

# Lab 10

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2024-03-21

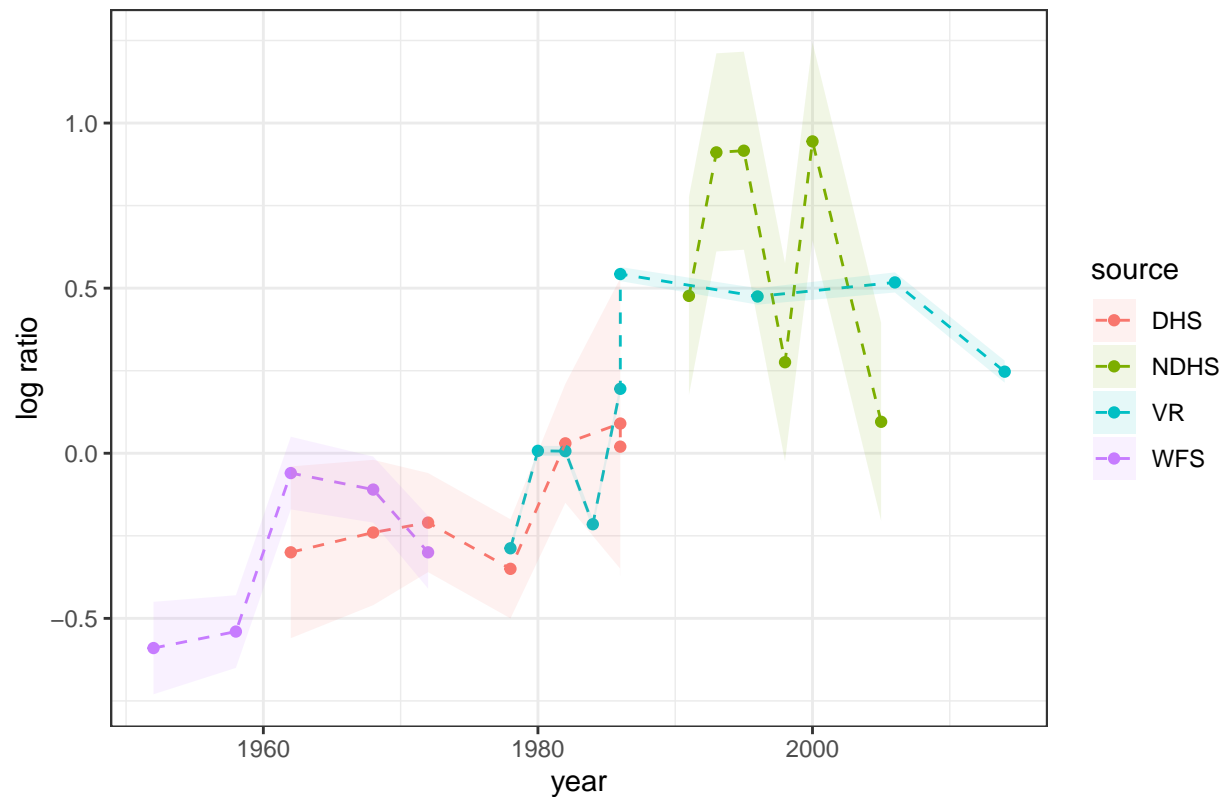
## Child mortality in Sri Lanka

In this lab you will be fitting a couple of different models to the data about child mortality in Sri Lanka, which was used in the lecture. Here's the data and the plot from the lecture:

```
library(tidyverse)
library(here)
library(rstan)
library(tidybayes)

lka <- read_csv("data/lka.csv")
ggplot(lka, aes(year, logit_ratio)) +
  geom_point(aes( color = source)) +
  geom_line(aes( color = source), lty = 2) +
  geom_ribbon(aes(ymin = logit_ratio - se,
                 ymax = logit_ratio + se,
                 fill = source), alpha = 0.1) +
  theme_bw() +
  labs(title = "Ratio of neonatal to other child mortality (logged), Sri Lanka", y = "log ratio")
```

## Ratio of neonatal to other child mortality (logged), Sri Lanka



## Fitting a linear model

Let's firstly fit a linear model in time to these data. Here's the code to do this:

```
observed_years <- lka$year
years <- min(observed_years):max(observed_years)
nyears <- length(years)

stan_data <- list(y = lka$logit_ratio,
                 year_i = observed_years - years[1]+1,
                 T = nyears,
                 years = years,
                 N = length(observed_years),
                 mid_year = mean(years),
                 se = lka$se)

mod <- stan(data = stan_data,
            file = "code/models/lka_linear_me.stan")
```

```
## Running /Library/Frameworks/R.framework/Resources/bin/R CMD SHLIB foo.c
## using C compiler: 'Apple clang version 14.0.3 (clang-1403.0.22.14.1)'
## using SDK: 'MacOSX13.3.sdk'
## clang -arch arm64 -I"/Library/Frameworks/R.framework/Resources/include" -DNDEBUG -I"/Library/Frame
## In file included from <built-in>:1:
```

```

## In file included from /Library/Frameworks/R.framework/Versions/4.3-arm64/Resources/library/StanHeader:
## In file included from /Library/Frameworks/R.framework/Versions/4.3-arm64/Resources/library/RcppEigen:
## In file included from /Library/Frameworks/R.framework/Versions/4.3-arm64/Resources/library/RcppEigen:
## /Library/Frameworks/R.framework/Versions/4.3-arm64/Resources/library/RcppEigen/include/Eigen/src/Core:
## namespace Eigen {
## ~
## /Library/Frameworks/R.framework/Versions/4.3-arm64/Resources/library/RcppEigen/include/Eigen/src/Core:
## namespace Eigen {
## ~
## ;
## In file included from <built-in>:1:
## In file included from /Library/Frameworks/R.framework/Versions/4.3-arm64/Resources/library/StanHeader:
## In file included from /Library/Frameworks/R.framework/Versions/4.3-arm64/Resources/library/RcppEigen:
## /Library/Frameworks/R.framework/Versions/4.3-arm64/Resources/library/RcppEigen/include/Eigen/Core:96
## #include <complex>
## ~~~~~
## 3 errors generated.
## make: *** [foo.o] Error 1
##
## SAMPLING FOR MODEL 'anon_model' NOW (CHAIN 1).
## Chain 1:
## Chain 1: Gradient evaluation took 2.2e-05 seconds
## Chain 1: 1000 transitions using 10 leapfrog steps per transition would take 0.22 seconds.
## Chain 1: Adjust your expectations accordingly!
## Chain 1:
## Chain 1:
## Chain 1: Iteration:    1 / 2000 [  0%] (Warmup)
## Chain 1: Iteration:   200 / 2000 [ 10%] (Warmup)
## Chain 1: Iteration:   400 / 2000 [ 20%] (Warmup)
## Chain 1: Iteration:   600 / 2000 [ 30%] (Warmup)
## Chain 1: Iteration:   800 / 2000 [ 40%] (Warmup)
## Chain 1: Iteration:  1000 / 2000 [ 50%] (Warmup)
## Chain 1: Iteration:  1001 / 2000 [ 50%] (Sampling)
## Chain 1: Iteration:  1200 / 2000 [ 60%] (Sampling)
## Chain 1: Iteration:  1400 / 2000 [ 70%] (Sampling)
## Chain 1: Iteration:  1600 / 2000 [ 80%] (Sampling)
## Chain 1: Iteration:  1800 / 2000 [ 90%] (Sampling)
## Chain 1: Iteration:  2000 / 2000 [100%] (Sampling)
## Chain 1:
## Chain 1: Elapsed Time: 0.022 seconds (Warm-up)
## Chain 1:                0.018 seconds (Sampling)
## Chain 1:                0.04 seconds (Total)
## Chain 1:
##
## SAMPLING FOR MODEL 'anon_model' NOW (CHAIN 2).
## Chain 2:
## Chain 2: Gradient evaluation took 2e-06 seconds
## Chain 2: 1000 transitions using 10 leapfrog steps per transition would take 0.02 seconds.
## Chain 2: Adjust your expectations accordingly!
## Chain 2:
## Chain 2:
## Chain 2: Iteration:    1 / 2000 [  0%] (Warmup)
## Chain 2: Iteration:   200 / 2000 [ 10%] (Warmup)
## Chain 2: Iteration:   400 / 2000 [ 20%] (Warmup)

```

```

## Chain 2: Iteration: 600 / 2000 [ 30%] (Warmup)
## Chain 2: Iteration: 800 / 2000 [ 40%] (Warmup)
## Chain 2: Iteration: 1000 / 2000 [ 50%] (Warmup)
## Chain 2: Iteration: 1001 / 2000 [ 50%] (Sampling)
## Chain 2: Iteration: 1200 / 2000 [ 60%] (Sampling)
## Chain 2: Iteration: 1400 / 2000 [ 70%] (Sampling)
## Chain 2: Iteration: 1600 / 2000 [ 80%] (Sampling)
## Chain 2: Iteration: 1800 / 2000 [ 90%] (Sampling)
## Chain 2: Iteration: 2000 / 2000 [100%] (Sampling)
## Chain 2:
## Chain 2: Elapsed Time: 0.022 seconds (Warm-up)
## Chain 2: 0.017 seconds (Sampling)
## Chain 2: 0.039 seconds (Total)
## Chain 2:
##
## SAMPLING FOR MODEL 'anon_model' NOW (CHAIN 3).
## Chain 3:
## Chain 3: Gradient evaluation took 2e-06 seconds
## Chain 3: 1000 transitions using 10 leapfrog steps per transition would take 0.02 seconds.
## Chain 3: Adjust your expectations accordingly!
## Chain 3:
## Chain 3:
## Chain 3: Iteration: 1 / 2000 [ 0%] (Warmup)
## Chain 3: Iteration: 200 / 2000 [ 10%] (Warmup)
## Chain 3: Iteration: 400 / 2000 [ 20%] (Warmup)
## Chain 3: Iteration: 600 / 2000 [ 30%] (Warmup)
## Chain 3: Iteration: 800 / 2000 [ 40%] (Warmup)
## Chain 3: Iteration: 1000 / 2000 [ 50%] (Warmup)
## Chain 3: Iteration: 1001 / 2000 [ 50%] (Sampling)
## Chain 3: Iteration: 1200 / 2000 [ 60%] (Sampling)
## Chain 3: Iteration: 1400 / 2000 [ 70%] (Sampling)
## Chain 3: Iteration: 1600 / 2000 [ 80%] (Sampling)
## Chain 3: Iteration: 1800 / 2000 [ 90%] (Sampling)
## Chain 3: Iteration: 2000 / 2000 [100%] (Sampling)
## Chain 3:
## Chain 3: Elapsed Time: 0.022 seconds (Warm-up)
## Chain 3: 0.018 seconds (Sampling)
## Chain 3: 0.04 seconds (Total)
## Chain 3:
##
## SAMPLING FOR MODEL 'anon_model' NOW (CHAIN 4).
## Chain 4:
## Chain 4: Gradient evaluation took 2e-06 seconds
## Chain 4: 1000 transitions using 10 leapfrog steps per transition would take 0.02 seconds.
## Chain 4: Adjust your expectations accordingly!
## Chain 4:
## Chain 4:
## Chain 4: Iteration: 1 / 2000 [ 0%] (Warmup)
## Chain 4: Iteration: 200 / 2000 [ 10%] (Warmup)
## Chain 4: Iteration: 400 / 2000 [ 20%] (Warmup)
## Chain 4: Iteration: 600 / 2000 [ 30%] (Warmup)
## Chain 4: Iteration: 800 / 2000 [ 40%] (Warmup)
## Chain 4: Iteration: 1000 / 2000 [ 50%] (Warmup)
## Chain 4: Iteration: 1001 / 2000 [ 50%] (Sampling)

```

```
## Chain 4: Iteration: 1200 / 2000 [ 60%] (Sampling)
## Chain 4: Iteration: 1400 / 2000 [ 70%] (Sampling)
## Chain 4: Iteration: 1600 / 2000 [ 80%] (Sampling)
## Chain 4: Iteration: 1800 / 2000 [ 90%] (Sampling)
## Chain 4: Iteration: 2000 / 2000 [100%] (Sampling)
## Chain 4:
## Chain 4: Elapsed Time: 0.023 seconds (Warm-up)
## Chain 4:           0.017 seconds (Sampling)
## Chain 4:           0.04 seconds (Total)
## Chain 4:
```

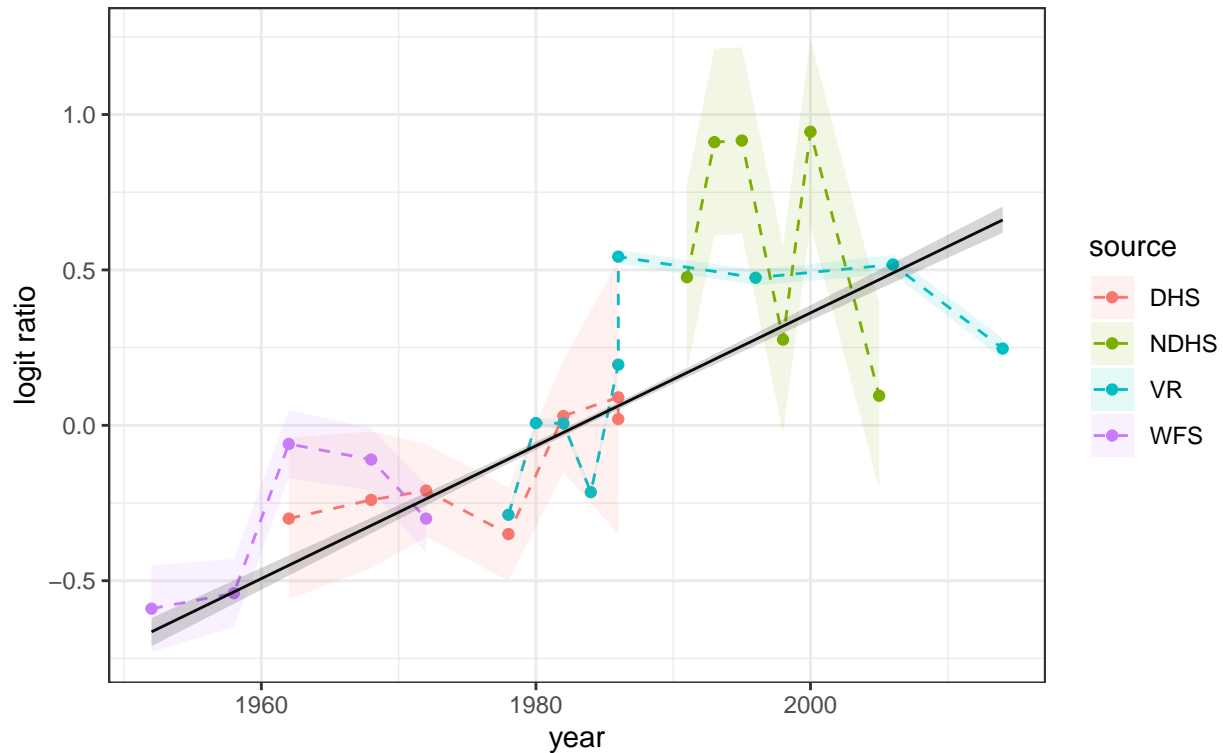
Extract the results:

```
res <- mod %>%
  gather_draws(mu[t]) %>%
  median_qi() %>%
  mutate(year = years[t])
```

Plot the results:

```
ggplot(lka, aes(year, logit_ratio)) +
  geom_point(aes( color = source)) +
  geom_line(aes( color = source), lty = 2) +
  geom_ribbon(aes(ymin = logit_ratio - se,
                  ymax = logit_ratio + se,
                  fill = source), alpha = 0.1) +
  theme_bw() +
  geom_line(data = res, aes(year, .value)) +
  geom_ribbon(data = res, aes(y = .value, ymin = .lower, ymax = .upper), alpha = 0.2) +
  theme_bw() +
  labs(title = "Ratio of neonatal to under-five child mortality (logit), Sri Lanka",
       y = "logit ratio", subtitle = "Linear fit shown in black")
```

Ratio of neonatal to under-five child mortality (logit), Sri Lanka  
Linear fit shown in black



## Question 1

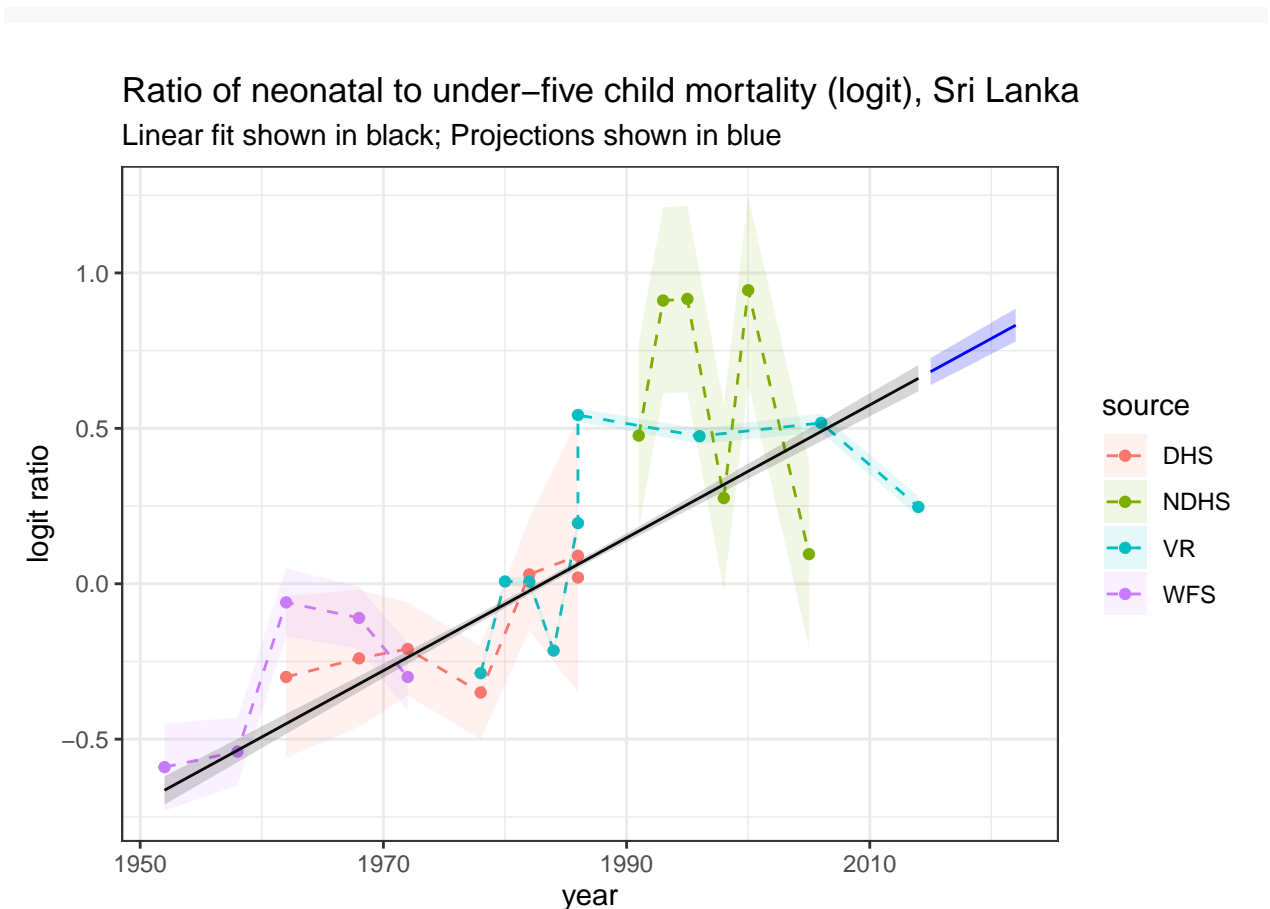
Project the linear model above out to 2022 by adding a `generated quantities` block in Stan (do the projections based on the expected value  $\mu$ ). Plot the resulting projections on a graph similar to that above.

Extract future predictions and plot the results:

```
pred <- mod %>%
  gather_draws(future_mu[t]) %>%
  median_qi() %>%
  mutate(year = max(years)+t)

ggplot(lka, aes(year, logit_ratio)) +
  geom_point(aes( color = source)) +
  geom_line(aes( color = source), lty = 2) +
  geom_ribbon(aes(ymin = logit_ratio - se,
                 ymax = logit_ratio + se,
                 fill = source), alpha = 0.1) +

  theme_bw() +
  geom_line(data = res, aes(year, .value)) +
  geom_line(data = pred, aes(year, .value), col="blue") +
  geom_ribbon(data = res, aes(y = .value, ymin = .lower, ymax = .upper), alpha = 0.2) +
  geom_ribbon(data = pred, aes(y = .value, ymin = .lower, ymax = .upper), alpha = 0.2, fill="blue") +
  theme_bw() +
  labs(title = "Ratio of neonatal to under-five child mortality (logit), Sri Lanka",
       y = "logit ratio", subtitle = "Linear fit shown in black; Projections shown in blue")
```



## Question 2

The projections above are for the logit of the ratio of neonatal to under-five child mortality. You can download estimates of the under-five child mortality from 1951 to 2022 here: <https://childmortality.org/all-cause-mortality/data/estimates?refArea=LKA>. Use these data to get estimates and projections of neonatal mortality for Sri Lanka, and plot the results.

Loading the estimates of the under-five child mortality from 1951 to 2022:

```
under_five <- read.csv("data/lka_under_five.csv")
```

Merge the under five mortality estimates with the logit ratios:

```
bind <- rbind(data.frame(Year = res$year, lratio = res$.value, ll = res$.lower, lu = res$.upper),
              data.frame(Year = pred$year, lratio = pred$.value, ll = pred$.lower, lu = pred$.upper))
bind$ratio <- plogis(bind$lratio)
bind$ratio_lower <- plogis(bind$ll)
bind$ratio_upper <- plogis(bind$lu)

bind <- merge(bind, under_five, by = "Year", all.x = TRUE)
```

Calculate estimates and projections as well as the lower bounds and upper bounds of neonatal mortality:

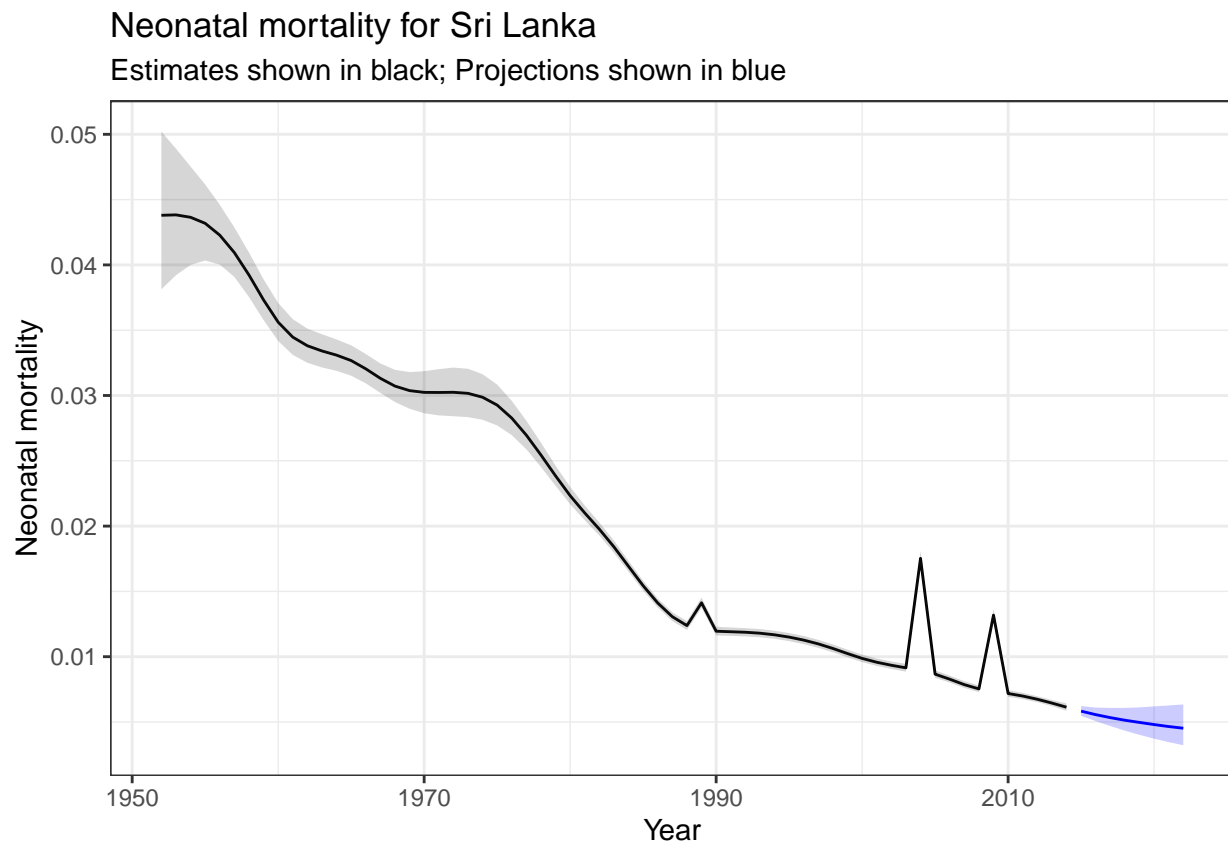
```
bind$neo <- bind$ratio * bind$Estimate / 1000
bind$neo_lower <- bind$ratio_lower * bind$Lower.bound / 1000
bind$neo_upper <- bind$ratio_upper * bind$Upper.bound / 1000
```

Plot the results:

```
bind_estimates <- bind |>
  filter(Year <= max(years))

bind_projections <- bind |>
  filter(Year > max(years))

ggplot(data = bind, aes(Year, neo)) +
  geom_line(data = bind_estimates, aes(Year, neo)) +
  geom_line(data = bind_projections, aes(Year, neo), col="blue") +
  geom_ribbon(data = bind_estimates, aes(y = neo, ymin = neo_lower, ymax = neo_upper), alpha = 0.2) +
  geom_ribbon(data = bind_projections, aes(y = neo, ymin = neo_lower, ymax = neo_upper), alpha = 0.2, fill="blue") +
  theme_bw() +
  labs(title = "Neonatal mortality for Sri Lanka",
       y = "Neonatal mortality", subtitle = "Estimates shown in black; Projections shown in blue")
```





### Question 3

```
stan_data3 <- list(N = length(observed_years),
  T = nyears,
  P = 8,
  mid_year = mean(years),
  y = lka$logit_ratio,
  se = lka$se,
  years = years,
  year_i = observed_years - years[1]+1
)

mod3 <- stan(data = stan_data3,
  file = "code/models/lka_Q3.stan",
  seed = 1234)
```

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```

## Chain 1: Iteration: 200 / 2000 [ 10%] (Warmup)
## Chain 1: Iteration: 400 / 2000 [ 20%] (Warmup)
## Chain 1: Iteration: 600 / 2000 [ 30%] (Warmup)
## Chain 1: Iteration: 800 / 2000 [ 40%] (Warmup)
## Chain 1: Iteration: 1000 / 2000 [ 50%] (Warmup)
## Chain 1: Iteration: 1001 / 2000 [ 50%] (Sampling)
## Chain 1: Iteration: 1200 / 2000 [ 60%] (Sampling)
## Chain 1: Iteration: 1400 / 2000 [ 70%] (Sampling)
## Chain 1: Iteration: 1600 / 2000 [ 80%] (Sampling)
## Chain 1: Iteration: 1800 / 2000 [ 90%] (Sampling)
## Chain 1: Iteration: 2000 / 2000 [100%] (Sampling)
## Chain 1:
## Chain 1: Elapsed Time: 0.138 seconds (Warm-up)
## Chain 1: 0.1 seconds (Sampling)
## Chain 1: 0.238 seconds (Total)
## Chain 1:
##
## SAMPLING FOR MODEL 'anon_model' NOW (CHAIN 2).
## Chain 2:
## Chain 2: Gradient evaluation took 5e-06 seconds
## Chain 2: 1000 transitions using 10 leapfrog steps per transition would take 0.05 seconds.
## Chain 2: Adjust your expectations accordingly!
## Chain 2:
## Chain 2:
## Chain 2: Iteration: 1 / 2000 [ 0%] (Warmup)
## Chain 2: Iteration: 200 / 2000 [ 10%] (Warmup)
## Chain 2: Iteration: 400 / 2000 [ 20%] (Warmup)
## Chain 2: Iteration: 600 / 2000 [ 30%] (Warmup)
## Chain 2: Iteration: 800 / 2000 [ 40%] (Warmup)
## Chain 2: Iteration: 1000 / 2000 [ 50%] (Warmup)
## Chain 2: Iteration: 1001 / 2000 [ 50%] (Sampling)
## Chain 2: Iteration: 1200 / 2000 [ 60%] (Sampling)
## Chain 2: Iteration: 1400 / 2000 [ 70%] (Sampling)
## Chain 2: Iteration: 1600 / 2000 [ 80%] (Sampling)
## Chain 2: Iteration: 1800 / 2000 [ 90%] (Sampling)
## Chain 2: Iteration: 2000 / 2000 [100%] (Sampling)
## Chain 2:
## Chain 2: Elapsed Time: 0.142 seconds (Warm-up)
## Chain 2: 0.115 seconds (Sampling)
## Chain 2: 0.257 seconds (Total)
## Chain 2:
##
## SAMPLING FOR MODEL 'anon_model' NOW (CHAIN 3).
## Chain 3:
## Chain 3: Gradient evaluation took 4e-06 seconds
## Chain 3: 1000 transitions using 10 leapfrog steps per transition would take 0.04 seconds.
## Chain 3: Adjust your expectations accordingly!
## Chain 3:
## Chain 3:
## Chain 3: Iteration: 1 / 2000 [ 0%] (Warmup)
## Chain 3: Iteration: 200 / 2000 [ 10%] (Warmup)
## Chain 3: Iteration: 400 / 2000 [ 20%] (Warmup)
## Chain 3: Iteration: 600 / 2000 [ 30%] (Warmup)
## Chain 3: Iteration: 800 / 2000 [ 40%] (Warmup)

```

```

## Chain 3: Iteration: 1000 / 2000 [ 50%] (Warmup)
## Chain 3: Iteration: 1001 / 2000 [ 50%] (Sampling)
## Chain 3: Iteration: 1200 / 2000 [ 60%] (Sampling)
## Chain 3: Iteration: 1400 / 2000 [ 70%] (Sampling)
## Chain 3: Iteration: 1600 / 2000 [ 80%] (Sampling)
## Chain 3: Iteration: 1800 / 2000 [ 90%] (Sampling)
## Chain 3: Iteration: 2000 / 2000 [100%] (Sampling)
## Chain 3:
## Chain 3: Elapsed Time: 0.142 seconds (Warm-up)
## Chain 3: 0.115 seconds (Sampling)
## Chain 3: 0.257 seconds (Total)
## Chain 3:
##
## SAMPLING FOR MODEL 'anon_model' NOW (CHAIN 4).
## Chain 4:
## Chain 4: Gradient evaluation took 5e-06 seconds
## Chain 4: 1000 transitions using 10 leapfrog steps per transition would take 0.05 seconds.
## Chain 4: Adjust your expectations accordingly!
## Chain 4:
## Chain 4:
## Chain 4: Iteration: 1 / 2000 [ 0%] (Warmup)
## Chain 4: Iteration: 200 / 2000 [ 10%] (Warmup)
## Chain 4: Iteration: 400 / 2000 [ 20%] (Warmup)
## Chain 4: Iteration: 600 / 2000 [ 30%] (Warmup)
## Chain 4: Iteration: 800 / 2000 [ 40%] (Warmup)
## Chain 4: Iteration: 1000 / 2000 [ 50%] (Warmup)
## Chain 4: Iteration: 1001 / 2000 [ 50%] (Sampling)
## Chain 4: Iteration: 1200 / 2000 [ 60%] (Sampling)
## Chain 4: Iteration: 1400 / 2000 [ 70%] (Sampling)
## Chain 4: Iteration: 1600 / 2000 [ 80%] (Sampling)
## Chain 4: Iteration: 1800 / 2000 [ 90%] (Sampling)
## Chain 4: Iteration: 2000 / 2000 [100%] (Sampling)
## Chain 4:
## Chain 4: Elapsed Time: 0.131 seconds (Warm-up)
## Chain 4: 0.111 seconds (Sampling)
## Chain 4: 0.242 seconds (Total)
## Chain 4:

```

Extract and plot the results:

```

res3 <- mod3 |>
  gather_draws(mu[t]) |>
  median_qi() |>
  mutate(year = years[t])

pred3 <- mod3 |>
  gather_draws(future_mu[p]) |>
  median_qi() |>
  mutate(year = max(years)+p)

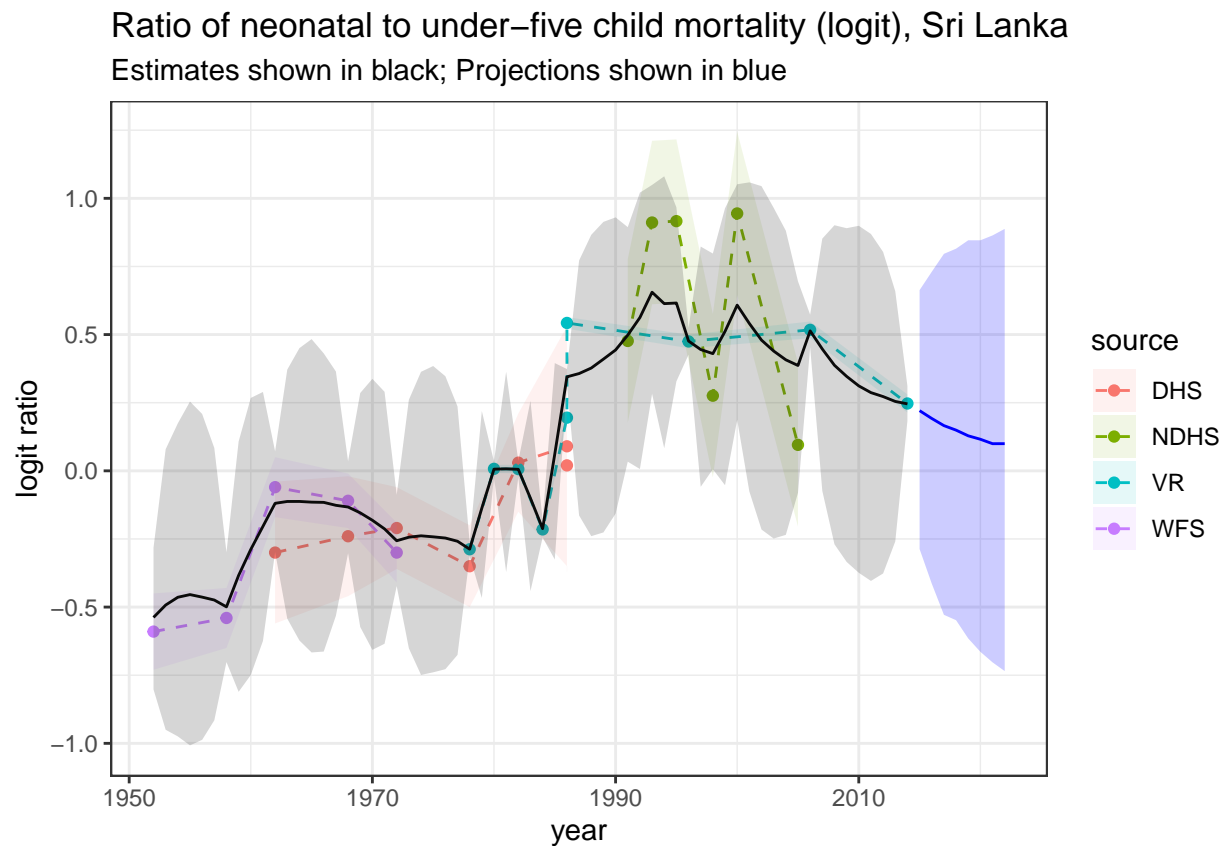
ggplot(lka, aes(year, logit_ratio)) +
  geom_point(aes( color = source)) +
  geom_line(aes( color = source), lty = 2) +
  geom_ribbon(aes(ymin = logit_ratio - se,

```

```

      ymax = logit_ratio + se,
      fill = source), alpha = 0.1) +
theme_bw()+
geom_line(data = res3, aes(year, .value)) +
geom_line(data = pred3, aes(year, .value), col="blue") +
geom_ribbon(data = res3, aes(y = .value, ymin = .lower, ymax = .upper), alpha = 0.2) +
geom_ribbon(data = pred3, aes(y = .value, ymin = .lower, ymax = .upper), alpha = 0.2, fill="blue") +
theme_bw()+
labs(title = "Ratio of neonatal to under-five child mortality (logit), Sri Lanka",
      y = "logit ratio", subtitle = "Estimates shown in black; Projections shown in blue")

```



#### Question 4

Now alter your model above to estimate and project a second-order random walk model (RW2).

```

stan_data4 <- list(N = length(observed_years),
  T = nyears,
  P = 8,
  mid_year = mean(years),
  y = lka$logit_ratio,
  se = lka$se,
  years = years,
  year_i = observed_years - years[1]+1
)

```

```
mod4 <- stan(data = stan_data4,
             file = "code/models/lka_Q4.stan",
             seed = 1234)
```

```
## Running /Library/Frameworks/R.framework/Resources/bin/R CMD SHLIB foo.c
## using C compiler: 'Apple clang version 14.0.3 (clang-1403.0.22.14.1)'
## using SDK: 'MacOSX13.3.sdk'
## clang -arch arm64 -I"/Library/Frameworks/R.framework/Resources/include" -DNDEBUG -I"/Library/Frameworks/R.framework/Versions/4.3-arm64/Resources/library/StanHeaders/include"
## In file included from <built-in>:1:
## In file included from /Library/Frameworks/R.framework/Versions/4.3-arm64/Resources/library/StanHeaders/include:
## In file included from /Library/Frameworks/R.framework/Versions/4.3-arm64/Resources/library/RcppEigen/include:
## In file included from /Library/Frameworks/R.framework/Versions/4.3-arm64/Resources/library/RcppEigen/include/Eigen/src/Core:
## namespace Eigen {
## ^
## /Library/Frameworks/R.framework/Versions/4.3-arm64/Resources/library/RcppEigen/include/Eigen/src/Core:
## namespace Eigen {
## ^
## ;
## In file included from <built-in>:1:
## In file included from /Library/Frameworks/R.framework/Versions/4.3-arm64/Resources/library/StanHeaders/include:
## In file included from /Library/Frameworks/R.framework/Versions/4.3-arm64/Resources/library/RcppEigen/include:
## /Library/Frameworks/R.framework/Versions/4.3-arm64/Resources/library/RcppEigen/include/Eigen/Core:96
## #include <complex>
## ~~~~~
## 3 errors generated.
## make: *** [foo.o] Error 1
##
## SAMPLING FOR MODEL 'anon_model' NOW (CHAIN 1).
## Chain 1:
## Chain 1: Gradient evaluation took 4.7e-05 seconds
## Chain 1: 1000 transitions using 10 leapfrog steps per transition would take 0.47 seconds.
## Chain 1: Adjust your expectations accordingly!
## Chain 1:
## Chain 1:
## Chain 1: Iteration: 1 / 2000 [ 0%] (Warmup)
## Chain 1: Iteration: 200 / 2000 [ 10%] (Warmup)
## Chain 1: Iteration: 400 / 2000 [ 20%] (Warmup)
## Chain 1: Iteration: 600 / 2000 [ 30%] (Warmup)
## Chain 1: Iteration: 800 / 2000 [ 40%] (Warmup)
## Chain 1: Iteration: 1000 / 2000 [ 50%] (Warmup)
## Chain 1: Iteration: 1001 / 2000 [ 50%] (Sampling)
## Chain 1: Iteration: 1200 / 2000 [ 60%] (Sampling)
## Chain 1: Iteration: 1400 / 2000 [ 70%] (Sampling)
## Chain 1: Iteration: 1600 / 2000 [ 80%] (Sampling)
## Chain 1: Iteration: 1800 / 2000 [ 90%] (Sampling)
## Chain 1: Iteration: 2000 / 2000 [100%] (Sampling)
## Chain 1:
## Chain 1: Elapsed Time: 0.173 seconds (Warm-up)
## Chain 1: 0.109 seconds (Sampling)
## Chain 1: 0.282 seconds (Total)
##
```

```

## SAMPLING FOR MODEL 'anon_model' NOW (CHAIN 2).
## Chain 2:
## Chain 2: Gradient evaluation took 8e-06 seconds
## Chain 2: 1000 transitions using 10 leapfrog steps per transition would take 0.08 seconds.
## Chain 2: Adjust your expectations accordingly!
## Chain 2:
## Chain 2:
## Chain 2: Iteration:    1 / 2000 [  0%] (Warmup)
## Chain 2: Iteration:   200 / 2000 [ 10%] (Warmup)
## Chain 2: Iteration:   400 / 2000 [ 20%] (Warmup)
## Chain 2: Iteration:   600 / 2000 [ 30%] (Warmup)
## Chain 2: Iteration:   800 / 2000 [ 40%] (Warmup)
## Chain 2: Iteration:  1000 / 2000 [ 50%] (Warmup)
## Chain 2: Iteration:  1001 / 2000 [ 50%] (Sampling)
## Chain 2: Iteration:  1200 / 2000 [ 60%] (Sampling)
## Chain 2: Iteration:  1400 / 2000 [ 70%] (Sampling)
## Chain 2: Iteration:  1600 / 2000 [ 80%] (Sampling)
## Chain 2: Iteration:  1800 / 2000 [ 90%] (Sampling)
## Chain 2: Iteration:  2000 / 2000 [100%] (Sampling)
## Chain 2:
## Chain 2: Elapsed Time: 0.163 seconds (Warm-up)
## Chain 2:                0.137 seconds (Sampling)
## Chain 2:                0.3 seconds (Total)
## Chain 2:
##
## SAMPLING FOR MODEL 'anon_model' NOW (CHAIN 3).
## Chain 3:
## Chain 3: Gradient evaluation took 7e-06 seconds
## Chain 3: 1000 transitions using 10 leapfrog steps per transition would take 0.07 seconds.
## Chain 3: Adjust your expectations accordingly!
## Chain 3:
## Chain 3:
## Chain 3: Iteration:    1 / 2000 [  0%] (Warmup)
## Chain 3: Iteration:   200 / 2000 [ 10%] (Warmup)
## Chain 3: Iteration:   400 / 2000 [ 20%] (Warmup)
## Chain 3: Iteration:   600 / 2000 [ 30%] (Warmup)
## Chain 3: Iteration:   800 / 2000 [ 40%] (Warmup)
## Chain 3: Iteration:  1000 / 2000 [ 50%] (Warmup)
## Chain 3: Iteration:  1001 / 2000 [ 50%] (Sampling)
## Chain 3: Iteration:  1200 / 2000 [ 60%] (Sampling)
## Chain 3: Iteration:  1400 / 2000 [ 70%] (Sampling)
## Chain 3: Iteration:  1600 / 2000 [ 80%] (Sampling)
## Chain 3: Iteration:  1800 / 2000 [ 90%] (Sampling)
## Chain 3: Iteration:  2000 / 2000 [100%] (Sampling)
## Chain 3:
## Chain 3: Elapsed Time: 0.174 seconds (Warm-up)
## Chain 3:                0.113 seconds (Sampling)
## Chain 3:                0.287 seconds (Total)
## Chain 3:
##
## SAMPLING FOR MODEL 'anon_model' NOW (CHAIN 4).
## Chain 4:
## Chain 4: Gradient evaluation took 7e-06 seconds
## Chain 4: 1000 transitions using 10 leapfrog steps per transition would take 0.07 seconds.

```

```
## Chain 4: Adjust your expectations accordingly!
## Chain 4:
## Chain 4:
## Chain 4: Iteration:    1 / 2000 [  0%] (Warmup)
## Chain 4: Iteration:   200 / 2000 [ 10%] (Warmup)
## Chain 4: Iteration:   400 / 2000 [ 20%] (Warmup)
## Chain 4: Iteration:   600 / 2000 [ 30%] (Warmup)
## Chain 4: Iteration:   800 / 2000 [ 40%] (Warmup)
## Chain 4: Iteration:  1000 / 2000 [ 50%] (Warmup)
## Chain 4: Iteration:  1001 / 2000 [ 50%] (Sampling)
## Chain 4: Iteration:  1200 / 2000 [ 60%] (Sampling)
## Chain 4: Iteration:  1400 / 2000 [ 70%] (Sampling)
## Chain 4: Iteration:  1600 / 2000 [ 80%] (Sampling)
## Chain 4: Iteration:  1800 / 2000 [ 90%] (Sampling)
## Chain 4: Iteration:  2000 / 2000 [100%] (Sampling)
## Chain 4:
## Chain 4: Elapsed Time: 0.165 seconds (Warm-up)
## Chain 4:                0.128 seconds (Sampling)
## Chain 4:                0.293 seconds (Total)
## Chain 4:
```

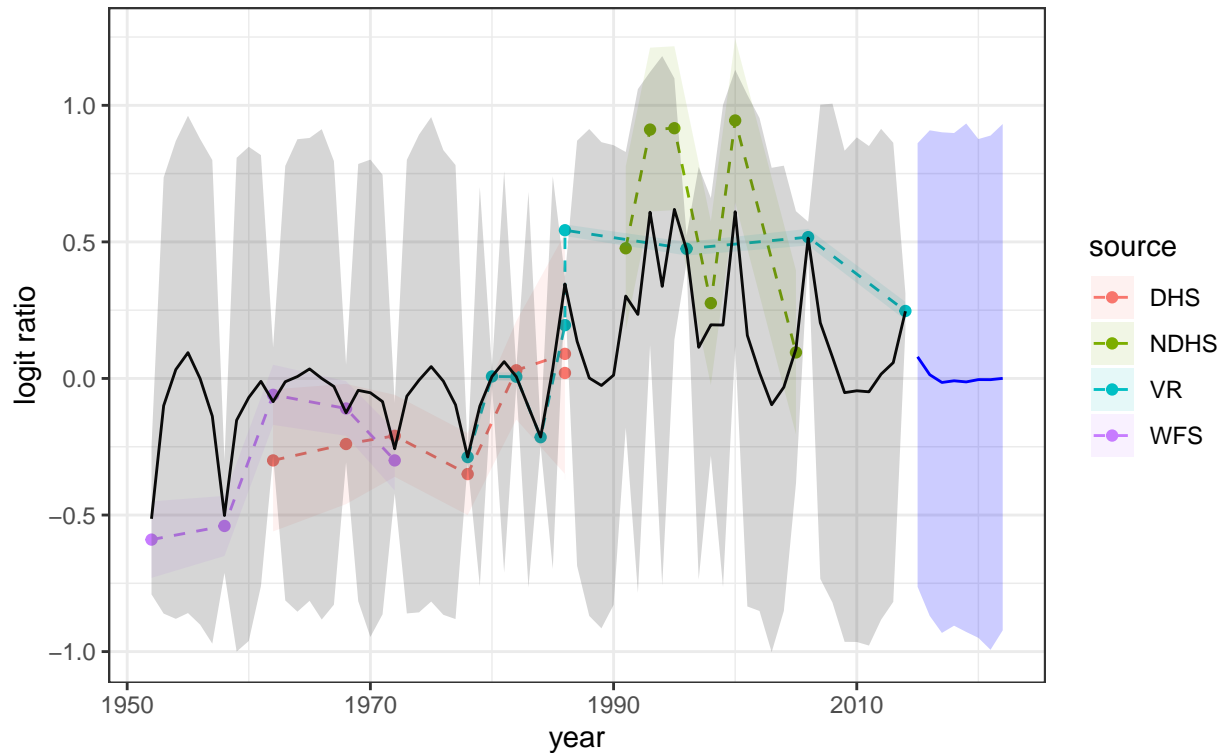
Extract and plot the results:

```
res4 <- mod4 |>
  gather_draws(mu[t]) |>
  median_qi() |>
  mutate(year = years[t])

pred4 <- mod4 |>
  gather_draws(future_mu[p]) |>
  median_qi() |>
  mutate(year = max(years)+p)

ggplot(lka, aes(year, logit_ratio)) +
  geom_point(aes( color = source)) +
  geom_line(aes( color = source), lty = 2) +
  geom_ribbon(aes(ymin = logit_ratio - se,
                 ymax = logit_ratio + se,
                 fill = source), alpha = 0.1) +
  theme_bw()+
  geom_line(data = res4, aes(year, .value)) +
  geom_line(data = pred4, aes(year, .value), col="blue") +
  geom_ribbon(data = res4, aes(y = .value, ymin = .lower, ymax = .upper), alpha = 0.2) +
  geom_ribbon(data = pred4, aes(y = .value, ymin = .lower, ymax = .upper), alpha = 0.2, fill="blue") +
  theme_bw()+
  labs(title = "Ratio of neonatal to under-five child mortality (logit), Sri Lanka",
       y = "logit ratio", subtitle = "Estimates shown in black; Projections shown in blue")
```

Ratio of neonatal to under-five child mortality (logit), Sri Lanka  
Estimates shown in black; Projections shown in blue



## Question 5

Run the first order and second order random walk models, including projections out to 2022. Compare these estimates with the linear fit by plotting everything on the same graph.

```
linear_fit <- rbind(res[, c(".value", ".lower", ".upper", "year")],
                  pred[, c(".value", ".lower", ".upper", "year")])
linear_fit$type <- "linear_fit"

rw1 <- rbind(res3[, c(".value", ".lower", ".upper", "year")],
            pred3[, c(".value", ".lower", ".upper", "year")])
rw1$type <- "RW1"

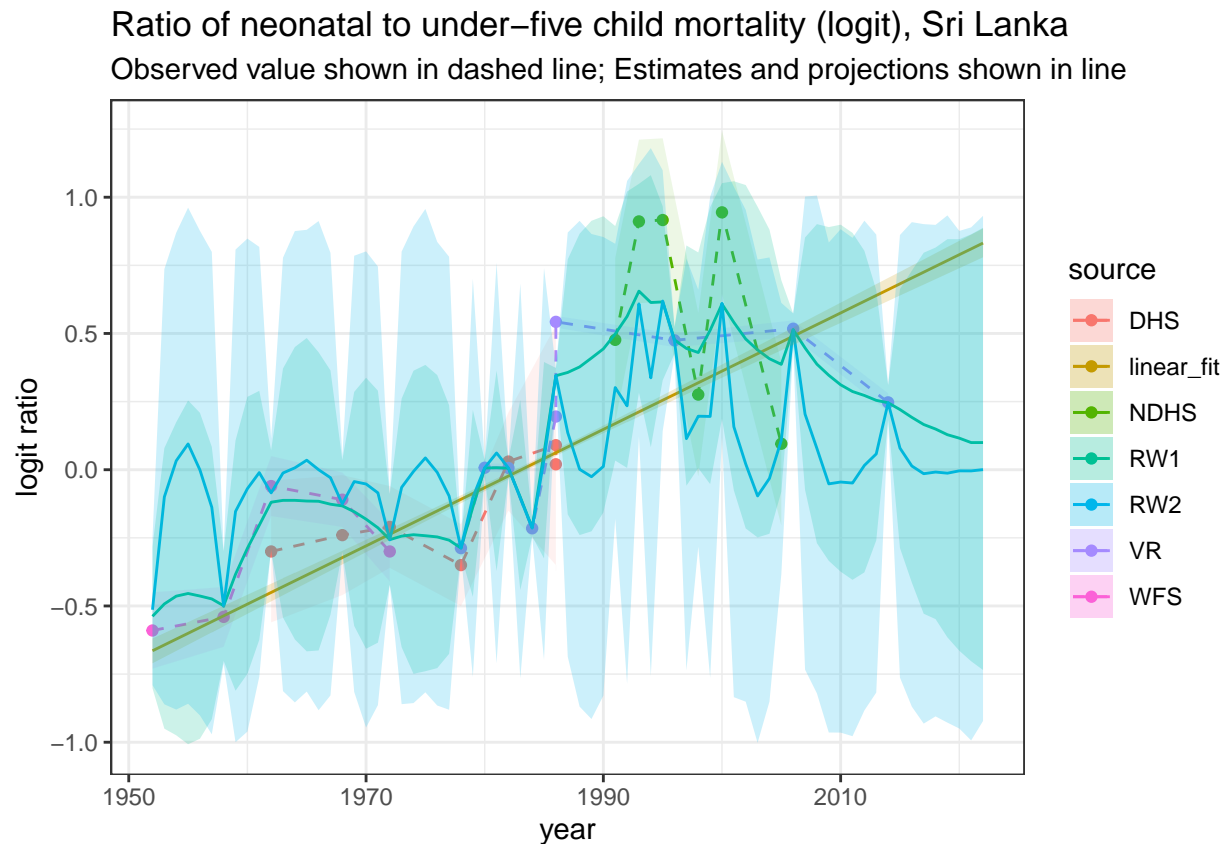
rw2 <- rbind(res4[, c(".value", ".lower", ".upper", "year")],
            pred4[, c(".value", ".lower", ".upper", "year")])
rw2$type <- "RW2"

plot_data <- rbind(linear_fit, rw1, rw2)

ggplot(lka, aes(year, logit_ratio)) +
  geom_point(aes(color = source)) +
  geom_line(aes(color = source), lty = 2) +
  geom_ribbon(aes(ymin = logit_ratio - se,
                ymax = logit_ratio + se,
                fill = source), alpha = 0.1) +
```



```
theme_bw() +
geom_line(data = plot_data, aes(year, .value, color = type)) +
geom_ribbon(data = plot_data, aes(y = .value, ymin = .lower, ymax = .upper, fill = type), alpha = 0.2) +
theme_bw() +
labs(title = "Ratio of neonatal to under-five child mortality (logit), Sri Lanka",
y = "logit ratio",
subtitle = "Observed value shown in dashed line; Estimates and projections shown in line")
```



## Question 6

Briefly comment on which model you think is most appropriate, or an alternative model that would be more appropriate in this context.

I think the first order random walk model is most appropriate. From the plot in question 5, we can see that the linear model underfits the data as it has large bias and small variance, and the second order random walk model overfits the data as it has small bias and large variance. The first order random walk model captures a more precise trend of the data than the linear model, and the manner in which it does so is not as oscillating as the second order model.