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## Marriage matters

### A practical guide to modelling contingent dependants

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Demographic Horizons™ team, Aon

Presented by webinar: Tuesday 4 June 2019 at 10.30

02 July 2019



## Contingent dependants

Dependant proportions and age difference – why do they matter?



### Increasingly material

- PV impact
- Pricing focus



### Increasing sophistication required

- Data and definitions
- Segmentation

Potential impact  $\pm 3\%$  of joint life PV

### Accuracy is paramount

- Insurer: *over-valuing* may lose deals, *under-valuing* may impair profitability or weaken reserves
- Scheme: *over-valuing* may lead to expensive risk settlement, *under-valuing* may reject attractive hedging opportunities and reduce benefit security



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## Agenda

- 1 **Modelling framework**
- 2 **Dependant proportions**
  - No data
  - Deaths data
  - Survey data
  - Tracing data
- 3 **Age difference**
- 4 **Summary**



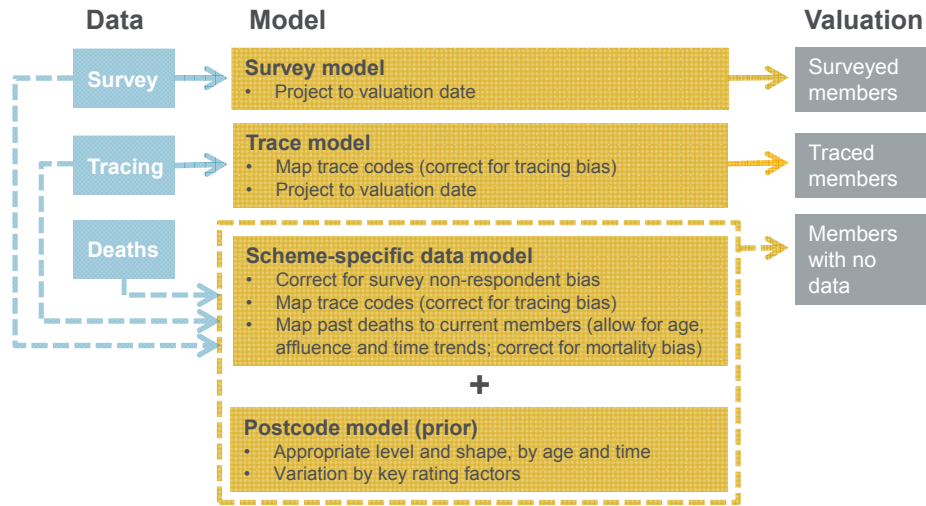
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## 1. Modelling framework

Expertise  
Sponsorship  
Thought leadership  
Progress  
Community  
Sessional Meetings  
Education  
Working parties  
Volunteering  
Research  
Shaping the future  
Networking  
Professional support  
Enterprise and risk  
Learned society  
Opportunity  
International profile  
Journals  
Supporting

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## Demographic Horizons dependants model



## Demographic Horizons dependants dataset

1. Over 300,000 members from 30 pension schemes spanning 2011-2019

2. Wide coverage of UK by

- geographic region
- age, sex and pension amount
- current vs future pensioners
- legal spouses vs wider financial dependants

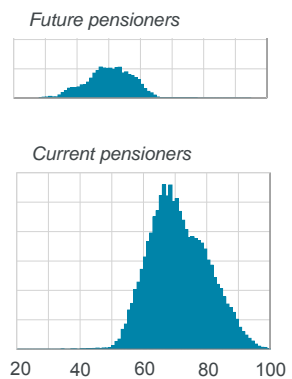
3. Multiple data sources for robust inference:



Geographic distribution



Pension distribution by age





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## 2. Dependant proportions

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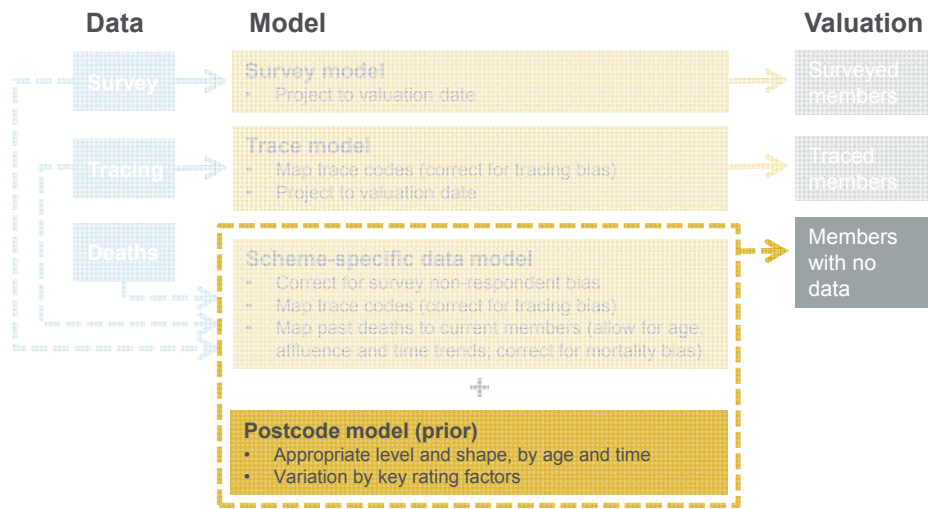
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## Scenario A – no data

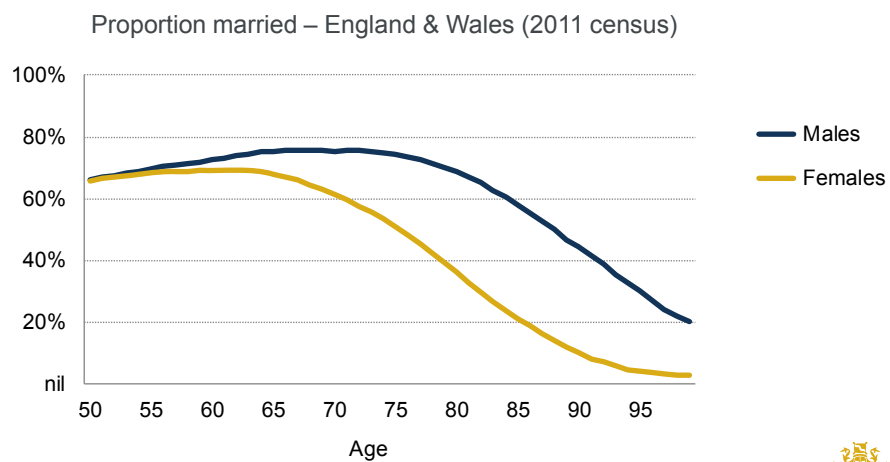
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## Demographic Horizons dependants model



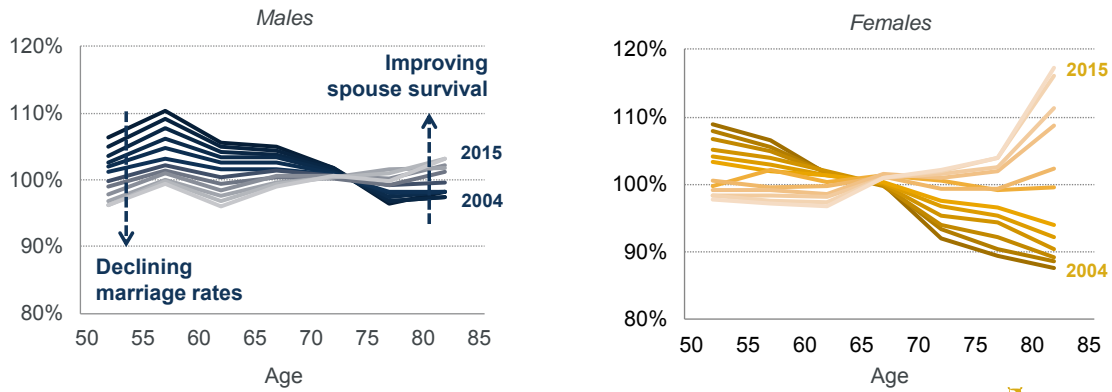
## National population



Source: ONS data with Aon calculations

## National population – time trends

Proportion married – England & Wales (5-year rolling averages relative to 2011)

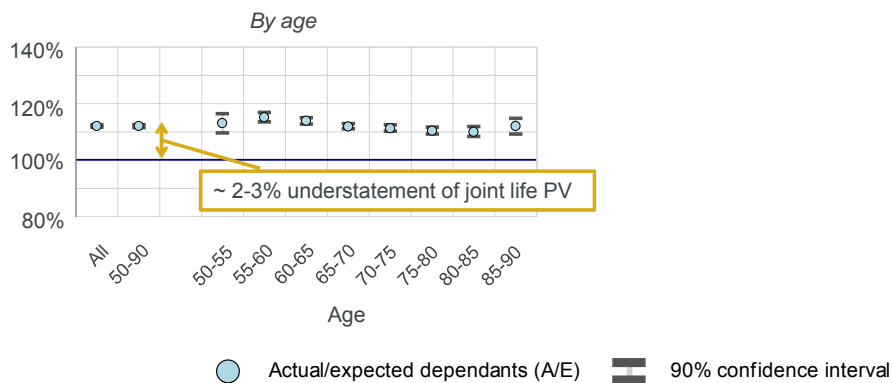


Source: ONS data with Aon calculations  
Annual variation in proportion married based on ONS Labour Force Survey adjusted for mortality improvement



## Pension scheme members

Proportion married – male pension scheme A/E vs England & Wales (amounts-weighted)\*

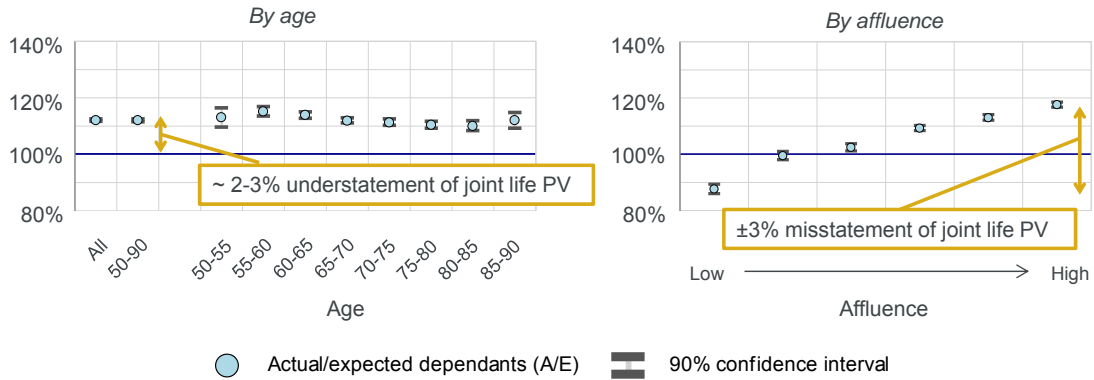


\* Demographic Horizons pension scheme survey data (adjusted for respondent bias) vs ONS E&W 2011 census data (projected from 2011 using annual adjustments from ONS Labour Force Survey)



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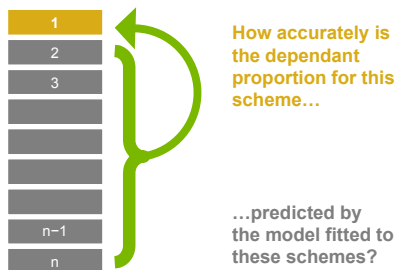
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## Testing the model – cross-validation

For each scheme in the dataset:

- re-fit the model *excluding* that scheme,
- then test its prediction against the observed data for that scheme

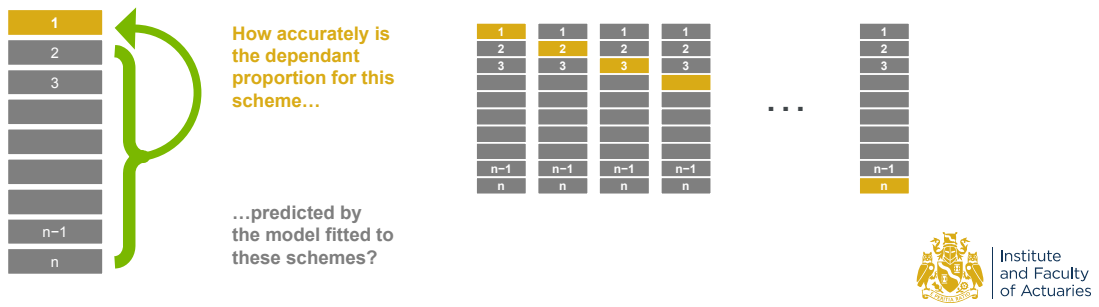


## Testing the model – cross-validation

For each scheme in the dataset:

- re-fit the model *excluding* that scheme,
- then test its prediction against the observed data for that scheme

Repeat across schemes to test actual *predictivity*, without cheating

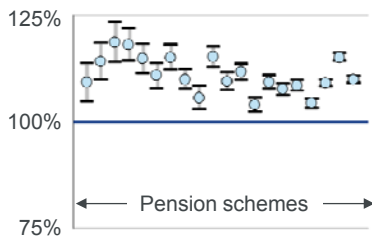


## Predictive performance

Cross-validation by pension scheme – male A/E for excluded scheme vs fitted model (amounts-weighted)\*

### 1. National data model

- Based on E&W proportion married
- Allowance for age and time trends



\* Demographic Horizons pension scheme survey and tracing data for 20 largest datasets (adjusted for respondent bias where relevant) vs ONS E&W 2011 census data (projected from 2011 using annual adjustments from ONS Labour Force Survey)

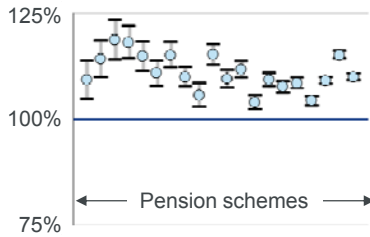


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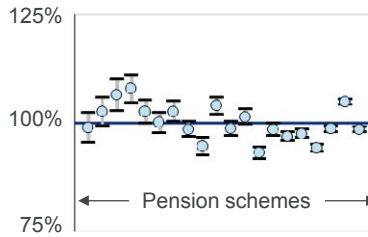
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### 2. Simple pension scheme model

- Fitted to actual pension scheme data
- Variation by age, sex and time only



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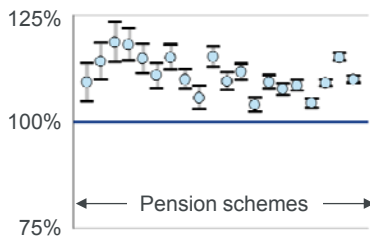


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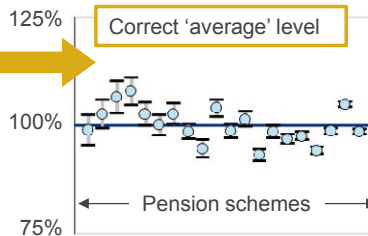
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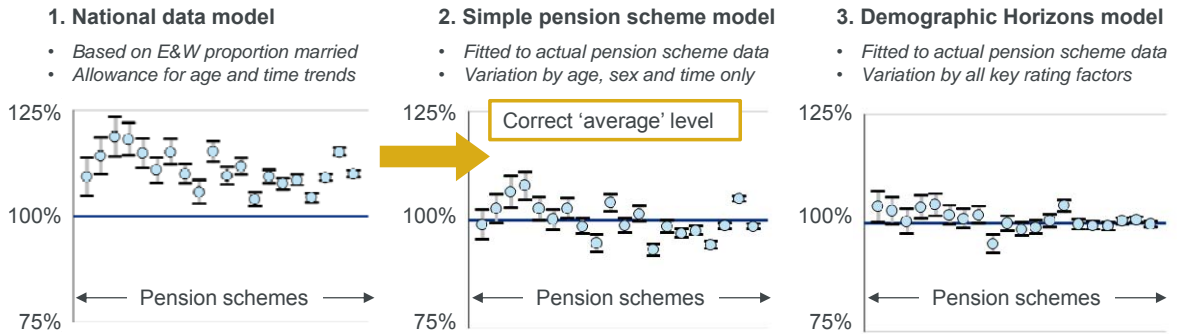


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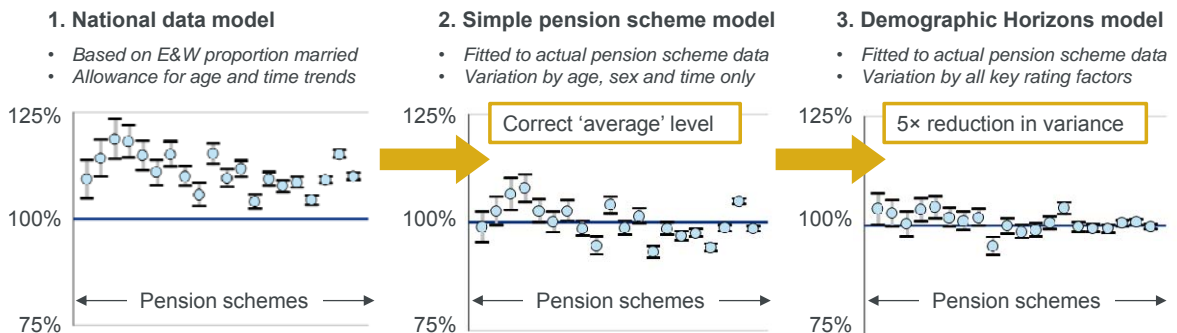


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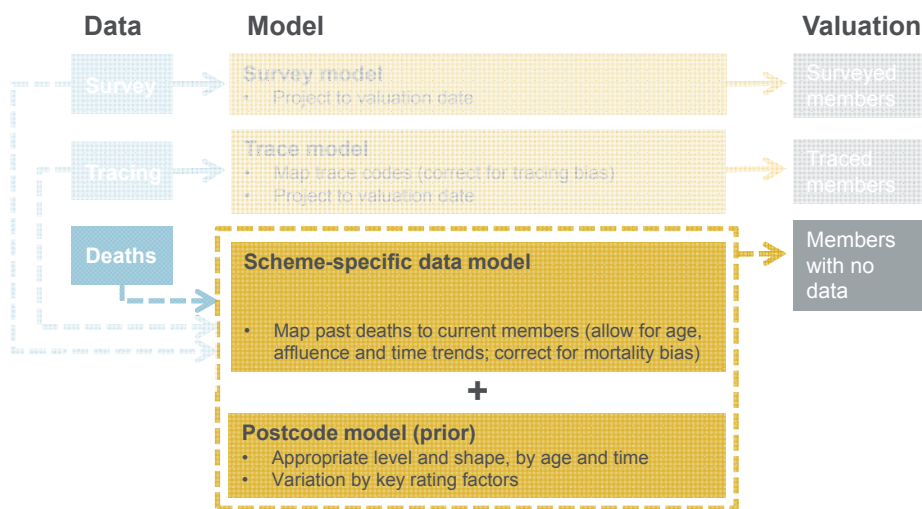


## Scenario B – deaths data

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Expertise  
Sponsorship  
Thought leadership  
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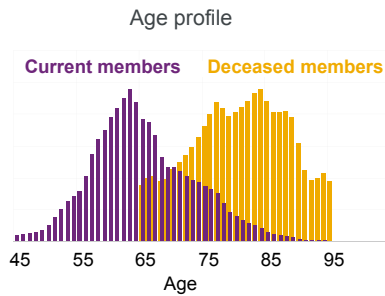
### Demographic Horizons dependants model



## Mapping past deaths to current members

Deceased vs current members may differ in terms of

- age profile
- socio-economic profile
- effective date of information



So care is needed when

- fitting a dependants model to deaths data and then
- applying it to value current lives

Demographic Horizons framework:

- proportional odds model

$$o_{it}(\beta) = o_{it}^{prior} \exp(\beta^T \phi_{it})$$

- where  $o_{it} = \frac{p_{it}}{1-p_{it}}$

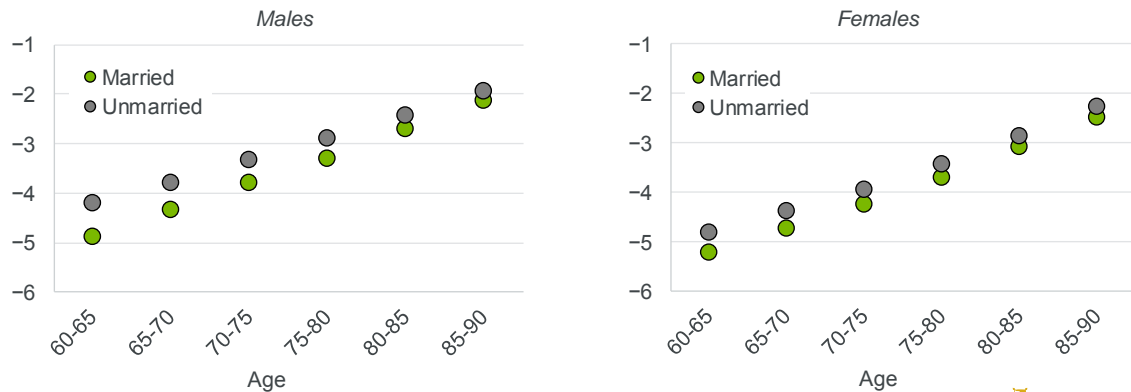
The prior model  $o^{prior}$  provides

- sensible age shape and rating factor variation, plus
- in-built allowance for time trends



## Mortality bias

Log mortality rates\* – England & Wales (2011)



\* Standardised by Index of Multiple Deprivation (IMD) decile, 2015 classification  
Source: ONS data with Aon calculations



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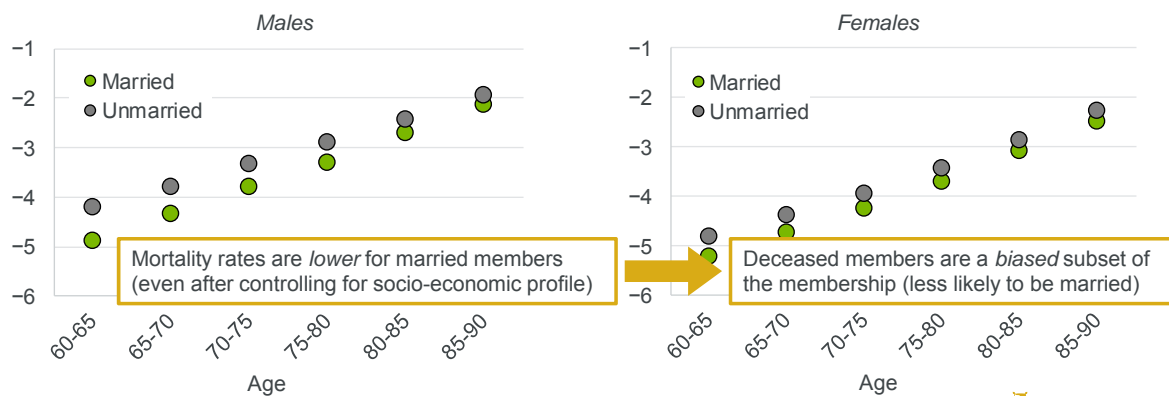


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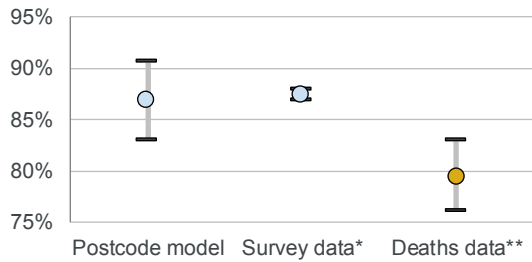
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## Mortality bias – real example

Implied dependant proportion at age 65 for current membership (male pensioners)

*Before mortality bias adjustment*



- Dependant proportion at 65
- 90% confidence interval

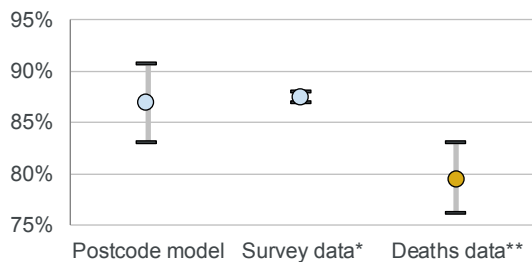
\* Adjusted for survey respondent bias and for age, sex and socio-economic profile of non-respondents  
 \*\* Adjusted for age, sex and socio-economic profile and for time trends



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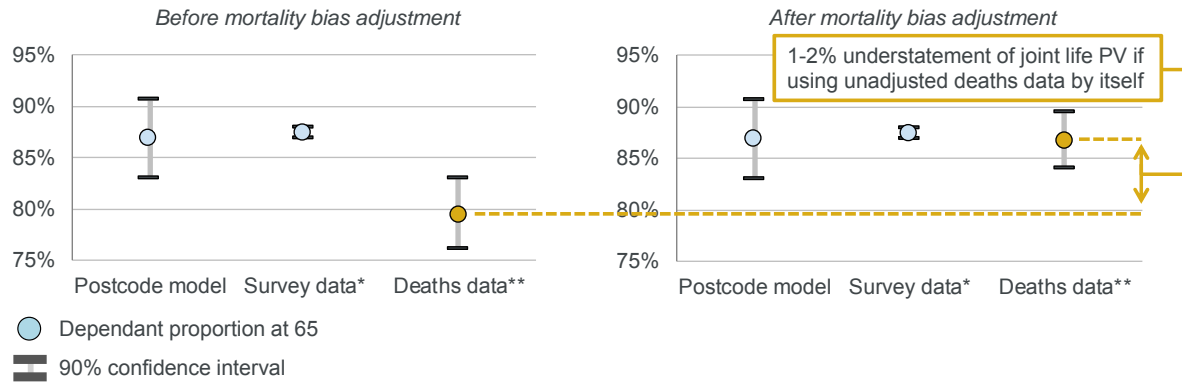
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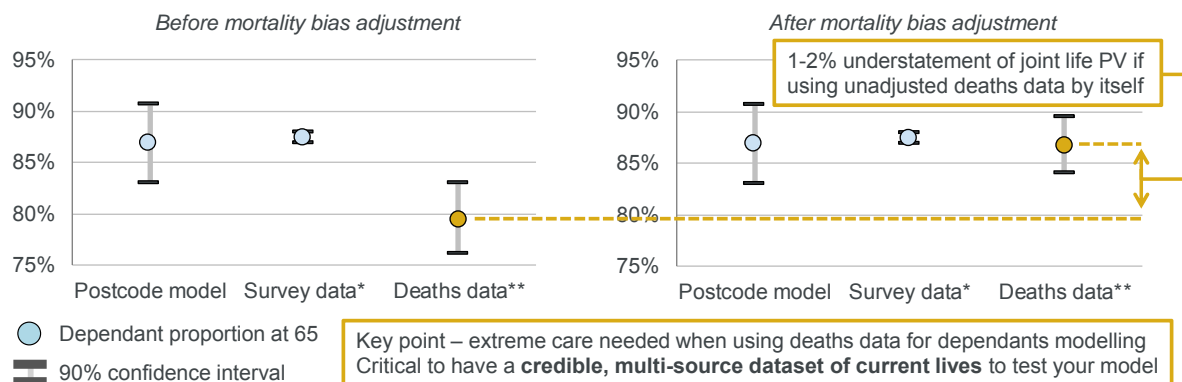


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## Mortality bias – real example

Implied dependant proportion at age 65 for current membership (male pensioners)



Key point – extreme care needed when using deaths data for dependants modelling  
Critical to have a **credible, multi-source dataset of current lives** to test your model

\* Adjusted for survey respondent bias and for age, sex and socio-economic profile of non-respondents  
\*\* Adjusted for age, sex and socio-economic profile and for time trends



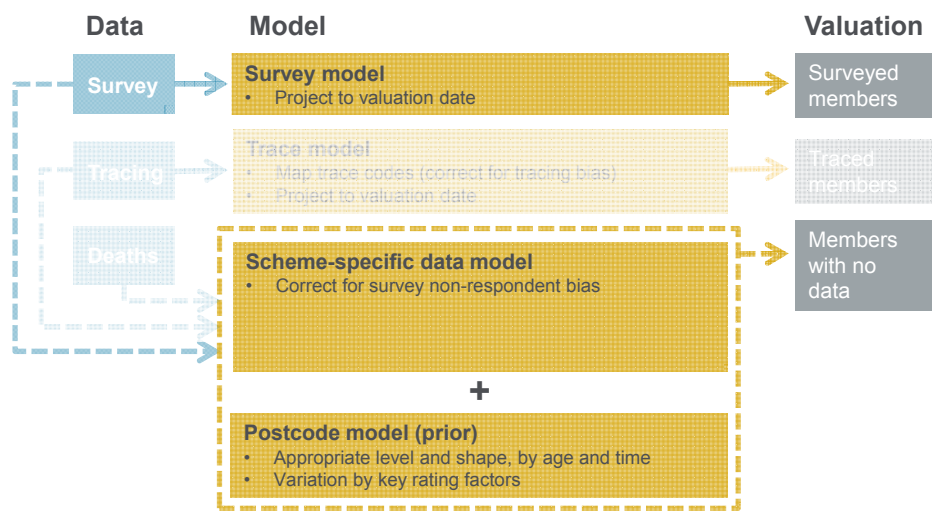


## Scenario C – survey data

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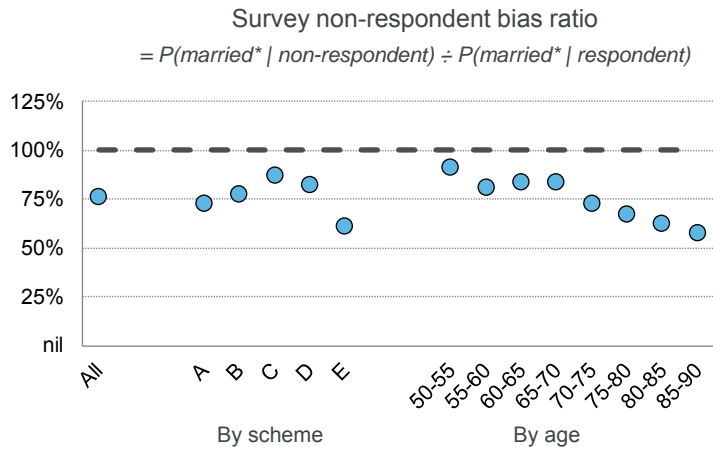
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### Demographic Horizons dependants model





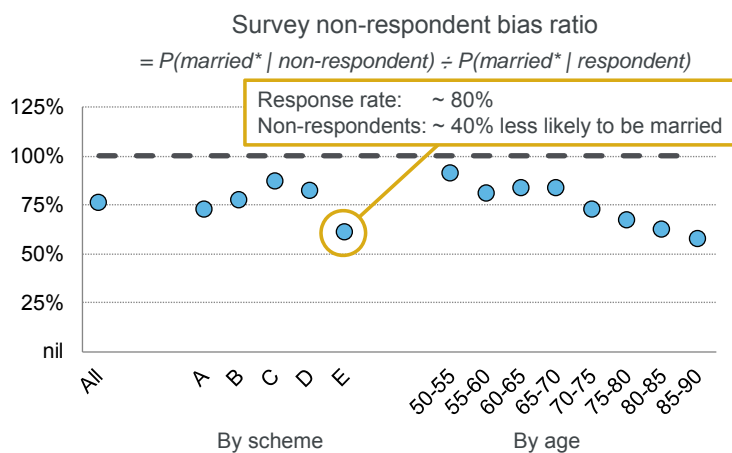
## Survey non-respondent bias



\* According to trace status  
 Source: Demographic Horizons dependants dataset



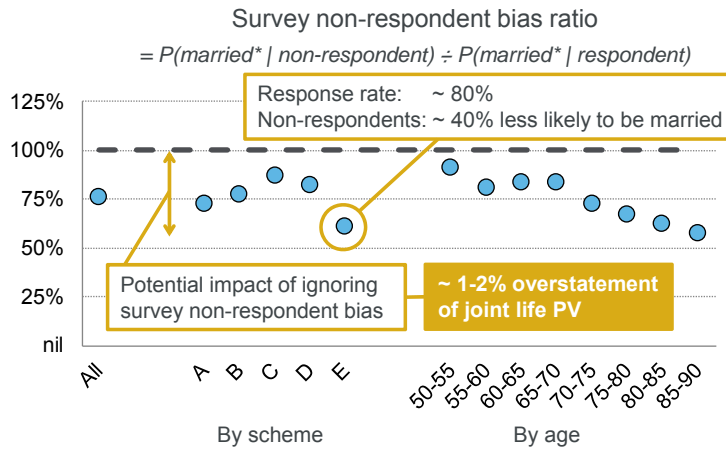
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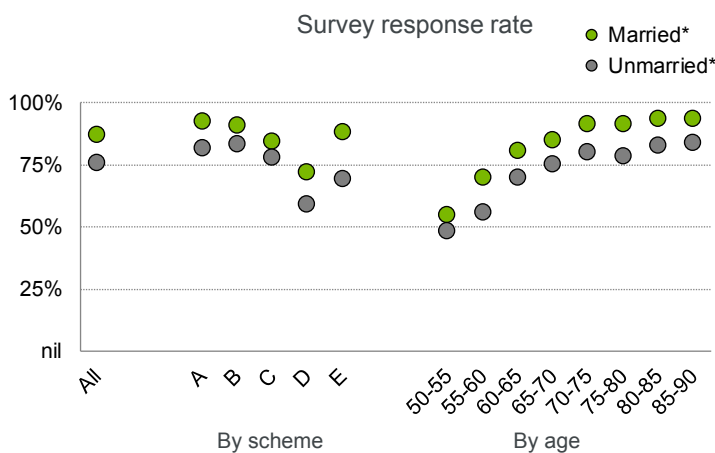
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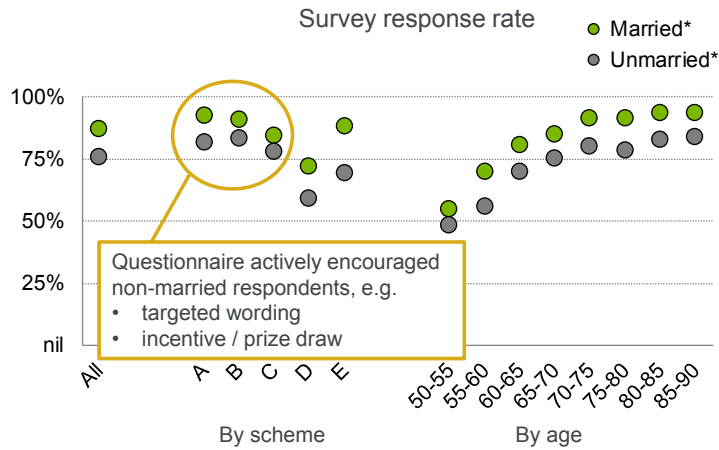
## Relative response rates



\* According to trace status  
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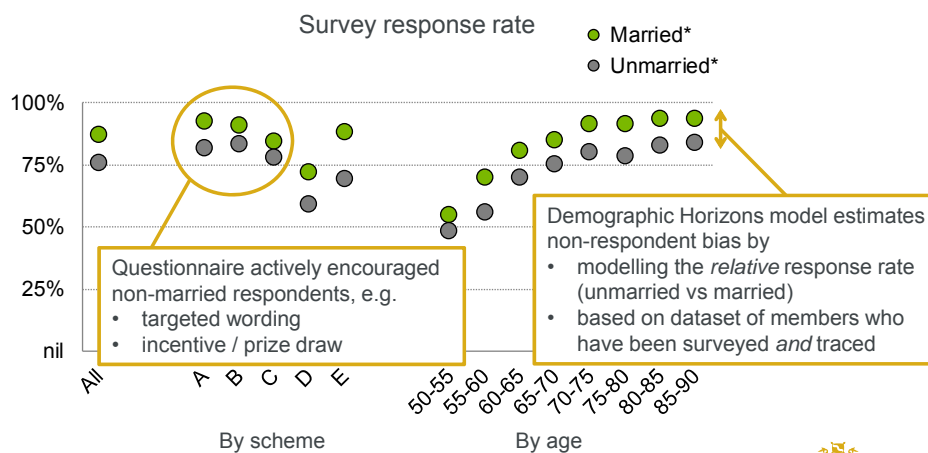
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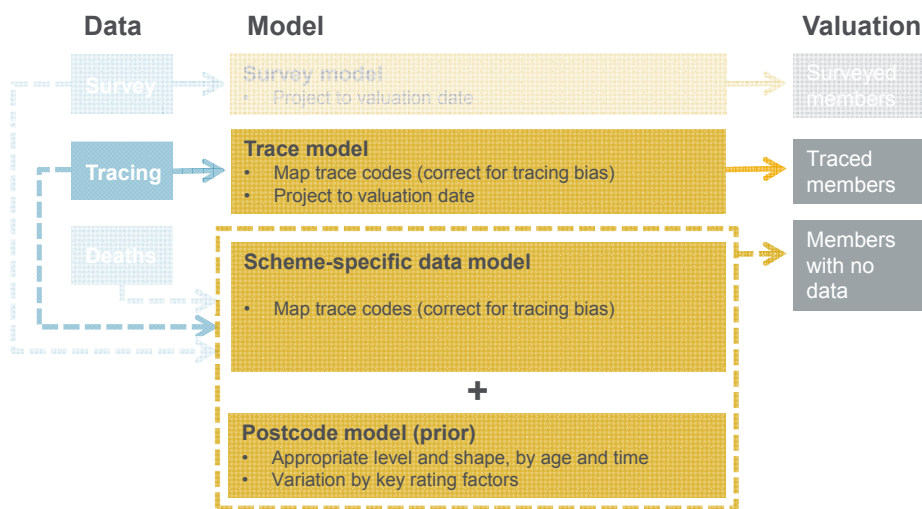
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## Scenario D – tracing data

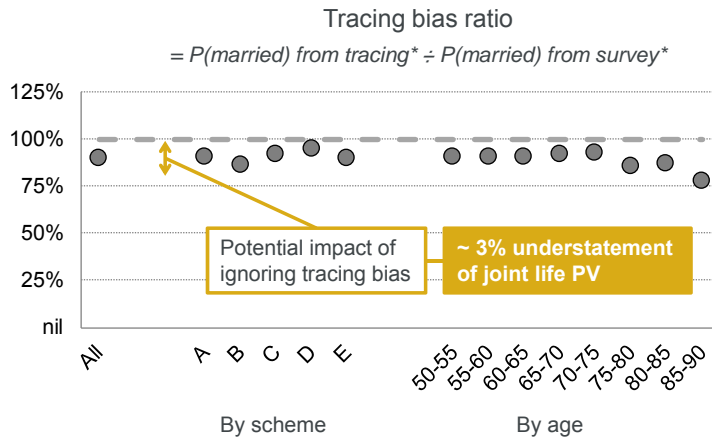
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### Demographic Horizons dependants model



## Tracing bias

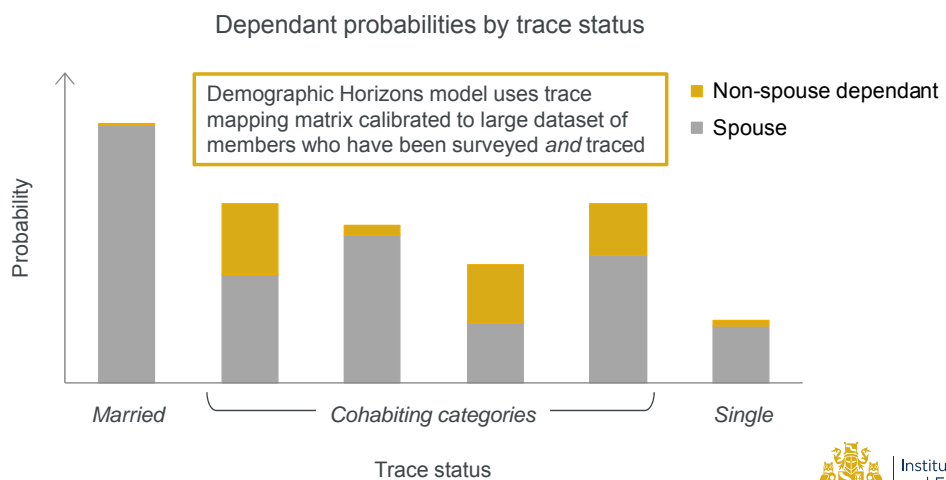


Source: Demographic Horizons dependants dataset

\* Restricting to members for whom both traced status and surveyed status are known

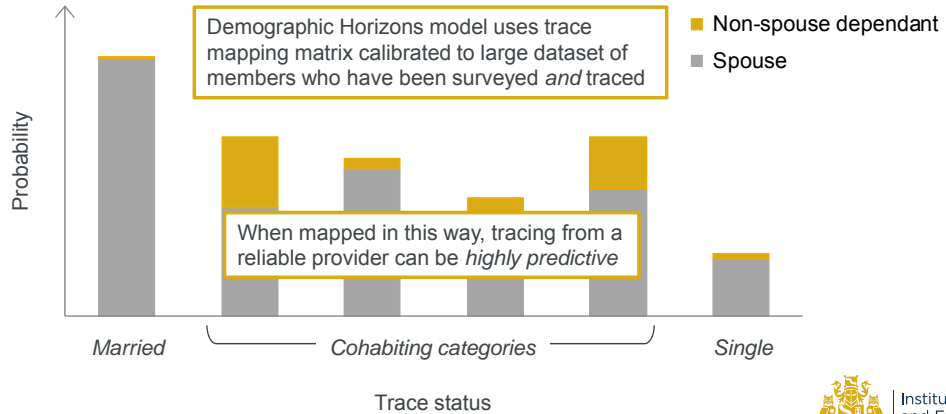


## Mapping trace codes



## Mapping trace codes

Dependant probabilities by trace status



## 3. Age difference

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## Spouse age difference

Examples of modelling pitfalls:

- Age shape
- Spread



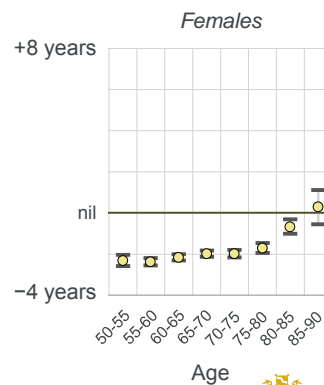
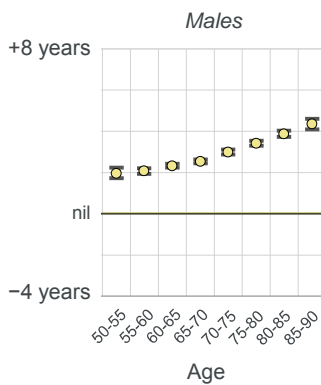
## Spouse age difference

Examples of modelling pitfalls:

- **Age shape**
- Spread

Spouse age difference – pension scheme data (amounts-weighted)\*

- Average age difference (member age minus spouse age)
- ▬ 90% confidence interval



\* Demographic Horizons pension scheme survey data for members with legal spouses

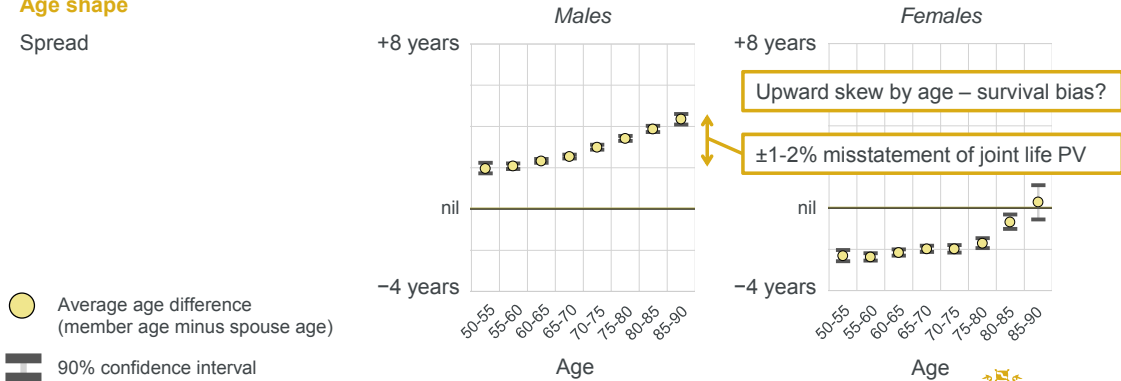


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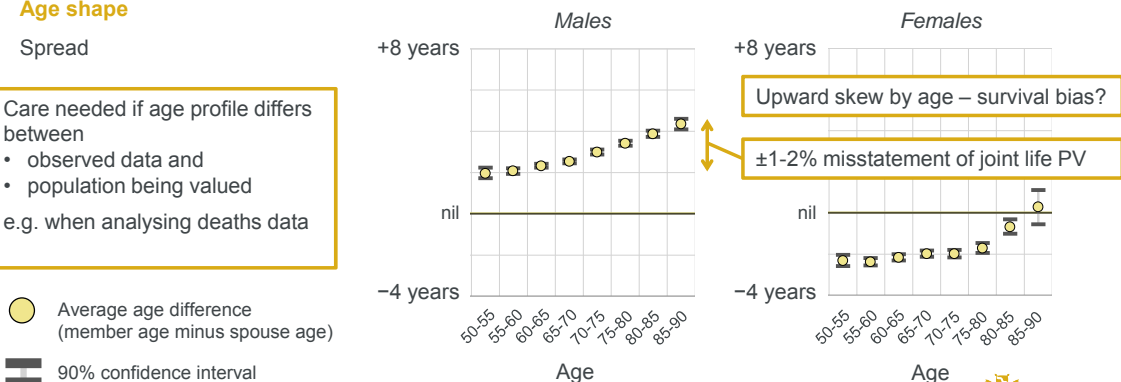
- Age shape
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Care needed if age profile differs between

- observed data and
- population being valued

e.g. when analysing deaths data

Spouse age difference – pension scheme data (amounts-weighted)\*



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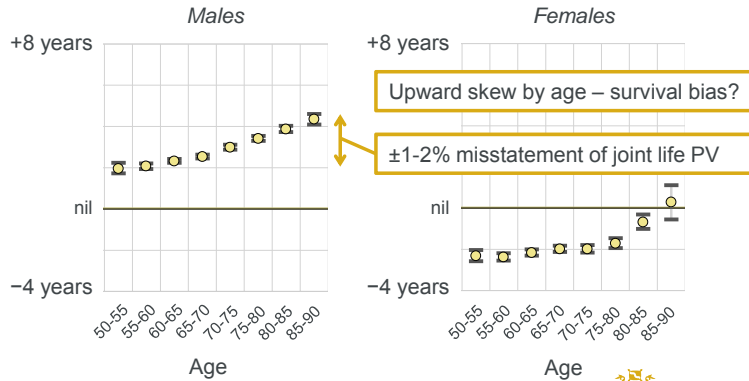
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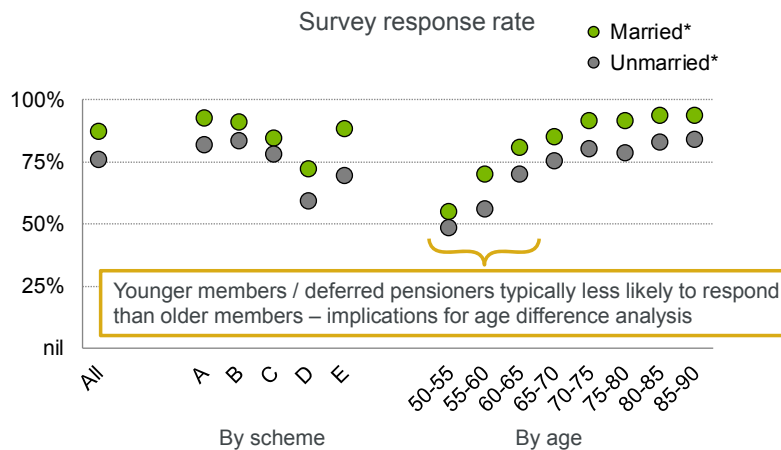
Spouse age difference – pension scheme data (amounts-weighted)\*



\* Demographic Horizons pension scheme survey data for members with legal spouses



## Spouse age difference – survey data



\* According to trace status  
Source: Demographic Horizons dependants dataset



## Spouse age difference

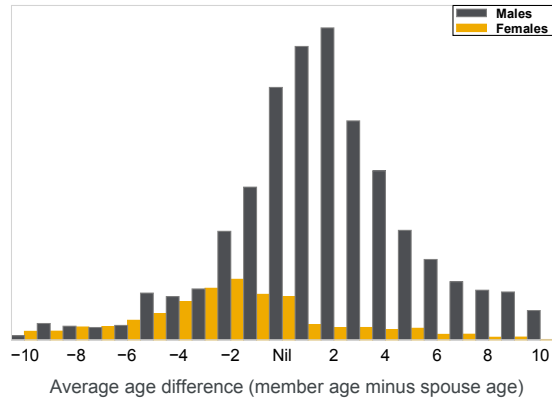
Examples of modelling pitfalls:

- Age shape
- **Spread**

Wide variation in age difference between individuals (even after controlling for age)

Spouse age difference – distribution (amounts-weighted)

*Sample pension scheme from Demographic Horizons dataset*



## Spouse age difference

Examples of modelling pitfalls:

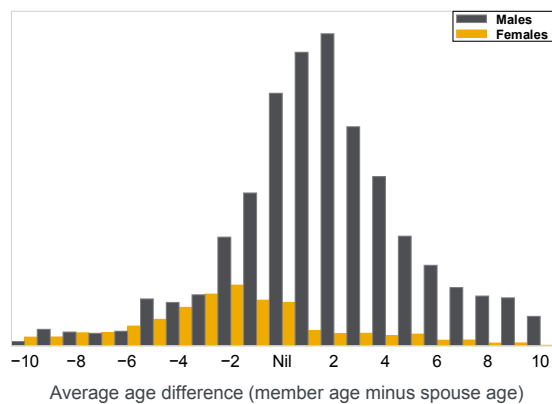
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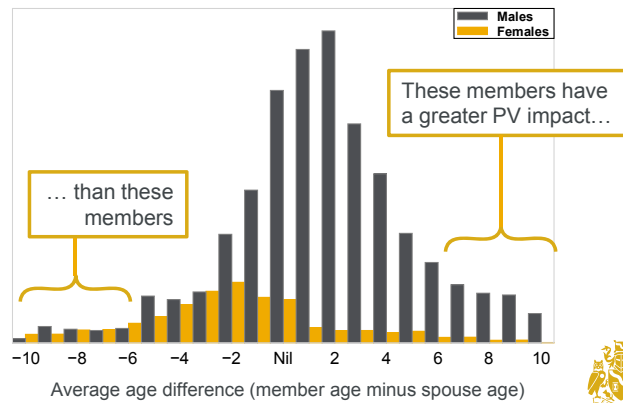
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## Spouse age difference

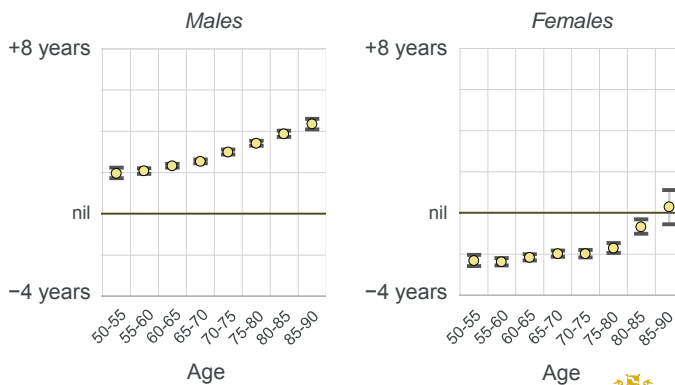
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\* Demographic Horizons pension scheme survey data for members with legal spouses



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So what?

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Spouse age difference – pension scheme data (**amounts-weighted**)\*



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Examples of modelling pitfalls:

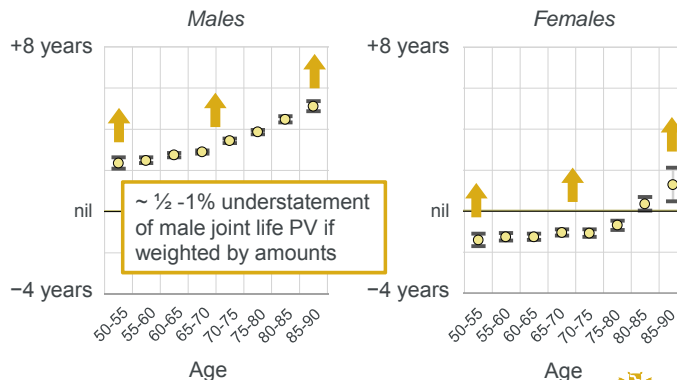
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Wide variation in age difference between individuals (even after controlling for age)

So what?

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- 90% confidence interval

Spouse age difference – pension scheme data (**PV-equivalent**)\*



\* Demographic Horizons pension scheme survey data for members with legal spouses





## 4. Summary

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## Summary

Dependant proportions and age difference *matter* for pricing:

- Increasingly material
- Growing focus of price assessment
- Increasing sophistication required to deal with different data sources, eligibility scope and slicing approaches

Analysis type	Data	Issue	Potential PV impact*
Dependant proportions	No data	Pension scheme vs national population Variation by socio-economic profile	2-3% understatement ±3% misstatement
	Deaths	Mortality bias	1-2% understatement
	Survey	Non-respondent bias	1-2% overstatement
	Tracing	Tracing bias	3% understatement
Age difference	All data	Age shape and spread	±2-3% misstatement

\* Illustrative impact of making no allowance (joint life PV)



## Solutions

Need a dependants model which

- is *robustly* calibrated to objective data
- captures key features
- corrects for survey, tracing and mortality bias
- incorporates scheme-specific data from *all* sources

### Best estimate

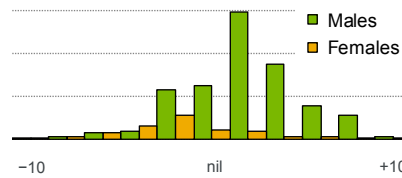
- ✓ *Dependant proportions and age difference*
- ✓ *By group and by data type*
- ✓ *Per member or PV-equivalent average*

### Diagnostics

- ✓ *A/E charts – lives, amounts or PV weighted*
- ✓ *Confidence intervals*
- ✓ *PV impact*



Age difference (member age minus dependant age)  
Amounts-weighted distribution by sex



Questions

Comments

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