

Bayesian Forecasting of Cohort Fertility

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*“It’s difficult to make predictions...
especially about the future.”*

-- Yogi Berra??



-- Niels Bohr??



-- Winston Churchill??



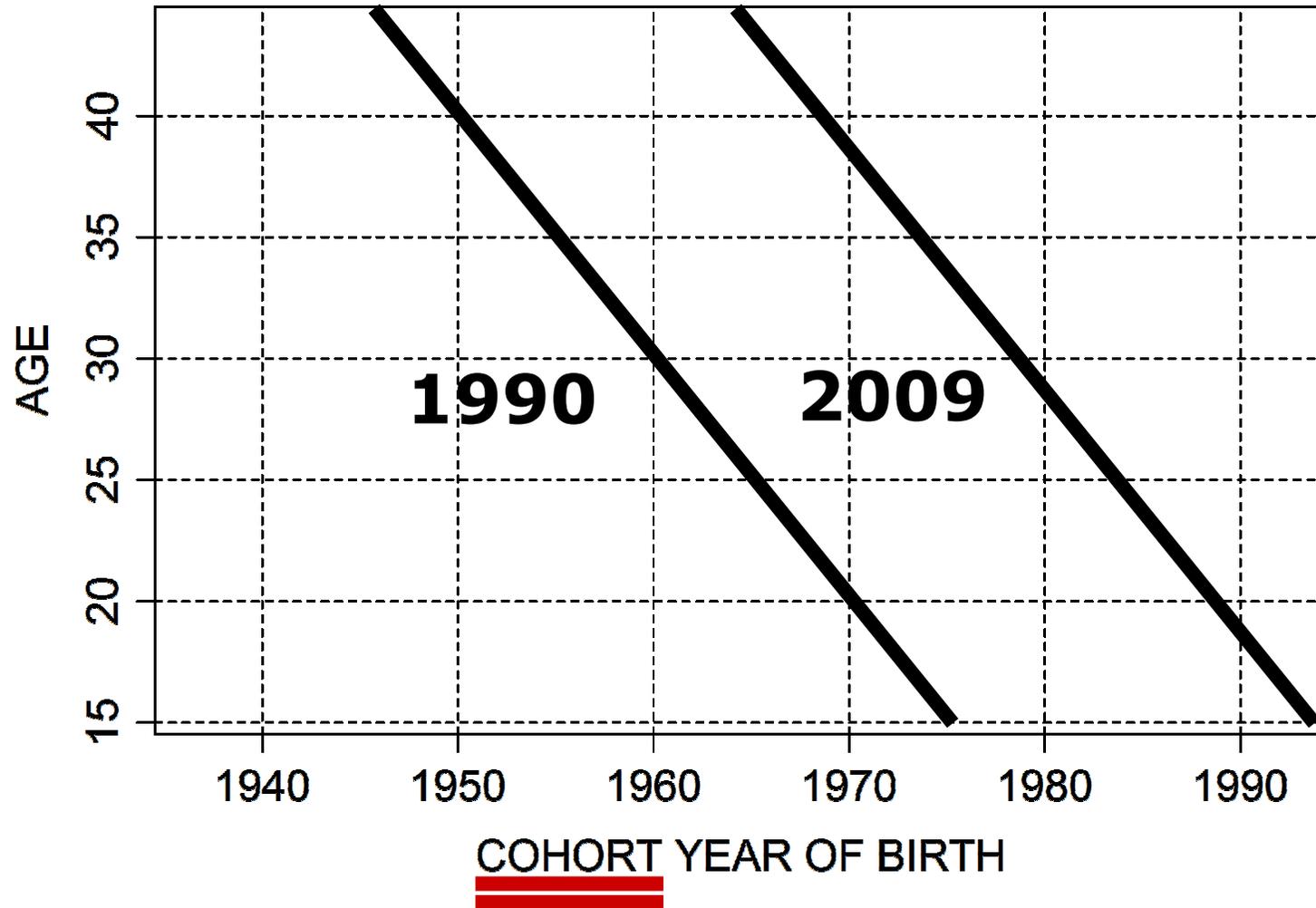
Motivation: CFR Rebound?

- PTFR up recently in many countries...
 - ... but CFR may be our real interest
 - Change in period measures from...
 - Increasing cohort levels? (CFR up)
 - Decelerating postponement? (CFR ???)
 - Both?
-

Objectives

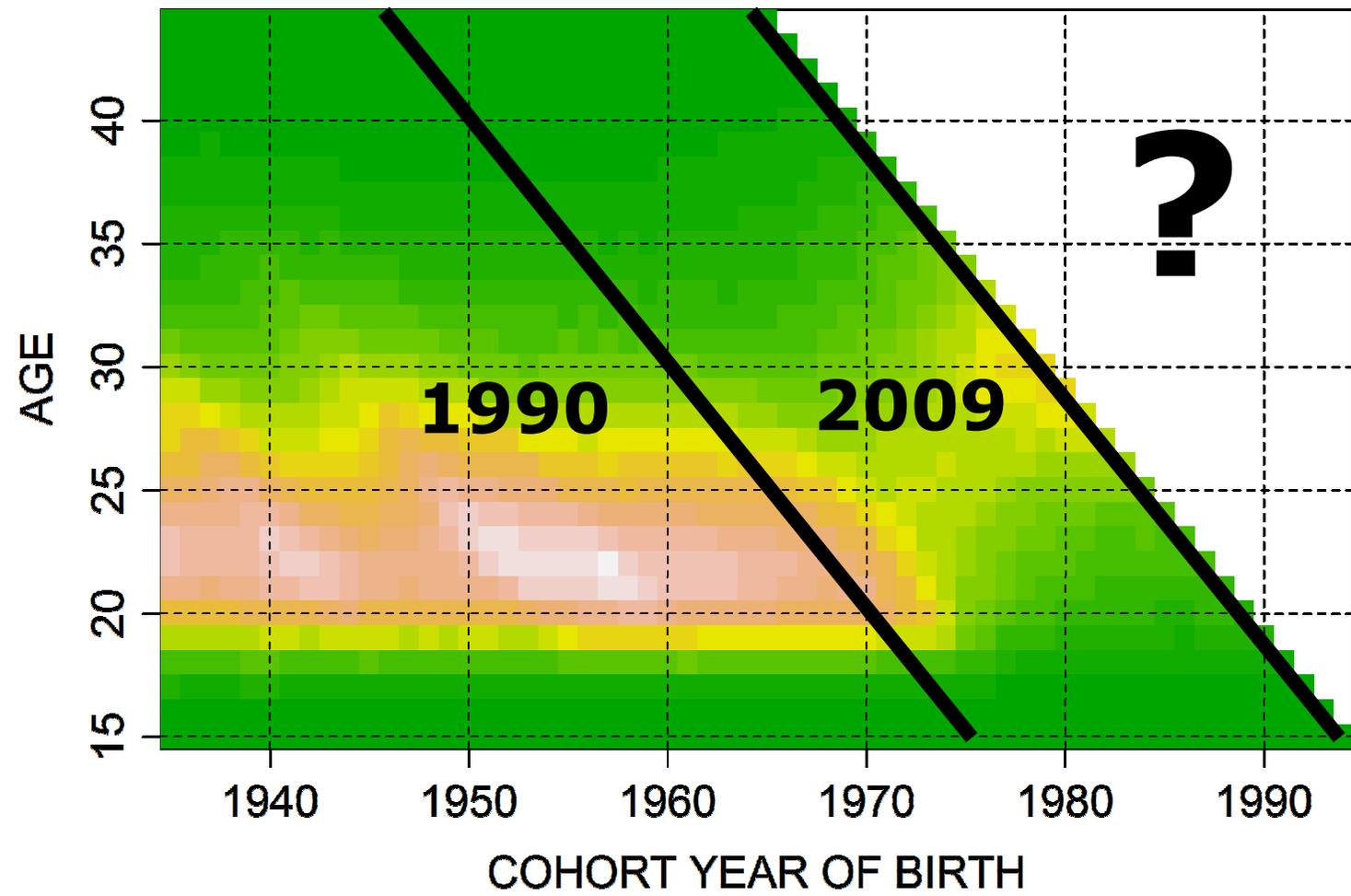
- Forecast completed CFR for cohorts already 15 but not yet 45
 - Build a procedure that automatically includes uncertainty estimates
 - Use historical data (**HFD**) to
 - design model
 - calibrate uncertainty
-

Cohort Lexis Surface

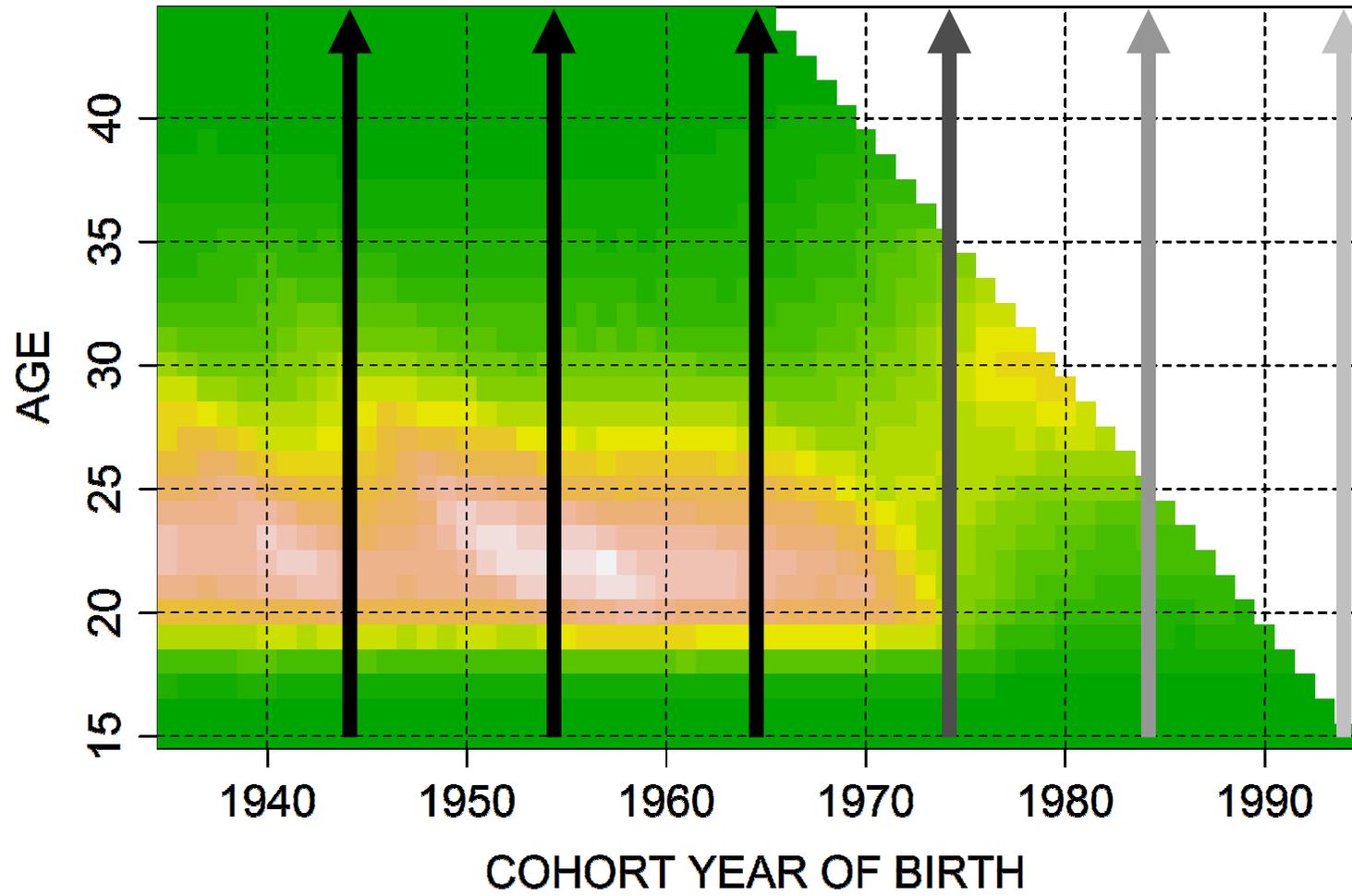


SOME HFD DATA...

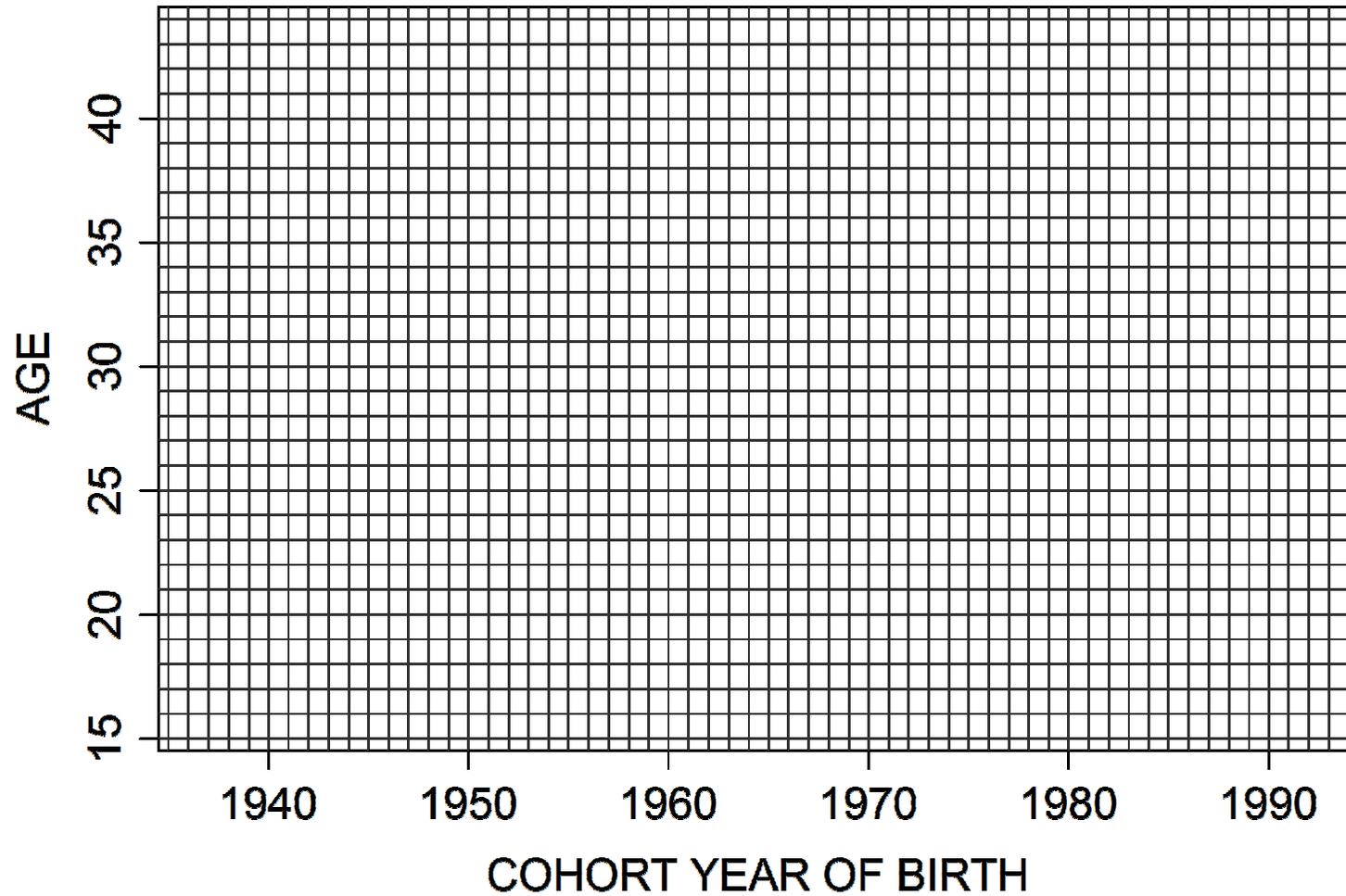
CZE Lexis Surface



1944 1954 1964 1974 1984 1994
2.05 2.08 1.97 1.16⁺ 0.33⁺ 0.0007⁺



**Our Strategy, inspired by Girosi & King (2008):
Model the entire surface non-parametrically
(i.e., one parameter per age-cohort cell)**

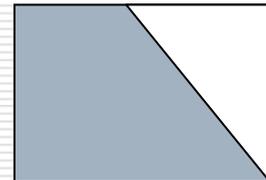


Bayesian Model

- $\theta = \{ \theta_{ac} \} = \mathbf{Surface}$
(e.g., $30 \times 60 = 1800$ parameters)



- $\{ \text{Estimates of some } \theta_{ac} \} = \mathbf{Data}$
(e.g., 1365 f_{ac} estimates from HFD)



- $L(\mathbf{Data} \mid \mathbf{Surface})$... std likelihood

- $f(\mathbf{Surface})$... prior distribution

In the absence of data, are some surfaces more likely than others?

Bayesian Model

$$P(\theta | \mathbf{Data}) \propto L(\mathbf{Data} | \theta) \cdot f(\theta)$$

Posterior

How likely are alternative surfaces θ , given our observations?

Likelihood

How likely are our observations for alternative surfaces θ ?

Prior

How likely are alternative surfaces θ , before we see data?

... informed by **HFD**

$$P(\theta \mid \mathbf{Data}, \mathbf{HFD}) \propto L(\mathbf{Data} \mid \theta) \cdot \underbrace{f(\theta \mid \mathbf{HFD})}$$

Prior

How common are alternative types of surfaces θ in the HFD?

**NORMAL
Posterior**



Proper NORMAL

**Improper NORMAL
with quadratic
penalties in θ**

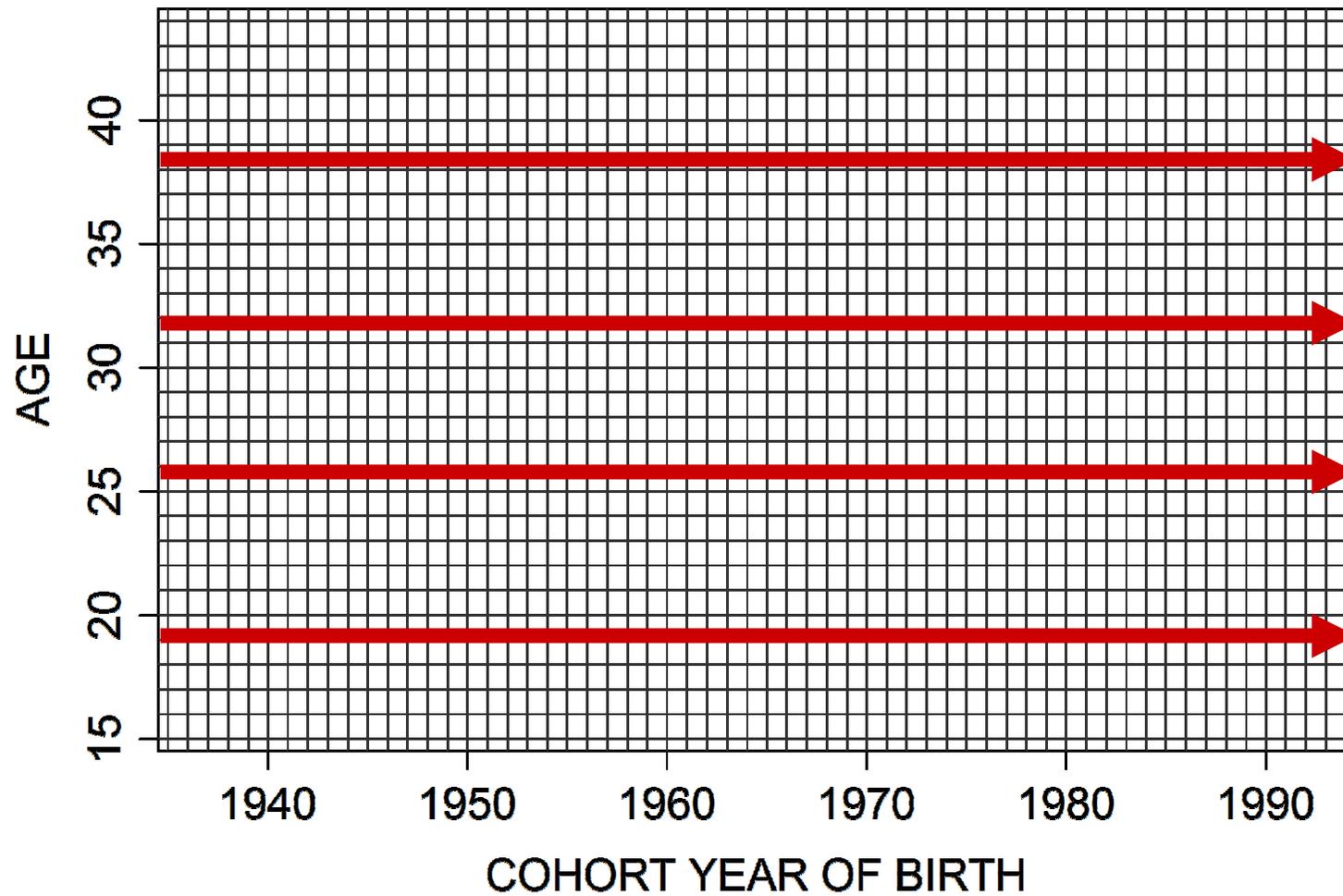
Bayesian Forecast Results

- (Closed-form) posterior mean vector and covariance matrix describe
 - Best-guess fit to observations
 - Best-guess forecasts
 - Uncertainty
 - Means and variances of **CFRs** and **ASFRs**
-

PRIOR #1:

How smooth is a time series likely to be at a given age?

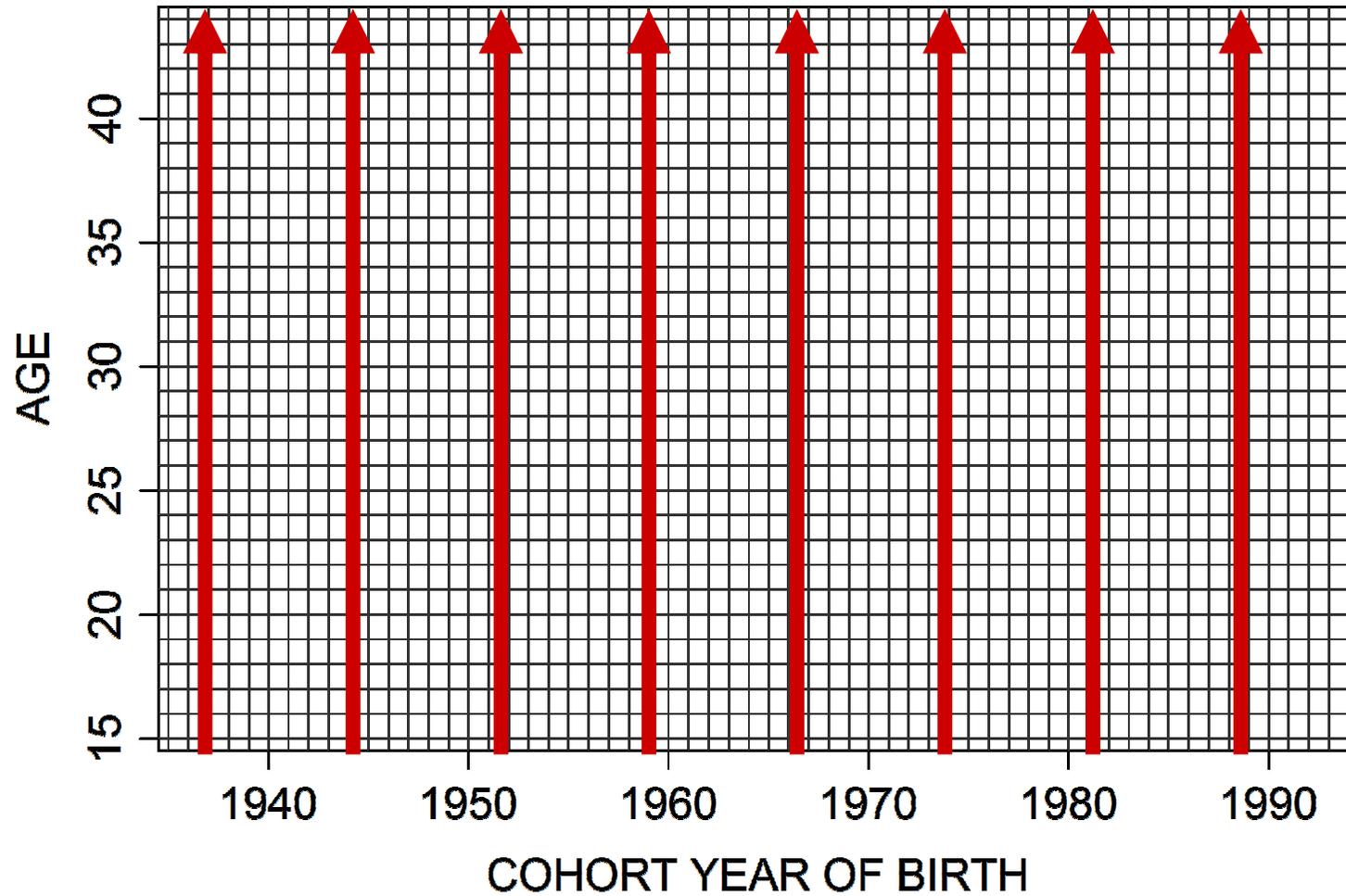
... find out from HFD



PRIOR #2:

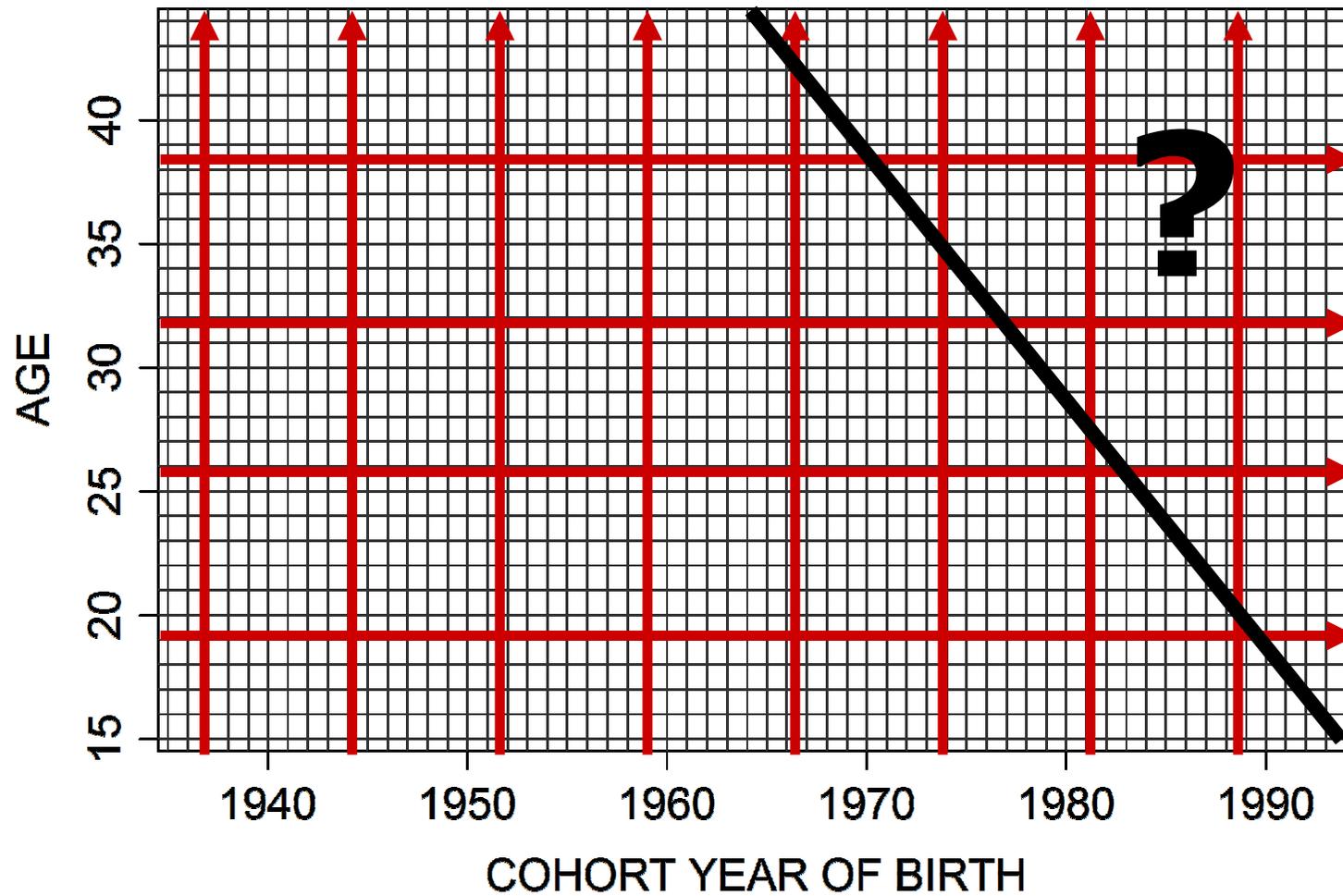
What are typical shapes of cohort schedules?

... find out from HFD



COMBINED PRIORS:

What are likely/unlikely Lexis surfaces? $f(\theta | \text{HFD})$

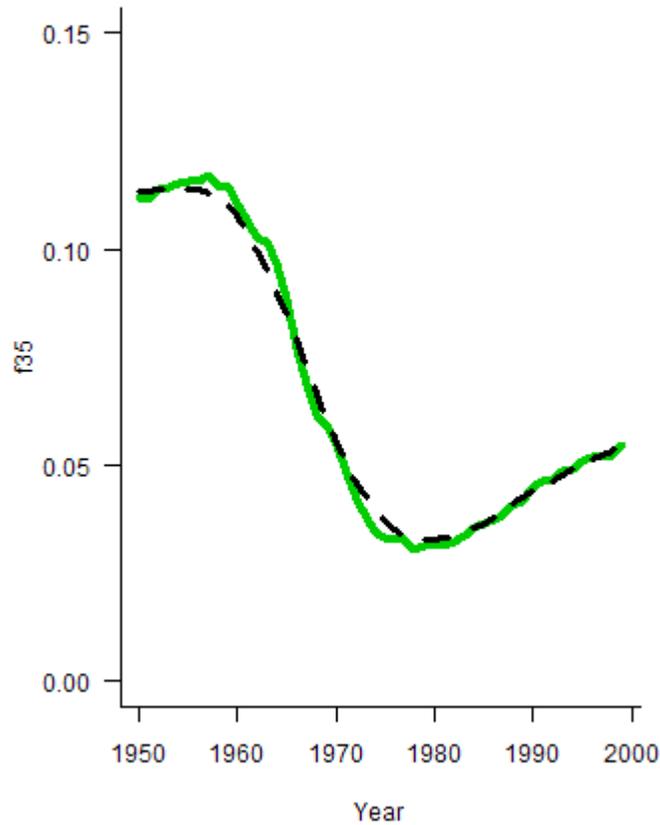


Using the HFD to build/calibrate

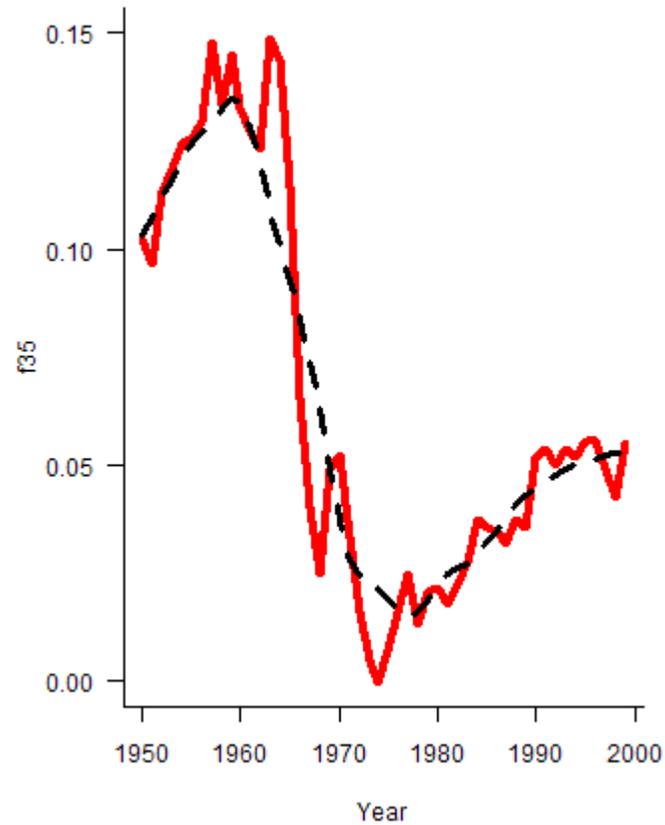
- Define squared-error penalties for each prior (high penalty → low prior prob.)
 - Calibrate penalty weights to HFD data
 - “time series as wiggly as in HFD”
 - “cohort shapes regular as in HFD”
-

PRIOR #1: Time Series are locally linear

MORE LIKELY

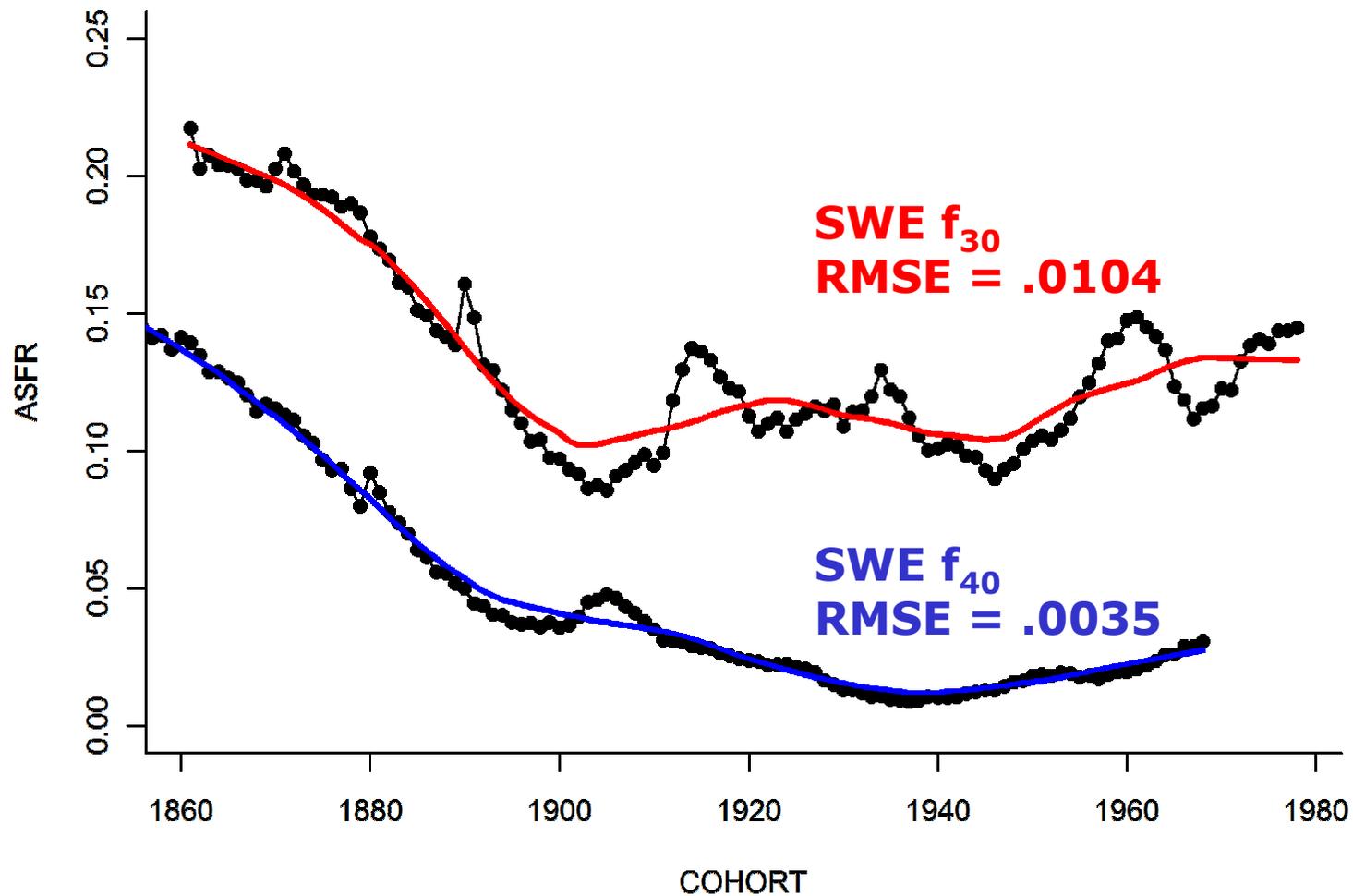


LESS LIKELY



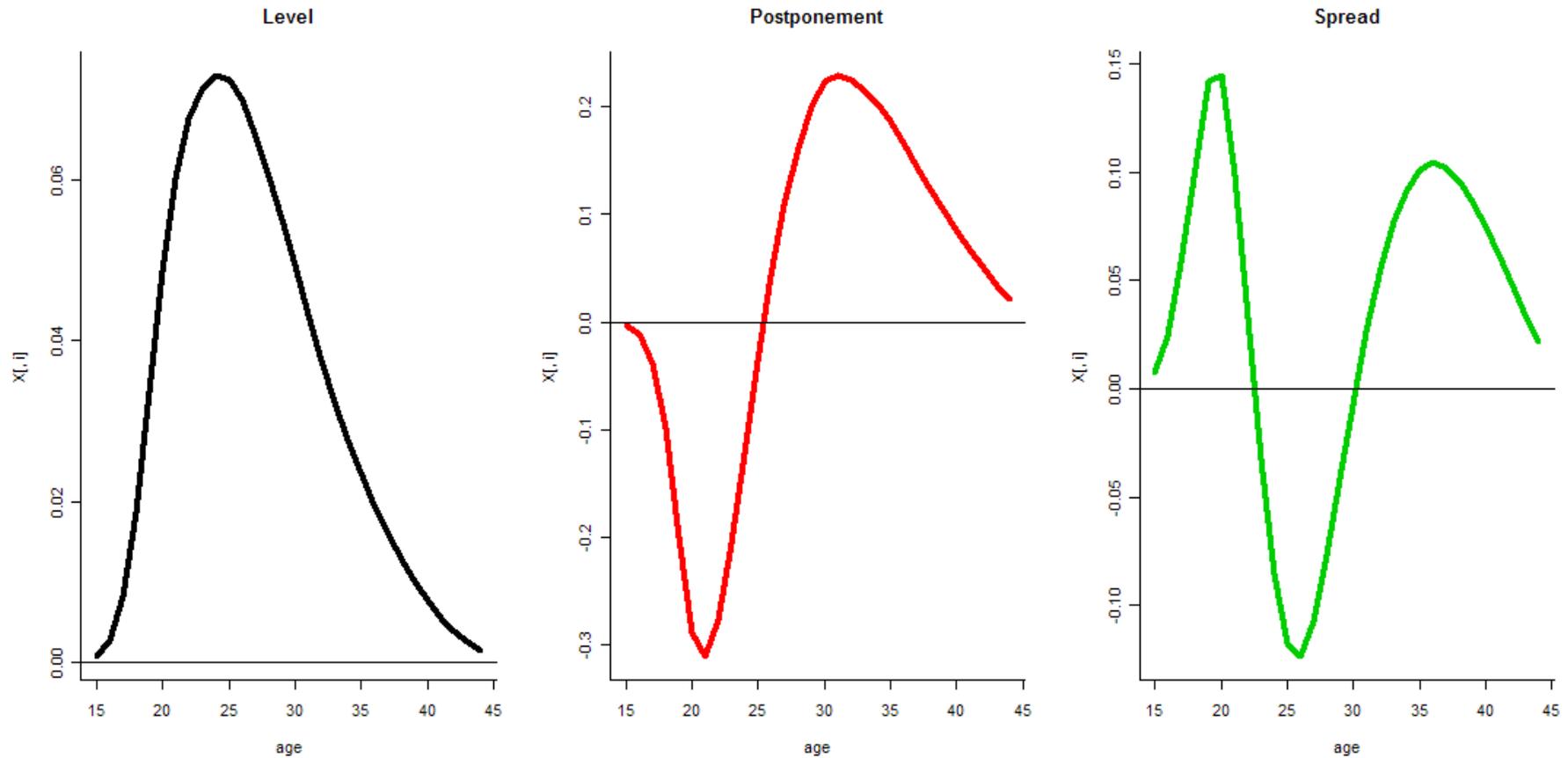
$$w_a \epsilon'_a \epsilon_a = w_a \phi'_a (I - S)' (I - S) \phi_a \quad a = 1 \dots A$$

PRIOR #1: Time Series are locally linear

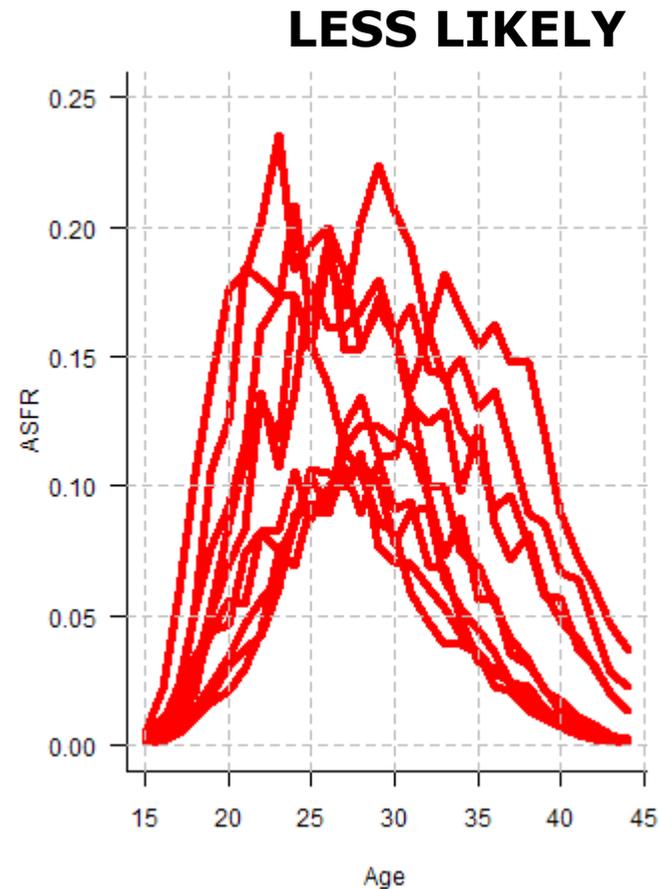
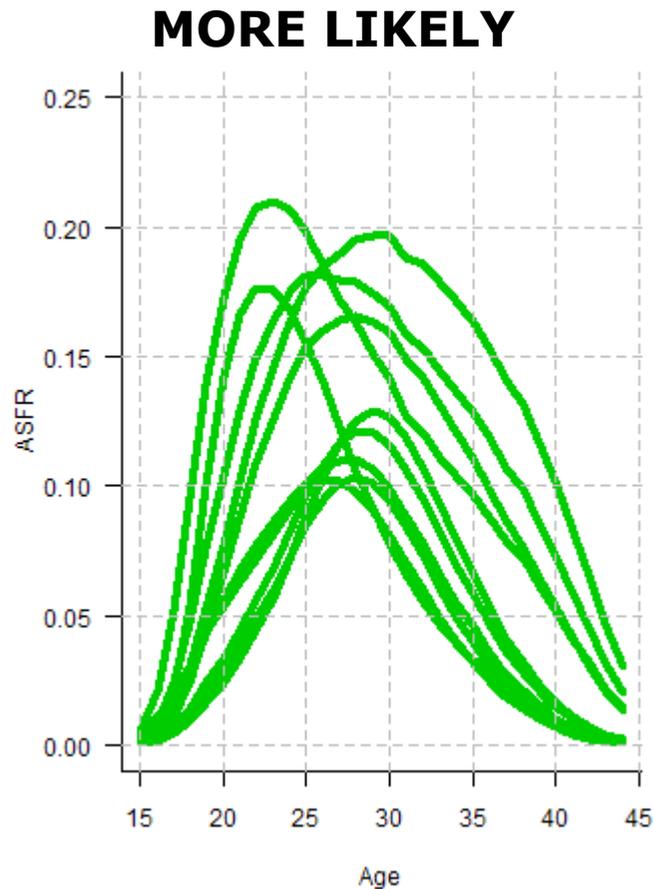


Calibrate prior so that $E_f[\text{RMSE}(\theta)] = \text{avg RMSE}(\theta)$ in HFD

PRIOR #2: Cohort schedules are well approx. by SVD components from **HFD**

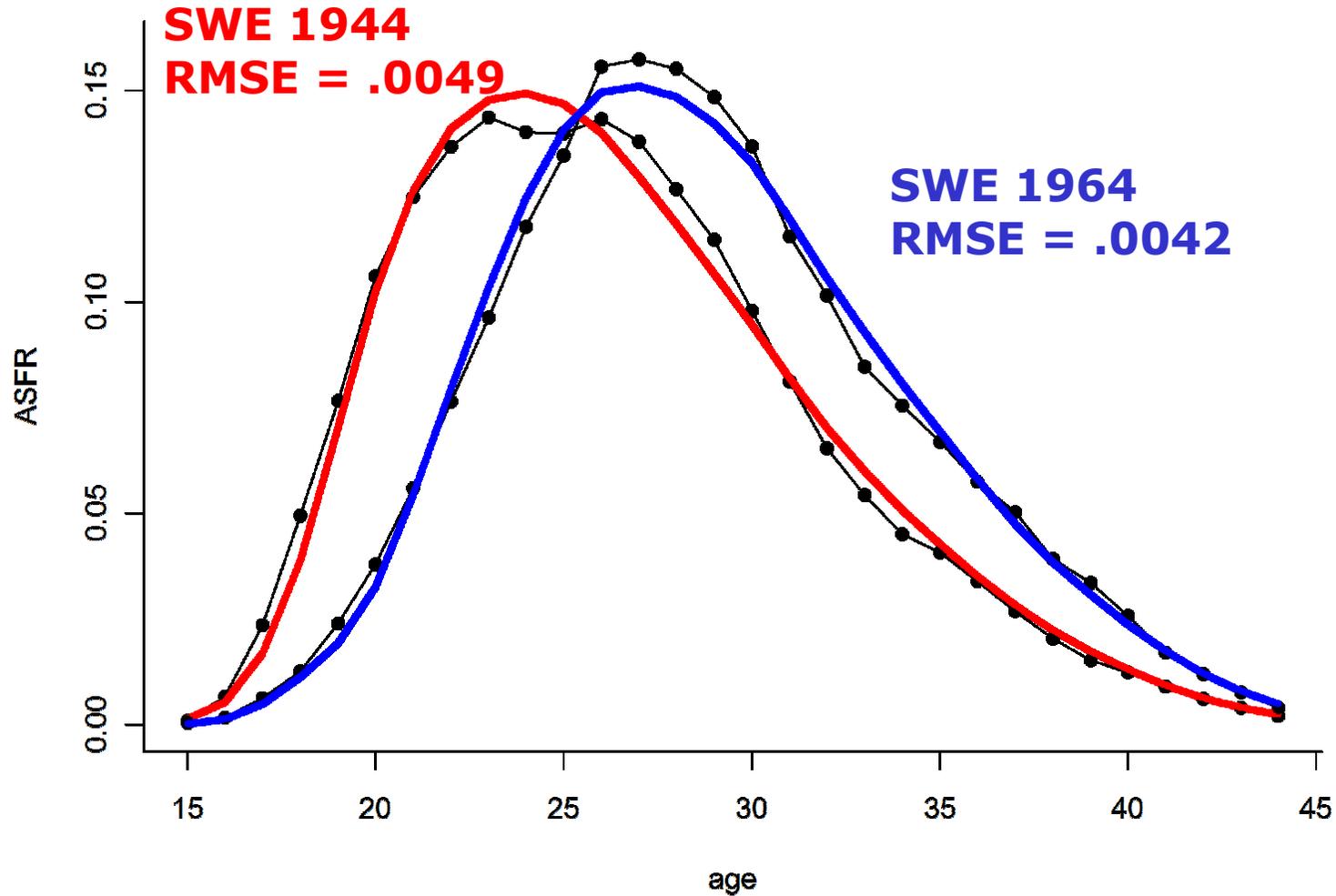


PRIOR #2: Cohort schedules are well approx.
by SVD components from **HFD**



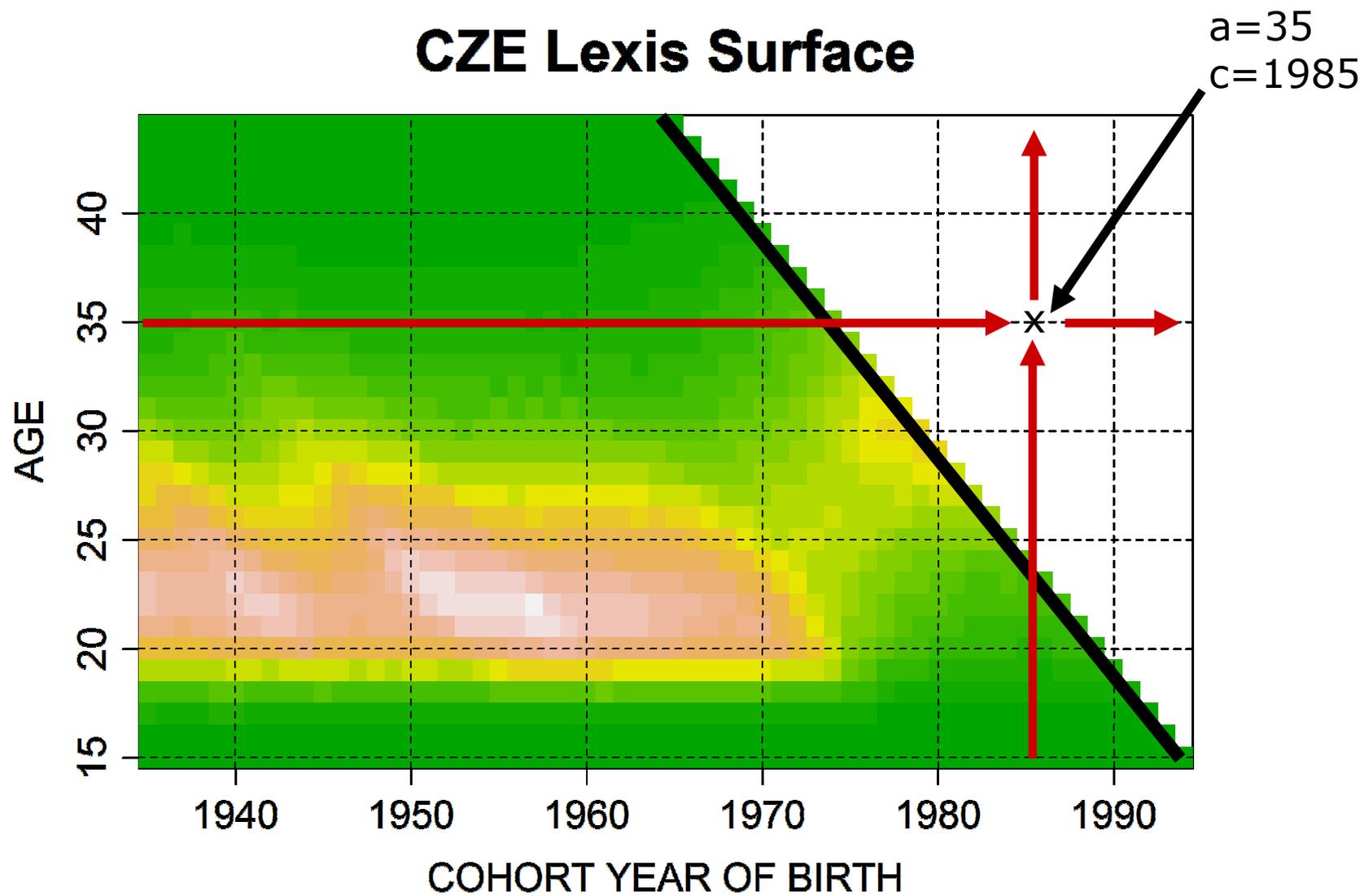
$$w_1 \varepsilon_t' \varepsilon_t = w_1 (\phi_t - \bar{H})' M (\phi_t - \bar{H}) \quad t = 1 \dots T$$

PRIOR #2: Cohort schedules are well approx.
by SVD components from **HFD**

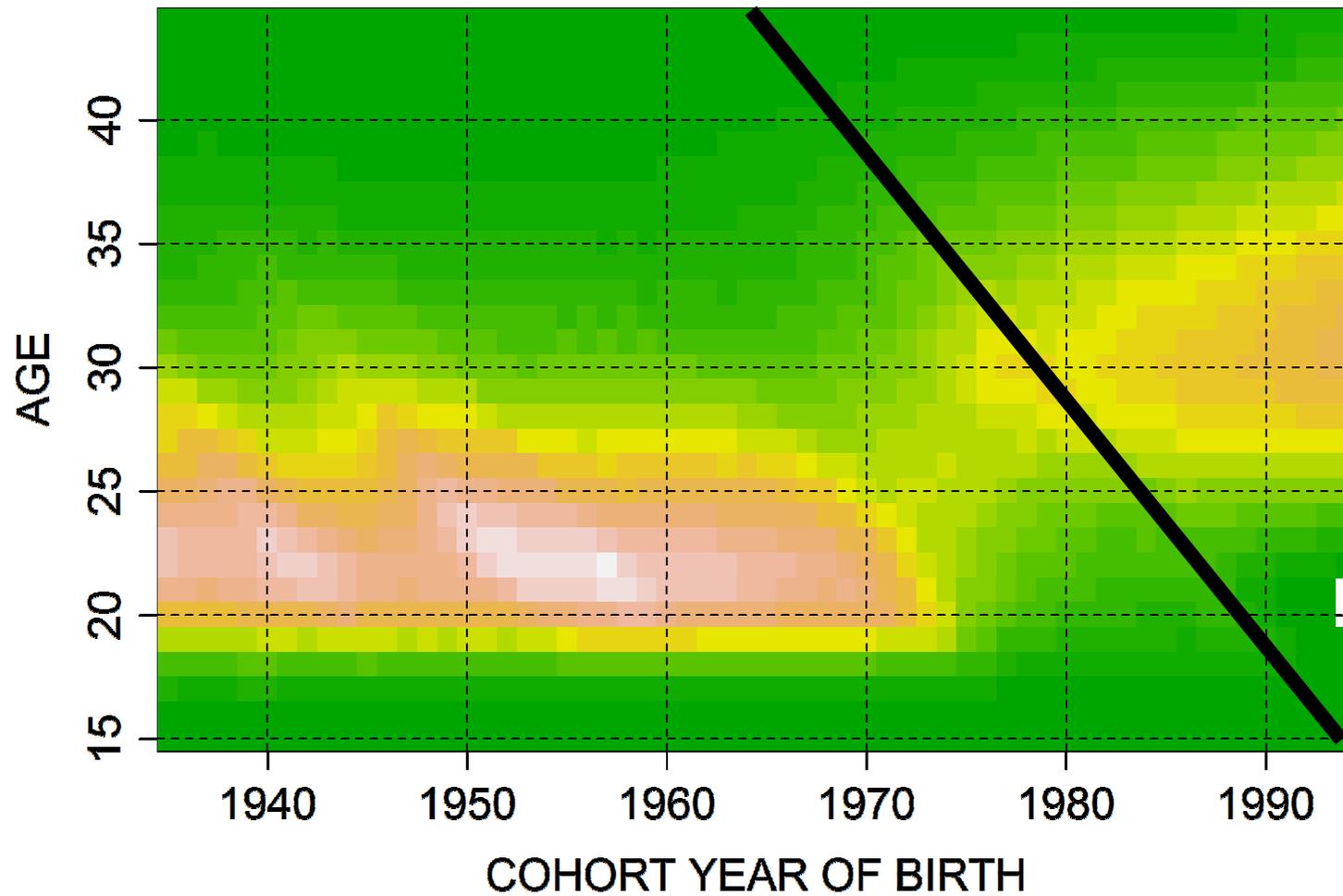


Calibrate prior so that $E_f[\text{RMSE}(\theta)] = \text{avg RMSE}(\theta)$ in HFD

CZE Lexis Surface

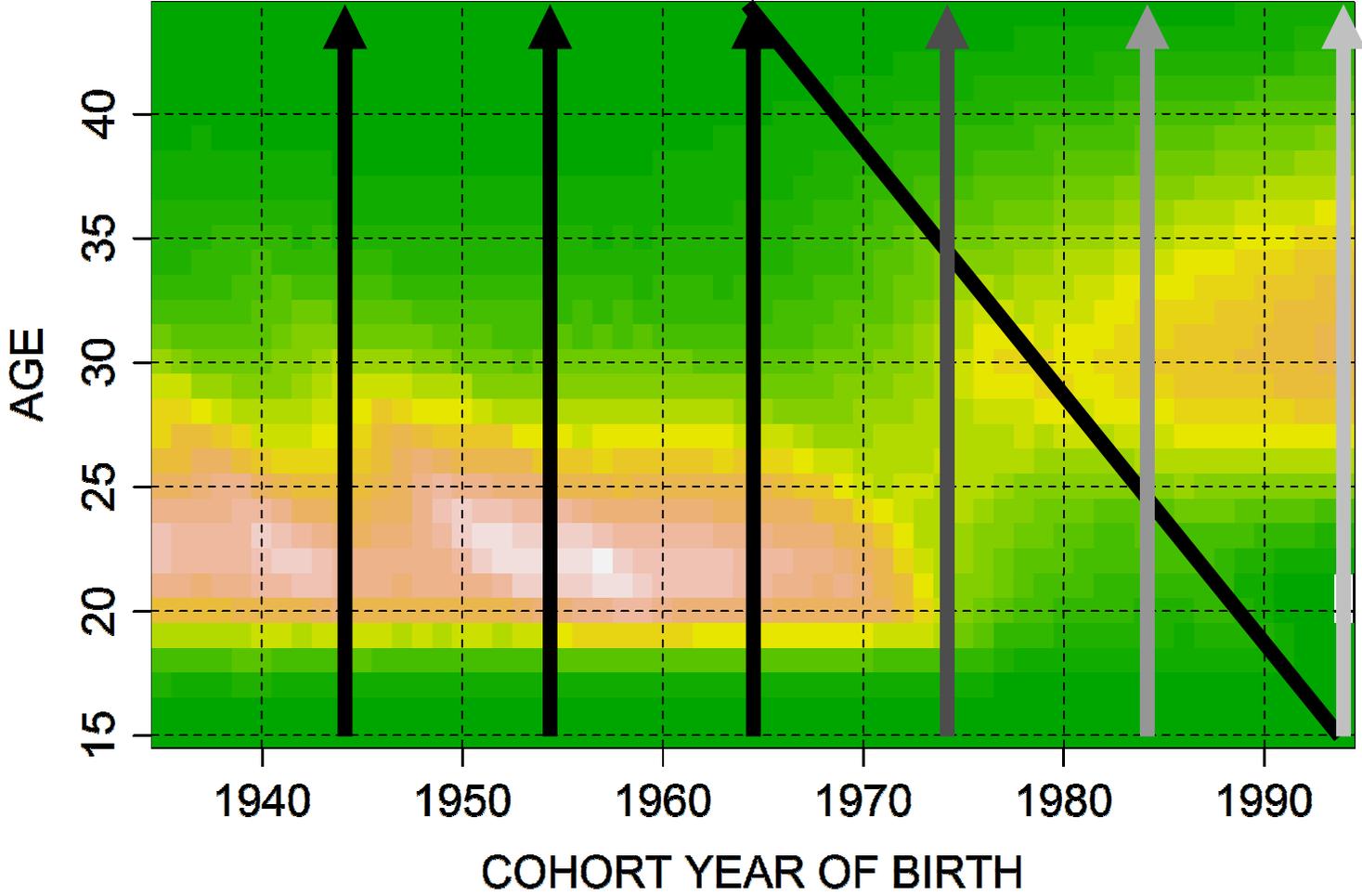


Maximum a posteriori surface (+ *sd* and covariances of cell estimates)

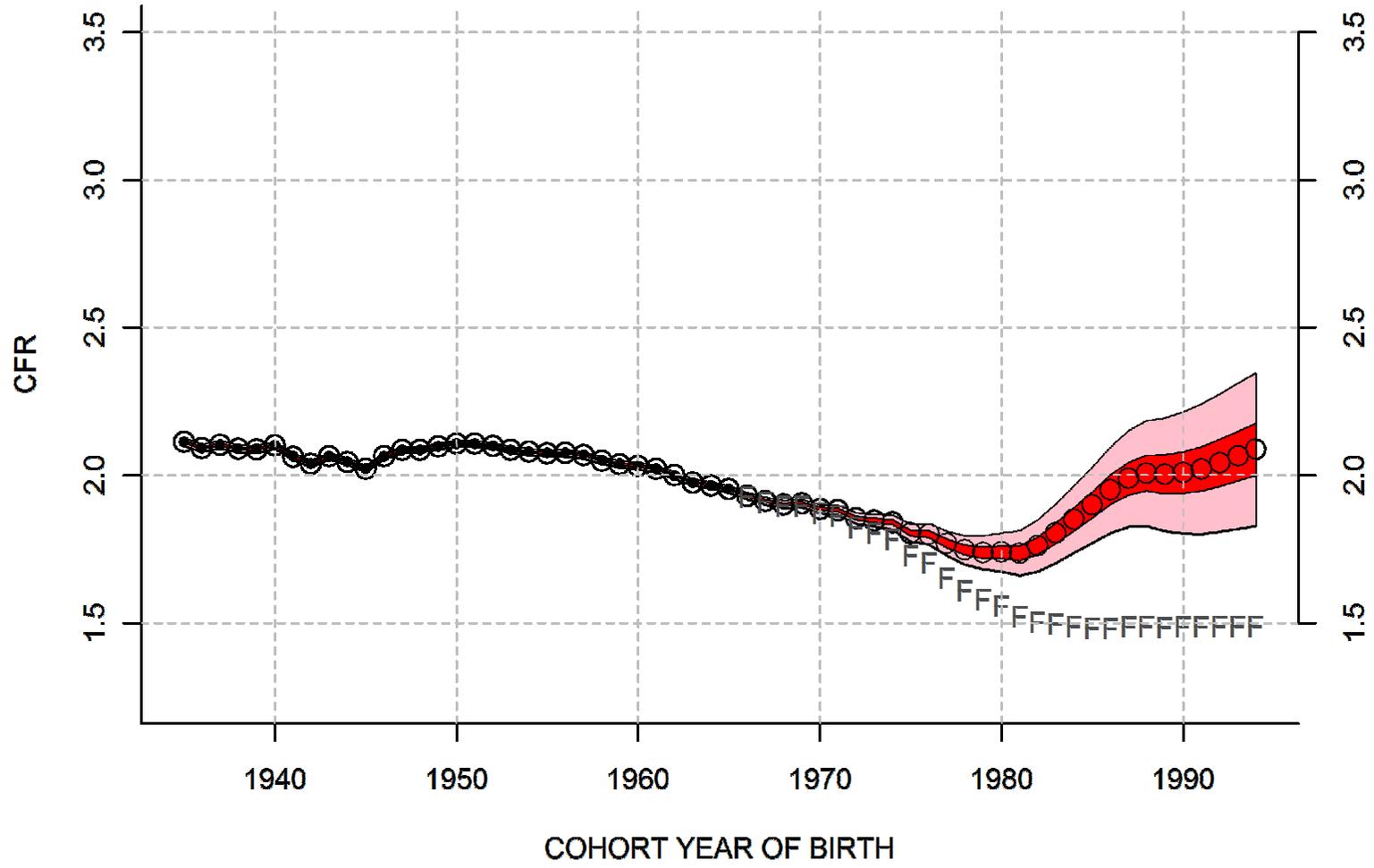


θ is uncertain \rightarrow std errors

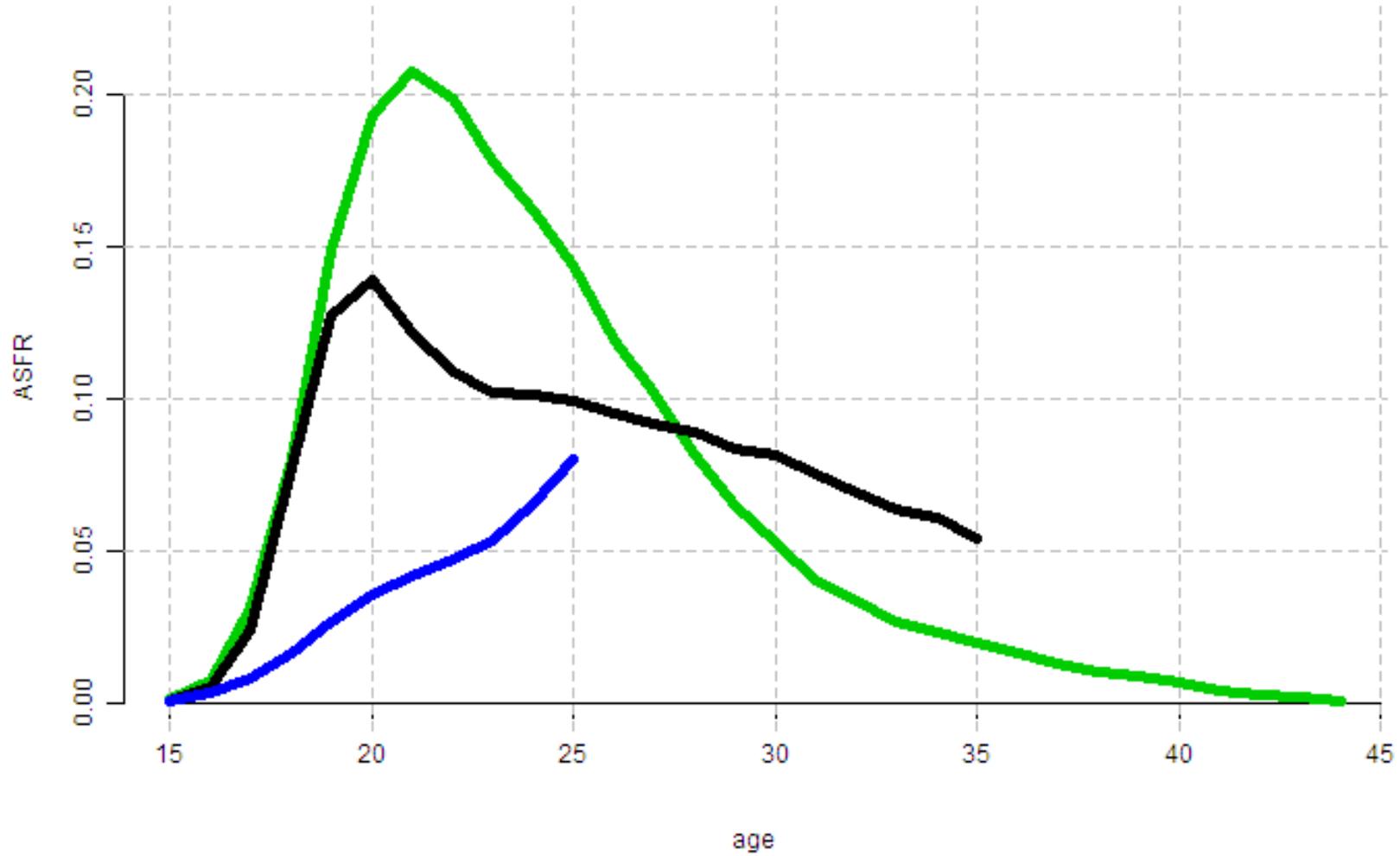
1944	1954	1964	1974	1984	1994
2.05	2.08	1.97	1.84	1.85	2.09



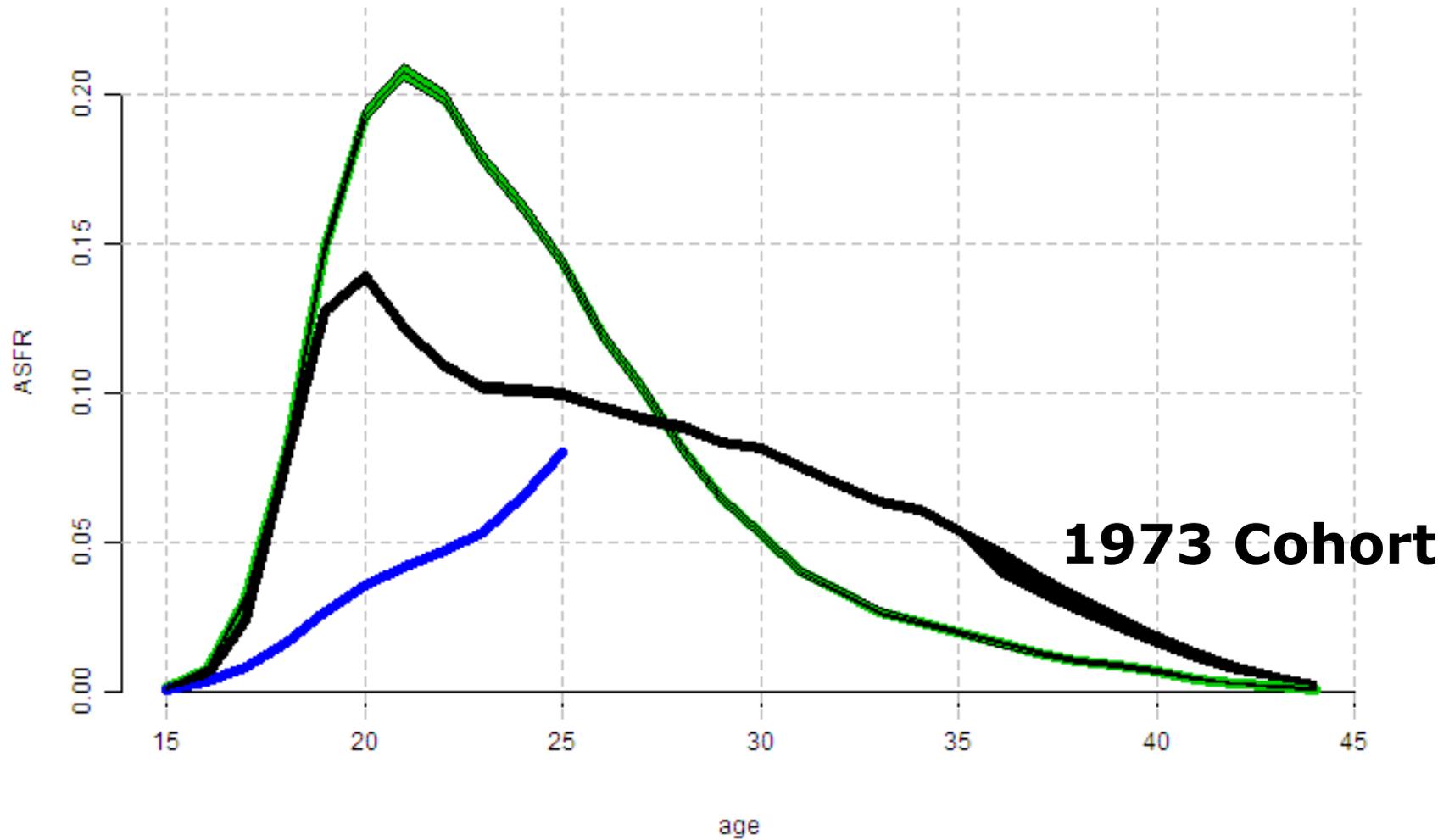
CZE



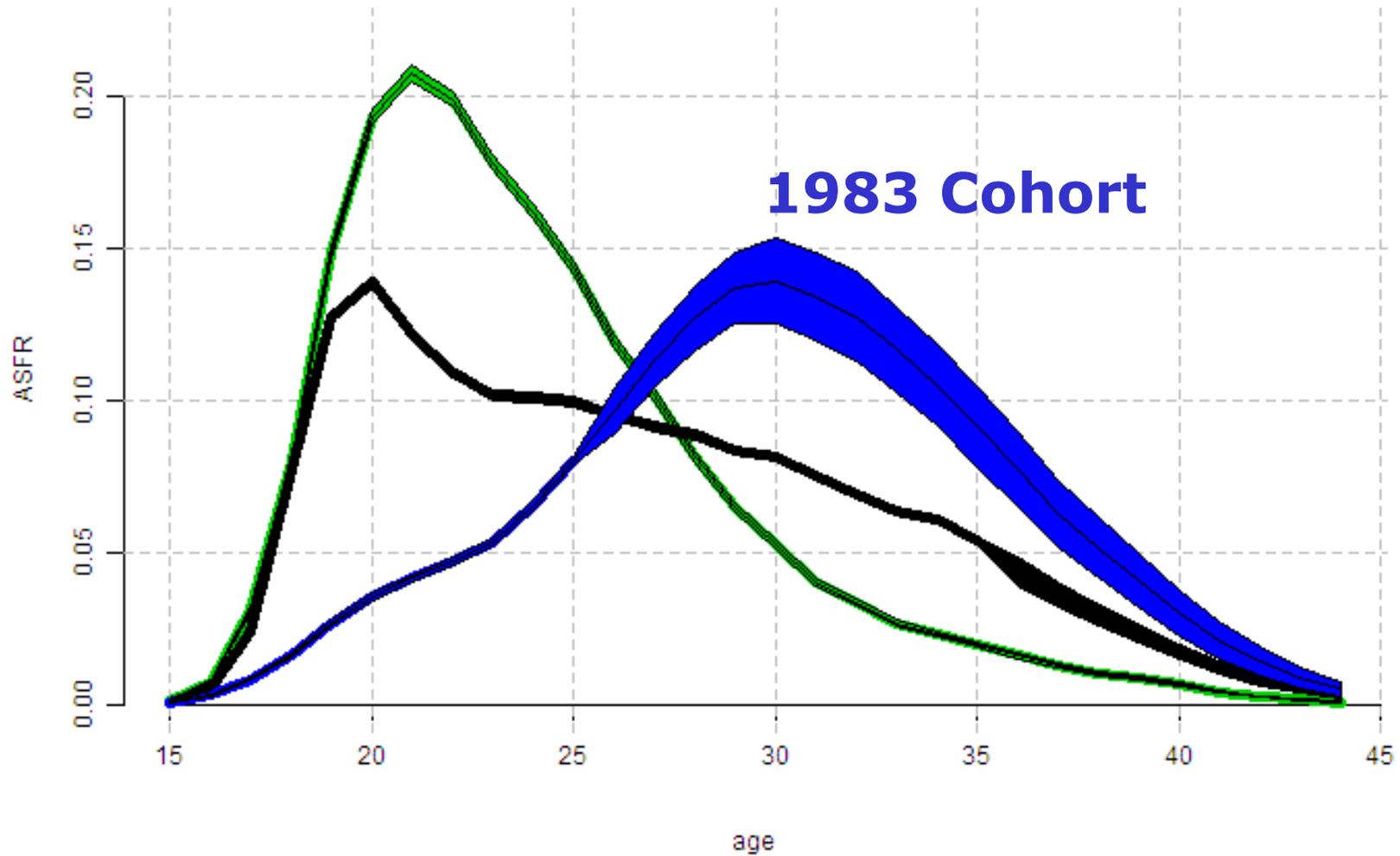
Bayesian Forecast Results: CZE Cohort Schedules



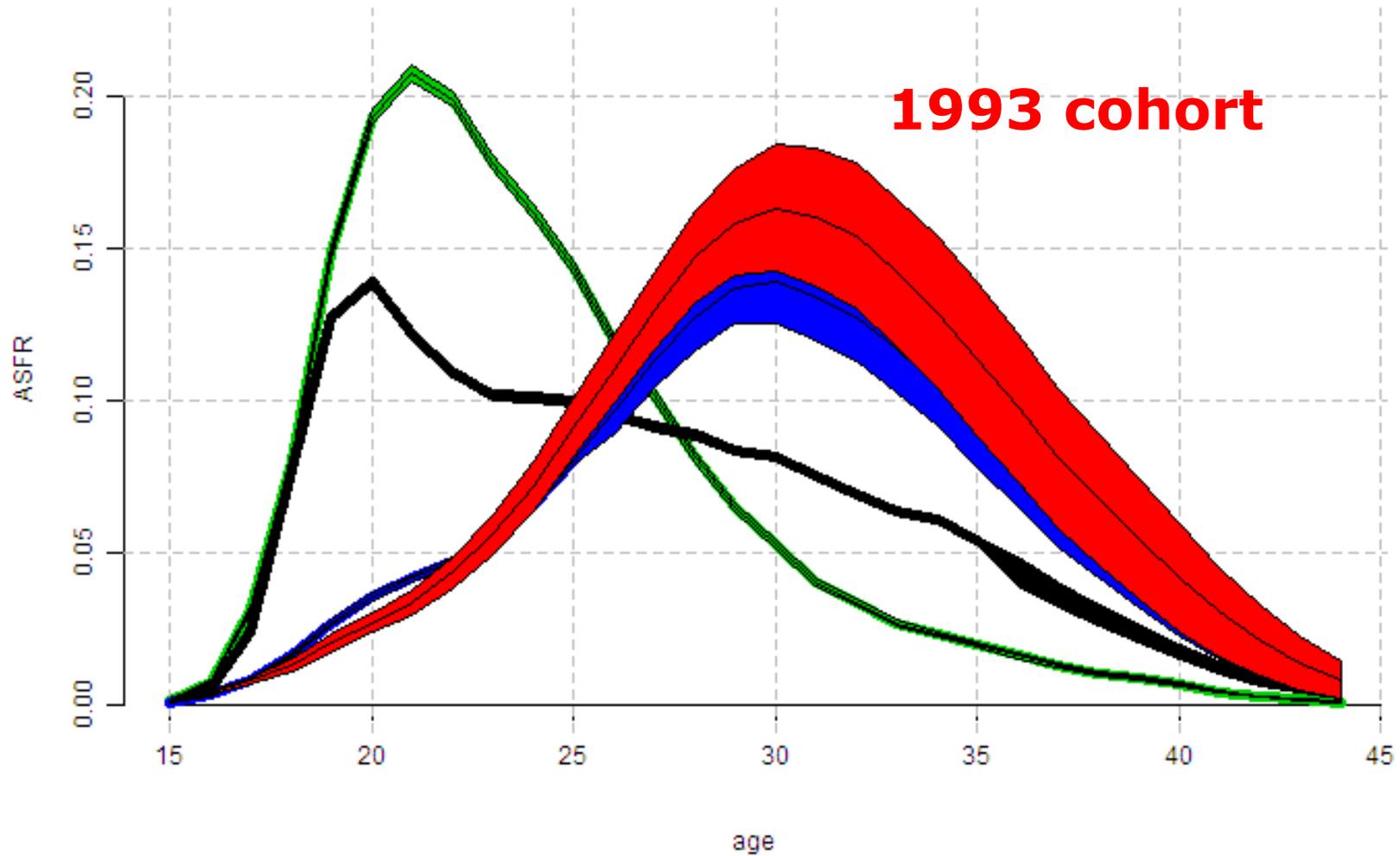
Bayesian Forecast Results: CZE Cohort Schedules



Bayesian Forecast Results: CZE Cohort Schedules



Bayesian Forecast Results: CZE Cohort Schedules



LESSONS LEARNED

- ❑ Incorporating qualitative information about Lexis surfaces into a forecast is feasible
 - ❑ HFD data are valuable for building priors that describe qualitative features of fertility surfaces (smoothness, shapes, etc.)
 - ❑ Uncertainty estimates **still need work**
 - ❑ Cohort CFR seems likely to rise, at least a little, in many low-fertility countries
-

Coming soon...

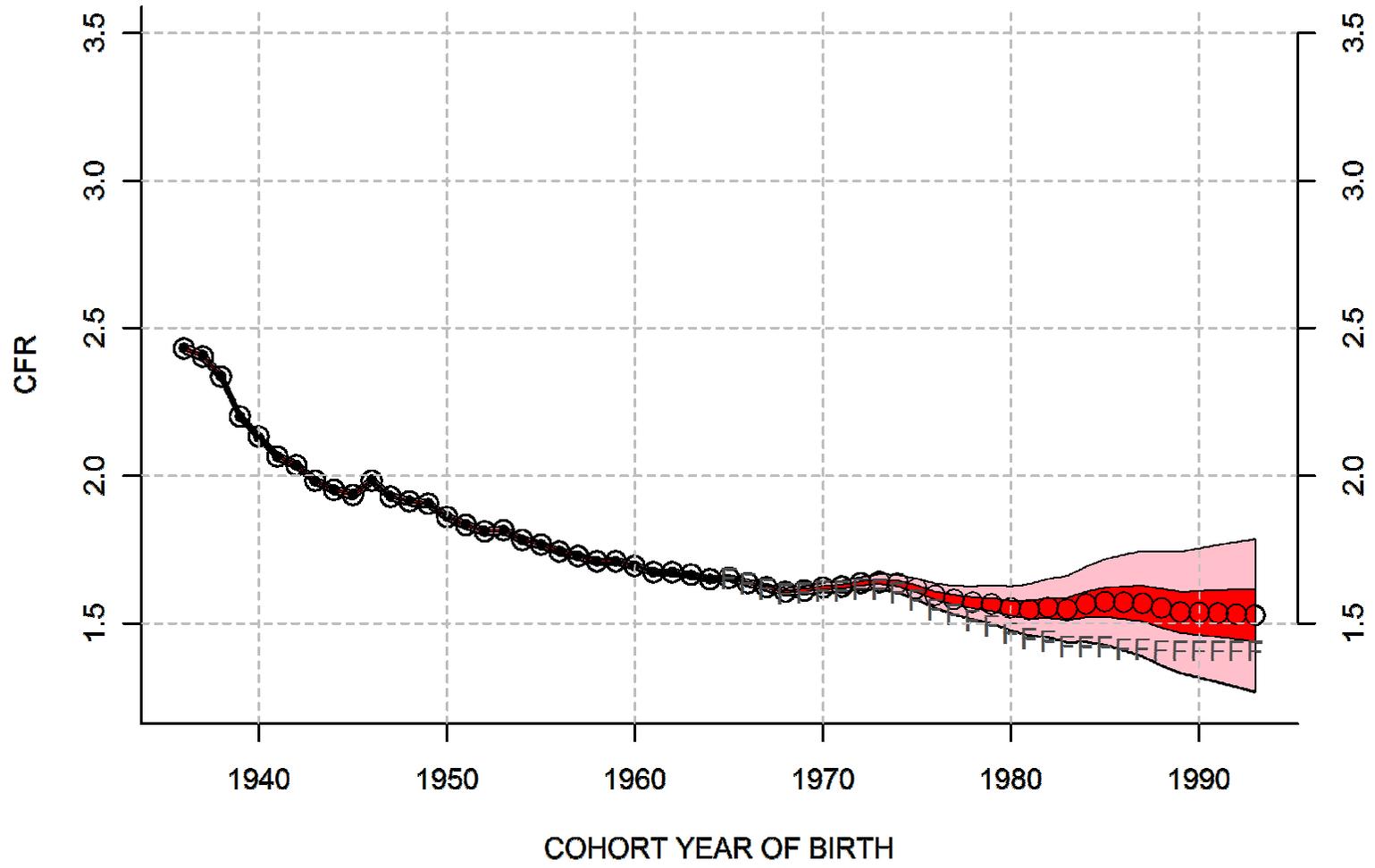
- ❑ Forecasts for other countries (esp. Southern Europe)
 - ❑ Evaluate uncertainty estimates: Simulate “forecasts” made in 1985, 1990,... and compare to later observations
 - ❑ Experiments with (much more flexible but much slower) MCMC estimation methods
-

Thanks!

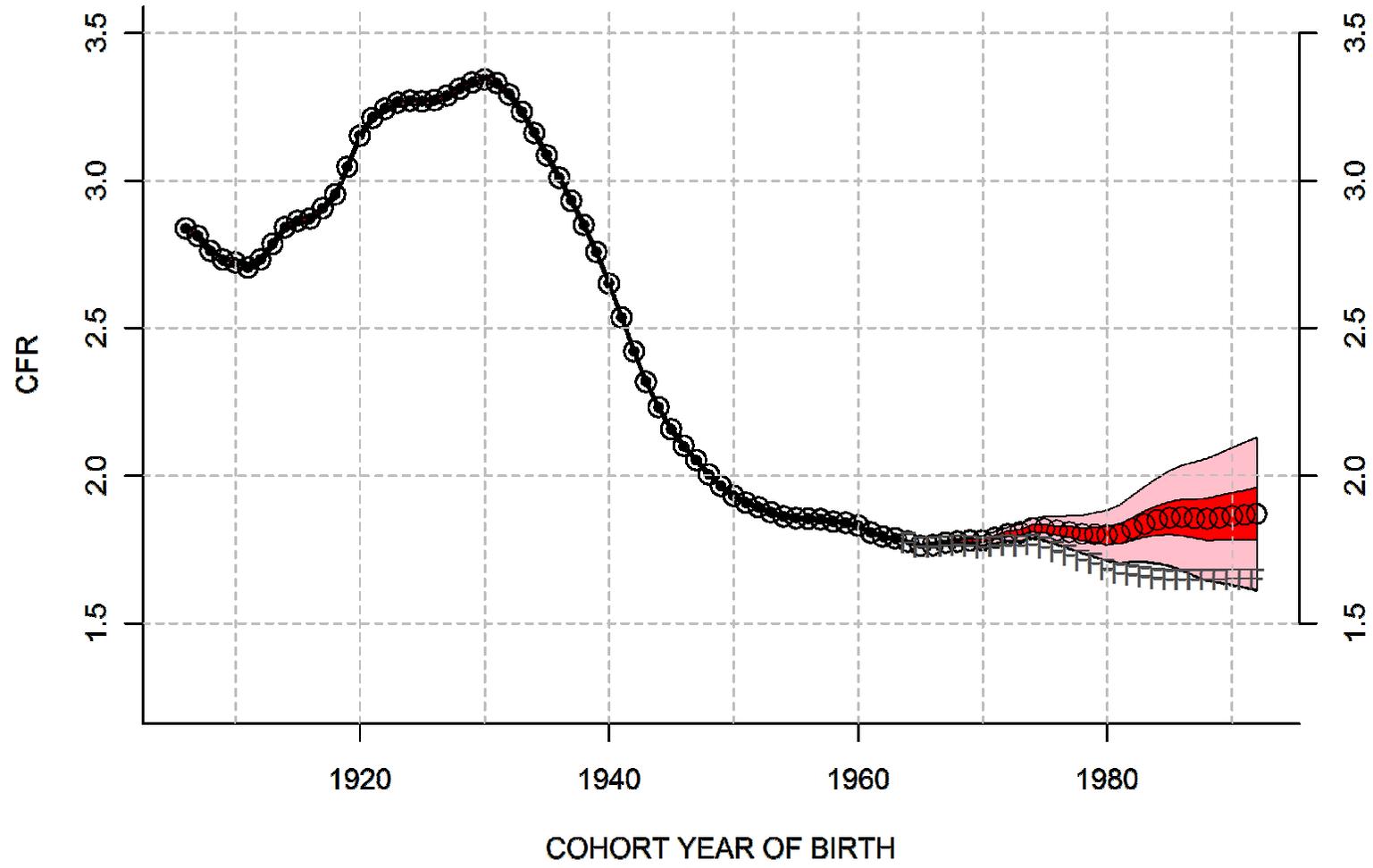
Vielen Dank!

Extra stuff...

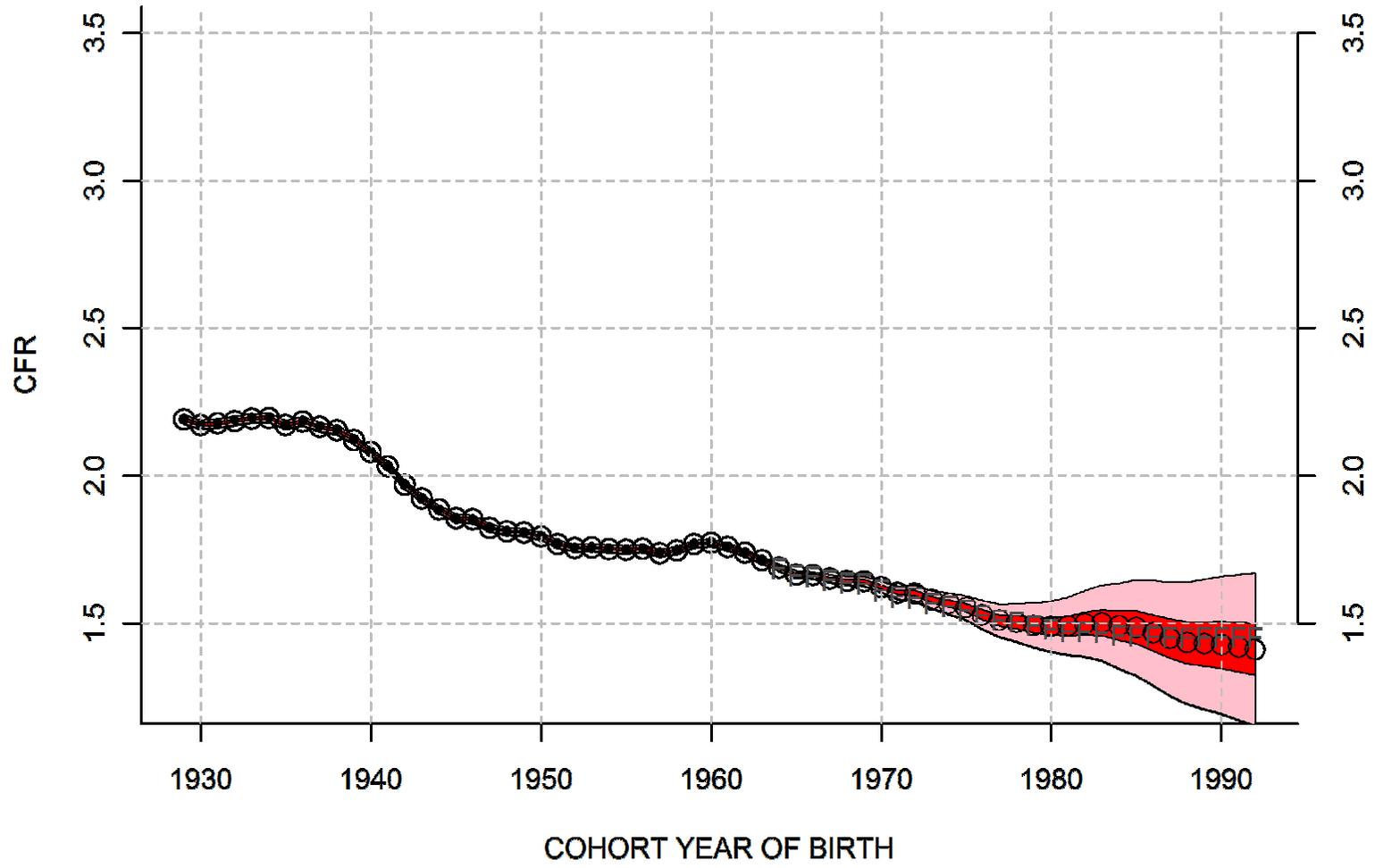
AUT



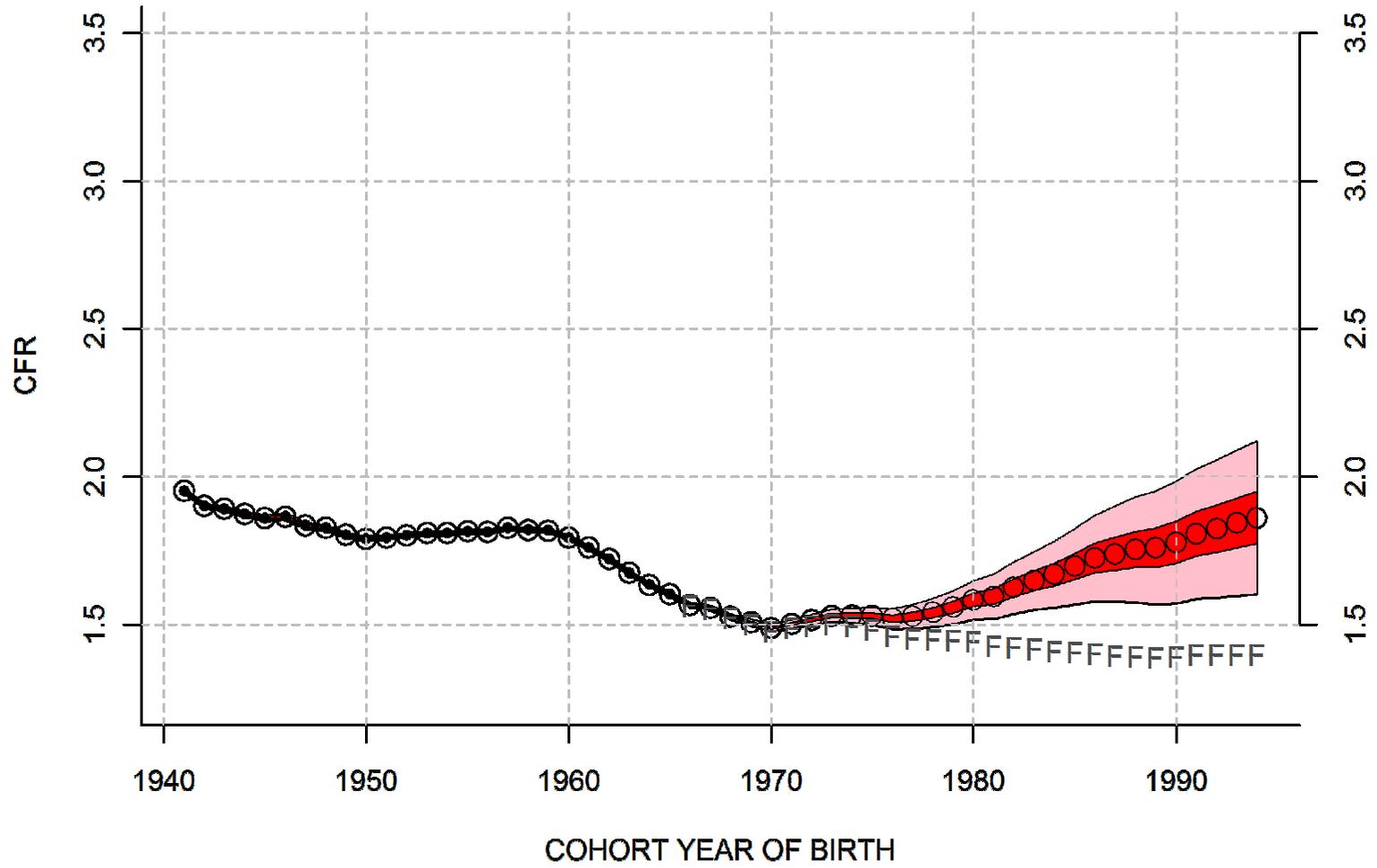
CAN



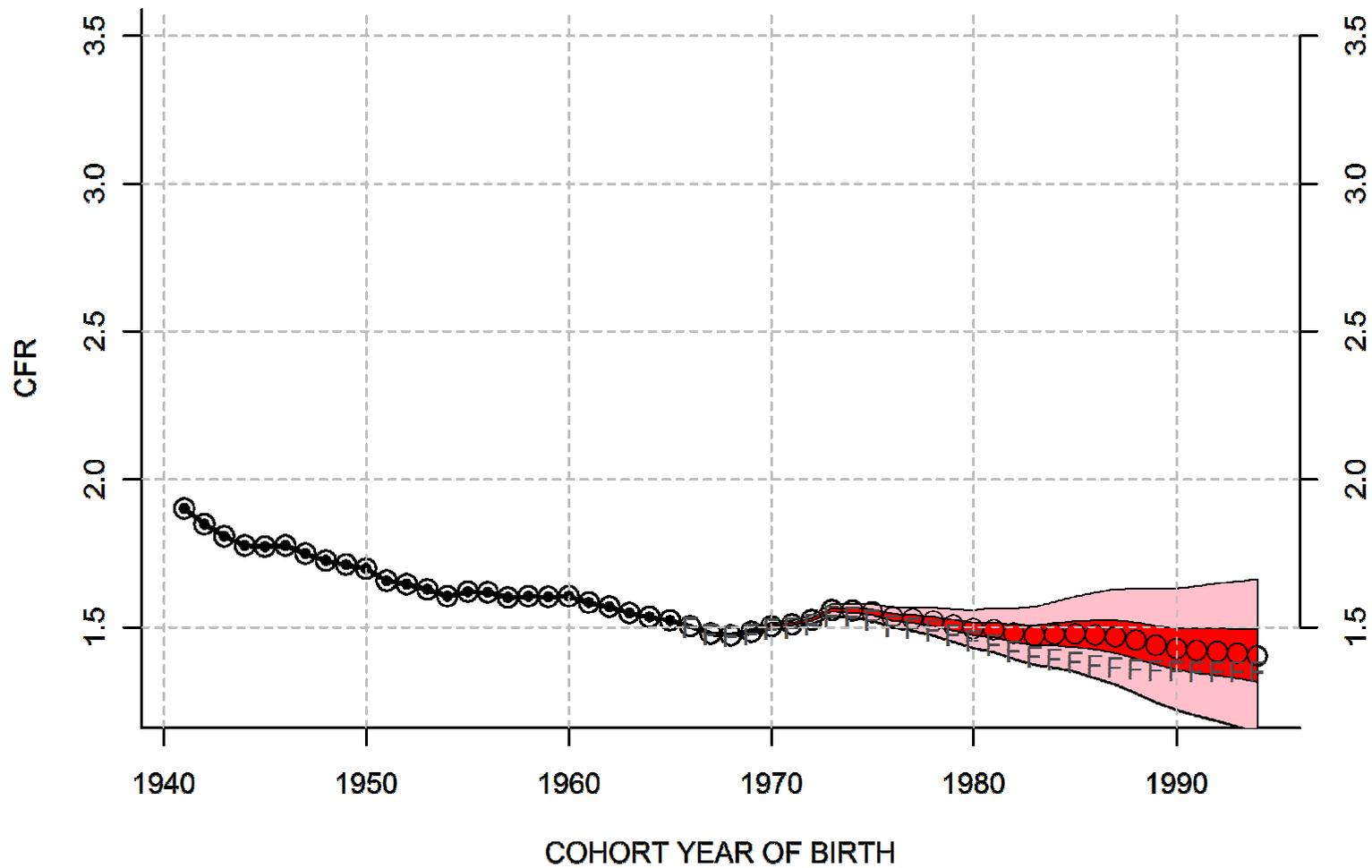
CHE



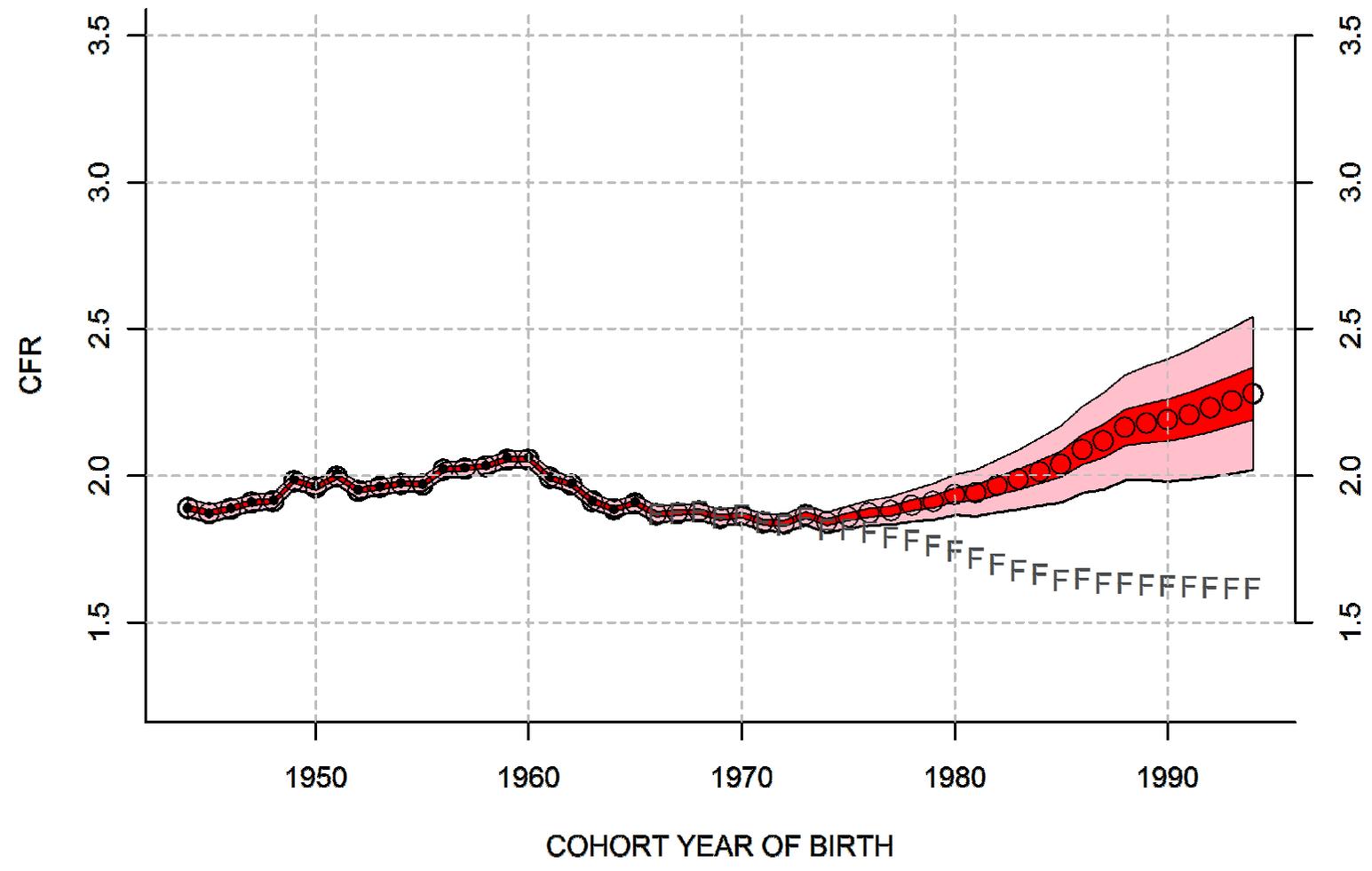
DEUTE



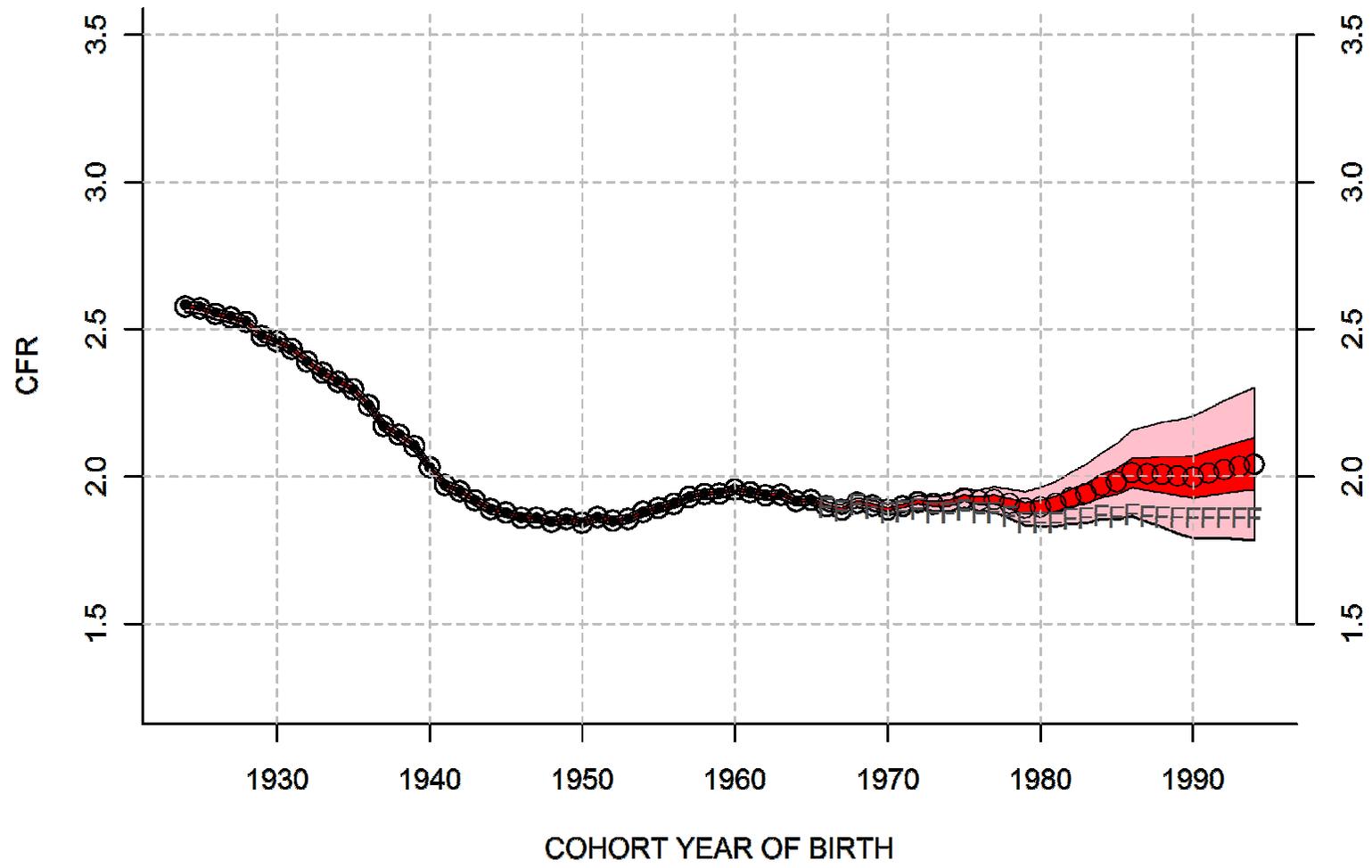
DEUTW



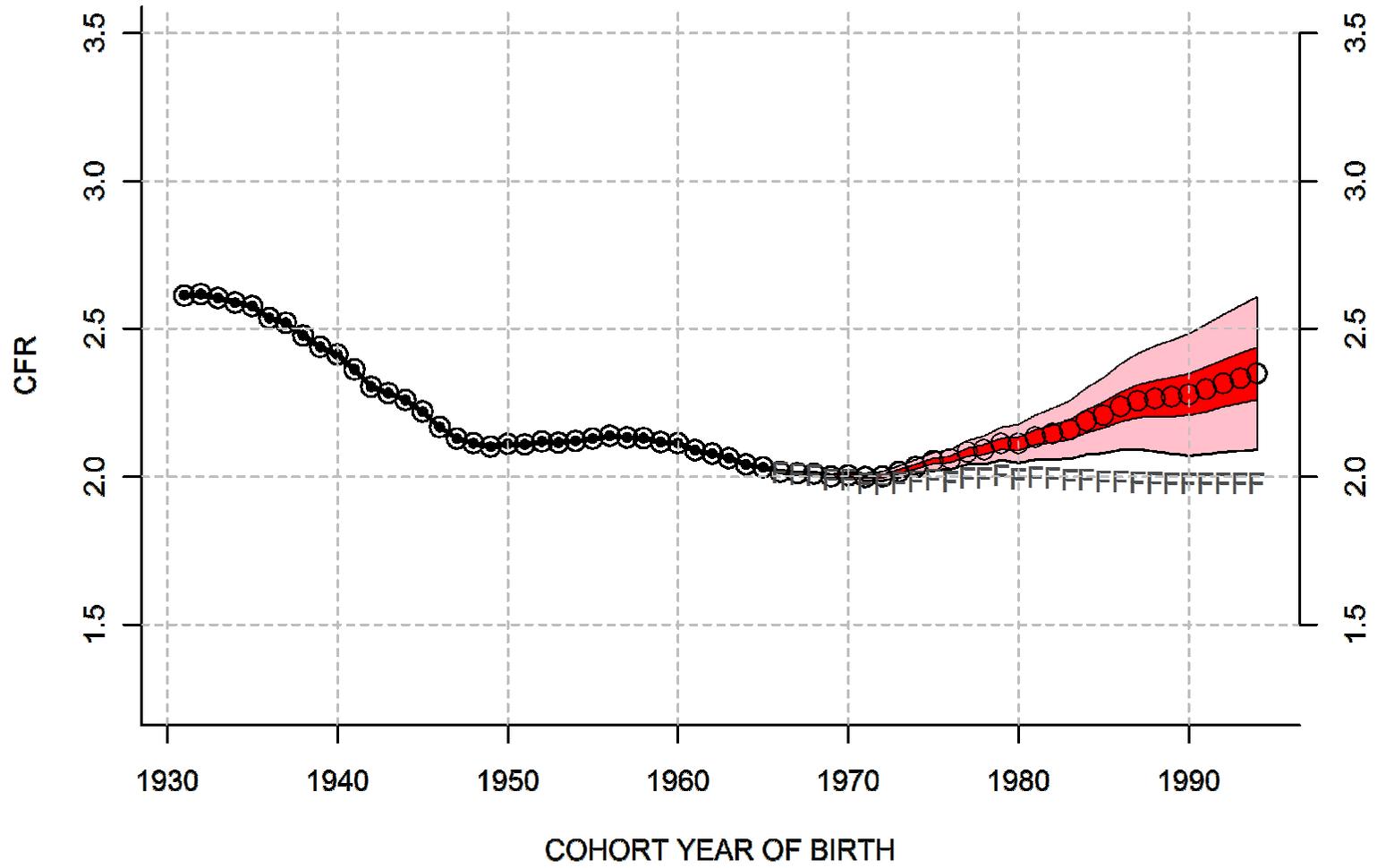
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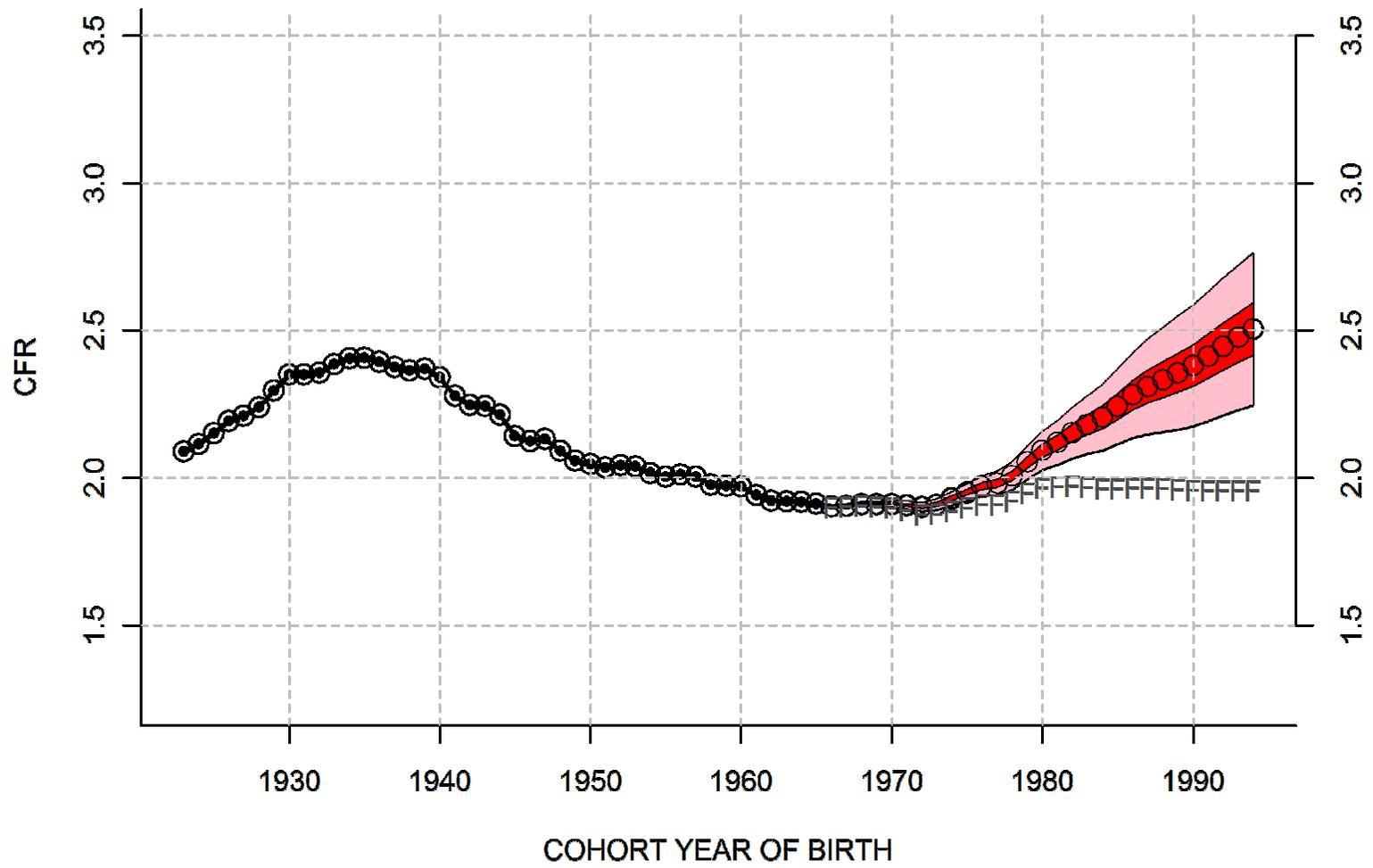
FIN



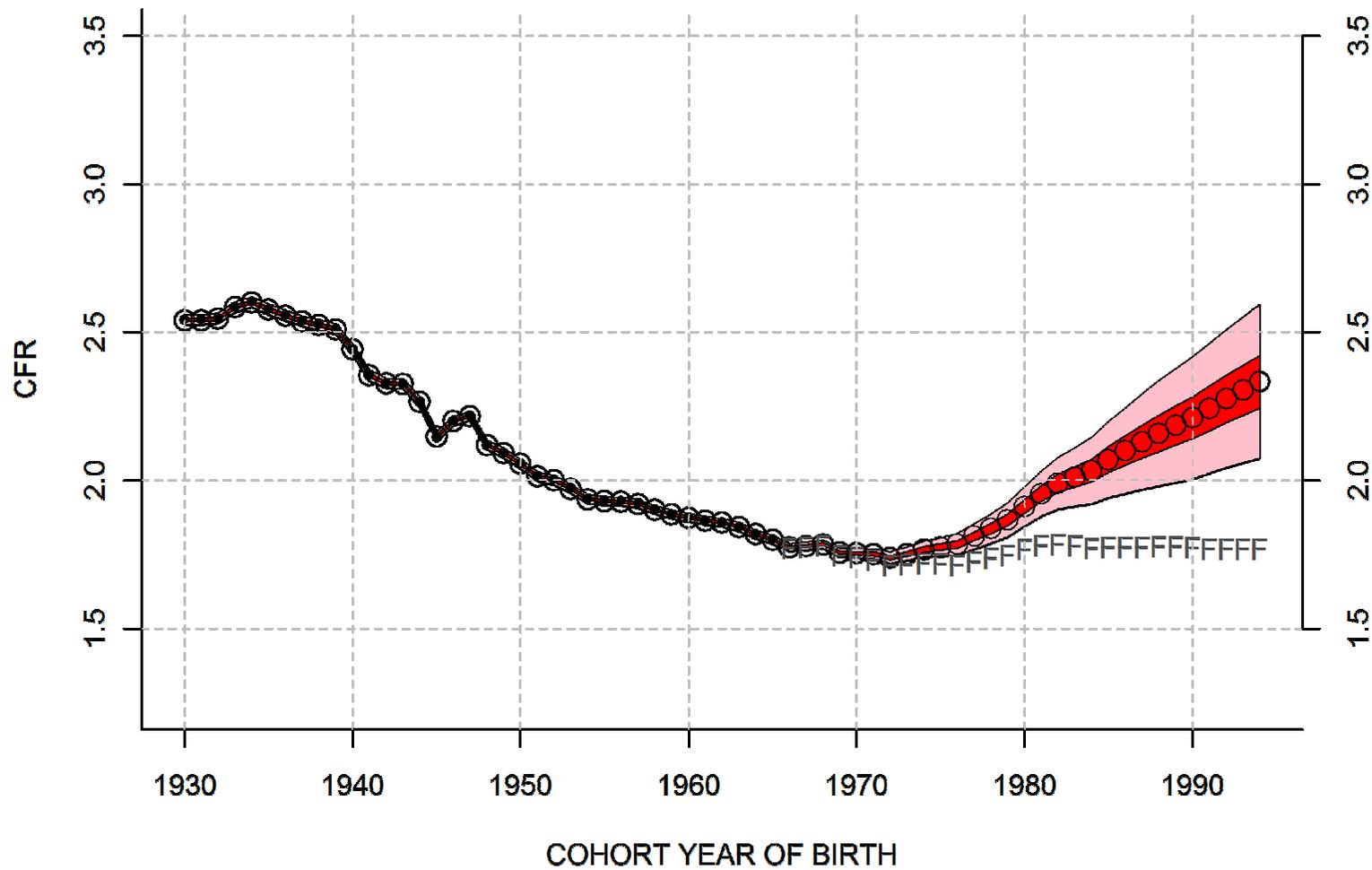
FRA



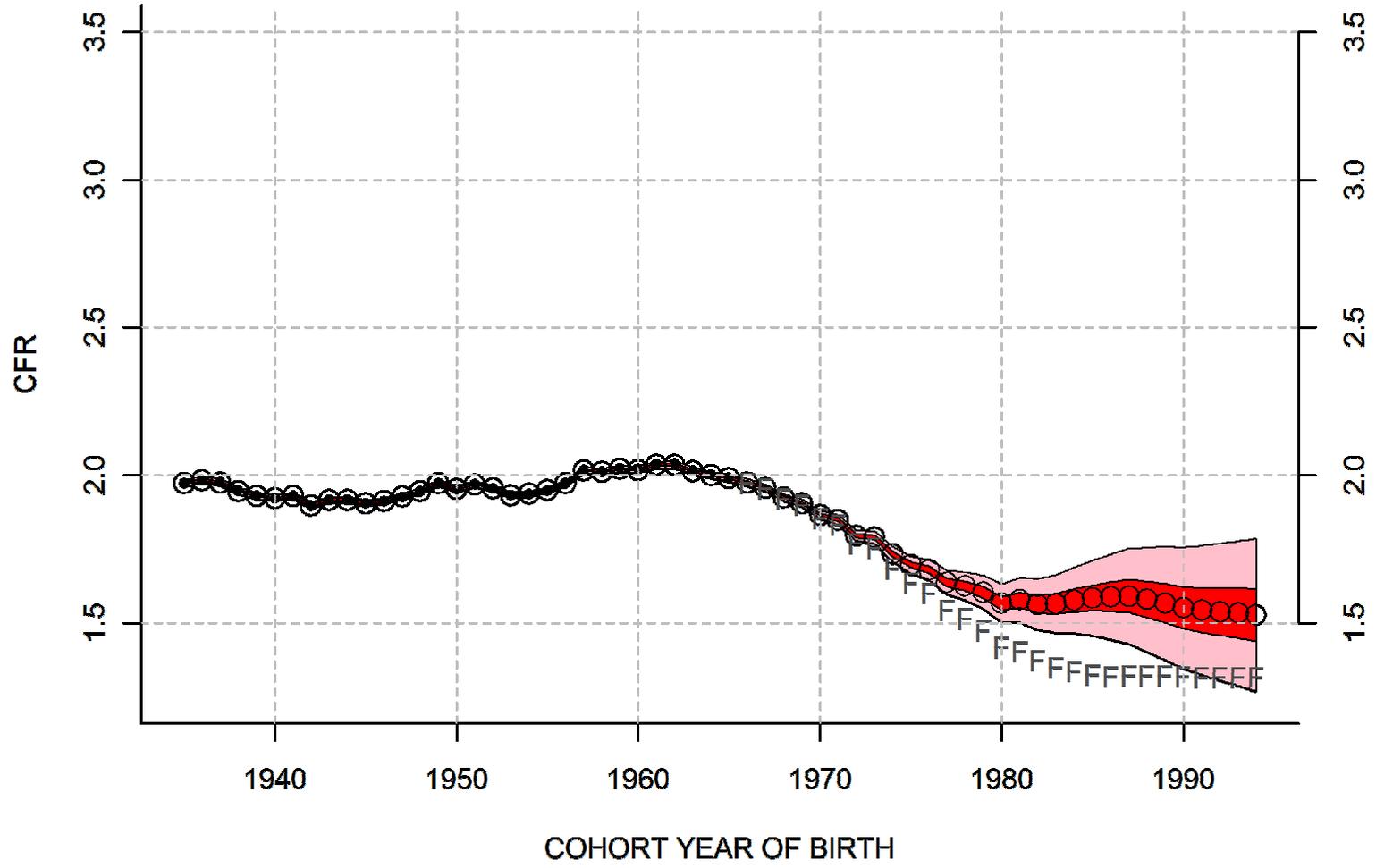
GBRTENW



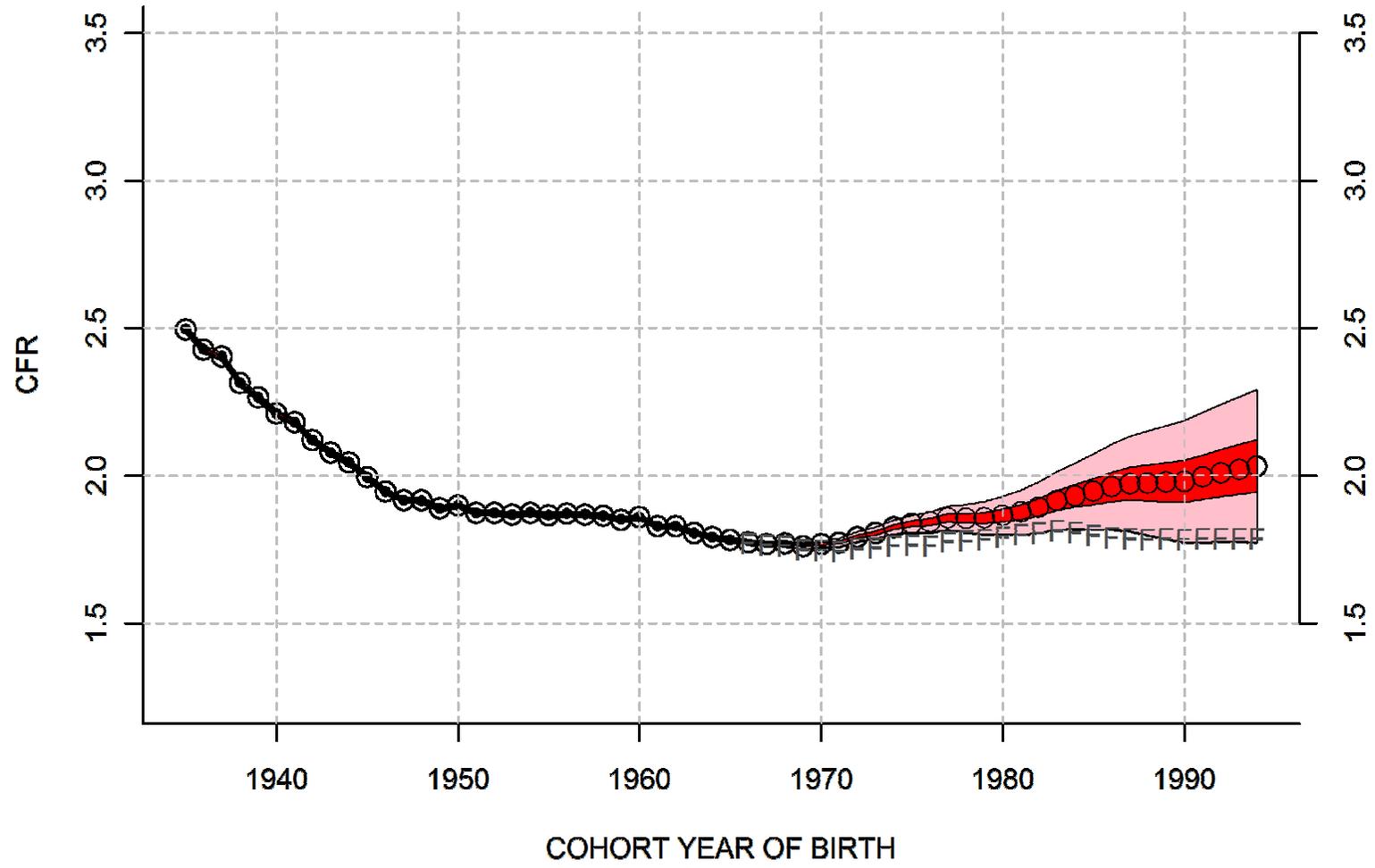
GBR_SCO



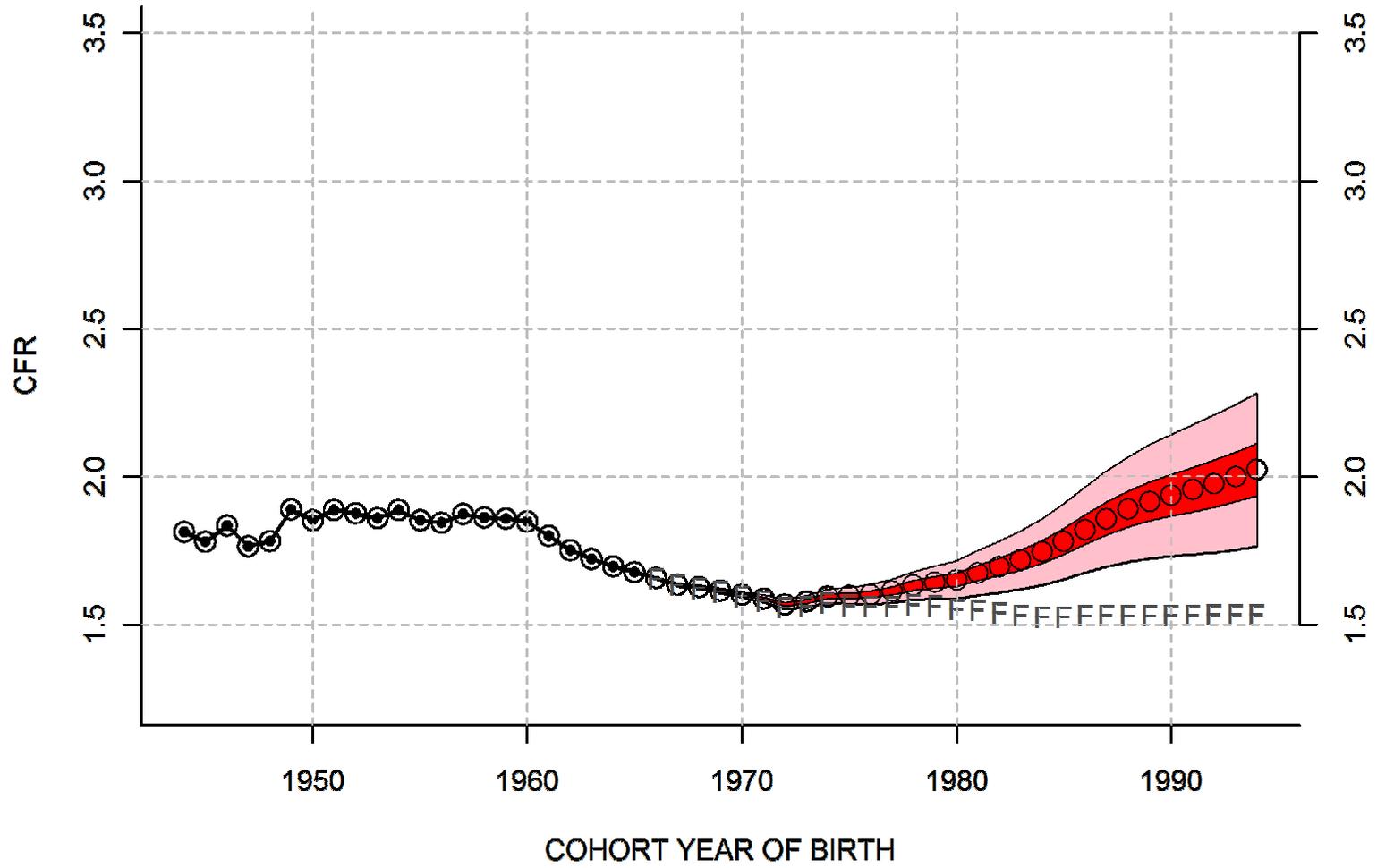
HUN



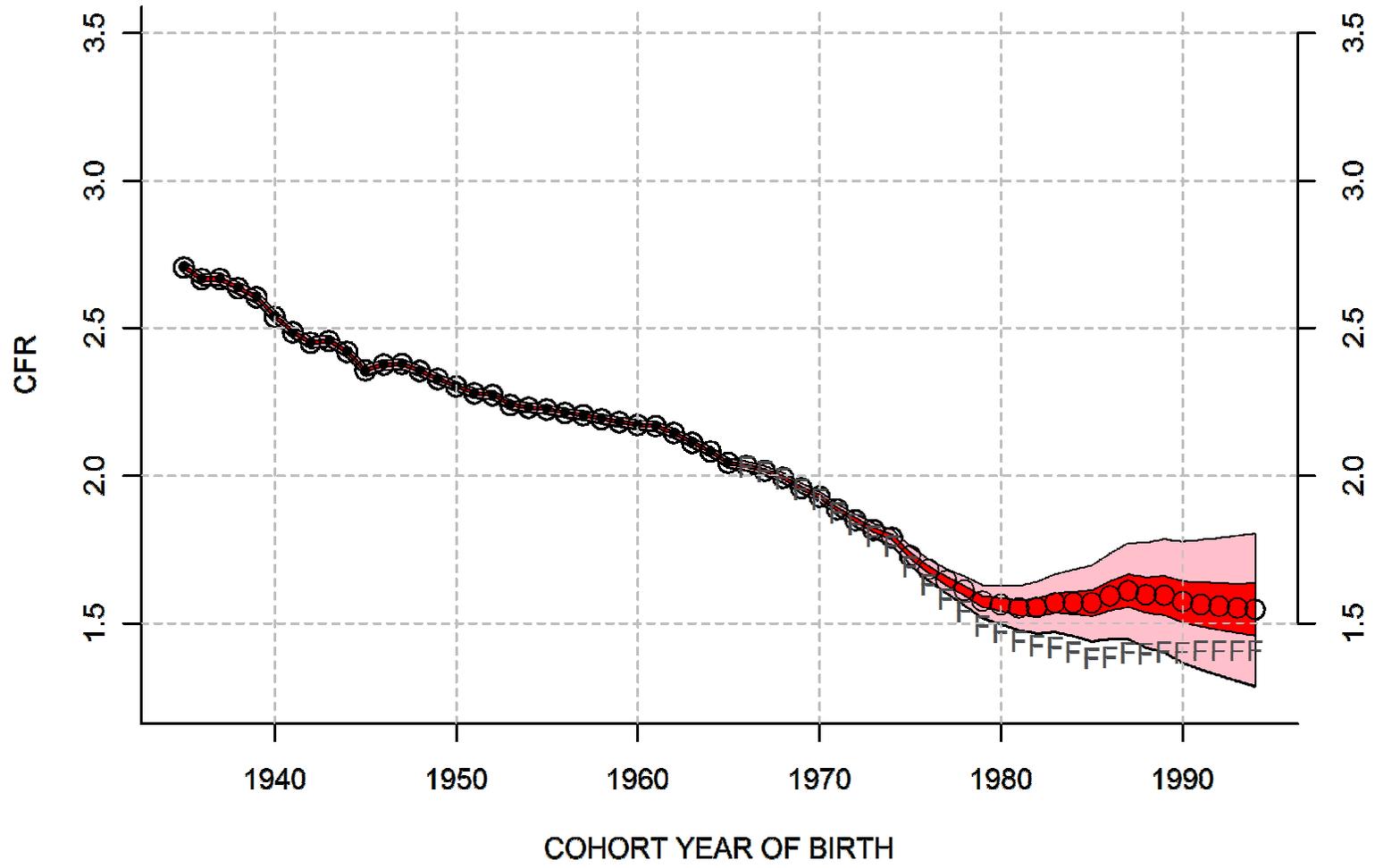
NLD



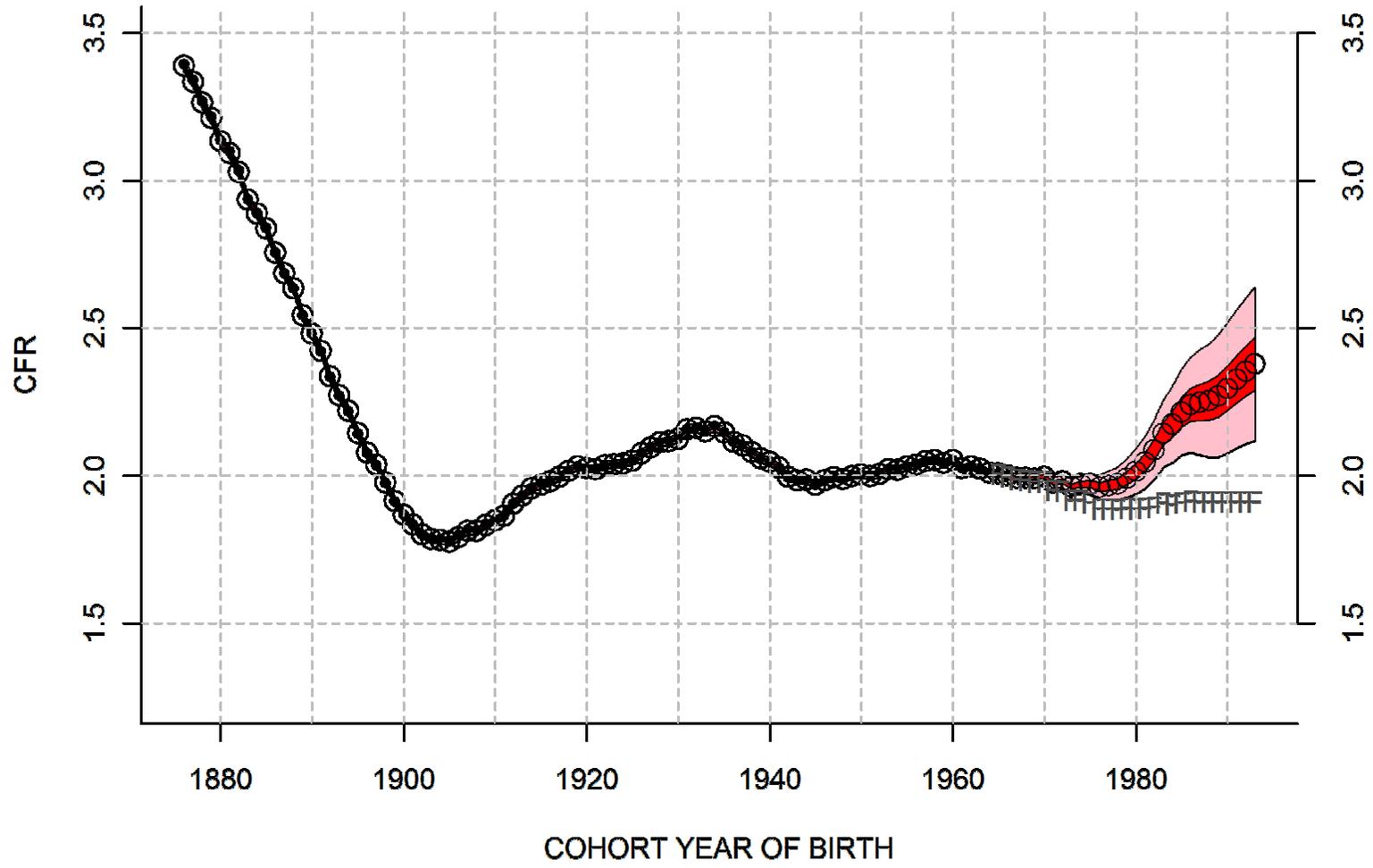
RUS



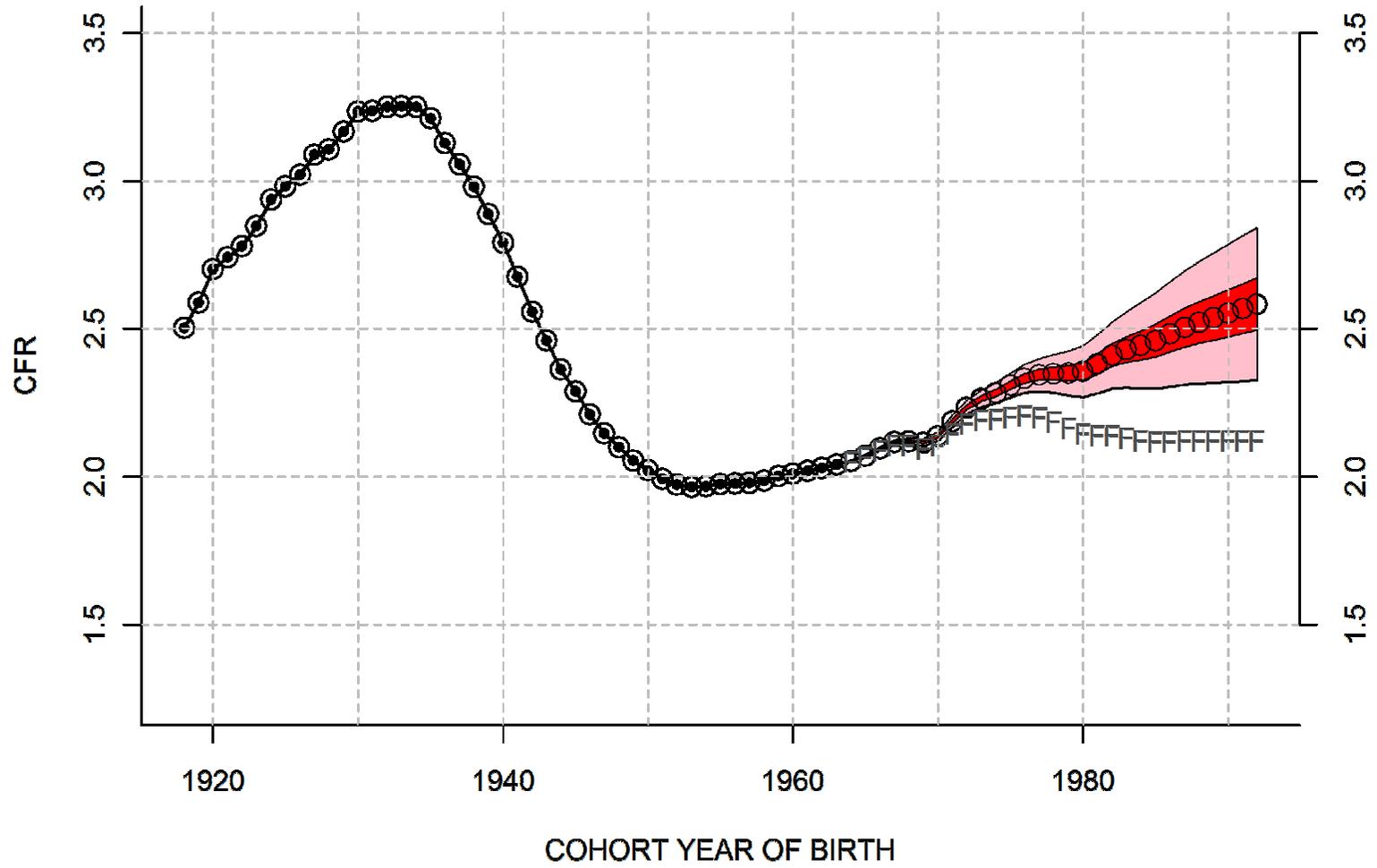
SVK



SWE

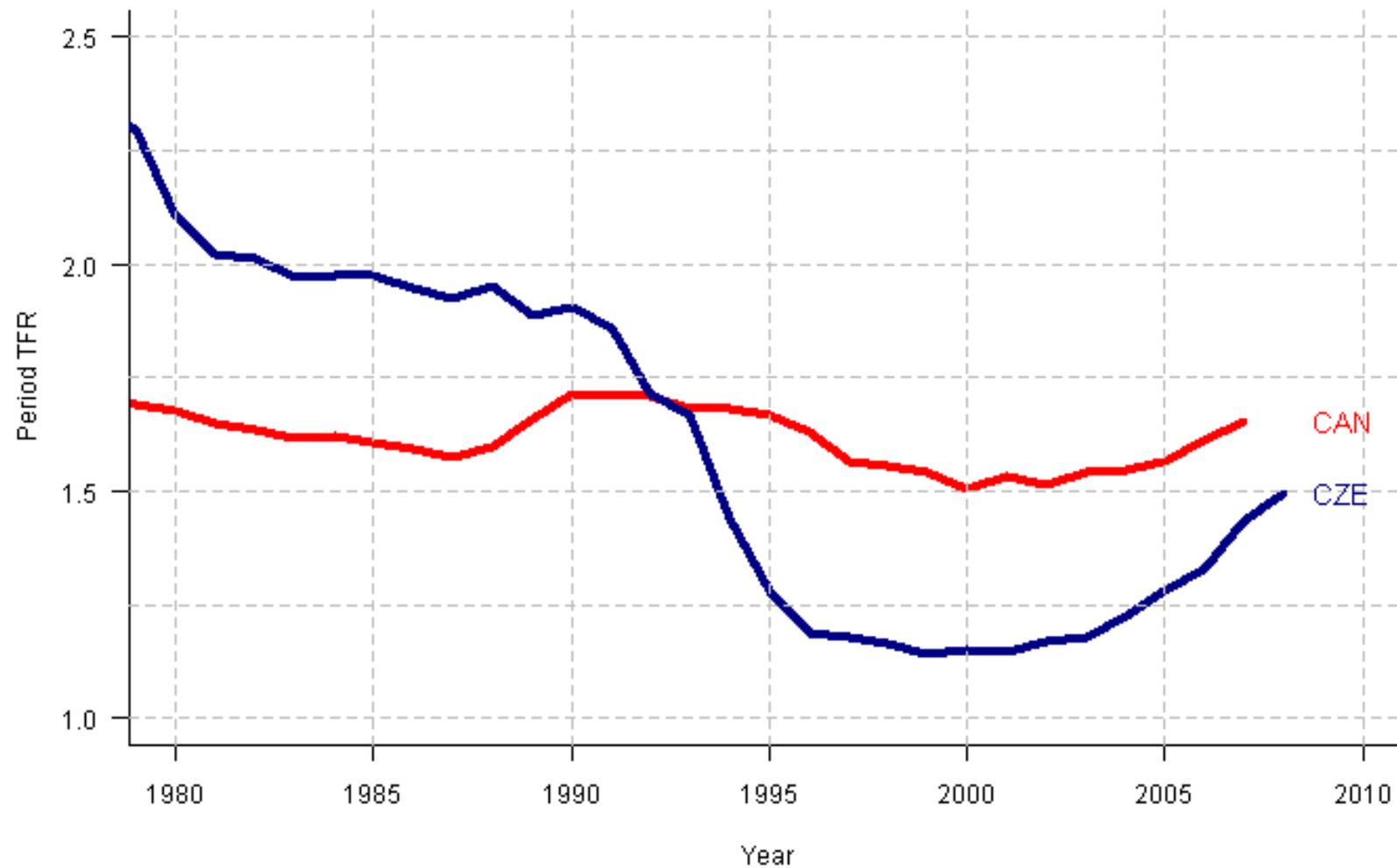


USA



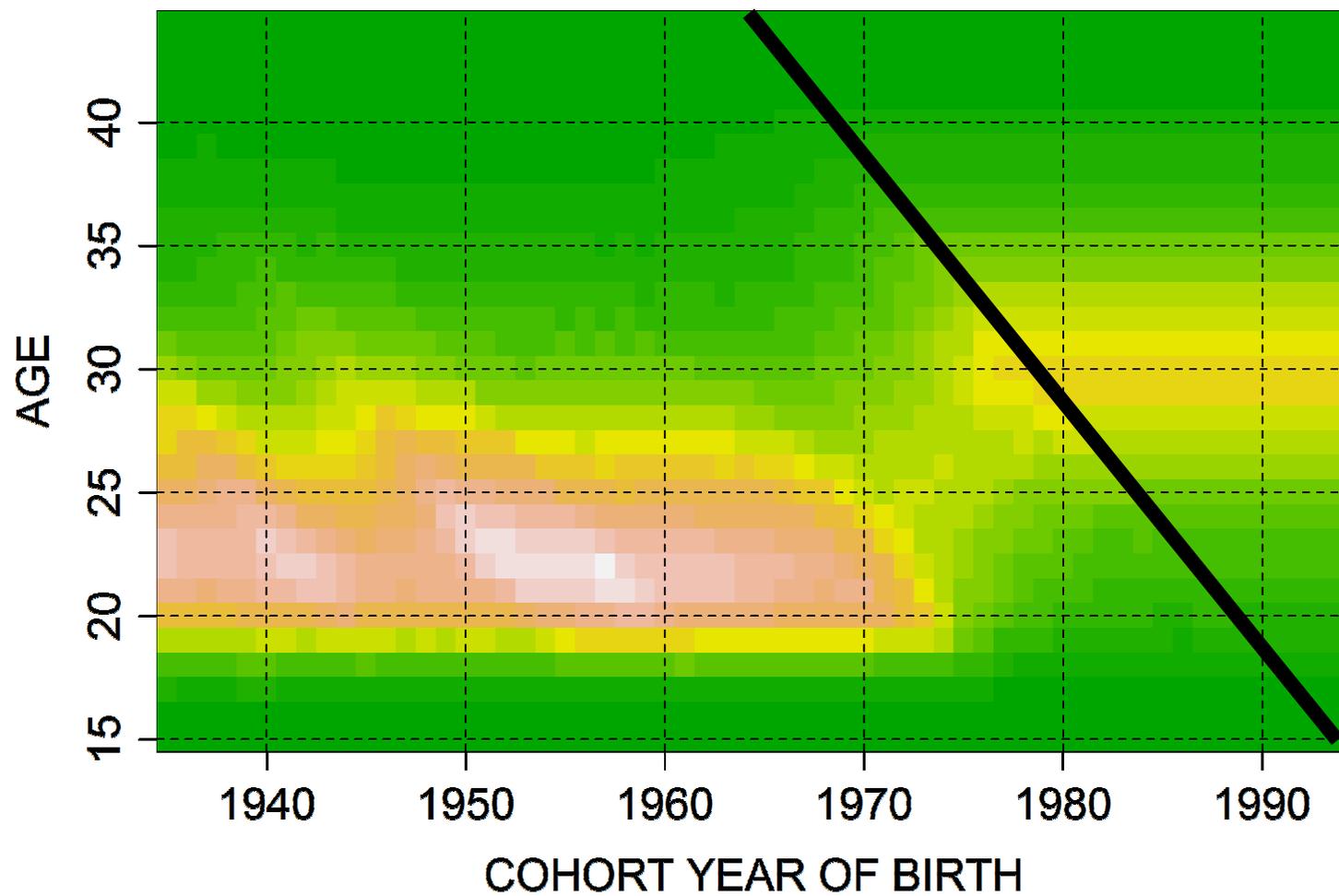
Period TFR 1980-2008

Canada and Czech Rep



Freeze Rate Surface

CZE Lexis Surface



Forecast Methods

□ Extrapolate time series $f(a,t)$

- Freeze Rates: no change in future

$$f(a, \text{NOW}+h) = f(a, \text{NOW})$$

- Freeze Slopes: change continues linearly

$$f(a, \text{NOW}+h) = f(a, \text{NOW}) + h * \text{slope}_{\text{NOW}}$$

Forecast Methods

- Model/Extrapolate cohort schedules
 - Li & Zheng (2003)
 - SVD decomposition of complete cohort data
 - Cohort schedules modeled as
$$f_{\text{coh}} = (\text{mean vec}) + k_{\text{coh}} * (1^{\text{st}} \text{ princ. comp.})$$
 - Estimate each k_{coh} from partial cohort history
 - Myrskylä & Goldstein (2010)
 - Parametric models for cohort schedules
-

Forecast Methods

ADVANTAGES for CFR estimation:

Freeze Rate Avoids “nonsensical” forecasts

Freeze Slope Utilizes recent trends

Cohort Model Focuses on correct dimension

DISADVANTAGES for CFR estimation:

Freeze Rate Ignores recent trends

Freeze Slope Possible “nonsensical” forecasts

Cohort Model Treats cohorts as independent
(does not ‘borrow strength’
across demographic dimensions)
