1.369	1.211	1.125	1.076	1.049	1.034	1.023	1.015	—
5-Year Volume-Weighted	**1.857**	**1.387**	1.210	1.129	1.077	1.049	1.034	1.024	1.015	—
5-Year Simple Average	1.854	1.386	1.209	1.128	1.076	1.049	1.034	1.023	1.015	—
3-Year Volume-Weighted	1.868	1.411	**1.230**	**1.145**	**1.084**	**1.050**	**1.034**	**1.024**	**1.015**	—
3-Year Simple Average	1.867	1.413	1.230	1.144	1.084	1.050	1.034	1.023	1.015	—
5-Year Medial (ex-Hi/Lo)	1.837	1.390	1.209	1.126	1.076	1.048	1.033	1.023	1.015	—
Selected →	1.857	1.387	1.230	1.145	1.084	1.050	1.034	1.024	1.015	1.050
Cumulative (CDF to Ult.)	4.658	2.508	1.809	1.471	1.285	1.185	1.128	1.091	1.066	1.050

We're all familiar with the traditional loss development method.

1. Paid Loss Triangle — Cumulative

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Cumulative (CDF to Ult.)	4.658	2.508	1.809	1.471	1.285	1.185	1.128	1.091	1.066	1.050

...but what is easy to forget is that an N x N triangle has 2N parameters!

1. Paid Loss Triangle — Cumulative

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Cumulative (CDF to Ult.)	4.658	2.508	1.809	1.471	1.285	1.185	1.128	1.091	1.066	1.050

4. Projected Ultimate by Accident Year

AY	Latest @ DY	Latest Cumulative	CDF to Ult.	Projected Ultimate
2016	10	427,540	1.050	**448,917**
2017	9	437,678	1.066	**466,628**
2018	8	463,879	1.091	**506,188**
2019	7	475,501	1.128	**536,418**
2020	6	463,515	1.185	**549,162**
2021	5	458,047	1.285	**588,533**
2022	4	455,045	1.471	**669,329**
2023	3	435,116	1.809	**787,098**
2024	2	343,471	2.508	**861,588**
2025	1	205,205	4.658	**955,839**
Total	—	4,164,997	—	6,369,699

...and is fit exactly to the latest observation of the cumulative development triangle.

An over-parameterized model risks being overfit to the noise in the observed data rather than the signal, producing poor estimates of future data.

1. Paid Loss Triangle — Cumulative

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2016	107,757	194,085	263,322	323,633	360,382	382,601	400,244	412,032	421,067	427,540
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Paid Loss Incremental

AY	1	2	3	4	5	6	7	8	9	10
2016	107,757	86,328	69,237	60,311	36,749	22,219	17,643	11,787	9,035	6,474
2017	112,292	94,470	73,058	56,585	34,052	24,222	18,824	13,485	10,689	
2018	123,923	107,057	72,663	53,487	37,313	31,586	20,498	17,351		
2019	138,552	99,713	73,958	56,475	48,297	33,954	24,552			
2020	120,993	100,276	84,223	65,995	53,137	38,892				
2021	122,929	103,380	91,522	77,274	62,941					
2022	139,729	115,306	114,997	85,013						
2023	162,470	151,918	120,728							
2024	186,539	156,931								
2025	205,205									

Statistically based regression models use incremental loss data as the input since cumulative observations are not independent (each observation contains the one before it) and CY trends exist only in the incremental data. More specifically, they use the log of the incremental losses, but I have converted everything back to the dollar scale for illustration here.

Paid Loss Incremental

AY	1	2	3	4	5	6	7	8	9	10
2016	107,757	86,328	69,237	60,311	36,749	22,219	17,643	11,787	9,035	6,474
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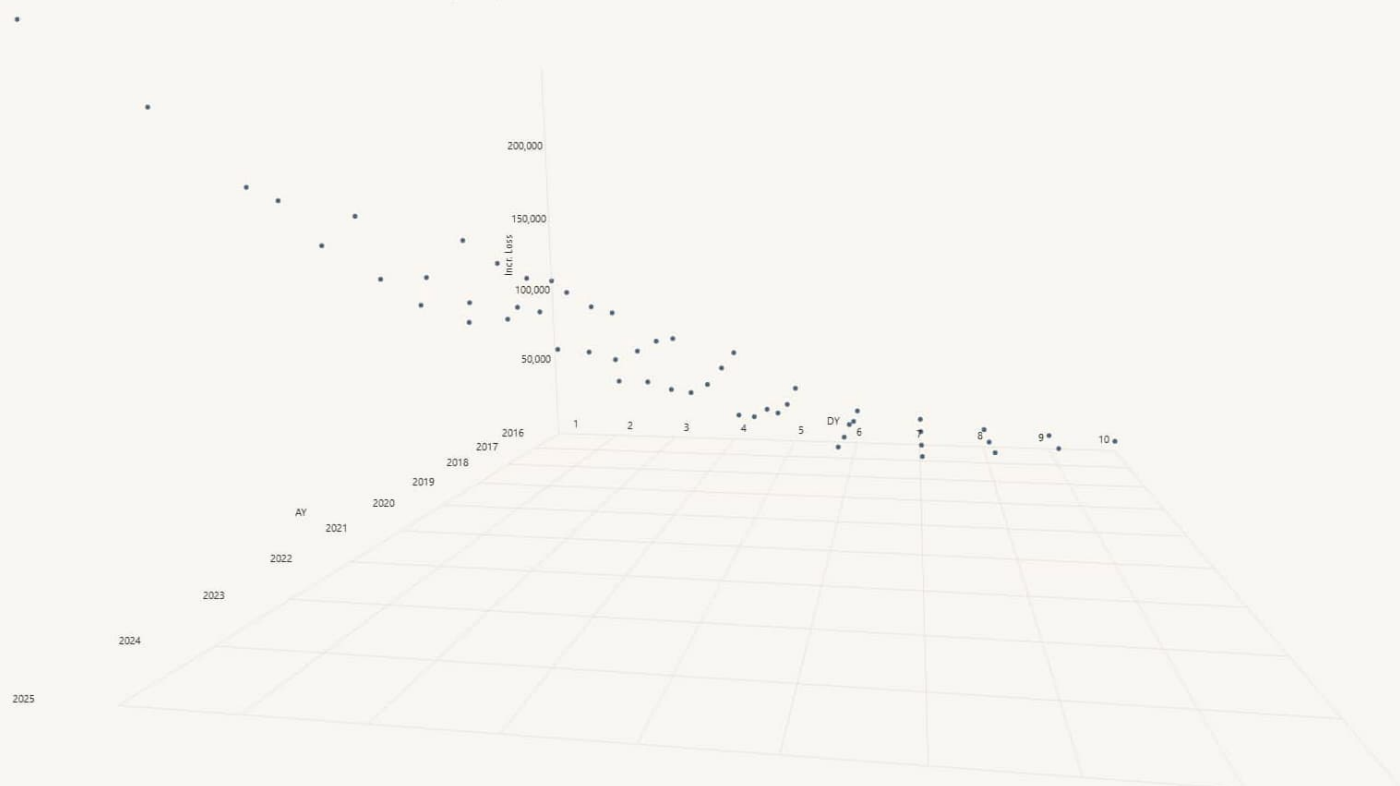
Modeled Paid Loss vs Observed — 3D, Incremental Dollar Scale ($000s)



To visualize this model, it helps to look at a 3-D rendering of the incremental development triangle.

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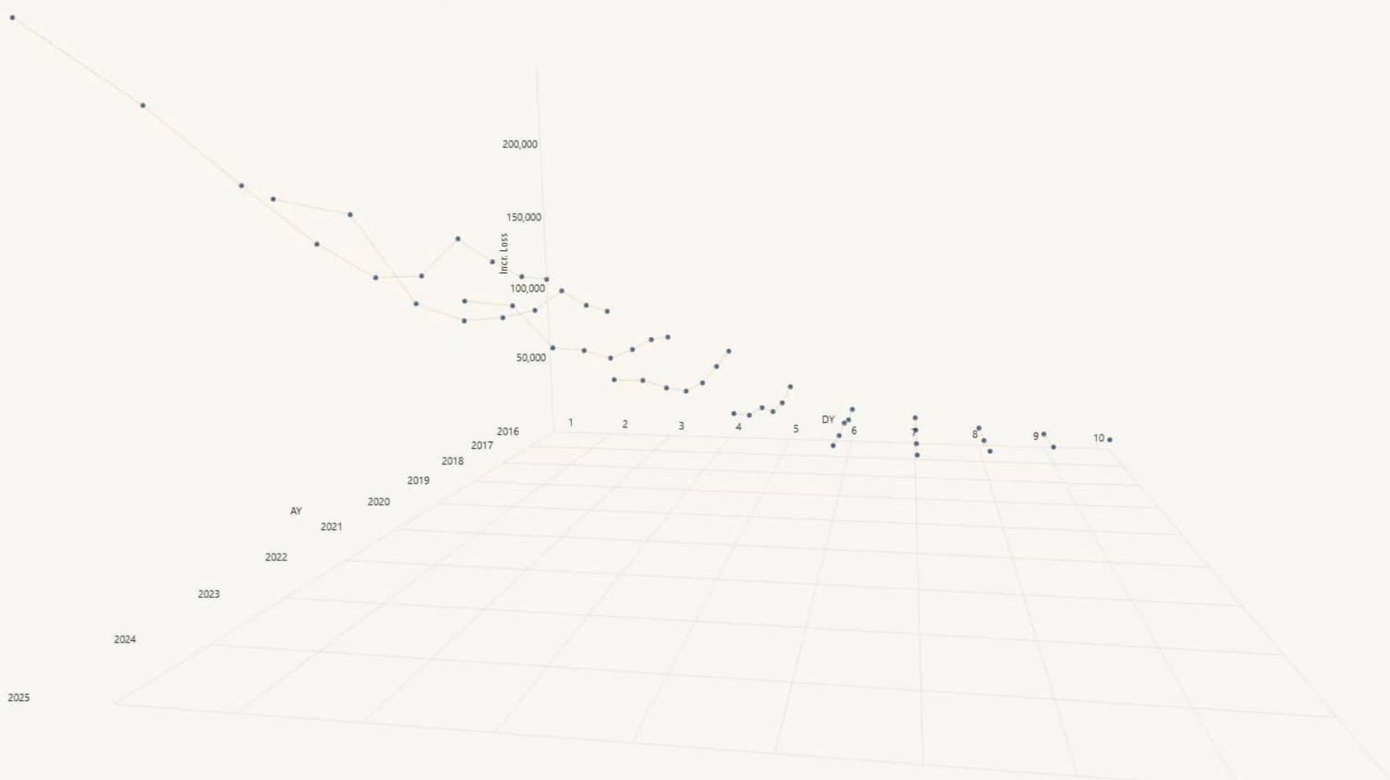

...and some subtle gridlines to help visualize the patterns.

Paid Loss Incremental

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2016	107,757	86,328	69,237	60,311	36,749	22,219	17,643	11,787	9,035	6,474
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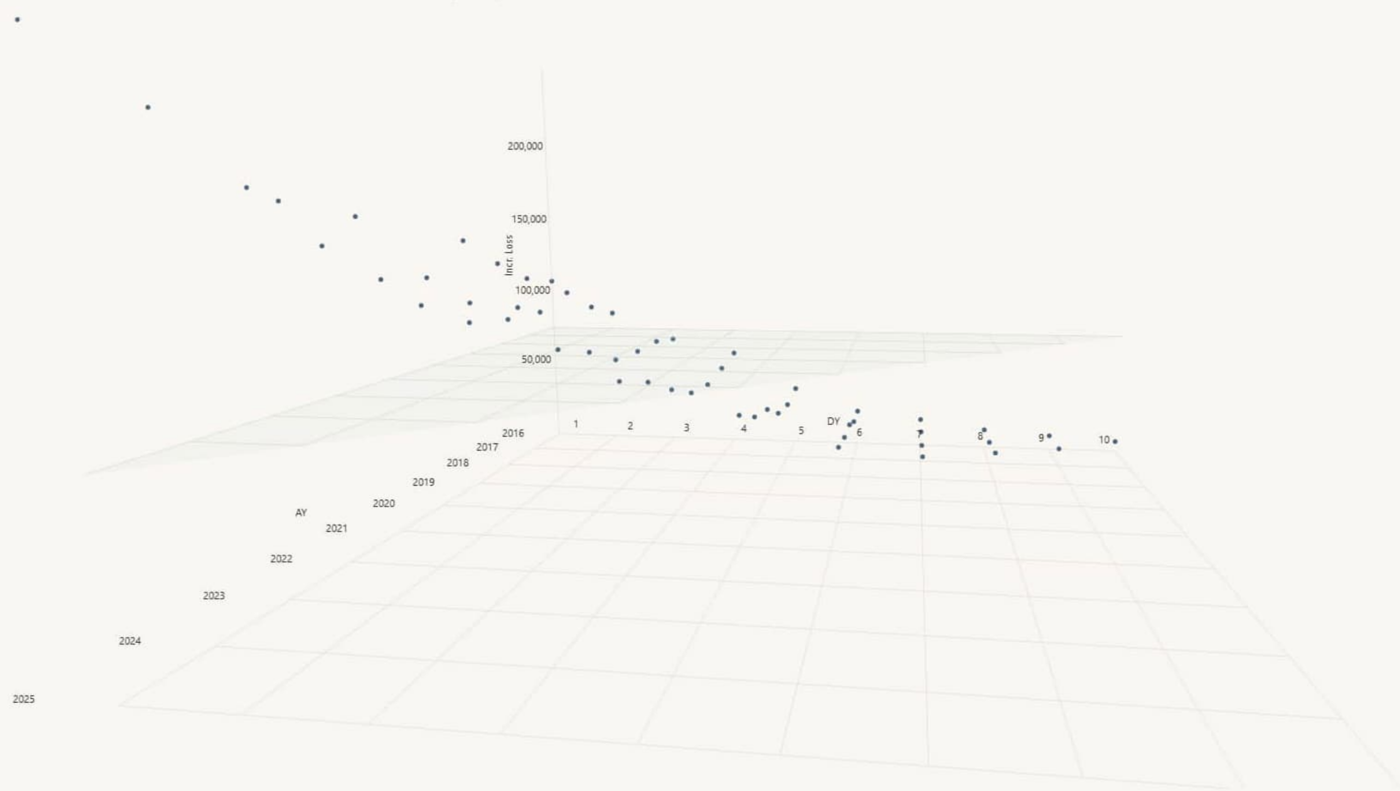


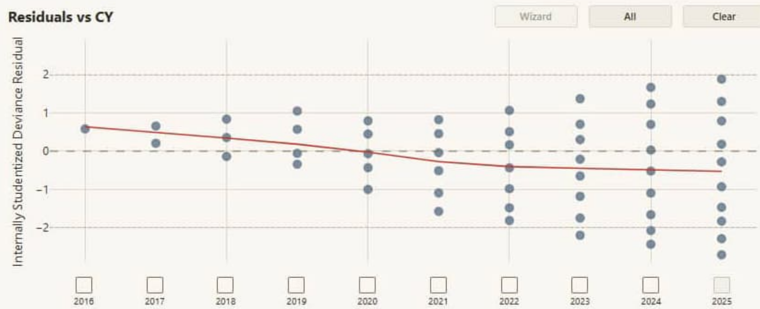
Let's now begin modeling these incremental losses. Prior to adding any parameters or breakpoints, we only have a constant equal to the average of all data points.

Residuals vs DY

Wizard selection: DY_1

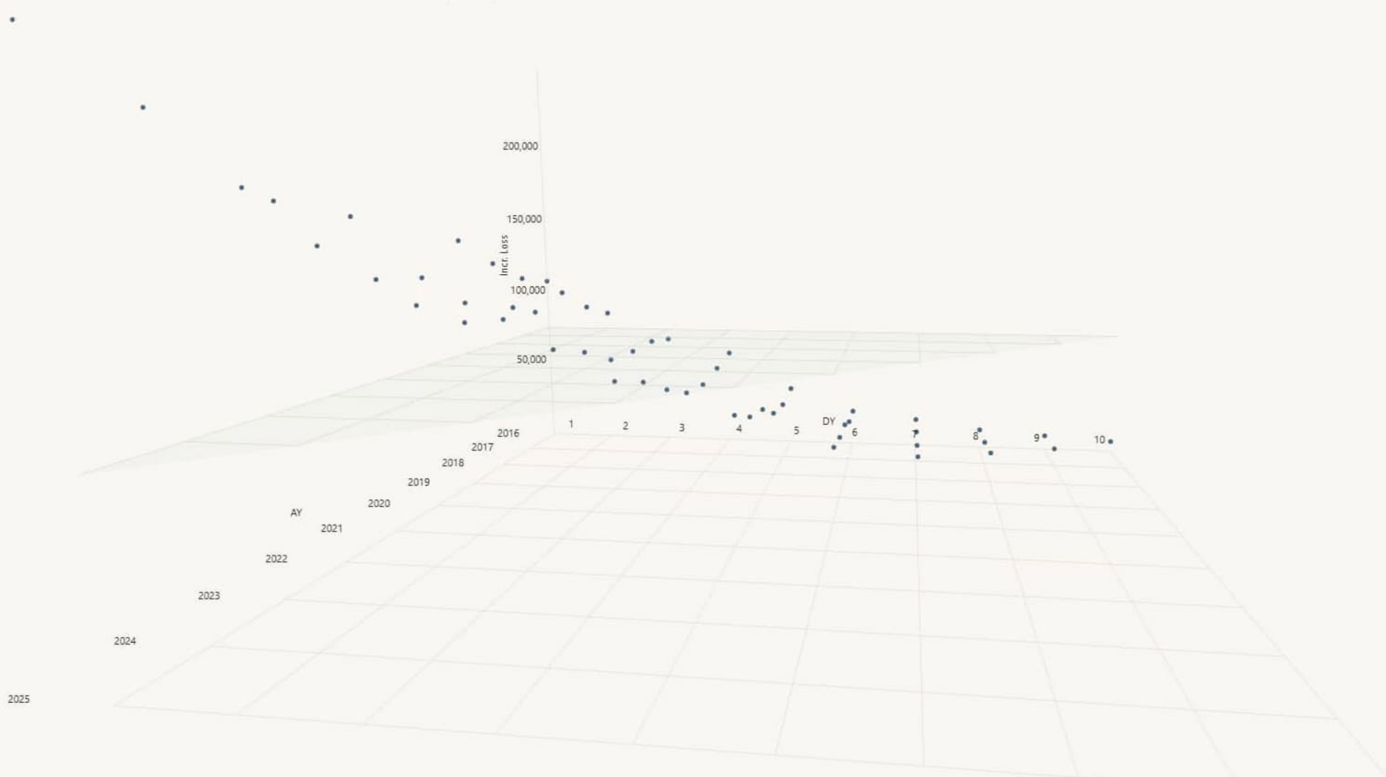
DY	1	2	3	4	5	6	7	8	9	10	Tail
Incr. Decay	—	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
± SE	—	—	—	—	—	—	—	—	—	—	—
t-stat	—	—	—	—	—	—	—	—	—	—	—
p-value	—	—	—	—	—	—	—	—	—	—	—

Residuals vs CY



CY	2016	2017	2018	2019	2020	2021	2022	2023	2024	2025	Future
Trend	—	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
± SE	—	—	—	—	—	—	—	—	—	—	—
t-stat	—	—	—	—	—	—	—	—	—	—	—
p-value	—	—	—	—	—	—	—	—	—	—	—

Modeled Paid Loss vs Observed — 3D, Incremental Dollar Scale ($000s)



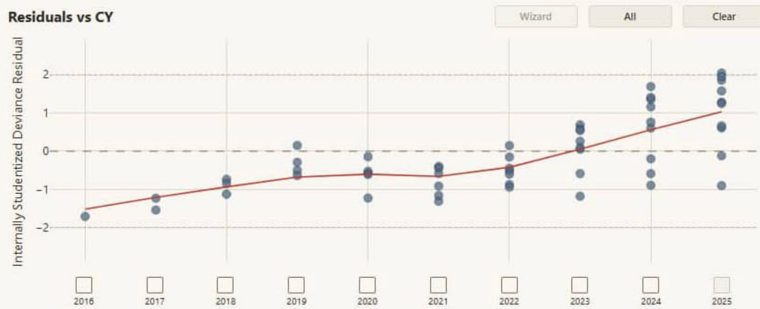
Clearly, the incremental losses are decreasing across development year, easily visible in both the 3-D graph and the residual graph above.

Residuals vs DY

Wizard selection: DY_1

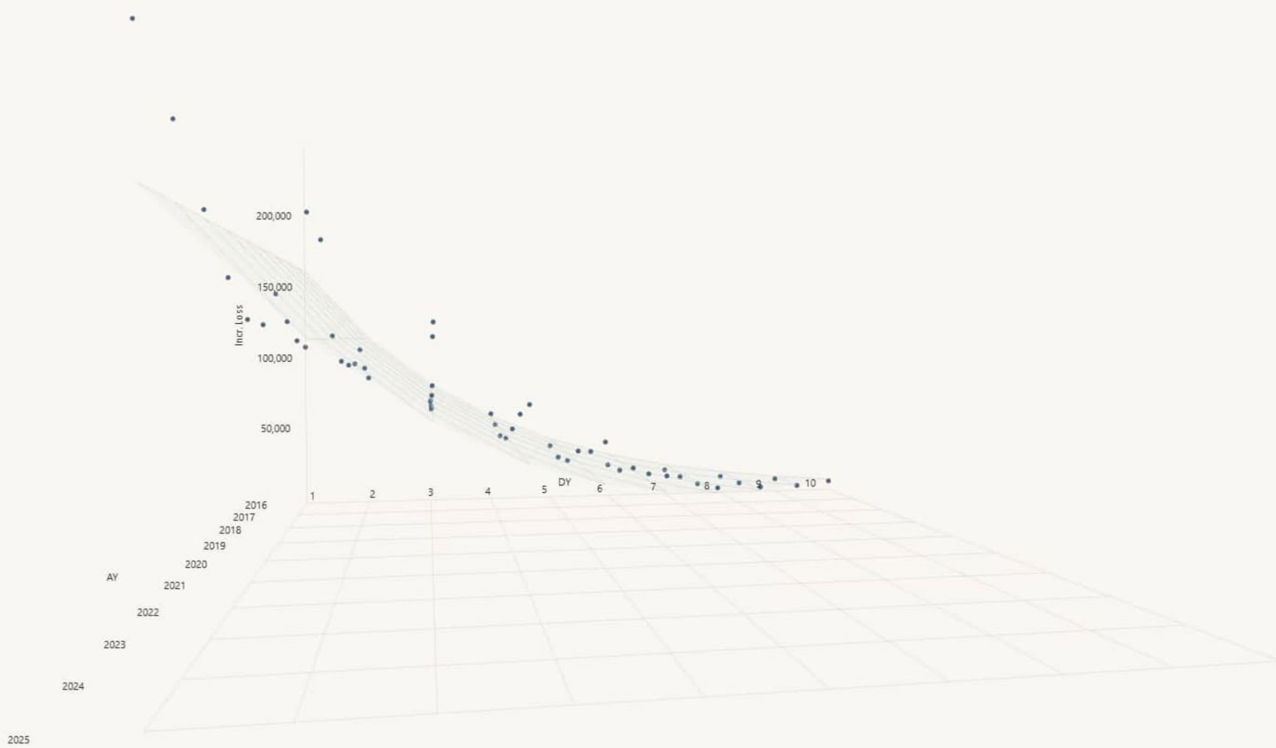
DY	1	2	3	4	5	6	7	8	9	10	Tail
Incr. Decay	—	-28.4%	-28.4%	-28.4%	-28.4%	-28.4%	-28.4%	-28.4%	-28.4%	-28.4%	-28.4%
± SE	—	±0.9%	±0.9%	±0.9%	±0.9%	±0.9%	±0.9%	±0.9%	±0.9%	±0.9%	±0.9%
t-stat	—	-27.8	—	—	—	—	—	—	—	—	—
p-value	—	<.001	—	—	—	—	—	—	—	—	—

Residuals vs CY



CY	2016	2017	2018	2019	2020	2021	2022	2023	2024	2025	Future
Trend	—	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
± SE	—	—	—	—	—	—	—	—	—	—	—
t-stat	—	—	—	—	—	—	—	—	—	—	—
p-value	—	—	—	—	—	—	—	—	—	—	—

Modeled Paid Loss vs Observed — 3D, Incremental Dollar Scale ($000s)



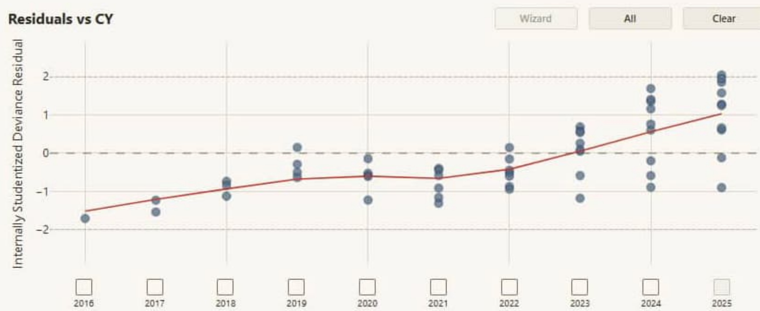
Adding a single DY parameter clearly improves the model. Remember, behind the scenes, the model is linear in the log of the data, so we see an exponential result on a dollar scale.

Residuals vs DY

Wizard selection: DY_1

DY	1	2	3	4	5	6	7	8	9	10	Tail
Incr. Decay	—	-28.4%	-28.4%	-28.4%	-28.4%	-28.4%	-28.4%	-28.4%	-28.4%	-28.4%	-28.4%
± SE	—	±0.9%	±0.9%	±0.9%	±0.9%	±0.9%	±0.9%	±0.9%	±0.9%	±0.9%	±0.9%
t-stat	—	-27.8	—	—	—	—	—	—	—	—	—
p-value	—	<.001	—	—	—	—	—	—	—	—	—

Residuals vs CY



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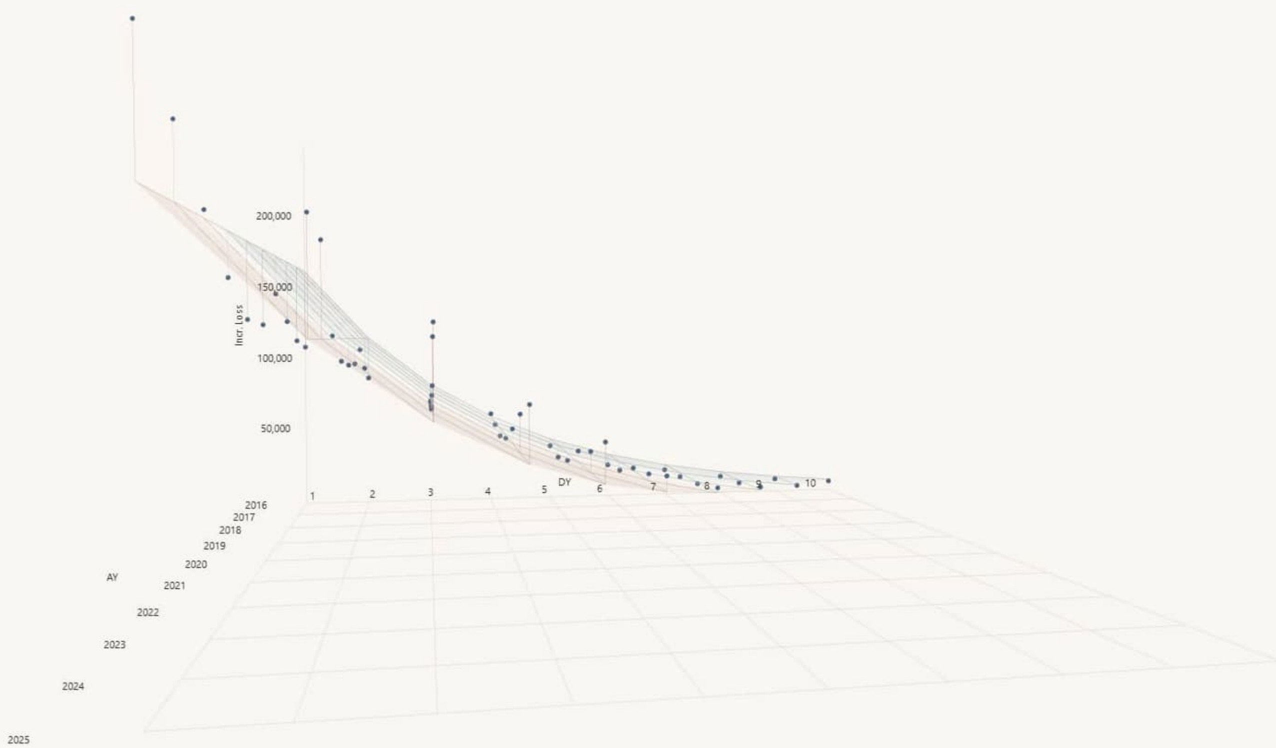
± SE	—	—	—	—	—	—	—	—	—	—	—
t-stat	—	—	—	—	—	—	—	—	—	—	—
p-value	—	—	—	—	—	—	—	—	—	—	—

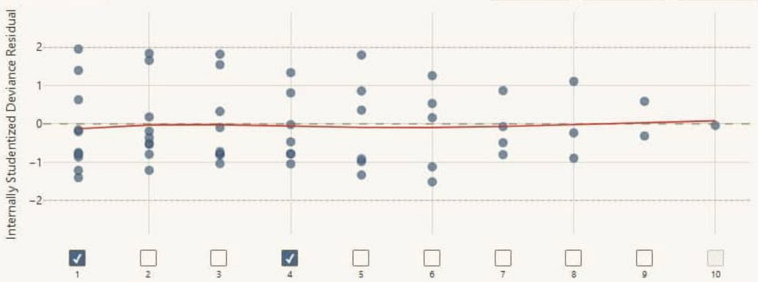
Modeled Paid Loss vs Observed — 3D, Incremental Dollar Scale ($000s)



Let's add a heat map to the model plane and vertical lines between the model plane and the observed data to help with the visualization. Based on the residual graph, there is a change in slope after DY 4.

Residuals vs DY

Wizard selection: DY_1

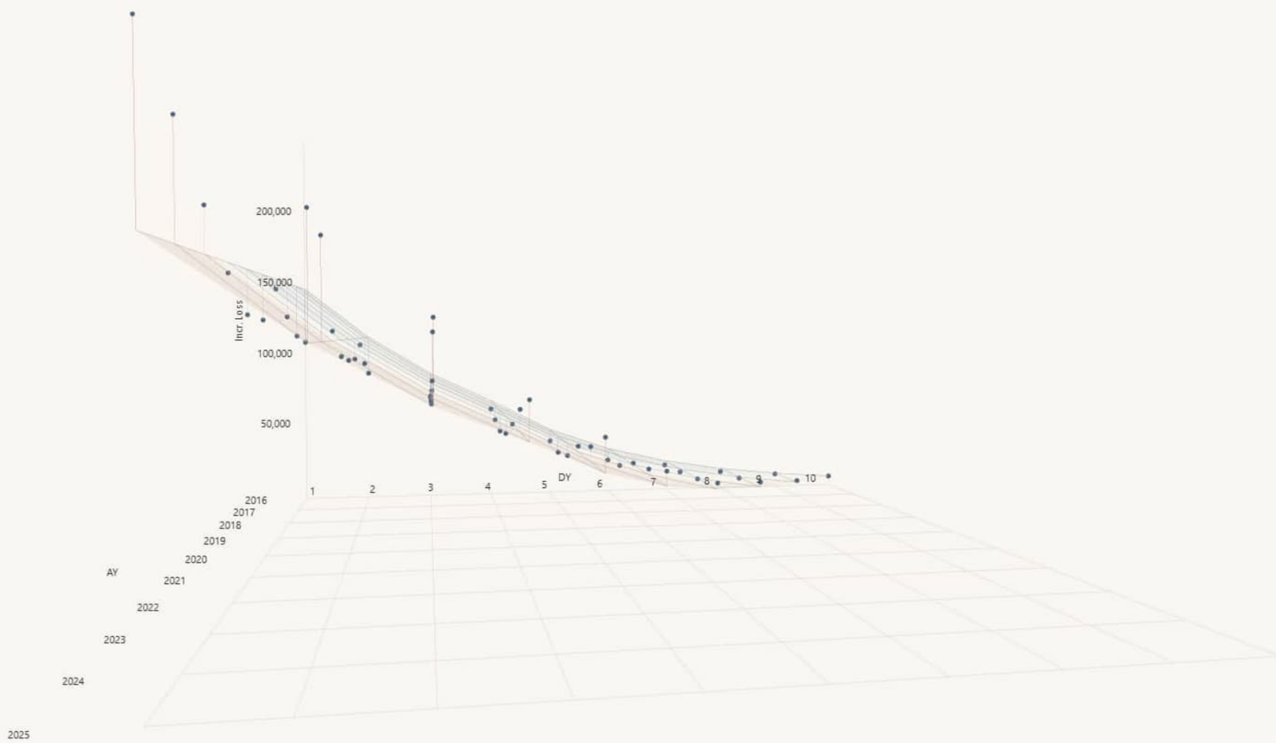


DY	1	2	3	4	5	6	7	8	9	10	Tail
Incr. Decay	—	-22.8%	-22.8%	-22.8%	-32.1%	-32.1%	-32.1%	-32.1%	-32.1%	-32.1%	-32.1%
± SE	—	±2.1%	±2.1%	±2.1%	±1.4%	±1.4%	±1.4%	±1.4%	±1.4%	±1.4%	±1.4%
t-stat	—	-9.3	—	—	-3.0	—	—	—	—	—	—
p-value	—	<.001	—	—	0.003	—	—	—	—	—	—

Residuals vs CY

CY	2016	2017	2018	2019	2020	2021	2022	2023	2024	2025	Future
Trend	—	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
± SE	—	—	—	—	—	—	—	—	—	—	—
t-stat	—	—	—	—	—	—	—	—	—	—	—
p-value	—	—	—	—	—	—	—	—	—	—	—

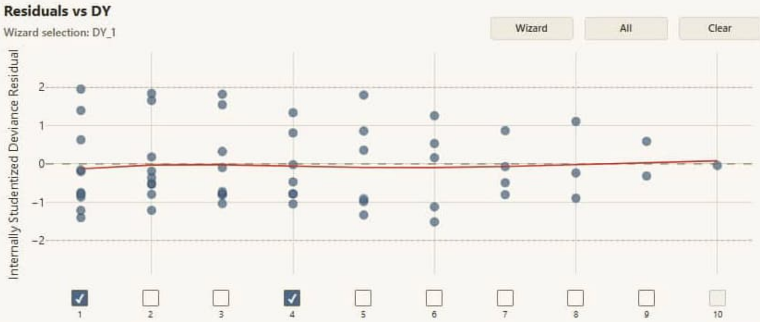
Modeled Paid Loss vs Observed — 3D, Incremental Dollar Scale ($000s)



Selecting a breakpoint at DY 4 flattens out the DY residual graph. The model currently varies only by development year, indicating a decrease in incremental loss of 22.8% per year through year 4, then 32.1% in year 5 and beyond.

Residuals vs DY

Wizard selection: DY_1

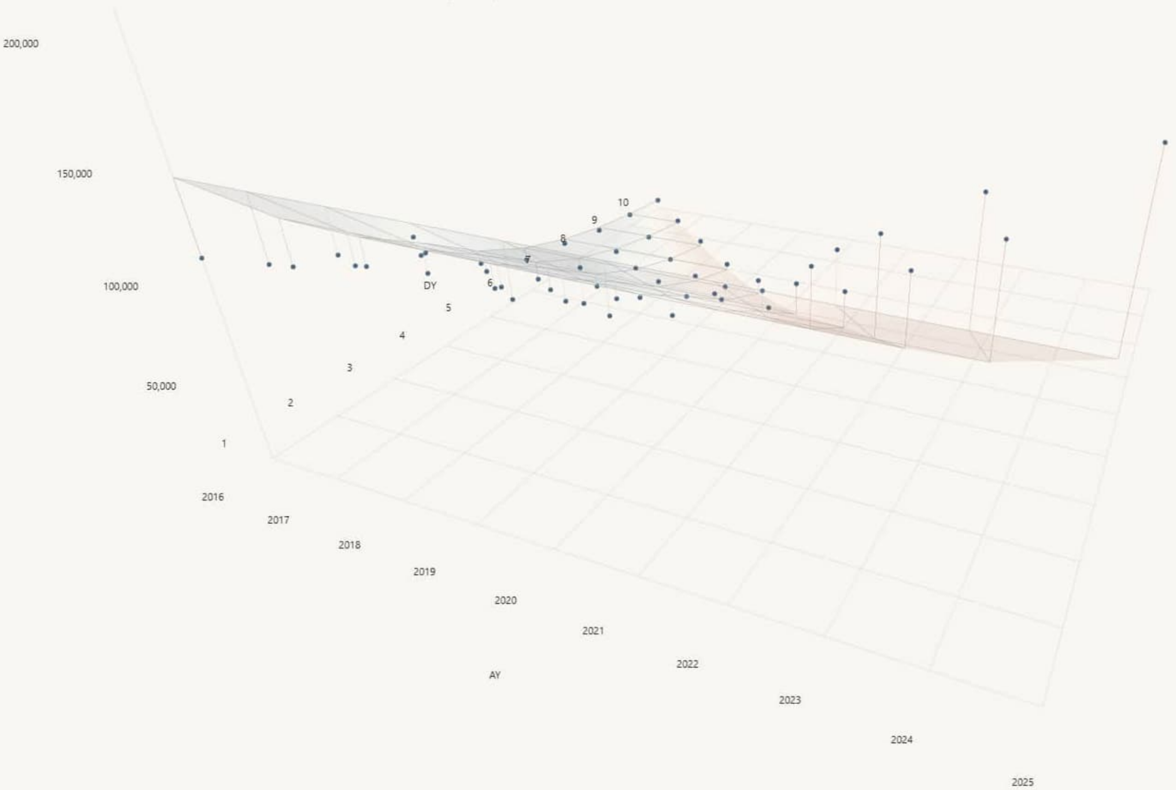


DY	1	2	3	4	5	6	7	8	9	10	Tail
Incr. Decay	—	-22.8%	-22.8%	-22.8%	-32.1%	-32.1%	-32.1%	-32.1%	-32.1%	-32.1%	-32.1%
± SE	—	±2.1%	±2.1%	±2.1%	±1.4%	±1.4%	±1.4%	±1.4%	±1.4%	±1.4%	±1.4%
t-stat	—	-9.3	—	—	-3.0	—	—	—	—	—	—
p-value	—	<.001	—	—	0.003	—	—	—	—	—	—

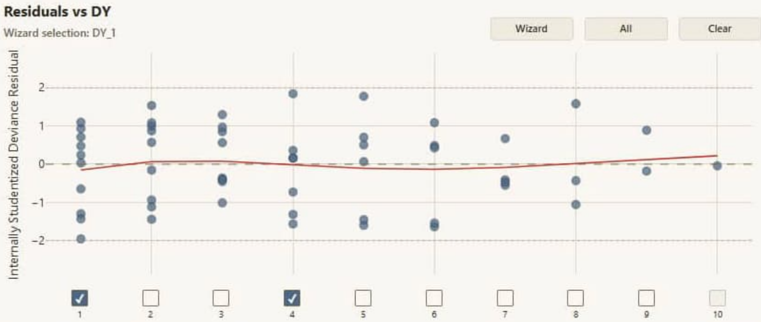
Residuals vs CY

CY	2016	2017	2018	2019	2020	2021	2022	2023	2024	2025	Future
Trend	—	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
± SE	—	—	—	—	—	—	—	—	—	—	—
t-stat	—	—	—	—	—	—	—	—	—	—	—
p-value	—	—	—	—	—	—	—	—	—	—	—

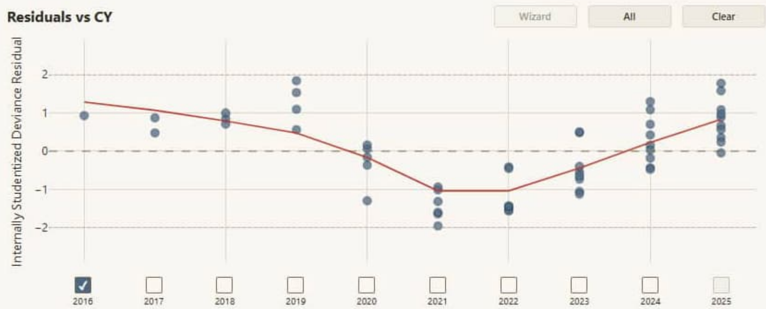
Modeled Paid Loss vs Observed — 3D, Incremental Dollar Scale ($000s)



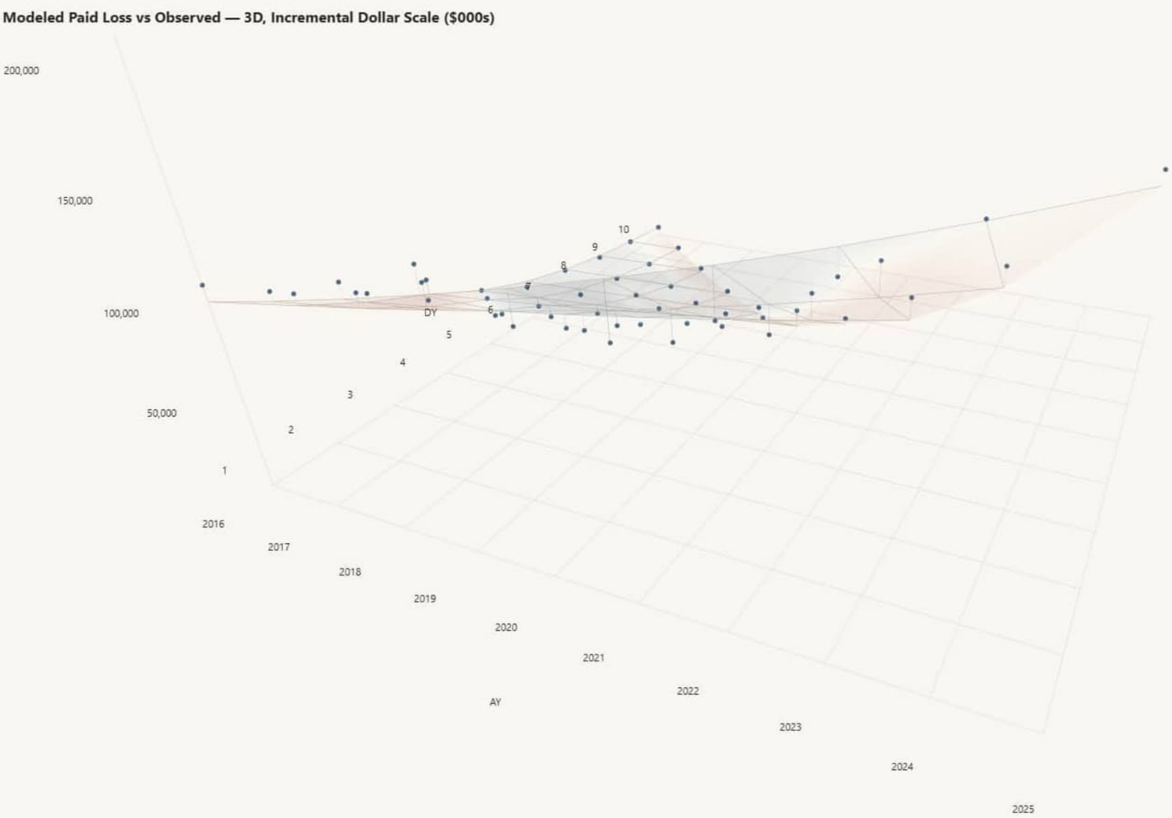
Looking at the 3-D rendering and the residual graph, there are clearly some CY trends in our data as well.



DY	1	2	3	4	5	6	7	8	9	10	Tail
Incr. Decay	—	-25.7%	-25.7%	-25.7%	-34.5%	-34.5%	-34.5%	-34.5%	-34.5%	-34.5%	-34.5%
± SE	—	±1.0%	±1.0%	±1.0%	±0.6%	±0.6%	±0.6%	±0.6%	±0.6%	±0.6%	±0.6%
t-stat	—	-23.0	—	—	-6.5	—	—	—	—	—	—
p-value	—	<.001	—	—	<.001	—	—	—	—	—	—



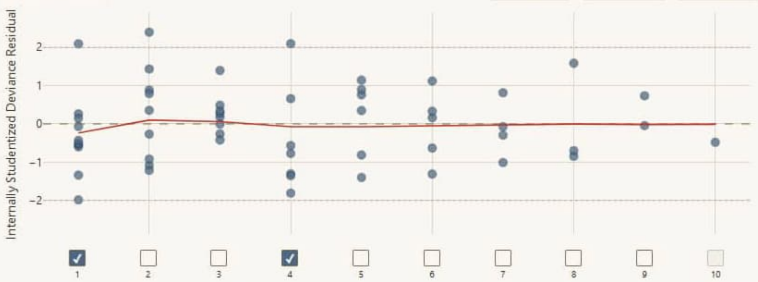
CY	2016	2017	2018	2019	2020	2021	2022	2023	2024	2025	Future
Trend	—	+8.1%	+8.1%	+8.1%	+8.1%	+8.1%	+8.1%	+8.1%	+8.1%	+8.1%	+8.1%
± SE	—	±0.6%	±0.6%	±0.6%	±0.6%	±0.6%	±0.6%	±0.6%	±0.6%	±0.6%	±0.6%
t-stat	—	13.3	—	—	—	—	—	—	—	—	—
p-value	—	<.001	—	—	—	—	—	—	—	—	—



Picking a single CY trend factor results in an estimate of +8.1% per year, but looking closer we see the trend seems to vary. The residuals bottom out in CY 2021 before turning upward– the same pattern we see in the 3-D graph, with observations falling below the model.

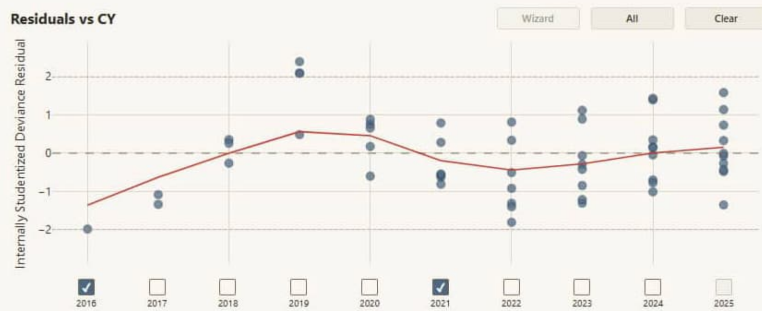
Residuals vs DY

Wizard selection: DY_1



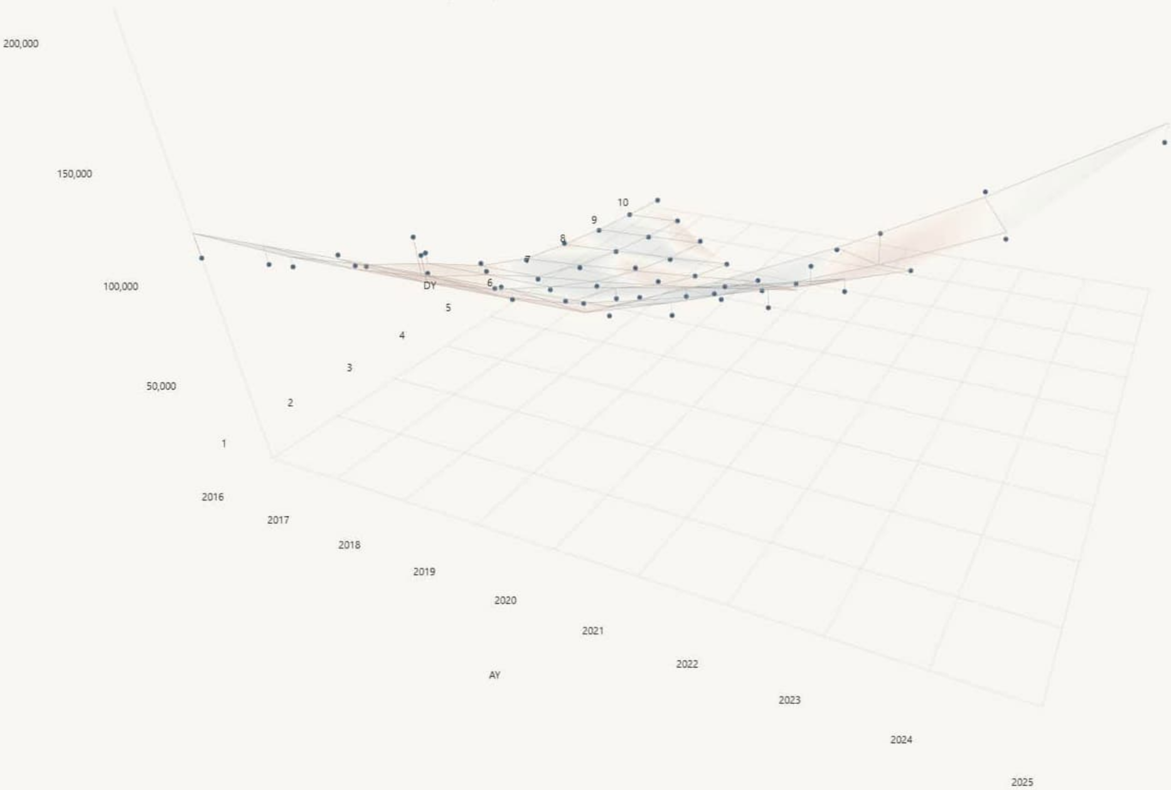
DY	1	2	3	4	5	6	7	8	9	10	Tail
Incr. Decay	—	-24.2%	-24.2%	-24.2%	-35.4%	-35.4%	-35.4%	-35.4%	-35.4%	-35.4%	-35.4%
± SE	—	±0.6%	±0.6%	±0.6%	±0.4%	±0.4%	±0.4%	±0.4%	±0.4%	±0.4%	±0.4%
t-stat	—	-32.6	—	—	-12.5	—	—	—	—	—	—
p-value	—	<.001	—	—	<.001	—	—	—	—	—	—

Residuals vs CY



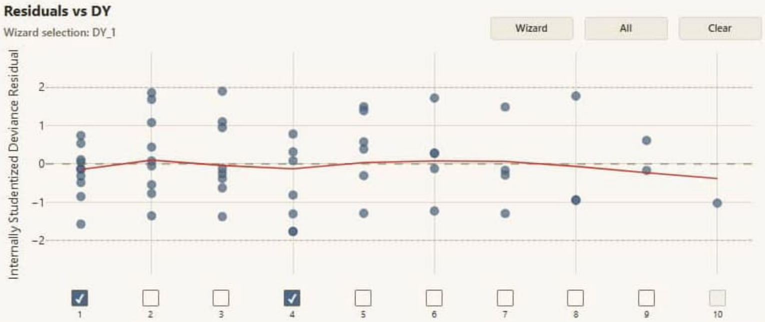
CY	2016	2017	2018	2019	2020	2021	2022	2023	2024	2025	Future
Trend	—	+1.2%	+1.2%	+1.2%	+1.2%	+1.2%	+13.5%	+13.5%	+13.5%	+13.5%	+13.5%
± SE	—	±0.8%	±0.8%	±0.8%	±0.8%	±0.8%	±0.7%	±0.7%	±0.7%	±0.7%	±0.7%
t-stat	—	1.5	—	—	—	—	9.1	—	—	—	—
p-value	—	0.14	—	—	—	—	<.001	—	—	—	—

Modeled Paid Loss vs Observed — 3D, Incremental Dollar Scale ($000s)



Adding a CY 2021 breakpoint shows the trend clearly varied before and after, but it appears there is another change in slope at CY 2019.

Residuals vs DY

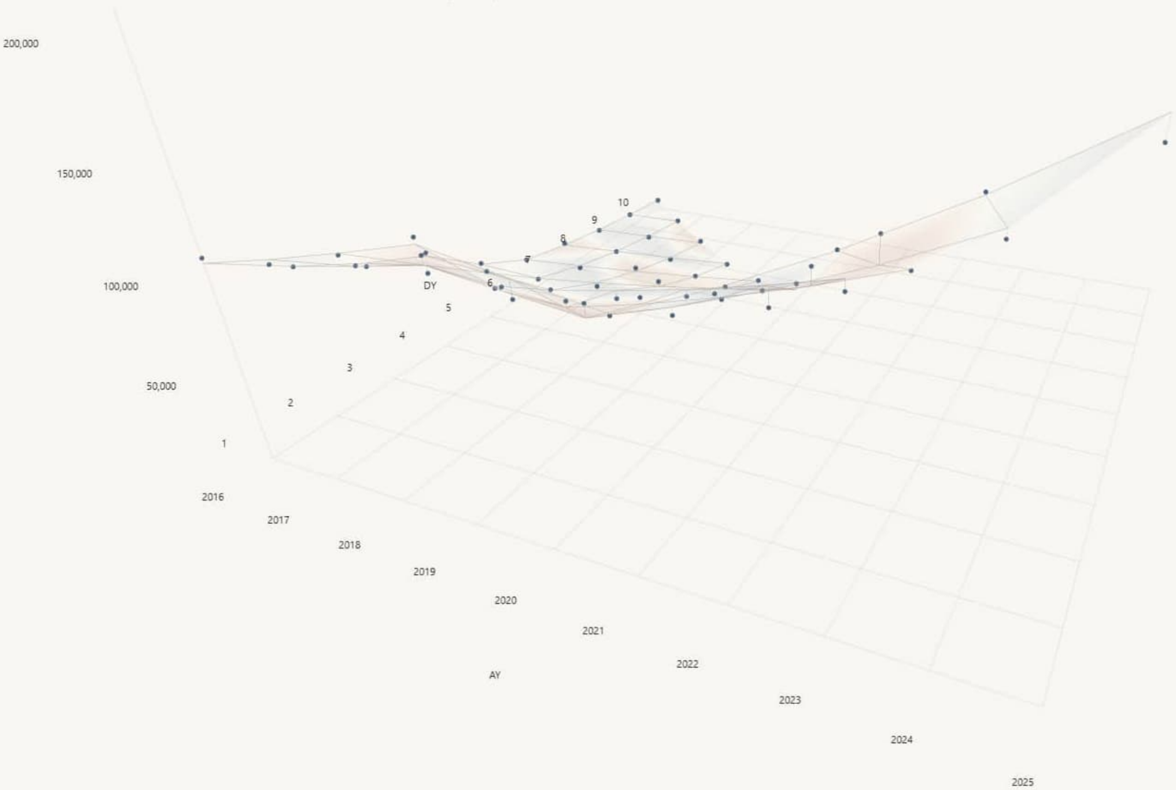


DY	1	2	3	4	5	6	7	8	9	10	Tail
Incr. Decay	—	-24.5%	-24.5%	-24.5%	-35.3%	-35.3%	-35.3%	-35.3%	-35.3%	-35.3%	-35.3%
± SE	—	±0.5%	±0.5%	±0.5%	±0.3%	±0.3%	±0.3%	±0.3%	±0.3%	±0.3%	±0.3%
t-stat	—	-42.4	—	—	-15.4	—	—	—	—	—	—
p-value	—	<.001	—	—	<.001	—	—	—	—	—	—

Residuals vs CY

CY	2016	2017	2018	2019	2020	2021	2022	2023	2024	2025	Future
Trend	—	+8.8%	+8.8%	+8.8%	-4.5%	-4.5%	+14.5%	+14.5%	+14.5%	+14.5%	+14.5%
± SE	—	±1.5%	±1.5%	±1.5%	±1.1%	±1.1%	±0.6%	±0.6%	±0.6%	±0.6%	±0.6%
t-stat	—	6.0	—	—	-5.7	—	11.8	—	—	—	—
p-value	—	<.001	—	—	<.001	—	<.001	—	—	—	—

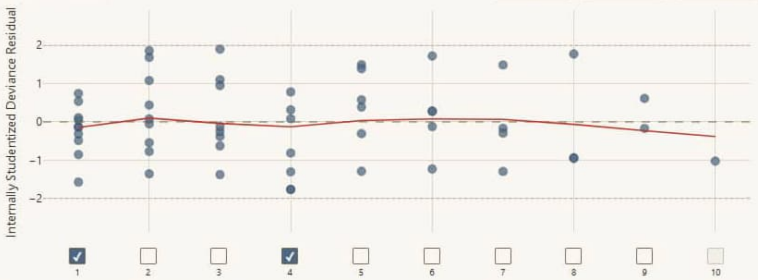
Modeled Paid Loss vs Observed — 3D, Incremental Dollar Scale ($000s)



Adding a CY 2019 breakpoint as well shows this data contains a common pattern seen in the industry: high CY trends prior to the pandemic, with low to negative trends during 2020-21 due to the lockdowns and court backlogs, followed by higher recent trends.

Residuals vs DY

Wizard selection: DY_1

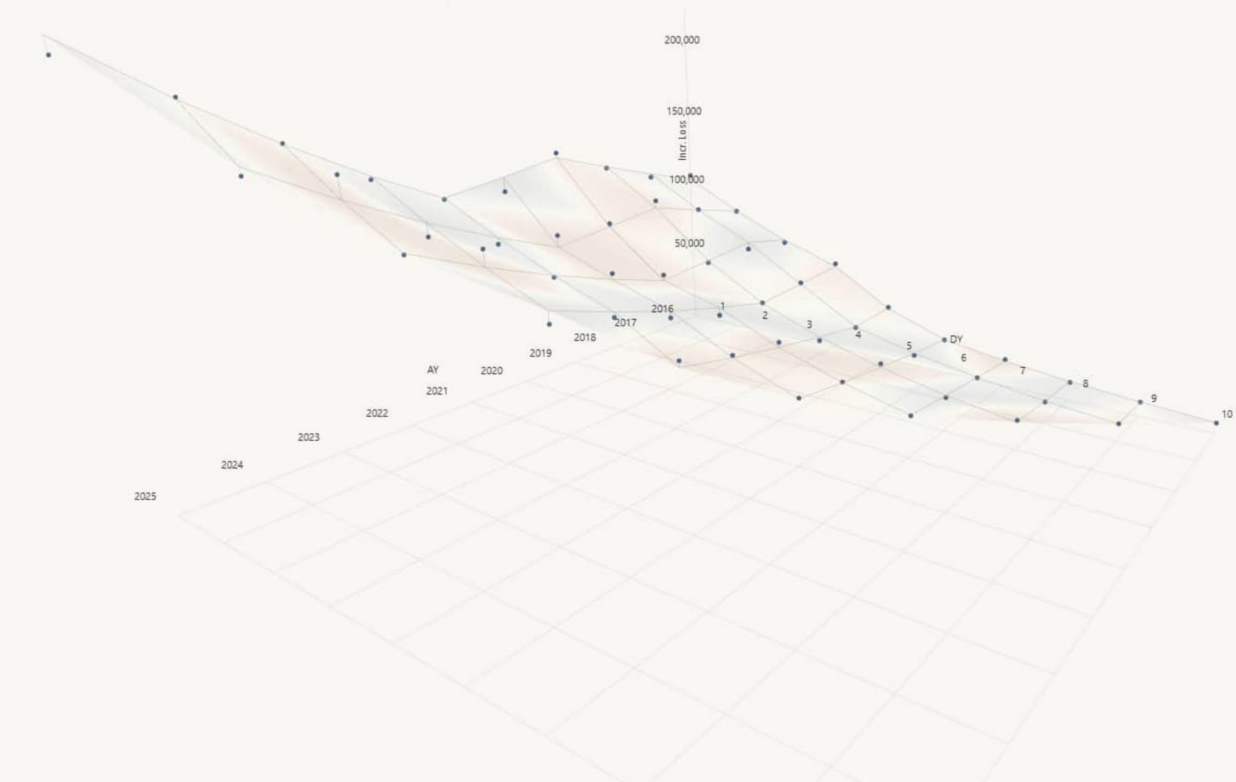


DY	1	2	3	4	5	6	7	8	9	10	Tail
Incr. Decay	—	-24.5%	-24.5%	-24.5%	-35.3%	-35.3%	-35.3%	-35.3%	-35.3%	-35.3%	-35.3%
± SE	—	±0.5%	±0.5%	±0.5%	±0.3%	±0.3%	±0.3%	±0.3%	±0.3%	±0.3%	±0.3%
t-stat	—	-42.4	—	—	-15.4	—	—	—	—	—	—
p-value	—	<.001	—	—	<.001	—	—	—	—	—	—

Residuals vs CY

CY	2016	2017	2018	2019	2020	2021	2022	2023	2024	2025	Future
Trend	—	+8.8%	+8.8%	+8.8%	-4.5%	-4.5%	+14.5%	+14.5%	+14.5%	+14.5%	+14.5%
± SE	—	±1.5%	±1.5%	±1.5%	±1.1%	±1.1%	±0.6%	±0.6%	±0.6%	±0.6%	±0.6%
t-stat	—	6.0	—	—	-5.7	—	11.8	—	—	—	—
p-value	—	<.001	—	—	<.001	—	<.001	—	—	—	—

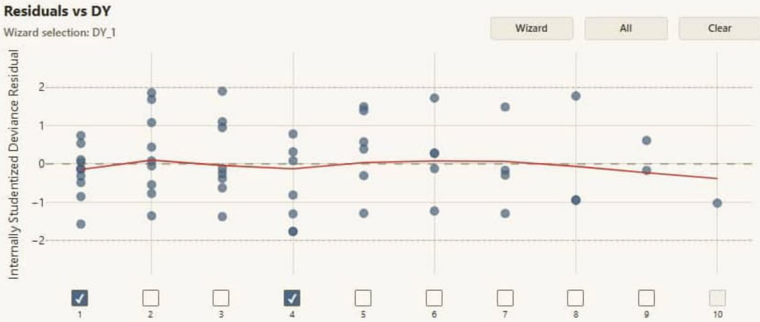
Modeled Paid Loss vs Observed — 3D, Incremental Dollar Scale ($000s)



We now have a model that fits our data very well, properly modeling the CY trends present in the data, with just 5 parameters. Recall that the traditional development method uses 20 parameters for a 10 x 10 triangle.

Residuals vs DY

Wizard selection: DY_1

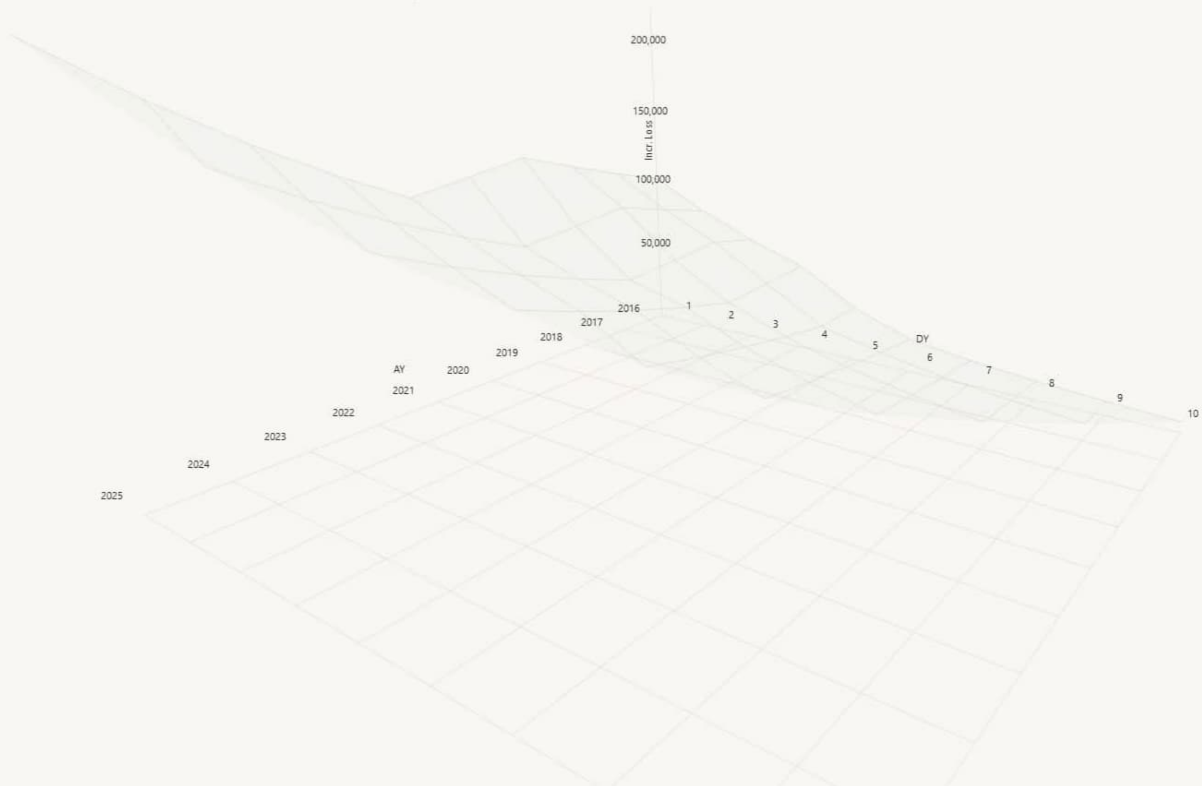


DY	1	2	3	4	5	6	7	8	9	10	Tail
Incr. Decay	—	-24.5%	-24.5%	-24.5%	-35.3%	-35.3%	-35.3%	-35.3%	-35.3%	-35.3%	-35.3%
± SE	—	±0.5%	±0.5%	±0.5%	±0.3%	±0.3%	±0.3%	±0.3%	±0.3%	±0.3%	±0.3%
t-stat	—	-42.4	—	—	-15.4	—	—	—	—	—	—
p-value	—	<.001	—	—	<.001	—	—	—	—	—	—

Residuals vs CY

CY	2016	2017	2018	2019	2020	2021	2022	2023	2024	2025	Future
Trend	—	+8.8%	+8.8%	+8.8%	-4.5%	-4.5%	+14.5%	+14.5%	+14.5%	+14.5%	+14.5%
± SE	—	±1.5%	±1.5%	±1.5%	±1.1%	±1.1%	±0.6%	±0.6%	±0.6%	±0.6%	±0.6%
t-stat	—	6.0	—	—	-5.7	—	11.8	—	—	—	—
p-value	—	<.001	—	—	<.001	—	<.001	—	—	—	—

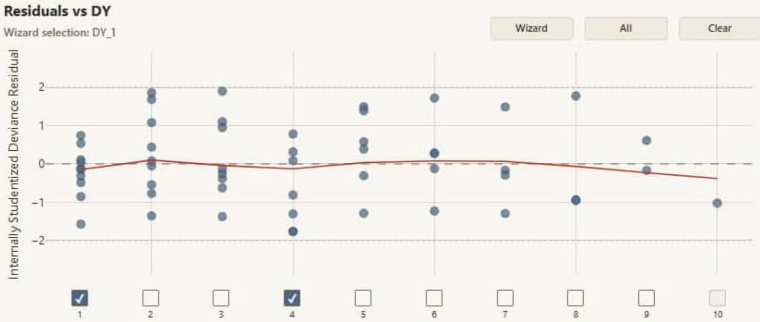
Modeled Paid Loss vs Observed — 3D, Incremental Dollar Scale ($000s)



It's important to know that these methods do not "develop" losses. Losses are predicted by the selected model form and the parameters, not by leveraging the latest diagonal (beyond its effect on the parameters).

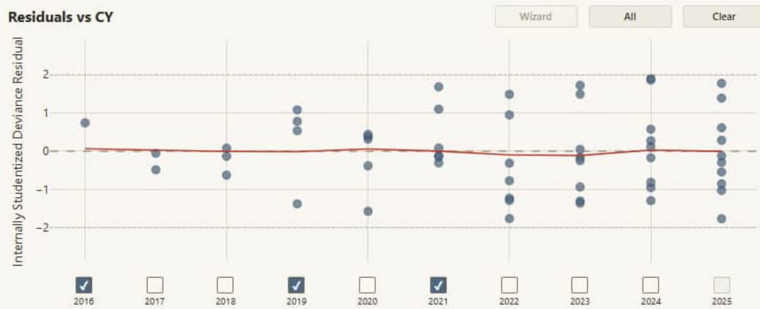
Residuals vs DY

Wizard selection: DY_1



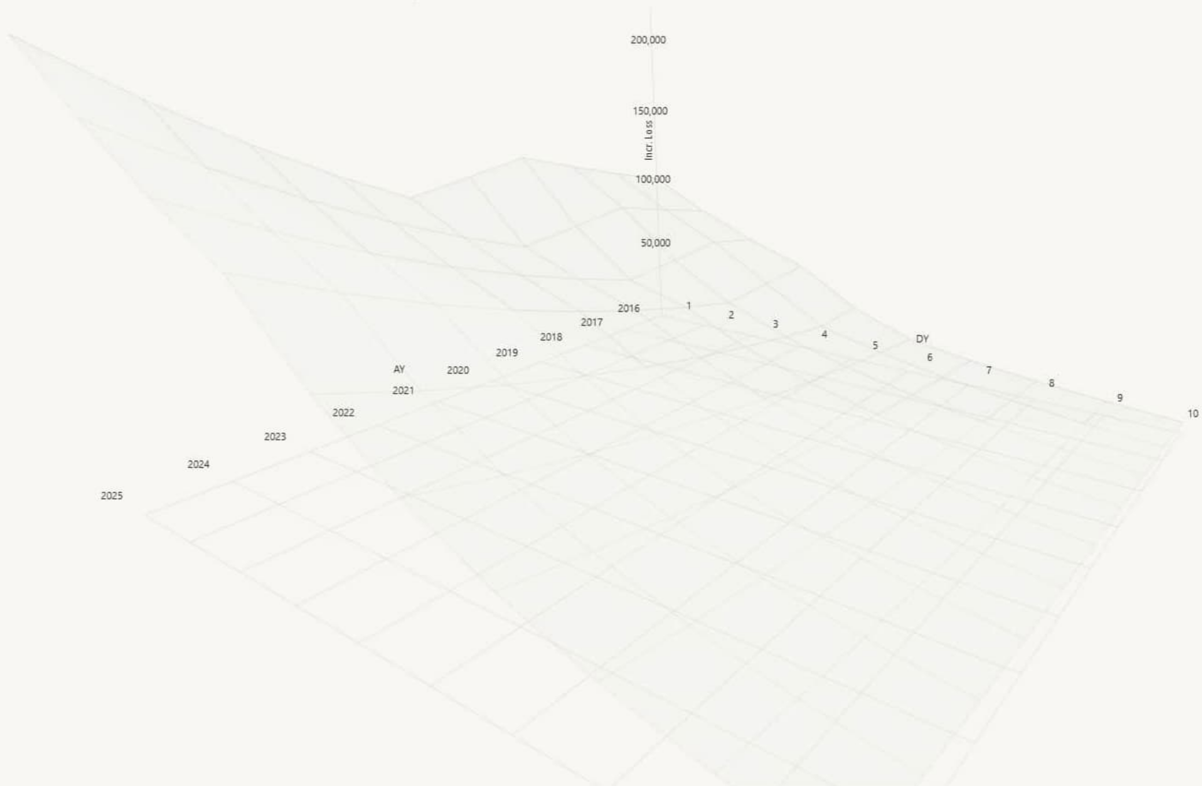
DY	1	2	3	4	5	6	7	8	9	10	Tail
Incr. Decay	—	-24.5%	-24.5%	-24.5%	-35.3%	-35.3%	-35.3%	-35.3%	-35.3%	-35.3%	-35.3%
± SE	—	±0.5%	±0.5%	±0.5%	±0.3%	±0.3%	±0.3%	±0.3%	±0.3%	±0.3%	±0.3%
t-stat	—	-42.4	—	—	-15.4	—	—	—	—	—	—
p-value	—	<.001	—	—	<.001	—	—	—	—	—	—

Residuals vs CY



CY	2016	2017	2018	2019	2020	2021	2022	2023	2024	2025	Future
Trend	—	+8.8%	+8.8%	+8.8%	-4.5%	-4.5%	+14.5%	+14.5%	+14.5%	+14.5%	+14.5%
± SE	—	±1.5%	±1.5%	±1.5%	±1.1%	±1.1%	±0.6%	±0.6%	±0.6%	±0.6%	±0.6%
t-stat	—	6.0	—	—	-5.7	—	11.8	—	—	—	—
p-value	—	<.001	—	—	<.001	—	<.001	—	—	—	—

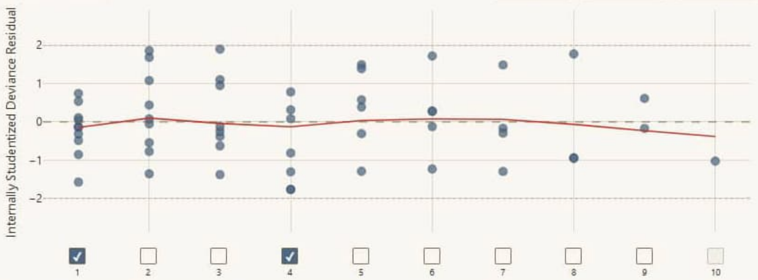
Modeled Paid Loss vs Observed — 3D, Incremental Dollar Scale ($000s)



Using these parameters (and future CY assumptions which we'll cover shortly), we can predict the bottom half of the triangle.

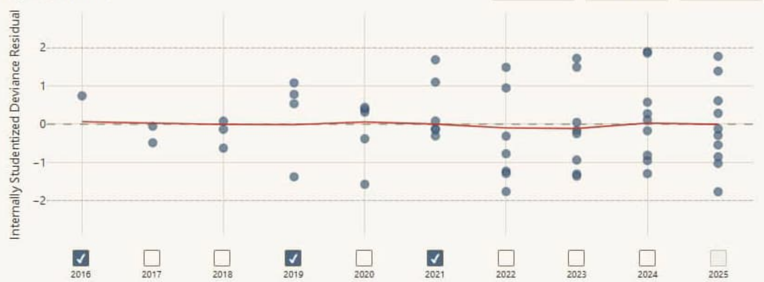
Residuals vs DY

Wizard selection: DY_1



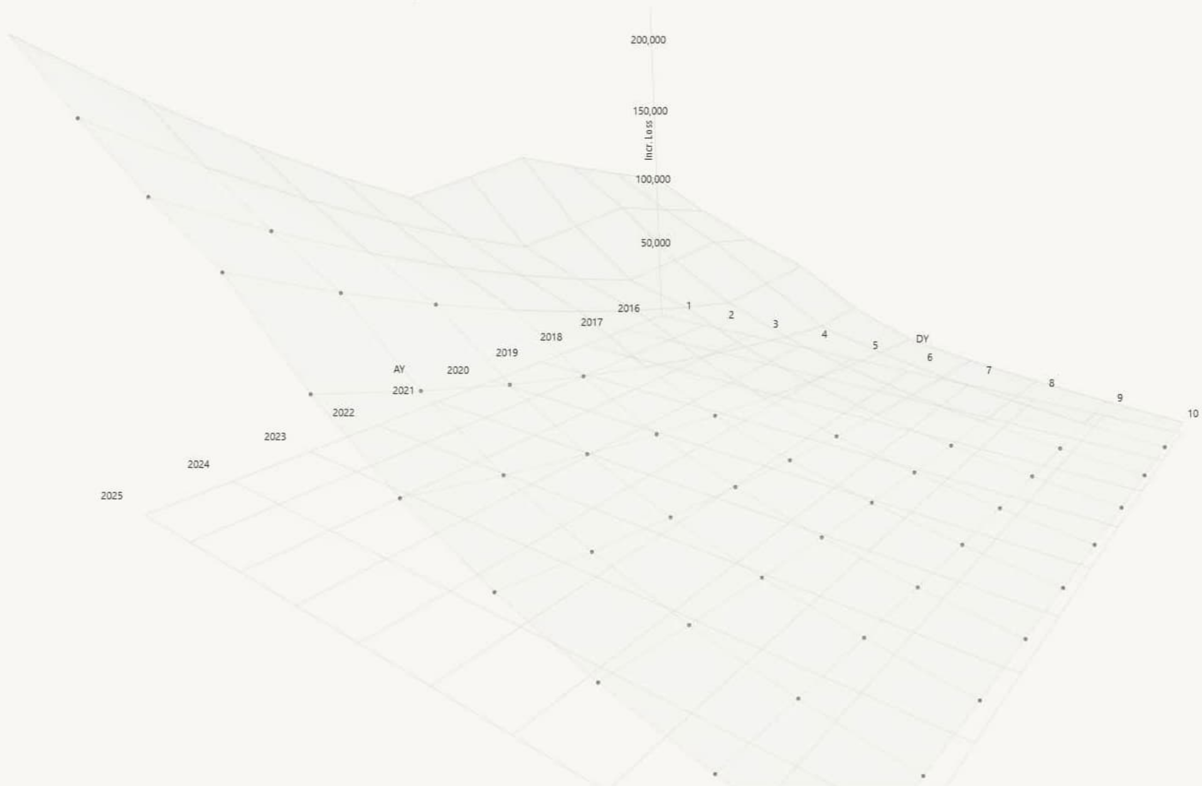
DY	1	2	3	4	5	6	7	8	9	10	Tail
Incr. Decay	—	-24.5%	-24.5%	-24.5%	-35.3%	-35.3%	-35.3%	-35.3%	-35.3%	-35.3%	-35.3%
± SE	—	±0.5%	±0.5%	±0.5%	±0.3%	±0.3%	±0.3%	±0.3%	±0.3%	±0.3%	±0.3%
t-stat	—	-42.4	—	—	-15.4	—	—	—	—	—	—
p-value	—	<.001	—	—	<.001	—	—	—	—	—	—

Residuals vs CY



CY	2016	2017	2018	2019	2020	2021	2022	2023	2024	2025	Future
Trend	—	+8.8%	+8.8%	+8.8%	-4.5%	-4.5%	+14.5%	+14.5%	+14.5%	+14.5%	+14.5%
± SE	—	±1.5%	±1.5%	±1.5%	±1.1%	±1.1%	±0.6%	±0.6%	±0.6%	±0.6%	±0.6%
t-stat	—	6.0	—	—	-5.7	—	11.8	—	—	—	—
p-value	—	<.001	—	—	<.001	—	<.001	—	—	—	—

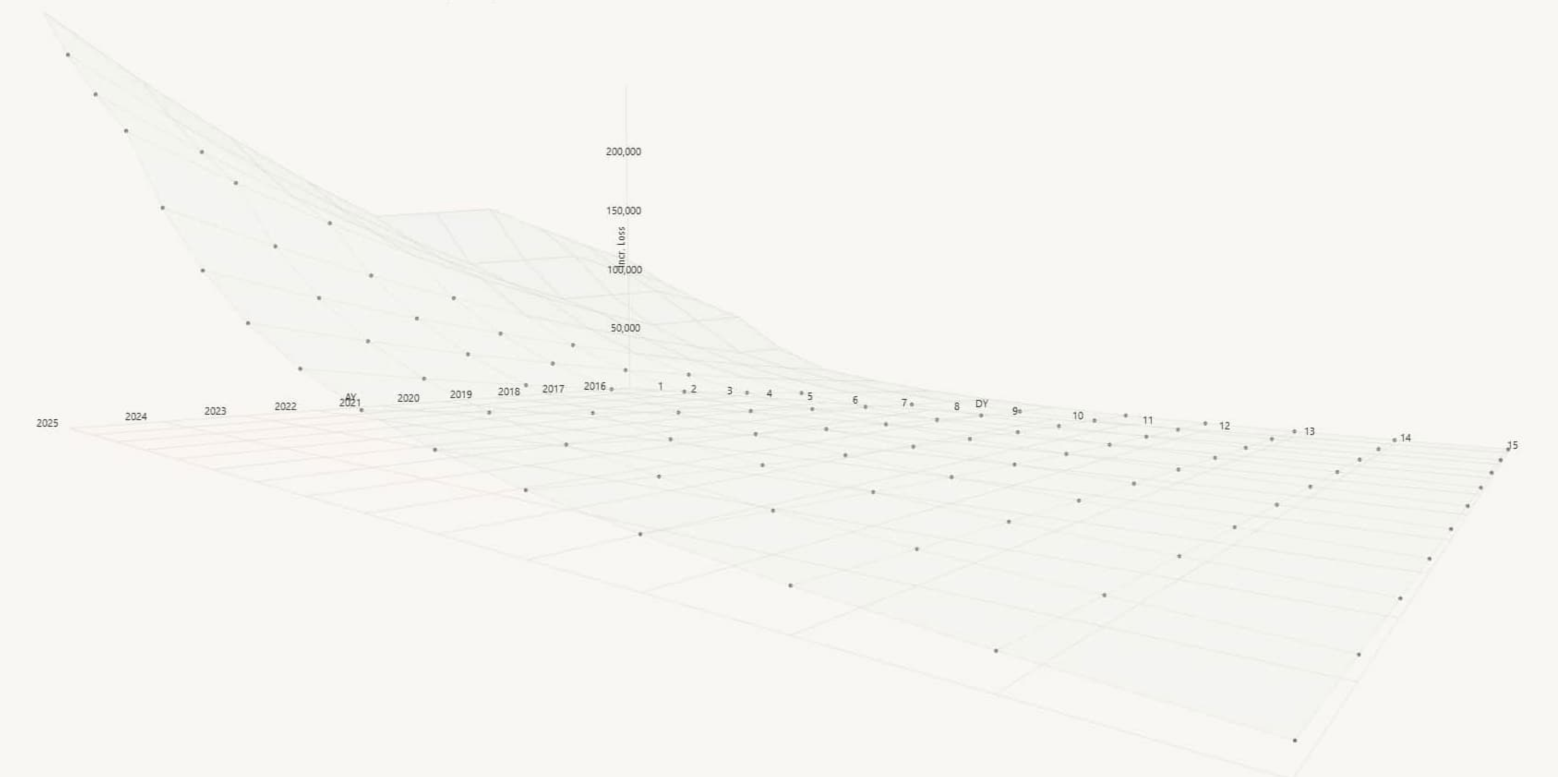
Modeled Paid Loss vs Observed — 3D, Incremental Dollar Scale ($000s)



The dots represent the estimated incremental losses at each future valuation.

We can extend the model further into the future to estimate tail losses beyond the given triangle. The default assumption is to carry the latest CY and DY parameters forward, as shown here.

Modeled Paid Loss vs Observed — 3D, Incremental Dollar Scale ($000s)



Future CY / DY Assumptions

Override the projected trend **Mean** in future calendar years (CY) or development years past the observed triangle (DY tail). The GLM Bootstrap re-centers its simulated trend on the mean you enter and supplies the uncertainty itself (it re-estimates the trend on every resample), so there is no σ to set here.

Model-implied future CY trend: +14.52% per CY

Future CY trend Restore Defaults

Mean (per yr) ☐ Vary by Year

14.52%

Model-implied DY tail decay: -35.26% per DY

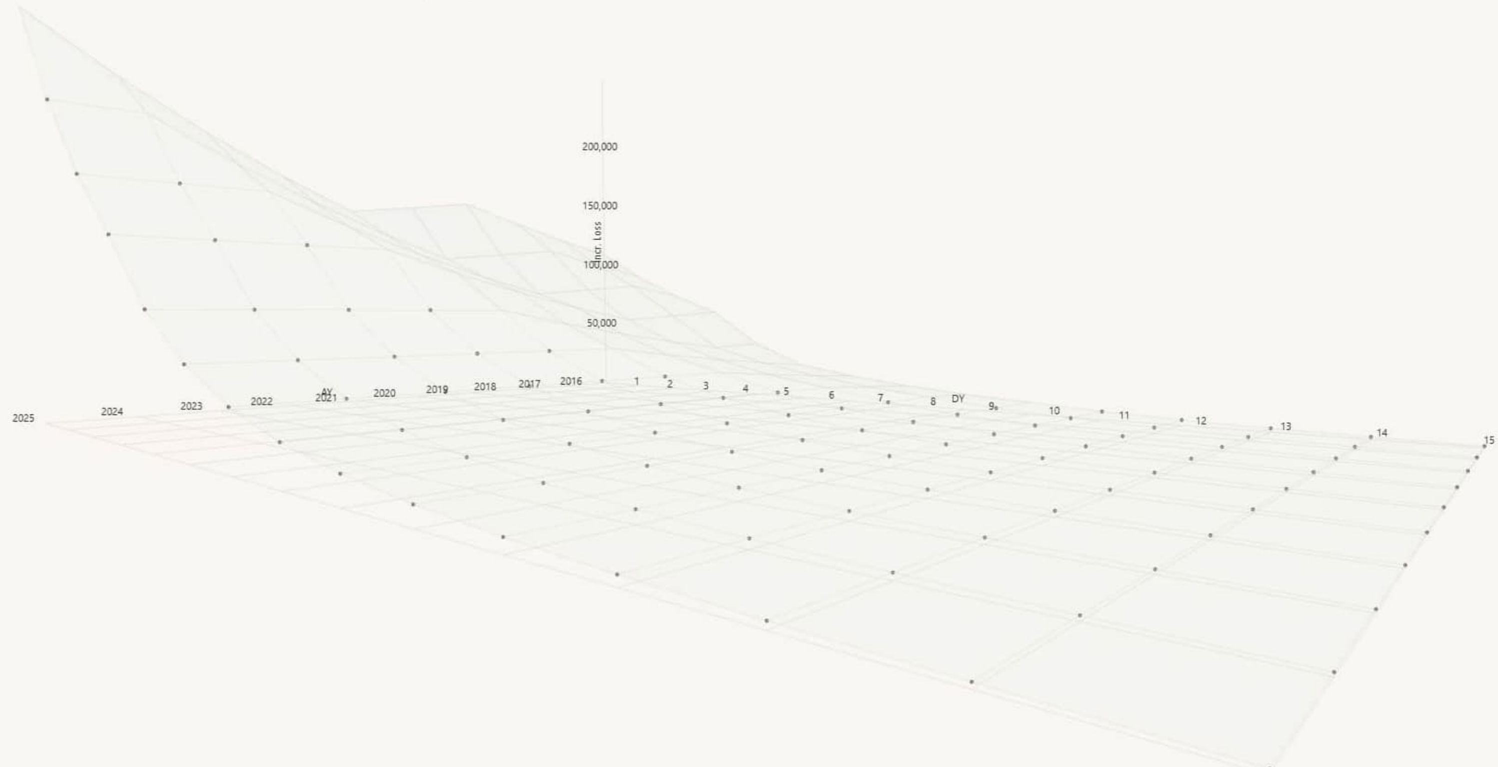
Future DY tail Restore Defaults

Mean (per yr) ☐ Vary by Year

-35.26%

Carrying forward the last parameter may or may not be a good assumption, so we have the ability to vary those future assumptions. To illustrate the effect on the tail estimates, I have entered a 0% future CY trend assumption below (certainly a poor estimate).

Modeled Paid Loss vs Observed — 3D, Incremental Dollar Scale ($000s)



Future CY / DY Assumptions

Override the projected trend **Mean** in future calendar years (CY) or development years past the observed triangle (DY tail). The GLM Bootstrap re-centers its simulated trend on the mean you enter and supplies the uncertainty itself (it re-estimates the trend on every resample), so there is no σ to set here.

Model-implied future CY trend: +14.52% per CY

Future CY trend Restore Defaults

Mean (per yr) ☐ Vary by Year

0%

Model-implied DY tail decay: -35.26% per DY

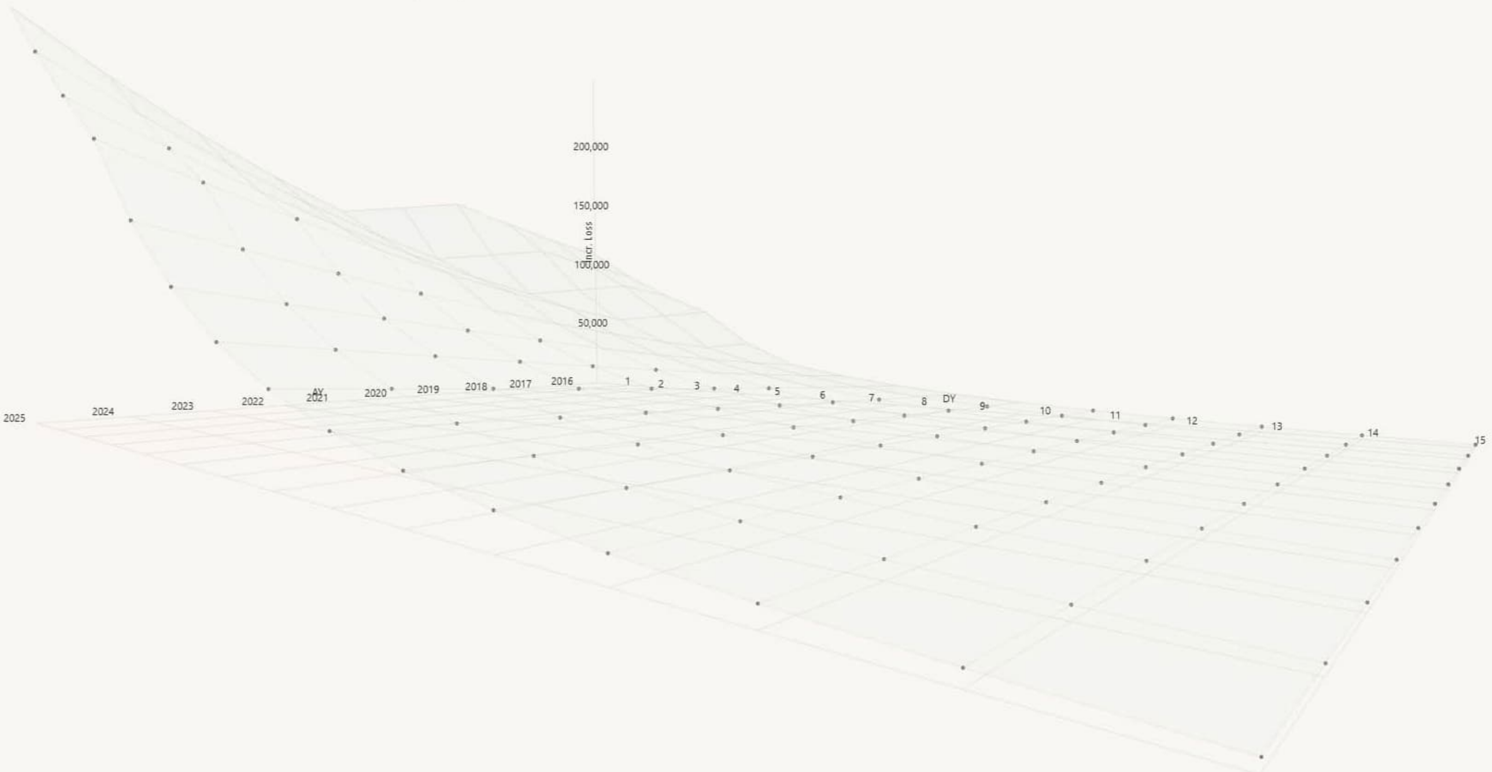
Future DY tail Restore Defaults

Mean (per yr) ☐ Vary by Year

-35.26%

One alternative assumption to carrying +14.5% forward indefinitely would be to assume trends drop a percentage point a year before flattening out. That assumption results in a tail between the default assumption and the prior illustration using 0%.

Modeled Paid Loss vs Observed — 3D, Incremental Dollar Scale ($000s)



Future CY / DY Assumptions

Override the projected trend **Mean** in future calendar years (CY) or development years past the observed triangle (DY tail). The GLM Bootstrap re-centers its simulated trend on the mean you enter and supplies the uncertainty itself (it re-estimates the trend on every resample), so there is no σ to set here.

Model-implied future CY trend: +14.52% per CY

Future CY trend Restore Defaults

Per-year mean (per yr) ☑ Vary by Year

2026	2027	2028	2029	2030	2031	2032	2033	2034	2035	2036	2037	2038	2039
14%	13%	12%	11%	10%	9%	8%	7%	6%	6%	5%	5%	5%	5%

Model-implied DY tail decay: -35.26% per DY

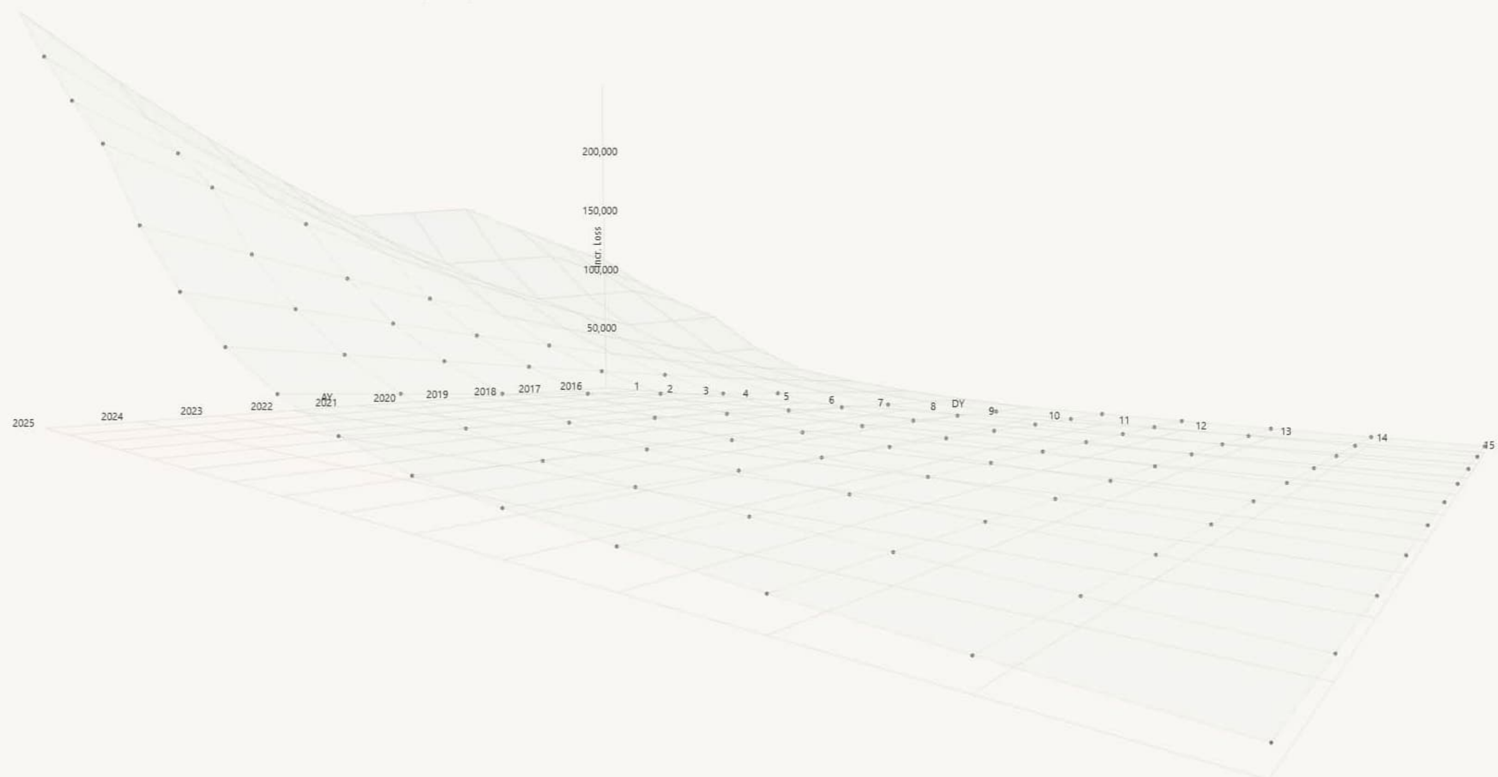
Future DY tail Restore Defaults

Mean (per yr) ☐ Vary by Year

-35.26%

Additionally, we can further calibrate our tail through the future DY trend (decay) factor. Here I have fattened the tail by assuming a 25% DY trend factor beyond the triangle, rather than the carried-forward 35.3%. We can also vary this by year if desired.

Modeled Paid Loss vs Observed — 3D, Incremental Dollar Scale ($000s)



Future CY / DY Assumptions

Override the projected trend **Mean** in future calendar years (CY) or development years past the observed triangle (DY tail). The GLM Bootstrap re-centers its simulated trend on the mean you enter and supplies the uncertainty itself (it re-estimates the trend on every resample), so there is no σ to set here.

Model-implied future CY trend: +14.52% per CY

Future CY trend Restore Defaults

Per-year mean (per yr) ☑ Vary by Year

2026	2027	2028	2029	2030	2031	2032	2033	2034	2035	2036	2037	2038	2039
14%	13%	12%	11%	10%	9%	8%	7%	6%	6%	5%	5%	5%	5%

Model-implied DY tail decay: -35.26% per DY

Future DY tail Restore Defaults

Mean (per yr) ☐ Vary by Year

-25%

Our ultimate loss estimates can be summarized in the following table with the actual losses in the upper portion of the triangle and the estimated losses shaded below. We can also calculate the implied tail factor to reconcile with any other tail factor analysis or benchmarks we have. Notice that changing CY trends by year results in varying traditional tail factors by AY.

Expected Incremental Triangle

Tan cells : projected expected incrementals. **Implied Tail Factor** = Ultimate / Cumulative projection at last triangle age.

AY	DY 1	DY 2	DY 3	DY 4	DY 5	DY 6	DY 7	DY 8	DY 9	DY 10	DY 11	DY 12	DY 13	DY 14	DY 15	Implied Tail Factor
2016	107,757	86,328	69,237	60,311	36,749	22,219	17,643	11,787	9,035	6,474	5,768	4,889	4,106	3,419	2,820	1.0491
2017	112,292	94,470	73,058	56,585	34,052	24,222	18,824	13,485	10,689	7,691	6,518	5,475	4,558	3,760	3,074	1.0525
2018	123,923	107,057	72,663	53,487	37,313	31,586	20,498	17,351	11,880	8,691	7,300	6,077	5,014	4,099	3,320	1.0533
2019	138,552	99,713	73,958	56,475	48,297	33,954	24,552	18,352	13,425	9,734	8,103	6,685	5,465	4,427	3,552	1.0546
2020	120,993	100,276	84,223	65,995	53,137	38,892	28,348	20,737	15,036	10,804	8,914	7,287	5,902	4,737	3,766	1.0568
2021	122,929	103,380	91,522	77,274	62,941	43,790	32,034	23,226	16,690	11,885	9,716	7,870	6,315	5,021	3,992	1.0562
2022	139,729	115,306	114,997	85,013	67,644	49,483	35,878	25,781	18,359	12,954	10,493	8,421	6,694	5,322	4,191	1.0528
2023	162,470	151,918	120,728	104,490	76,437	55,421	39,824	28,359	20,011	13,991	11,228	8,926	7,096	5,588	4,401	1.0481
2024	186,539	156,931	138,322	118,074	85,610	61,517	43,806	30,911	21,612	14,970	11,901	9,461	7,451	5,868	4,621	1.0458
2025	205,205	183,107	156,304	132,243	95,027	67,669	47,749	33,384	23,125	15,868	12,615	9,935	7,823	6,161	4,852	1.0431

Learn more about the benefits of this framework and how the BASR software is built to make implementing it in your reserving process as easy as possible at bedfordactuarial.com/basr

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