



Care Home Confounder Removed?

Introducing a Characteristic Postcode for Postcode Mortality Modelling based on Address History

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Introducing the authors

Jibreel Ismail – Actuarial Consultant, Ad Res

- 2020 – NMG Consulting
- 2021 – Ad Res Advanced Reinsurance Services GmbH

Lee Saunders – Lead Data Engineer, LexisNexis Risk Solutions

- 2002 – Legal & General
- 2010 – DAS Insurance
- 2011 – Allianz Insurance
- 2018 – LexisNexis Risk Solutions

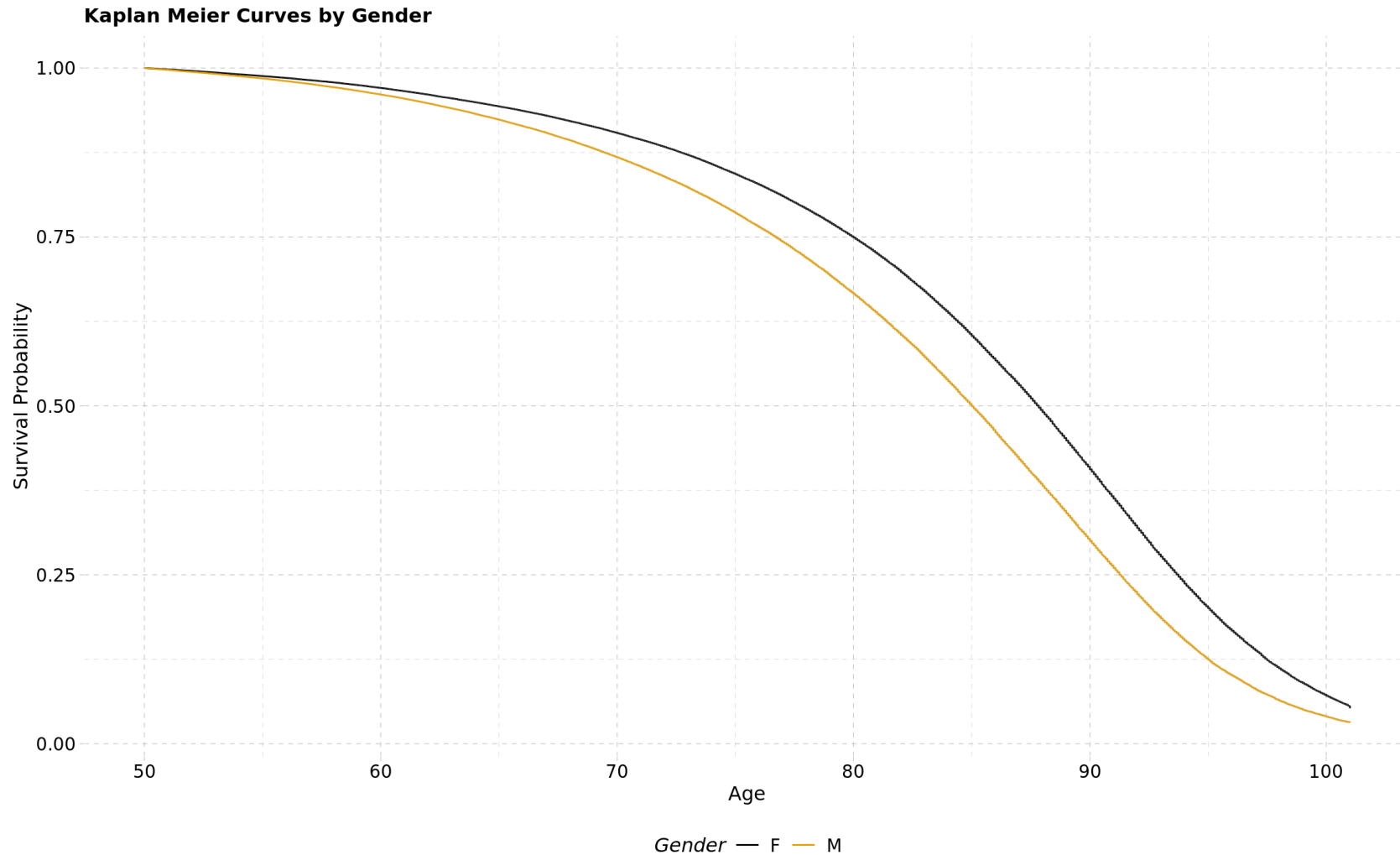
Kai Kaufhold – Managing Director, Ad Res

- 1996 – Zurich Re (Cologne),
- 2000 – Manulife Reinsurance, Toronto, from 2003: Cologne
- 2011 – Ad Res Advanced Reinsurance Services GmbH

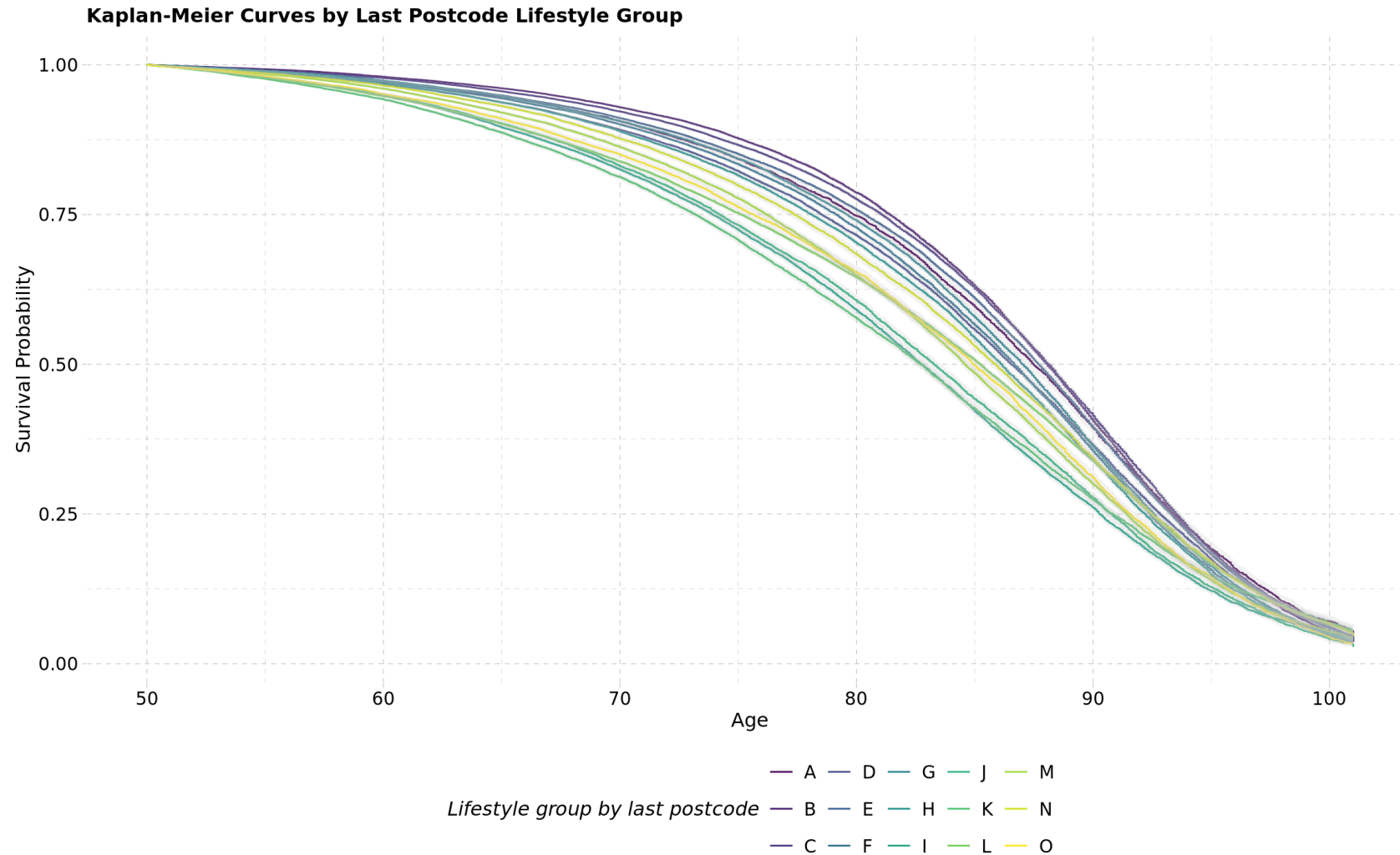
Agenda

- Motivation
 - What's the matter with nursing homes?
- Model
 - Hermite-spline hazards
- Data
 - Largest longevity dataset ever
- Results
 - New postcode definition revealed
- Discussion
 - What's missing?

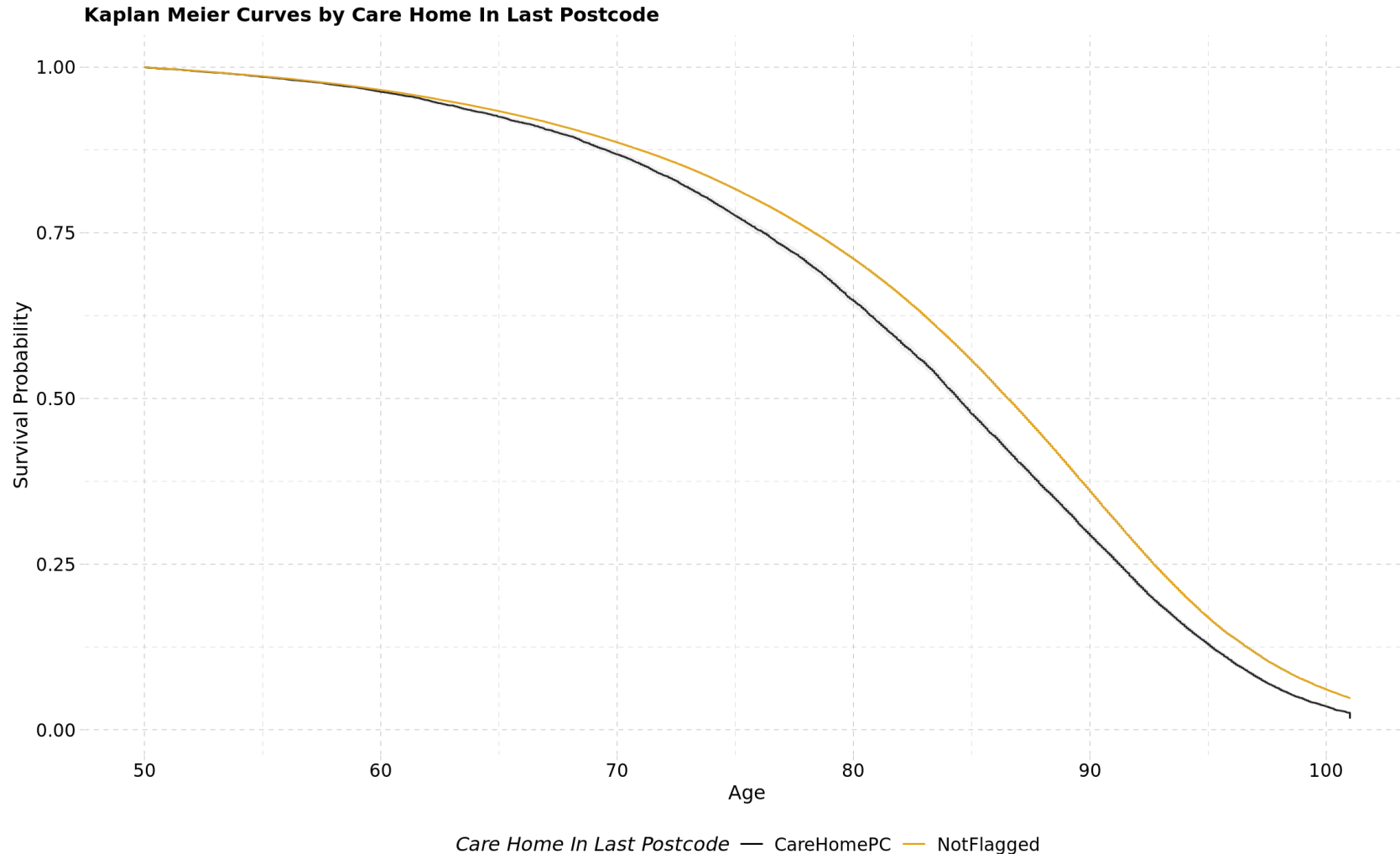
Gender differentials (just checking)



Postcodes are predictive



Care home experience is naturally biased



Motivation

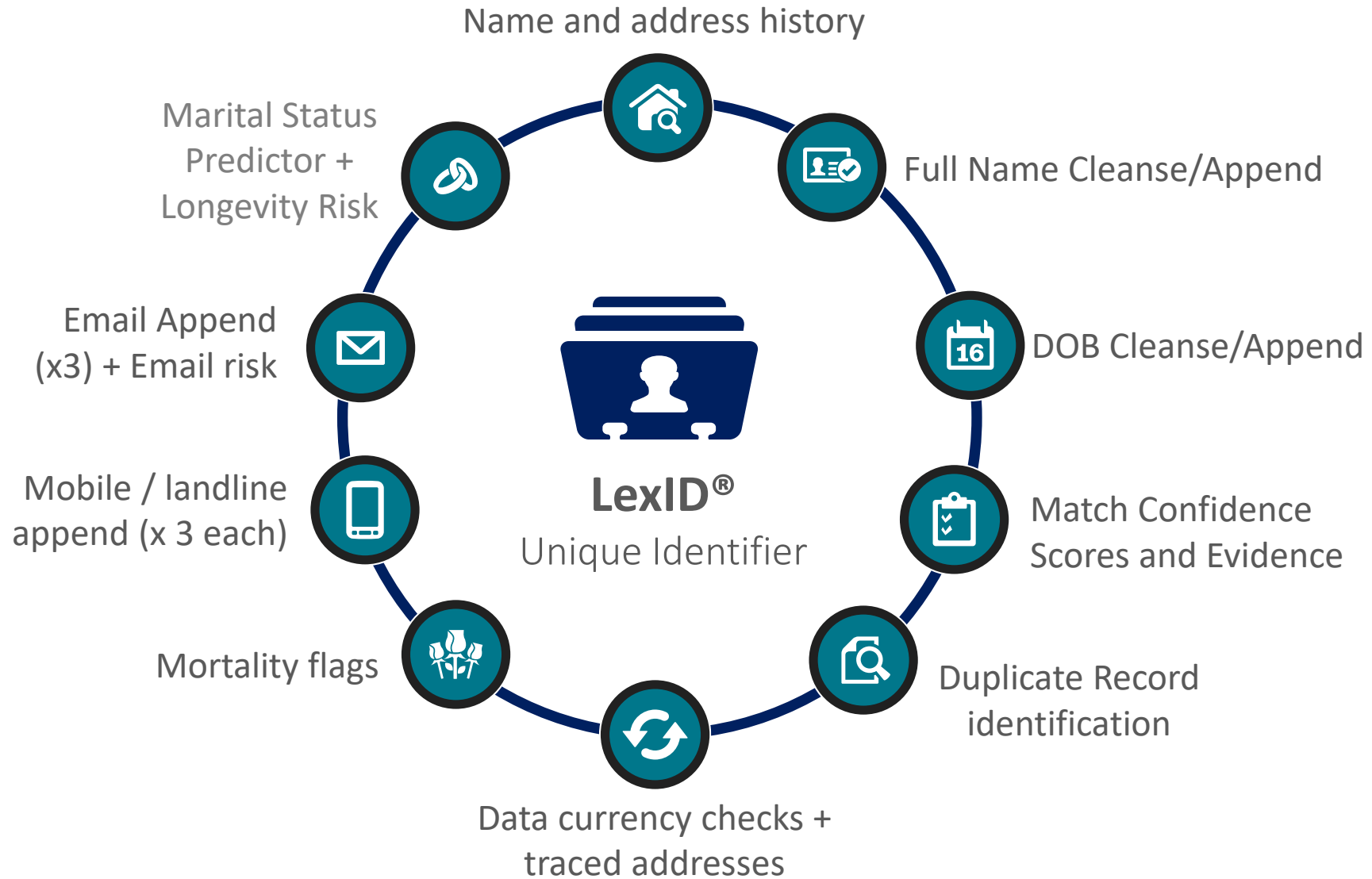
- Mortality in care home postcodes heavier than socio-economic segmentation predicts
- Last known postcode is therefore biased
- Remove bias by finding alternative postcode definitions based on address history
 - Second last postcode
 - Postcode with longest residence
 - Postcode at 65



LexisNexis Data

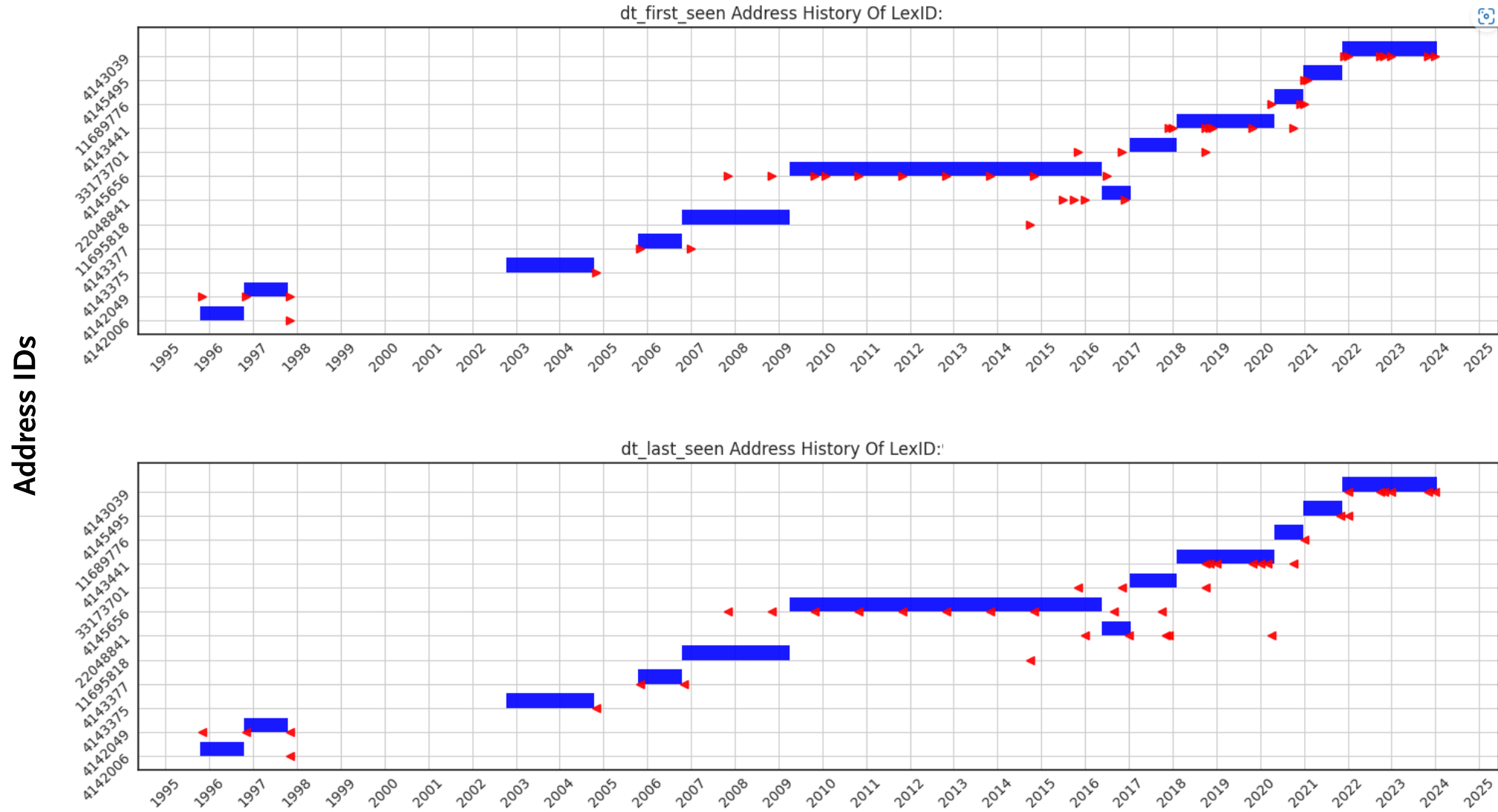
Individual-level mortality experience data from the entire U.K. population

LexisNexis Core Dataset: 56.8M records – updated fortnightly



| Source | Content | Update frequency |
|----------------------|---|-----------------------------|
| 2 x CRA product data | CRA suppliers include 650+ organisations who offer a credit product: Banks, Building Societies, other Financial Services, Insurance, Media, Energy and Water companies. No payment information. | Monthly updates |
| CRA application data | As above – useful for early signs of address moves & people coming of age, new to country | Monthly updates |
| Postal address file | List of all UK addresses | Daily updates |
| Public data | CCJs / IVAs / Bankruptcies | Daily updates |
| Council Tax data | Property valuation (as at 1991) | Half yearly |
| LexisNexis Smartlink | Address links / movers | 24/7 |
| Electoral roll | As the UK's 4 th CRA (Crediva) LexisNexis have access to the full ER. Compliance rules must be adhered to | Weekly for rolling register |
| Lifestyle data | Source for emails / mobiles | Daily / weekly / monthly |
| Deceased data | Variety of sources | Weekly / monthly |

Tracing the address history of a sample LexID



How many people do the records below relate to?

| Title | First Name | Surname | Address 1 | Postcode | DOB |
|-------|------------|------------|-------------------|----------|------------|
| | E | Miggins | 43 Pie Shop Lane | EC1A 4SK | 1954-05-02 |
| Miss | Elizabeth | Miggins | 43 Pie Shop Lane | EC1A 4SK | |
| | Elizabeth | Miggins | 43 Pie Shop Lane | EC1A 4SK | 1954-02-05 |
| Miss | L | Miggins | 43 Pie Shop Lane | EC1A 4SK | |
| Miss | Liz | Miggins | 43 Pie Shop Lane | EC1A 4SK | |
| Miss | Lizzy | Miggins | 43 Pie Shop Lane | EC1A 4SK | 1954-05-02 |
| Mrs | Betty | Blackadder | 16 Palace Gardens | SW4 2CM | 1954-05-02 |

LexisNexis Data: Years 2015 – 2019, ages 50 – 100

| Risk Group | Lives | Exposure | Deaths |
|--------------------|--------------|-----------------|---------------|
| All | 30,029,850 | 126,675,740 | 2,321,930 |
| Females | 15,425,260 | 65,354,050 | 1,164,330 |
| Males | 14,604,590 | 61,321,690 | 1,157,600 |
| Care Home Postcode | 1,231,020 | 4,994,030 | 156,620 |
| No Care Home Flag | 28,798,830 | 121,681,710 | 2,165,310 |

Pension Scheme Data (for testing): Years 2015 – 2019, ages 50 – 100

| Risk Group | Lives | Exposure | Deaths |
|--------------------|--------------|-----------------|---------------|
| All | 171,823 | 729,972 | 19,935 |
| Females | 54,599 | 224,761 | 6,719 |
| Males | 117,224 | 505,211 | 13,216 |
| Care Home Postcode | 9,753 | 40,218 | 1,872 |
| No Care Home Flag | 162,070 | 689,754 | 18,063 |

Model Specification

Hermite-spline Hazard Rate Model with Interactions



Hermite-splines for modelling mortality

$$\log(\mu_{x,y}) = \alpha h_{00}(t) + \omega h_{01}(t) + m_0 h_{10}(t) + \eta h_q(t) + \delta y$$

$$t = (x - x_0)/(x_1 - x_0)$$

$$h_{00}(t) = (1 + 2t)(1 - t)^2$$

$$h_{01}(t) = t^2(3 - 2t)$$

$$h_{10}(t) = t(1 - t)^2$$

$$h_q(t) = 16t^2(1 - t)^2$$

The coefficients each have an intuitive meaning:

α – describes the log mortality at beginning of age range x_0

ω – describes the log mortality at the end of the age range x_1

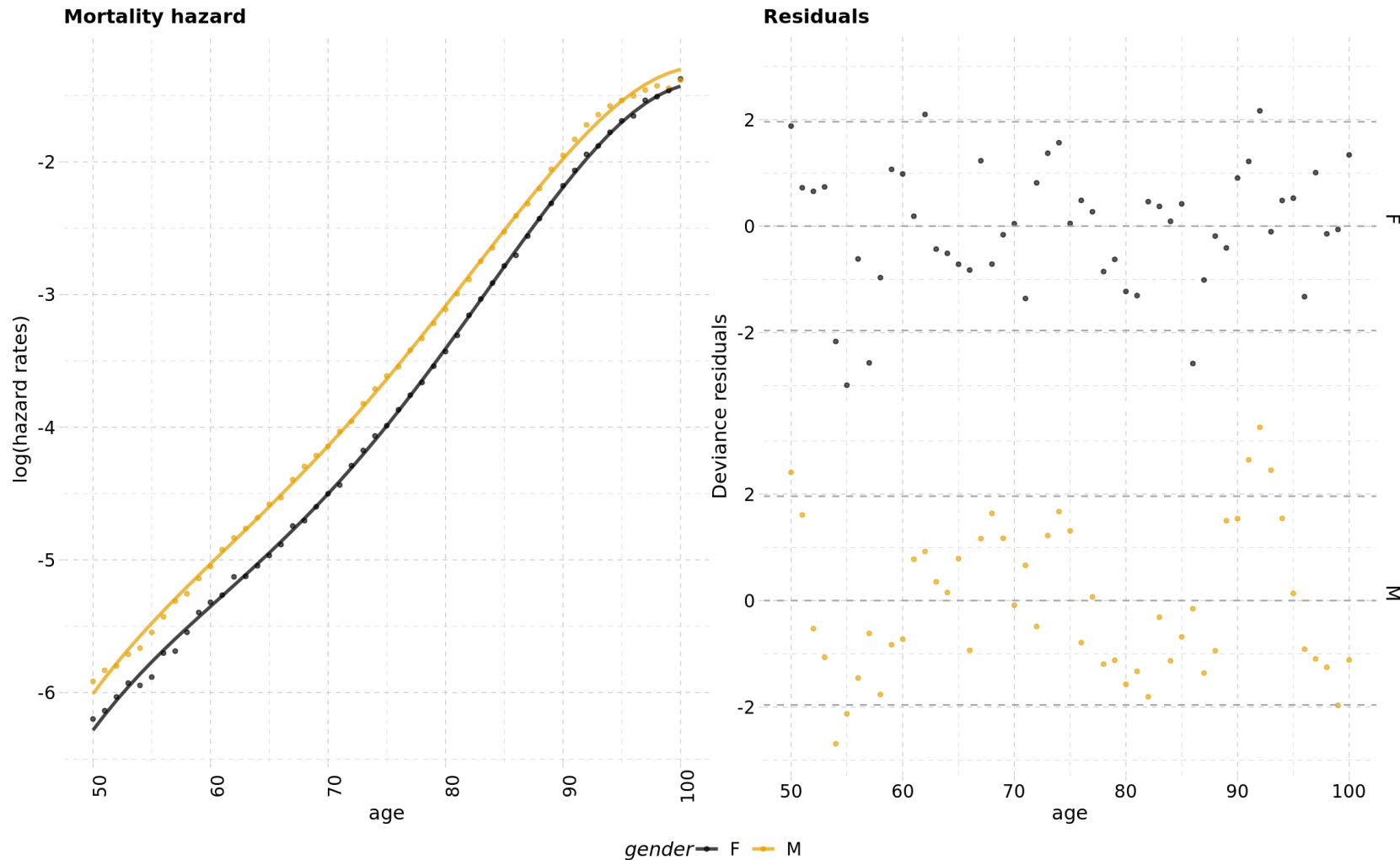
m_0 – describes the slope at the beginning of the age range x_0

η – influences the log mortality in the middle of the age range

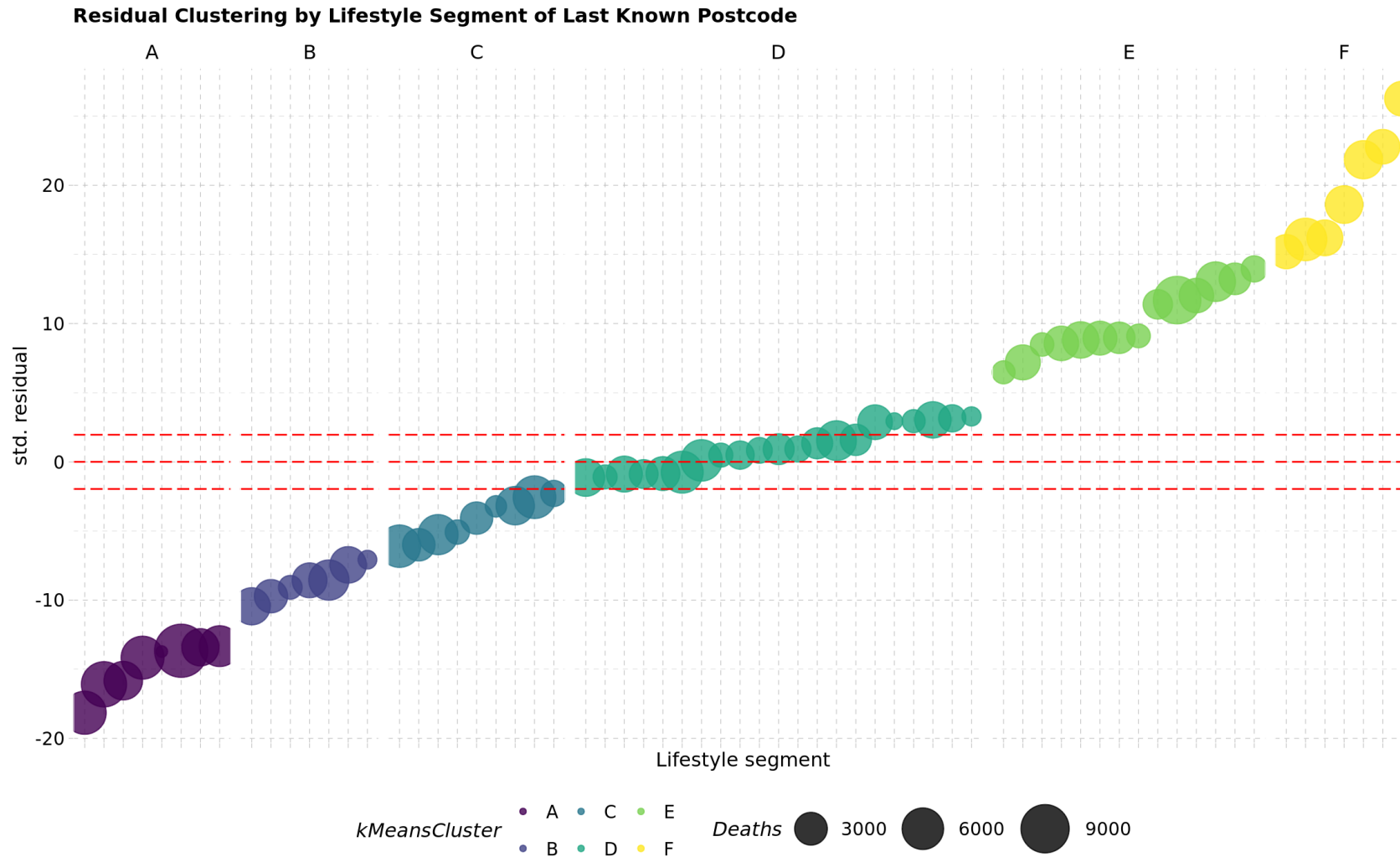
δ – describes an age-independent trend by calendar time y

See Richards (2019) and Ramonat (2024)

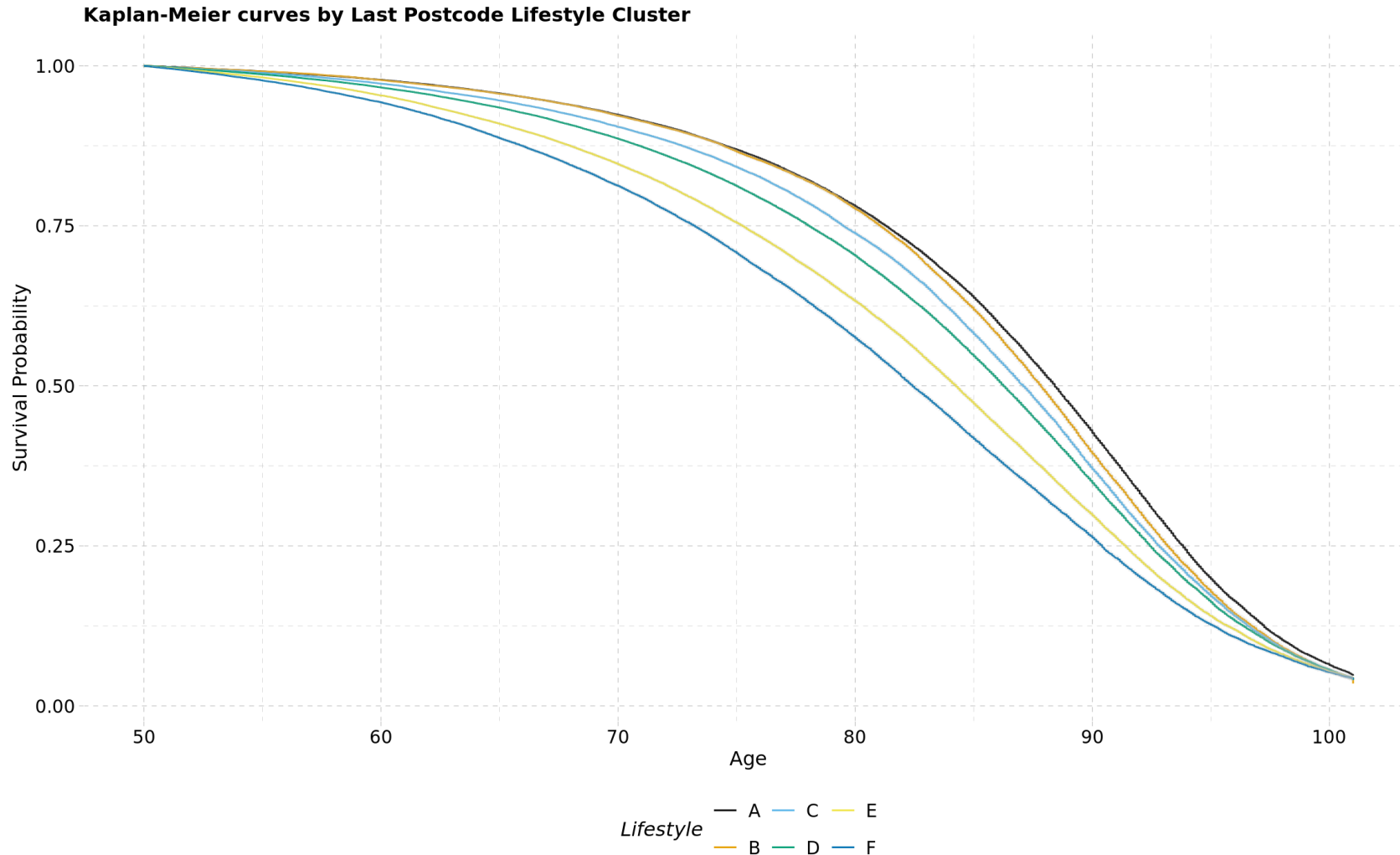
Captures age-shape of mortality



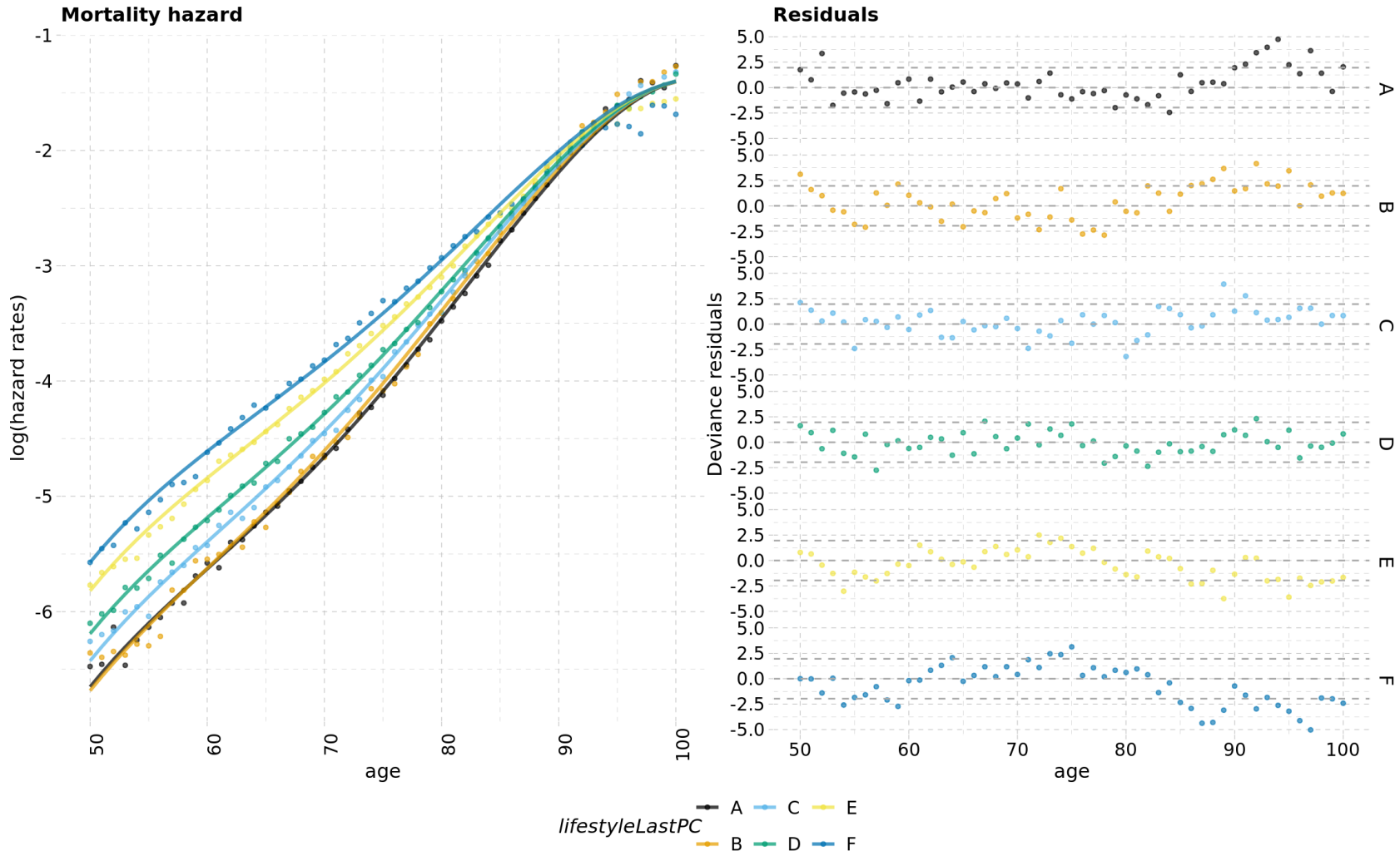
Clustering Lifestyle segments by residual



Clustering Lifestyles by residual



Model for Lifestyle Clusters

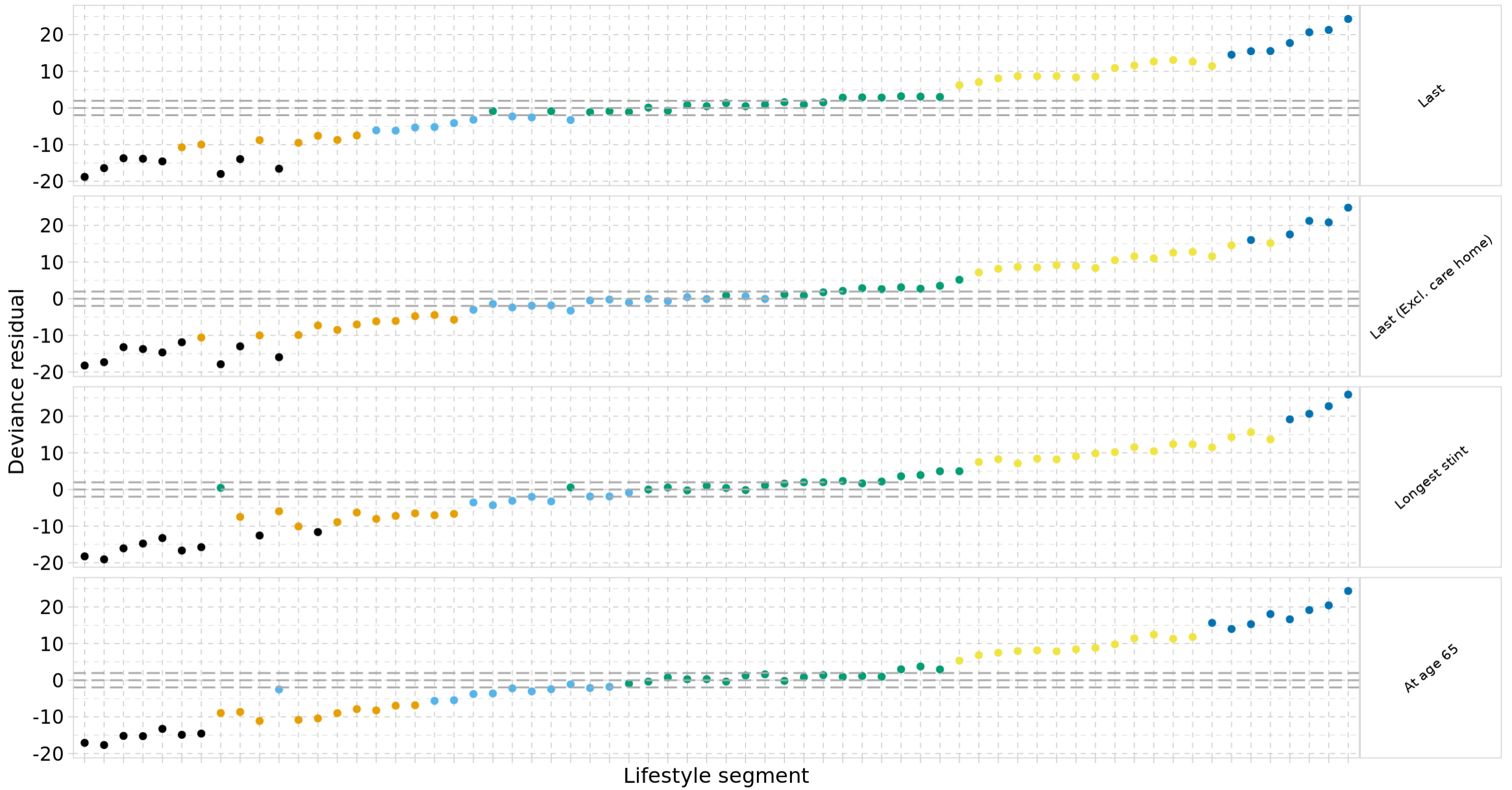




Results

Comparing four postcode definitions

Comparison of lifestyle cluster by postcode definition



Last

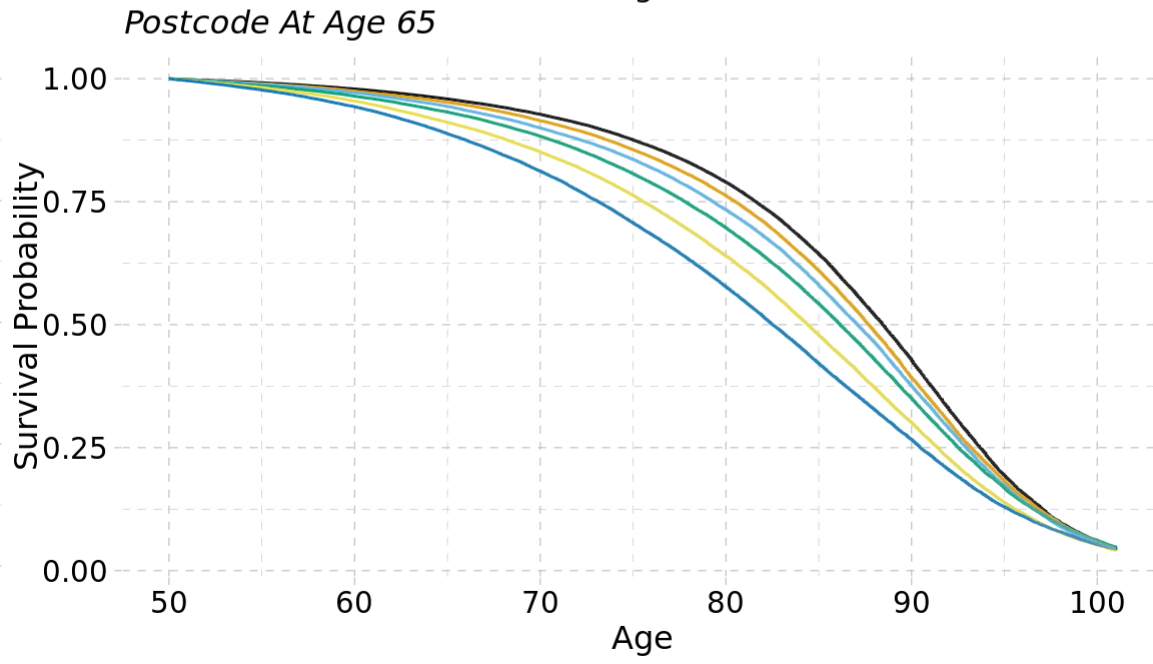
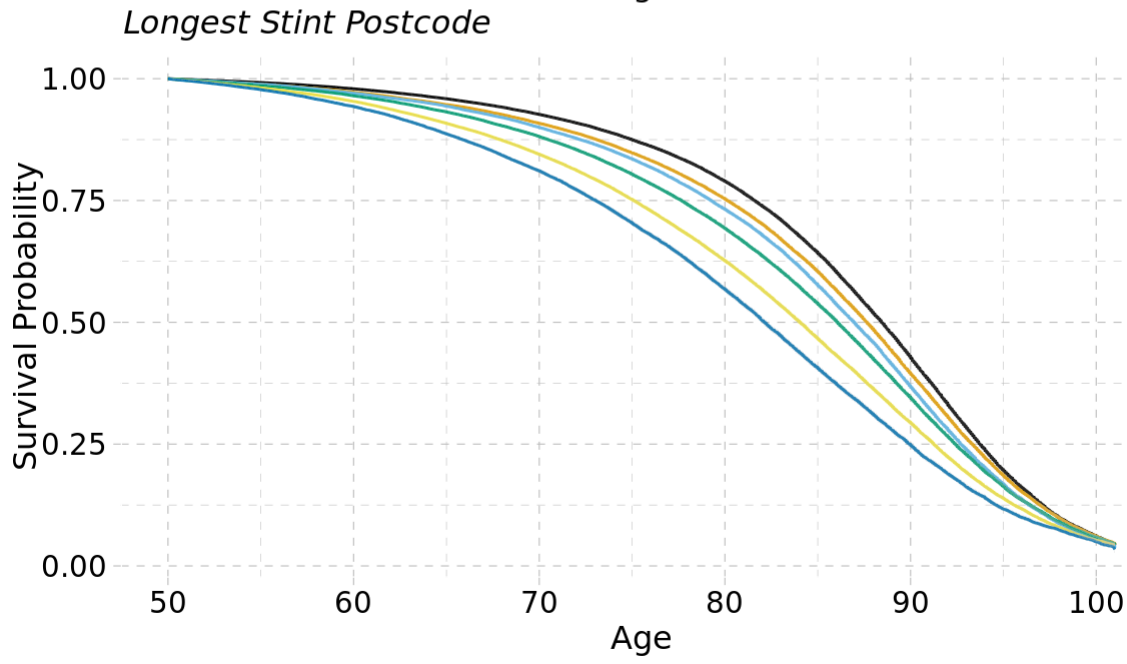
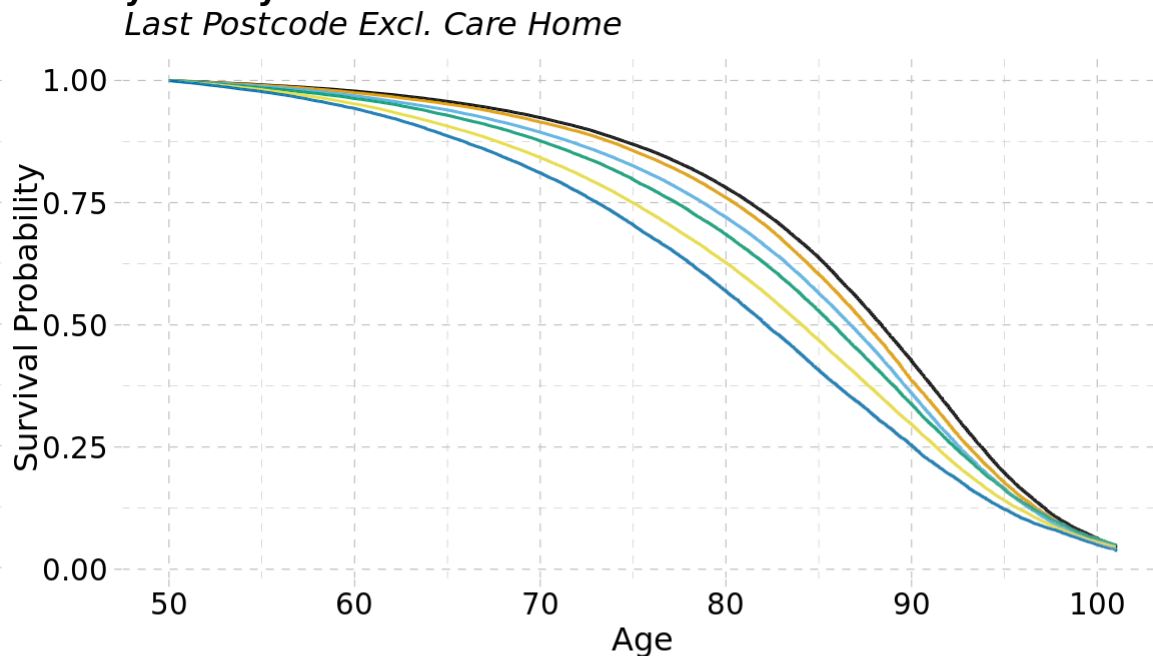
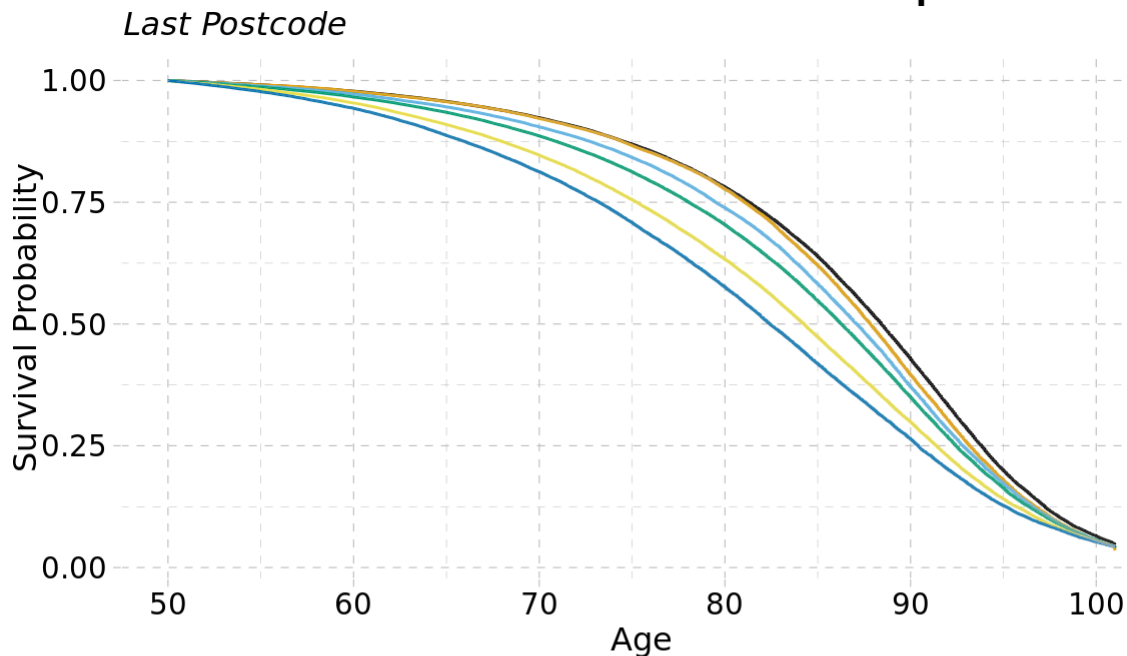
Last (Excl. care home)

Longest stint

At age 65

lifestyle ● A ● B ● C ● D ● E ● F

Kaplan-Meier curves by Lifestyle



Lifestyle — A — B — C — D — E — F

And the winner is ...

Lifestyle Models based on LexisNexis Data

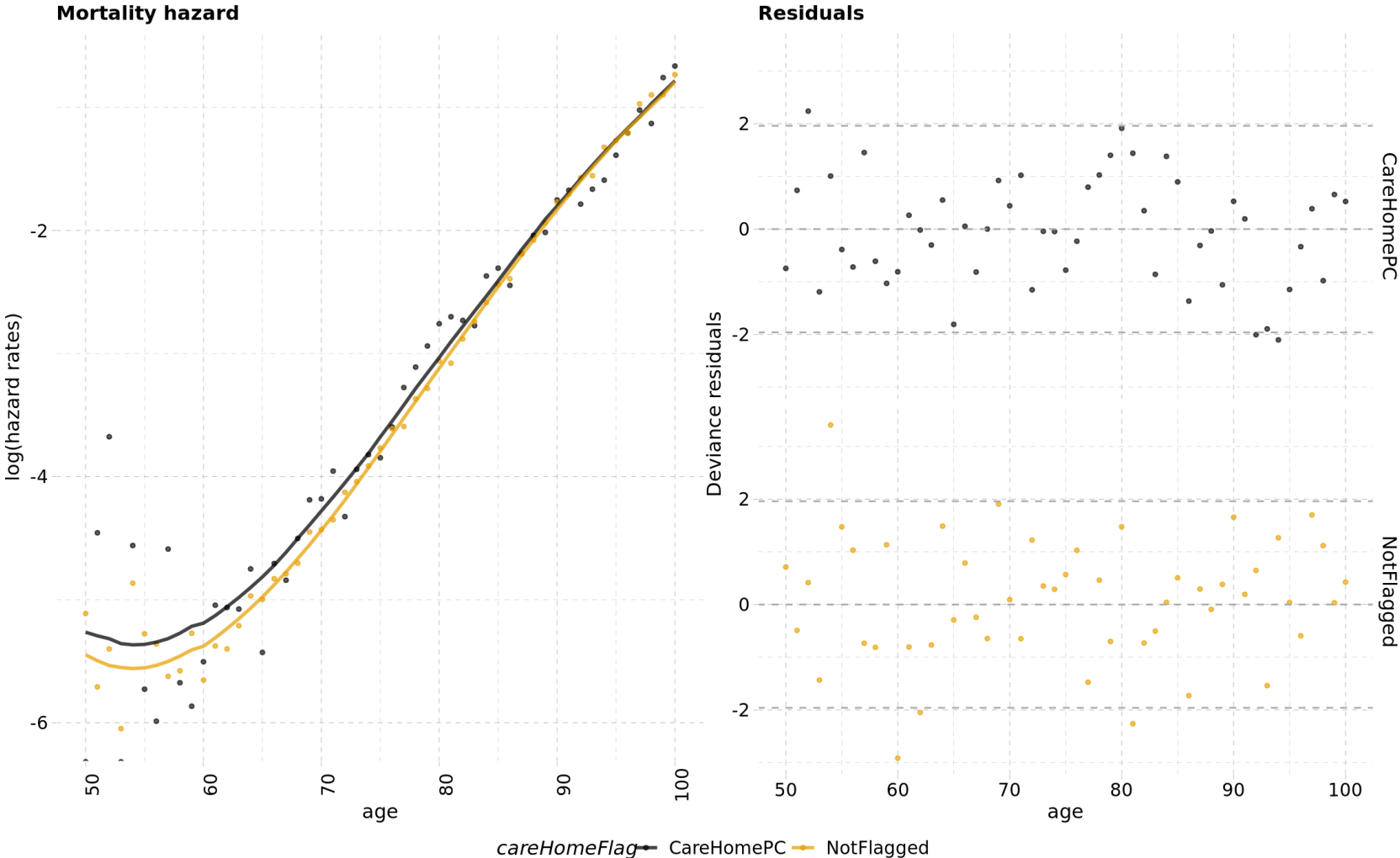
| Lifestyle basis | AIC | AIC Reduction from Base Model |
|---------------------------|------------------|-------------------------------|
| Last postcode | 1,974,553 | -9,871.0 |
| Pre-care home-postcode | 1,974,660 | -9,764.4 |
| Longest stint postcode | 1,974,585 | -9,839.0 |
| Postcode at age 65 | 1,974,382 | -10,042.5 |

... but is it really?

Lifestyle Models based on Pensioner Data

| Lifestyle basis | AIC | AIC Reduction from Base Model |
|------------------------|-----------|-------------------------------|
| Last postcode | 152,470.0 | -472.9 |
| Pre-care home-postcode | 152,483.1 | -459.8 |
| Longest stint postcode | 152,527.0 | -415.9 |
| Postcode at age 65 | 152,472.5 | -470.4 |

Mortality of pensioners in care homes



Discussion

Summary

- Care home postcodes display heavier mortality
- For large dataset, postcode at 65 is most predictive of socio-economic mortality differentials
- Care home postcode still shows heavier mortality
- Confounder NOT removed, but alleviated

Future Research

1. Improve socio-economic lifestyle clusters
2. Systematically test prediction accuracy and precision to optimise classification method

References

- Ramonat, S. J. (2024). Extending the Hermite-spline basis for mortality modelling. *Working Paper*.
- Richards, S. J. (2019). A Hermite-spline model of post-retirement mortality. *Scandinavian Actuarial Journal*, 2020(2), 110–127.
<https://doi.org/10.1080/03461238.2019.1642239>
- Wen J, Cairns AJG, Kleinow T. (2023) Modelling socio-economic mortality at neighbourhood level. *ASTIN Bulletin*. 53(2):285-310. doi:10.1017/asb.2023.12

See you tomorrow!

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