

# Homework 06

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# 1 Questions

## 1.1 Q1

### 1.1.1 Q1.a

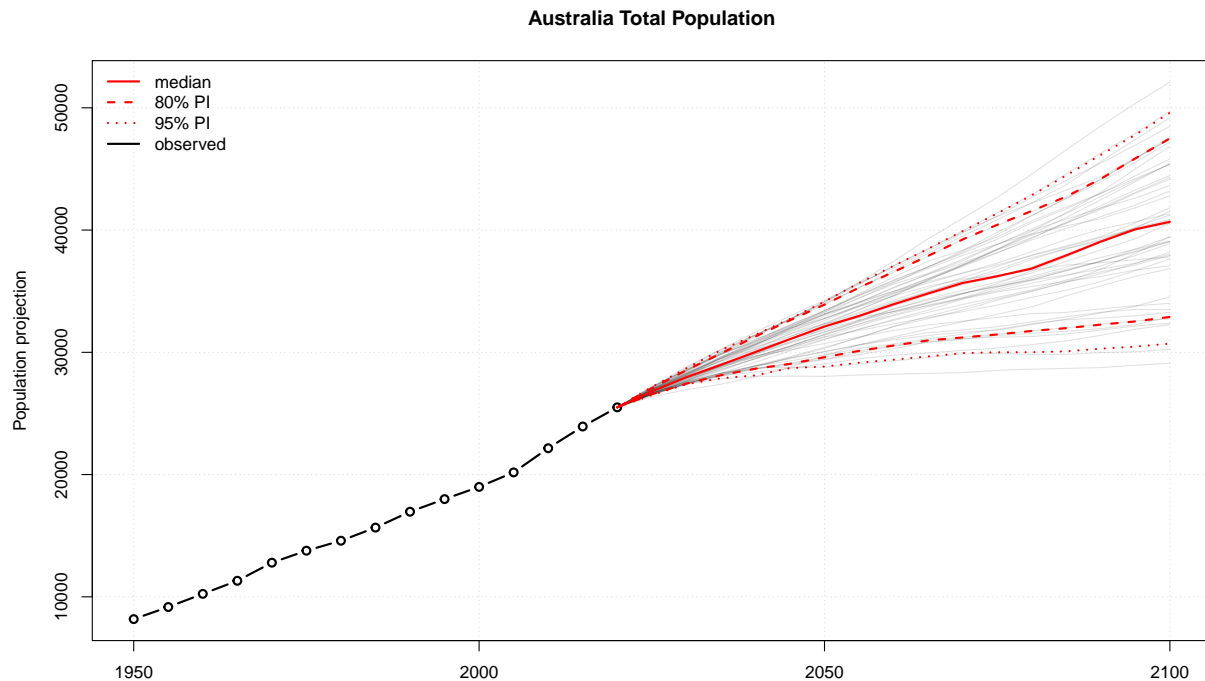
In `bayes.pop`, One can specify the quantities derived from population projections using `pop.expressions`.

As another example, the potential support ratio can be defined as “PFR[5:13] / PFR[14:27]”.  
(Ševčíková, Raftery 2016)

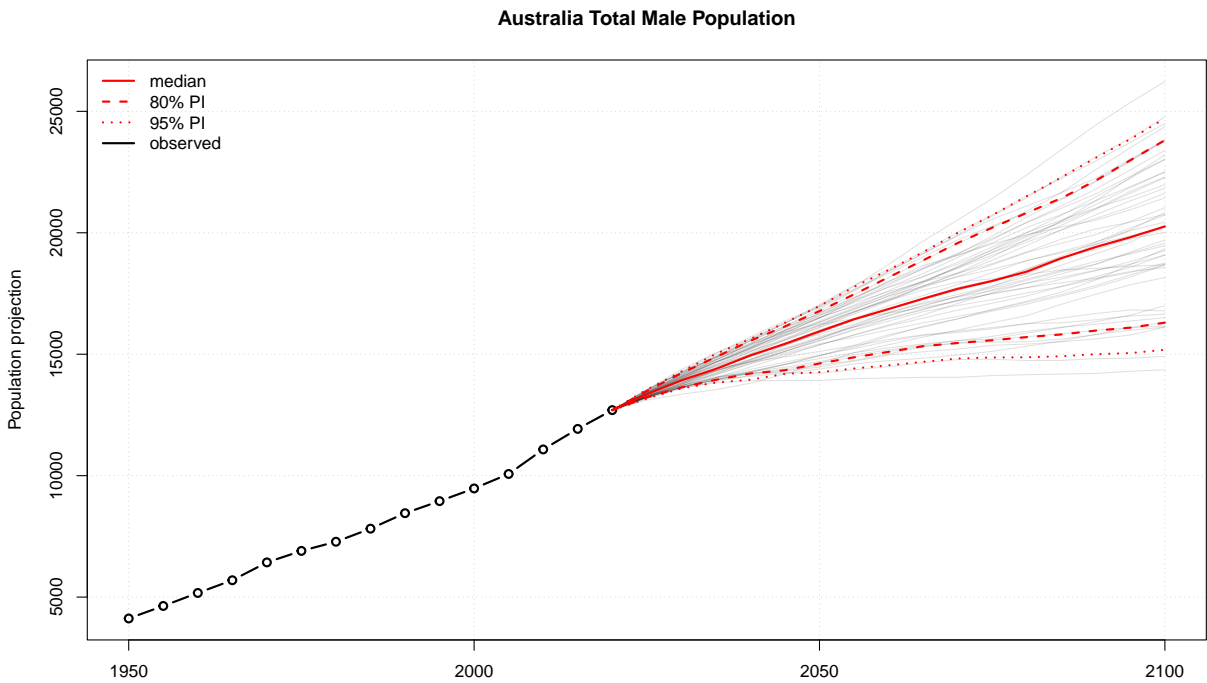
Ševčíková, H., & Raftery, A. E. (2016). bayesPop: Probabilistic Population Projections. Journal of Statistical Software, 75(5), 1–29. <https://doi.org/10.18637/jss.v075.i05>

Using our converged life expectancy at birth and total fertility rate simulations, we can create probabilistic projections of the following population quantities:

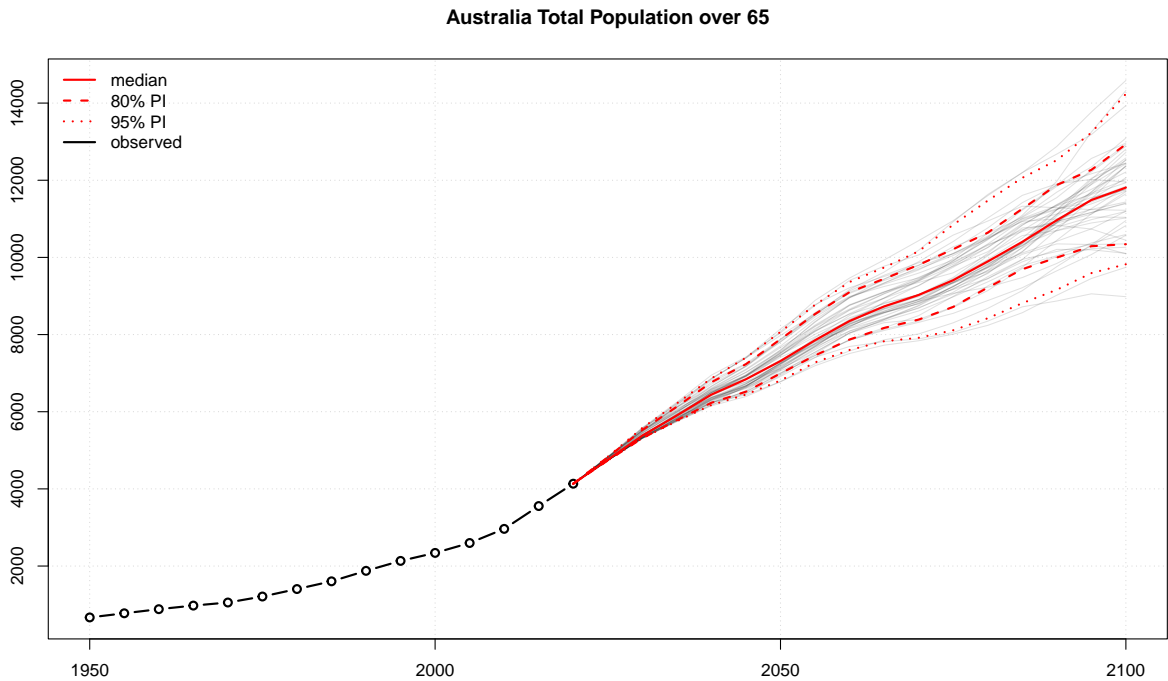
*Note that the “Potential Support Ratio” is defined as:  $\frac{\text{people aged 20-64}}{\text{people aged 65 and over}}$*



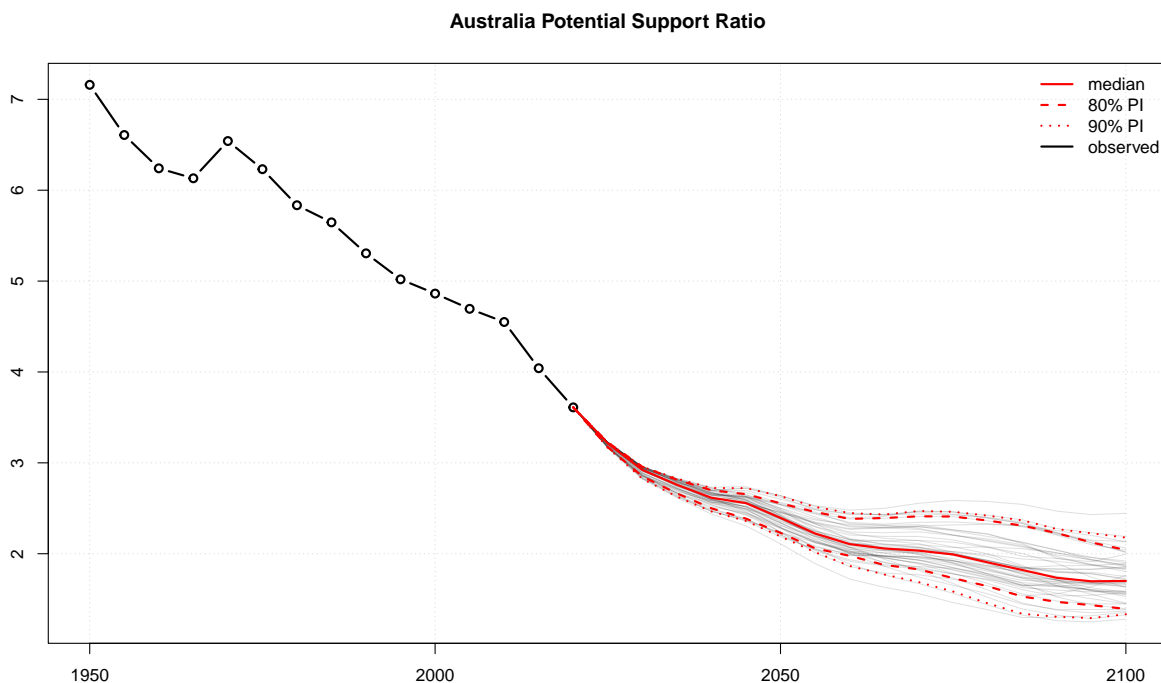
1.1.2 Q1.b



1.1.3 Q1.c



### 1.1.4 Q1.d



Looking at the projections of potential support ratio, we see continued declines into the future, though eventually at a slower rate. This indicates Australia's age structure is likely to continue shifting to older ages. From a social security perspective, this means that Australia's number of workers per retiree is going to decrease from 2020-2100.

## 1.2 Q2

### 1.2.1 Q2.a

Table 1: Crude net migration rate (CNMR) for Australia, 1950-2100

| Period start | CNMR   |
|--------------|--------|
| 1950         | 9.134  |
| 1955         | 8.235  |
| 1960         | 7.132  |
| 1965         | 13.377 |
| 1970         | 3.908  |
| 1975         | 3.325  |
| 1980         | 5.997  |
| 1985         | 8.021  |
| 1990         | 4.018  |
| 1995         | 4.201  |
| 2000         | 6.018  |
| 2005         | 11.441 |

| Period start | CNMR  |
|--------------|-------|
| 2010         | 8.587 |
| 2015         | 6.403 |

### 1.2.2 Q2.b

I fit an order 1 autoregressive model to the subset of Australia Crude Net Migration Rates obtained from UN, and extract some model parameters below. *Note that the AR(1) model was fit using the “mle” method.*

Table 2: AR(1) Model for Australia CNMR, 1950-2020

| Model 1   |                    |
|-----------|--------------------|
| ar1       | 0.07 [−0.45, 0.58] |
| intercept | 7.13 [5.56, 8.71]  |
| Num.Obs.  | 14                 |
| AIC       | 74.8               |
| BIC       | 76.7               |
| Log.Lik.  | −34.385            |

### 1.2.3 Q2.c

Using these model parameters, we can find an analytic solution for the predictive probability distribution of net migration rates in Australia for 2020-2025, which takes the form:

$$(F_{t+1} - \mu) = \rho * (F_t - \mu) + \epsilon$$

$$\sigma^2 = \frac{\sum_{i=1}^N (\hat{y}_i - y_i)^2}{N}$$

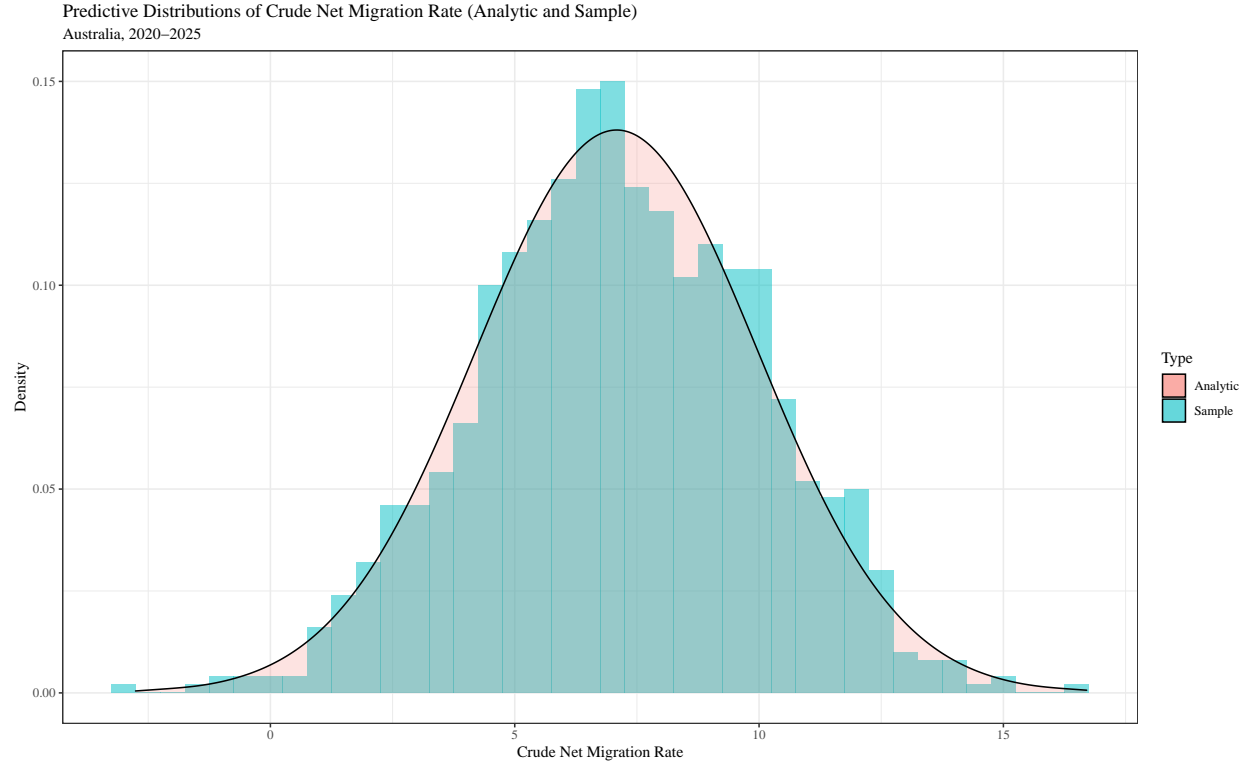
- $\sigma^2 = 7.9562007$
- $F_{2020} = 7.0860154$

Table 3: Predictive Distribution of Australia Crude Net Migration Rate, 2020-2025

| Mean  | Median | 2.5% CI | 97.5% CI |
|-------|--------|---------|----------|
| 7.086 | 7.086  | 1.557   | 12.615   |

### 1.2.4 Q2.d

We can also sample from this distribution to show it does indeed follow what we predict analytically:



### 1.2.5 *Q2.e*

Assuming that age and sex distribution of migrants has not changed from 2012, which is the last time the UN reported age/sex-specific net migration rates.

Based on age distribution of net migration stocks in 2012, I decomposed the projected migration rate for 2020 by age groups using the formula:

$$\text{ASMR}_{20} = \text{PASMR}_{12} * \text{CNMR}_{20}$$

Table 4: Predicted Age-specific Migration Rates (ASMR) for Australia, 2020-2025

| Age Grop | PASMR | ASMR  |
|----------|-------|-------|
| 0-4      | 0.11  | 0.76  |
| 5-9      | 0.10  | 0.69  |
| 10-14    | 0.10  | 0.74  |
| 15-19    | 0.12  | 0.87  |
| 20-24    | 0.14  | 0.97  |
| 25-29    | 0.13  | 0.93  |
| 30-34    | 0.12  | 0.82  |
| 35-39    | 0.09  | 0.65  |
| 40-44    | 0.06  | 0.42  |
| 45-49    | 0.03  | 0.22  |
| 50-54    | 0.01  | 0.07  |
| 55-59    | 0.00  | 0.01  |
| 60-64    | 0.00  | -0.02 |
| 65-69    | 0.00  | -0.02 |
| 70-74    | 0.00  | -0.01 |
| 75-79    | 0.00  | 0.00  |
| 80-84    | 0.00  | 0.00  |
| 85-89    | 0.00  | 0.00  |
| 90-94    | 0.00  | 0.00  |
| 95-99    | 0.00  | 0.00  |
| 100+     | 0.00  | 0.00  |

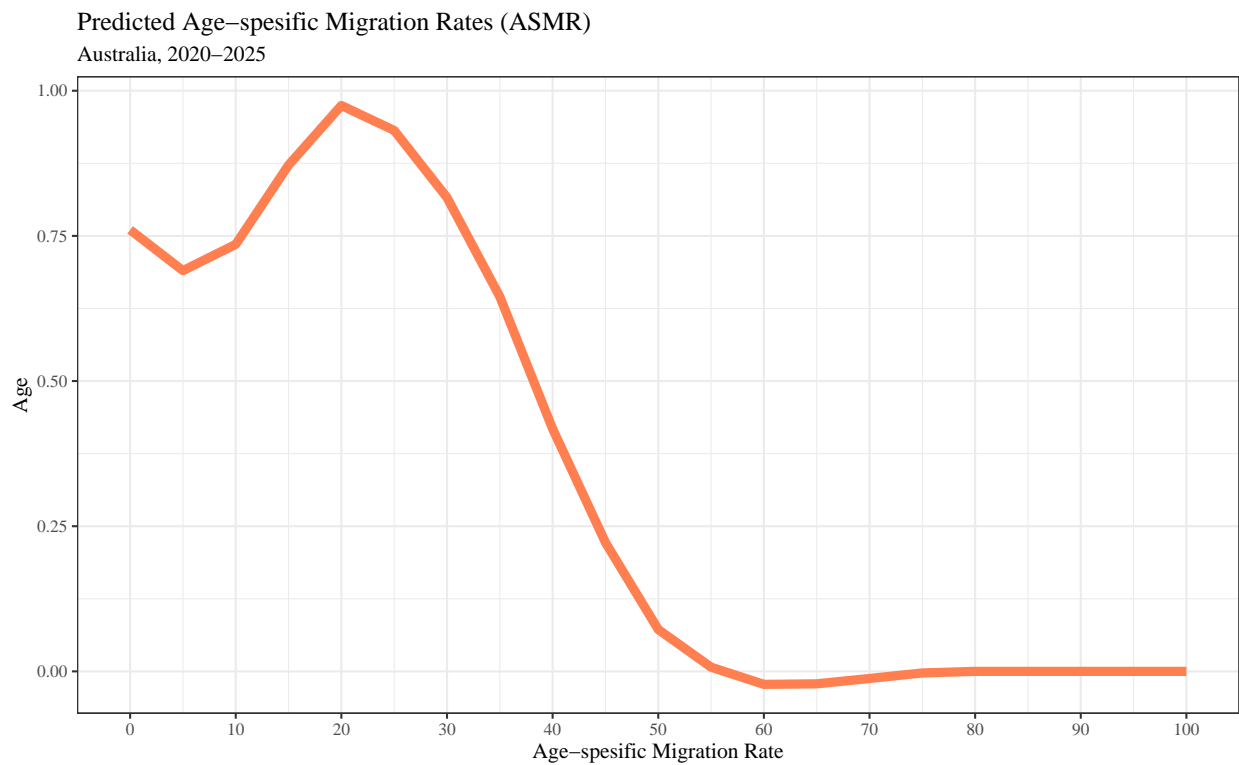


Table 5: Rogers-Castro Model Age-specific Migration Rates (ASMR) for Australia, 2020-2025

| Age Grop | ASMR |
|----------|------|
| 0-4      | 0.13 |
| 5-9      | 0.09 |
| 10-14    | 0.06 |
| 15-19    | 0.08 |
| 20-24    | 0.23 |
| 25-29    | 0.21 |
| 30-34    | 0.15 |
| 35-39    | 0.10 |
| 40-44    | 0.07 |
| 45-49    | 0.05 |
| 50-54    | 0.04 |
| 55-59    | 0.03 |
| 60-64    | 0.03 |
| 65-69    | 0.02 |
| 70-74    | 0.02 |
| 75-79    | 0.02 |
| 80-84    | 0.02 |
| 85-89    | 0.02 |
| 90-94    | 0.02 |
| 95-99    | 0.02 |
| 100+     | 0.02 |

### 1.2.6 *Q2e* Alternative

Migration schedules without a retirement peak may be represented by a “reduced” model with seven parameters, because in such instances the *post-labor force* component of the model is omitted (Rogers & Castro 1981). The simplified 7 parameter model:

$$M(x) = a_1 e^{-\alpha_1 x} + a_2 e^{-\alpha_2(x-\mu) - e^{-\lambda(x-\mu)}} + c$$

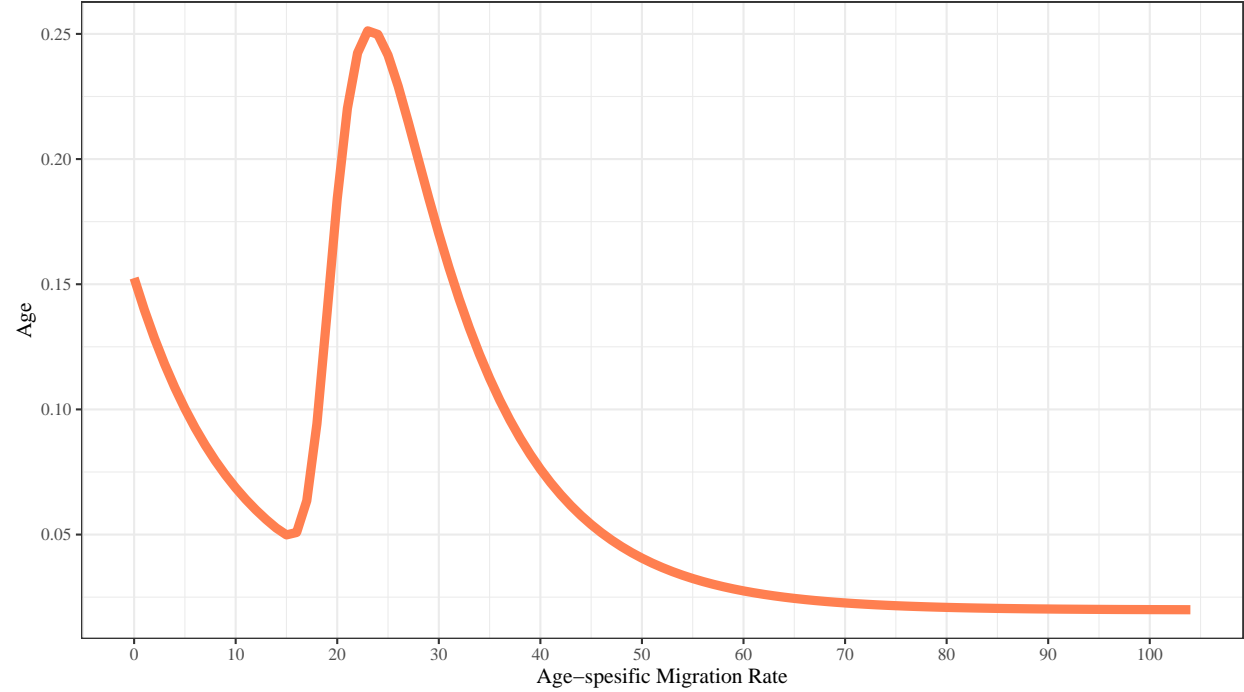
`migest` package provides fundamental parameters for Rogers-Castro migration schedule. I plug them into the equation above:

$$M(x) = 0.02e^{-0.1x} + 0.06e^{-0.1(x-20) - e^{-0.4x-20}} + 0.003$$

The result is modeled age schedule for migration rates. Hence, if we multiply the resulting vector with the predicted migration rate for 2020-2025, we get age-specific migration rates for 2020-2025. We need to standardize the output so that it sums to 1.



Rogers–Castro Model Age-specific Migration Rates (ASMR)  
Australia, 2020–2025

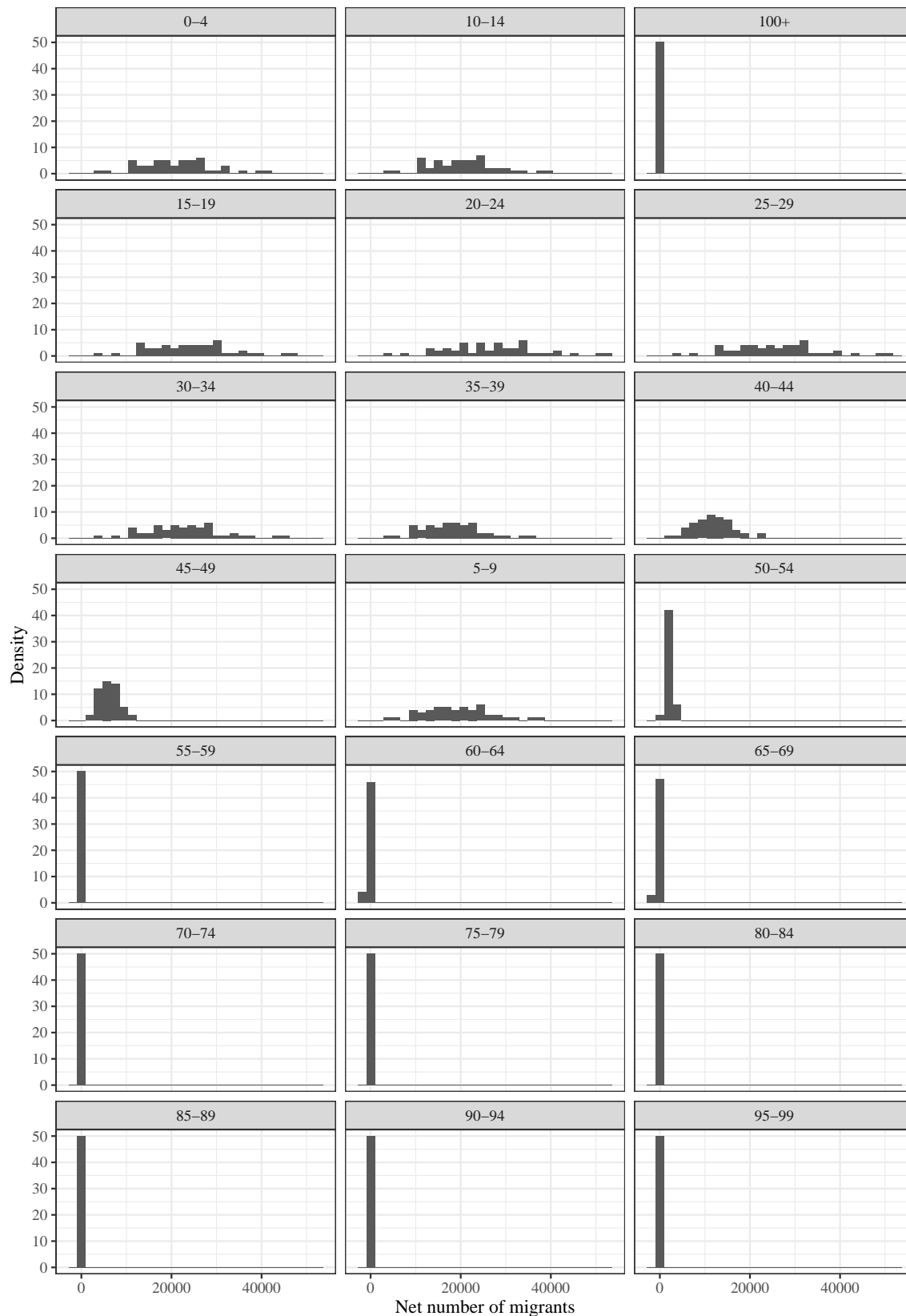


### 1.2.7 *Q2.f*

For this question, I created 50 different migration rate estimates for 2025 based on the AR(1) model *Q2.c*. Then, using the same age schedule from *Q2.e*, I created age-specific migration rates for each sample. Here is the pseudo-equation:

$$\begin{aligned}\text{ASMR}_{2025} &= \text{TotalPop}_{2020} \times \text{NMR}_{2025} \times \text{PASM}_{2012} \\ \text{NMR}_{2025} &= N(\mu = 7.0860154, \sigma = 2.8206738)\end{aligned}$$

# Projected Age-Specific Net Migration Numbers Australia, 2020–2025



### 1.2.8 *Q2.g*

We will use the same code we used to generate population projections in *Q1*, except we will plug our migration estimates into the `pop.predict` function. `pop.predict` function has a built-in function to disaggregate total net migration into age-specific migration by applying a Rogers-Castro schedule. Hence, we only need to plug the total migration estimates for 2025.

The challenge in this question is to transform our predicted trajectories into a format that `pop.predict` function understands. Here is the relevant section from the vignette:

`migMtraj`, `migFtraj`, `migtraj` Comma-delimited CSV file with male/female age-specific migration trajectories, or total migration trajectories (`migtraj`). If present, it replaces deterministic projections given by the `mig*` items. It has a similar format as e.g. `e0M.file` with columns “LocID”, “Year”, “Trajectory”, “Age” (except for `migtraj`) and “Migration”. For a five-year simulation, the “Age” column must have values “0-4”, “5-9”, “10-14”, ..., “95-99”, “100+”. In an annual simulation, age is given by a single number between 0 and 100.

Australia Country Code: 36

Table 6: Predicted MalePopulation for Australia, 2020-2025

| Age     | Median | 2.5% PI | 97.5 PI |
|---------|--------|---------|---------|
| 0-4     | 817.36 | 648.97  | 992.38  |
| 5-9     | 889.81 | 889.81  | 889.97  |
| 10-14   | 874.63 | 874.63  | 874.73  |
| 15-19   | 863.87 | 863.87  | 864.07  |
| 20-24   | 817.81 | 817.81  | 818.20  |
| 25-29   | 848.48 | 848.48  | 848.97  |
| 30-34   | 941.95 | 941.95  | 942.54  |
| 35-39   | 964.47 | 964.46  | 965.22  |
| 40-44   | 935.42 | 935.42  | 936.44  |
| 45-49   | 813.85 | 813.85  | 815.19  |
| 50-54   | 824.41 | 824.41  | 826.54  |
| 55-59   | 756.04 | 756.03  | 759.10  |
| 60-64   | 746.22 | 746.21  | 750.96  |
| 65-69   | 663.26 | 663.25  | 670.00  |
| 70-74   | 559.24 | 559.22  | 568.36  |
| 75-79   | 465.68 | 465.66  | 478.11  |
| 80-84   | 291.47 | 291.44  | 303.82  |
| 85-89   | 158.28 | 158.26  | 168.23  |
| 90-94   | 63.69  | 63.68   | 68.86   |
| 95-99   | 15.33  | 15.33   | 16.66   |
| 100-104 | 1.54   | 1.54    | 1.65    |
| 105-109 | 0.05   | 0.05    | 0.05    |
| 110-114 | 0.00   | 0.00    | 0.00    |
| 115-119 | 0.00   | 0.00    | 0.00    |
| 120-124 | 0.00   | 0.00    | 0.00    |
| 125-129 | 0.00   | 0.00    | 0.00    |
| 130+    | 0.00   | 0.00    | 0.00    |

The following projections include estimated migration counts for 2025. This is for the male population by age:

This is for the female population by age:

Table 7: Predicted Female Population for Australia, 2020-2025

| Age     | Median | 2.5% PI | 97.5 PI |
|---------|--------|---------|---------|
| 0-4     | 777.14 | 617.62  | 943.11  |
| 5-9     | 844.68 | 844.64  | 844.78  |
| 10-14   | 831.95 | 831.93  | 832.01  |
| 15-19   | 823.16 | 823.12  | 823.25  |
| 20-24   | 783.85 | 783.79  | 783.99  |
| 25-29   | 822.12 | 822.06  | 822.27  |
| 30-34   | 905.34 | 905.27  | 905.54  |
| 35-39   | 962.99 | 962.88  | 963.29  |
| 40-44   | 937.72 | 937.55  | 938.18  |
| 45-49   | 824.73 | 824.48  | 825.37  |
| 50-54   | 842.92 | 842.51  | 843.98  |
| 55-59   | 782.47 | 781.88  | 783.98  |
| 60-64   | 770.09 | 769.18  | 772.39  |
| 65-69   | 707.12 | 705.80  | 710.43  |
| 70-74   | 605.20 | 603.35  | 609.83  |
| 75-79   | 516.66 | 514.03  | 523.31  |
| 80-84   | 345.36 | 342.52  | 352.72  |
| 85-89   | 211.23 | 208.49  | 218.57  |
| 90-94   | 107.72 | 105.80  | 113.04  |
| 95-99   | 34.06  | 33.37   | 36.02   |
| 100-104 | 5.03   | 4.94    | 5.27    |
| 105-109 | 0.25   | 0.25    | 0.26    |
| 110-114 | 0.00   | 0.00    | 0.00    |
| 115-119 | 0.00   | 0.00    | 0.00    |
| 120-124 | 0.00   | 0.00    | 0.00    |
| 125-129 | 0.00   | 0.00    | 0.00    |
| 130+    | 0.00   | 0.00    | 0.00    |

## 2 Appendix

```
# Prep work -----

# Load libraries
library(tidyverse)
library(bayesLife)
library(bayesPop)
library(migest)

# Data folders
e0.dir <- "../data/e0/sim03092016"
tfr.dir <- "../data/tfr/sim01192018"
pop.dir <- "../data/pop/sim05222022"
mig.file <- "../data/WPP2019_Period_Indicators_Medium.csv"

# Control randomness
set.seed(57)
options(scipen = 999)

# Question 1 -----

# Run this once to get pop predictions
# pop.pred <- pop.predict(
#   end.year = 2100, start.year = 1950, present.year = 2020,
#   wpp.year = 2019, output.dir = pop.dir, nr.traj = 50,
#   inputs = list(tfr.sim.dir = tfr.dir,
#                 e0F.sim.dir = e0.dir,
#                 e0M.sim.dir = "joint_"),
#   keep.vital.events = FALSE, replace.output=TRUE)

pop_sim_pred <- get.pop.prediction(pop.dir)

# Question 1a -----

# Defined using `?pop.expressions`
over65_exp <- "PAU[14:27]"
support_exp <- "PAU[5:13] / PAU[14:27]"

pop.trajectories.plot(
  pop_sim_pred, "Australia",
  sex = "both",
  sum.over.ages = TRUE,
  main = "Australia Total Population"
)

# Question 1b -----

pop.trajectories.plot(
  pop_sim_pred, "Australia",
  sex = "male",
  sum.over.ages = TRUE,
```

```

    main = "Australia Total Male Population"
  )

# Question 1c -----

pop.trajectories.plot(
  pop_sim_pred, "Australia",
  expression = over65_exp,
  sex = "both",
  sum.over.ages = TRUE,
  main = "Australia Total Population over 65"
)

# Question 1d -----

pop.trajectories.plot(
  pop_sim_pred, "Australia",
  expression = support_exp,
  sex = "both",
  sum.over.ages = TRUE,
  main = "Australia Potential Support Ratio",
  show.legend = FALSE)

legend("topright", c("median", "80% PI", "90% PI", "observed"),
      col = c("red", "red", "red", "black"),
      lty = c(1,2,3, 1), cex = 1, bty = "n", lwd = c(2,2,2,2))

# Question 2 -----

au_mig <- read_csv(mig.file) %>%
  filter(Location == "Australia") %>%
  transmute(year = MidPeriod - 3, nmr = CNMR, nm = NetMigrations) %>%
  filter(year < 2020)

# Question 2a -----

au_mig %>%
  select(-nm) %>%
  knitr::kable(
    booktabs = TRUE, digits = 3,
    col.names = c("Period start", "CNMR"),
    caption = "Crude net migration rate (CNMR) for Australia, 1950-2100"
  )

# Question 2b -----

au_ts <- au_mig %>%
  pull(nmr) %>%
  ts()

au_model = arima(au_ts, order=c(1,0,0))
modelsummary::msummary(au_model,
  estimate = "{estimate} [{conf.low}, {conf.high}]",

```



```

      statistic = NULL, fmt = 2, output = "kableExtra",
      caption = "AR(1) Model for Australia CNMR, 1950-2020") %>%
kableExtra::kable_styling(latex_options = "hold_position")

# Question 2c -----

au_mig_last = au_mig$nmr[length(au_mig$nmr)]
au_sd = sqrt(au_model$sigma2)
au_mean = au_model$coef["intercept"]
au_ar1 = au_model$coef["ar1"]
au_mean_pred = unname(au_ar1) * (au_mig_last - au_mean) + au_mean
au_pred_dist <- qnorm(seq(.001, .999, .001), mean = au_mean_pred, sd = au_sd)

au_pred_tbl <- tibble(
  Mean = au_mean_pred,
  Median = au_mean_pred,
  `2.5% CI` = Mean - 1.96 * au_sd,
  `97.5% CI` = Mean + 1.96 * au_sd)
knitr::kable(
  au_pred_tbl,
  booktabs = TRUE,
  digits = 3,
  caption = "Predictive Distribution of Australia Crude Net Migration Rate, 2020-2025") %>%
kableExtra::kable_styling(latex_options = "hold_position")

# Question 2d -----

au_pred_dist <- qnorm(seq(.0005, .9995, .001), mean = au_mean_pred, sd = au_sd)

au_2020_sample <- rnorm(1000, mean = au_mean_pred, sd = au_sd)

au_2020_tbl <-
  tibble(
    Analytic = au_pred_dist,
    Sample = au_2020_sample
  ) %>%
  pivot_longer(everything(), names_to = "dist", values_to = "value")

ggplot(au_2020_tbl, aes(x = value, fill = dist)) +
  geom_histogram(
    data = filter(au_2020_tbl, dist == "Sample"),
    aes(y = ..density..),
    binwidth = .5,
    alpha = .5) +
  geom_density(
    data = filter(au_2020_tbl, dist == "Analytic"),
    alpha = .2) +
  theme_bw() +
  theme(text = element_text(family = "serif")) +
  labs(
    title = "Predictive Distributions of Crude Net Migration Rate (Analytic and Sample)",
    subtitle = "Australia, 2020-2025",

```

```

    x = "Crude Net Migration Rate",
    y = "Density",
    fill = "Type"
  )

# Question 2e -----

library(wpp2012)
data("migrationF", package = "wpp2012")
data("migrationM", package = "wpp2012")

au_mig12 <- bind_cols(
  migrationF %>%
    filter(country == "Australia") %>%
    select(age, migF = `2015-2020`),
  migrationM %>%
    filter(country == "Australia") %>%
    select(migM = `2015-2020`) %>%
    mutate(migTotal = migF + migM,
           pasmr = migTotal/sum(migTotal))

au_mig20 = tibble(age = au_mig12$age, pasmr = au_mig12$pasmr) %>%
  mutate(asmr = pasmr * au_mean_pred)

au_mig20 %>%
  knitr::kable(
    booktabs = TRUE, digits = 2,
    col.names = c("Age Grop", "PASMR", "ASMR"),
    caption = "Predicted Age-spesific Migration Rates (ASMR) for Australia, 2020-2025",
  )

au_mig20 %>%
  mutate(age = seq(0, 100, 5)) %>%
  ggplot(aes(age, asmr)) +
  geom_line(color="coral", size=3) +
  theme_bw(base_size = 15) +
  theme(text = element_text(family = "serif")) +
  labs(
    title = "Predicted Age-spesific Migration Rates (ASMR)",
    subtitle = "Australia, 2020-2025",
    x = "Age-spesific Migration Rate",
    y = "Age" ) +
  scale_x_continuous(n.breaks = 10)
rc_decomposition = function(x, params){
  a1 = params[["a1"]]
  alpha1 = params[["alpha1"]]
  a2 = params[["a2"]]
  alpha2 = params[["alpha2"]]
  mu = params[["mu2"]]
  lambda = params[["lambda2"]]
  c = params[["c"]]

```

```

mx = a1 * exp(-alpha1 * x) + #first component
  a2 * exp(-alpha2 * (x - mu) - exp(-lambda * (x - mu))) + #second component
  c #constant component

return(mx)
}

rc_params = deframe(migest::rc_model_fund)
au_mig20_alt = tibble(age = 0:104) %>%
  mutate(pasmr = rc_decomposition(age, rc_params),
         pasmr = pasmr/sum(pasmr),
         asmr = pasmr * au_mean_pred)

au_alt_grouped = au_mig20_alt %>%
  mutate(age_group = rep(1:21, each=5))%>%
  group_by(age_group) %>%
  summarise(asmr = mean(asmr)) %>%
  mutate(age_group = factor(age_group, labels = au_mig12$age))

au_alt_grouped %>%
  knitr::kable(
    booktabs = TRUE, digits = 2,
    col.names = c("Age Groop", "ASMR"),
    caption = "Rogers-Castro Model Age-spesific Migration Rates (ASMR) for Australia, 2020-2025",
  )

au_mig20_alt %>%
  ggplot(aes(x=age, y=asmr )) +
  geom_line(color = "coral", size = 3) +
  theme_bw(base_size = 15) +
  theme(text = element_text(family = "serif")) +
  labs(
    title = "Rogers-Castro Model Age-spesific Migration Rates (ASMR)",
    subtitle = "Australia, 2020-2025",
    x = "Age-spesific Migration Rate",
    y = "Age" ) +
  scale_x_continuous(n.breaks = 10)

# Question 2f -----
data("pop", package="wpp2019")
au_pop20 = pop %>% filter(name == "Australia") %>% pull(`2020`)
mig_est = rnorm(50, mean = au_mean_pred, au_sd)
# storing age categories as a sepearate variable
age_cat = au_mig12$age
pasmr = au_mig12 %>% select(age, pasmr)

au_mig25 =
  tibble(sample = 1:50,
         pop20 = au_pop20,
         nmr25 = mig_est) %>%
  mutate(mig25 = au_pop20 * mig_est) %>%
  slice(rep(1:n(), each = 21)) %>%
  mutate(age = rep_len(age_cat, length.out = n()), .after=sample) %>%
  left_join(pasmr, by = "age") %>%

```

```

mutate(mig_counts25 = mig25*pasmr)

ggplot(au_mig25, aes(x = mig_counts25)) +
  geom_histogram() +
  facet_wrap(vars(age), ncol = 3) +
  theme_bw() +
  theme(text = element_text(family = "serif")) +
  labs(
    title = "Projected Age-Specific Net Migration Numbers",
    subtitle = "Australia, 2020-2025",
    x = "Net number of migrants",
    y = "Density"
  )
# Question 2g -----
out.dir = "../data/au_2025"
mig.traj = "../data/mig/mig_trajectories.csv"

mig_out =
  au_mig25 %>%
  mutate(LocID = "36", Period = "2020-2025", Year = "2023") %>%
  #mutate(mig25 = mig25*1000) %>%
  select(LocID, Year, Trajectory=sample, Migration=mig25) %>%
  distinct(Trajectory, .keep_all = TRUE)

#write_csv(mig_out,mig.traj)

# # Run this once to get pop predictions
# pop.pred <- pop.predict(
#   end.year = 2100, start.year = 1950, present.year = 2020,
#   wpp.year = 2019, output.dir = out.dir, nr.traj = 50,
#   countries = "Australia",
#   inputs = list(tfr.sim.dir = tfr.dir,
#                 e0F.sim.dir = e0.dir,
#                 e0M.sim.dir = "joint_",
#                 migtraj = mig.traj),
#   keep.vital.events = FALSE, replace.output=FALSE)

au_pred_25 <- get.pop.prediction(out.dir)

outM = bayesPop::pop.byage.table(au_pred_25, country = "Australia",
                                sex=c("male"), year = 2025)
outF = bayesPop::pop.byage.table(au_pred_25, country = "Australia",
                                sex=c("female"), year = 2025)

tblM = outM %>%

```

```

as.data.frame() %>%
tibble::rownames_to_column(var = "age") %>%
select(-`0.1`, -`0.9`)

tblF = outF %>%
  as.data.frame() %>%
  tibble::rownames_to_column(var = "age") %>%
  select(-`0.1`, -`0.9`)

tblM %>%
  knitr::kable(
    booktabs = TRUE, digits = 2,
    col.names = c("Age", "Median", "2.5% PI", "97.5 PI"),
    caption = "Predicted MalePopulation for Australia, 2020-2025")
tblF %>%
  knitr::kable(
    booktabs = TRUE, digits = 2,
    col.names = c("Age", "Median", "2.5% PI", "97.5 PI"),
    caption = "Predicted Female Population for Australia, 2020-2025")

```