

# Homeowners Modeling

2006 CAS Seminar on  
Predictive Modeling

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# Agenda

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- Case for unbundling the perils
- Traditional rating variables
- New rating variables





# Legacy of indivisible premium for residential property lines

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- Package policy formed when Fire was major % of total losses (1950s)
- Remnant of paper manuals and inflexible quoting systems
- Lack of attention to specific cause of loss trends
- Comfort in status quo





## **In contrast, personal auto premium**

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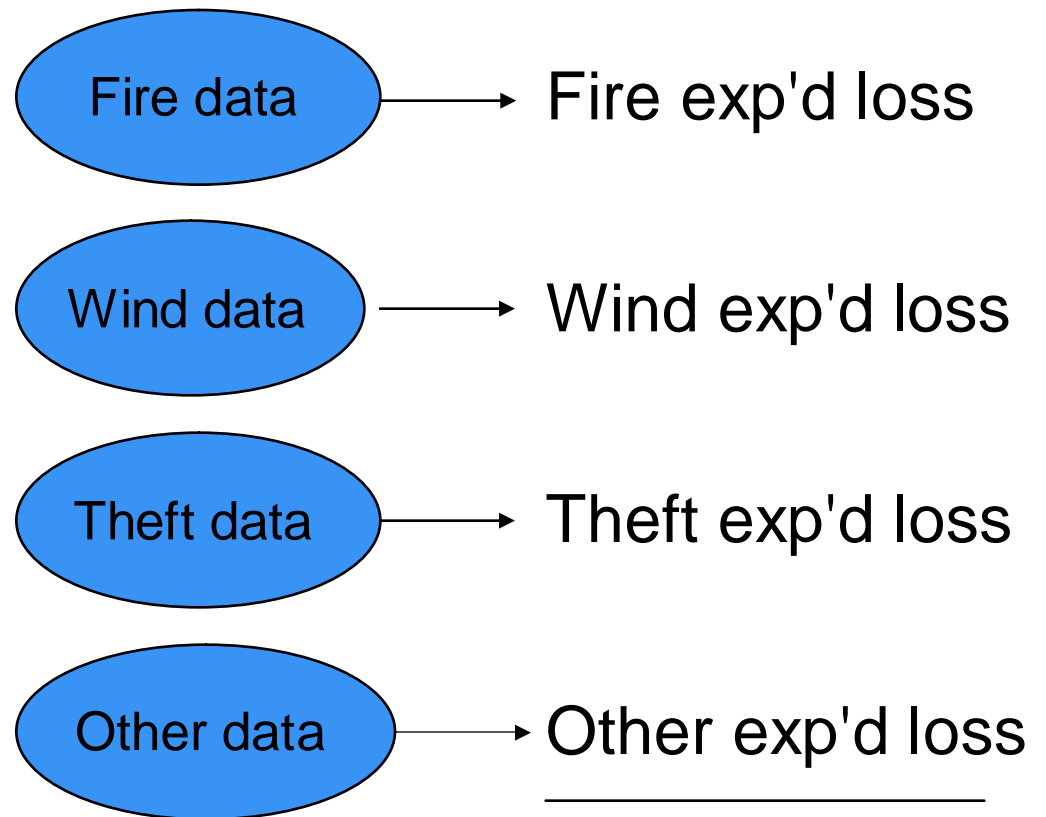
- Coverages are priced with modular approach
- Accepted by customers, agents, regulators, etc.
- In general, more pricing segmentation than homeowners
- More responsive trend detection (eg liability trends vs parts/labor trends)
- Matches how experience is monitored



# Unbundling the analysis



Total  
Expected  
Losses



= Total Expected Losses



# Why unbundle?

- Improved rating accuracy
  - rate classification equity
  - favorable selection
  - better competitive position
  - improved profitability
- Improved ability to monitor and respond to trends and emerging causes of loss





## More detailed reasons...

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- The share of loss costs by peril varies considerably by geography
- Effect of rating factors varies considerably by peril
  - traditional rating factors
  - territory
  - inhabitant info
  - external info



# Percent of losses by peril varies across territories



## 10% Theft system discount

- Territory A: credits more premium (\$10) than losses expected from theft (\$7)
- Territory B: credit (\$10) may represent appropriate amount of savings in total theft losses (\$27)







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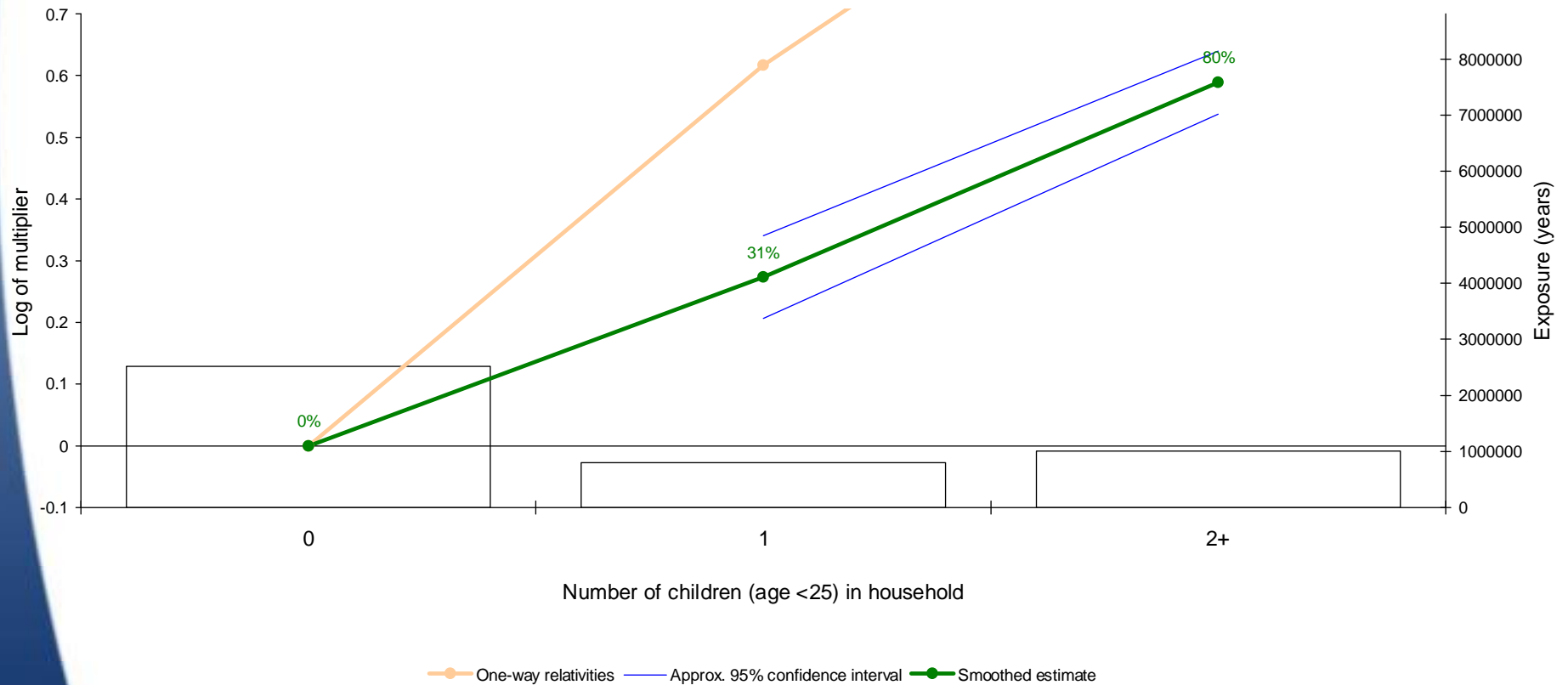




# Inhabitant information: Effect of children on Liability

## Demonstration Homeowners Data

Liability frequency

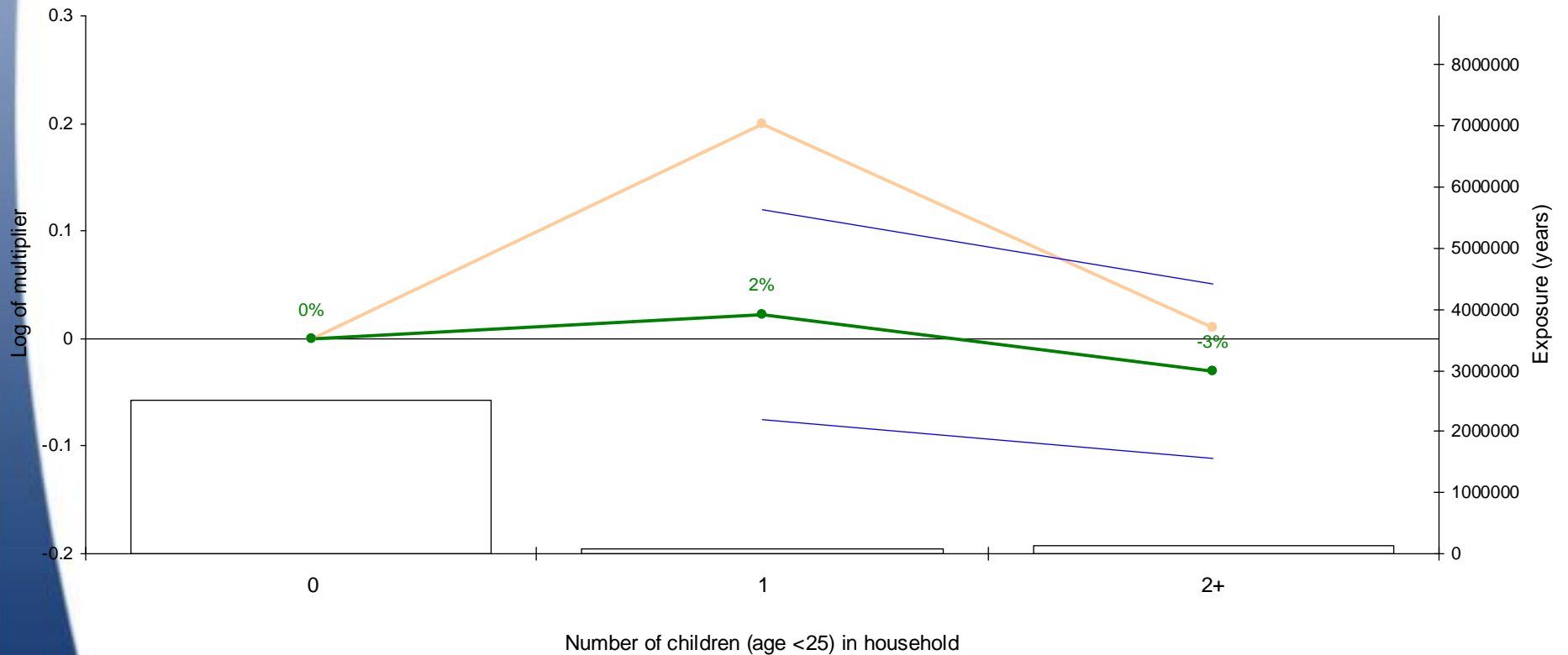




# Inhabitant information: Effect of children on Wind

## Demonstration Homeowners Data

Wind frequency



— One-way relativities — Approx. 95% confidence interval — Smoothed estimate





## **More detailed reasons (cont'd)**

- Model dwelling and contents separately
- Separate territories by peril
  - liability affected by demographics, but sinkhole affected by meteorological and geological phenomena
  - level of needed granularity may differ by peril
- Variable categorization by peril
  - AOI granularity may differ by peril
  - deductible options may differ by peril
- Large loss thresholds by peril





## **More detailed reasons (cont'd)**

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- Different ratemaking analysis methods to be applied to each peril
  - loss trends and development
  - data used (eg company experience for non-cat and simulated data for cat)
  - expenses allocation
  - cost of capital considerations
- Benchmark rate relativities are often based on specific peril (eg windstorm mitigation credits in FL apply only to windstorm premium)





## **More detailed reasons (cont'd)**

- Facilitates separation of liability for loss reserving and monitoring
- Facilitates endorsement pricing (for those tied to specific peril)





# Practical considerations for by-peril pricing

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- Volume required
- Point of sale algorithm
- IT concerns (eg separate territory definitions by peril?)
- Complication by form
- Lack of competitive benchmarks by peril
- Endorsements priced as % of base premium
- Incorporating catastrophe loads
- Statistical plan requirements



# Volume

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- Generally seek a few thousand claims per claim type to attain meaningful models
- Depends on the number of variables to be examined







# Practical considerations for by-peril pricing

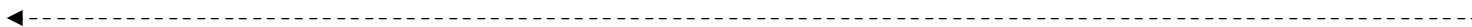
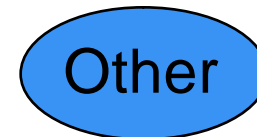
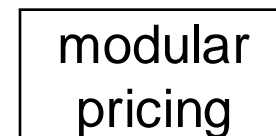
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- Volume required
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# Point of sale options



*Least  
accurate*

*Most  
accurate*

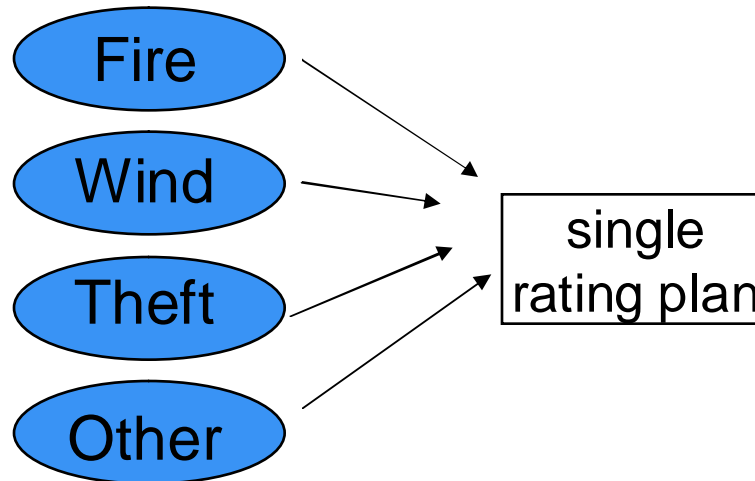


# Point of sale options



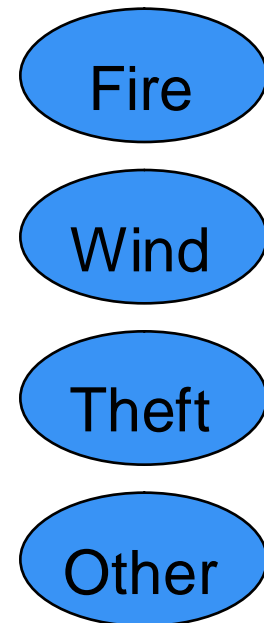
single  
rating plan

*Least  
accurate*



*Investigation of  
practical compromise*

modular  
pricing



*Most  
accurate*





# Investigating practical compromise

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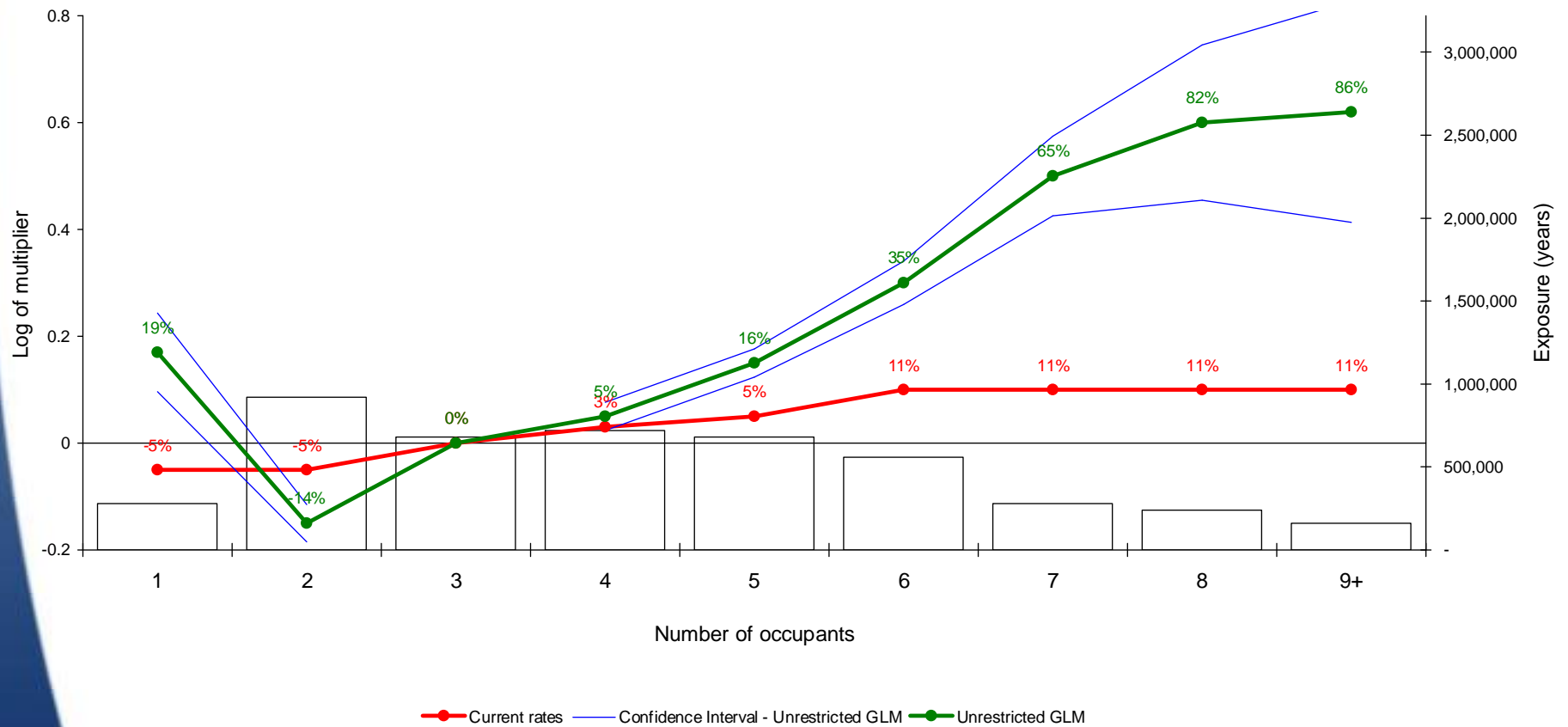
- Global risk premium across all perils
  - populate fitted values by peril for each individual record
  - fit model to field representing sum of expected loss costs by peril
  - somewhat analogous to a single loss-weighted average of underlying by-peril models
- Investigate loss of accuracy in global risk premium model



# Sample output - risk premium by peril

## Demonstration Homeowners Data

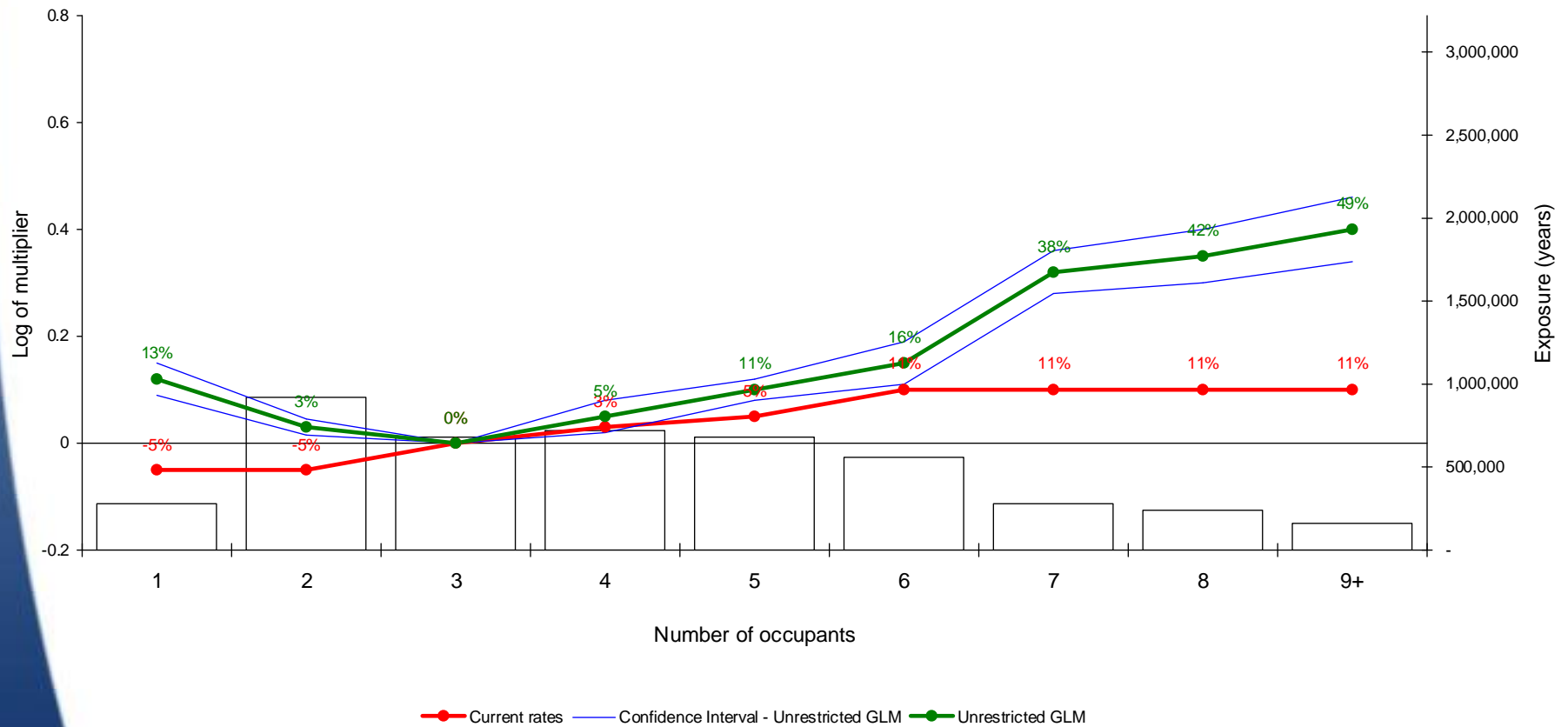
Run 5 Model 1 All Other Peril Risk Premium



# Sample output - global risk premium

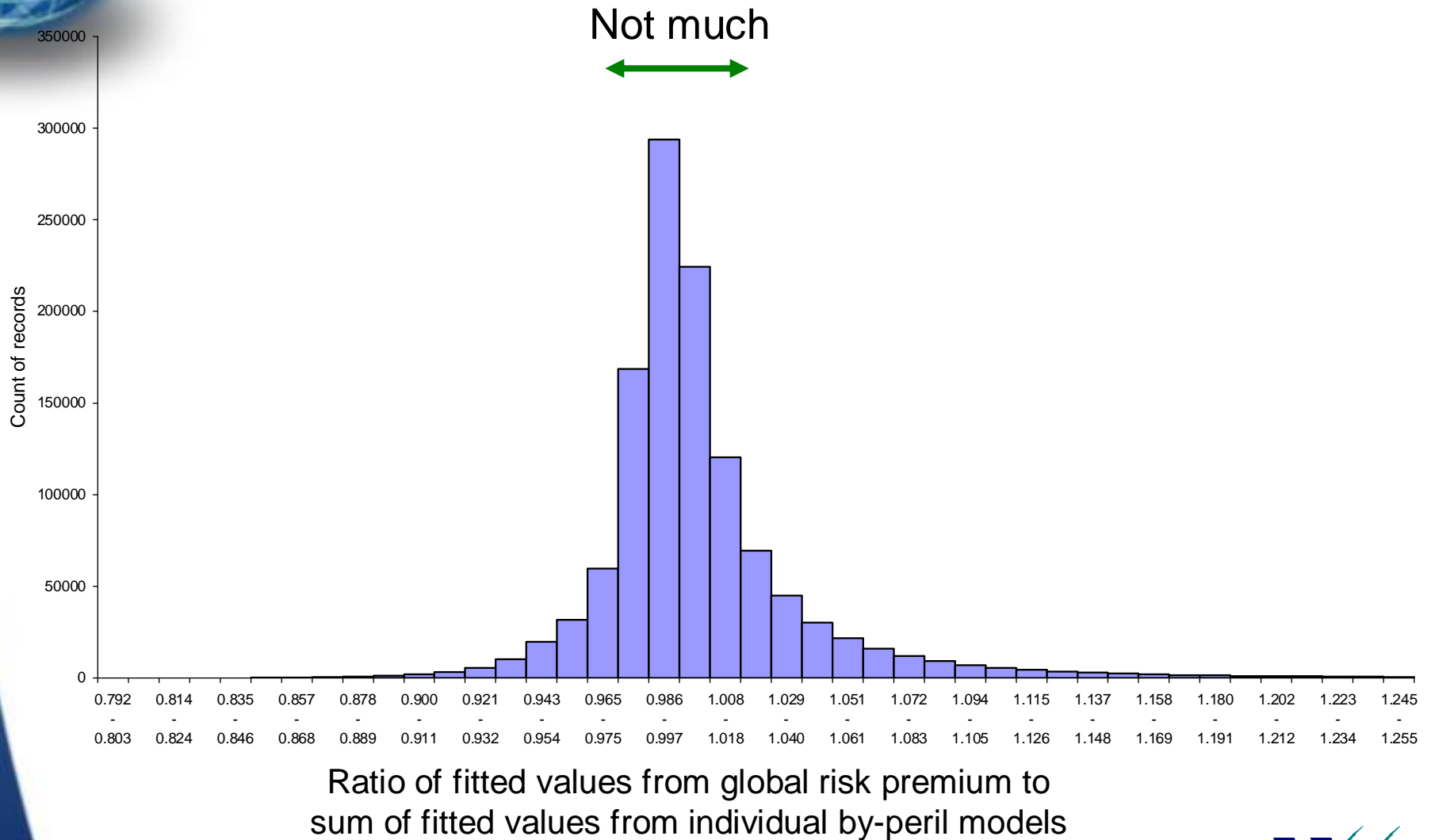
## Demonstration Homeowners Data

Run 7 Model 1 Global Risk Premium





# Investigating loss of accuracy





# Other practical considerations for by-peril pricing

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- Volume required
- Point of sale algorithm
- IT concerns (eg separate territory definitions by peril)
- Lack of competitive benchmarks by peril
- Complication by policy form
- Endorsements priced as % of base premium
- Incorporating catastrophe loads
- Statistical plan requirements







# Agenda

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- Case for unbundling the perils
- Traditional rating variables – for example:
  - policy form
  - AOI
  - deductible
- New rating variables



# Policy form

- Model separately by form allows
  - different variable categorization by form (eg amount of insurance)
  - different large loss thresholds
  - understanding loss cost effects by form
- Model homeowners and renters/condo separately and include form as an independent variable
- Model all combined with form as an independent variable
- Consider interactions by form





# Amount of insurance (AOI)

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- Could model AOI as a categorical factor with many levels (consider categories that straddle common AOIs eg \$98.5-101.5K)
  - this allows the true effect to be seen for both frequency and amounts models
  - smooth the relativities carefully so that the risk premium result for AOI shows a sensible progression
  - either charge a premium based on interpolated banded AOI, or perform simple interpolation between exposure weighted mid points of the bands to get a continuous scale
- Alternatively fit a regression spline to AOI and incorporate in rating algorithm or use to populate a detailed table





# Deductible

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- Model incurred losses net of deductible
- Include in underlying frequency and severity models
- If results counter-intuitive, may need to remove factor and offset model by log of relativities from external study (eg current relativities or results from LER)
- Careful of changing selection behavior in future





# Agenda

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- Case for unbundling the perils
- Traditional rating variables
- **New rating variables**
  - concern over missing levels
  - investigate consistency over time
  - internal information (eg inhabitant info)
  - external information (eg geodemographics)





# Factors with missing levels

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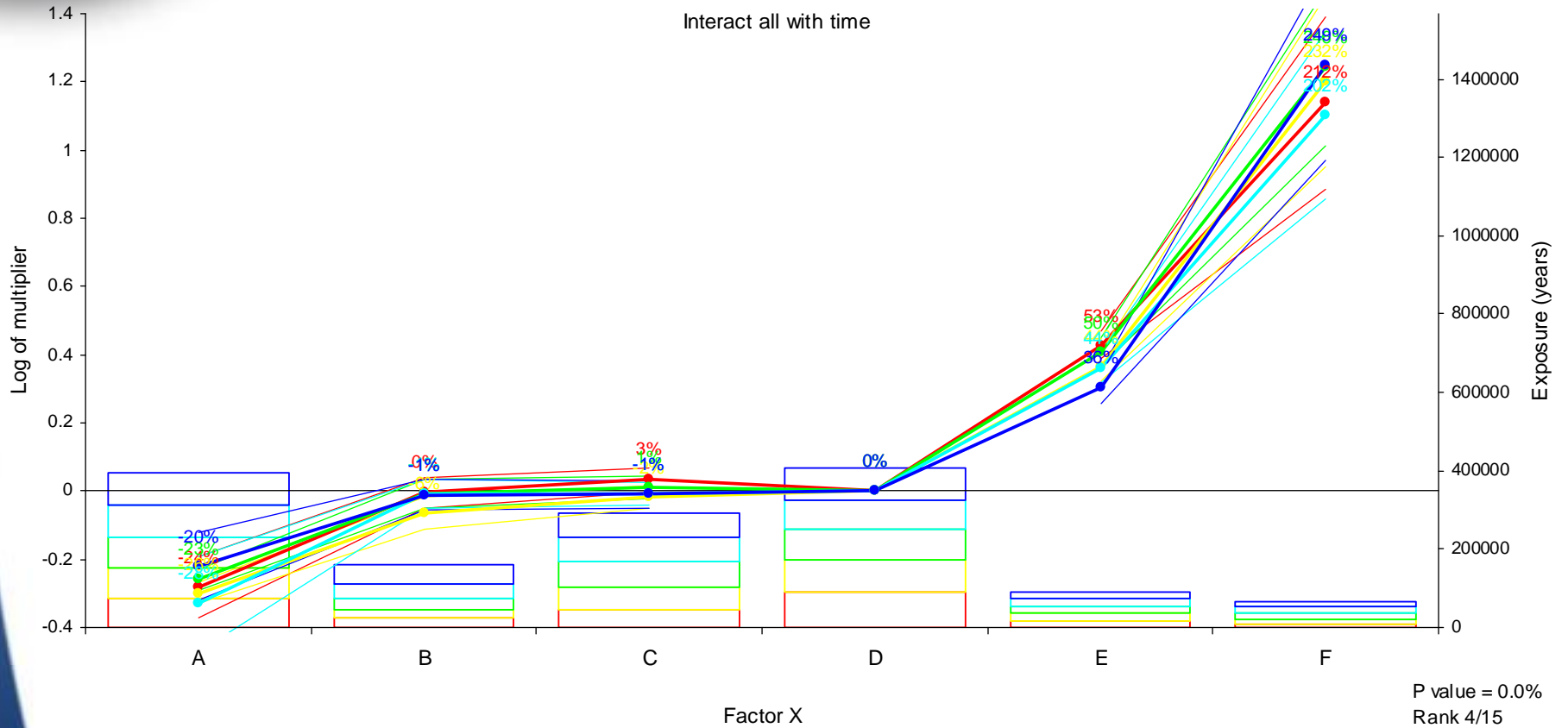
- Common problem as information may not be collected on every exposure
- Do not choose "missing" as base level
- Investigate exposure distribution of missing level with other factors - eg does missing occur only on older years or older houses?
  - consider altering data to alleviate problem (eg use more recent years)
  - consider changing order of factors in the model to force alias in another variable
- Model with and without factor to understand effect



# Consistency over time

## Demonstration Homeowners Data

Interact all with time



— Approx 95% conf int, Year: 2000    — Approx 95% conf int, Year: 2001    — Approx 95% conf int, Year: 2002    — Approx 95% conf int, Year: 2003    — Approx 95% conf int, Year: 2004  
 ● Parameter estimate, Year: 2000    ● Parameter estimate, Year: 2001    ● Parameter estimate, Year: 2002    ● Parameter estimate, Year: 2003    ● Parameter estimate, Year: 2004



# Internal variables

- Inhabitant information
  - # occupants
  - age, gender, marital status
  - unusual exposure (eg dogs)
- Relationship with company
  - optional endorsements
  - products held
  - # years with company
  - affinity membership





# Internal variables

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- Detailed information on property
  - square feet
  - number of rooms
  - foundation shape
  - roof attributes (shape, covering)
  - interior construction materials
  - pool/spa



# Property characteristics

- Consider correlation with AOI – ie could something inherent to AOI algorithm actually predict risk better than AOI?
- Could you live without AOI?





# Score based on property characteristics

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- Fit GLM with traditional rating factors and several property characteristics (eg  $R_1 \times R_2 \times R_3 \times P_1 \times P_2 \times P_3$ )
- Transform model results for property variables ( $P_1 \times P_2 \times P_3$ ) into points-based score variable =  $R_4$
- Categorize score variable appropriately
  - consider # of categories & proportion of business in each
- Include new score variable in claims model (ie  $R_1 \times R_2 \times R_3 \times R_4$ ) and consider interacting with other variables





# External information

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- Geodemographics (avg characteristics in an area)
  - population density
  - length of home ownership
  - average age of residents
  - financial information
- Weather data per area (relating to vulnerability of buildings)
  - max wind speed
  - avg rainfall

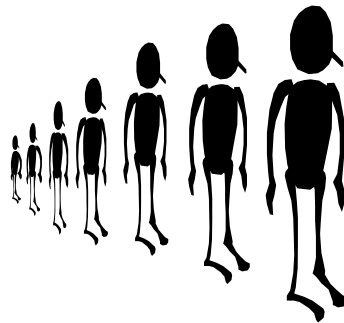




# Geodemographic data

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- Often designed for marketing retail products
- Attaches to zip code therefore easy to use at point of sale
- Marketing segment types often not predictive
- Underlying data often more interesting
- Simple measure of urban density often predictive





## **Example of effect of urban density on homeowners theft frequency**

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Real GLM output cannot be disclosed in handouts

Graph in presentation showed strong multivariate  
effect of urban density





## Effect of density varies

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- Effect of increasing density on risk:

	Frequency	Severity
Theft	↑	↑
Fire	↓	↑
"Other"	↑	↑

# Geodemographics can be rather related!

	R1	R2	R3	R4	G1	G2	G3	G4	G5	G6	
R1											
R2		11%									
R3		<b>32%</b>	3%								
R4		17%	7%	<b>58%</b>							
G1		8%	2%	<b>57%</b>	16%						
G2		8%	2%	<b>53%</b>	15%	<b>49%</b>					
G3		7%	3%	<b>44%</b>	14%	<b>33%</b>	<b>33%</b>				
G4		5%	4%	<b>21%</b>	8%	<b>30%</b>	<b>30%</b>	<b>30%</b>			
G5		3%	2%	<b>31%</b>	6%	<b>36%</b>	<b>35%</b>	<b>34%</b>	<b>31%</b>		
G6		8%	2%	<b>65%</b>	16%	<b>37%</b>	<b>35%</b>	<b>31%</b>	<b>29%</b>	<b>34%</b>	
G7		8%	2%	<b>65%</b>	16%	<b>36%</b>	<b>34%</b>	<b>30%</b>	<b>30%</b>	<b>34%</b>	<b>71%</b>

Cramer's V for a selection of standard rating factors (R1, ..., R4) and geodemographic factors (G1, ..., G4)







# Coping with related factors

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- Can be hard to interpret output from a GLM that includes a very large number of related characteristics
- Options
  - test related factors (within "families") one at a time to find most predictive member (eg # of late pays in 60 days may be most predictive of "late pay" family)
  - apply principal components analysis first





## **Example of geodemographic factors**

Real GLM output cannot be disclosed in handouts

Graph in presentation showed strong multivariate effect of geodemographic factor related to average life-stage of an area





## **Example of geodemographic factors**

Real GLM output cannot be disclosed in handouts

Graph in presentation showed strong multivariate effect of another geodemographic factor





## **Example of geodemographic factors**

Real GLM output cannot be disclosed in handouts

Graph in presentation showed strong multivariate effect of average type of building in area



# External information

- Geodemographics (avg characteristics in an area)
  - population density
  - length of home ownership
  - average age of residents
- Weather data per area (relating to vulnerability of buildings)
  - max wind speed
  - avg rainfall
  - soil type





# **Examples of geophysical data**

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Graph in presentation showed strong multivariate effect of weather-related geophysical data item





# **Examples of geophysical data**

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# External data

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- Can add predictive power and thus give competitive pricing edge
- Can improve speed and accuracy of quotation process
- Can help assess risk when own data insufficient
- New philosophy for agents, regulators, etc.
- May complicate ability to compare to existing rates on factor by factor basis (eg comparing "old" territory to "new" territory plus population density)

*Must balance accuracy with model parsimony and point of sale concerns.*





# Example homeowners rating factors UK

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- Post code (so geodemographic and geophysical factors can be derived)
- Amount of insurance
- Number of rooms / bedrooms
- Wall type
- Roof type
- State of repair
- Extensions
- Ownership status (rent/own)
- Occupancy in day
- Neighborhood watch scheme
- Approved locks, alarms, smoke detectors
- Deductibles
- Riders purchased, value > £x
- How long held insurance / when last claimed
- Policyholder details
  - Age
  - Sex
  - Marital status
  - Number of children
  - Occupation
  - Residency
  - Criminal convictions
  - Claims in past 2/5 years
- Smokers present in house
- Non family members sharing house
- Length of time living at property
- Use (principal/ second / business / let)
- Cover selected (buildings/contents/both)
- Source business (eg internet)





# Organizational insights

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- Review/discuss variables in advance with other areas of the company (underwriting, legal, marketing, IT)
- Review integrity of data (especially if can't explain effects)
- Aim for visual aids (including maps)
- Address what matters most to the organization (removal of cross-subsidy, change in competitive position, policyholder dislocation, etc)
- Examine effect of commercial decisions (i.e. penalty to theoretical)



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