

Many Variables (Part 1)

EES 5891-03

Bayesian Statistical Methods

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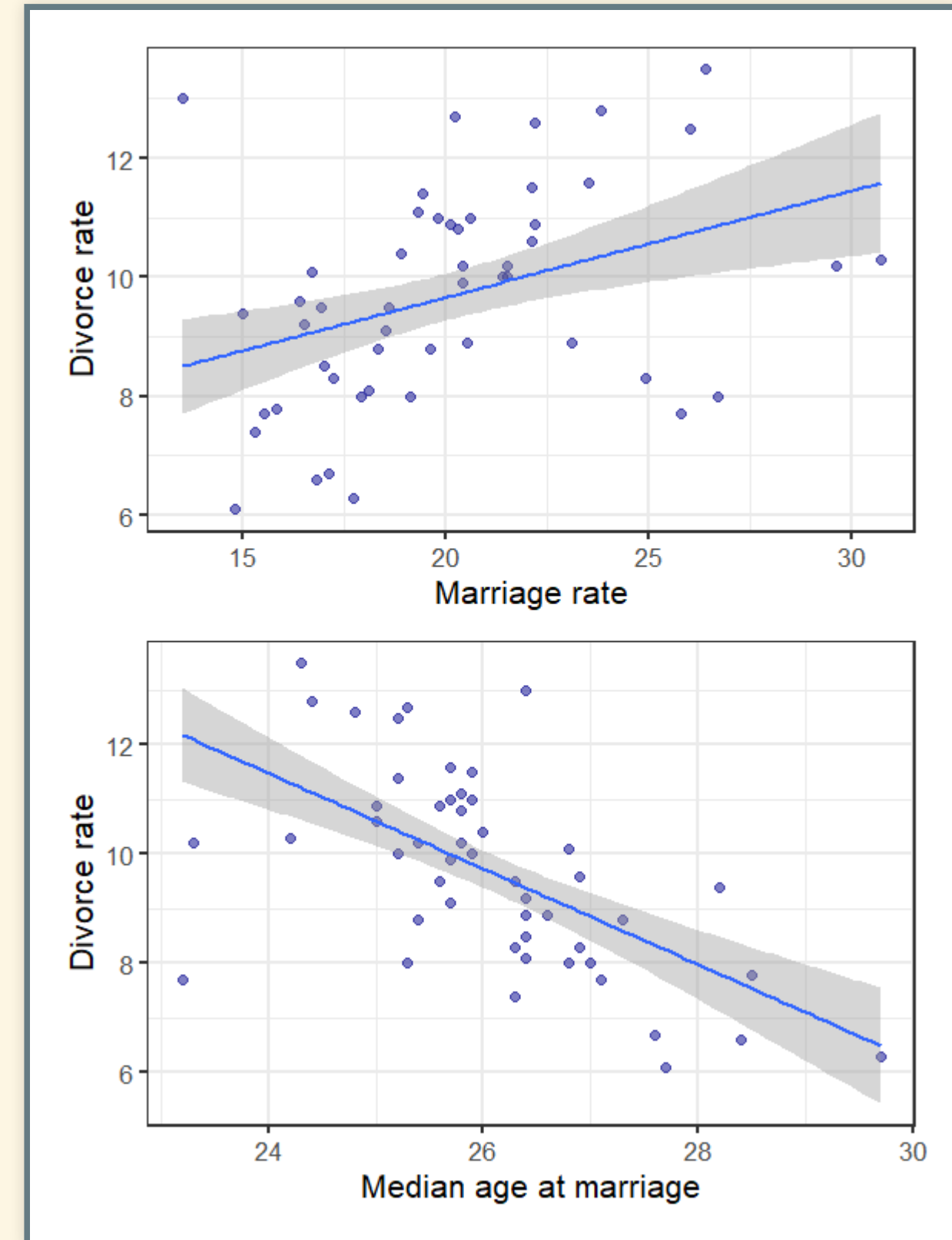
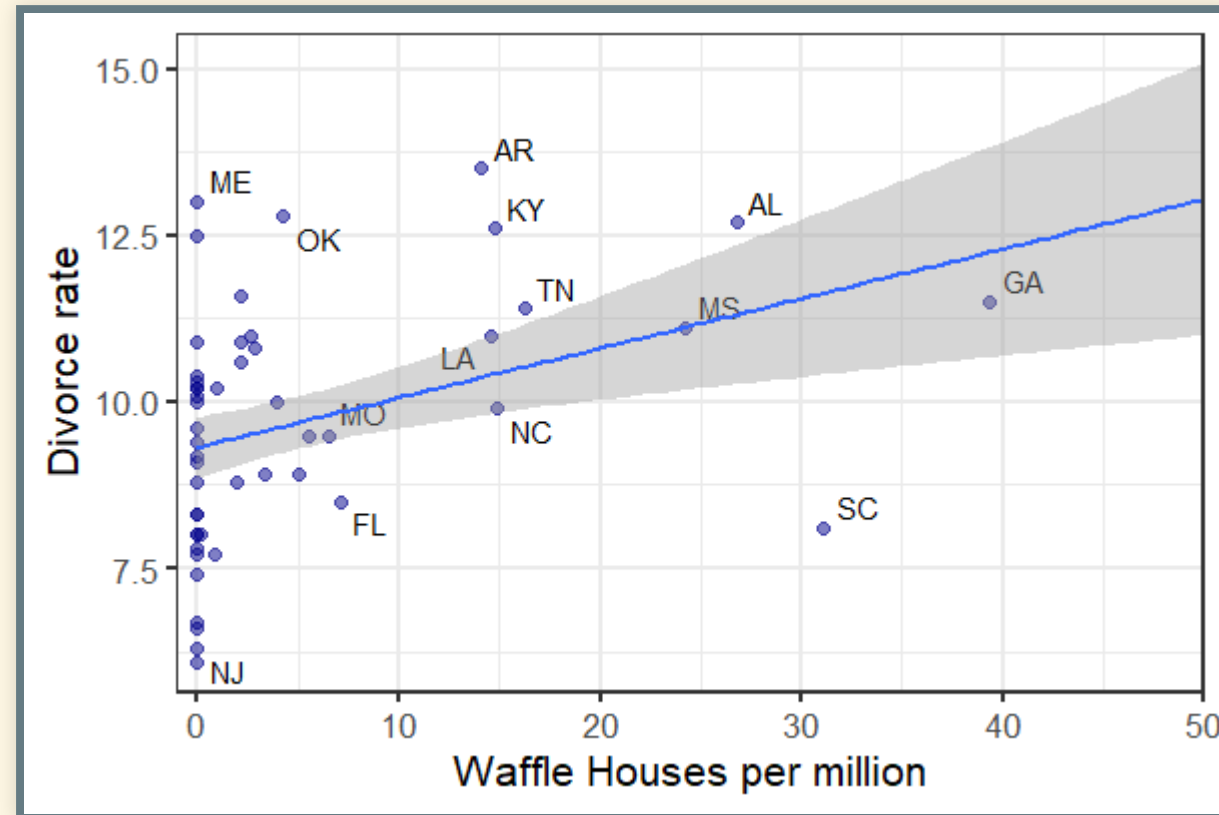
Class #6: Tuesday, September 13 2022

Multiple Regression

Multiple Regression

- Single Regression:
 - Dependent variable depends on one independent (predictor) variable
- Multiple Regression:
 - Dependent variable depends on multiple independent variables.
 - Why?
 - Statistical controls for confounding effects
 - On average, men are taller than women
 - Studies of how income correlates with height should control for sex.
 - Multiple causes and complex causation
 - Earth's temperature depends on
 - Greenhouse gas concentrations
 - Albedo (reflection of sunlight)
 - Brightness of the sun
 - Interactions (Chapter 8)
 - Smoking increases risk of lung cancer
 - Exposure to radon increases risk of lung cancer
 - The increase is much greater among smokers

Spurious Association



Standardize Data

```
library(rethinking)
data(WaffleDivorce)
d <- WaffleDivorce %>% mutate(
  D = standardize(Divorce),
  M = standardize(Marriage),
  A = standardize(MedianAgeMarriage)
)
```

```
mdl_A <- quap(
  alist(
    D ~ dnorm(mu, sigma),
    mu <- a + bA * A,
    a ~ dnorm(0, 0.2),
    bA ~ dnorm(0, 0.5),
    sigma ~ dexp(1)
  ), data = d)
```

```
mdl_M <- quap(
  alist(
    D ~ dnorm(mu, sigma),
    mu <- a + bM * M,
    a ~ dnorm(0, 0.2),
    bM ~ dnorm(0, 0.5),
    sigma ~ dexp(1)
  ), data = d)
```

- Model

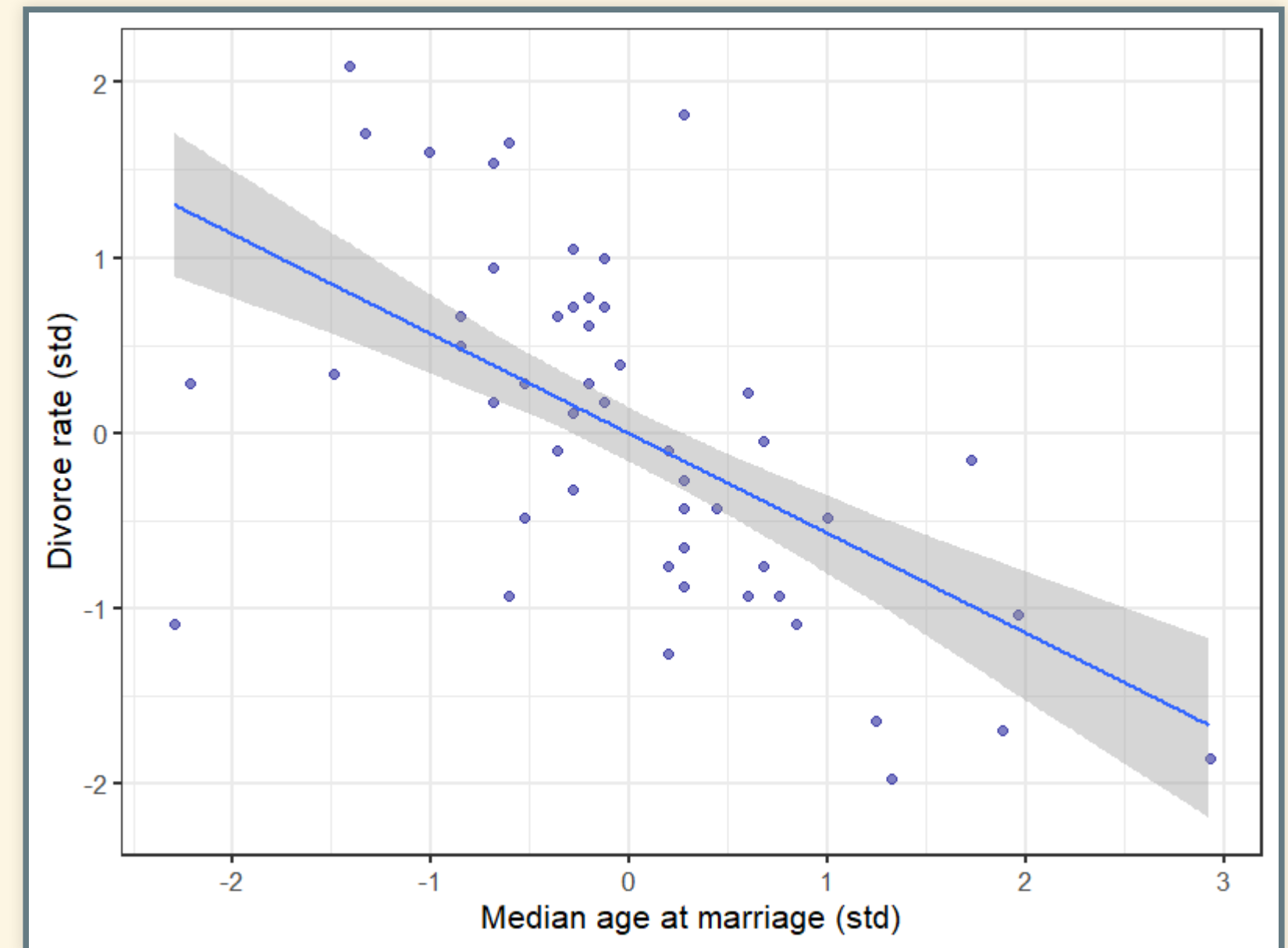
$$D_i \sim \text{Normal}(\mu_i, \sigma)$$

$$\mu_i = \alpha + \beta_A A_i$$

$$\alpha \sim \text{Normal}(0, 0.2)$$

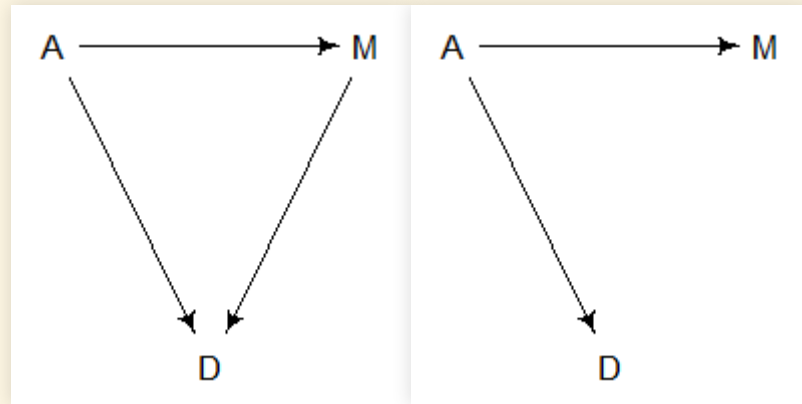
$$\beta_A \sim \text{Normal}(0, 0.5)$$

$$\sigma \sim \text{Exponential}(1)$$

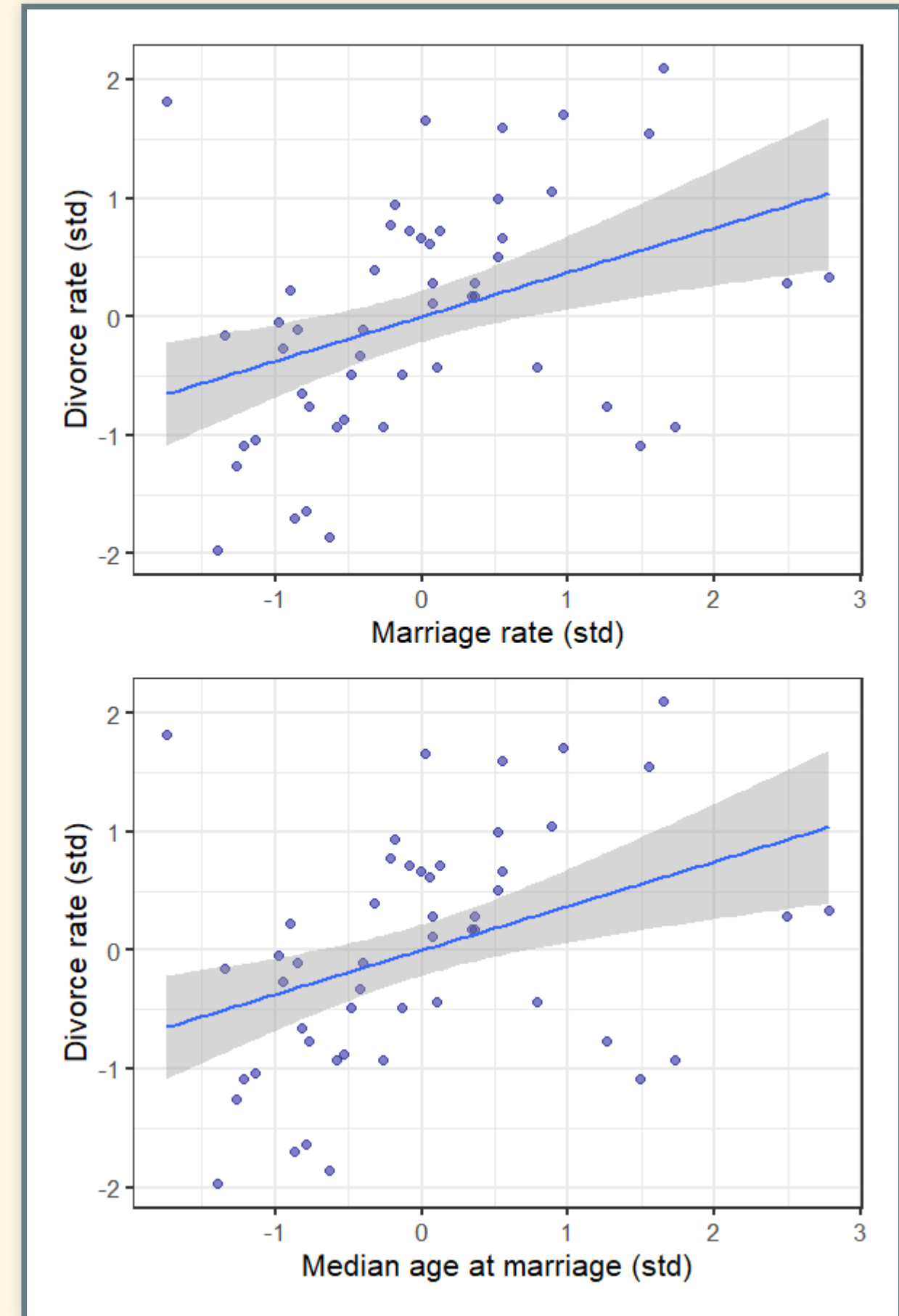


Caustal Relationships

- Think before you regress
 - The pattern we see here is typical when one variable influences the dependent variable and also the other independent variable.
 - Two possible causal relationships

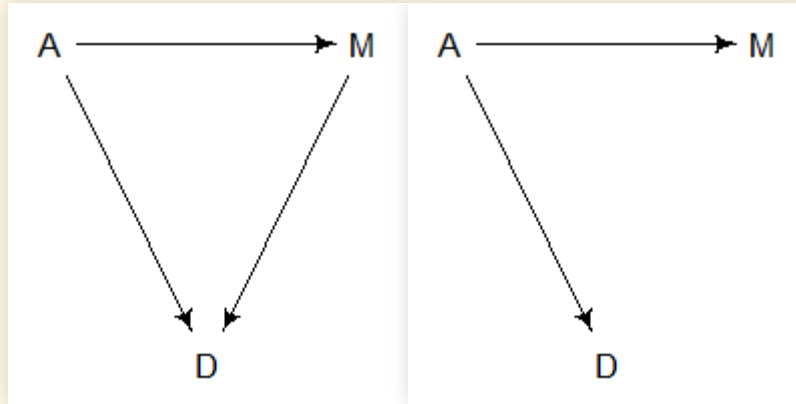


- Which is it?



Testable Implications

- What are the possible *testable implications* of these DAGs?
- Left DAG:



- Conditional independencies:**

- Which variables should be associated in the data?
- Which variables become dis-associated when we *condition* on another set of variables

- **Conditioning:** Y is independent of X , conditioned on Z ($Y \perp\!\!\!\perp X|Z$) if X doesn't give us any additional information about Y when we already know Z .
- Left DAG: There shouldn't be any independence among D , A , and M .
- Right DAG: $D \perp\!\!\!\perp M|A$.

```
library(dagitty)
DMA_dag1 <- dagitty("dag{ D <- A -> M -> D
                    }")
impliedConditionalIndependencies(DMA_dag1)
```

- No conditional independencies

- Right DAG:

```
DMA_dag2 <- dagitty("dag{ D <- A -> M }")
impliedConditionalIndependencies(DMA_dag2)
```

```
## D _||_ M | A
```

Multiple Regression Models

Multiple Regression Notation

$$D_i \sim \text{Normal}(\mu_i, \sigma)$$

$$\mu_i = \alpha + \beta_M M_i + \beta_A A_i$$

$$\alpha \sim \text{Normal}(0, 0.2)$$

$$\beta_M \sim \text{Normal}(0, 0.5)$$

$$\beta_A \sim \text{Normal}(0, 0.5)$$

$$\sigma \sim \text{Exponential}(1)$$

```
mdl_multi <- quap(  
  alist(  
    D ~ dnorm(mu, sigma),  
    mu <- a + bM * M + bA * A,  
    a ~ dnorm(0, 0.2),  
    bM ~ dnorm(0, 0.5),  
    bA ~ dnorm(0, 0.5),  
    sigma ~ dexp(1)  
  ), data = d  
)  
  
precis_show(precis(mdl_multi, digits=2))
```

##		mean	sd	5.5%	94.5%
##	a	0.00	0.10	-0.16	0.16
##	bM	-0.07	0.15	-0.31	0.18
##	bA	-0.61	0.15	-0.85	-0.37
##	sigma	0.79	0.08	0.66	0.91

Comparing Models

Diagnostic Posterior Plots

Diagnostic Posterior Plots

- We can also learn from plotting the posterior in different ways.
 1. **Predictor residual plots:** Data versus residual predictor values.
 - These are only useful for understanding the model itself.
 2. **Posterior prediction plots:** Predictions versus raw data.
 - Useful for checking how well the model fits the data.
 - Don't tell us about causal relationships.
 3. **Counterfactual plots:** Implied predictions for imaginary experiments.
 - Useful for exploring causal implications.

Predictor Residual Plots

- Predict M from A

```
library(ggrepel)

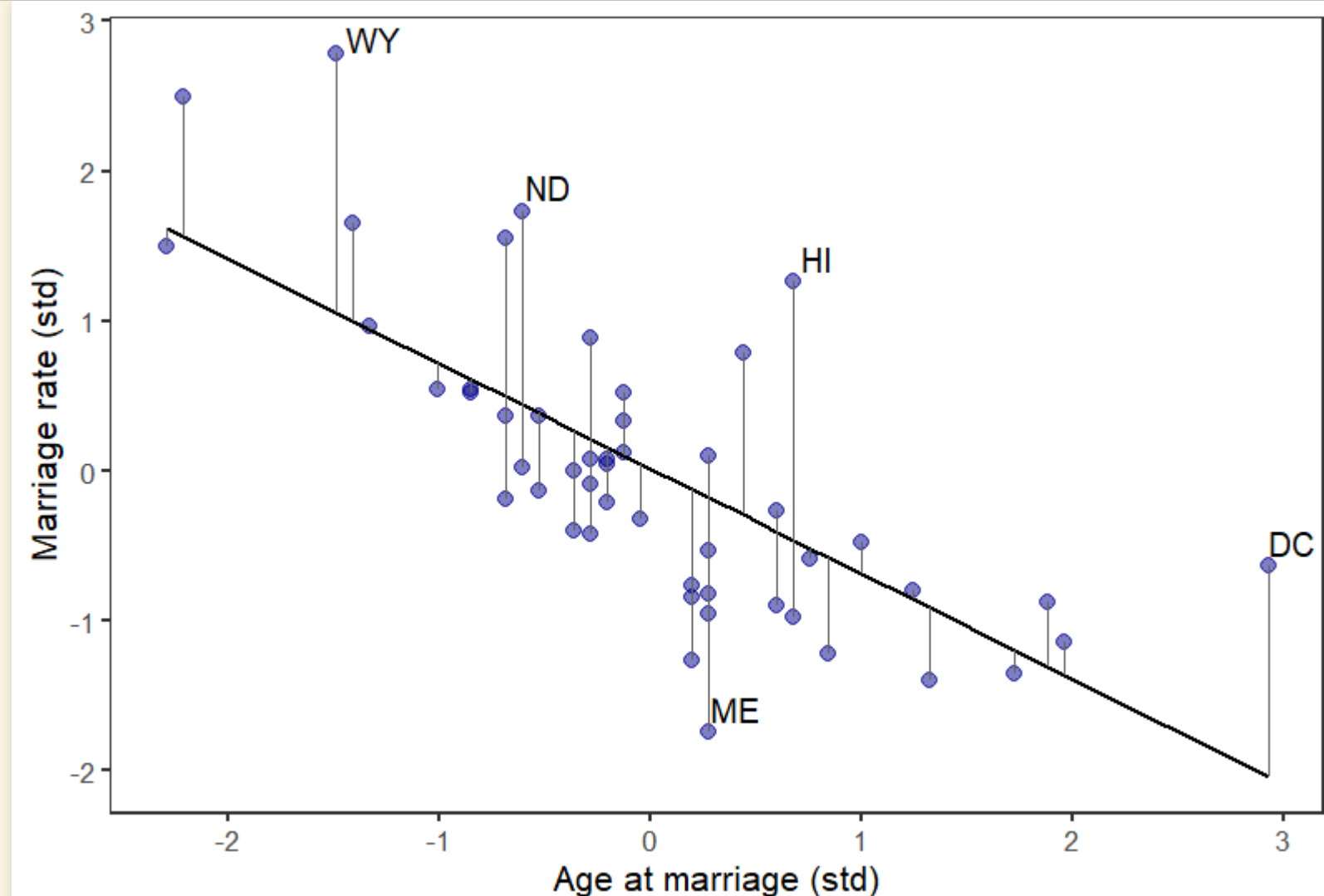
mdl_MA <- quap(
  alist(
    M ~ dnorm(mu, sigma),
    mu <- a + b * A,
    a ~ dnorm(0, 0.2),
    b ~ dnorm(0, 0.5),
    sigma ~ dexp(1)
  ), data = d
)

new_data <- select(d, D, A, M, Loc)
notable_states <- c("WY", "ND", "ME", "HI",
  "DC")

post <- linpred_draws(
  mdl_MA, new_data,
  value = "mu", ndraws = 100
) %>%
  group_by(Loc, D, A, M) %>%
  summarize(estimate = mean(mu)) %>%
  ungroup()
```

```
library(ggrepel)

ggplot(post, aes(x = A, y = M)) +
  geom_point(size = 3, color = "darkblue", alpha = 0.5) +
  geom_line(aes(y = estimate), size = 1, color = "black") +
  geom_segment(aes(xend = A, yend = estimate), size = 0.25,
    color = "gray40") +
  geom_text_repel(data = . %>% filter(Loc %in% notable_states),
    aes(label = Loc), size = 5,
    nudge_x = 0.01, nudge_y = 0.05) +
  labs(x = "Age at marriage (std)", y = "Marriage rate (std)") +
  theme_bw(base_size = 15) +
  theme(panel.grid = element_blank())
```



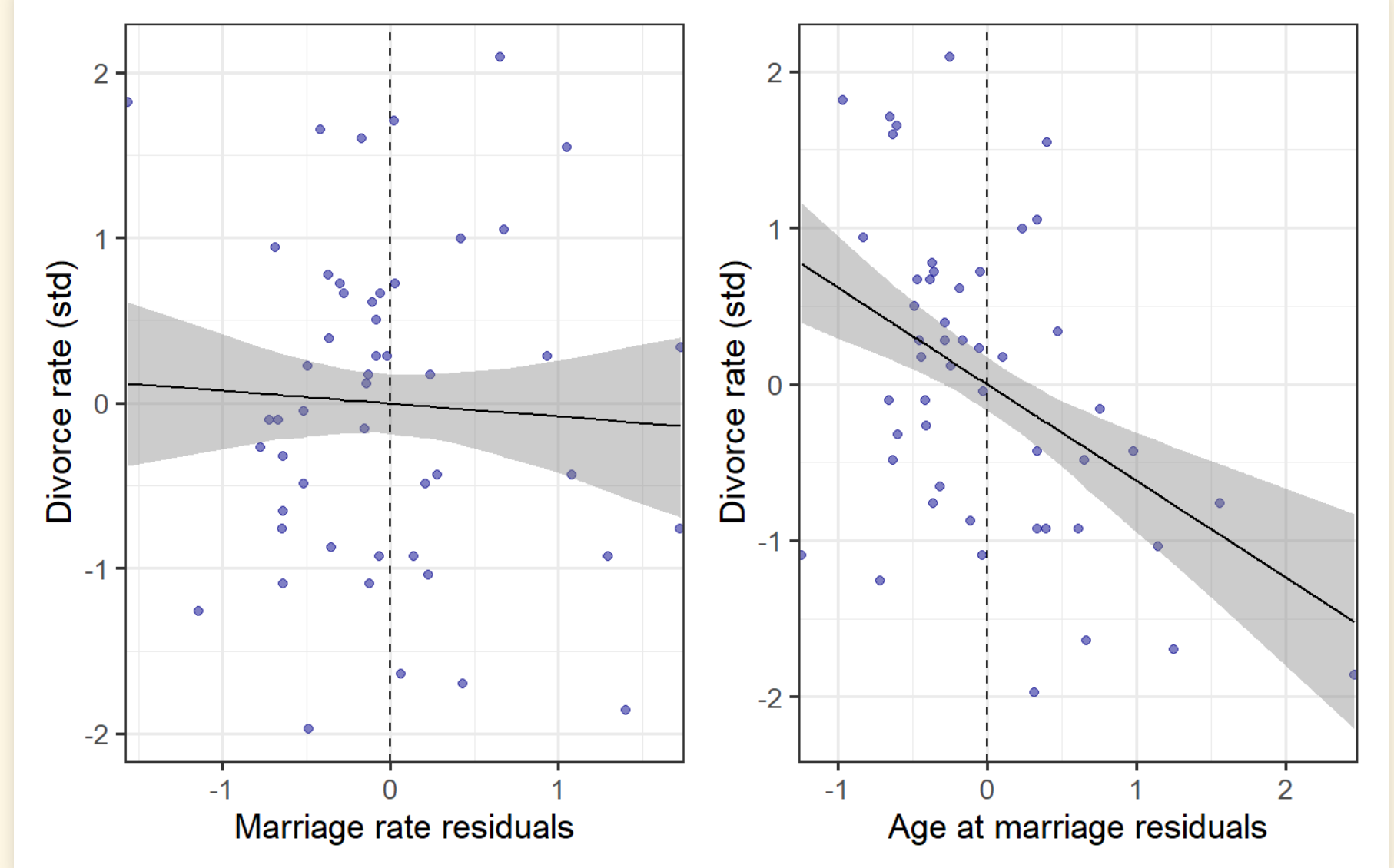
More Residual Plots

```
d2 <- post %>% mutate(resid = M - estimate)

mdl_resid <- quap(
  alist(
    D ~ dnorm(mu, sigma),
    mu <- a + b_res * resid,
    a ~ dnorm(0, 0.2),
    b_res ~ dnorm(0, 0.5),
    sigma ~ dexp(1)
  ), data = d2
)

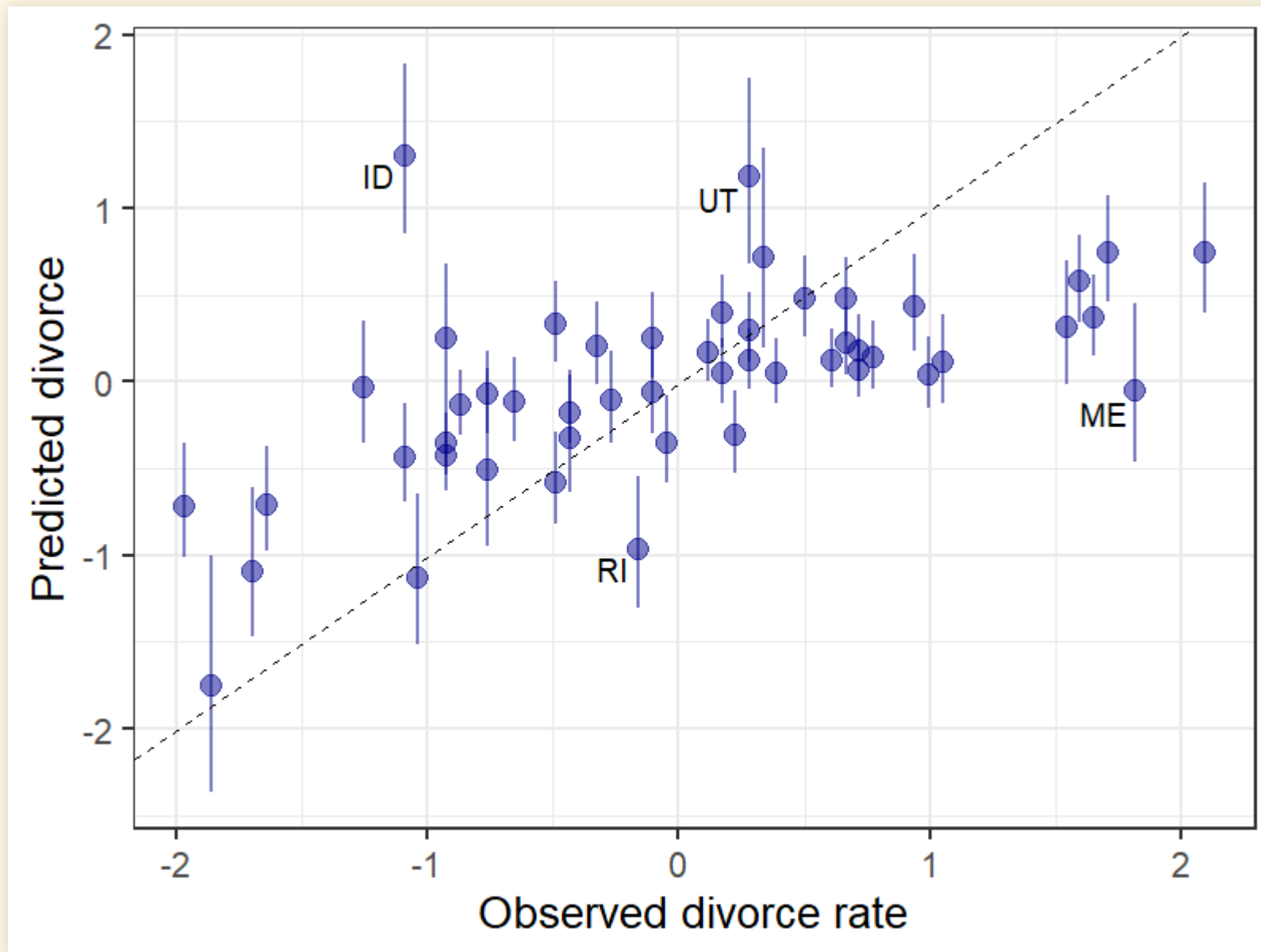
post_MA <- linpred_draws(mdl_resid, select(d2, resid),
  ndraws = 1000, value = "estimate")

%>%
group_by(resid) %>%
summarize(mean = mean(estimate),
  lower = quantile(estimate, 0.055),
  upper = quantile(estimate, 0.945)) %>%
ungroup()
```



- Look for structure in the residuals.
 - Is the trend line consistent with being flat?
 - Marriage rate residuals?
 - Age at marriage residuals?
 - The error in marriage rate isn't correlated with divorce rate, but the error in age at marriage is.

Posterior Predictive Plots



```
mu <- linpred_draws(mdl_multi, select(d, D, A, M, Loc),
                    ndraws = 1000, value = "mu")

d2 <- mu %>% group_by(Loc, D, A, M) %>%
  summarize(estimate = mean(mu), lower = quantile(mu,
    0.055),
    upper = quantile(mu, 0.975)) %>% ungroup()

notable_states <- c("ID", "UT", "RI", "ME")

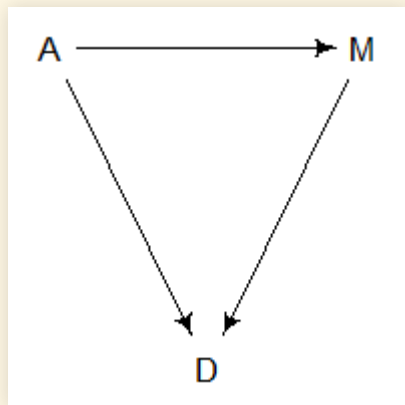
ggplot(d2, aes(x = D, y = estimate,
               ymax = upper, ymin = lower)) +
  geom_pointrange(size = 1, color = "darkblue", alpha =
    0.5) +
  geom_text_repel(data = . %>% filter(Loc %in%
    notable_states),
    aes(label = Loc), size = 5) +
  geom_abline(slope = 1, intercept = 0, color = "black",
    linetype = "dashed") +
  labs(x = "Observed divorce rate",
    y = "Predicted divorce")
```

1. How well does the posterior distribution match the data?
 2. When the model fails, **how** does it fail?
- Notice that I use `linpred_draws` (equivalent to `link`), not `predicted_draws` (equivalent to `extract.samples`)

Counterfactual Models

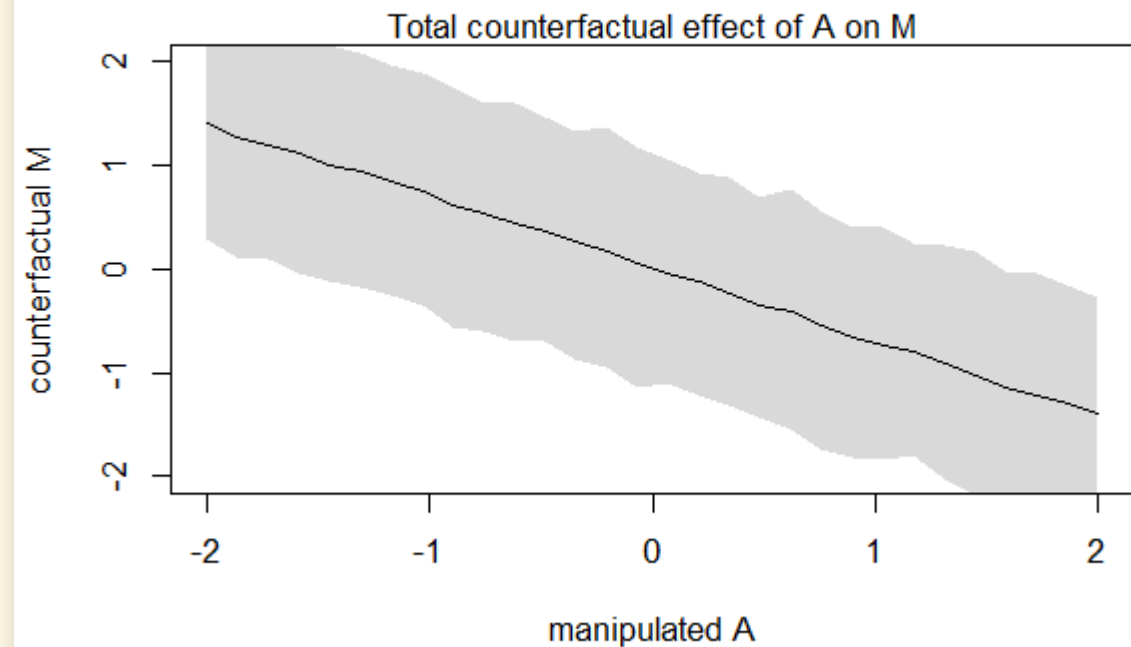
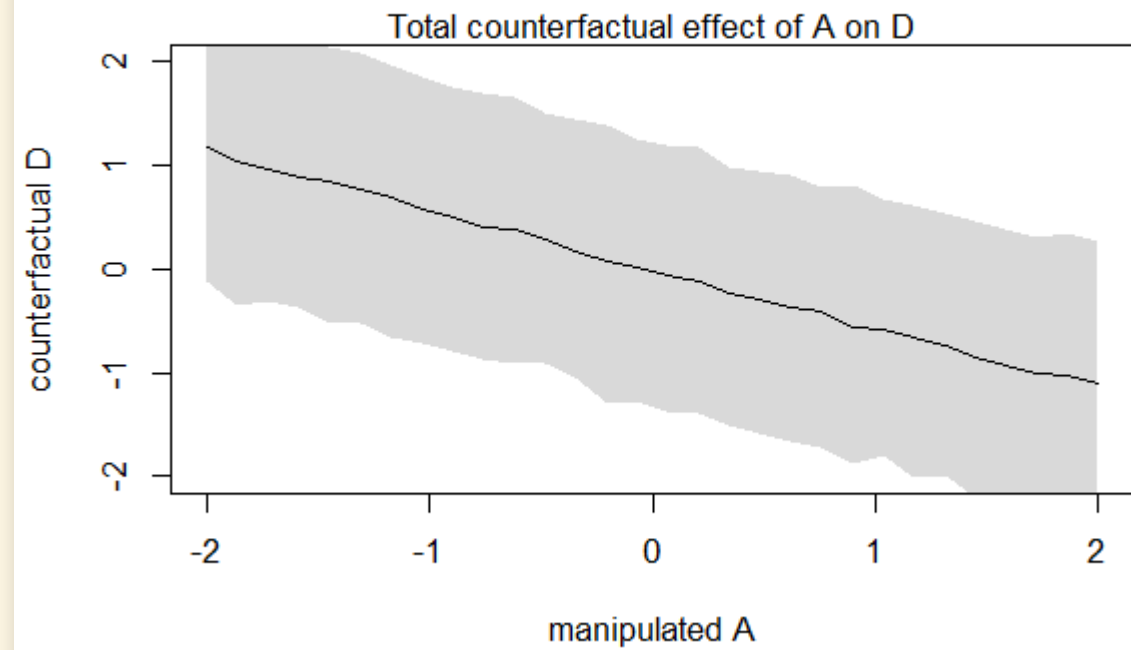
Counterfactual Models

- Counterfactual models:
 - Explore what the model would look like with data very different to what you actually observe.
 - What happens if no one gets married before they're 35?
- Process:
 1. Pick a variable to manipulate (the *intervention variable*)
 2. Define a range of values for it
 3. For each value, use the causal model to simulate values for other variables.
- Simulate the causal model where A influences M and D and M also influences D .



```
mdl_cf <- quap(  
  alist(  
    D ~ dnorm(mu, sigma),  
    mu <- a + bM * M + bA * A,  
    a ~ dnorm(0, 0.2),  
    bM ~ dnorm(0, 0.5),  
    bA ~ dnorm(0, 0.5),  
    sigma ~ dexp(1),  
  
    M ~ dnorm(mu_M, sigma_M),  
    mu_M <- aM + baM * A,  
    aM ~ dnorm(0, 0.2),  
    baM ~ dnorm(0, 0.5),  
    sigma_M ~ dexp(1)  
  ), data = d  
)
```

Manipulating the Counterfactual Model



```
sim_dat <- data.frame(A = seq(-2, 2, length.out = 30))
```

```
s <- sim mdl_cf, data = sim_dat, vars = c("M", "D"))
```

```
plot(sim_dat$A, colMeans(s$D), ylim = c(-2,2), type = "l",  
      xlab = "manipulated A", ylab = "counterfactual D")
```

```
shade(apply(s$D, 2, PI), sim_dat$A)
```

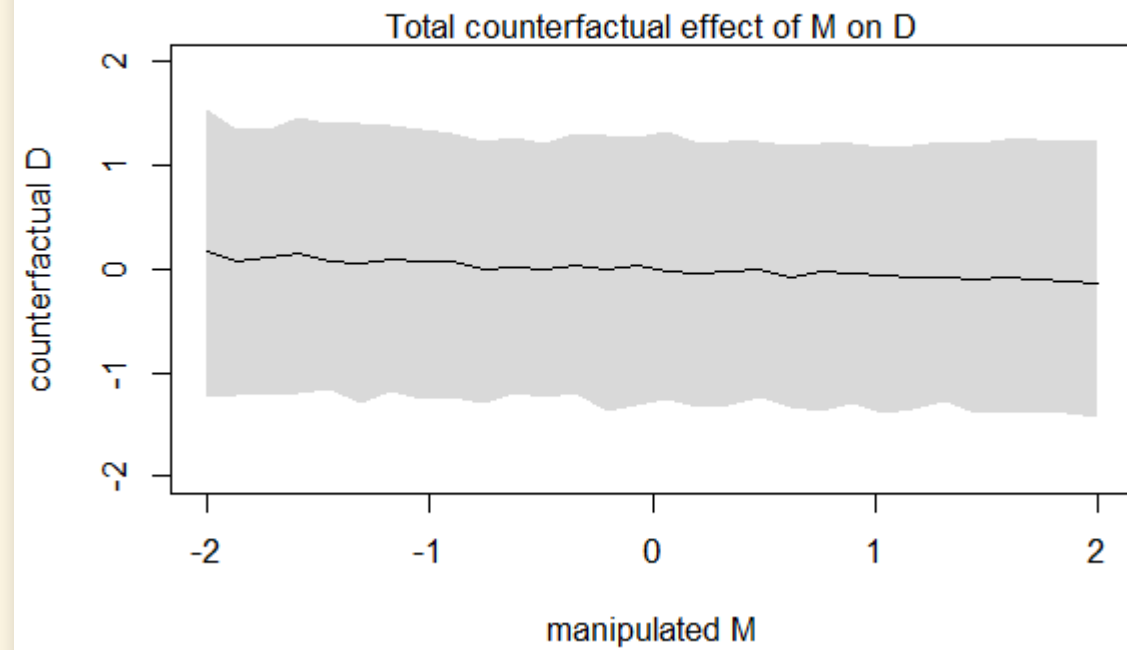
```
mtext( "Total counterfactual effect of A on D")
```

```
plot(sim_dat$A, colMeans(s$M), ylim = c(-2,2), type = "l",  
      xlab = "manipulated A", ylab = "counterfactual M")
```

```
shade(apply(s$M, 2, PI), sim_dat$A)
```

```
mtext( "Total counterfactual effect of A on M")
```

More Counterfactual Manipulations



```
sim_dat <- data.frame(M = seq(-2, 2, length.out = 30), A =  
  0)  
  
s <- sim mdl_cf, data = sim_dat, vars = c("D"))  
  
plot(sim_dat$M, colMeans(s), ylim = c(-2,2), type = "l",  
      xlab = "manipulated M", ylab = "counterfactual D")  
shade(apply(s, 2, PI), sim_dat$M)  
mtext( "Total counterfactual effect of M on D")
```