

Not Pricing for John Smith

Measuring the uncertainty in Pricing

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Agenda

1. Background
2. Theoretical Pricing Uncertainty
3. Emperical Pricing Uncertainty
4. Practical applications of Pricing Uncertainty
5. Practical applications within the Customer Lifetime Value framework
6. Wrap up

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Background: Why build pricing models?

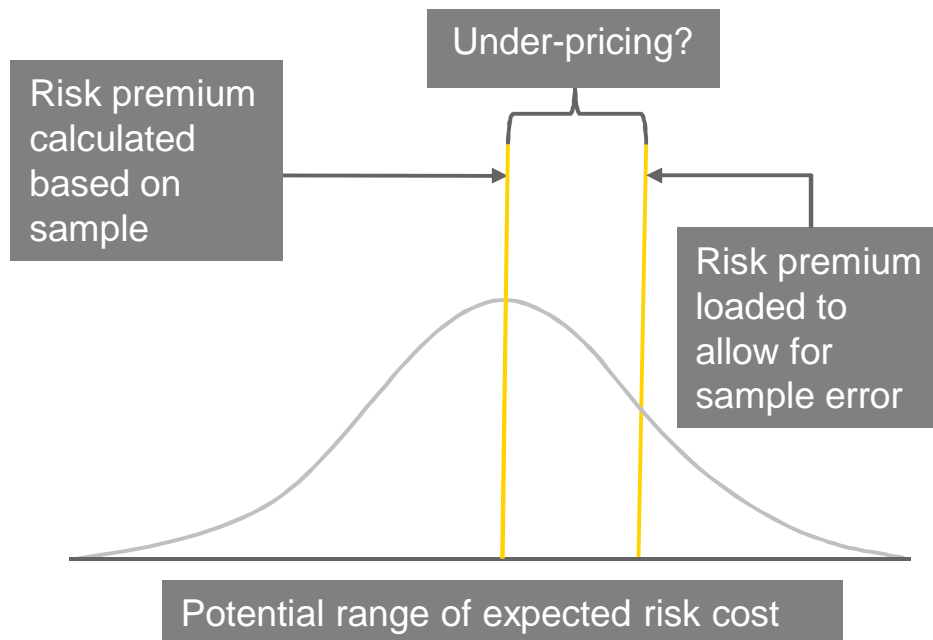
- ▶ Statistical pricing models help to:
 - ▶ Avoid anti-selection
 - ▶ Target the right segment of customers
 - ▶ Enhance profitability
 - ▶ Gain competitive advantage
- ▶ All statistical models have an element of uncertainty around their estimates.
- ▶ A simplistic application of statistical models that ignores this inherent uncertainty can actually be detrimental to profit.

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Pricing uncertainty

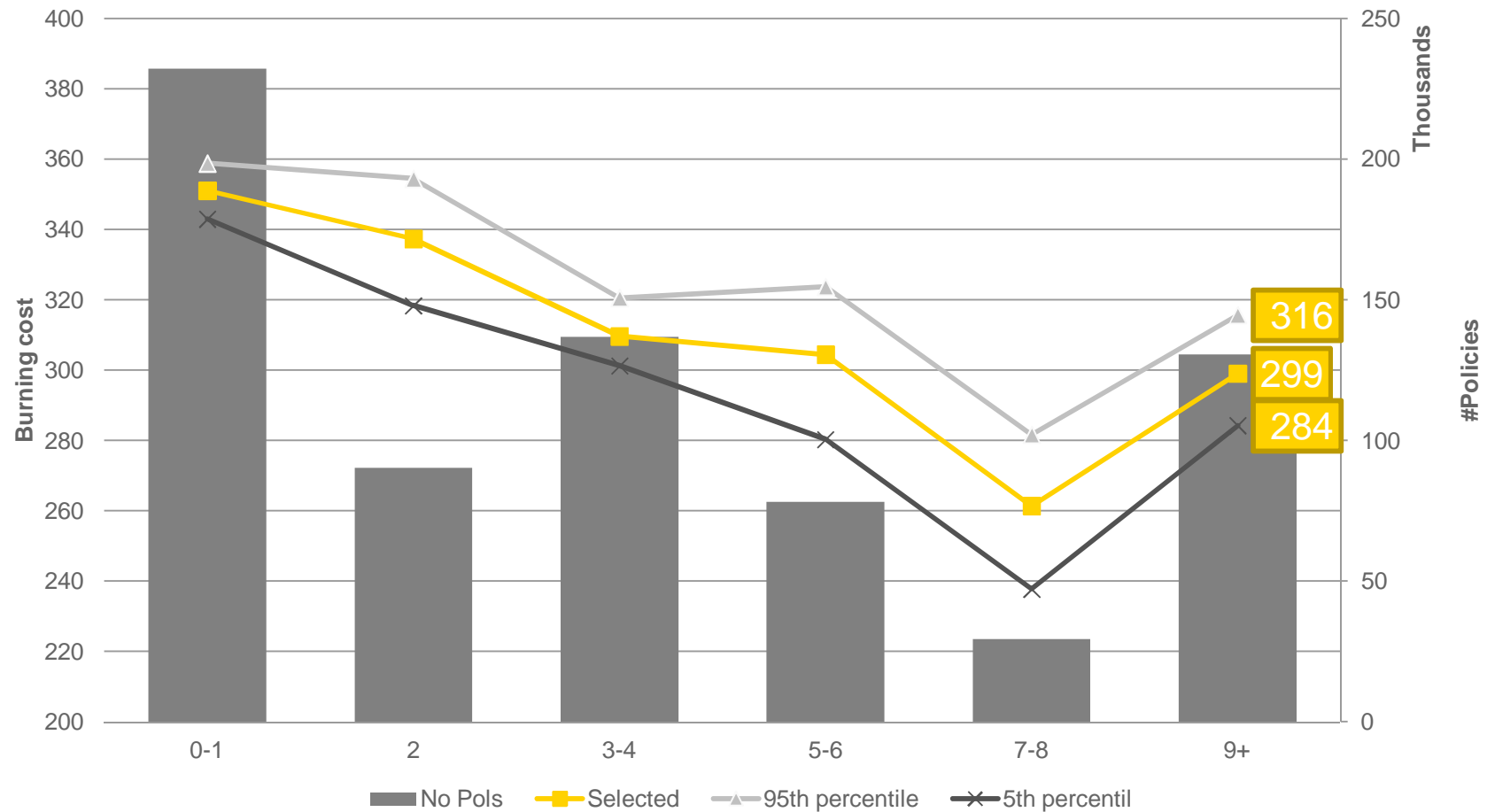
- ▶ Hypothesis:
 - ▶ Every insurer's own experience is only a sample of the overall market experience for any risk.
 - ▶ The smaller the sample the higher the risk of mispricing due to sample error.
 - ▶ Overpricing: less of an issue unless segment is critical to insurer's strategy.
 - ▶ Under-pricing: can be a significant issue, especially in the aggregator world.



Challenges:

- ▶ Working out by customer segment how much to adjust the basic risk price to allow for sample error.
- ▶ Checking the under-pricing risk across the portfolio is within the insurer's risk appetite.
- ▶ Putting in place real-time portfolio management.

The estimated burning cost can have significant variation



Estimating the burning cost in practice

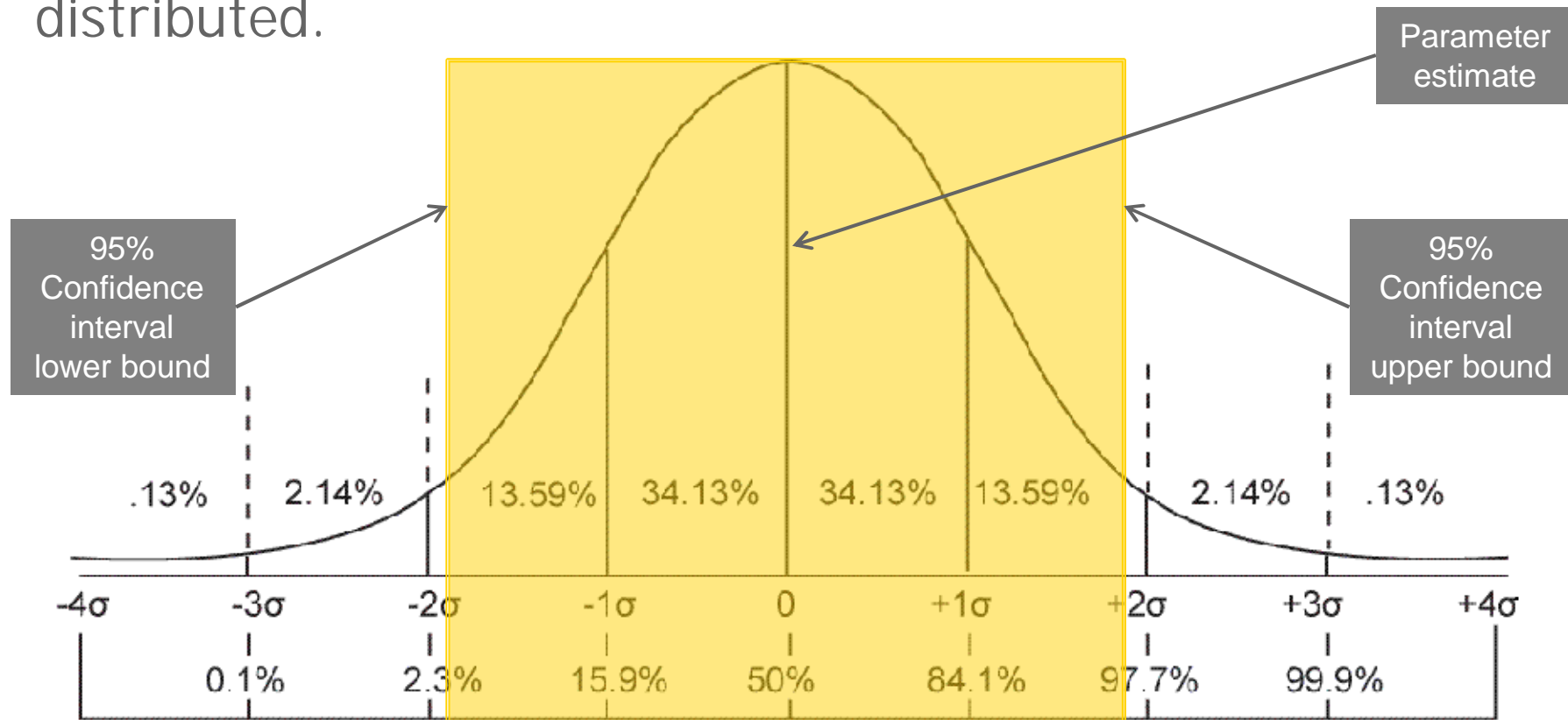
- ▶ The standard approach is to separately parameterise:
 - ▶ Frequency model => Number of Claims per Policy
 - ▶ Severity model => Average Cost per Claim

- ▶ To obtain the combined model:
 - ▶ Burning Costs = Frequency x Severity
 => Average cost per policy

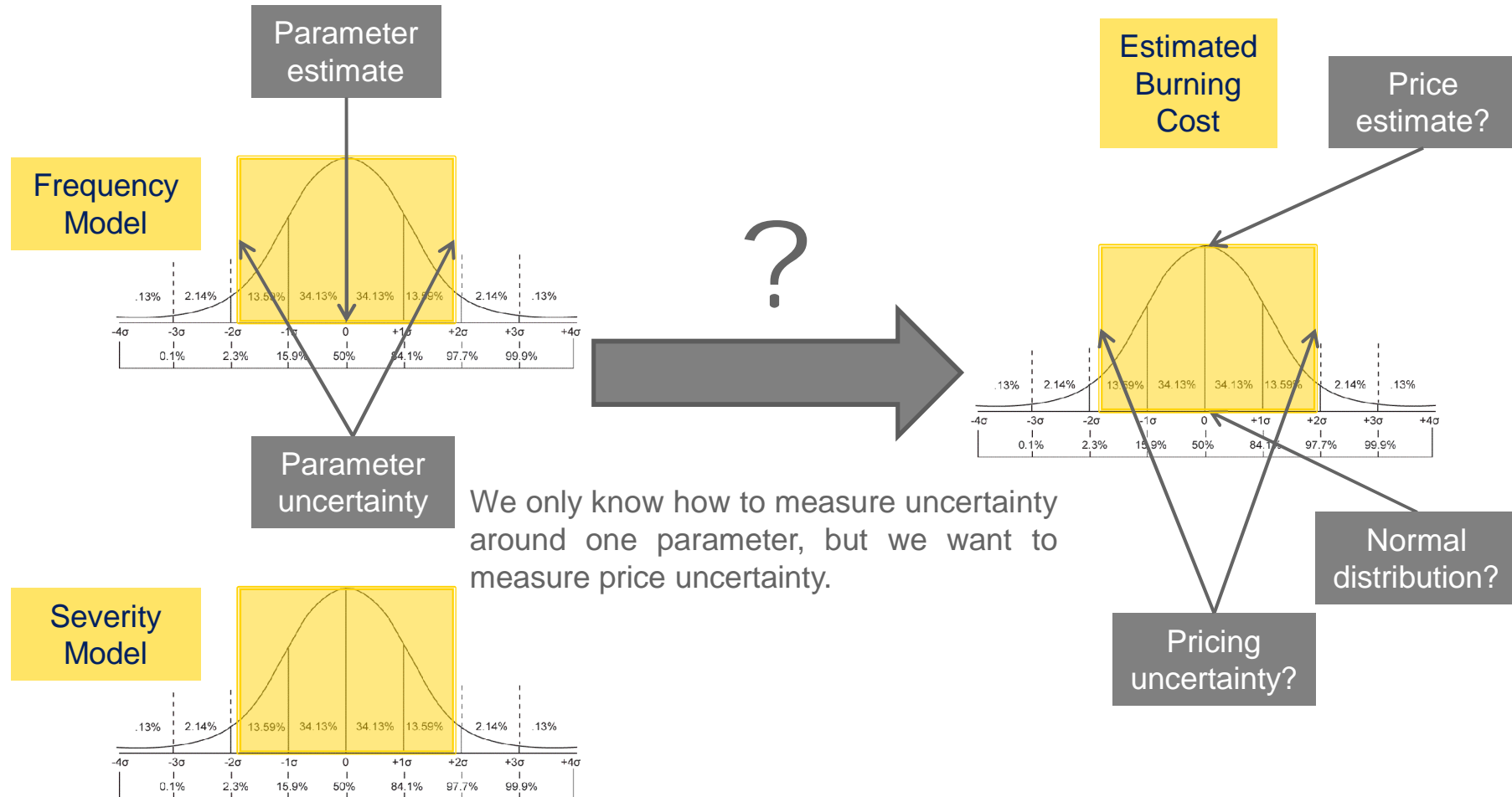
- ▶ The Frequency and Severity models are appropriately chosen via Generalized Linear Models (GLMs).

How to measure the uncertainty around the parameter estimates?

Assuming the dataset is sufficiently large, the parameter estimates are asymptotically multivariate normal distributed.



But it's only the burning cost that really matters!



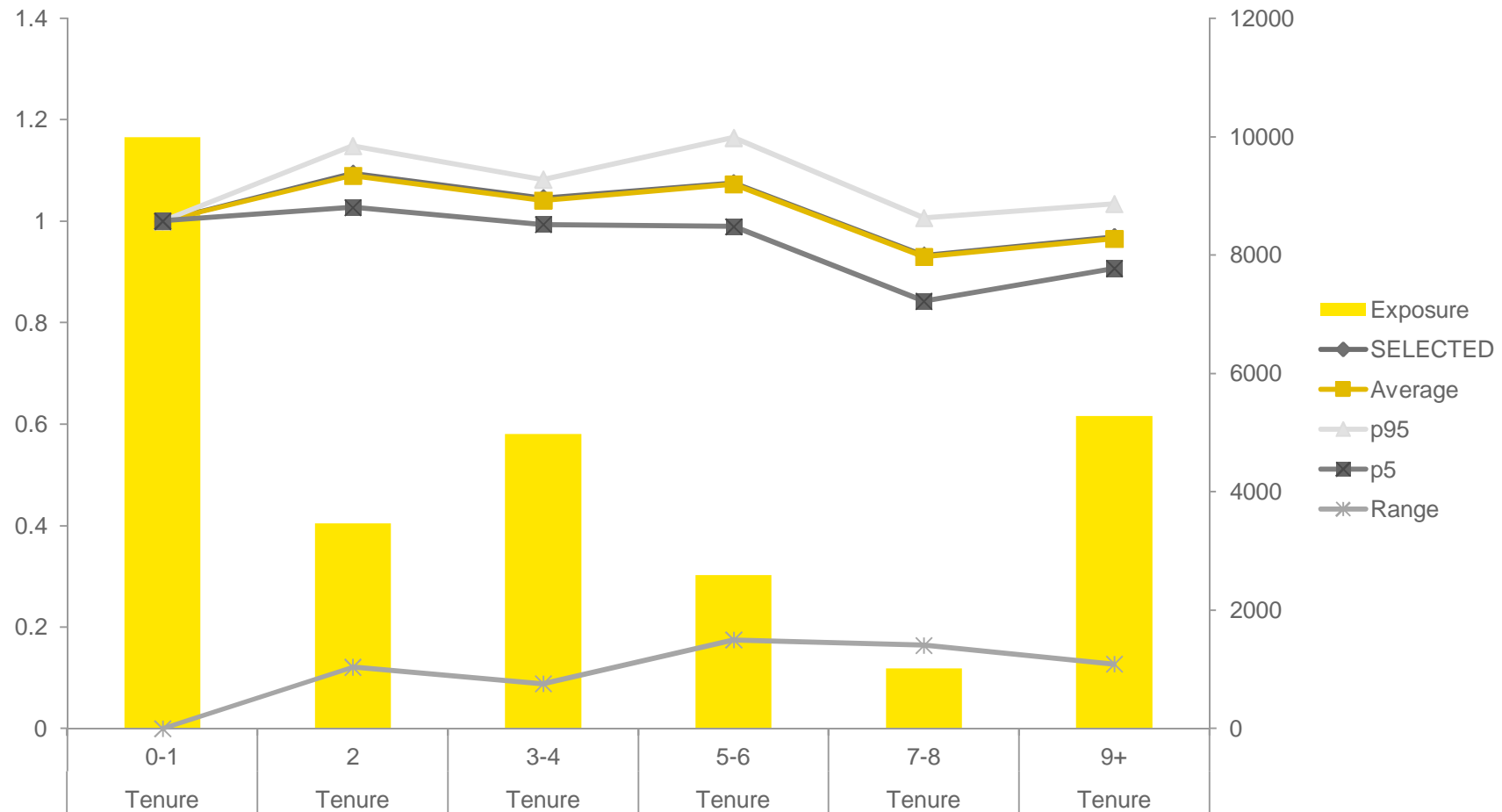
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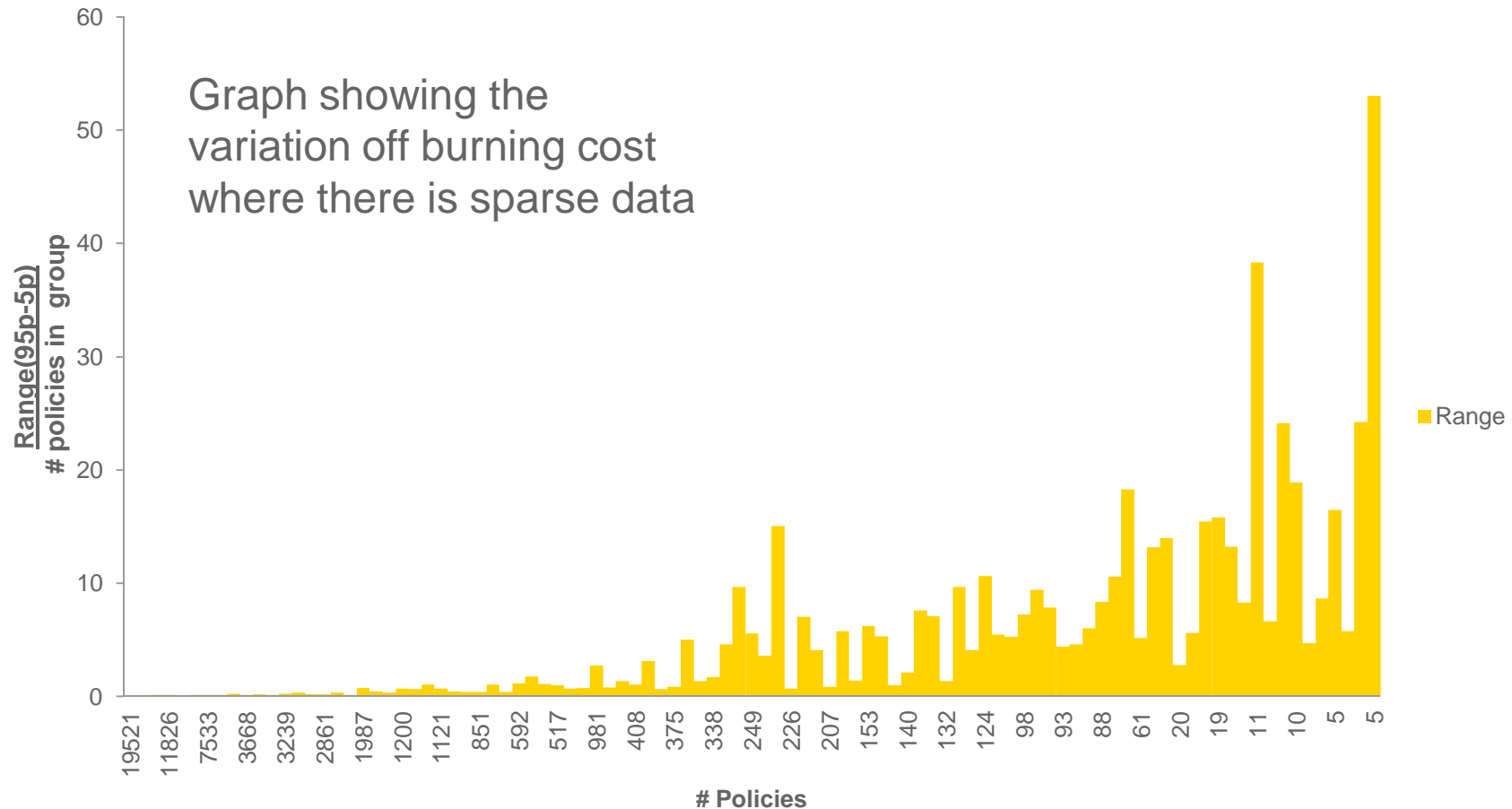
What empirical method to use for determining pricing uncertainty?

- ▶ Randomly sample (with replacement) a dataset. This results in a set of different datasets that are only marginally different.
- ▶ Fit the same Model to all the datasets.
- ▶ Consider the variation of parameter estimates and predicted values or the fitted models.

What are the relative estimates for the Tenure factor in the Severity model?



How does the range of the prediction intervals vary with the number of policies?



Why (not) to use bootstrapping?

Advantages

- ▶ Bootstrapping is a very simple method
- ▶ Bootstrapping lets the data speak for itself
- ▶ It is easy to implement
- ▶ It is an appropriate way to control and check the stability of results

Disadvantages

- ▶ Bootstrapping is computationally heavy
- ▶ Important assumptions are being made when undertaking the analysis (Independence of samples, good representation of population)
- ▶ Difficult to derive an uncertainty measure out of the results

So what are the other options?

- ▶ It would be easier to calculate a prediction interval directly around a price in the same way as you would a confidence interval around a parameter estimate.
- ▶ There is a closed form uncertainty measure, which allows calculation of the prediction interval without having to use bootstrapping.
- ▶ This allows us to industrialise calculating a measure and fit it into BAU.

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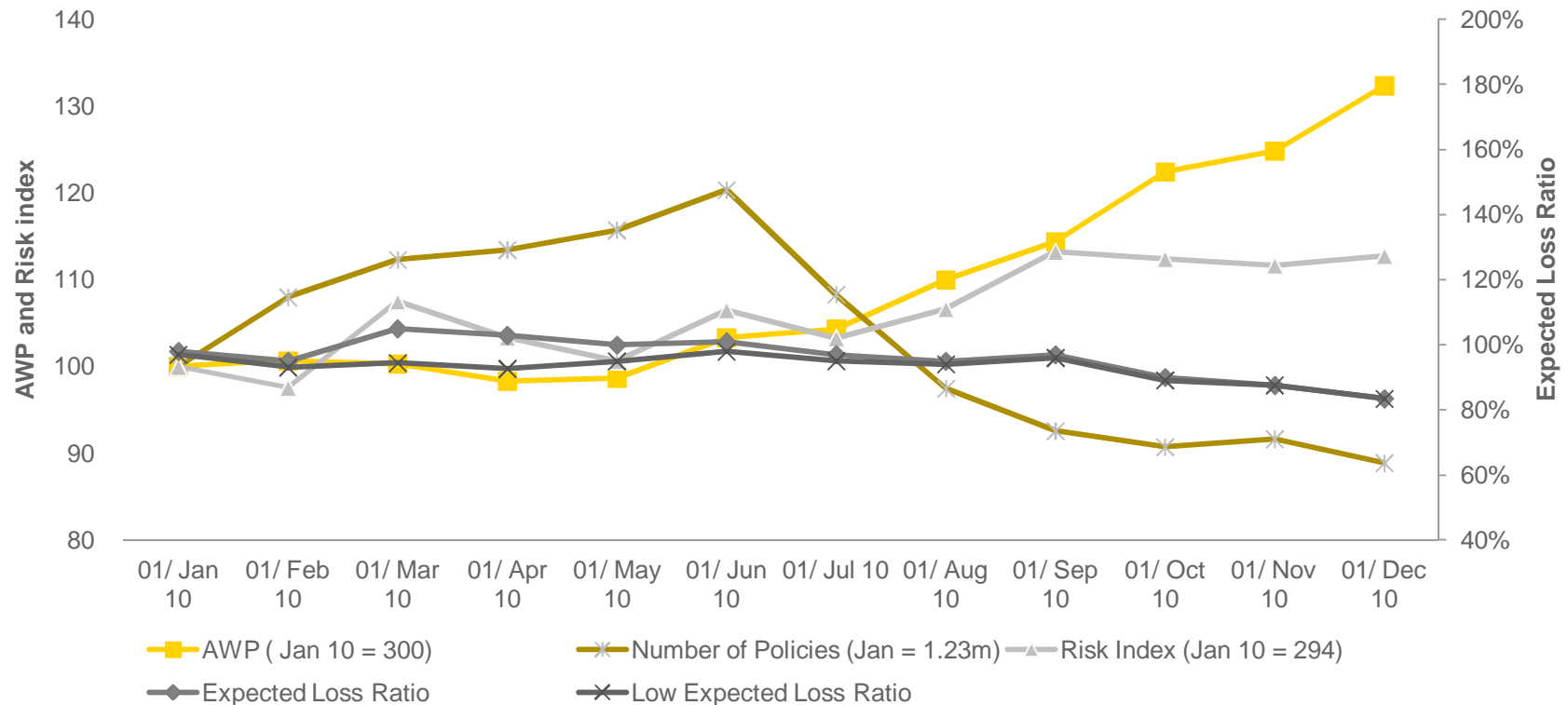
Pricing decisions...

- ▶ Insurers must offer a competitive price given changing market dynamics (price comparison websites).
- ▶ The understanding of the upside and downside risk of a point estimate for risk costs or any other model (e.g. elasticity) will :
 - ▶ Help to indentify risks where we are more 'certain' of a risk's expected profitability to us – important when considering Winners curse.
 - ▶ Give confidence to RI that risks are adequately priced.
 - ▶ Help to build rate monitors and develop new risk monitors.

Rank	Insurer	Price	Price Uncertainty	Potential High price	Potential Low price
	1 Alpha	347 (1)	unk	347 (1)	347 (1)
	2 Battle	370 (2)	unk	370 (2)	370 (3)
	3 Zypher	389 (3)	10%	428 (5)	350 (2)
	4 Rhubarb	398 (4)	unk	398 (3)	398 (4)
	5 Tango	402 (5)	unk	402 (4)	402 (5)

How to balance maximising revenue and risk appetite?

- ▶ The expected loss ratio looks out of control, so the company has significantly increases rates to bring the expected loss ratio under control again. But at the cost of losing many policies.



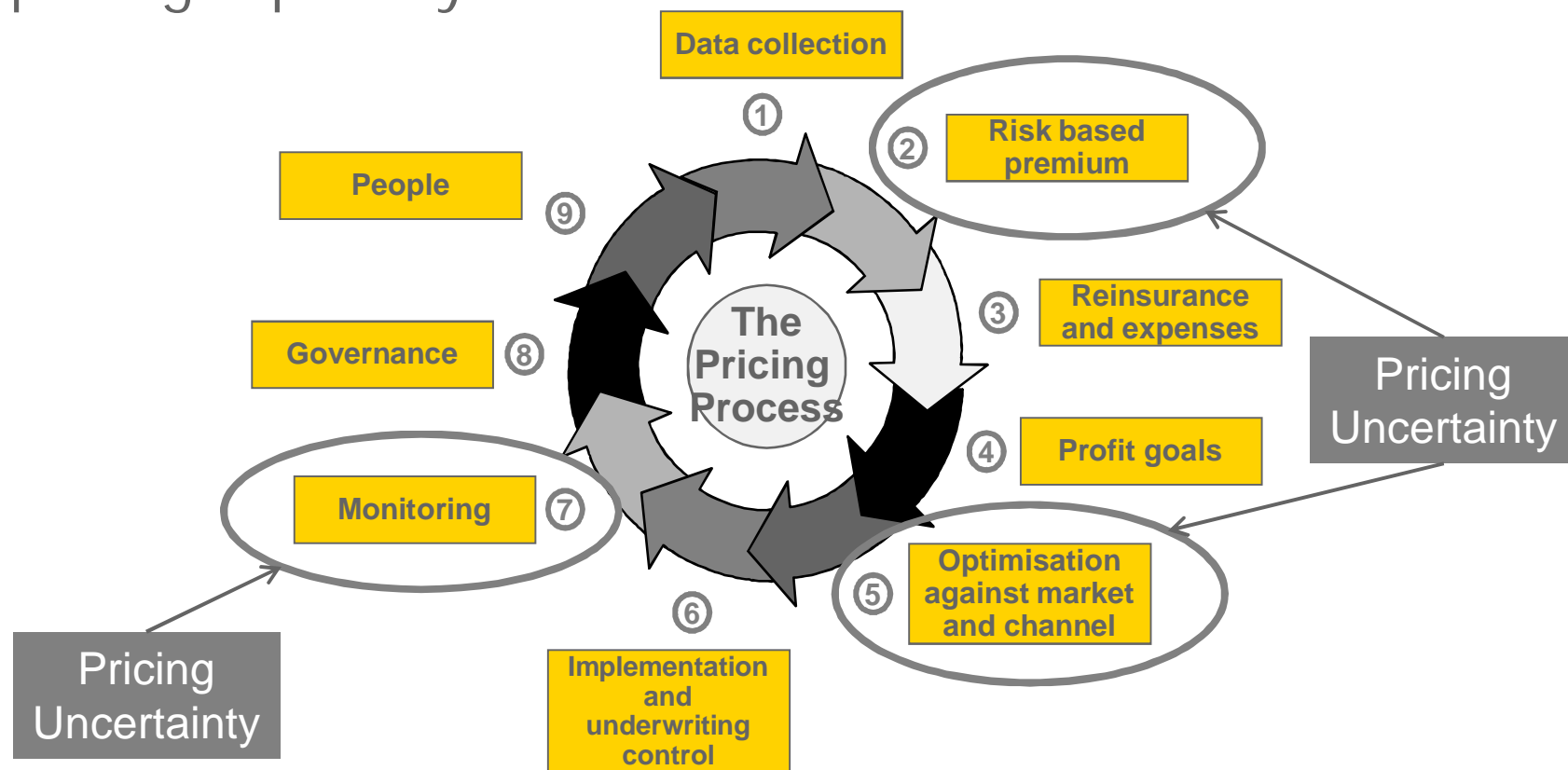
- ▶ If the firm had considered the uncertainty around their pricing decisions then possibly such heavy rate increases may be deemed unnecessary, as the Low Expected loss ratio is close to 90%.

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How to use pricing uncertainty in the Pricing Process?

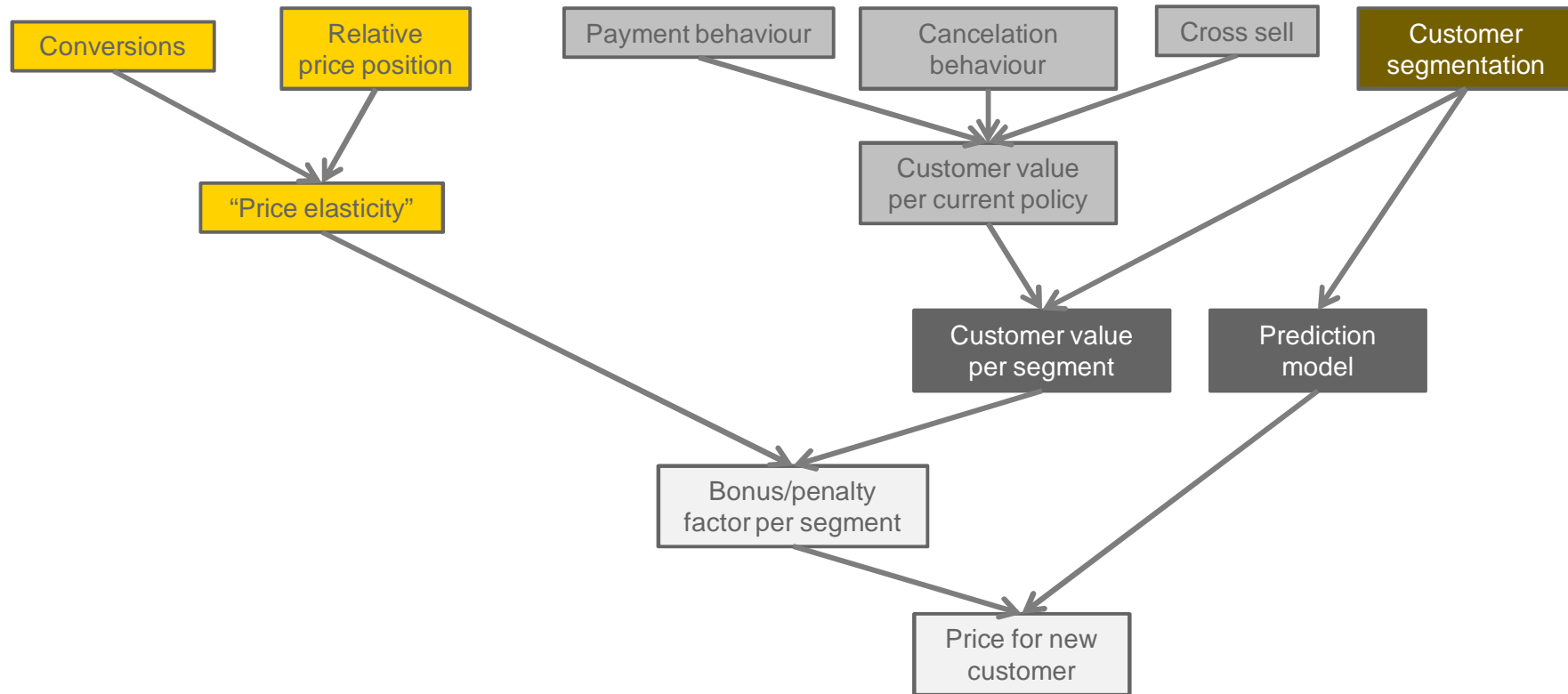
The Pricing Wheel provides a framework to help improve pricing capability.



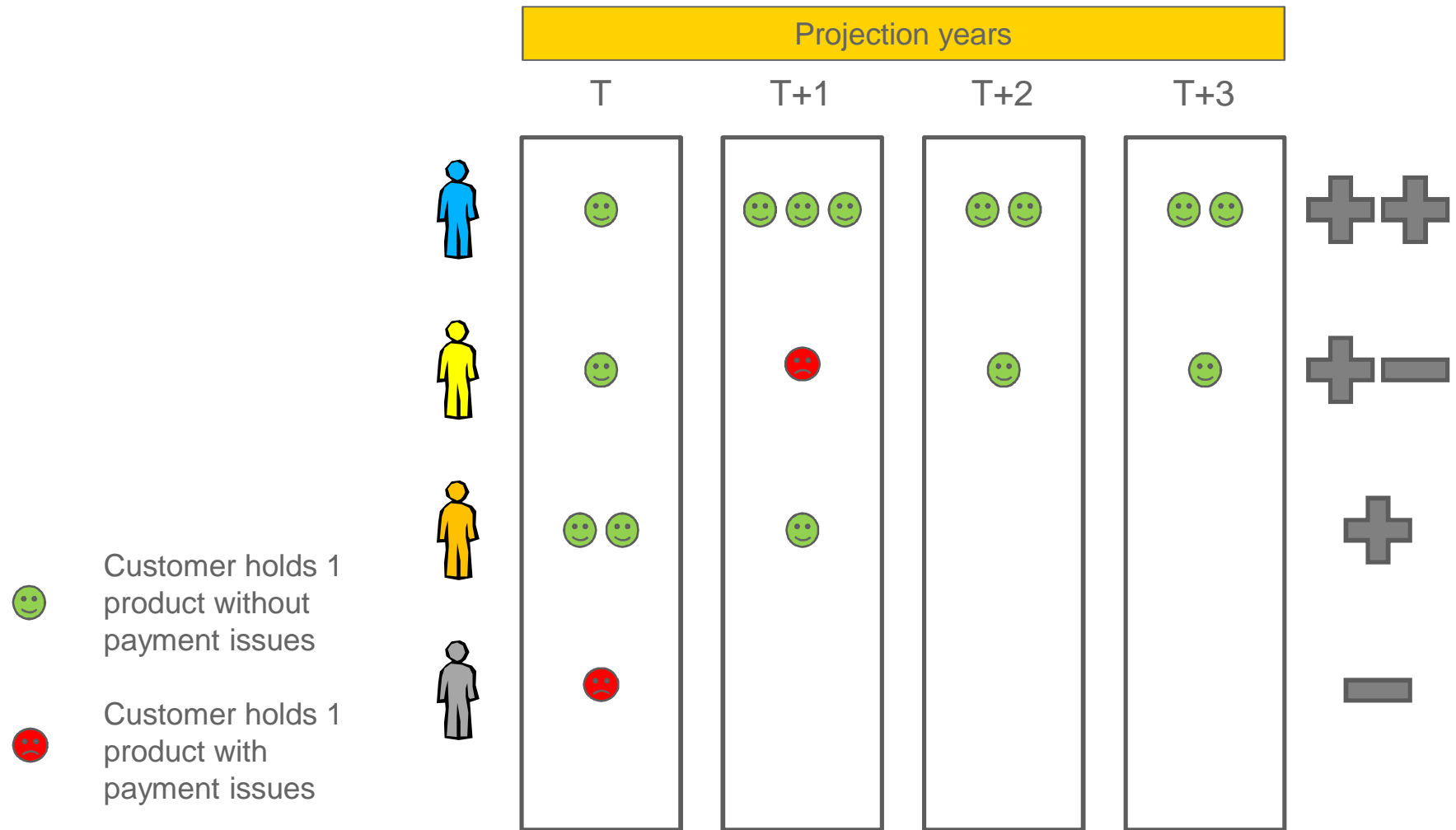
And how can we use this for optimisation against market and channel?

- ▶ CLV is based on numerous models all with a single point estimates.
- ▶ Understanding the prediction interval allows to adjust the amount of uncertainty risk.
- ▶ Reduce premium by a proportion of the prediction interval in segments where there is a higher Customer Lifetime Value.
- ▶ Get more good business without exceeding the uncertainty threshold.

How does this model work together with price optimisation?



But what is Customer Lifetime Value?



The Customer Lifetime Value model is very intuitive

Using the company's client data to model client behaviour:

- ▶ A higher lapse rate results in a lower customer value.
- ▶ A higher probability of non-payment results in a lower customer value.
- ▶ A higher rate of cross selling results in a higher customer value.
- ▶ A higher product yield results in a higher customer value.

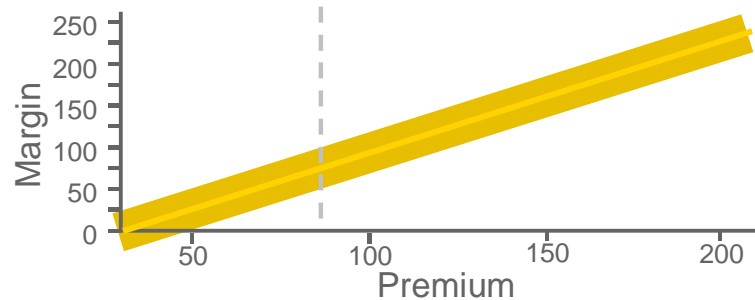
Assign a “pound value” to predicted client behaviour

- ▶ Administrative costs (e.g. dept collectors)
- ▶ Fixed cost per policy
- ▶ Profit per policy

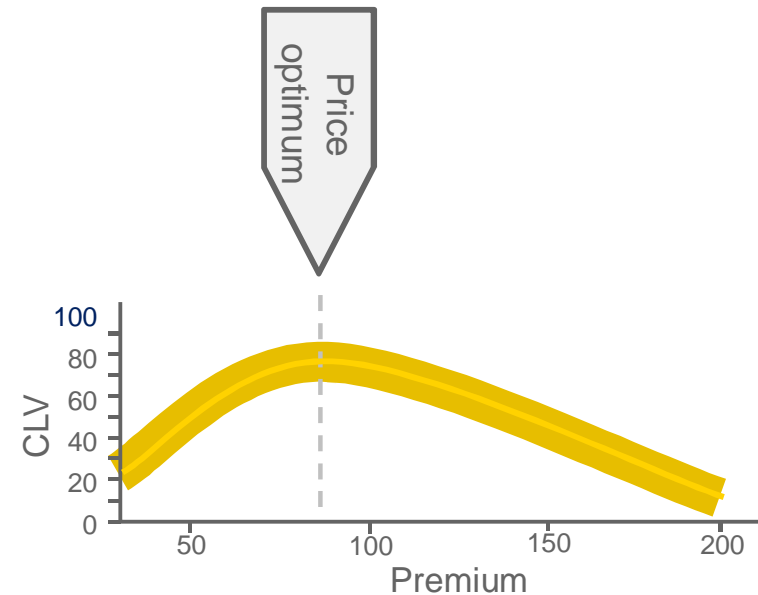
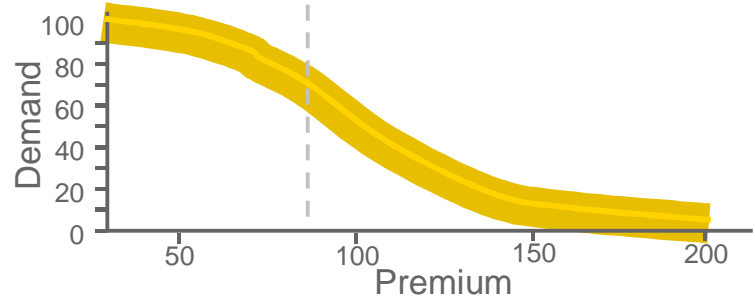
How to use Customer Lifetime Value and pricing uncertainty in price optimisation?

The risk premium prediction interval is used to determine the allowable variation around your premium, while maintaining sufficient overall income to cover your burning costs.

Margin vs. Premium



Demand vs. Premium



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Wrap up

- ▶ Where there less data available there is more uncertainty in a model's output.
- ▶ We have defined this variability as pricing uncertainty.
- ▶ By considering this uncertainty we can significantly alter the pricing decisions.
- ▶ We could use it as a reporting function or within a customer lifetime value or price optimisation framework.