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Dependencies

Diversification Benefit – Understanding
drivers and building trust in the numbers¹

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¹Based on a booklet produced for the Institute of Risk Managers
Internal Model Industry Forum of the same name

Overview

- Dependencies:
 - Are difficult to implement, calibrate, validate and communicate
 - Can have material impact on the capital result
 - Lack of data (and probably always will be)
- But all is not lost!
 - The issues with dependencies are a reflection of reality
 - Shift the focus:
 - From getting the “right” number to getting a “reasonable” number
 - Improving insight and understanding by going through the process
 - It will take time: multi-year process
- Thesis: By having a model which focuses on systemic drivers of risk we are able to meaningfully, design, calibrate and validate model dependency structures



Introduction

- Start with collection of all available **knowledge on aggregation of risk** which exists within the business:
 - Stress and Scenario tests
 - Board and Risk Committee discussions
 - Price monitoring exercises which articulate causes for trends in experience
 - Claims departments reports which track leading indicators of risk
 - Independent assessments from CRO, Actuaries and Underwriters
- Designing a dependency structure should **reflect key drivers** and incorporate qualitative and quantitative information
- Models can incorporate **structural or statistical** dependencies



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An example: Dependencies between classes

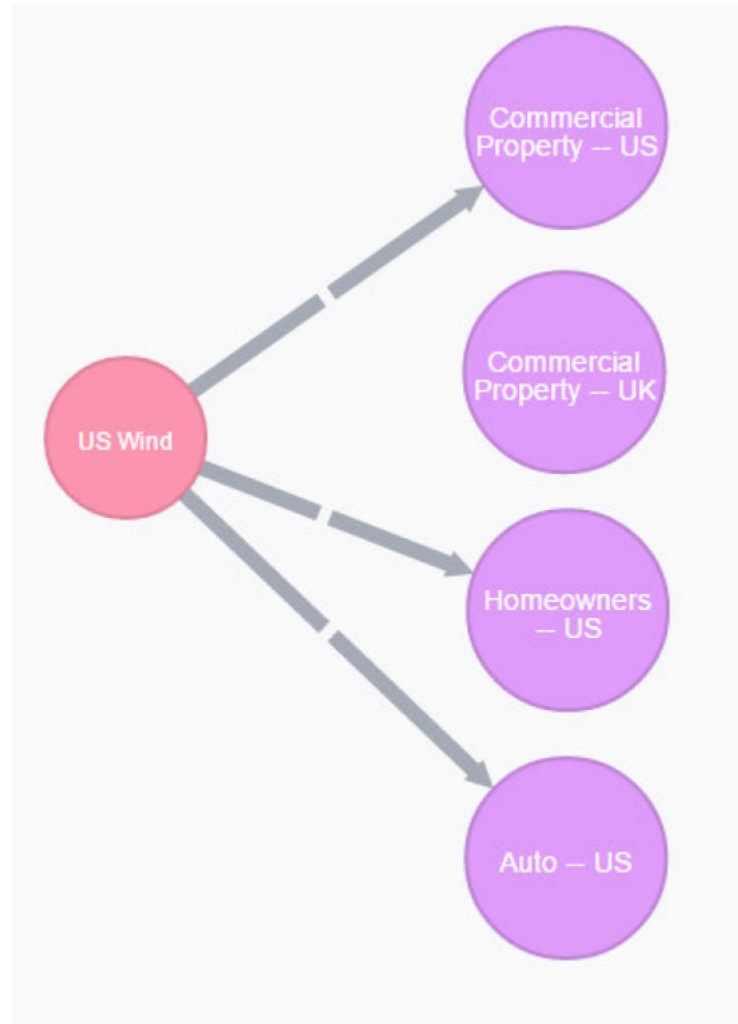


An example: Dependencies between classes

Factors affecting frequency of claims

Factor:

Natural
Catastrophes



Explanation:

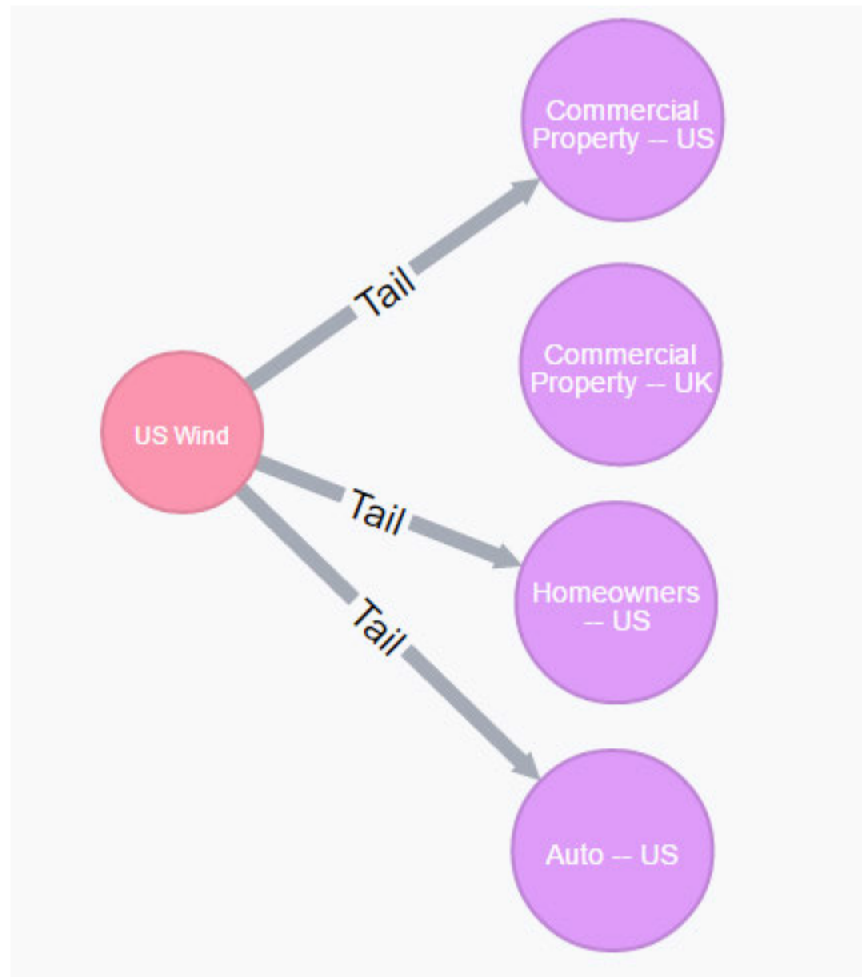
A cat will cause aggregation of risk across classes of business in the same geographic region as they are exposed to the same systemic risk



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An example: Dependencies between classes

Factors affecting frequency of claims

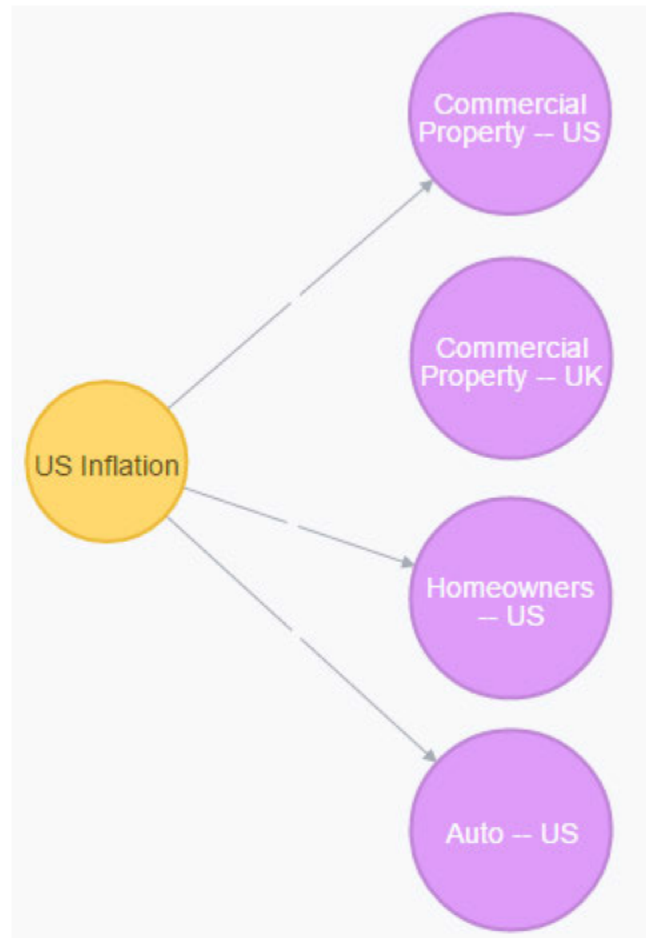


An example: Dependencies between classes

Factors affecting **severity of claims**

Factor:

Inflation



Explanation:

Increases in claims severity, if caused by inflation, can be a systemic risk factor affecting multiple classes of business and across time periods



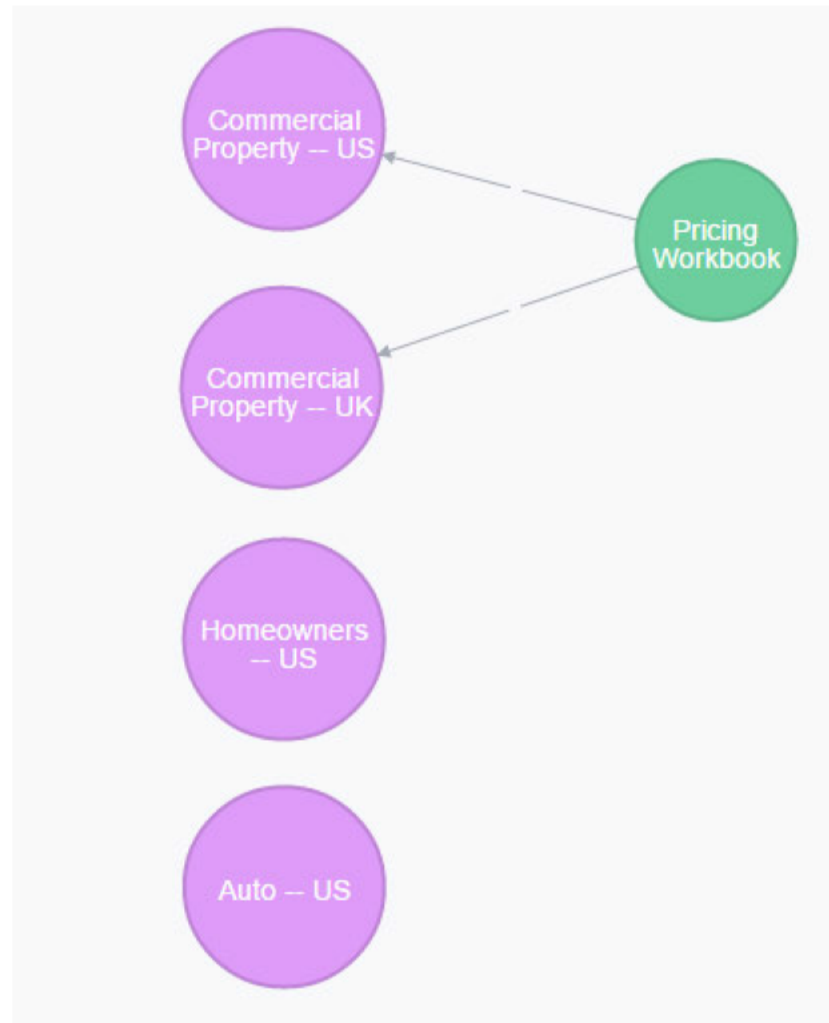
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An example: Dependencies between classes

Factors affecting **frequency and/or severity of claims**

Factor:

Pricing
Workbooks



Explanation:

Common pricing techniques and prior year assumptions can lead to systemic rate deviations



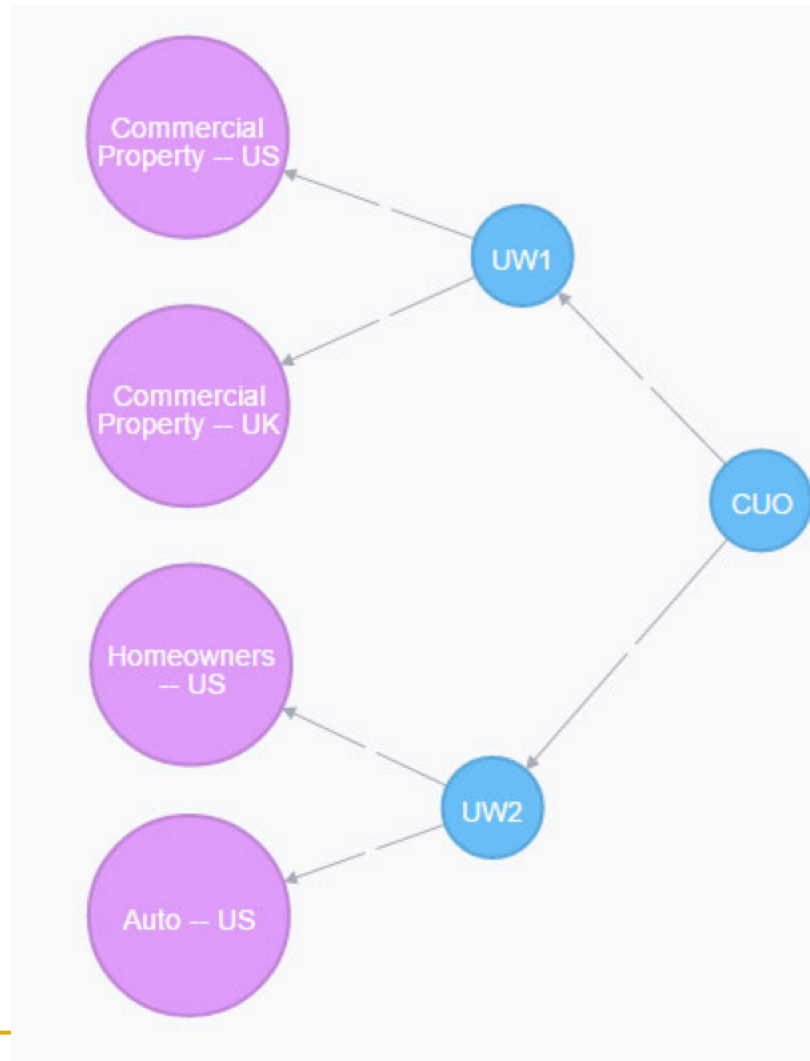
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An example: Dependencies between classes

Factors affecting **frequency and/or severity of claims**

Factor:

Common
underwriting



Explanation:

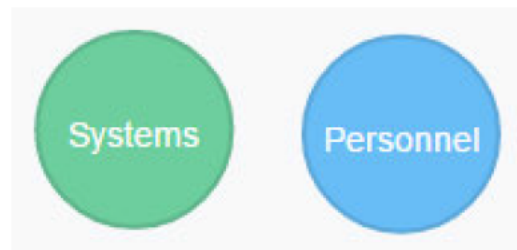
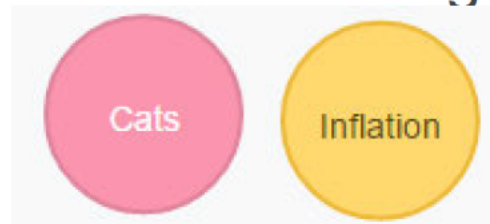
Behavioural factors and company incentives can cause correlation in extreme circumstances. Examples: incentive to write riskier business to meet profit targets



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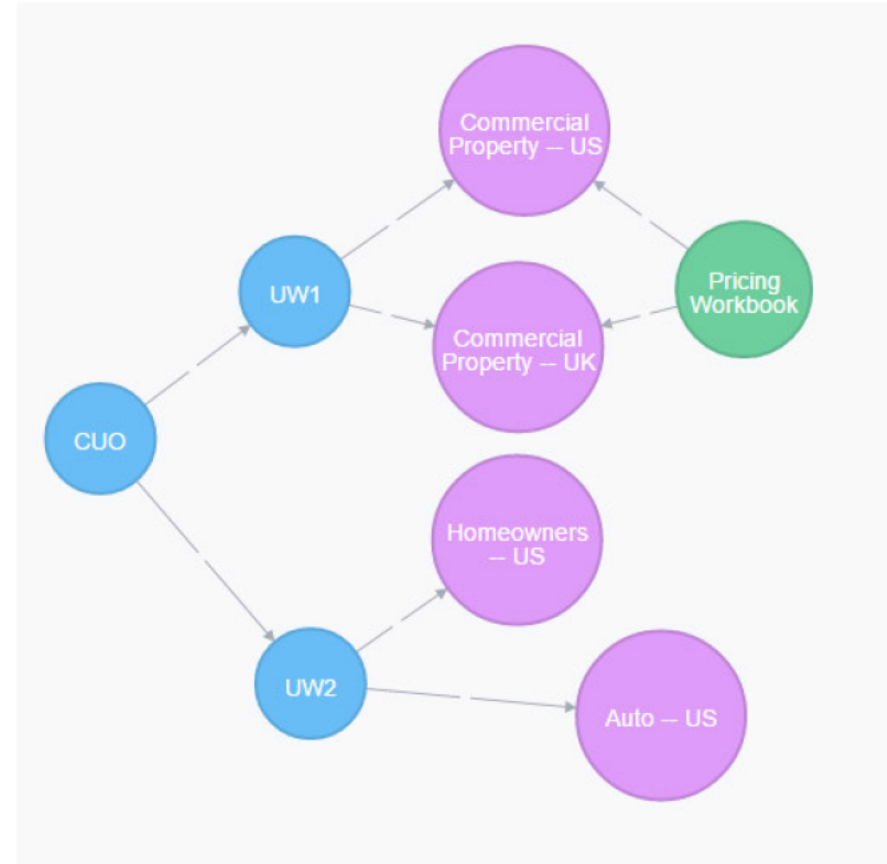
Themes from the example

- Some dependencies amenable to causal modelling
 - Models & data available (Cat, ESGs)
 - Market practice
 - Materiality / Model Runtime / Parameterisation time / Stability
- Others difficult to explicitly model
 - Worth having the conversation
 - But there may be enough to give a **residual** correlation



Copula Calibration Pass 1: Determine the form and rank the strength

- Perform for each copula-based dependency in the model:
 - Aiming to rank the strength of correlation between pairs/groups
 - Aiming to match copula types
 - Zero, positive, negative correlation
 - Tail dependencies (and in which quadrant)
- **Graph technologies** can help visualise and compute strengths between nodes
 - Milliman's use Dacord in booklet
 - Neo4j (open source)



Copula Calibration Pass 2: Estimate the strength

- Remove trends, beware of time series
 - **Sample correlations should generally be calculated from ‘Actual less Expected’ data**
- Correlation measures
- Record uncertainty in estimates
 - 10 data pts: inter-quartile range up to $\pm 25\%$
 - 20 data pts: inter-quartile range up to $\pm 15\%$
 - Use Fisher’s z-transformation / look up tables
- Ensure results consistent with ‘Pass 1’: a good first pass cuts down the range of values available



Validation Tests

Validation Test	Pitfalls
Independent assessment	Beware of biases in opinion and those that are not mathematically possible
Back-testing and aggregation testing using company's own data	Experience can change in time. Beware of noise in the data
Benchmarking - reports from Lloyd's, brokers or consultancies	Every company will deviate from the average, eg geographic diversification
Sensitivity testing	Helps to prioritize but does not give a final answer
Conditional probability testing focusing on the tail	Limited historical data to measure extreme outcomes
Risk ranking to judge appropriateness of relativities	Based on expert judgement
Profit and loss attribution	Will not identify underlying drivers

Conclusion

- Have a healthy model development and validation cycle, as findings year on year create a feedback loop
 - Uses, risk management processes, model testing all help to enhance the quality of the model
 - New experience and data helps to expand knowledge base
 - Keep investing in analytical techniques and follow an evidence based approach
- Conclusion
 - Yes it's difficult & will take time but don't stop trying / make a start
 - Internal models not internal formulae



Appendix: Further Links

- IRM Booklet (along with other IMIF booklets)
 - <https://www.theirm.org/knowledge-and-resources/guides-and-briefings.aspx>
- Classic actuarial paper on dependencies
 - <https://www.actuaries.org.uk/documents/measurement-and-modelling-dependencies-economic-capital-discussion-paper>
- Github for downloadable resources discussed in this presentation
 - <https://github.com/giro2016dependencies/giro2016dependencies>
- Dacord: <https://www.dacord.co.uk/>
- Neo4j: <https://neo4j.com/>



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