Bringing Advanced Analytics to Reserving

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A view of Actuarial Modeling

- Our team focuses on bringing advanced analytics to the reserving process
- Independent group, outside of the reserving team made up of Data Scientists, Actuaries and actuarial students.
- Given the nature of the problems we study, our primary responsibility is to build claim level reserve models

Claim level data contains a lot of information

Claim Identifier	Paid Loss	Incurred Loss	Industry	Litigation Status	Injury Type	…
123456	$175,000	$200,000	Construction	Closed	Struck By	…
123457	$0	$1,000,000	Mining	Open	Asbestos	…
123458	$4,000	$4,000	Retail	No Litigation	Slip & Fall	…
123459	$0	$0	Retail	Open	Slip & Fall	…
123460	$35,000	$35,000	Financial	No Litigation	Repetitive Motion	…
123461	$1,000,000	$1,000,000	Construction	No Litigation	Slip & Fall	…
123462	$2,000	$25,000	Education	No Litigation	Slip & Fall	…
…	…	…	…	…	…	…

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- Traditional reserving methods often focus solely on paid or incurred loss

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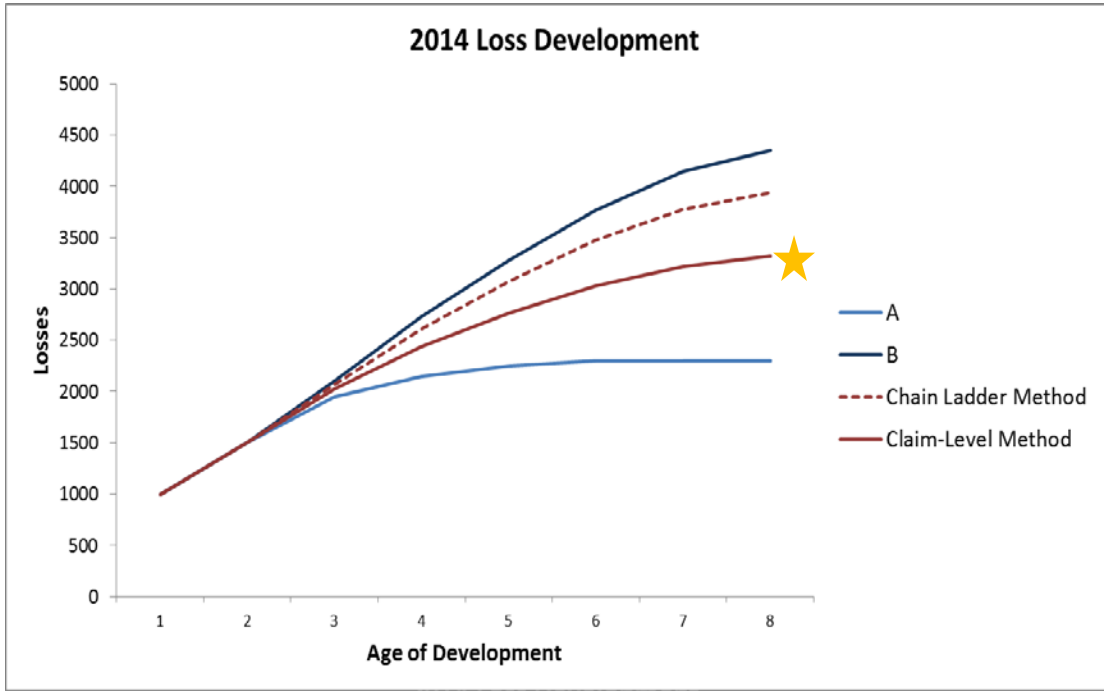
- Utilizing more data allows for increased understanding of losses

Claim level reserving and mix shift

Claim level reserving can identify and account for shifts in the mix of business

Aggregate techniques like chain ladder pick up trends, but with significant lag



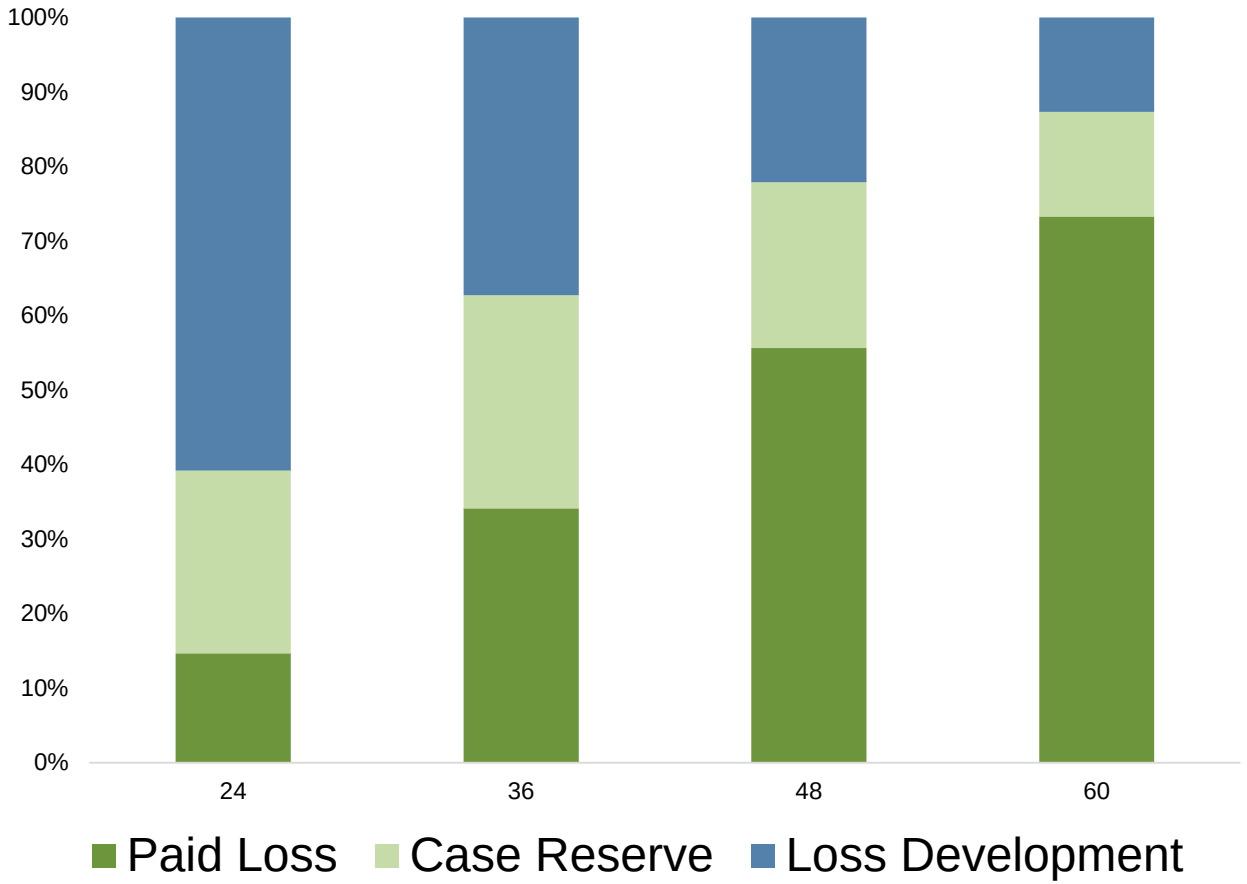
	Segment	
	A	B
Historical Mix:	20%	80%
2014 Mix:	50%	50%

- **Chain ladder methods** work well when current and historic mixes are similar
- **Claim level models** look at actual distribution of claims allowing for more accurate estimating with changing mix of business

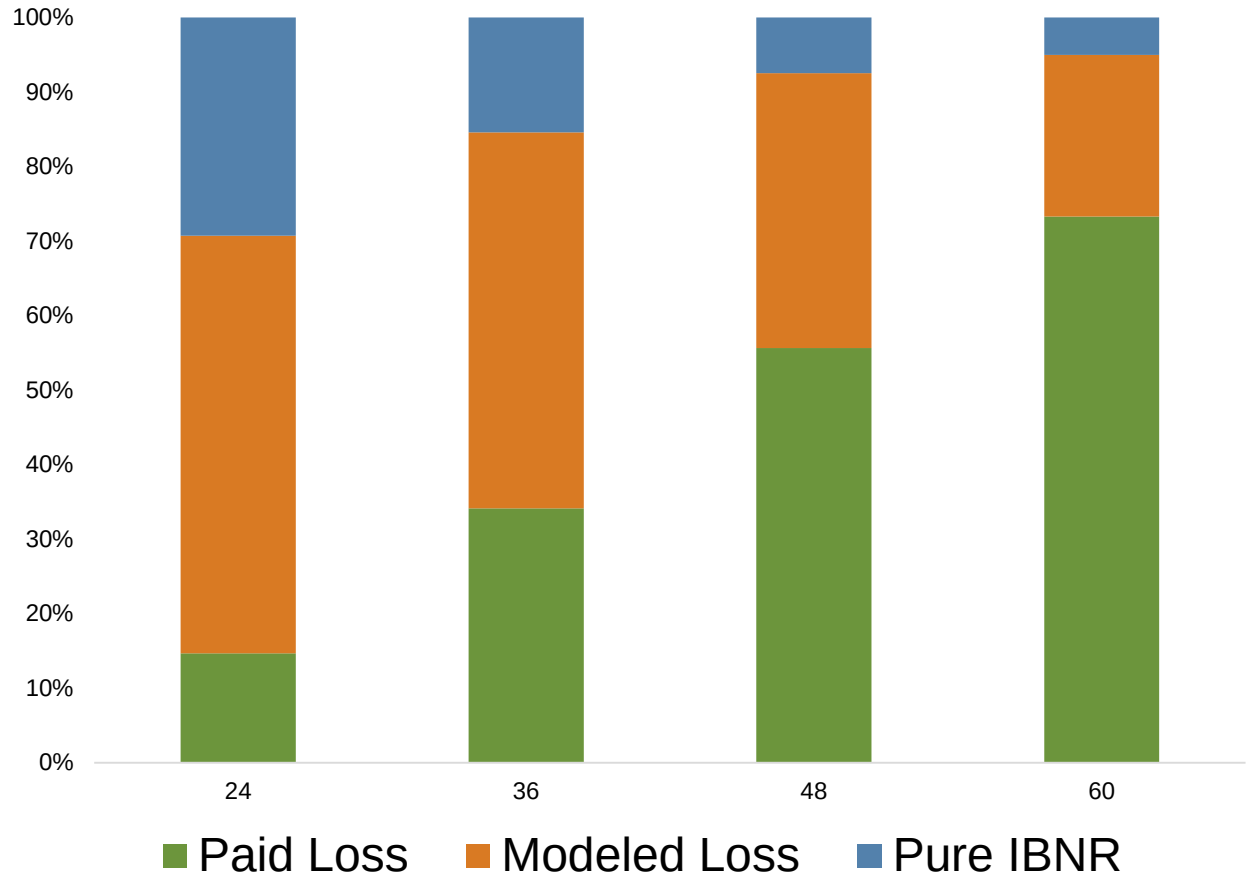
Claim level models allow us to understand *why* development is changing

Allows for a more refined view of ultimate loss

Aggregate Reserving Methods



Claim Level Reserve Modeling

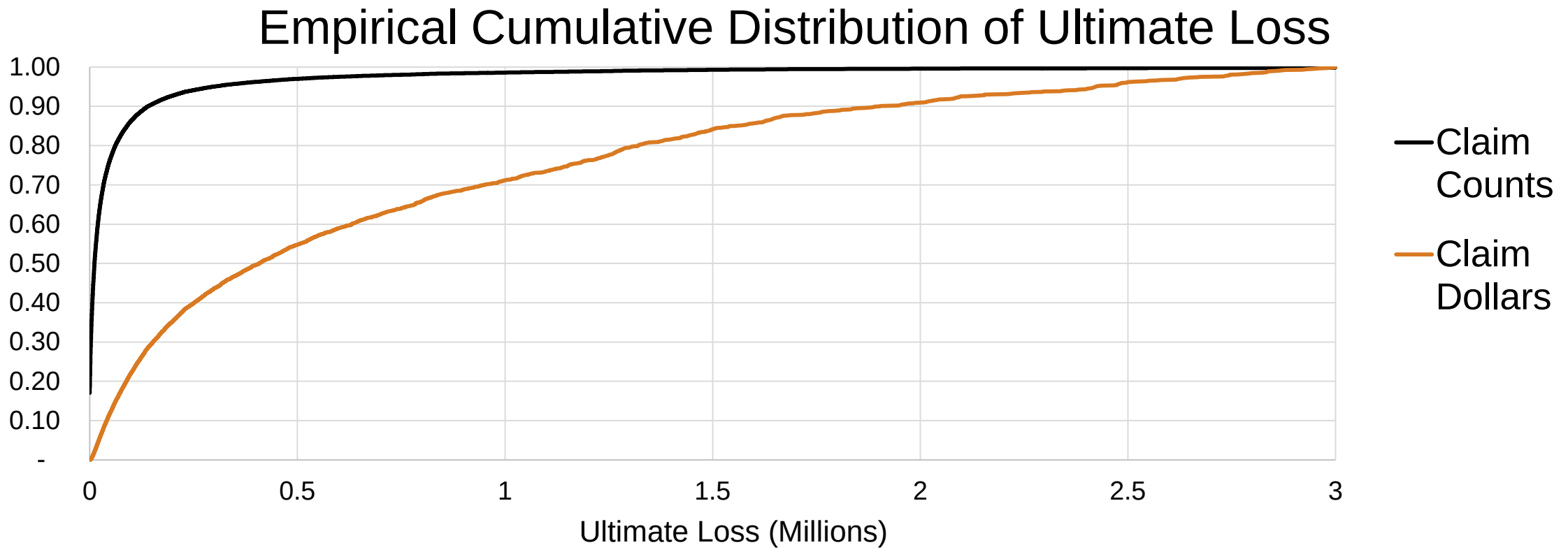


Applying predictive analytics in the reserving space

- Predictive modeling used extensively in product pricing
  - GLMs are common in the industry and understood by regulators
  - Some assumptions of GLMs break down especially for longer tailed lines

- Are there some alternative, claim level, statistical techniques we could use?

Some long tailed lines have skewed loss distributions



- Most GLMs require specification of the underlying loss distribution– this is pretty tricky

Longer tailed lines require use of old data

Accident Year	12	24	36	48	60	72	84	96	108	120
2001	7.9	22.9	30.0	37.9	43.4	50.5	52.1	51.3	52.9	56.0
2002	5.5	15.0	23.7	30.0	39.5	42.6	43.4	46.6	47.4	48.9
2003	6.3	11.8	21.3	26.8	29.2	34.7	34.7	35.5	37.9	39.5
2004	3.2	7.9	14.2	18.9	23.7	26.8	27.6	29.2	32.4	33.2
2005	3.9	11.1	13.4	16.6	16.6	17.4	17.4	18.2	18.9	18.9
2006	5.5	12.6	16.6	18.2	20.5	21.3	22.1	22.9	22.9	23.7
2007	3.2	6.3	12.6	15.0	16.6	18.2	17.4	18.2	18.9	
2008	3.2	7.9	14.2	18.9	21.3	22.9	23.7	25.3		
2009	1.6	5.5	8.7	14.2	15.8	17.4	18.9			
2010	3.9	11.8	16.6	18.9	23.7	26.1				
2011	5.5	11.8	17.4	25.3	32.4					
2012	3.9	9.5	17.4	22.1						
2013	2.4	7.1	9.5							
2014	2.4	3.9								
2015	2.4									

- For longer tailed lines models must be built on older data, which could be less appropriate.
- Data that has not reached maturity cannot be used.
- Alternative could be to use age-to-age models. That however comes with a host of other issues.

Survival Analysis

- Survival analysis is a branch of statistics that deals with the analysis of time duration.
- Traditionally models “time to event” data
- Answers questions like:
  - What proportion of a population will survive past (or up to) point t?
  - Of those that survive, what rate do they die or fail?

Survival models handle these challenges

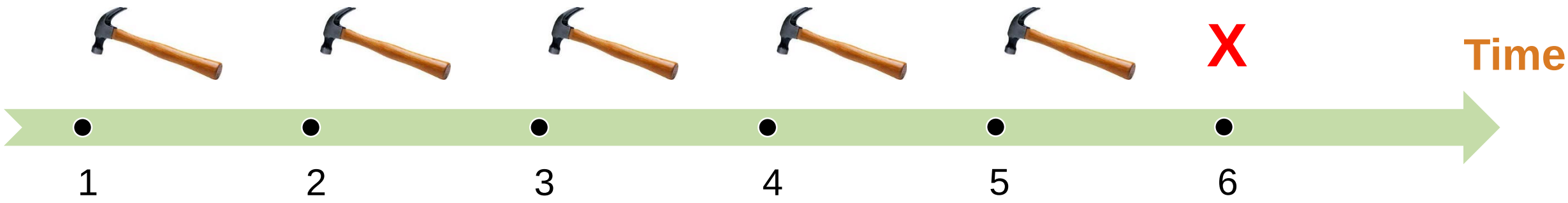
- Traditional GLM are less appropriate for longer tailed lines
  - Data extremely skewed
  - Long development patterns limit use of recent data

- Survival Modeling (Cox Proportional) solves these two issues
  - Non-parametric (uses empirical distribution)
  - Can use all information, including those claims that have not reached their ultimate values

- In our analysis, we ignore time, and chart the path of a claim through dollars

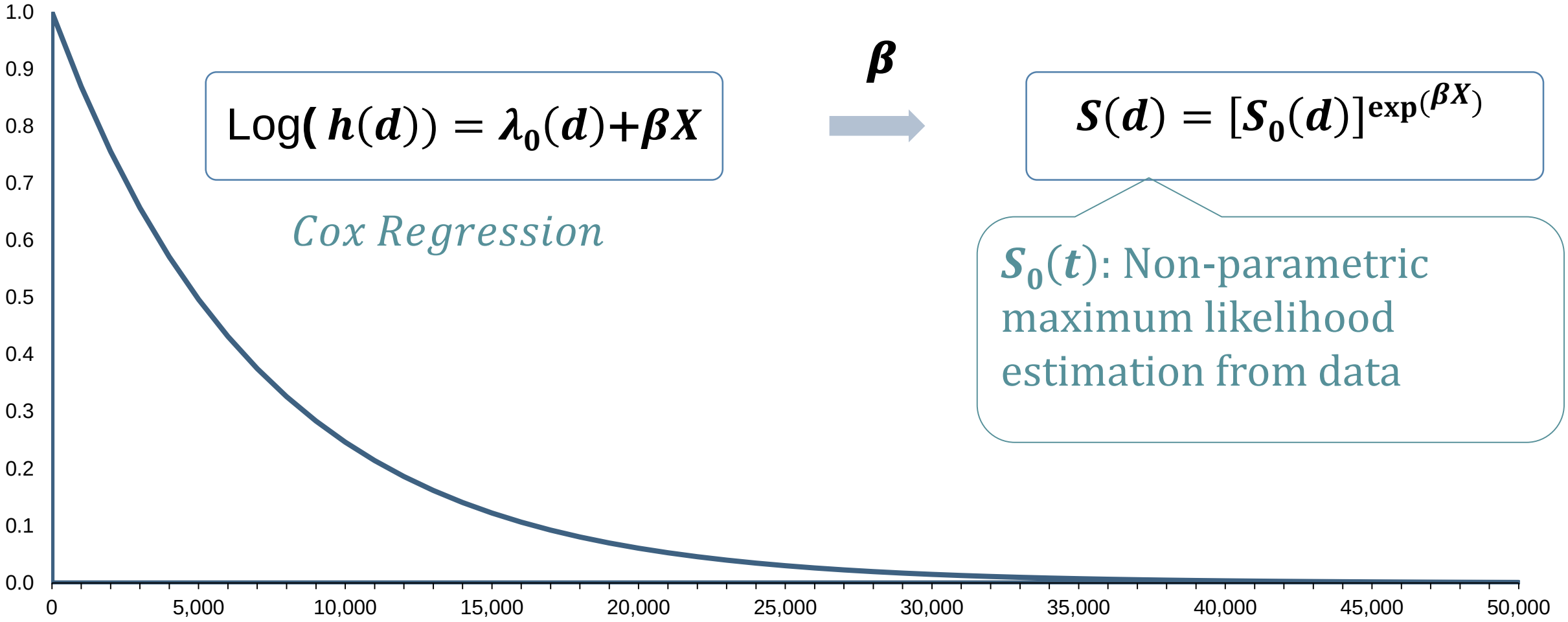
Survival modeling through dollars not time

- Traditional survival analysis models time to event



- That doesn't answer our question – we need to know dollars at claim close

Predicting Ultimate Loss with Cox Proportional Hazard Model



$$\text{Log}(h(d)) = \lambda_0(d) + \beta X$$

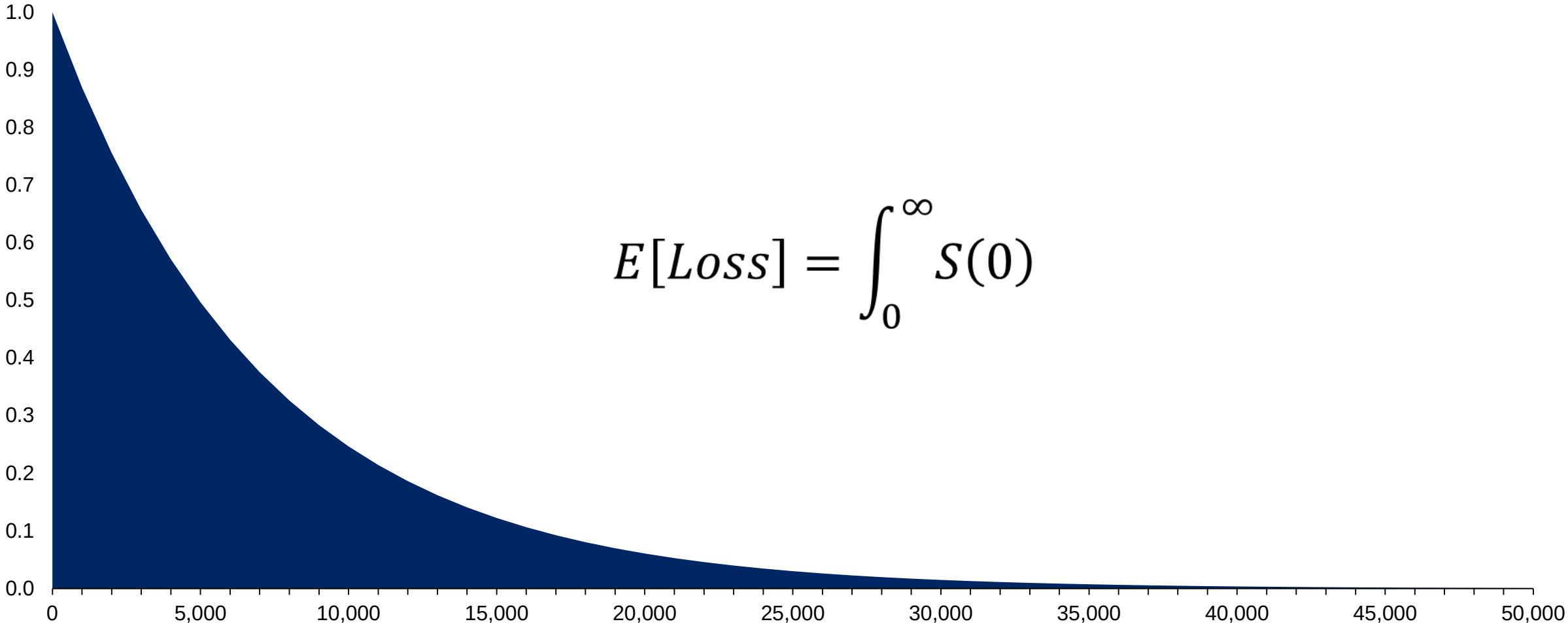
Cox Regression

β

$$S(d) = [S_0(d)]^{\exp(\beta X)}$$

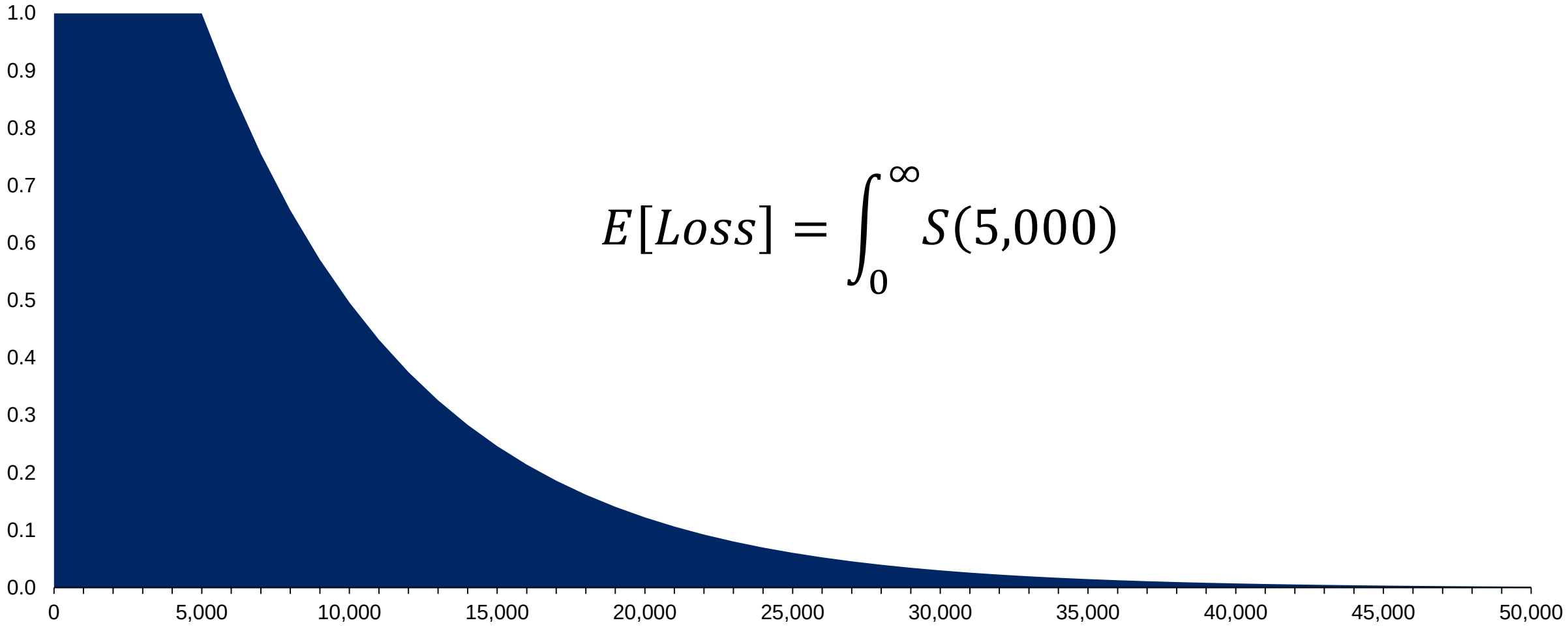
$S_0(t)$: Non-parametric maximum likelihood estimation from data

Predicting Ultimate Loss with Cox Proportional Hazard Model



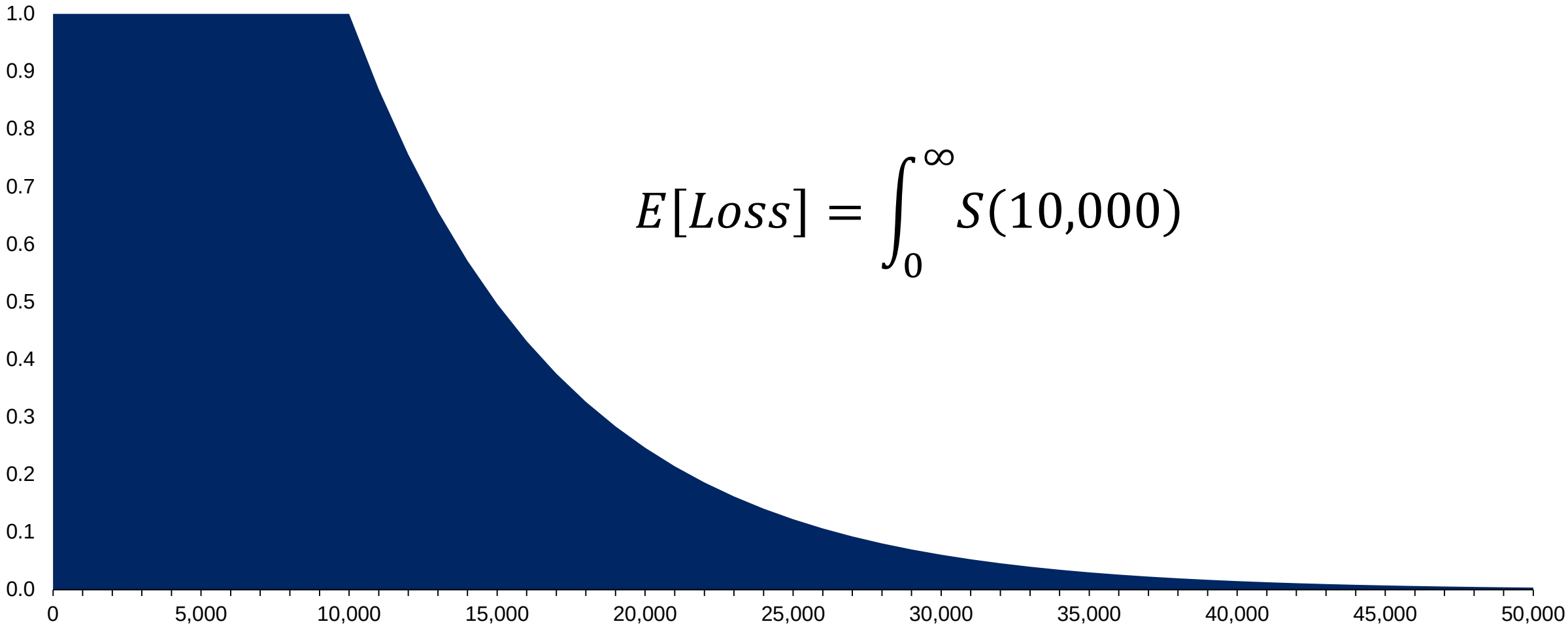
$$E[Loss] = \int_0^{\infty} S(0)$$

Predicting Ultimate Loss with Cox Proportional Hazard Model



$$E[Loss] = \int_0^{\infty} S(5{,}000)$$

Predicting Ultimate Loss with Cox Proportional Hazard Model



$$E[Loss] = \int_0^{\infty} S(10{,}000)$$

Challenges we faced

- Problem: Time-dependent covariates => dollar-dependent covariates
  - Covariates can change with an associated dollar change, but no changes can occur unless we move forward in dollars
  - Time cannot exist in our model

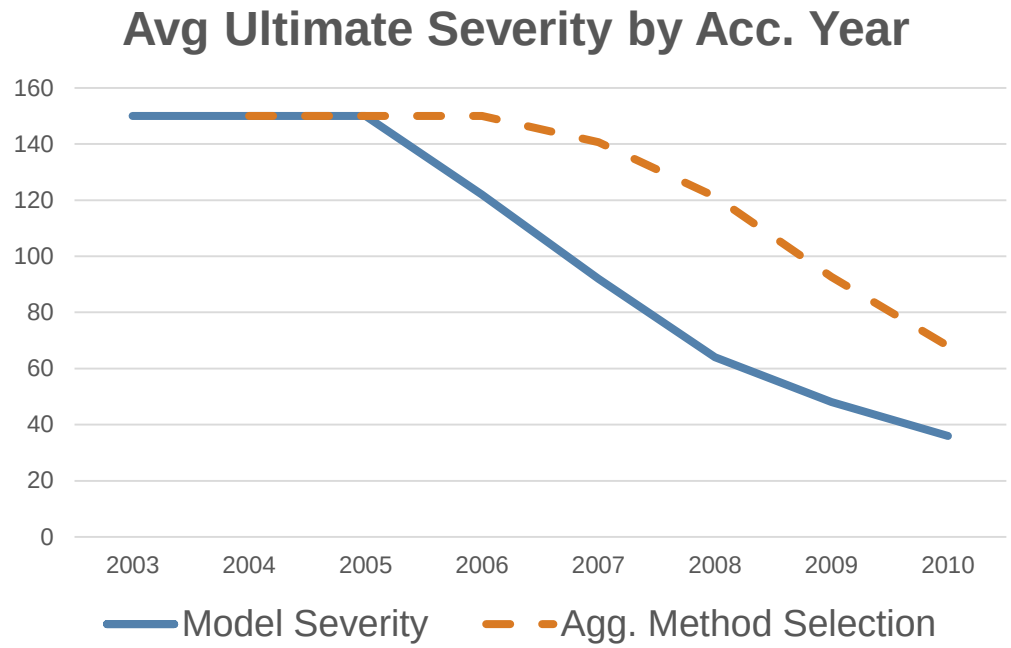
- Problem: You cannot move backward in dollars

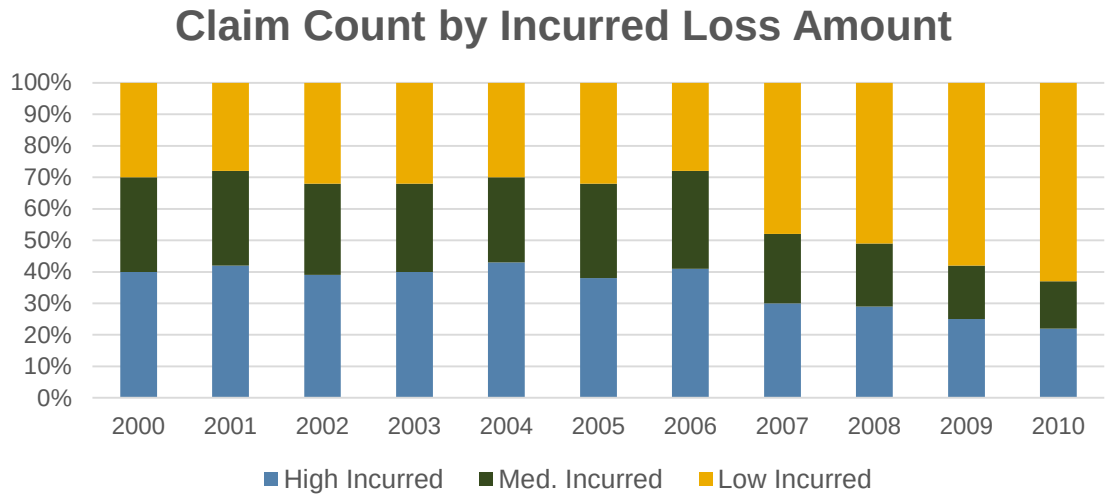
- Problem: Validation of your models becomes more tricky– once you include censored data, how do you validate if your model is working

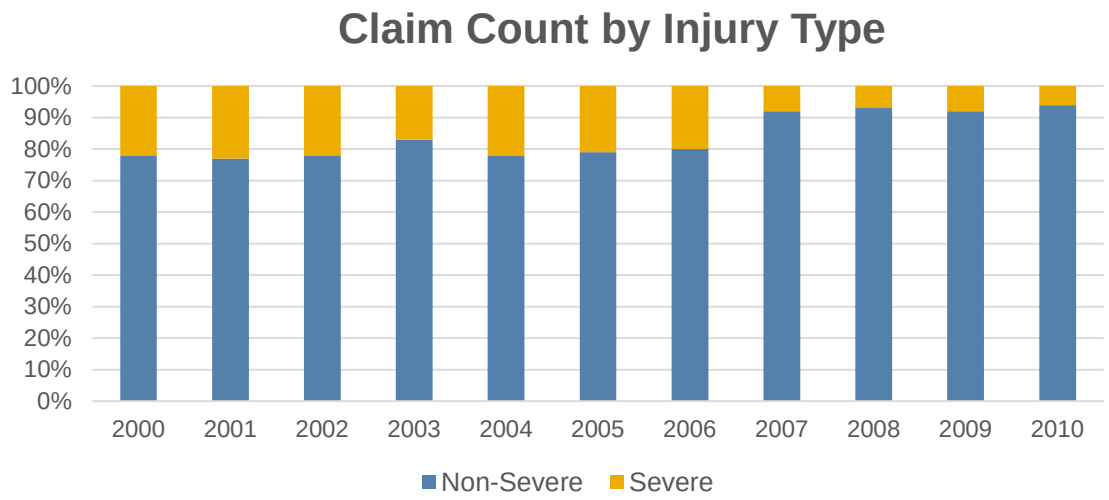
Applications of the Model

- Our model will produce an alternate estimate of ultimate liabilities
- The model can produce results quickly after data is available
- While the model can produce estimated liabilities, it also has alternative applications to help you better understand book changes

Allows Deeper Analysis of Effects of Book Shifts







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and
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