

Actuarial

When to Model Stochastically (*and when not to*)

Roger Loomis, FSA, MAAA

Principal & Director of Health Consulting

www.arcval.com



16th Annual Intercompany Long Term Care Insurance Conference

Why Use Stochastic Models?



There are two broad categories of reasons:

- To model path-dependent contingencies with first-principles
- To evaluate risk



- A contingency is path-dependent if the benefit available for a claim incurred at time t or the probability of the claim incurring at time t is a function of the prior history of the policy.

Examples of Path-Dependent Contingencies



- Shared-care benefits
- Combo products
- Indemnity benefits without restoration-of-benefits feature
- Pool-of-money benefits
- Transitions between sites of care
- Relapse



An actuarial model is a first-principles model if the contingencies in the model reflect the contingencies in the real world in a direct and natural way.

Advantages of First Principles



First-principle models are in general more useful:

- Provide more insight into business
- Contain assumptions that more closely represent operational metrics
- Easier to set and update assumptions
- Easier to understand
- Easier to validate
- Easier to reconcile with emerging results

Three Choices for LTCi Models



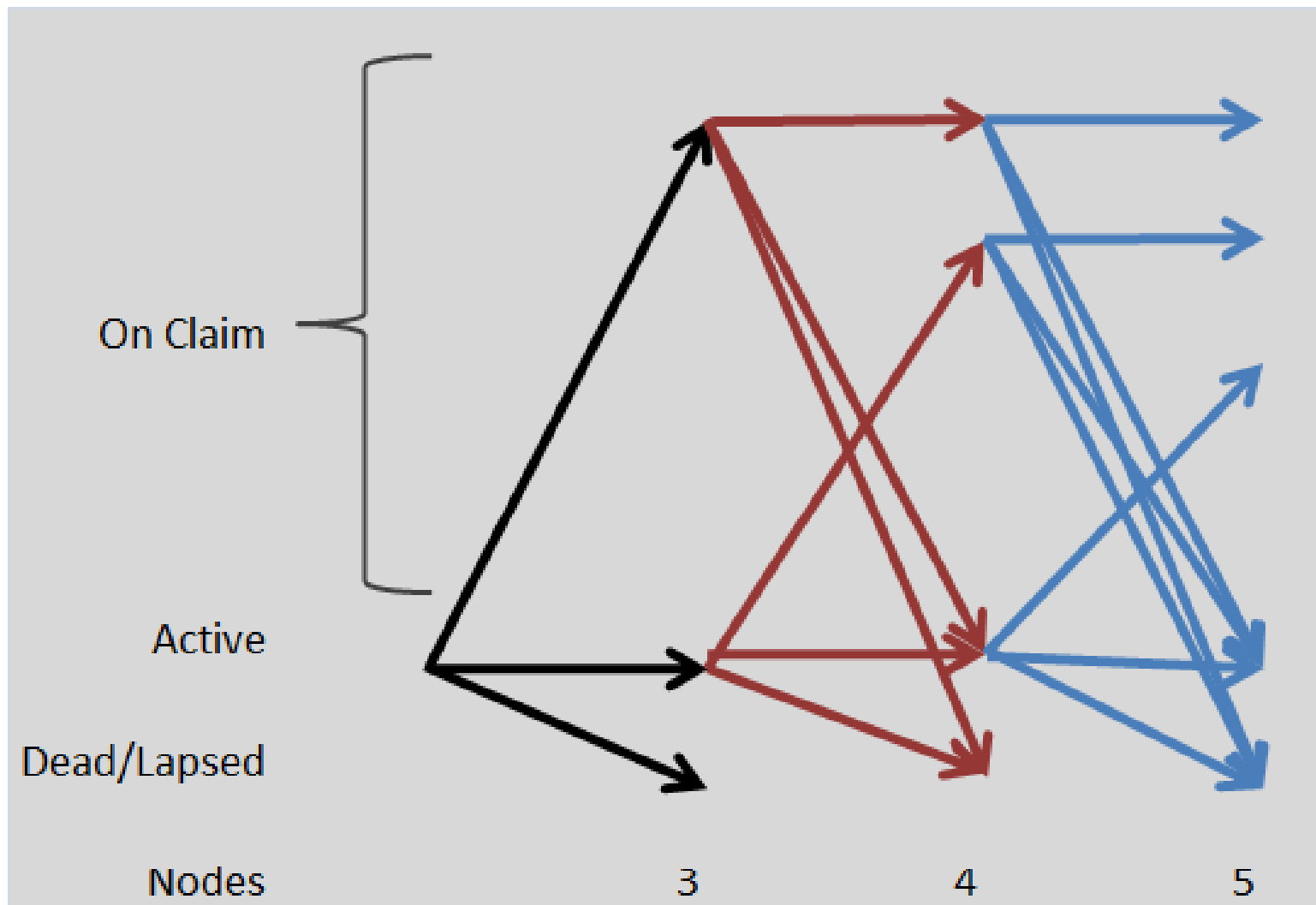
Choice	Model Type
Shoehorn into Life Insurance Model	Claim-cost model
Shoehorn into a Disability Model	Quasi-first principles
Use Monte Carlo Simulation	True First Principles



How Can This Best be Modeled?

- Basic LTC Policy
- Indemnity style benefits
- Restoration of Benefits rider Included
- Company believes probability of relapse is equal to probability of initial claim at that attained age and policy duration
- First principles model desired

Basic Nature of Deterministic DI Models





- Result in array of size $\omega^2 \div 2$
- For example 240 months \rightarrow 28,800 cells
- Relatively Unwieldy
- Relatively Slow Runtimes
- But Relatively Manageable

- Works okay

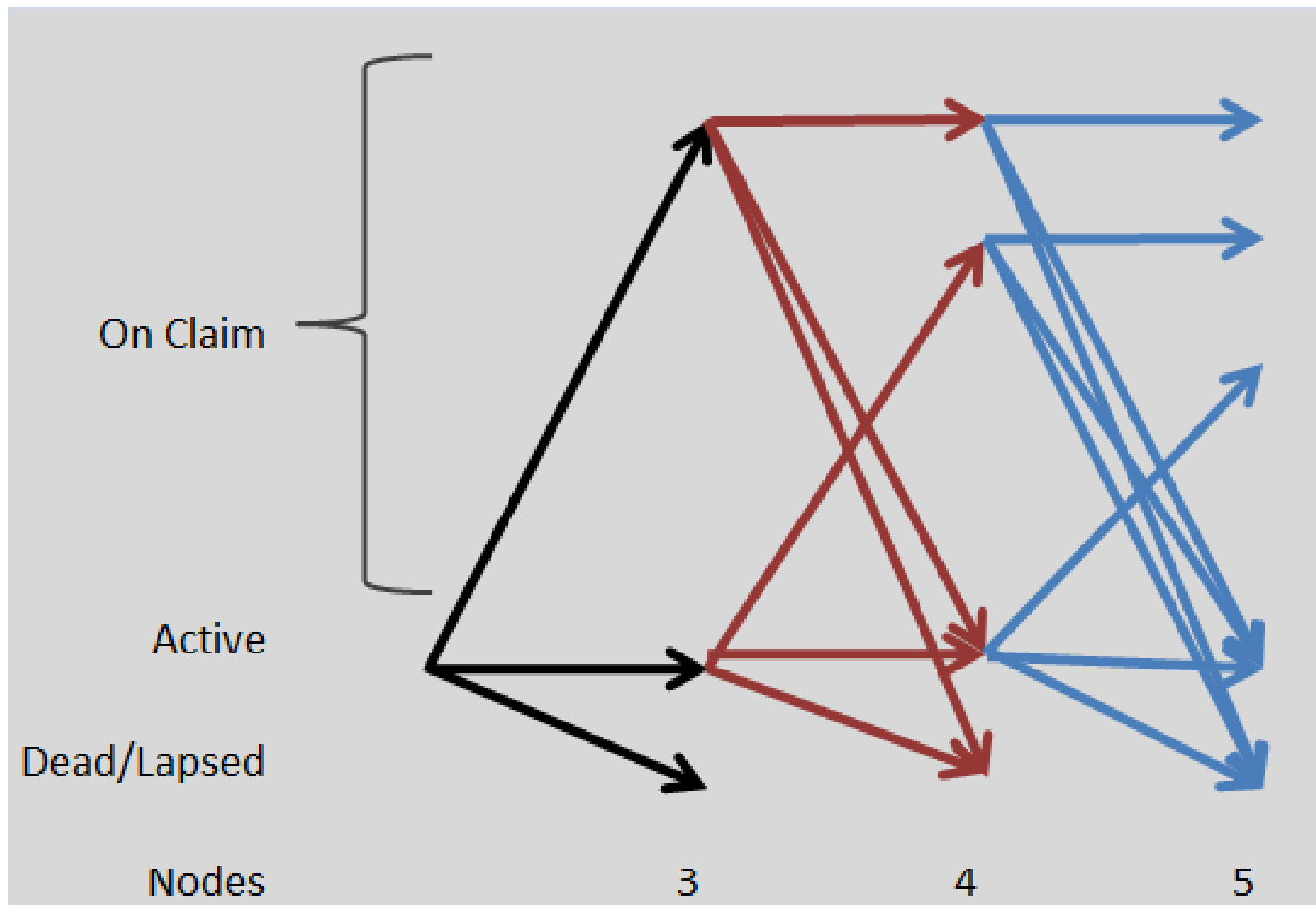


We could shoehorn into deterministic model by doing the following*:

1. Estimate probability that active policies at every age will have previously been on claim
 2. Estimate the average benefit that will have been utilized on previous claims at every age
 3. Estimate a weighted-average remaining BP at every attained age
 4. Substitute the estimated weighted-average remaining BP for the actual BP for every future age
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* See “First Principles LTC–Restoration of Benefits” by Robert W. Darnell in *LTC News*, May 2012, Issue 31

Basic Nature of Deterministic DI Models



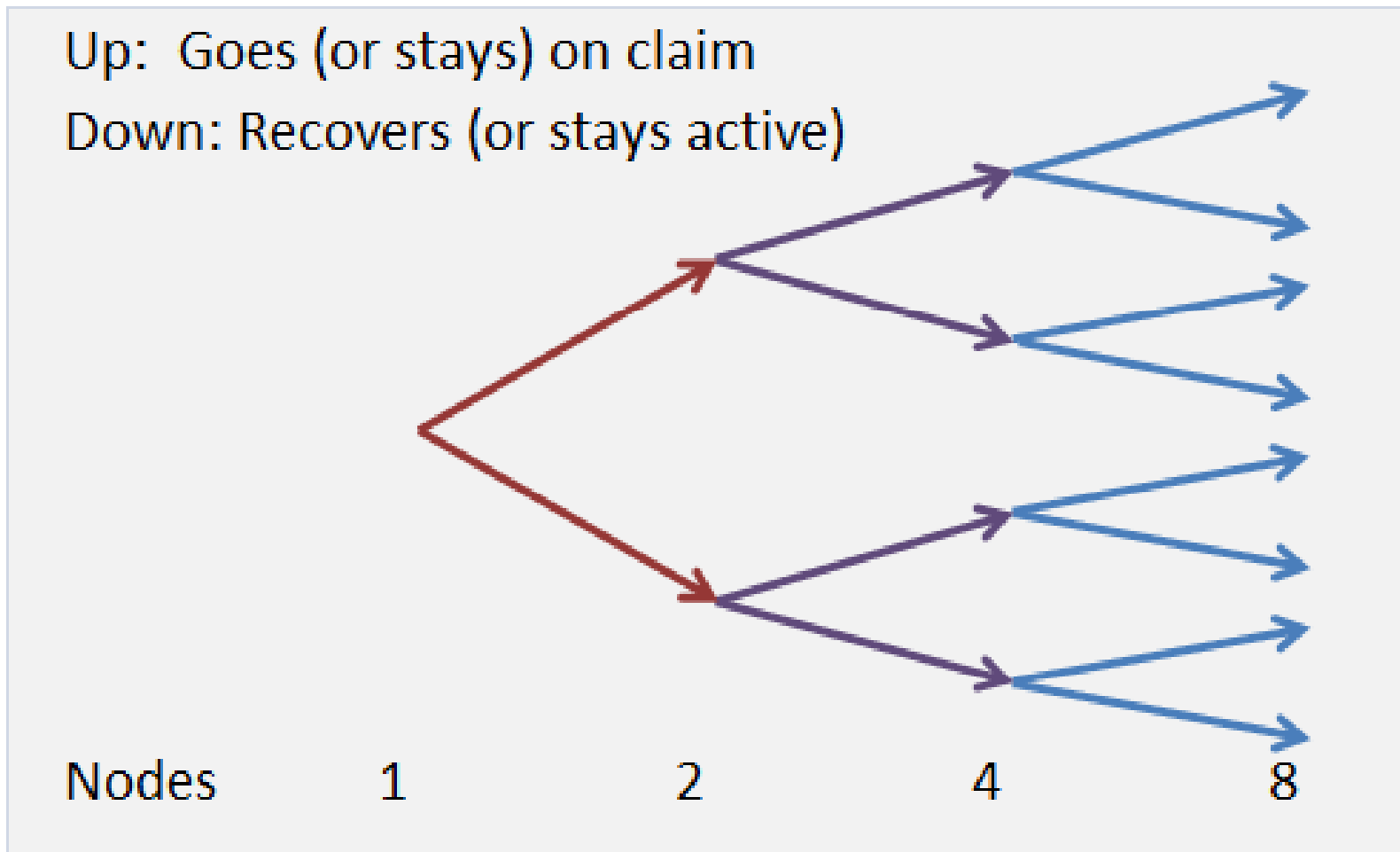


This shoehorning type of process needs to be done for all of the path-dependent contingencies of LTC:

- Recoveries
- Status transitions
- Utilization rates
- Path-dependent benefits

The more shoehorning done, the less the model can rightly be called “first principles”

True First-Principles Deterministic Model



True First-Principles Deterministic Model



- Result in 2^{ω} paths
- E.g. 240 months $\rightarrow 2^{240}$ Paths



Objection 1: Too Complicated



- Two things make deterministic models complicated:
 1. Large arrays of statuses
 - Managing the arrays
 - Calculations across the arrays
 2. Shoehorning

Why Deterministic Models are Difficult



In the above example, there were 28,800 nodes

- Each node needs calculations for benefits, reserves, premiums, expenses, etc.
- The most efficient array structure for each element needs to be determined and loaded
- Path-dependent contingencies then need to be shoe-horned into these arrays as appropriate
- The results then need to be summed into model output
- Then it needs to be understood!

Why Simulation Models are Simple



- If the above example is done with simulation, only 240 nodes to manage
- Elements of the nodes are simple and directly reflect the way policies work:
 - Policy duration
 - Current status
 - Duration in current status
 - Amount of money in benefit pool
 - Other path-dependent details as required
 - Cash flows given status and history

Why Simulation Models are Simple



- The actuarial assumptions of Monte Carlo models directly represent the contingencies the company can easily and directly measure:
 - Transition probabilities between statuses
 - Benefit utilization rates
- The premiums, benefits, reserves, deductions to benefit pool, etc. are then easy—just administer the actual policy features

Objection 2: Deterministic Model First



“Let’s first get our deterministic model working right, and then add stochastic functionality.”

You can add stochastic transitions to a DI quasi-first principles model

- Allows you to measure process risk

Objection 2: Deterministic Model First



Adding stochastic transitions to a deterministic DI model retains the same limiting structure as the deterministic model:

- Still complicated
- Still has shoe-horned assumptions
- Still not truly first-principles

Objection 3: Stochastic Is To Slow!



- Quasi-first principle models are slow because of the large arrays
- Single Monte Carlo simulations are very simple and very fast
- But how many simulations are required?

Number of Simulations



- As a rule of thumb, 20,000 simulations is enough for the simulation mean to be close to the true mean
- To decrease the standard deviation by 50%, you need to increase the number of trials by a factor of 4

Number of Simulations



- So as a pricing exercise, prepare to run at least 20,000 simulations for each pricing cell
- In a well-designed model, 20,000 Monte Carlo simulations will run almost as fast as a single deterministic run with 28,800 nodes
- Still slow, but not out of line with quasi-first principal models

Number of Simulations



- But what if I have a block of business with 25,000 policies? I don't have resources to run 20,000 simulations of each of 25,000 policies!
- Because of the law of large numbers, a single simulation of 25,000 policies provides a reasonable approximation for how the block will do as a whole
- 100 simulations is more than enough
- Probably faster than single run of DI-style model

Objection 4: Stochastic Interest



I'd like to model my block using first principles, but I need to do cash flow testing. I can't run thousands of morbidity scenarios for each of a thousand economic scenarios!



- Provided the block is of reasonable size (e.g. $> 10,000$ policies), you could run one Monte Carlo simulation through each of the 1,000 interest scenarios
- You could run 5 or 10 or 100 simulations through each scenario if you want, but in aggregate it shouldn't materially change the results

Objection 5: Reports



Management is accustomed to deterministic reports, and wants to see the deterministic results we've always shown



- What management really wants is to understand the model and the business
- Monte Carlo Models are more insightful and understandable
- Simulation can give you a mean of the financial statements and operational metrics
- ...and confidence intervals around the results
- This is more useful, first-principle based information

When to Use Stochastic Models?



(and when not to)

There are two broad categories of reasons:

- To model path-dependent contingencies with first-principles
- To evaluate risk

In which category are policy reserves?

Actuarial

**Stochastic Modeling:
Experience Reporting Forms
Case Study**

**Christopher J. Giese, FSA, MAAA
Principal and Consulting Actuary
Milliman**



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How Much Can Claims Change?



- Many potential opportunities to go “off track”
 - Morbidity: Incidence, utilization, continuance
 - Persistency: Mortality, lapse, exhaust
- Many influences on these assumptions
 - Demographics (age, gender, marital status)
 - Benefit Features (BP/EP, inflation)
 - Underwriting Level / Risk Mix (data considered, rating tiers)
 - Time (policy year, calendar year)



- Experience Reporting Forms (ERFs) data for insights
- Volatility / Variance (Process Risk)
 - Results bounce around a mean
 - What is “normal” volatility in results?
- Misestimation / Trend (Parameter Risk)
 - Results consistently vary / move in one direction
 - How much can be explained by misestimation of underlying mean?

2014 ERF Data – Form 1 (Claims)



Incurred Claims Historical "Misestimation" Overall 2009-2014 A/E Ratio					
Top 20 Companies	Average	113%	Next 20 Companies	Average	120%
	Min	75%		Min	51%
	Max	172%		Max	249%
	Std Deviation	24%		Std Deviation	54%

Incurred Claims Historical "Volatility" Yearly 2009-2014 A/E Ratio - "Normalized" to Overall A/E					
Top 20 Companies	Min	79%	Next 20 Companies	Min	46%
	Max	141%		Max	236%
	Std Deviation	8%		Std Deviation	27%

Source: Metrics developed from SNL Financial data based on company specific annual statement reporting.

2014 ERF Data – Form 1 (Terminations)



Lives Terminations Historical “Misestimation” Overall 2009-2014 A/E Ratio					
Top 20 Companies	Average	91%	Next 20 Companies	Average	77%
	Min	53%		Min	39%
	Max	168%		Max	180%
	Std Deviation	29%		Std Deviation	29%

Lives Terminations Historical “Volatility” Yearly 2009-2014 A/E Ratio - “Normalized” to Overall A/E					
Top 20 Companies	Min	41%	Next 20 Companies	Min	10%
	Max	174%		Max	330%
	Std Deviation	19%		Std Deviation	42%

Source: Metrics developed from SNL Financial data based on company specific annual statement reporting. Converted Lives A/E to implied miss on persistency assuming 5% annual termination.



Simulation Modeling Using ERF Data



- Data points from ERFs
 - Separate sets for Top 20 and Next Top 20 size companies
 - Separate sets for claims and terminations
- Volatility “adjustments”
 - 120 ERF A/E data points (20 companies x 6 years)
- Misestimation “adjustments”
 - 20 ERF data points (overall company A/E across 6 years)



- Simulate adjustments
 - Each data point has equal likelihood
 - Volatility independent each year
 - Misestimation applied to all years
- Yearly claims and terminations
 - Starting data = projection results from pricing cell for policy commonly sold today
 - Morbidity = industry estimate
 - Terminations = 90% 94GAM, 1% ultimate lapse
 - Apply simulated adjustments / recalculate claims

Morbidity Process Risk – Claims Impact



Morbidity Process Risk Testing Results Using Top 20 - “Larger” Companies Data Incurred Claims			
	Duration 15	Duration 15-17	NPV – All Years
	Estimates as % of Mean		
One Standard Deviation	8.0%	4.8%	1.3%
Cover 60% of Scenarios	0.8%	0.3%	0.3%
Cover 70% of Scenarios	2.2%	1.5%	0.6%
Cover 80% of Scenarios	4.5%	3.1%	1.1%
Cover 90% of Scenarios	10.1%	6.0%	1.8%
Cover 95% of Scenarios	16.6%	8.5%	2.3%

Morbidity Process Risk – Claims Impact



Morbidity Process Risk Testing Results Using Next Top 20 - “Smaller” Companies Data Incurred Claims			
	Duration 15	Duration 15-17	NPV – All Years
	Estimates as % of Mean		
One Standard Deviation	25.7%	14.7%	4.4%
Cover 60% of Scenarios	5.0%	1.7%	0.6%
Cover 70% of Scenarios	9.8%	4.6%	1.9%
Cover 80% of Scenarios	14.7%	9.3%	3.5%
Cover 90% of Scenarios	23.2%	17.1%	5.7%
Cover 95% of Scenarios	40.4%	30.2%	7.6%

Termination Process Risk – Claims Impact



Termination Process Risk Testing Results Using Top 20 - “Larger” Companies Data Incurred Claims			
	Duration 15	Duration 15-17	NPV – All Years
	Estimates as % of Mean		
One Standard Deviation	2.2%	2.2%	3.7%
Cover 60% of Scenarios	0.6%	0.6%	0.7%
Cover 70% of Scenarios	1.1%	1.2%	1.7%
Cover 80% of Scenarios	1.8%	1.8%	3.0%
Cover 90% of Scenarios	2.7%	2.7%	5.0%
Cover 95% of Scenarios	3.7%	4.0%	6.7%

Termination Process Risk – Claims Impact



Termination Process Risk Testing Results Using Next Top 20 - “Smaller” Companies Data Incurred Claims

	Duration 15	Duration 15-17	NPV – All Years
	Estimates as % of Mean		
One Standard Deviation	4.9%	5.1%	8.6%
Cover 60% of Scenarios	1.3%	1.2%	1.6%
Cover 70% of Scenarios	2.7%	2.7%	4.0%
Cover 80% of Scenarios	4.1%	4.2%	7.1%
Cover 90% of Scenarios	6.5%	6.7%	10.9%
Cover 95% of Scenarios	7.7%	8.1%	14.9%

Combined Process Risk – Claims Impact



Combined Morbidity and Termination Process Risk Testing Incurred Claims NPV All Years		
	Larger Company	Smaller Company
	Estimates as % of Mean	
One Standard Deviation	4.0%	9.3%
Cover 60% of Scenarios	0.7%	2.7%
Cover 70% of Scenarios	1.7%	4.9%
Cover 80% of Scenarios	3.2%	8.1%
Cover 90% of Scenarios	5.2%	12.0%
Cover 95% of Scenarios	6.9%	16.1%

Morbidity - Add Parameter Risk



Morbidity Process + Parameter Risk Testing Incurred Claims NPV All Years				
	Larger Company		Smaller Company	
	Process Risk Only	Process + Parameter Risk	Process Risk Only	Process + Parameter Risk
	Estimates as % of Mean			
One Standard Deviation	1.3%	20.4%	4.4%	42.8%
Cover 60% of Scenarios	0.3%	0.9%	0.6%	1.7%
Cover 70% of Scenarios	0.6%	4.4%	1.9%	16.1%
Cover 80% of Scenarios	1.1%	7.6%	3.5%	32.6%
Cover 90% of Scenarios	1.8%	43.6%	5.7%	59.1%
Cover 95% of Scenarios	2.3%	49.2%	7.6%	89.2%



- Only a simplified example – did not account for all variables driving experience
 - Results should not be viewed as suggested morbidity pads
- Caution when using historical data
 - Normalize data to understand deviations
 - Pitfall: trend vs. “uncontrolled” variable
 - Past volatility and misestimation may not be good predictors of future (model risk)
 - Think about correlations



- Process risk observations
 - Company size important consideration
 - Morbidity risk lower for longer periods
 - Up's / Down's have “canceling out” effect
- Process risk is only part of the story
 - Don't forget parameter risk!
- Helpful simulation uses
 - Inform amount for adverse deviation loads
 - Monitor / evaluate emerging experience

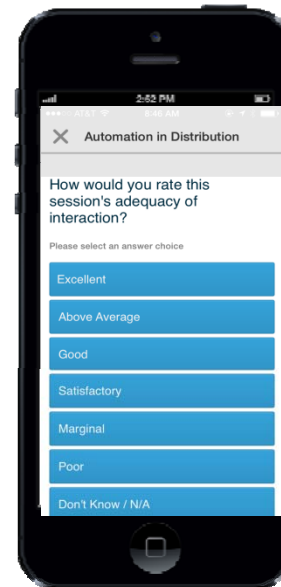
Don't forget to fill out the survey!



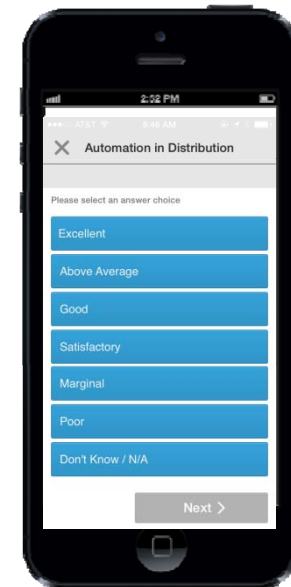
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**Tap on the
answer you wish
to submit**



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