A quantum leap in benchmarking P&C aggregate unpaid distributions

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Even well-crafted and precisely executed unpaid claim and loss distribution models can still be tripped up at one of the last crucial steps of the risk assessment process: aggregating loss distributions from different segments. Confined by limited data, the aggregation process is typically riddled with volatility that can skew the view of an entity's risk and capital needs. What has long been missing, at least until recently, is a reliable benchmark for identifying and quantifying the risk dependencies among segments that underlie the loss aggregation process.

Understanding risk dependencies among segments is a fundamental part of the process for property and casualty (P&C) insurers in forming conclusions about the interactions of loss distributions: What is the likelihood that losses in different segments will occur simultaneously? The answer determines whether an aggregate distribution of unpaid claims should be much narrower than the sum of the individual segment distributions, as in the case of segments that are largely independent of one another, or closer to the sum if the segments have strong positive correlations. In either case, the impact on capital needs and reinsurance optimization can be substantial.

As crucial as these correlations are, they either are often inadequately modeled, because of the inherent difficulties of working with limited data, or they rely on actuarial judgment without statistical justification. This situation has changed with the introduction of new claims variability guidelines (CVG), which allow actuaries to gauge the reasonableness of their correlations against benchmark correlations.

The guidelines are derived from extensive testing of common models, using more than 30,000 data triangle sets involving all long-tail Schedule P lines of business. They were rigorously back-tested and adjusted to compensate for underestimations many commonly used models are susceptible to when estimating unpaid claims patterns and loss distributions, topics discussed in two previous articles in this series. With benchmark correlations, an actuary can extend the unpaid claim distribution analysis to gain a better understanding of the degree of variability in the aggregation of these loss distributions.

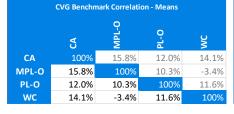
The guidelines' back-tested output also includes correlations for all pairs of an insurance entity's lines of business for both paid and incurred claims, including adjustments for the statistical significance for each correlation coefficient. The robustness of the back-testing provides actuaries with form and structure for evaluating potential risk dependencies among their entities' segments and for determining their entities' capital needs.

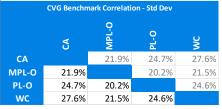
Real-life scenarios

How the correlations can be applied in practice can be seen using representative data sets from randomly selected companies of four different sizes: A) small, B) regional, C) small national, and D) large national. Minor changes were made to the data in order to protect the identities of the entities.¹

FIGURE 1: CORRELATION FOR COMPANY A

	Model Correlation				
CA MPL-O PL-O					
CA	100%	34.1%	-17.4%	46.6%	
MPL-O	34.1%	100%	-19.4%	29.9%	
PL-O	-17.4%	-19.4%	100%	10.5%	
WC	46.6%	29.9%	10.5%	100%	





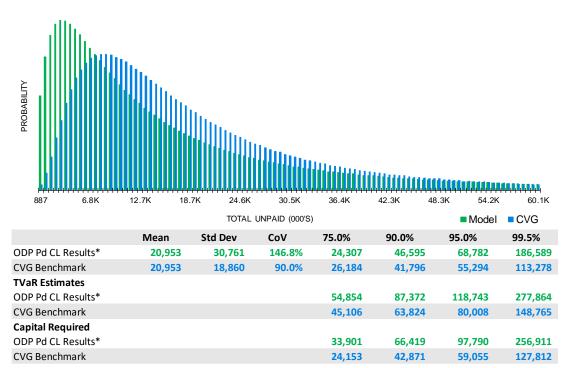
Orrelations and loss aggregation results for all entities, which include a small, regional, small national, and large national company, are shown in the Appendix.

Actuaries can use the benchmark to determine the reasonableness of their own, often volatile, observed correlation coefficients. As an example, in Figure 1, the ODP Bootstrap paid chain ladder (ODP Pd CL)² was used to develop correlations for a small entity. The small entity's model indicates that commercial auto has a 34.1% correlation with Medical Professional Liability, -17.4% with Product Liability-Occurrence, and 46.6% with Workers' Compensation. The benchmark indicates more stable correlations of 15.8%, 12%, and 14.1%, respectively.³ Which correlations are more reasonable? The guidelines'? The small entity model's? Other estimates?

Intended to supplement internal modeling, the benchmark correlations together with the underlying uncertainty give actuaries the ability to more confidently investigate the adequacy of their internal modeling for aggregating loss distributions and a measure for determining the potential volatility of correlations.

The stability or volatility of the correlations has a direct impact on the Tail Value at Risk (TVaR) and therefore on capital needs.⁴ In addition, the impact observed for companies that disregard model risk and continue to base segment uncertainty on a single-model approach (i.e., rather than a multiple-model approach,⁵ supplemented by CVG benchmark guidance) can have as strong an impact as the correlation assumptions on capital requirements.

FIGURE 2: AGGREGATE DISTRIBUTION AND CAPITAL REQUIREMENTS FOR COMPANY A



st Using only the ODP Bootstrap model for Paid data for each LOB.

² The ODP Pd CL model is used to approximate a single-model approach. The single-model approach is the common process of assuming the actuary's central estimate is the mean and a single model, such as Mack or ODP Bootstrap, is used to estimate the variance.

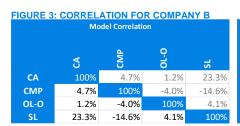
³ Statistically speaking, the actuary could assess the quality of the correlation coefficients indicated from models using the P-Values. For the CVG benchmarks, the mean values are a weighted average using the P-Values to assign more weight to stronger correlation values.

Other risk measures, such as Value at Risk (VaR) used for Solvency II, could be used instead of TVaR. While the specific capital requirement calculated using another risk measure would be different from the examples in this article, the direction and magnitude of the various comparisons would be consistent.

⁵ A multiple-model approach involves using multiple stochastic models and weighting the models together.

The potential magnitude of this impact can be seen in Figure 2, which compares aggregate loss distributions developed from the ODP Pd CL model and guidelines for the small entity. Factoring the correlations into estimates of aggregate losses reveals that

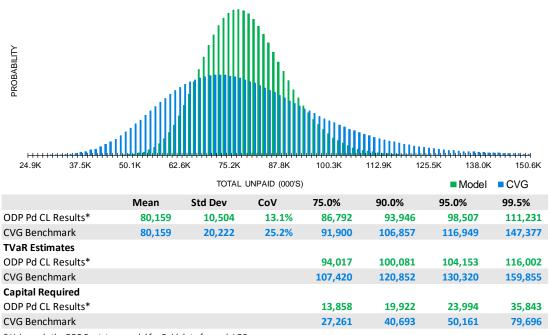
the TVaR for the ODP Pd CL model is approaching twice that of the benchmark losses. The difference produces a capital need for the ODP Pd CL model that is likewise nearly twice as much as that for the benchmark.⁷



CVG Benchmark Correlation - Means				
	5	CMP	0-10	SL
CA	100%	13.1%	14.8%	9.2%
СМР	13.1%	100%	10.9%	8.3%
OL-O	14.8%	10.9%	100%	3.6%
SL	9.2%	8.3%	3.6%	100%

CVG Benchmark Correlation - Std Dev				
	5	CMP	0-10	SL
CA		24.6%	23.1%	22.4%
CMP	24.6%		23.7%	24.4%
OL-O	23.1%	23.7%		21.9%
SL	22.4%	24.4%	21.9%	

FIGURE 4: AGGREGATE DISTRIBUTION AND CAPITAL REQUIREMENTS FOR COMPANY B



st Using only the ODP Bootstrap model for Paid data for each LOB.

For all of the models used in these illustrations, only standard model assumptions were used in order to replicate how an actuary might approach these estimates in practice. No attempt was made to calibrate the model assumptions to the benchmarks.

For Figure 2, a segment in which the ODP Pd CL model estimated a wider distribution than the guidelines also corresponded to a correlation coefficient that was larger than the guidelines.

What becomes clear is that, the stronger the correlation among segments, the bigger the impact on the 99.5th percentile. This phenomenon can be seen in Figure 3 above, which provides another set of correlations, in this example for a regional entity. For this entity, the benchmark developed correlations for commercial auto of 13.1% for Commercial Multi-Peril, 14.8% for Other Liability-Occurrence, and 9.2% for Special Lines. This compares with results of 4.7%, 1.2%, and 23.3%, respectively, for the ODP Pd CL model using company data. Likewise, the TVaR for the benchmark in Figure 4, driven by stronger correlations, is greater than that for the ODP Pd CL model at every percentile shown along the distribution, and the capital

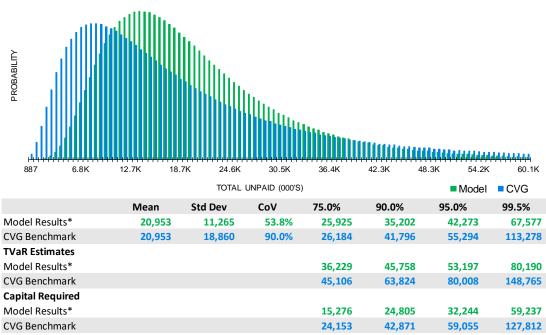
need developed from the benchmark is double that for the ODP Pd CL model.

Absent a benchmark, an actuary has effectively no objective measure to assess whether the output from an internal model is reasonable.

A better way: Using multiple models

Increased credibility can however be built into an internal process with the use of multiple weighted models. But even here large disparities in output can occur, especially for entities with small exposure bases.

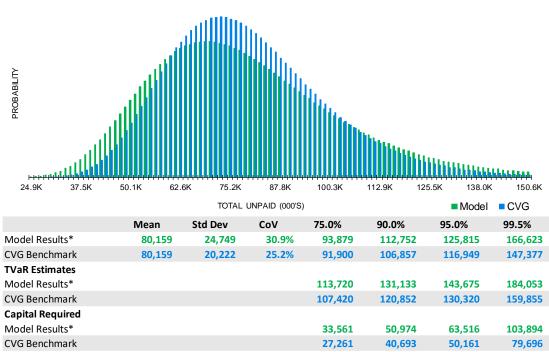
FIGURE 5: AGGREGATE DISTRIBUTION AND CAPITAL REQUIREMENTS FOR COMPANY A



^{*} Model Results based on weighting of 4 different models for each LOB.

FIGURE 6: AGGREGATE DISTRIBUTION AND CAPITAL REQUIREMENTS FOR COMPANY B

COMPANY B - AGGREGATE ALL LINES OF BUSINESS



^{*} Model Results based on weighting of 4 different models for each LOB.

While a multiple-model approach brings the TVaR for the small entity's model estimates much closer to the benchmark TVaR in Figure 5, there is still a gap but for different reasons. In this case, the modeled distributions were closer to the benchmark, but some of the modeled correlations were significantly less than the benchmark. These different results can pose a quandary for the actuary who is faced with two vastly different 99.5% TVaR estimates of 278 million for the ODP Pd CL (in Figure 2) and 80 million for the multiple-model (in Figure 5). The benchmark, which in this case falls between the two figures, can give the actuary direction and focus moving through revisions of the model, lending support for modifications that seem reasonable and eliminating others that move the process further off track.

As the size of an entity's exposure base increases, the output from a multiple-model approach tends to move closer to the benchmark. For example, when a multiple-model approach is used with the regional entity, the 99.5% TVaR moves from \$116 million for

No matter what the level of modeling sophistication, actuaries now have a benchmark that can be used to better calibrate internal models and more reliably assess the risk dependencies among segments. Supported by these rigorously tested benchmark correlations, actuaries can now make capital recommendations with more confidence that their estimates more realistically reflect their own risk profiles relative to indications from elsewhere in the market.

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ODP Pd CL model (in Figure 4) to \$184 for the multiple-model (in Figure 6), more closely approximating the benchmark of \$160 million, which can help validate modeled results.

The four models used are all based on the ODP Bootstrap model framework described in the Shapland monograph for paid and incurred data using the chain ladder and Bornhuetter-Ferguson algorithms. For simplicity all four models were given equal weight for each accident year.

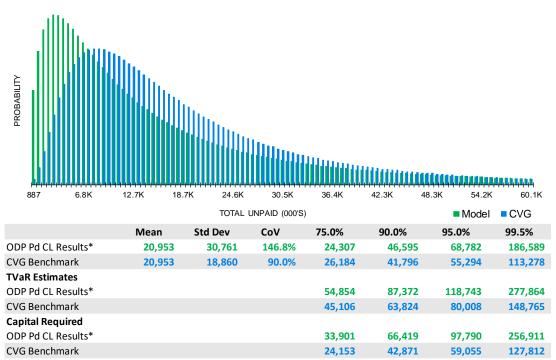
FIGURE A-17: CORRELATION FOR COMPANY A

Model Correlation					
CA MPL-O PL-O					
CA	100%	34.1%	-17.4%	46.6%	
MPL-O	34.1%	100%	-19.4%	29.9%	
PL-O	-17.4%	-19.4%	100%	10.5%	
WC	46.6%	29.9%	10.5%	100%	

CVG Benchmark Correlation - Means					
	CA MPL-O PL-O				
CA	100%	15.8%	12.0%	14.1%	
MPL-O	15.8%	100%	10.3%	-3.4%	
PL-O	12.0%	10.3%	100%	11.6%	
WC	14.1%	-3.4%	11.6%	100%	

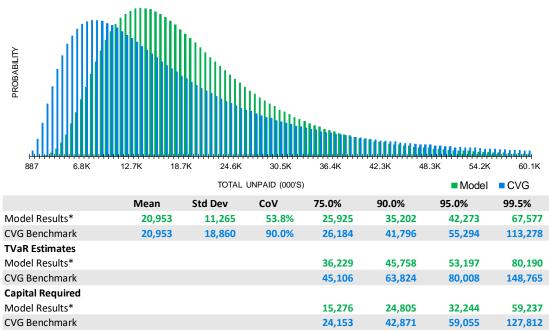
CVG Benchmark Correlation - Std Dev				
	S	MPL-0	PL-0	WC
CA		21.9%	24.7%	27.6%
MPL-O	21.9%		20.2%	21.5%
PL-O	24.7%	20.2%		24.6%
WC	27.6%	21.5%	24.6%	

FIGURE A-28: AGGREGATE DISTRIBUTION & AND CAPITAL REQUIREMENTS FOR COMPANY A



^{*} Using only the ODP Bootstrap model for Paid data for each LOB.

FIGURE A-39: AGGREGATE DISTRIBUTION & AND CAPITAL REQUIREMENTS FOR COMPANY A



^{*} Model Results based on weighting of 4 different models for each LOB.

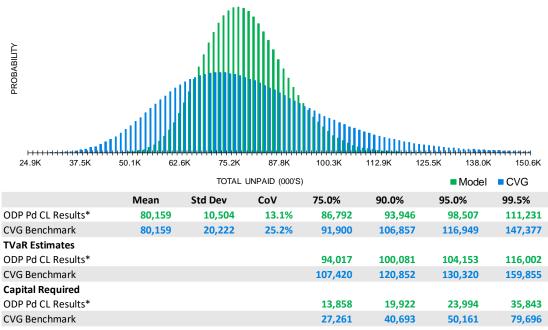
FIGURE B-110: CORRELATION FOR COMPANY B

Model Correlation					
CMP OL-O					
CA	100%	4.7%	1.2%	23.3%	
CMP	4.7%	100%	-4.0%	-14.6%	
OL-O	1.2%	-4.0%	100%	4.1%	
SL	23.3%	-14.6%	4.1%	100%	

CVG Benchmark Correlation - Means					
	CA CCMP				
CA	100%	13.1%	14.8%	9.2%	
CMP	13.1%	100%	10.9%	8.3%	
OL-O	14.8%	10.9%	100%	3.6%	
SL	9.2%	8.3%	3.6%	100%	

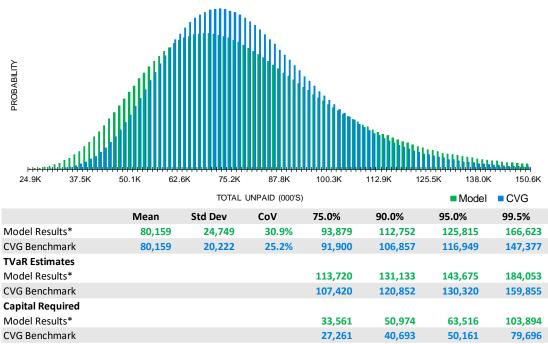
	CVG Benchmark Correlation - Std Dev			
	క	СМР	0-10	S
CA		24.6%	23.1%	22.4%
CMP	24.6%		23.7%	24.4%
OL-O	23.1%	23.7%		21.9%
SL	22.4%	24.4%	21.9%	

FIGURE 8-211: AGGREGATE DISTRIBUTION & AND CAPITAL REQUIREMENTS FOR COMPANY B



^{*} Using only the ODP Bootstrap model for Paid data for each LOB.

FIGURE B-312: AGGREGATE DISTRIBUTION & AND CAPITAL REQUIREMENTS FOR COMPANY B



^{*} Model Results based on weighting of 4 different models for each LOB.

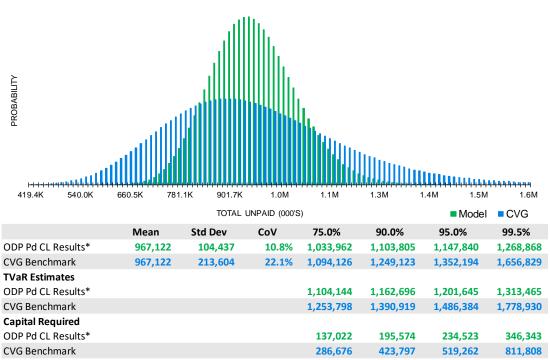
FIGURE C-113: CORRELATION FOR COMPANY C

Model Correlation				
	Prop			
	5	RE-Liab	RE-F	
CA	100%	10.1%	15.8%	
RE-Liab	10.1%	100%	2.8%	
RE-Prop	15.8%	2.8%	100%	

CVG Benchmark Correlation - Means				
		qe		
	8	RE-Liab	RE-Prop	
CA	100%	5.9%	3.4%	
RE-Liab	5.9%	100%	21.4%	
RE-Prop	3.4%	21.4%	100%	

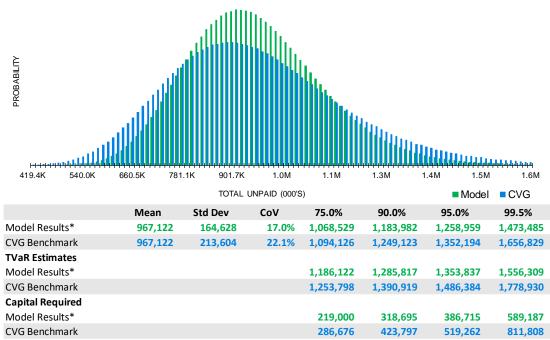
CVG Benchmark Correlation - Std Dev				
	Liab		rop	
	S	RE-L	RE-P	
CA		23.3%	21.2%	
RE-Liab	23.3%		30.0%	
RE-Prop	21.2%	30.0%		

FIGURE 6-214: AGGREGATE DISTRIBUTION & AND CAPITAL REQUIREMENTS FOR COMPANY C



^{*} Using only the ODP Bootstrap model for Paid data for each LOB.

FIGURE C-315: AGGREGATE DISTRIBUTION & AND CAPITAL REQUIREMENTS FOR COMPANY C



^{*} Model Results based on weighting of 4 different models for each LOB.

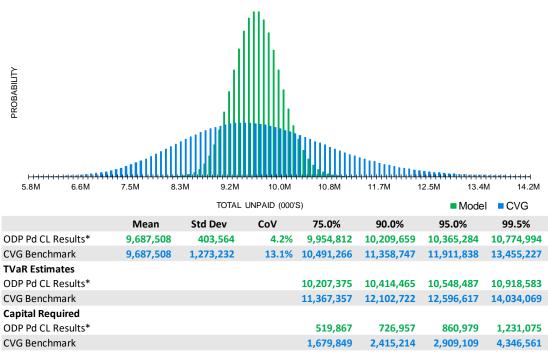
FIGURE D-116: CORRELATION FOR COMPANY D

Model Correlation				
	S	오	РРА	
CA	100%	6.9%	53.0%	
НО	6.9%	100%	26.5%	
PPA	53.0%	26.5%	100%	

CVG Benchmark Correlation - Means					
	5	오	PPA		
CA	100%	9.0%	20.0%		
НО	9.0%	100%	14.5%		
PPA	20.0%	14.5%	100%		

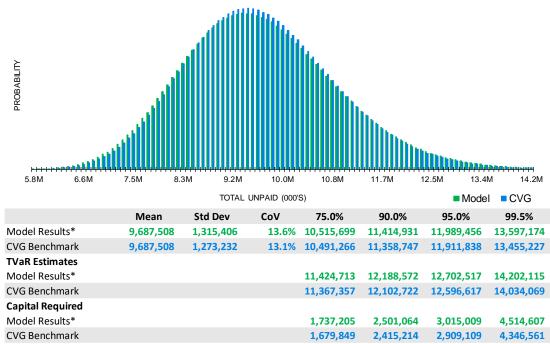
CVG Benchmark Correlation - Std Dev					
	V	오	PPA		
CA		21.2%	25.1%		
НО	21.2%		22.8%		
PPA	25.1%	22.8%			

FIGURE D-217: AGGREGATE DISTRIBUTION & AND CAPITAL REQUIREMENTS FOR COMPANY D



^{*} Using only the ODP Bootstrap model for Paid data for each LOB.

FIGURE D-318: AGGREGATE DISTRIBUTION & CAPITAL REQUIREMENTS FOR COMPANY D



^{*} Model Results based on weighting of 4 different models for each LOB.