Measuring and understanding inequalities in parental loss

New statistical methods and estimates

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Introduction

- Demographer, with a background in statistics
- Interested in demographic questions in contexts where populations/outcomes are hard to measure
- A large part of my work centres on developing Bayesian methods for demographic estimation

BAYESIAN DEMOGRAPHY LAB

Grew up in Hobart, Tasmania, Australia

Masters/PhD at UC Berkeley

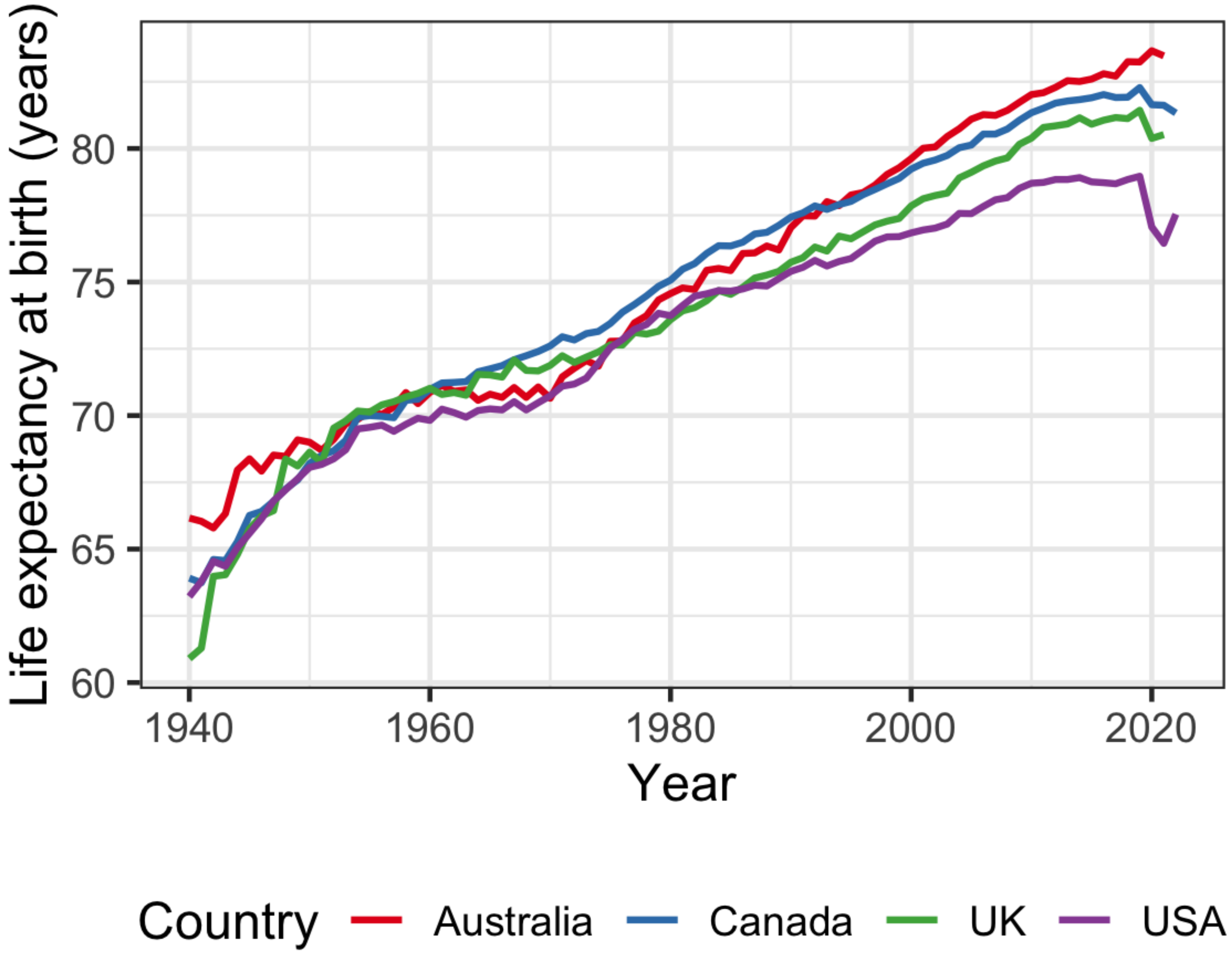
Associate Prof at University of Toronto

Motivation

- Life expectancy in the United States has been stagnating (Abrams et al, 2023)

- The rise of young- and middle-age adult mortality is a well-documented contributor (Polizzi and Dowd, 2024)

- Disparities in mortality by race/ethnicity persist (Dwyer-Lindgren et al, 2022, Hendi 2024)



Source: Own calculations from HMD

Beyond death counts: changing the viewpoint

- Focus on **parental loss**
- An increase in adult mortality implies an increase in children who have lost a parent at a young age
- Taking key demographic quantities and changing the viewpoint
- Analyzing demographic rates from a different perspective uncovers new information about social phenomena (e.g. Bumpass and Lu 2000; Alburez-Gutierrez 2022)

The importance of studying parental loss

- The premature death of a parent is negatively associated with a range of outcomes (educational, health, economic) (Niederkrotenthaler et al. 2012; Pham et al. 2018; Patterson et al. 2022)

- Differing levels of parental death in different societies has implications for evolution of family structure, support of extended kin (Umberson 1995; Daw et al. 2016; Jiang et al. 2023)

- Macro implications of support required from healthcare and foster care systems (Roehrkasse 2021)

- Substantial racial/ethnic disparities in mortality translate into vastly different exposures to parental death, contributing to cumulative disadvantage (Umberson 2017, Umberson et al. 2017)

This talk

- Two projects on parental loss in the United States context
    - Youth who have lost a parent due to drugs and firearms
    - Time lived without parents
    - Highlight differences by race/ethnicity
- Methodological contributions:
    - Extend existing demographic methods to estimate parental loss by cause
    - Develop a Bayesian statistical framework to combine multiple data sources on parental loss

Youth experiencing parental deaths due to drug poisonings and firearm violence

Motivation

- The United States is experiencing dual and overlapping public health crises: drug poisonings and firearm deaths
- Since 1999, over 1 million people have died due to drug overdoses, and more than 750,000 by firearms (NCHS 2024)
- The majority of these deaths occur to those aged 15-54, a period when many have young children (NCHS 2024)
- Drug and firearms deaths have also increased for youths (<18 years); drug poisonings now the third leading cause of death (Goldstick et al 2022, Woolf et al 2023)
- Dual burden for youth: increased mortality, and losing a parent

How do we estimate parental loss?

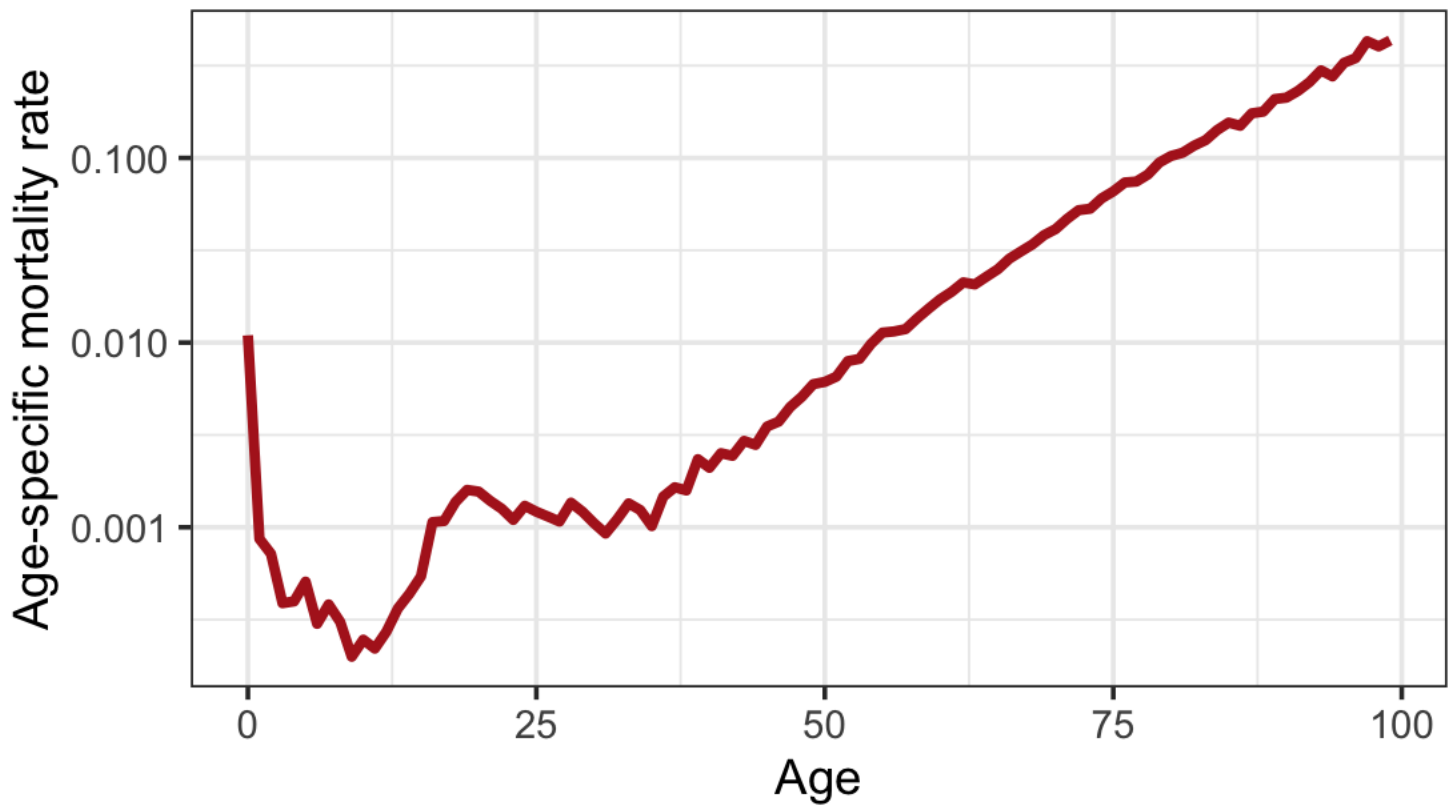
- Quantifying the number of children who have lost a parent is not necessarily straightforward
- Not recorded on death certificates, linked data is restricted
- Parental loss captured in some surveys, but sample sizes are small, some groups are underrepresented, and cause of death is usually not known

There are no data available on parental loss by cause, so we obtain estimates using a demographic projection model

Estimating parental loss with demographic rates

Estimating parental loss with demographic rates

Intuition: If you know the mortality rates by age and the fertility rates by age in a population, then you can estimate expected number of mothers / fathers still alive



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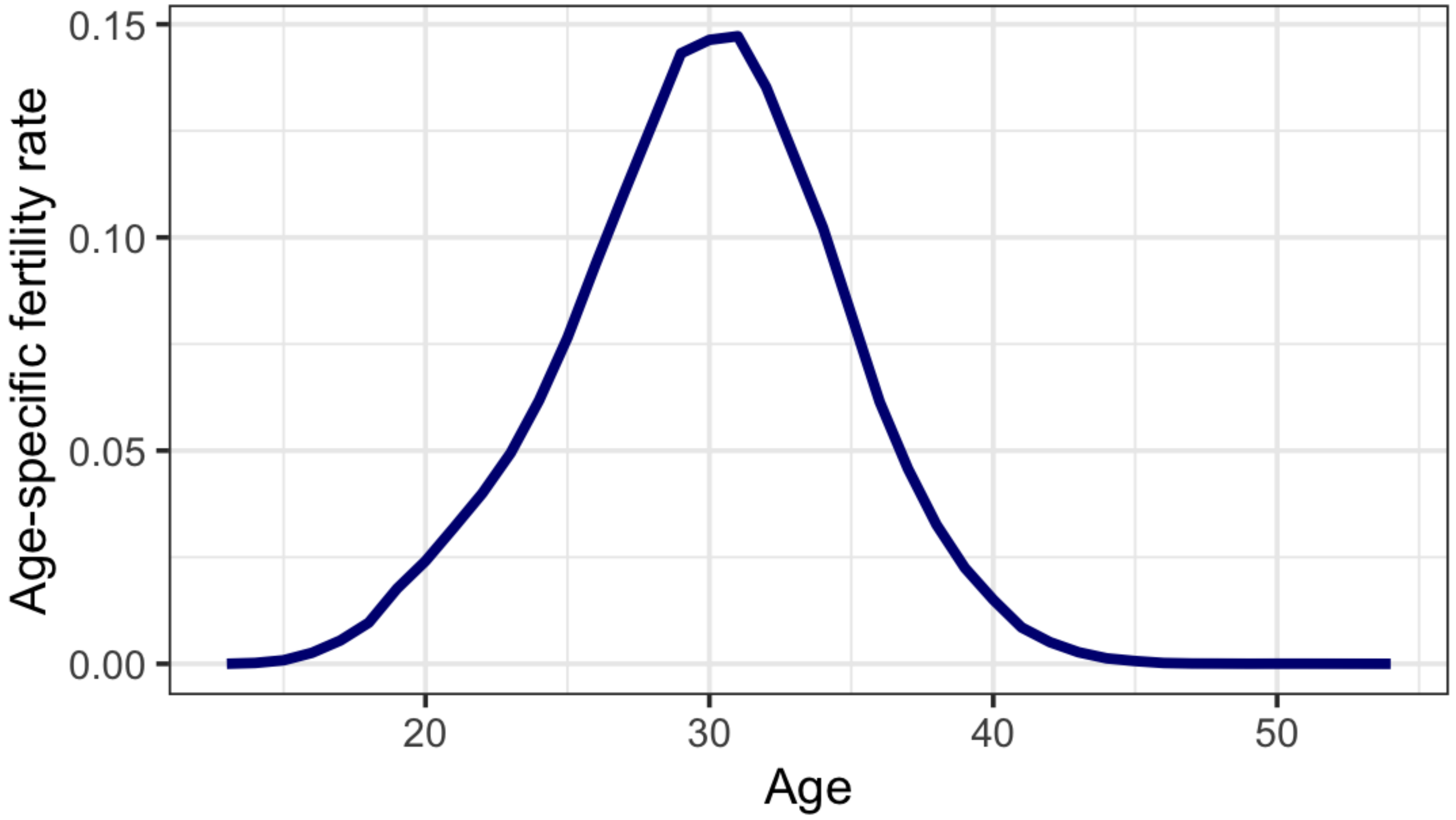


Estimating parental loss with demographic rates

Goodman, Keyfitz, and Pullum (1974) laid out the mathematical foundations for quantifying surviving kin using demographic rates. E.g.

$$M_1(a) = \int_\alpha^\beta \left(\frac{l_{a+x}}{l_x} \right) W(x \mid t - a)dx$$

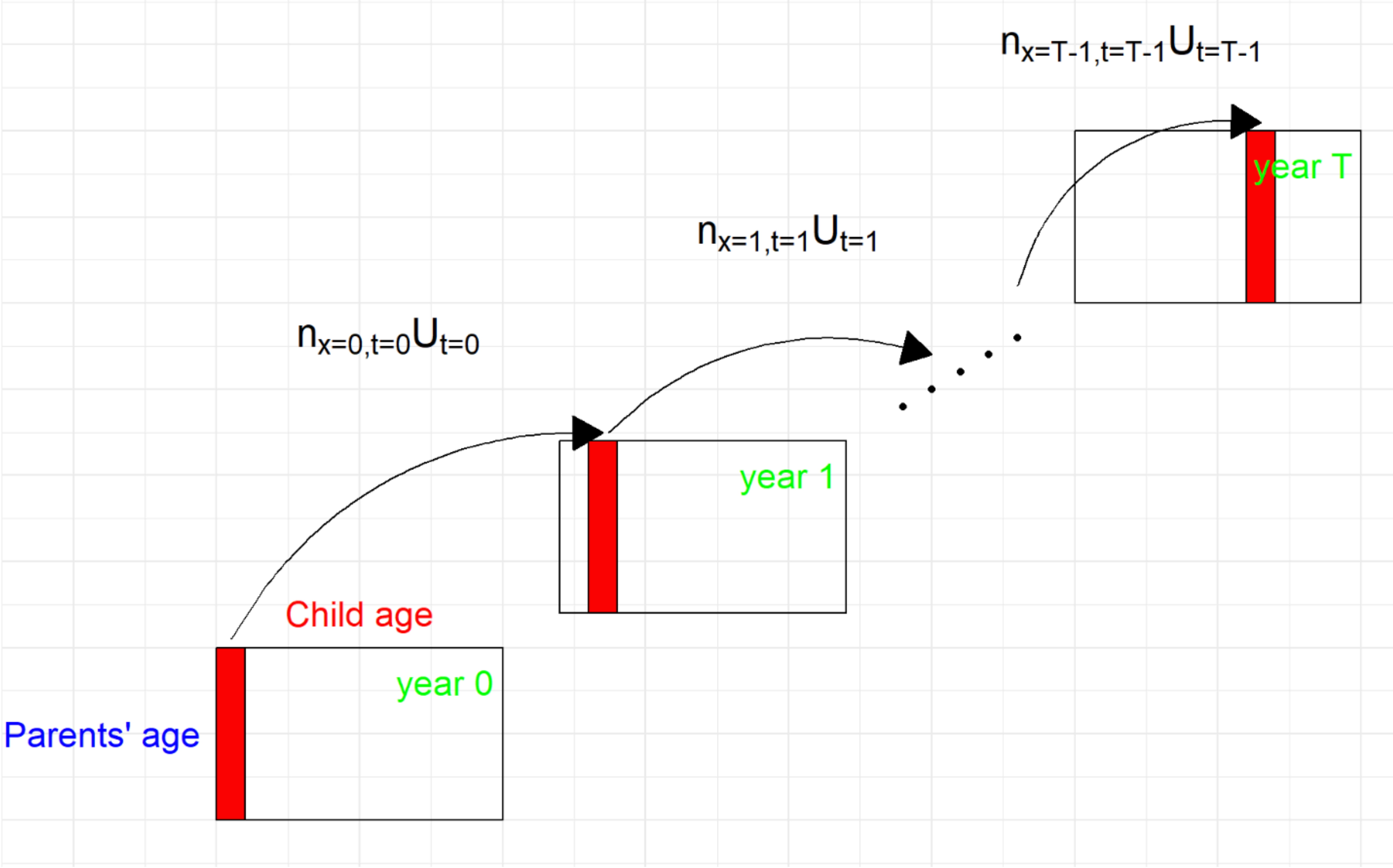
Probability that mother is still alive when daughter is age *a*

Survival of mother

Age distribution of fertility

Enter the Matrix

- Caswell (2019+): takes the Goodman, Keyfitz, Pullum equations, and turns them into a matrix projection model
- Extends the idea of the cohort component projection model
- Treat the children and parents as two different, but connected, populations
- We extended to allow us to track deaths of parents by cause (drugs, firearms, all other causes)



Data

Sources: National Center for Health Statistics (NCHS) and US Census Bureau

- Multiple causes of death (ICD10 codes) from 1999 (firearm-related, drug-related deaths, all other causes of death combined)
- Calculated cause-specific deaths for all NCHS/CDC bridged-race groups by one-year age, and sex
    - Non-Hispanic Black, non-Hispanic White, Hispanic, and Total
- Age- and race/ethnicity-specific female fertility rates
- Population counts by age, sex, and race/ethnicity

Reproducible materials

- Paper was published in *JAMA* in 2024: doi:10.1001/jama.2024.8391

- All the data and code to produce the results, plots, and supplementary analyses is here: https://github.com/benjisamschlu/parental_deaths

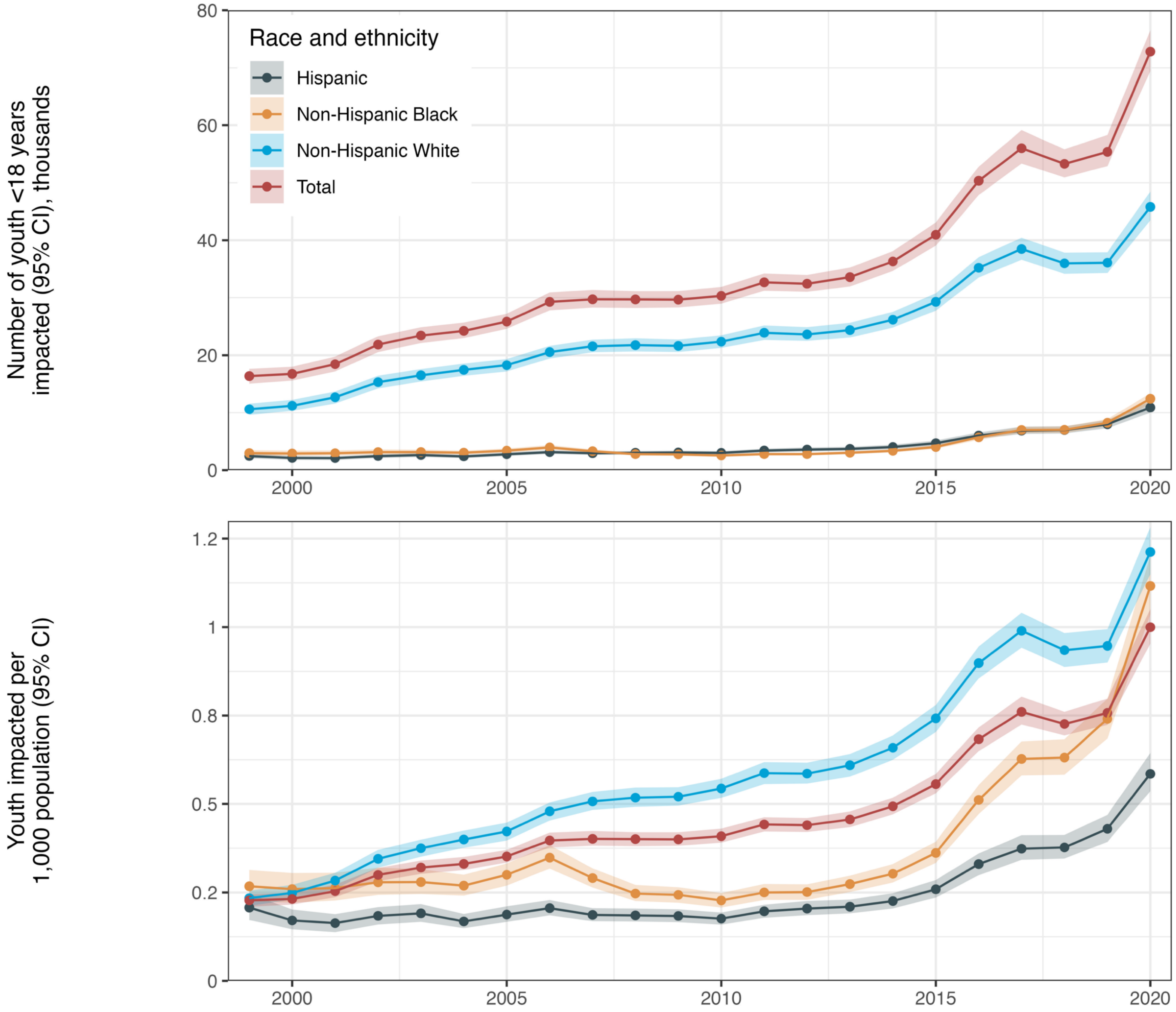
Notes on Reproducibility

We use publicly available data and provide code that will download and/or munge these data as necessary. For full reproducibility, we also provide all of our simulation files, which will allow for exact reproduction of our results. These files are stores on the Harvard Dataverse; however, due to limitations on file size, we split each of the (>5GB) simulation files into 10 smaller chunks and provide code to recombine them (`./codes/00_combine_sim_files.R`). If you wish to fully reproduce our results, use the `00` code file to download the files noting that they take up approximately 55GB of space and require ~16GB of RAM (each file) to recombine.

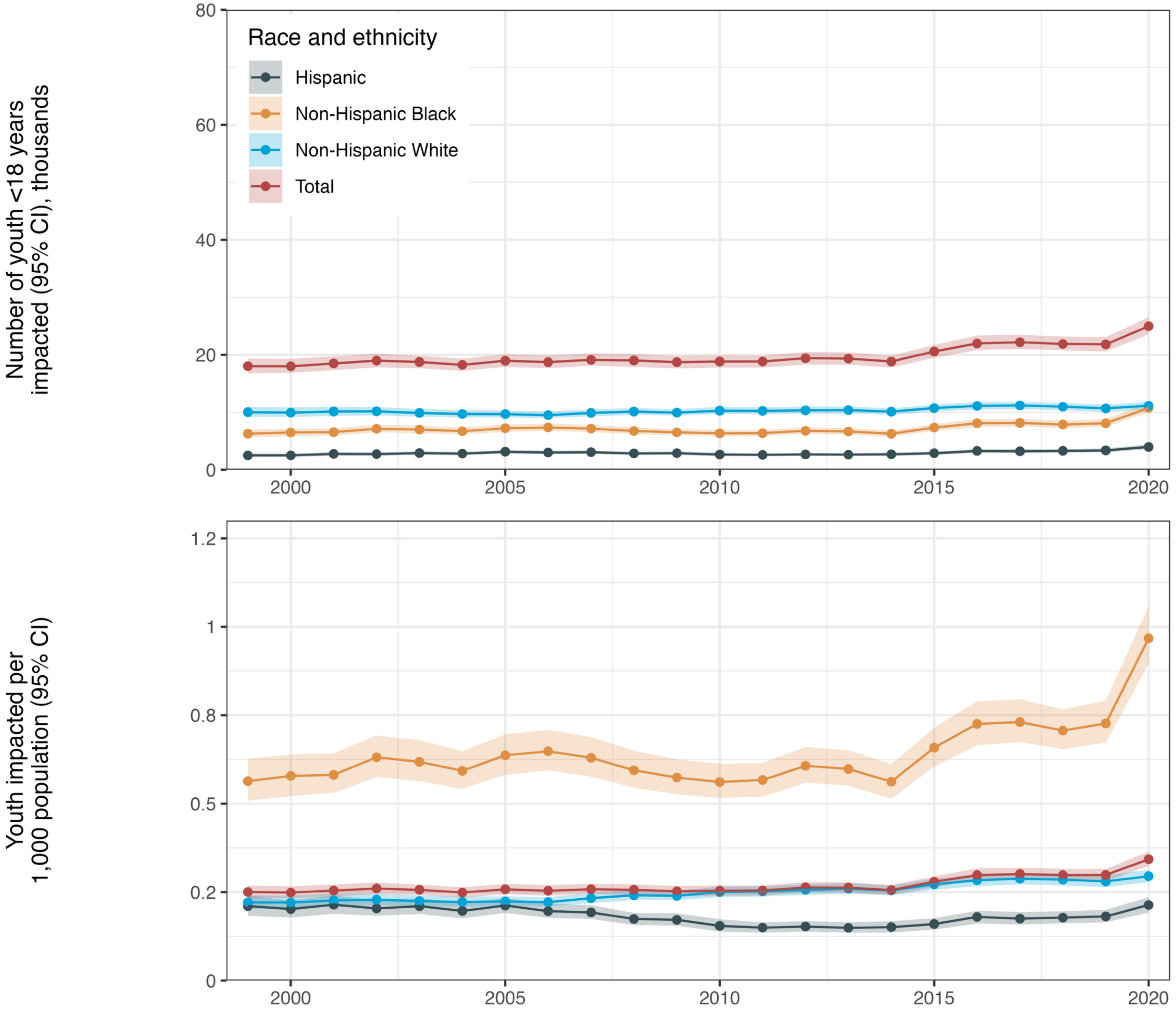
We use `renv` for package management but below we also post the relevant session information to ensure full reproducibility.

Results

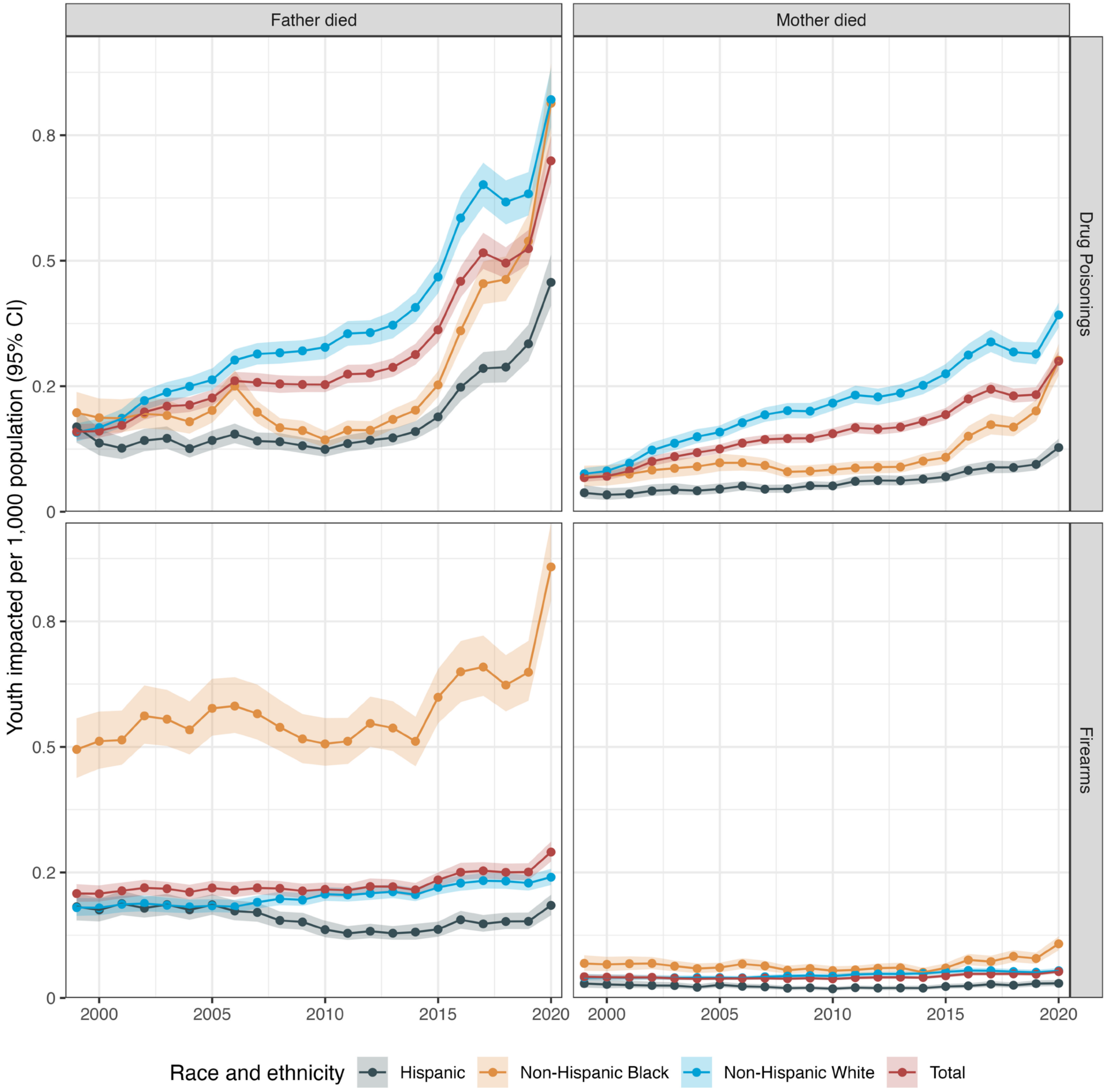
Parental loss due to drugs



Due to firearms



By parent


Father died
Mother died
Drug Poisonings
Firearms
Youth impacted per 1,000 population (95% CI)
0
0.2
0.5
0.8
2000
2005
2010
2015
2020
Race and ethnicity
Hispanic
Non-Hispanic Black
Non-Hispanic White
Total

Takeaways

- An estimated more than 1 million youth lost a parent due to drugs or firearms over the period 1999-2020
- In 2020, drugs and firearms accounted for almost a quarter of all parental deaths (double the 1999 level)
- Black youth experienced a disproportionate burden of parental deaths, primarily due to firearm deaths among fathers
- A whole generation of youth who have lost a parent to traumatic causes
- Shifting policy to think about the indirect impact on families (US Surgeon General 2024)

Methodological assumptions and limitations

These are model-based estimates!

- Definition of a parent, assumption of two parents
- Homogeneity of fertility
- Race classification, no multi-racial groups
- Uncertainty is most likely underreported

We did validation and sensitivity tests, but potential for future methodological work

Estimating years of life lived without parents

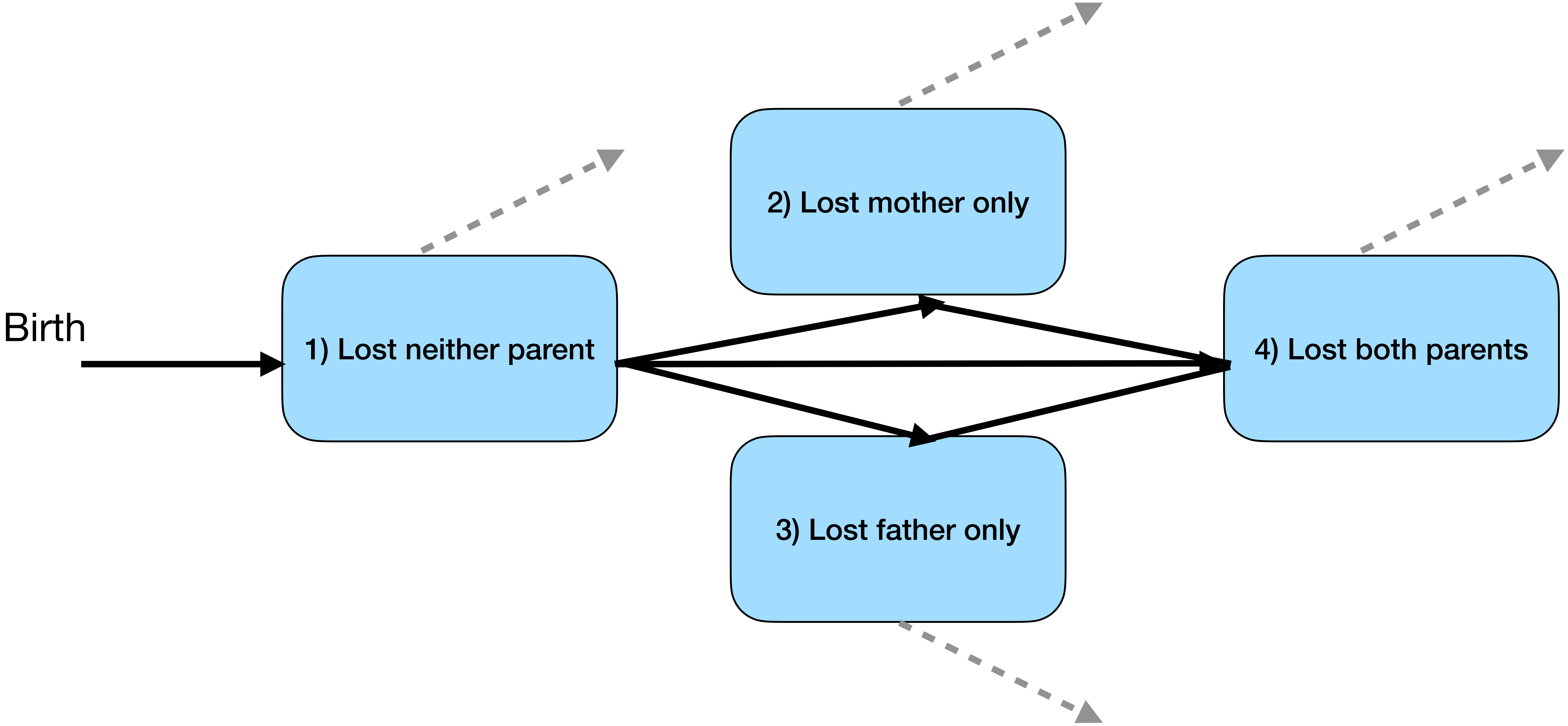
Motivation

- Shifting focus from magnitude to timing and **length of exposure to parental loss**
- How much time can we expect to have with our parents?
- A function of mortality/fertility of parents and also mortality of ego
- Presence of parents at key points in life course (Cox et al 2016, Liu et al 2022)
- Shared lifetimes, shared resources, multigenerational mobility and capital (Song and Mare 2019)
- Uncertainty about lifespan of family members affects planning (van Raalte 2011, Grote and Pfrombeck 2020)

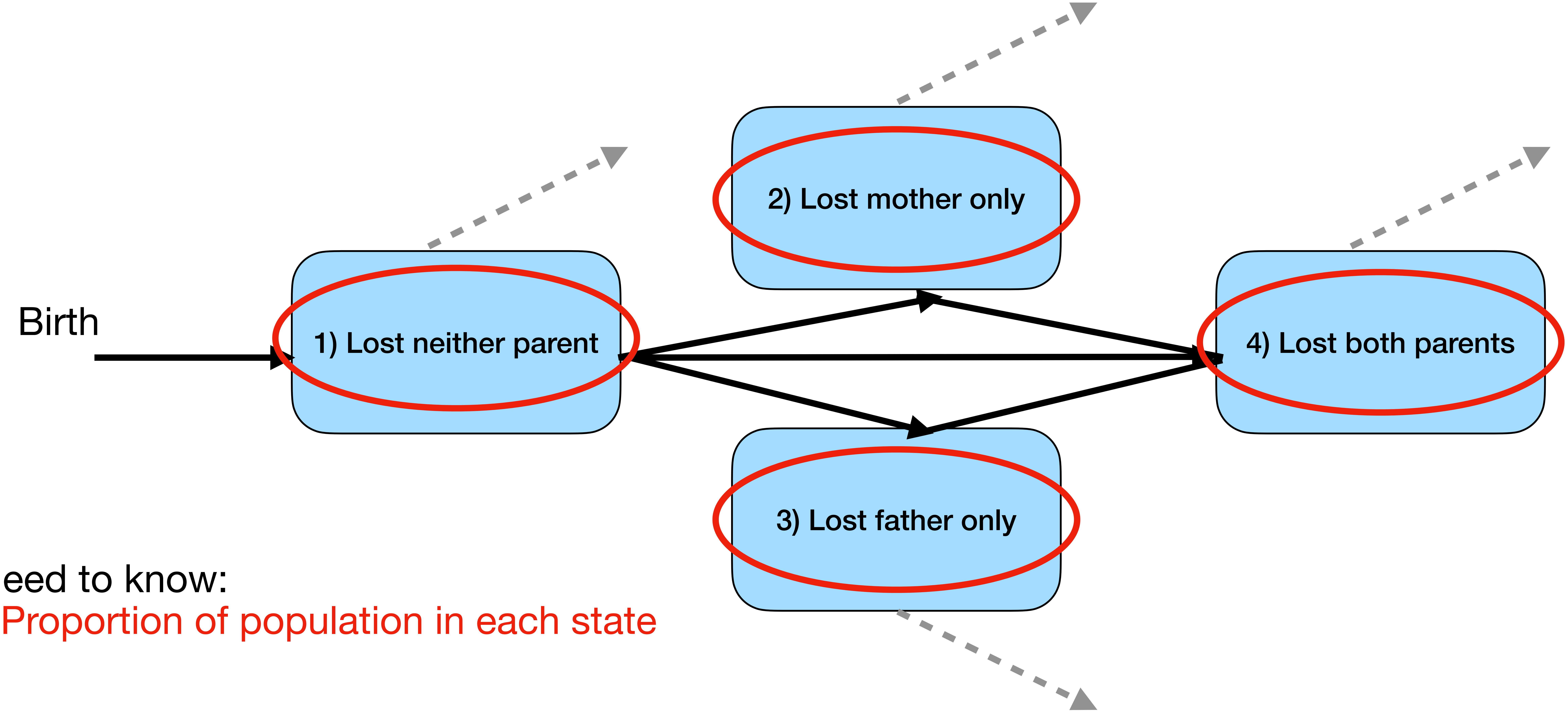
Estimating time lived without parents

- We use a multistate life table approach
- Multistate lifetables track the mortality experience for a cohort of people over age, partitioning them into different ‘states’
- Here, our states relate to parental loss: 1) lost neither, 2) lost mother only, 3) lost father only, 4), lost both
- Key quantity of interest: life expectancy above age x in each state j, $e_x(j)$
- For example: $e_0(1)$ is an estimate of the number of years a baby could expect to live with both of their parents alive

States of parental loss

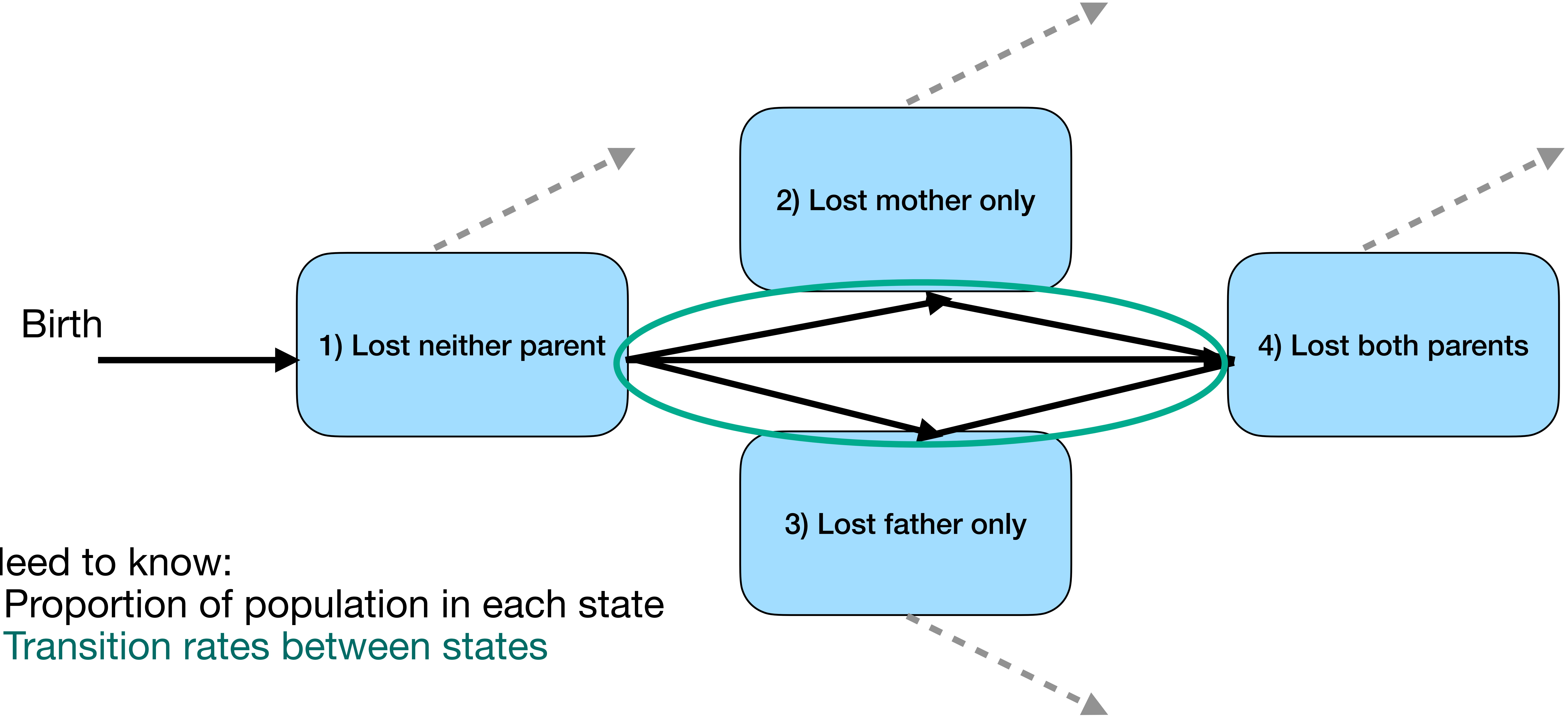


States of parental loss



Need to know:
- Proportion of population in each state

States of parental loss



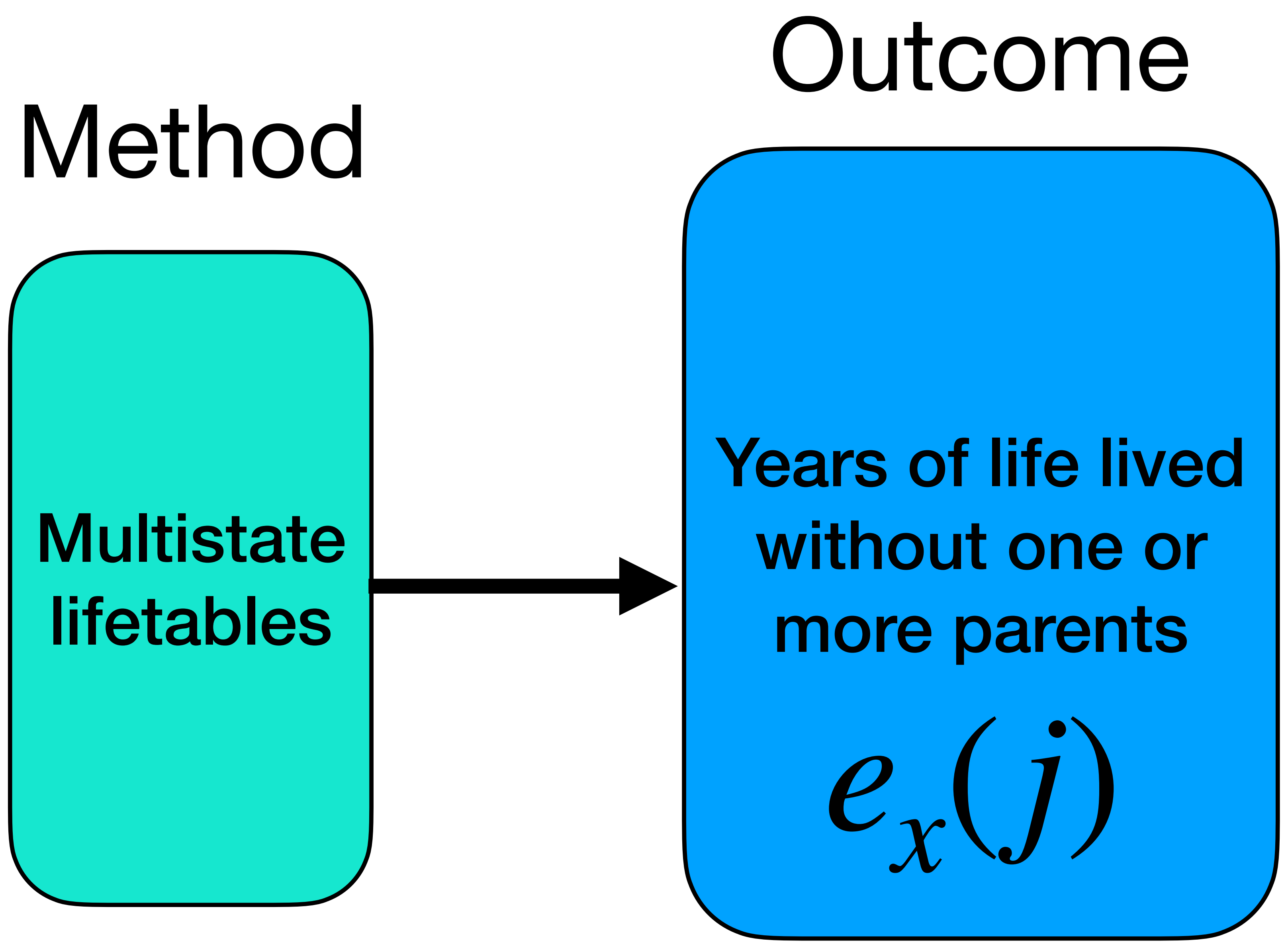
Need to know:
- Proportion of population in each state
- Transition rates between states

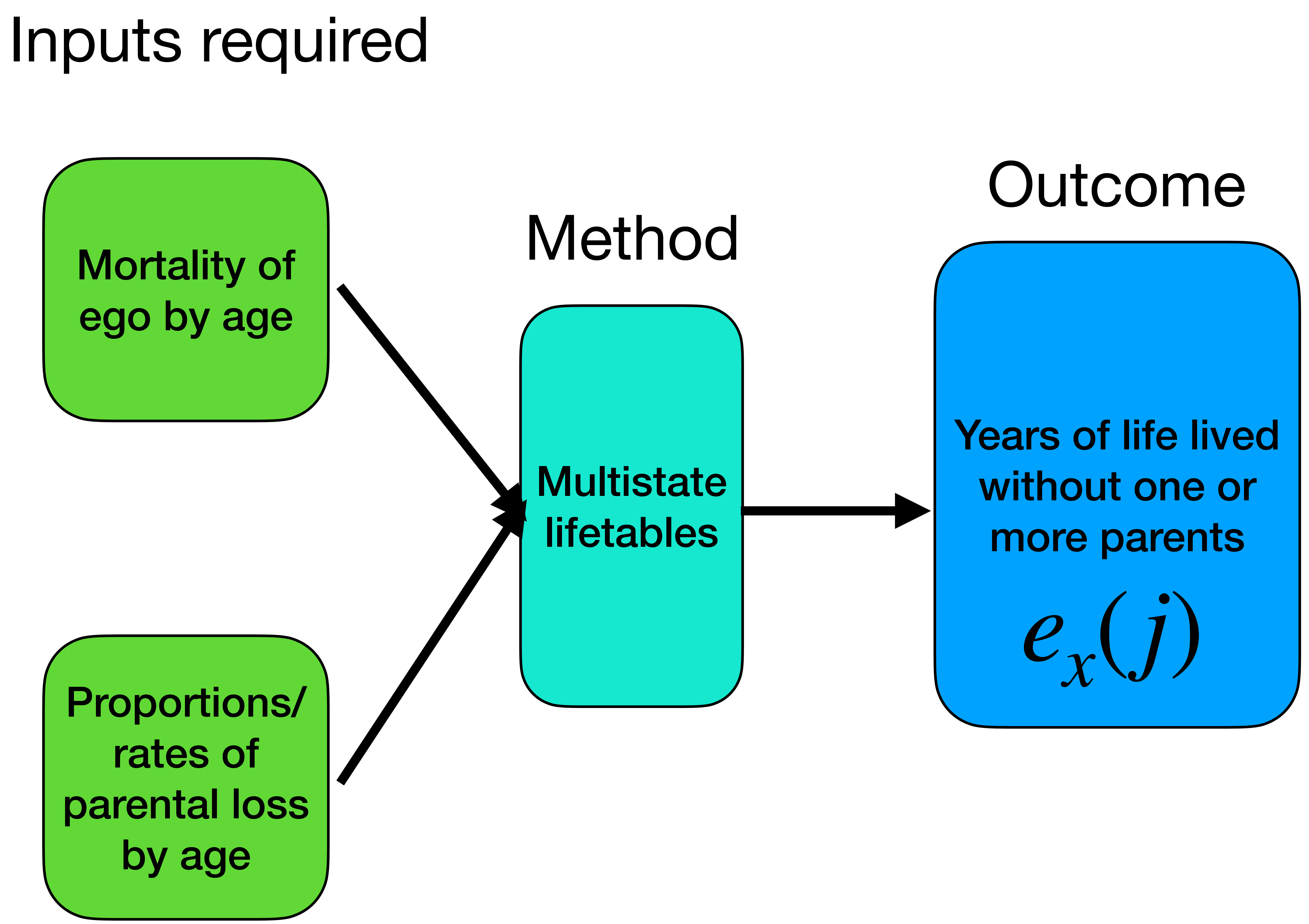
What information do we need?

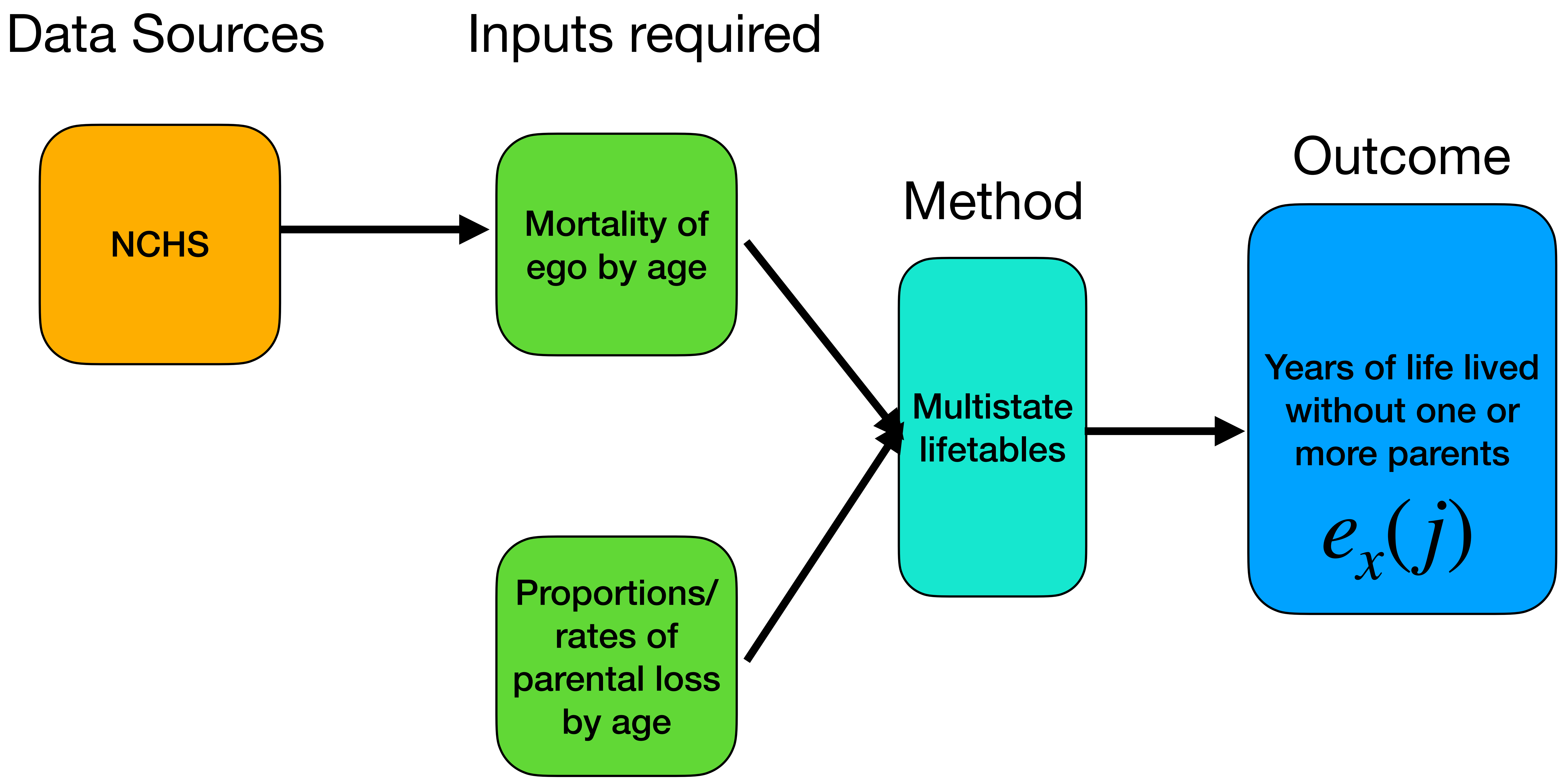
Outcome

Years of life lived without one or more parents

$$e_x(j)$$


Method
Outcome
Multistate lifetables
Years of life lived without one or more parents
$e_x(j)$


Inputs required
Mortality of ego by age
Proportions/ rates of parental loss by age
Method
Multistate lifetables
Outcome
Years of life lived without one or more parents
$e_x(j)$


Data Sources
Inputs required
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Mortality of ego by age
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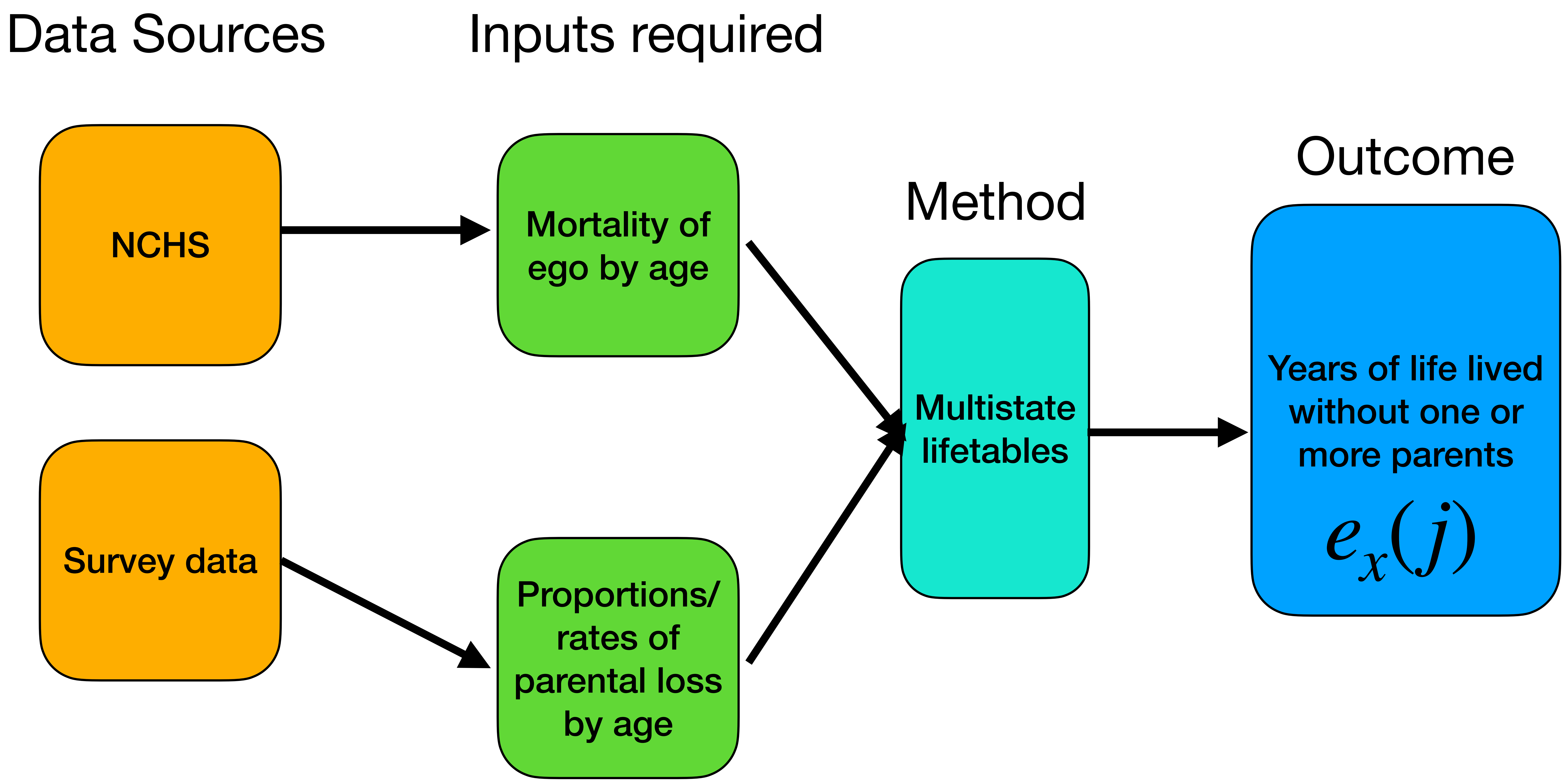
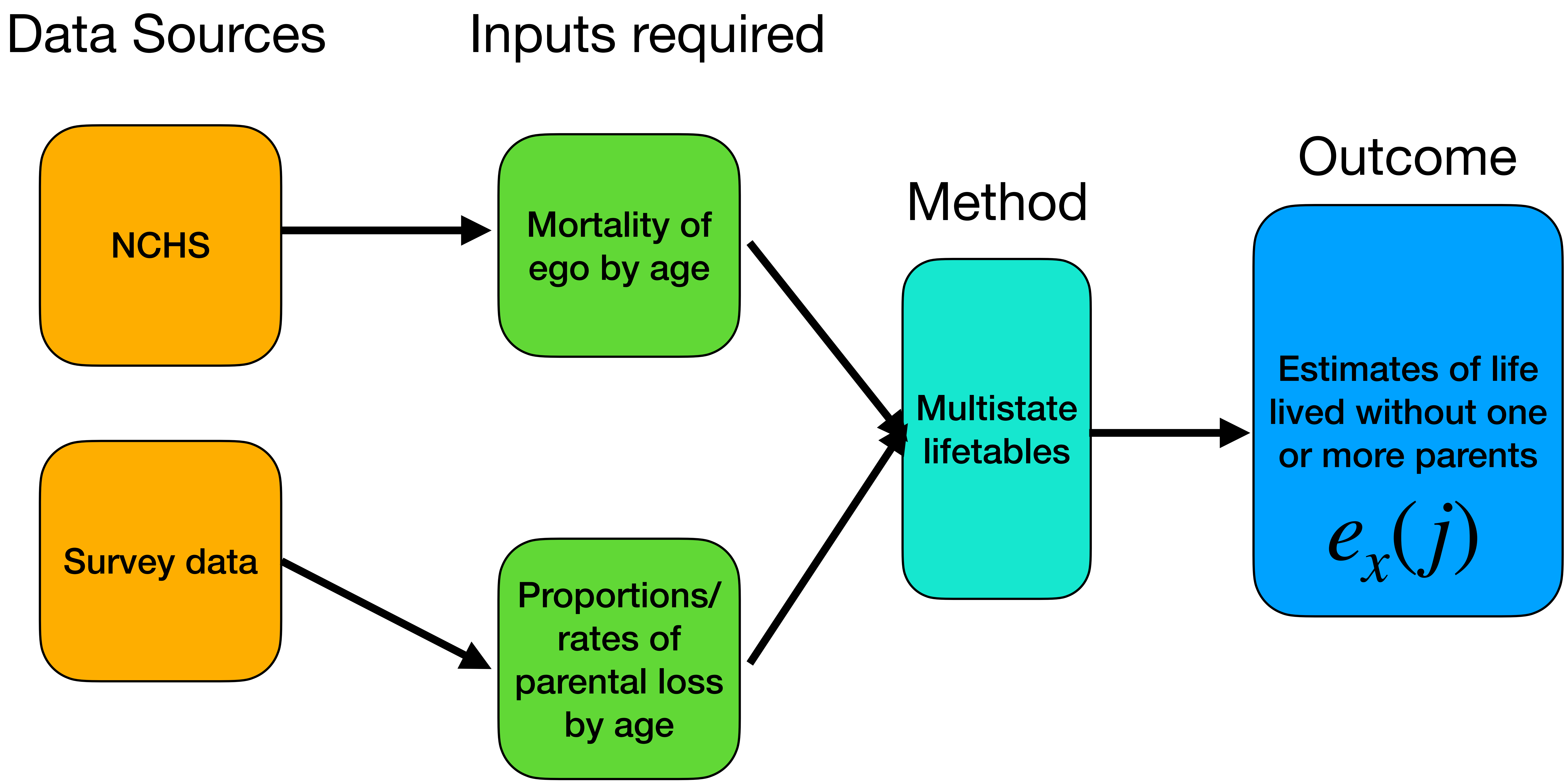
Multistate lifetables
Years of life lived without one or more parents
$e_x(j)$


Data Sources
Inputs required
Method
Outcome
NCHS
Survey data
Mortality of ego by age
Proportions/ rates of parental loss by age
Multistate lifetables
Years of life lived without one or more parents
$e_x(j)$

Survey data on parental loss

- Survey of Income and Program Participation (SIPP) (2021)
- Run by US Census Bureau. Nationally representative longitudinal survey, on income, employment, household composition, and includes the family context of individuals
- Survey asked whether parents were alive or deceased as well as the participant’s age at the time of losing each parent
- Sample size: 43,400 respondents (30,700 NHW; 8,300 Hispanic; 4,400 NHB)
- But many (10-15%) age-specific rates are missing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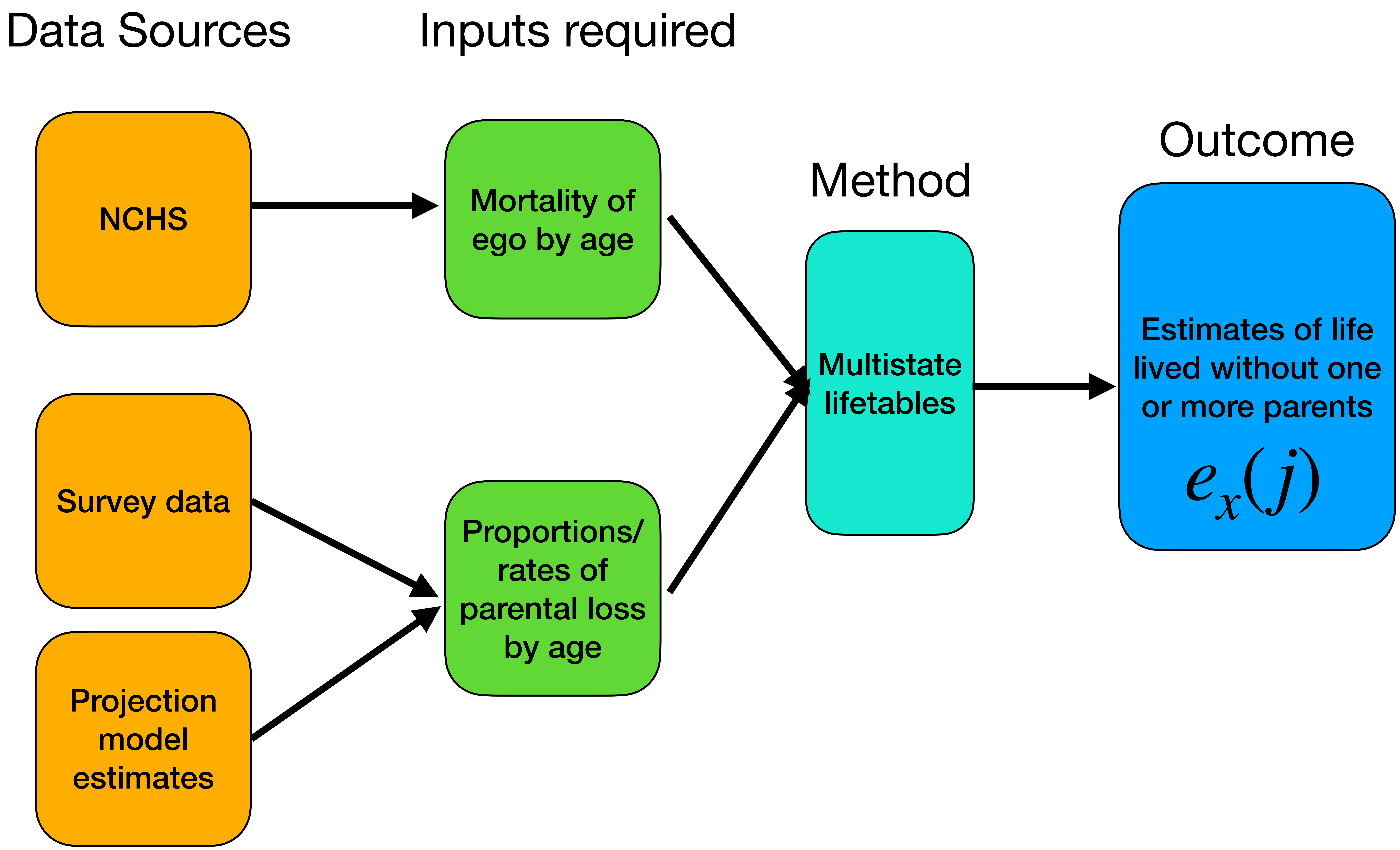
Mortality of ego by age
Multistate lifetables
Estimates of life lived without one or more parents
$e_x(j)$
Survey data
Proportions/ rates of parental loss by age



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Projection model estimates
Mortality of ego by age
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Estimates of life lived without one or more parents
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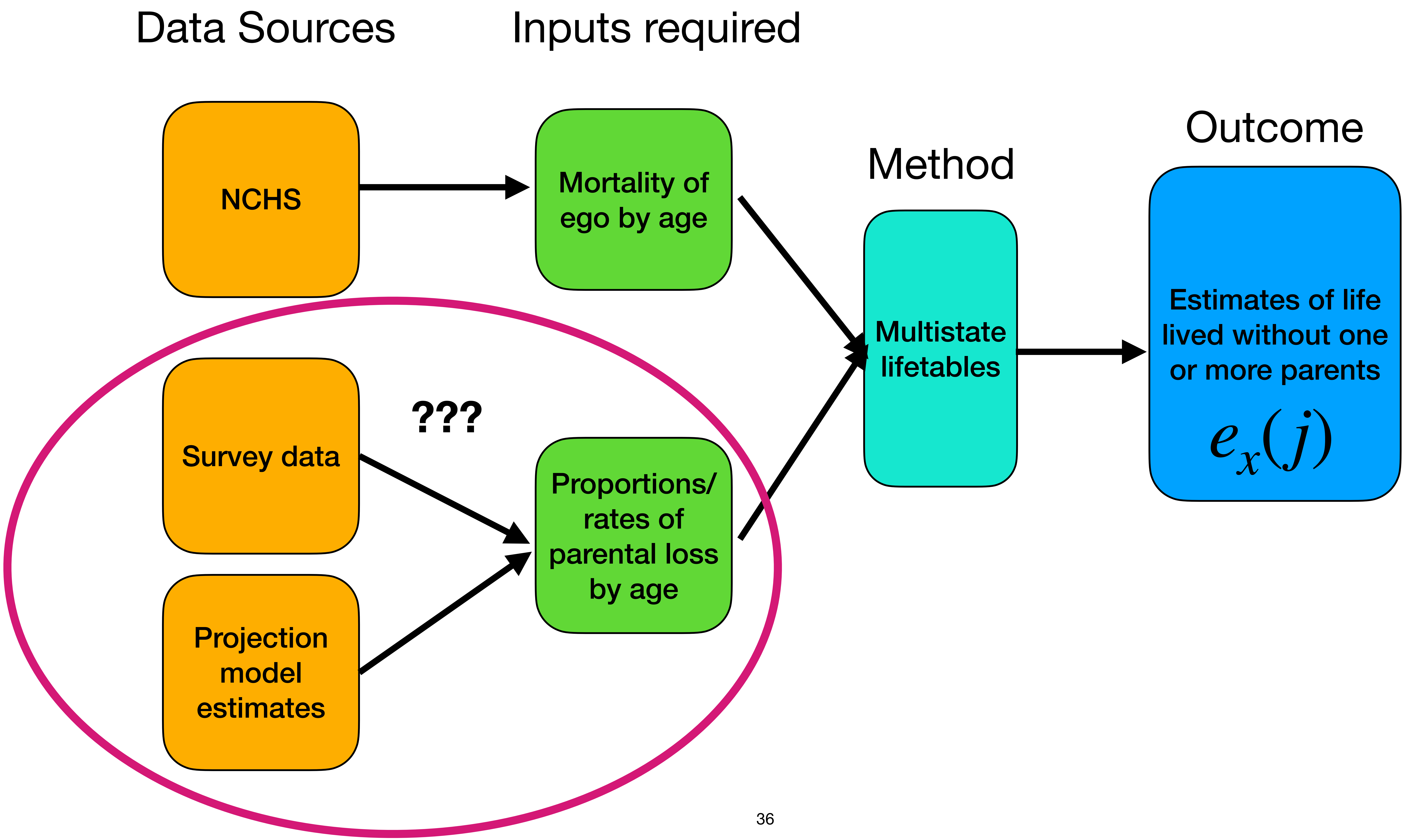
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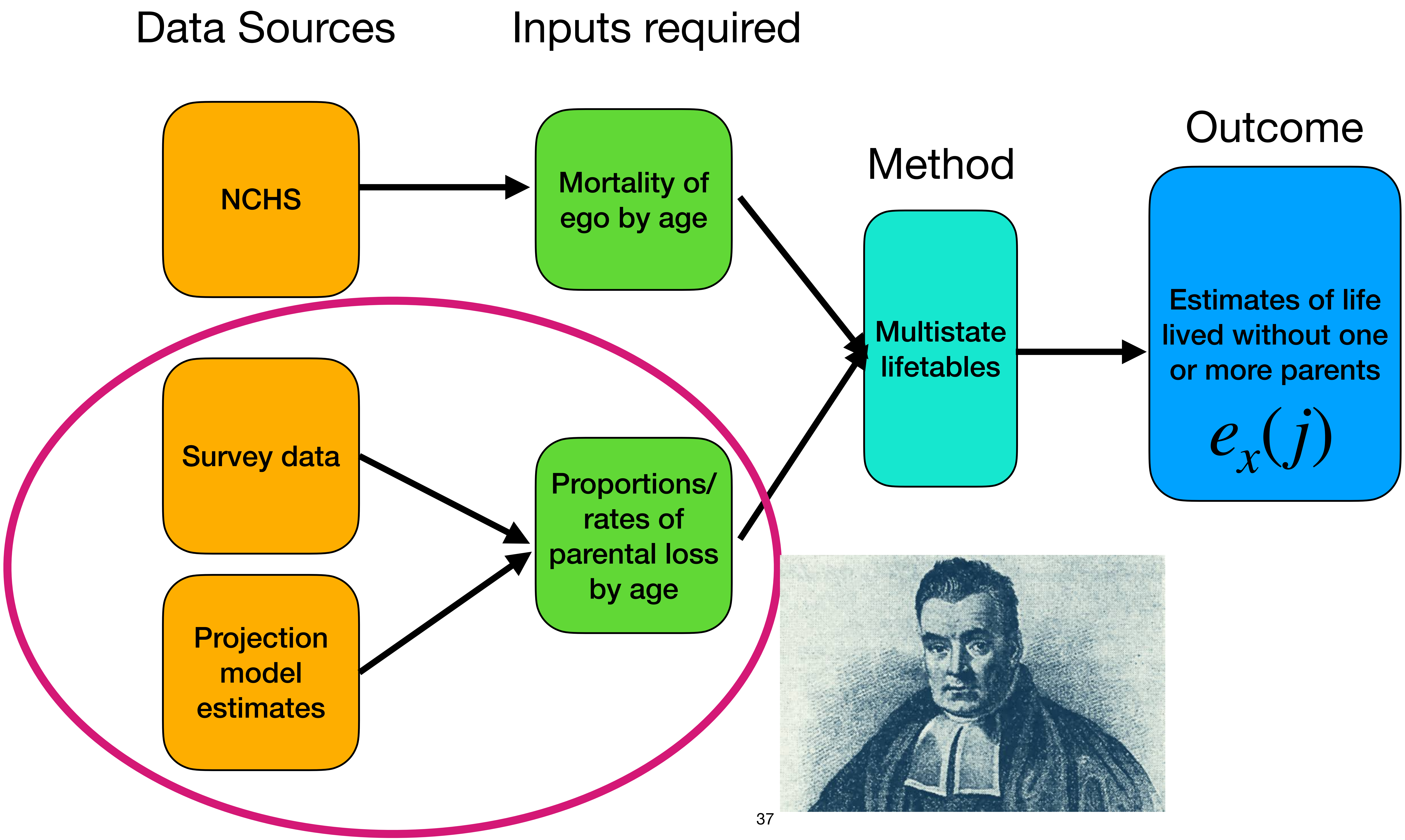
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Proportions/ rates of parental loss by age
Multistate lifetables
Estimates of life lived without one or more parents
$e_x(j)$

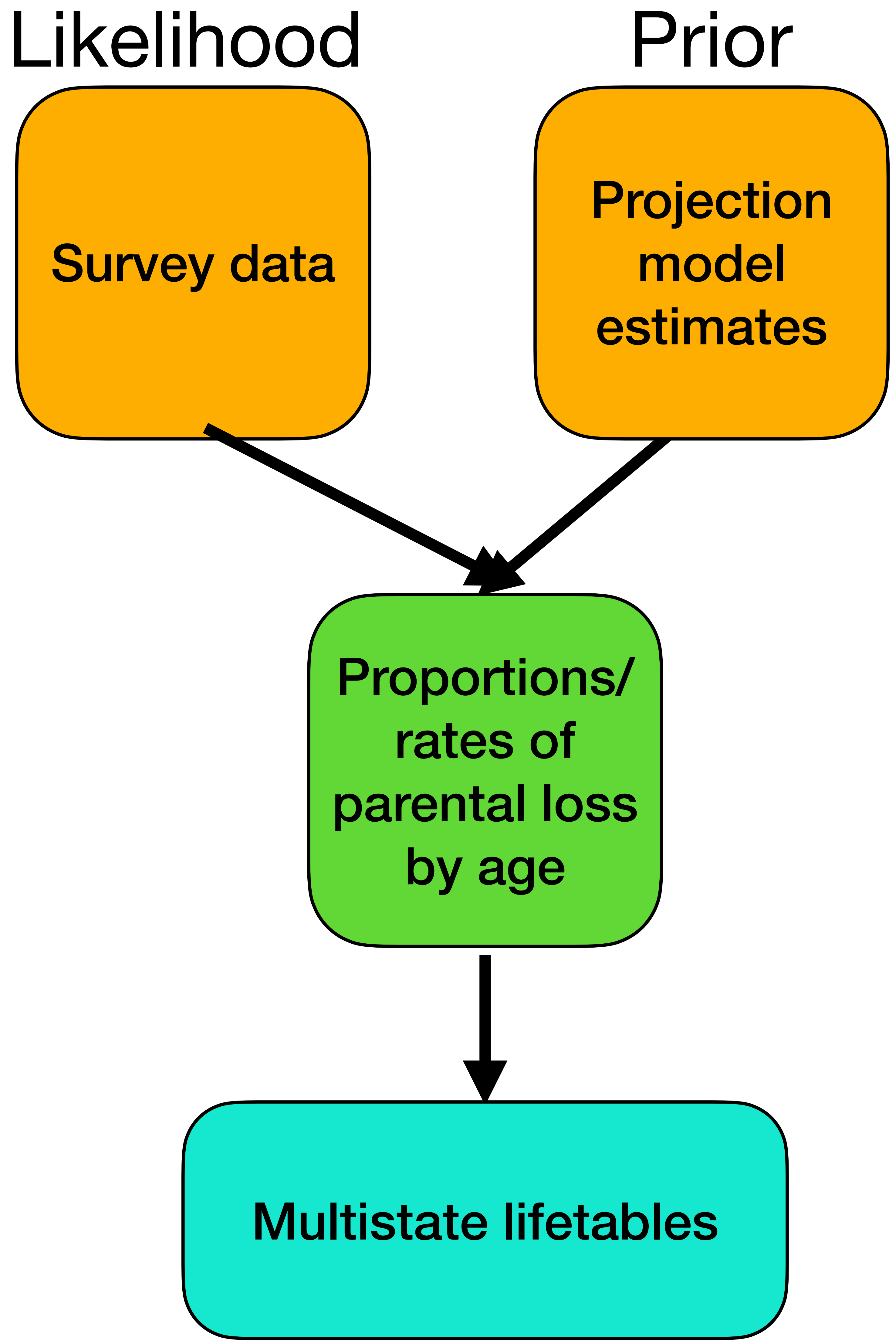
Bayesian estimation of the parental loss

- In this case, we have some idea of the rates of parental loss from the demographic projection model, even before we ‘see’ survey data **(prior)**

- Evidence from survey data is encoded through the **likelihood**

- The resulting **posterior** distribution of the rates is informed by both sources

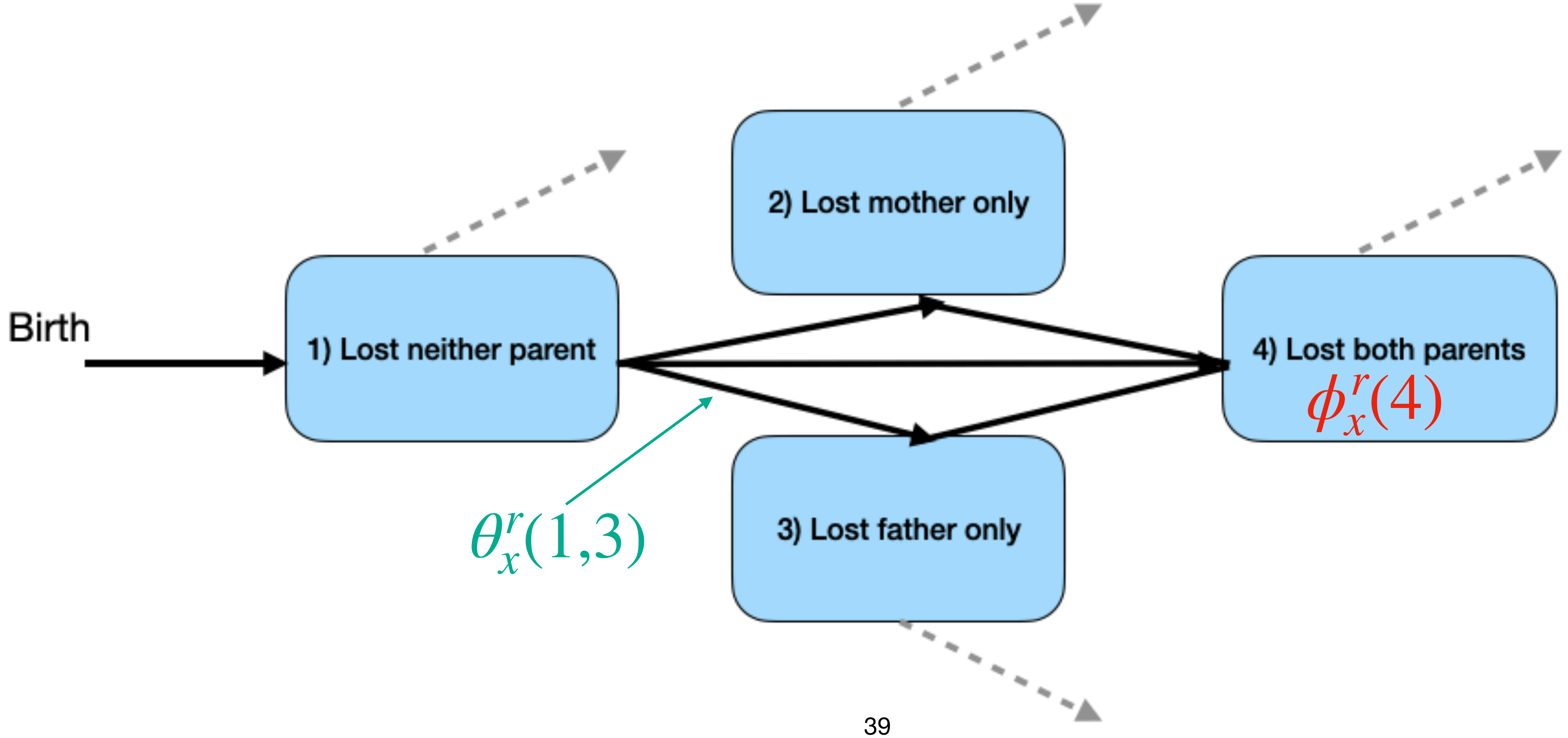
- These estimates (and their uncertainty) are then used to generate multistate lifetables (with uncertainty)



Model overview

- Denote $\theta_x^r(u, v)$ to be the **latent transition rate** at age x, race r, from state u to state v

- Also denote $\phi_x^r(l)$ as the **latent proportion** of the population in state l



How does the survey data enter the model?

- For example, the **observed transition rates** from SIPP are denoted $m_x^r(u,v)$ and assumed to follow a Normal likelihood

$$m_x^r(u,v)\,|\,\theta_x^r(u,v) \sim N\left(\theta_x^r(u,v), \left(SE\left(m_x^r(u,v)\right)\right)^2\right)$$

- Where $SE\left(m_x^r(u,v)\right)$ are the sampling standard errors (calculated taking sampling design into account)

How do projection estimates enter the model?

- The projection estimates only give us partial information!
- E.g. we know whether an individual has lost a mother, but not the state of the father (could be lost mother only [state 2] or lost both [state 4])
- That is, we only know the marginal transition rates. Denote these $\hat{m}_x^r(\,.\,, v)$ (for $v = 2{,}3$)
- Can still use these to partially inform the estimates of interest, θ_x^r

How do projection estimates enter the model?

- Can express the latent marginal transitions as a function of θ_x^r and ϕ_x^r. e.g. for losing a mother:

$$\theta_x^r(.,2) = \frac{\left(\theta_x^r(1,2) + \theta_x^r(1,4)\right) \cdot \phi_x^r(1) + \theta_x^r(3,4) \cdot \phi_x^r(3)}{\phi_x^r(1) + \phi_x^r(3)}$$

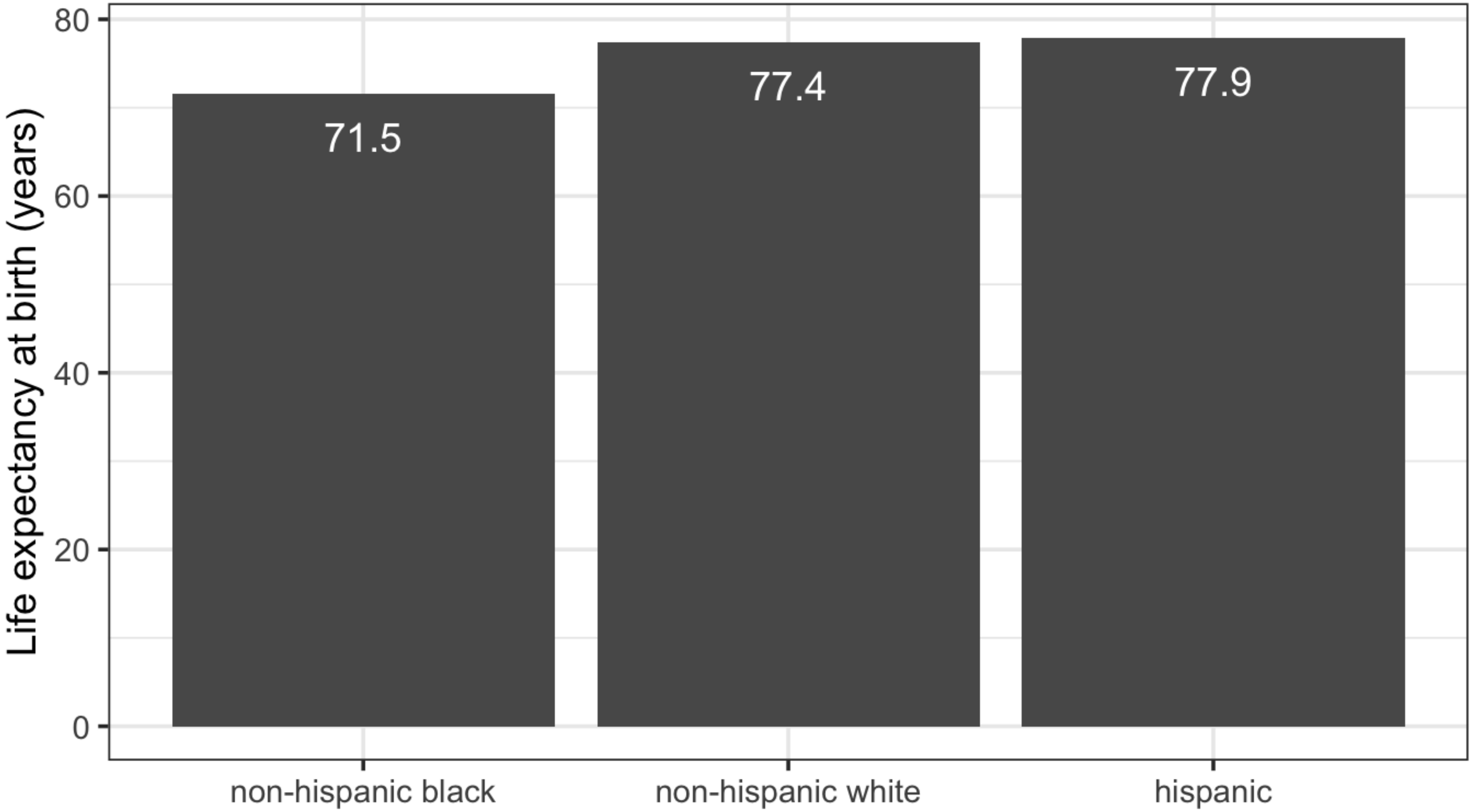
- The latent marginal rates then have prior distributions that are informed by the estimates from the projection model:

$$\theta_x^r(\,.\,,v) \,|\, \sigma_v^2 \sim N(\hat{m}_x^r(\,.\,,v), \sigma_v^2)$$

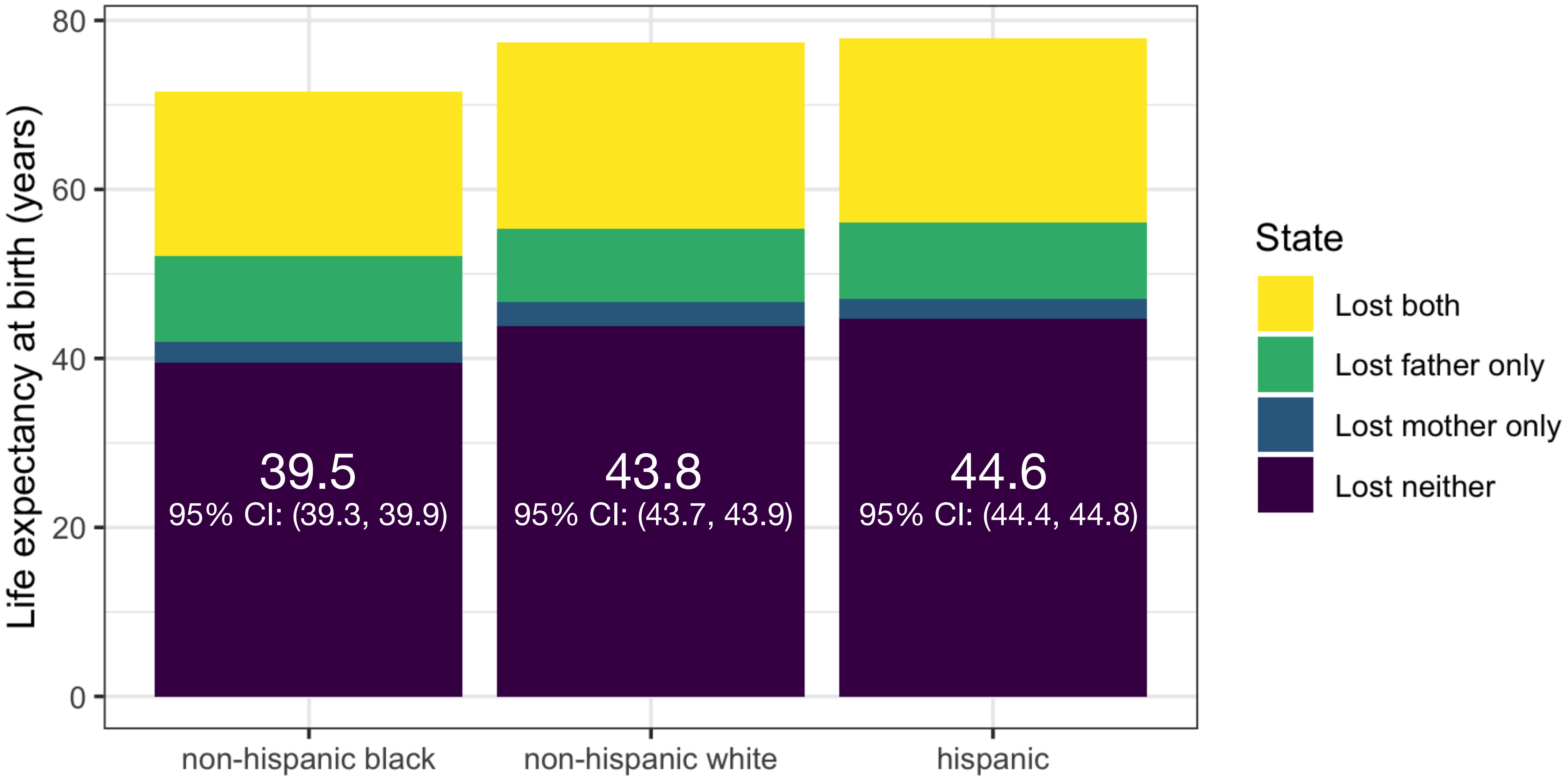
- The resulting posterior estimates for θ_x^r are thus informed by both survey data and the projection model

Results

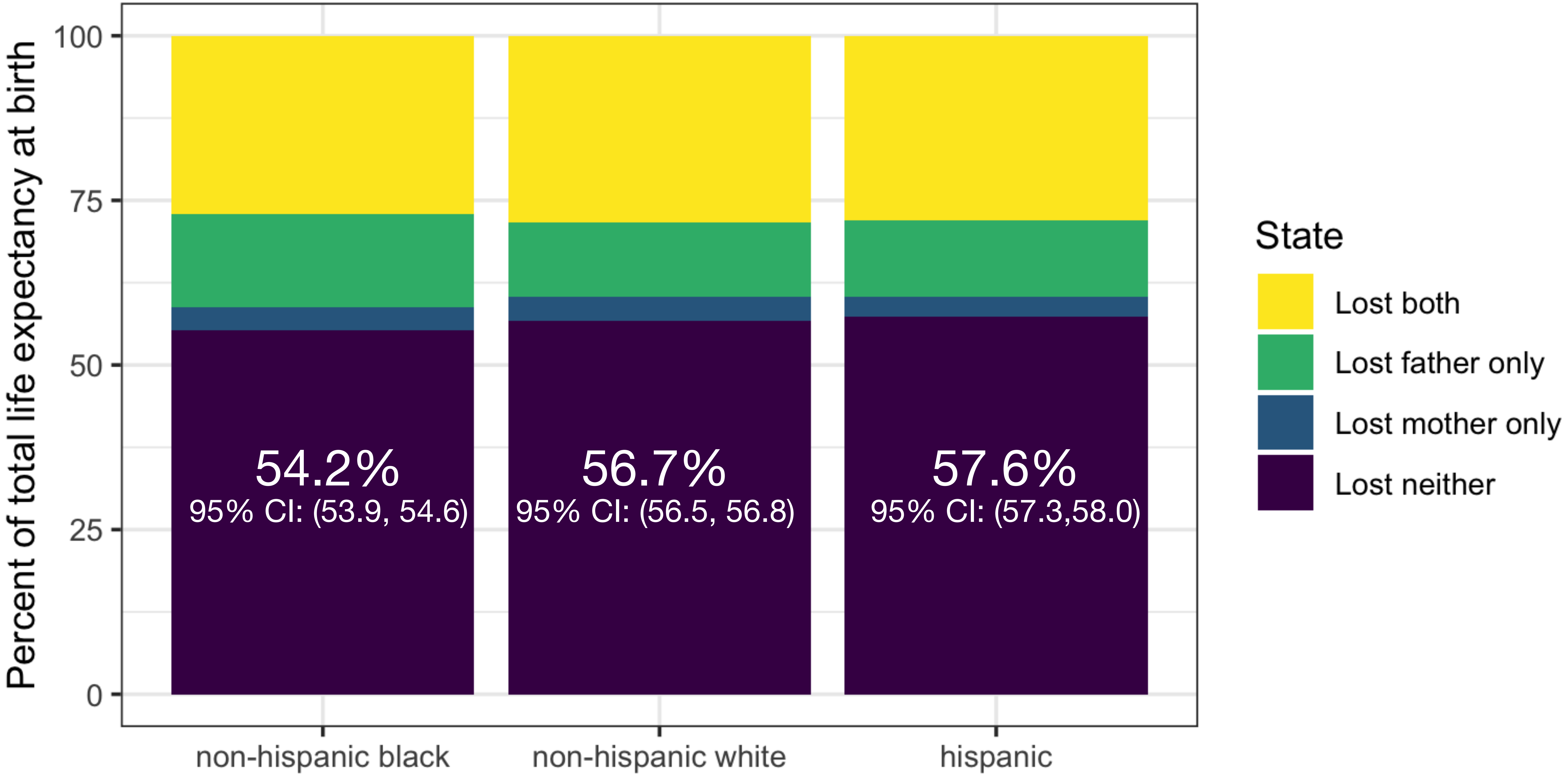
Life expectancy at birth



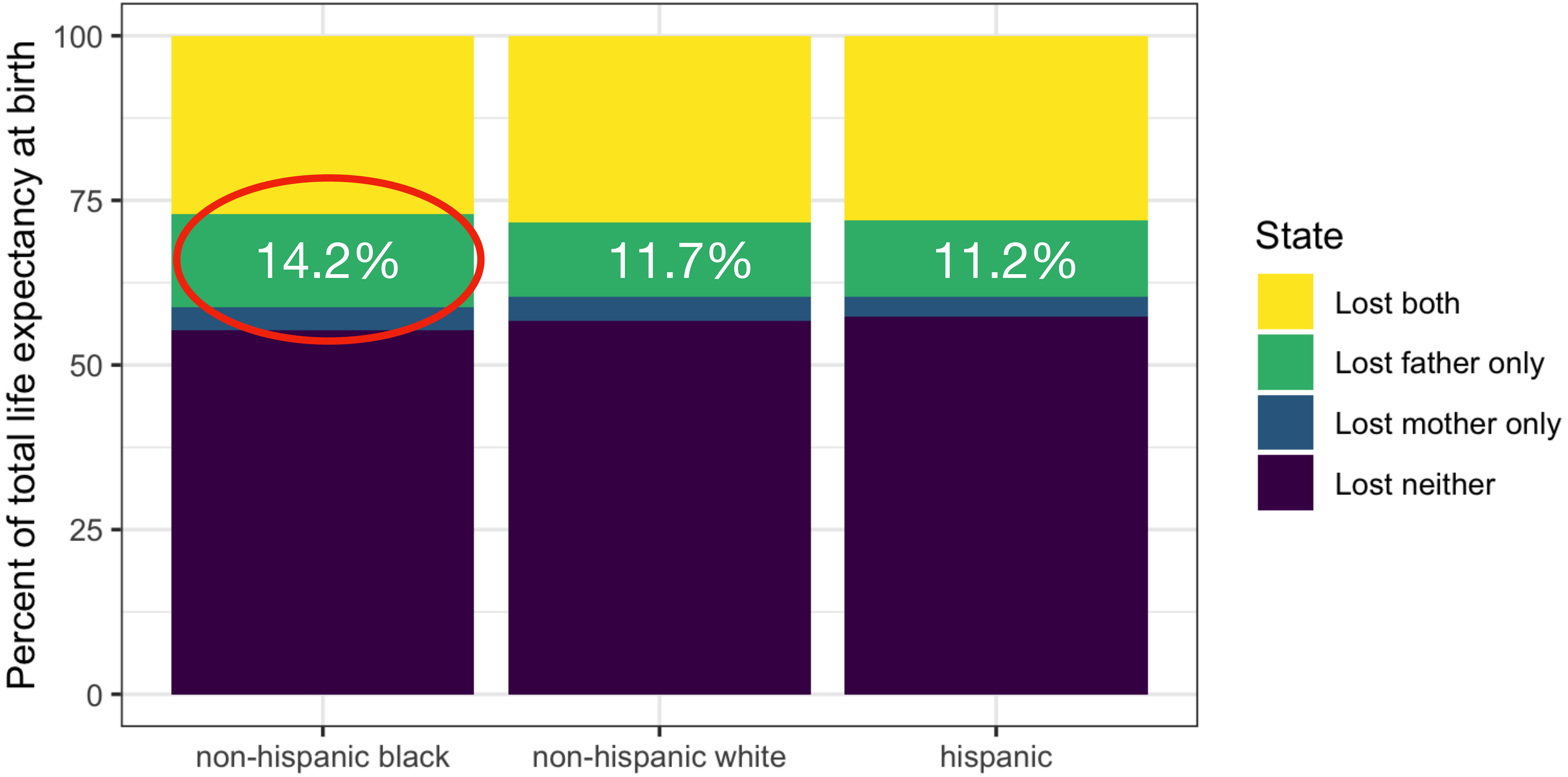
By parental loss state



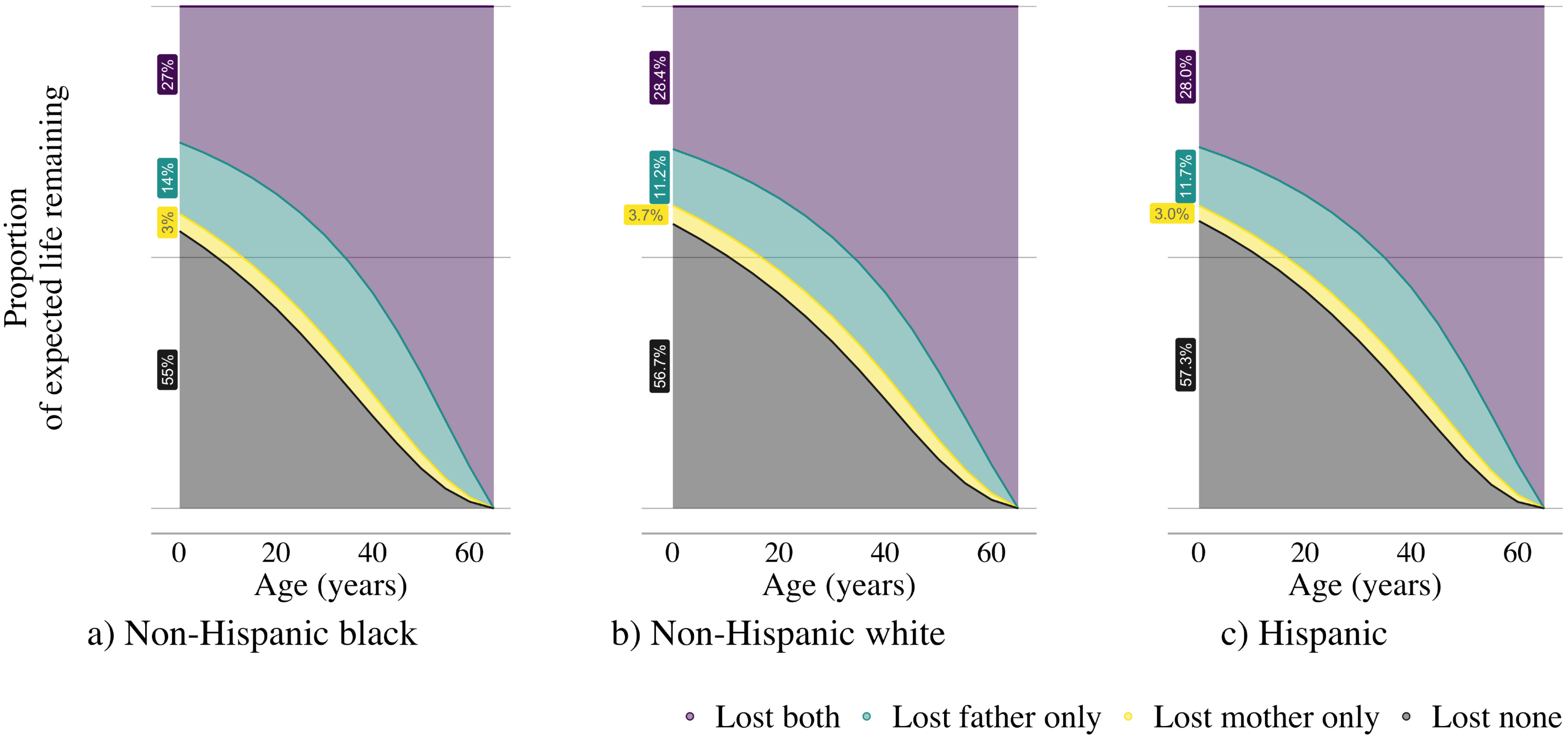
Percent of total life expectancy



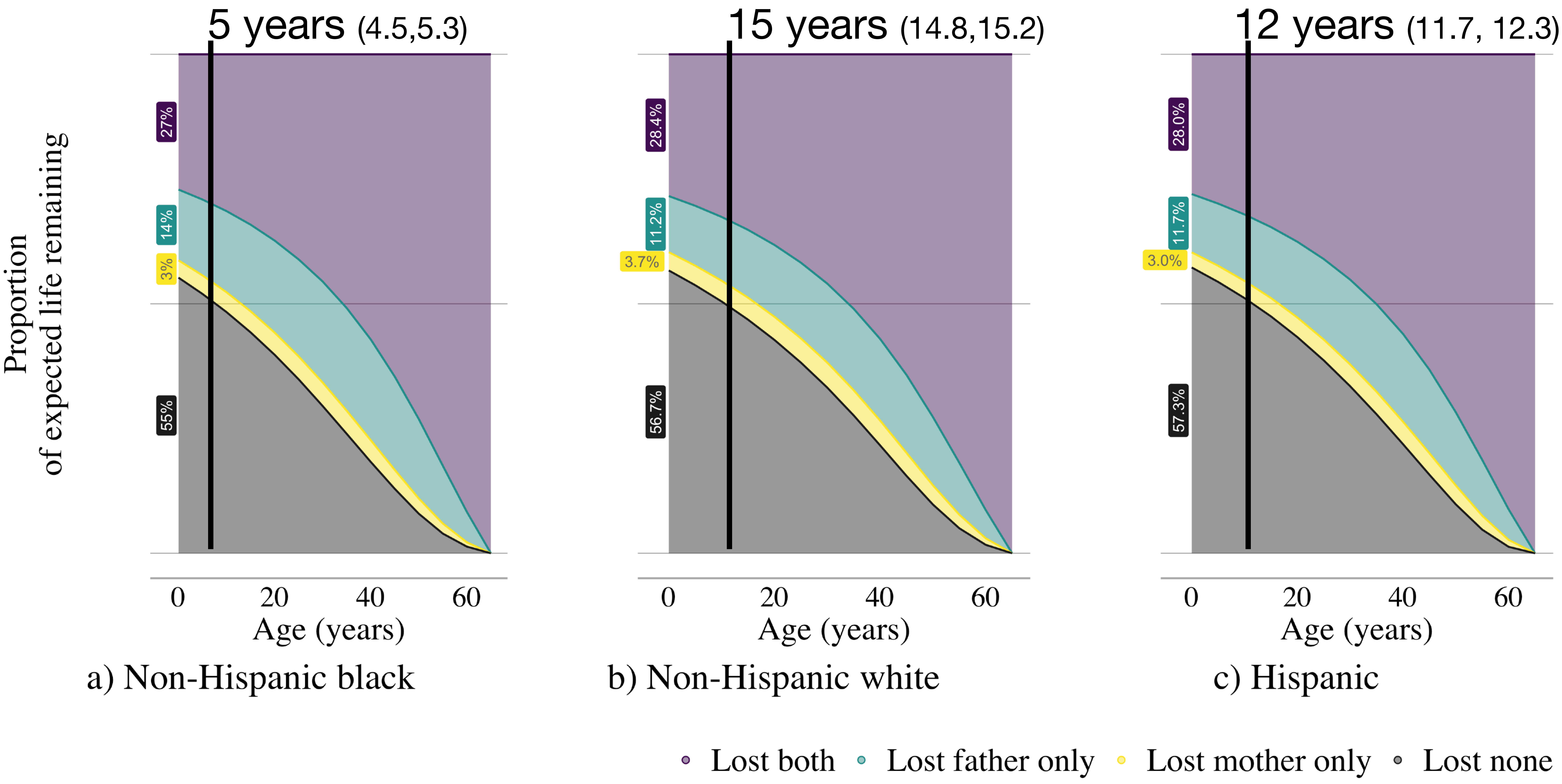
Percent of total life expectancy



Over the life course



Age at which majority of life is without both parents



Takeaways

- At birth, can expect to live 42-46% of life without at least one parent
- Black children have less time with their parents but also are expected to lose a parent at a younger age
- Biggest difference across racial/ethnic lines is loss of father: Black children can expect to live 2 years longer without their father alive, even though overall life expectancy is ~6 years shorter
- Implications for life course outcomes and transitions
- Different consequences based on timing in life course: early loss versus sandwich generation

Summary and future work

Summary

- Demographic processes link the individual to the aggregate, and back again
- Transitions in demographic rates have implications for the availability of different types of kin, which impacts individual level outcomes
- Patterns of parental loss in the United States are not constant
- Increase in premature parental loss due to traumatic causes
- Loss of a parent is racially patterned in both magnitude and timing

Estimates here help to quantify and reframe, but it’s just one piece

Future work

- Estimation and understanding in low- and middle-income countries
    - Cause of death data often comes from verbal autopies
    - Text-based methods to improve cause of death classification
- Extension of statistical models to more complex kin structures

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Thanks!

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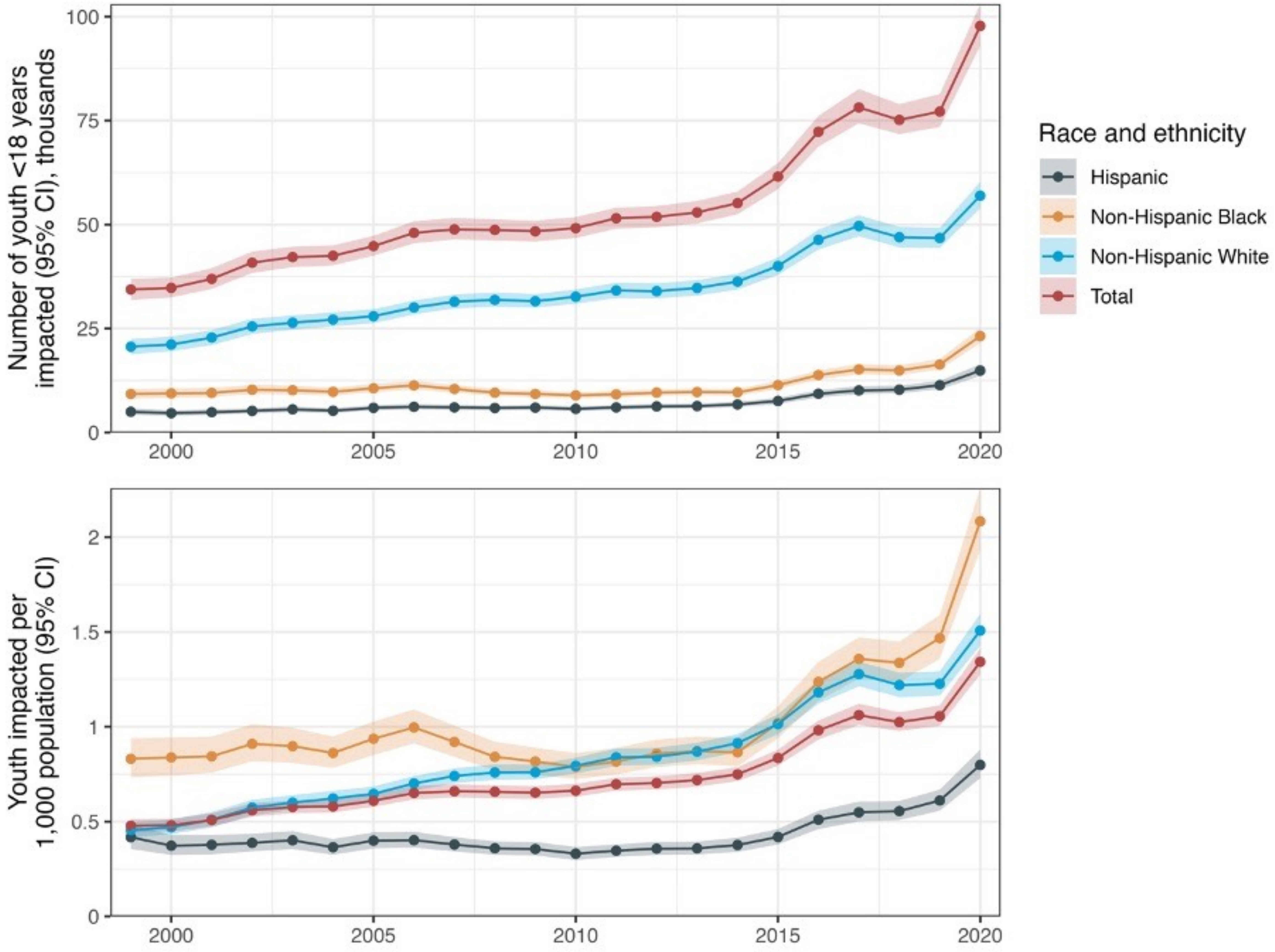
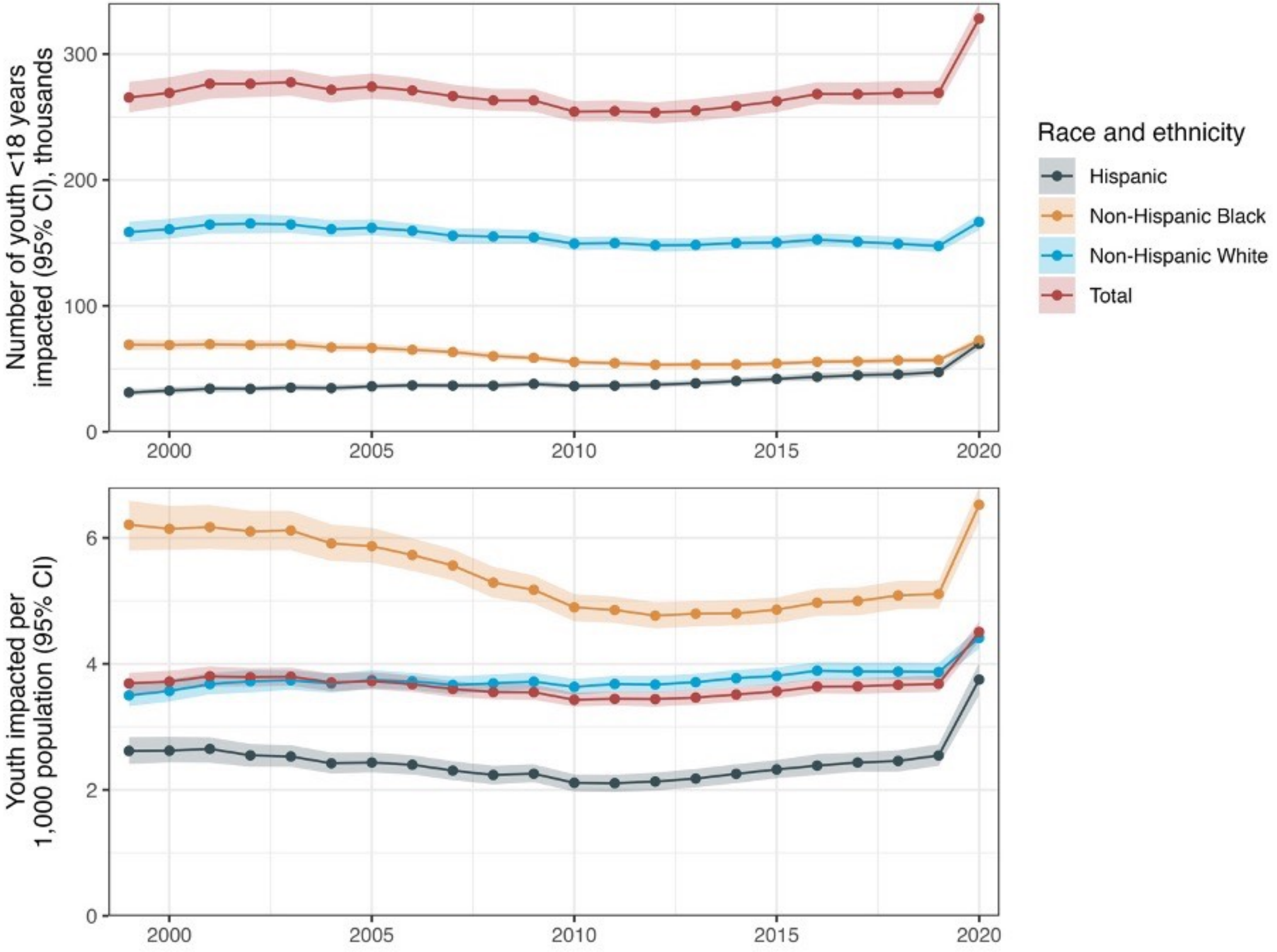
Extra

Project 1

Both causes combined

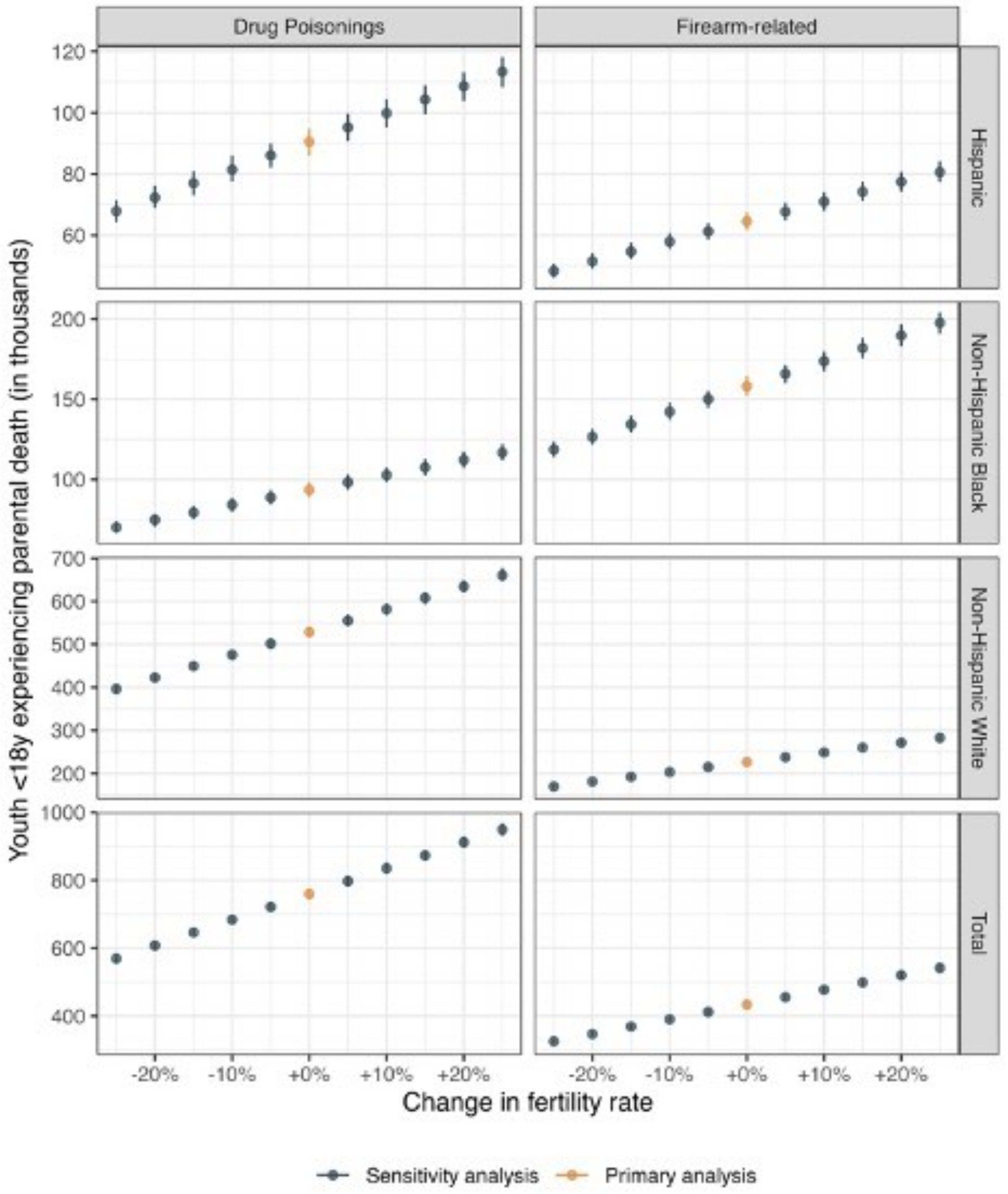


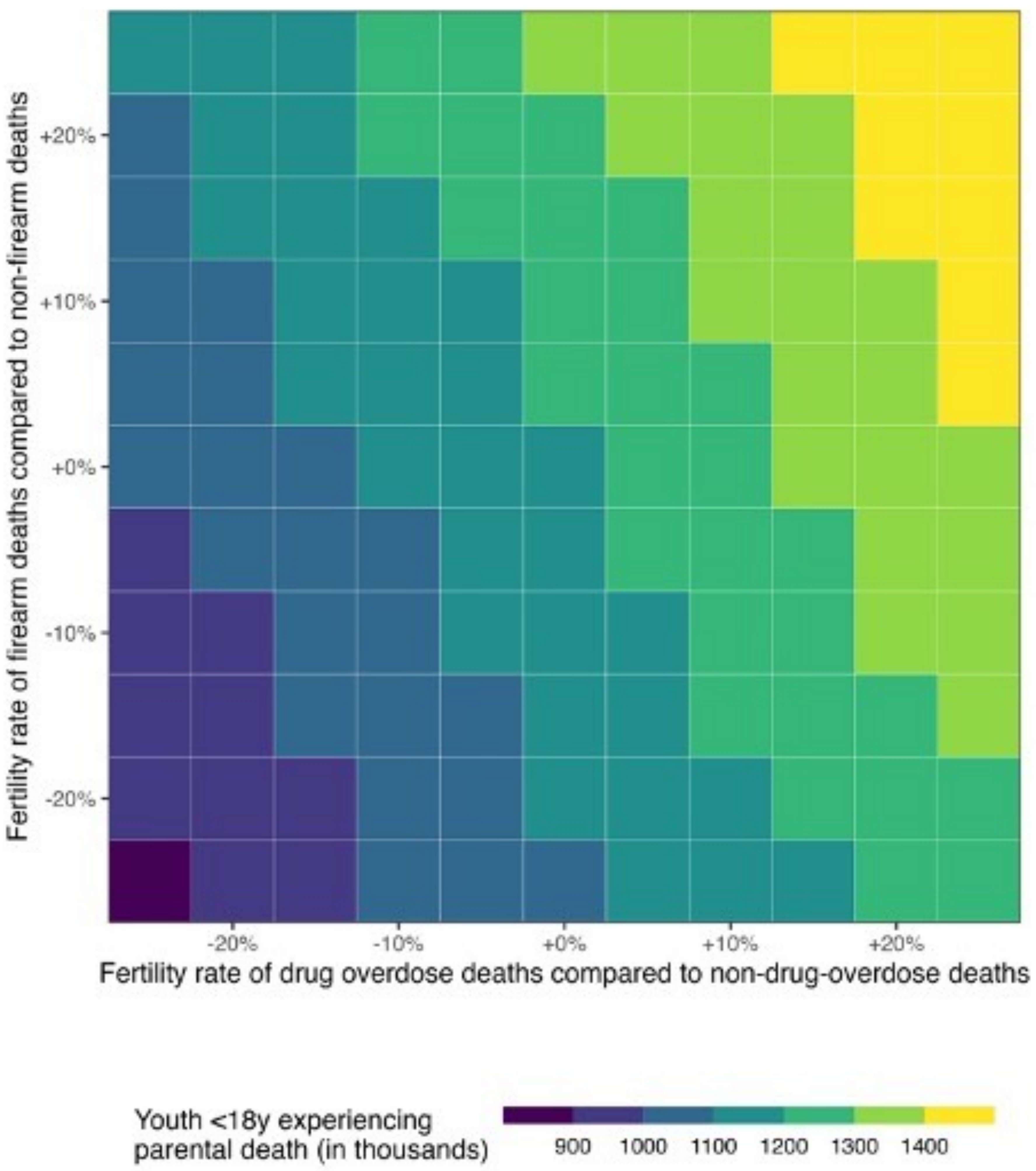
All causes



Number of youth <18 years impacted (95% CI), thousands
300
200
100
0
2000
2005
2010
2015
2020
Race and ethnicity
Hispanic
Non-Hispanic Black
Non-Hispanic White
Total
Youth impacted per 1,000 population (95% CI)
6
4
2
0
2000
2005
2010
2015
2020

Sensitivity





Expected number of living children

$$\begin{pmatrix} a^f \\ a^m \end{pmatrix}(x+1, t+1) = \begin{pmatrix} U_t^f & 0 \\ 0 & U_t^m \end{pmatrix}\begin{pmatrix} a^f \\ a^m \end{pmatrix}(x, t) + \begin{pmatrix} \bar{\alpha}F_t^f & \bar{\alpha}F_t^m \\ \alpha F_t^f & \alpha F_t^m \end{pmatrix}\begin{pmatrix} \phi^f \\ \phi^m \end{pmatrix}(x, t)$$

Quantities of interest

First, we only consider the first 18 entries of $a^f(x,t)$ and $a^m(x,t)$ reflecting the expected number of living children less than 18 years old of an individual aged x in year t, and sum these entries over both child sexes. Define this quantity to $a_{<18}(x,t)$. In any given year, we can estimate the number of children losing a parent as

$$Number\ of\ children\ <18\ yo\ experiencing\ parental\ death = \sum_{x=0}^{\omega} a_{<18}(x,t) \times D(x,t) \quad (4)$$

where $D(x,t)$ reflects the death counts of individuals aged x, in year t, from a given cause. This term can be computed by sex, giving the number of children who lost a mother (father). The probability for youth aged less than 18 years old experiencing a parental death by cause in year t, can be expressed as the ratio

$$p^g(t) = \frac{Number\ of\ children\ <18\ yo\ experiencing\ parental\ death}{Number\ of\ children\ <18\ yo} = \frac{\sum_{x=0}^{\omega} a_{<18}(x,t) \times D(x,t)}{\sum_{x=0}^{\omega} a_{<18}(x,t) \times N(x,t)}$$

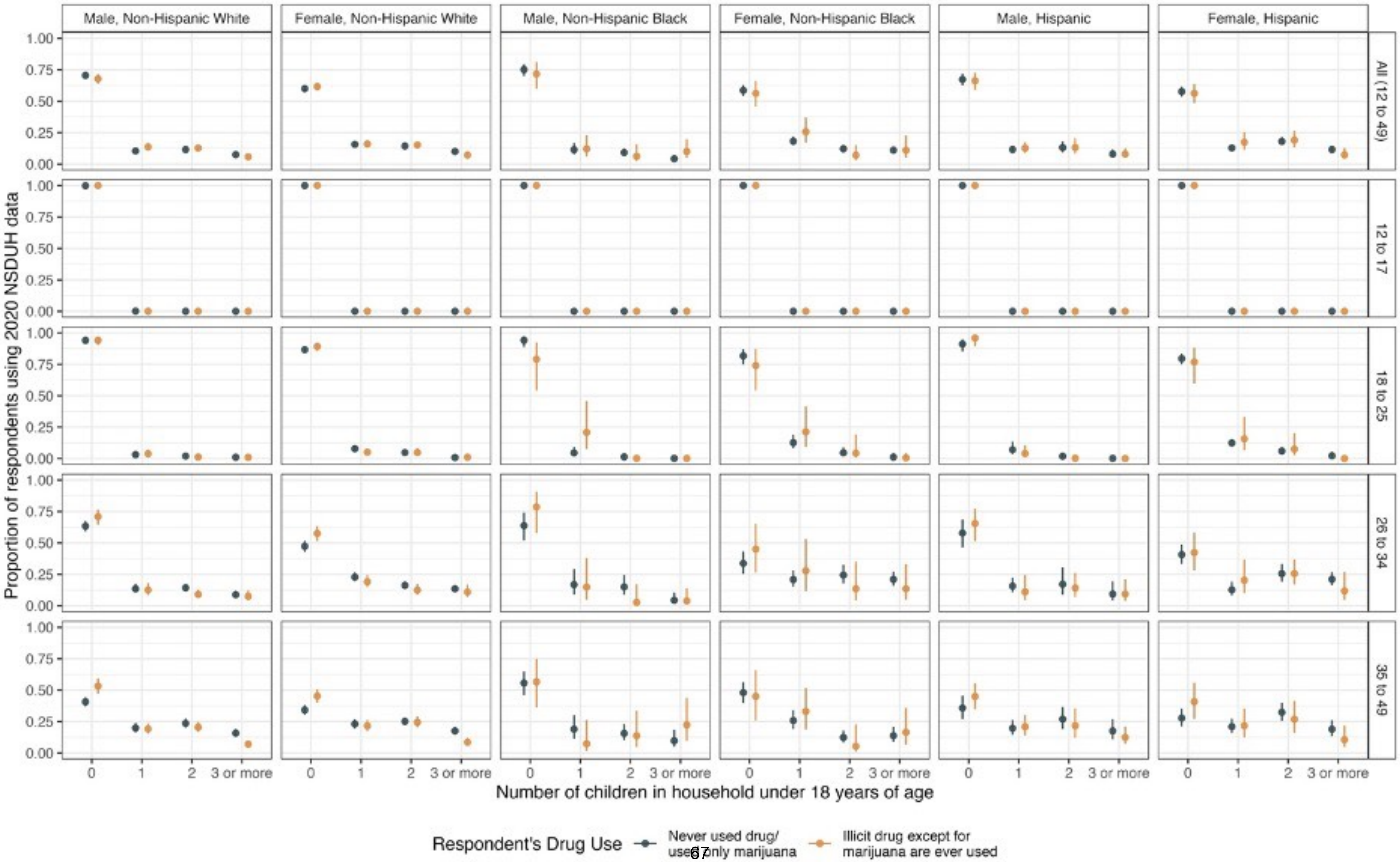
Male fertility

- Model ratio of race/ethnicity fertility to national fertility over time
- Male race/ethnicity specific fertility is:

Ratio x male national fertility x race-specific female national fertility x (male/female national fertility)

$$\hat{f}_{r,a,t} = \left(\widehat{\alpha_{a,r}} + \hat{\beta}_{a,r} t\right) \times F_{a,t} \times TFR_{r,,t} \times \frac{TFR_{M,t}}{TFR_{F,t}}$$

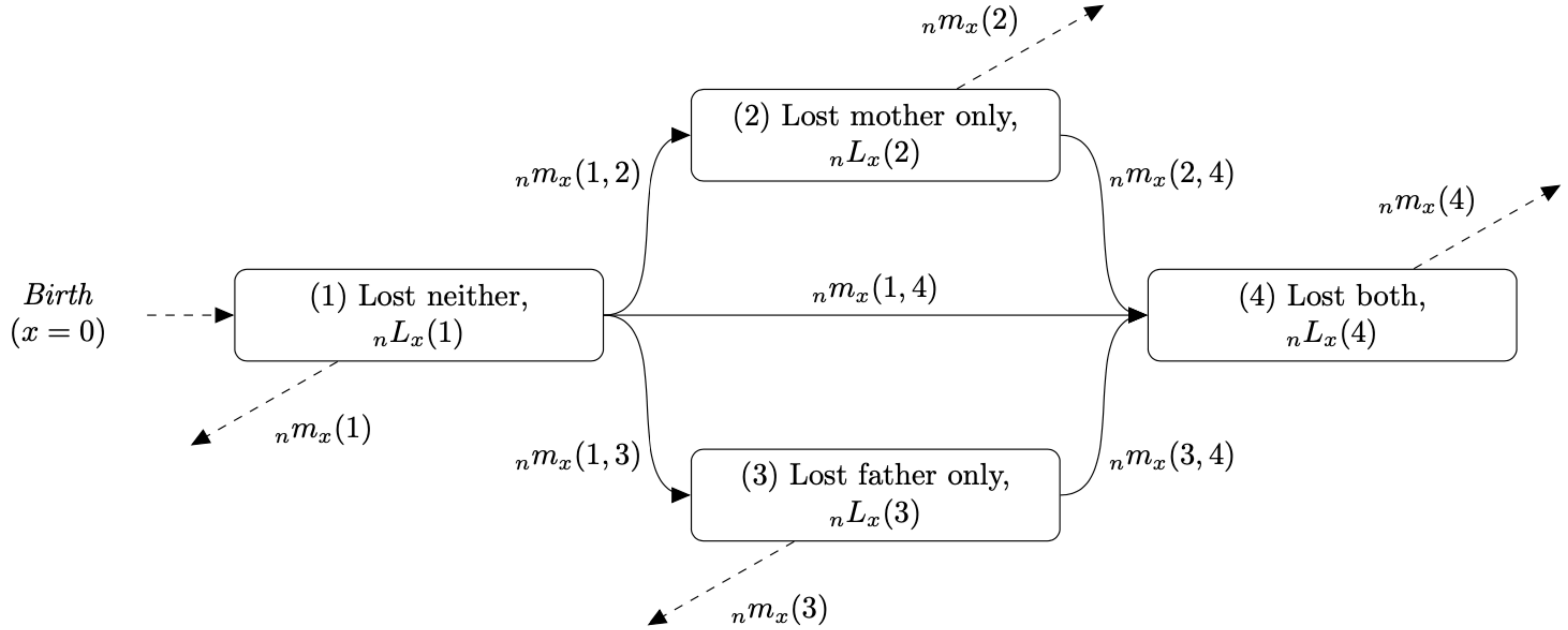
NSDUH



Male, Non-Hispanic White
Female, Non-Hispanic White
Male, Non-Hispanic Black
Female, Non-Hispanic Black
Male, Hispanic
Female, Hispanic
All (12 to 49)
12 to 17
18 to 25
26 to 34
35 to 49
Proportion of respondents using 2020 NSDUH data
1.00
0.75
0.50
0.25
0.00
0
1
2
3 or more
Number of children in household under 18 years of age
Respondent's Drug Use
Never used drug/ used only marijuana
Illicit drug except for marijuana are ever used

Project 2

States of parental loss



Multistate lifetable for parental loss

- Interested in four different states over age (lost none, lost mother, lost father, lost both)

- Partition person-years lived in each age group into person-years in each state

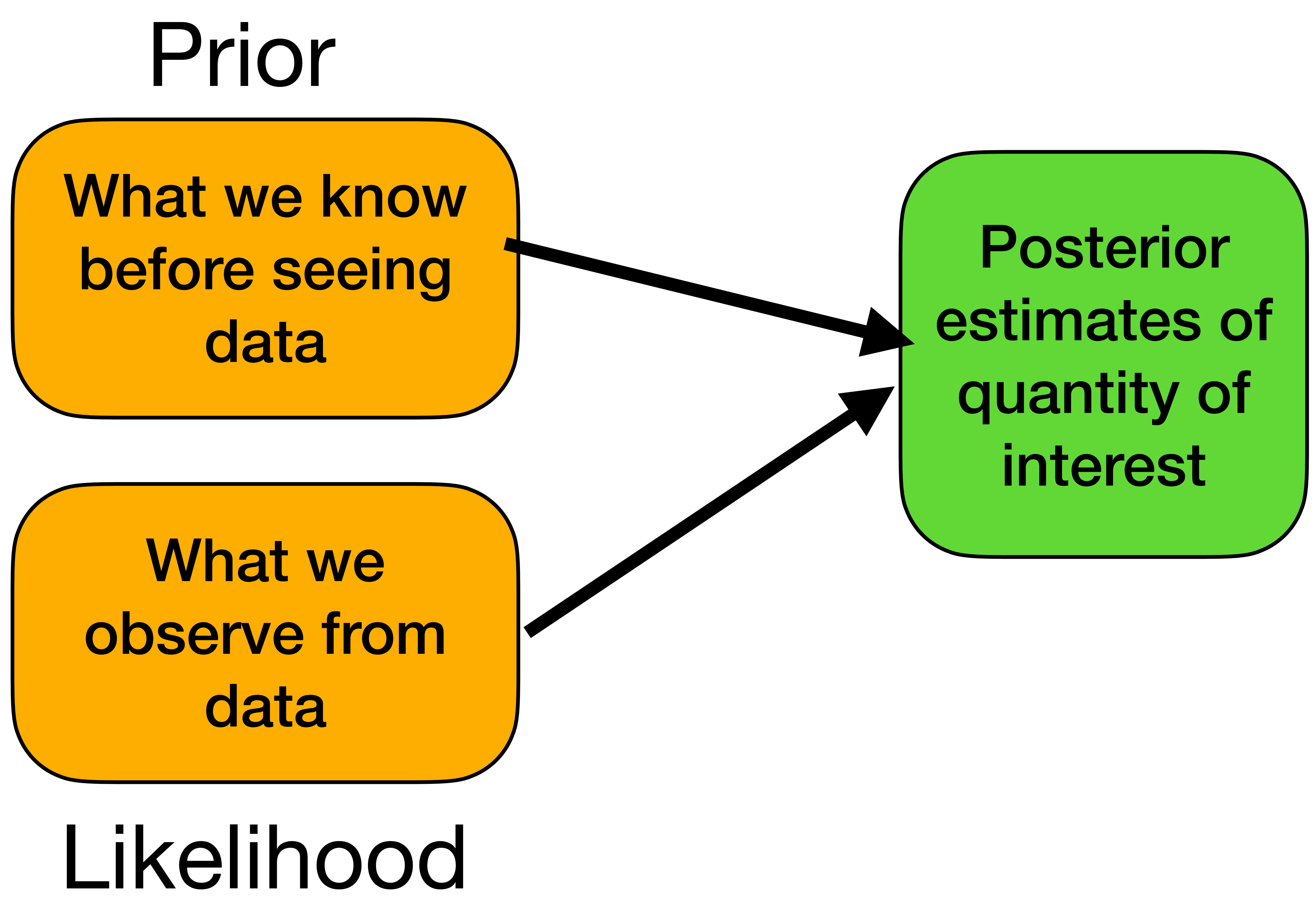
- Calculate the life expectancy lived in each state i for each age x

$$e_x(i) = \frac{\sum_{k=0n}^{\infty} L_{(x+k\cdot n)}(i)}{\ell_x} \quad \text{for } i = 1,2,3,4$$

- E.g. $e_0(1)$ is the expected number of years lived with both parents at age 0.

Using Bayesian methods to combine data sources

- Estimates of quantity of interest are a combination of the **prior** knowledge and evidence we see from data, encoded in the **likelihood**
- The **posterior** combines both of these types of evidence to give estimates of the quantity of interest
- Bayesian inference is very useful in a wide range of demographic settings:
    - Dealing with multiple data sources
    - Different types of uncertainty
    - Hierarchical structures



More model details

Data models (Likelihoods)

- Transition rates: $m_x^r(u,v) \,|\, \theta_x^r(u,v) \sim N\left(\theta_x^r(u,v), \left(SE\left(m_x^r(u,v)\right)\right)^2\right)$
- Proportions: $p_x^r(l) \,|\, \phi_x^r(l) \sim N\left(\phi_x^r(l), \left(SE\left(p_x^r(l)\right)\right)^2\right)$

Process models

- Transition rates: $\log\theta_x^r(u,v) = \alpha_{u,v,r} + \beta_{u,v,r}x$
- Proportions: $\mathrm{logit}\phi_x^r(l) = \gamma_{l,r} + \eta_{l,r}x$

More model details

Priors

- Transition rates: $\theta_x^r(\,.\,, v)\,|\,\sigma_v^2 \sim N(\hat{m}_x^r(\,.\,, v), \sigma_v^2)$ with

$$\theta_x^r(.,2) = \frac{\left(\theta_x^r(1,2) + \theta_x^r(1,4)\right) \cdot \phi_x^r(1) + \theta_x^r(3,4) \cdot \phi_x^r(3)}{\phi_x^r(1) + \phi_x^r(3)}$$ and

$$\theta_x^r(.,3) = \frac{\left(\theta_x^r(1,3) + \theta_x^r(3,4)\right) \cdot \phi_x^r(1) + \theta_x^r(2,4) \cdot \phi_x^r(2)}{\phi_x^r(1) + \phi_x^r(2)}$$

- Proportions: $\phi_x^r(\,.\,, l)\,|\,\sigma_v^2 \sim N(\hat{p}_x^r(\,.\,, l), \sigma_l^2)$ with

$\phi_x^r(.,2) = \phi_x^r(2) + \phi_x^r(4)$ and $\phi_x^r(.,3) = \phi_x^r(3) + \phi_x^r(4)$

Hyperpriors

- $\alpha, \beta, \gamma, \eta \sim N(0,1)$

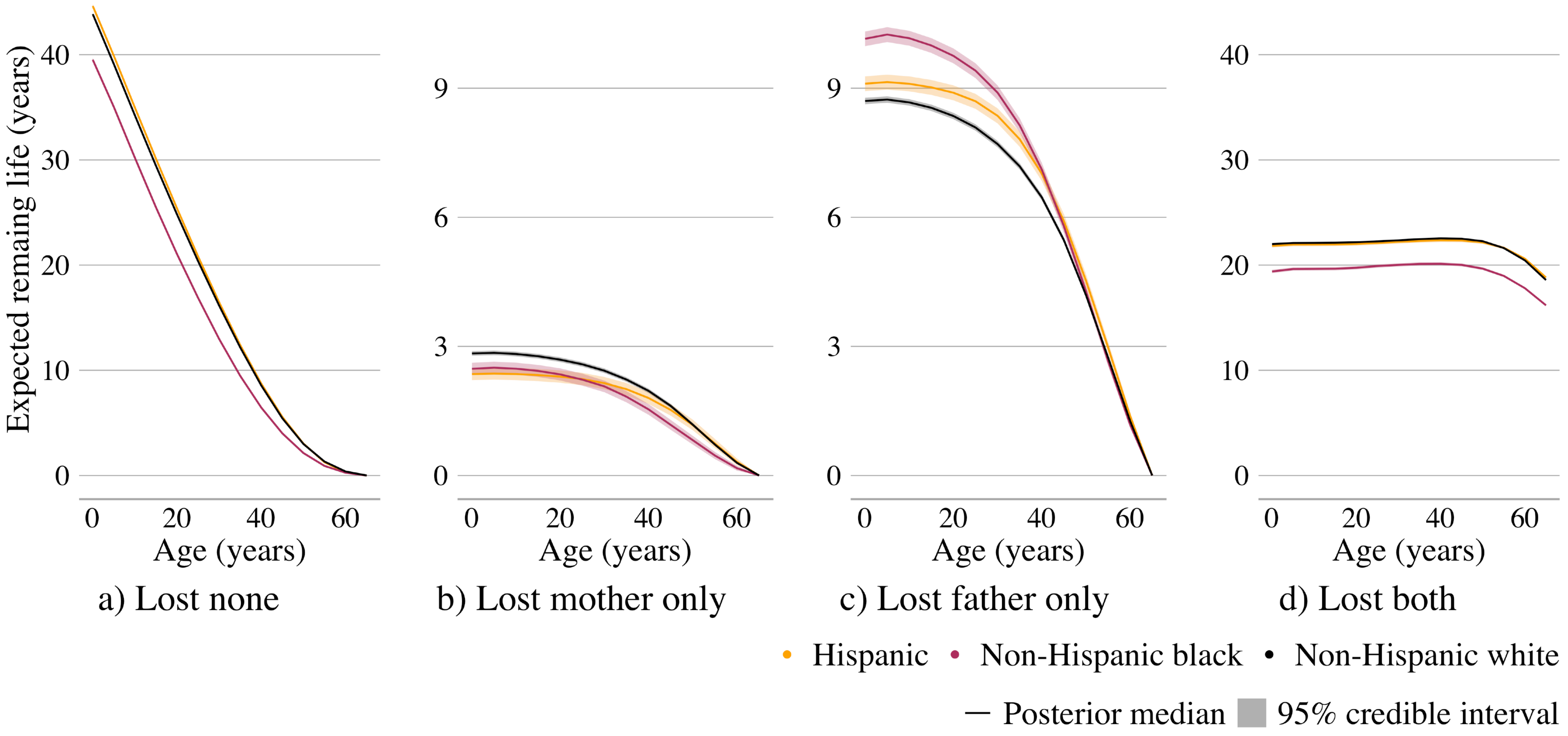
Computation

- Samples from the posterior distribution for the transition rates (and proportions) are obtained using a Markov Chain Monte Carlo (MCMC) algorithm (using Stan in R)

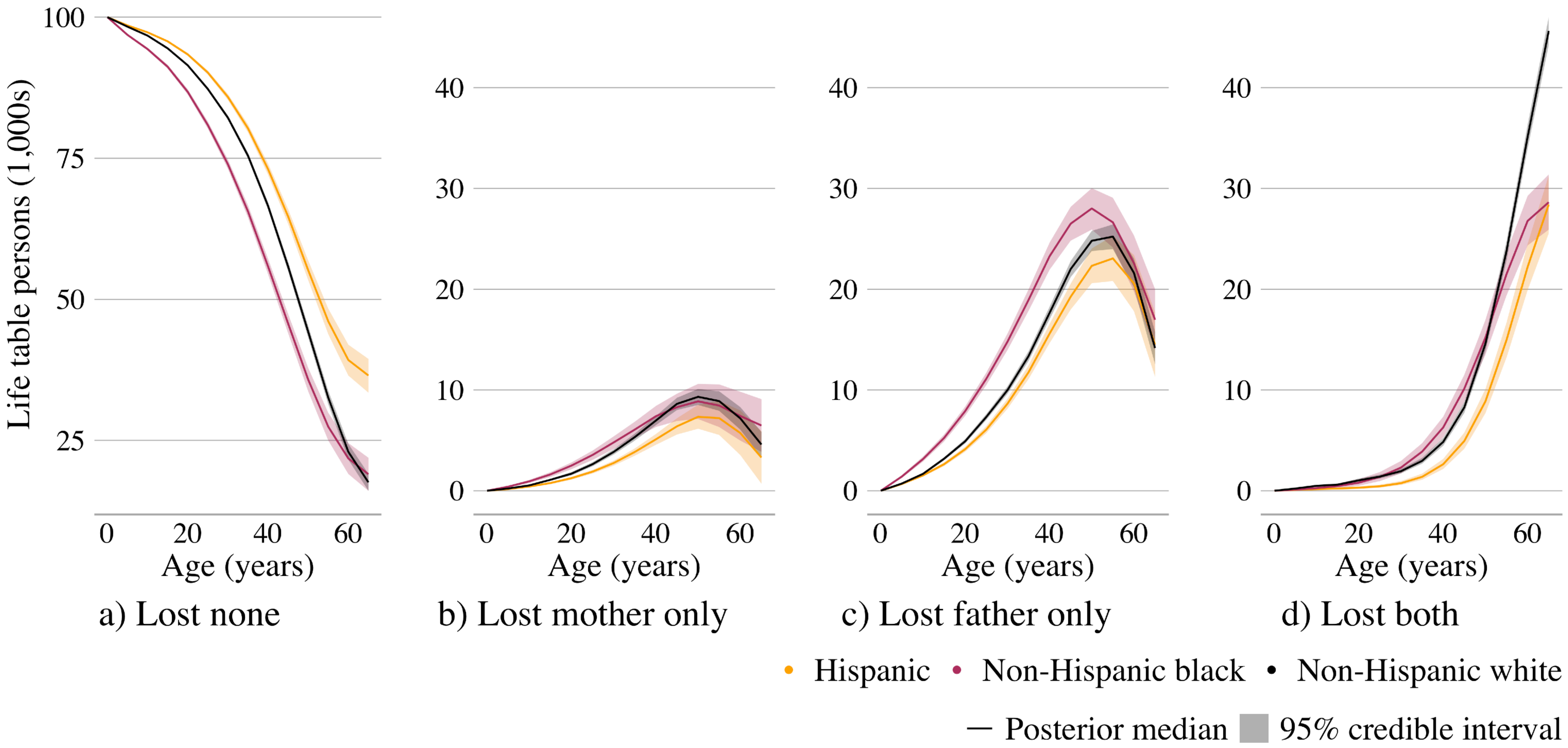
- Posterior samples for rates and proportions are then used to calculate posterior samples of multistate lifetables by parental mortality status

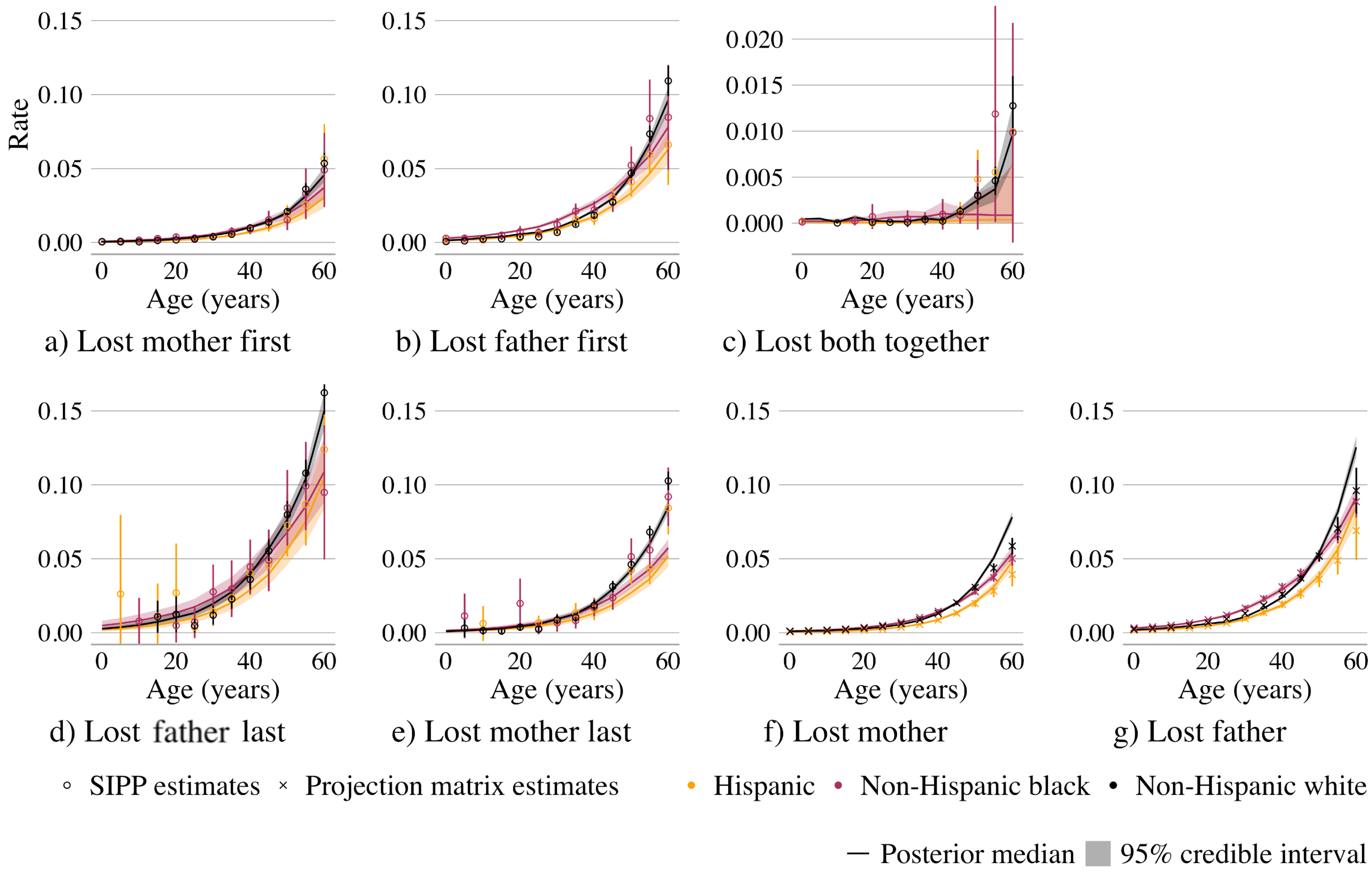
- 95% credible intervals are calculated based on the 2.5th and 97.5th percentiles

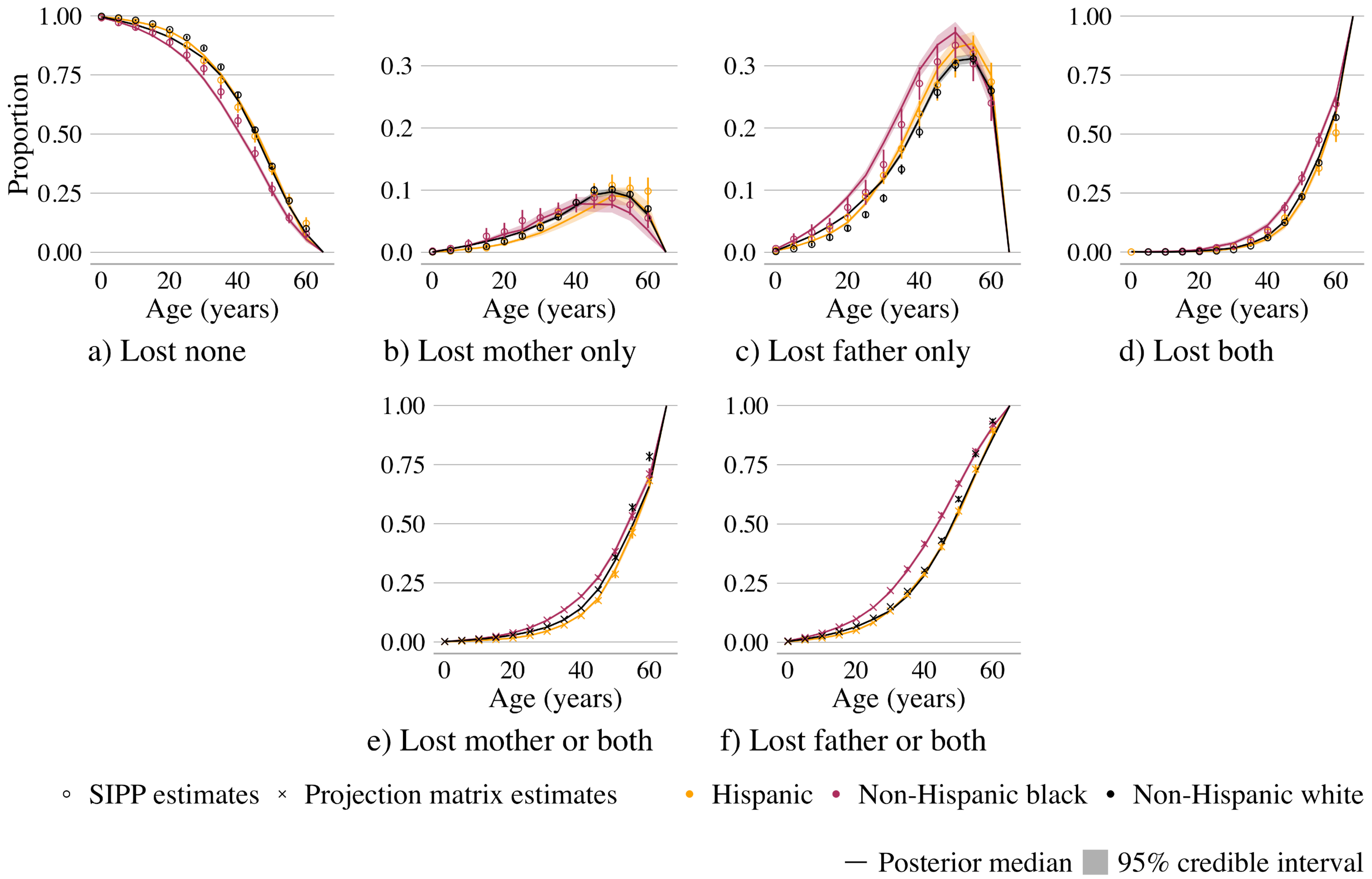
Remaining life expectancy

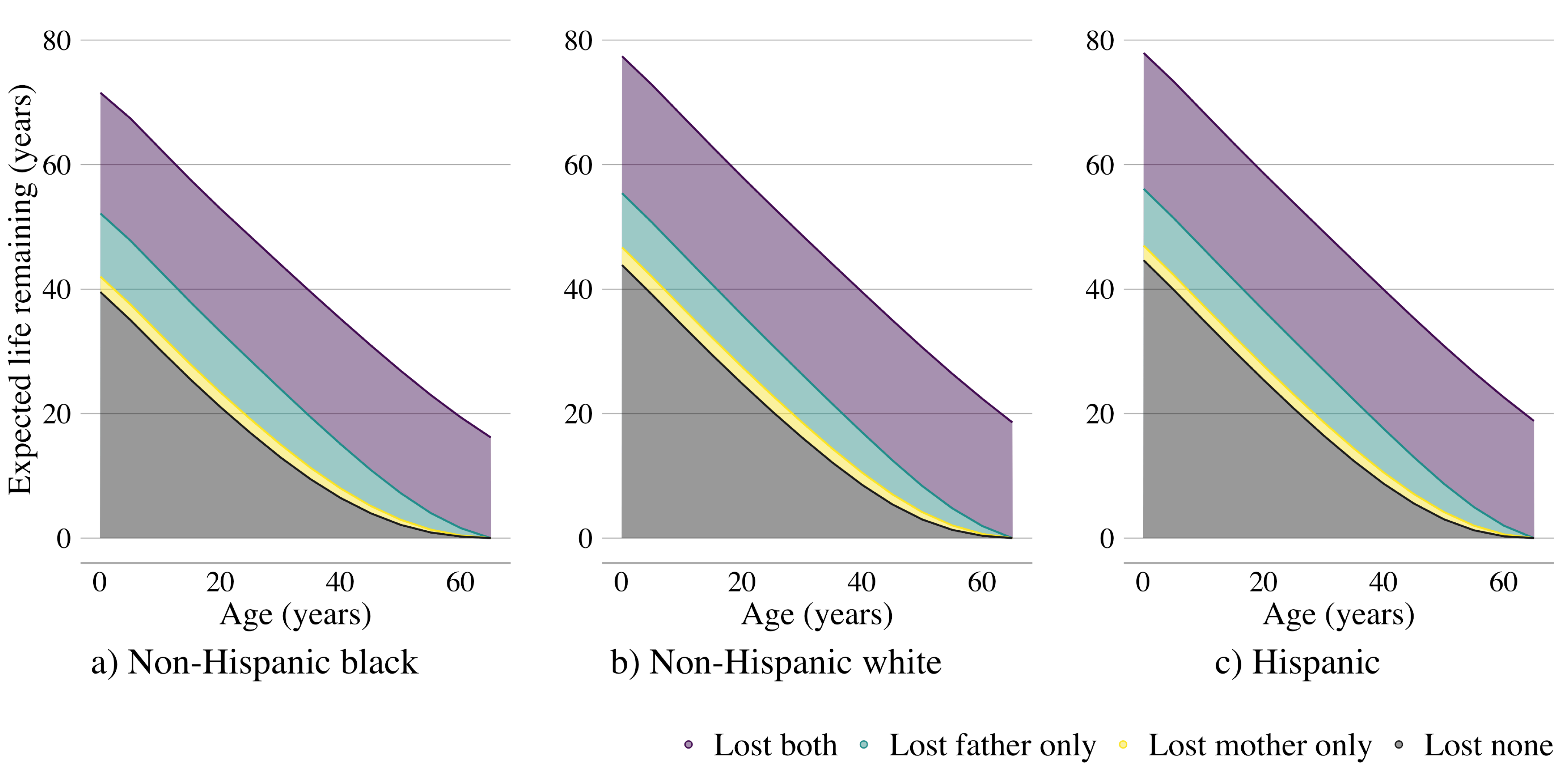


Survivors by age




Rate
0.15
0.10
0.05
0.00
0.020
0.015
0.010
0.005
0.000
0
20
40
60
Age (years)
a) Lost mother first
b) Lost father first
c) Lost both together
d) Lost father last
e) Lost mother last
f) Lost mother
g) Lost father
SIPP estimates
Projection matrix estimates
Hispanic
Non-Hispanic black
Non-Hispanic white
Posterior median
95% credible interval


Proportion
1.00
0.75
0.50
0.25
0.00
0.3
0.2
0.1
0.0
0
20
40
60
Age (years)
a) Lost none
b) Lost mother only
c) Lost father only
d) Lost both
e) Lost mother or both
f) Lost father or both
SIPP estimates
Projection matrix estimates
Hispanic
Non-Hispanic black
Non-Hispanic white
Posterior median
95% credible interval



Expected life remaining (years)
80
60
40
20
0
0
20
40
60
Age (years)
a) Non-Hispanic black
b) Non-Hispanic white
c) Hispanic
Lost both
Lost father only
Lost mother only
Lost none