

Causal Modeling in R: Whole Game

Malcolm Barrett
Stanford University

- 1 Specify causal question (e.g. target trial)
- 2 Draw assumptions (causal diagram)
- 3 Model assumptions (e.g., propensity)
- 4 Diagnose model (e.g., balance)
- 5 Estimate causal effects (e.g., IPW)
- 6 Sensitivity analysis (more later!)

We'll focus on the broader ideas behind each step and what they look like all together; we don't expect you to fully digest each idea. We'll spend the rest of the workshop taking up each step in detail

Do people who quit smoking gain weight?

```

1 library(causaldata)
2 nhefs_complete_uc <- nhefs_complete |>
3   filter(censored == 0)
4 nhefs_complete_uc

```

A tibble: 1,566 × 67

	seqn	qsmk	death	yrdth	modth	dadth	sbp	dbp	sex
	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>	<fct>
1	233	0	0	NA	NA	NA	175	96	0
2	235	0	0	NA	NA	NA	123	80	0
3	244	0	0	NA	NA	NA	115	75	1
4	245	0	1	85	2	14	148	78	0
5	252	0	0	NA	NA	NA	118	77	0
6	257	0	0	NA	NA	NA	141	83	1
7	262	0	0	NA	NA	NA	132	69	1
8	266	0	0	NA	NA	NA	100	53	1
9	419	0	1	84	10	13	163	79	0
10	420	0	1	86	10	17	184	106	0

A tibble: 1,566 × 67

Did those who quit smoking gain weight?

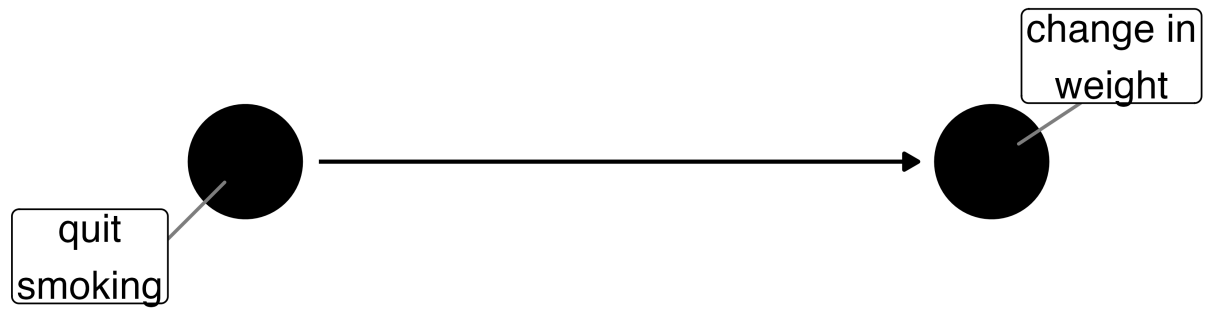
Did those who quit smoking gain weight?

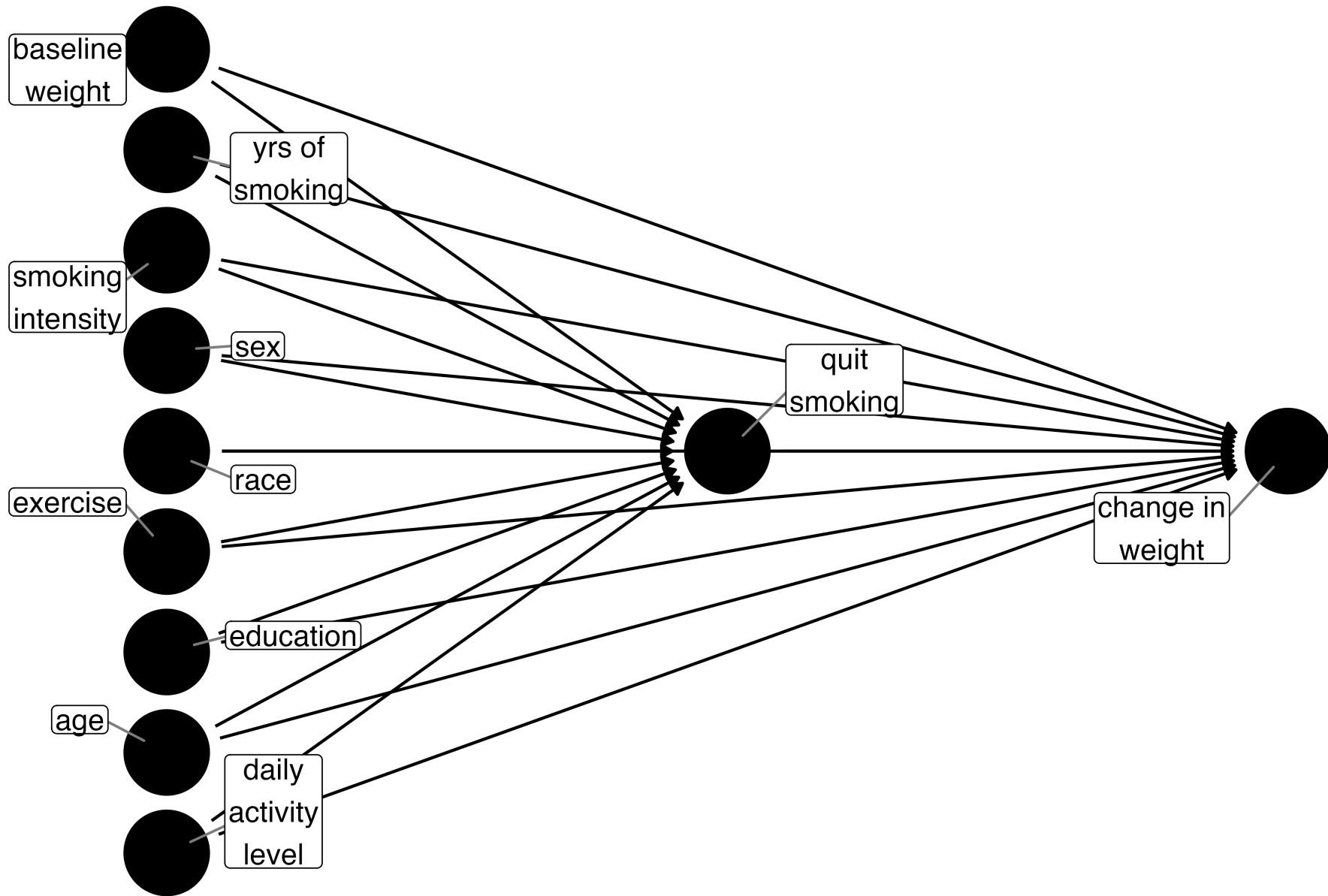
```
1 # ~2.5 KGs gained for quit vs. not quit
2 nhefs_complete_uc |>
3   group_by(qsmk) |>
4   summarize(
5     mean_weight_change = mean(wt82_71),
6     sd = sd(wt82_71),
7     .groups = "drop"
8   )
```

A tibble: 2 × 3

	qsmk	mean_weight_change	sd
	<dbl>	<dbl>	<dbl>
1	0	1.98	7.45
2	1	4.53	8.75

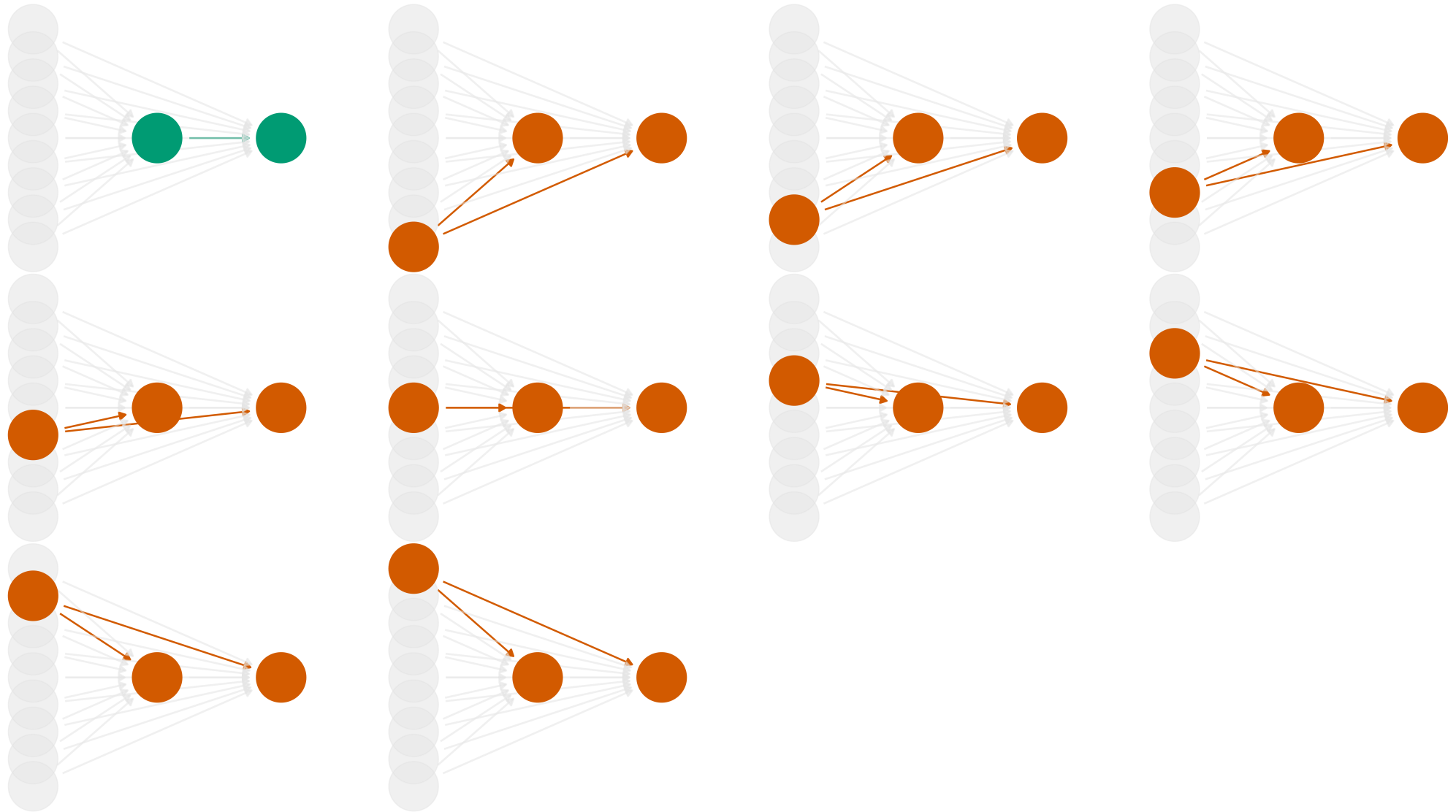
draw your assumptions



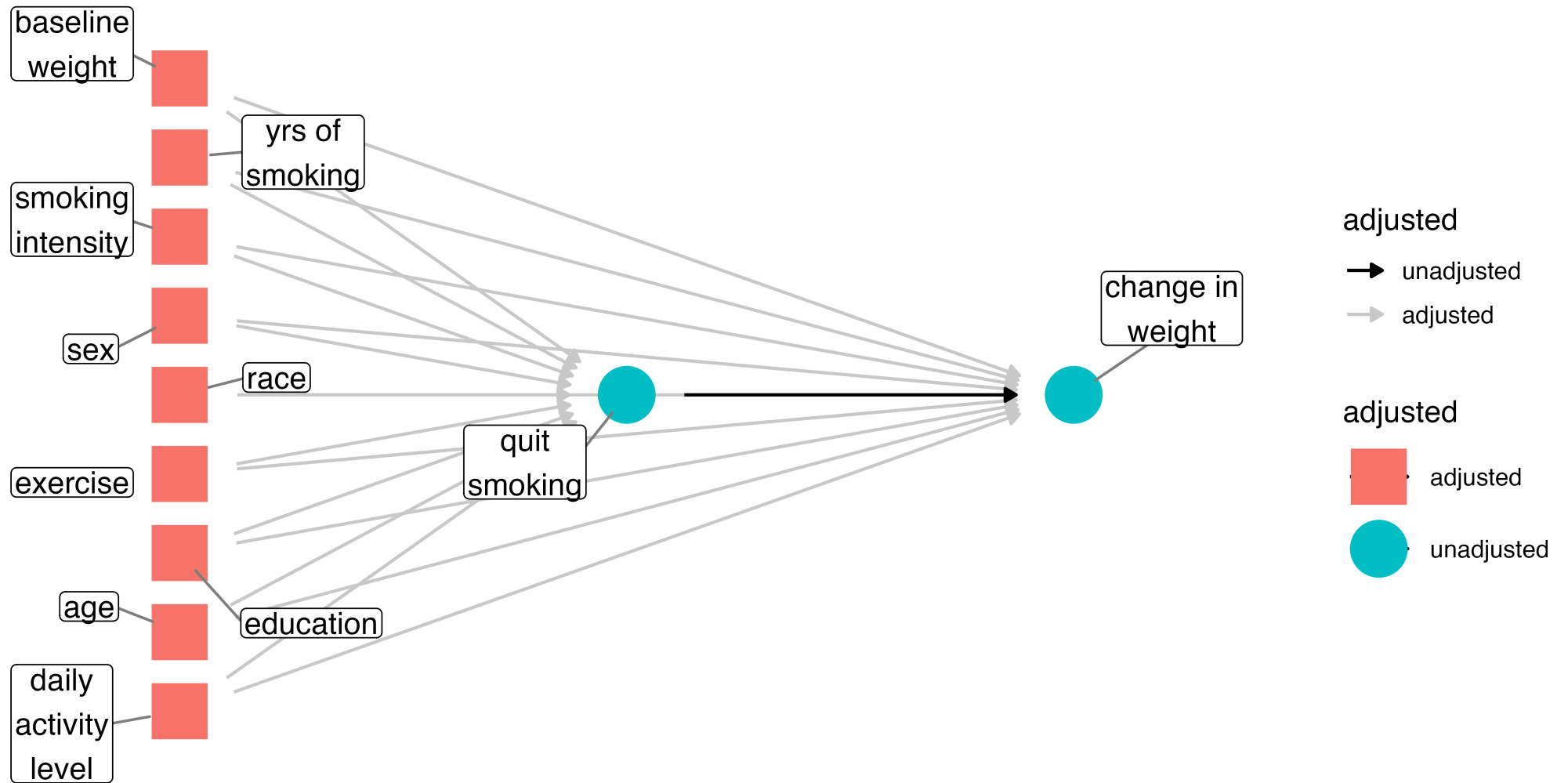


What do I need to control for?

■ true effect ■ confounding effect



**{active, age, education, exercise,
race, sex, smokeintensity, smokeyrs,
wt71}**



Multivariable regression: what's the association?

```
1 lm(  
2   wt82_71 ~ qsmk + sex +  
3     race + age + I(age^2) + education +  
4     smokeintensity + I(smokeintensity^2) +  
5     smokeyrs + I(smokeyrs^2) + exercise + active +  
6     wt71 + I(wt71^2),  
7   data = nhfs_complete_uc  
8 ) |>  
9 tidy(conf.int = TRUE) |>  
10 filter(term == "qsmk")
```

```
# A tibble: 1 × 7  
  term      estimate std.error statistic  p.value conf.low  
  <chr>      <dbl>     <dbl>     <dbl>    <dbl>    <dbl>  
1 qsmk        3.46      0.438      7.90 5.36e-15     2.60  
# i 1 more variable: conf.high <dbl>
```

model your assumptions

**counterfactual: what if everyone quit smoking
vs. what if no one quit smoking**

Fit propensity score model

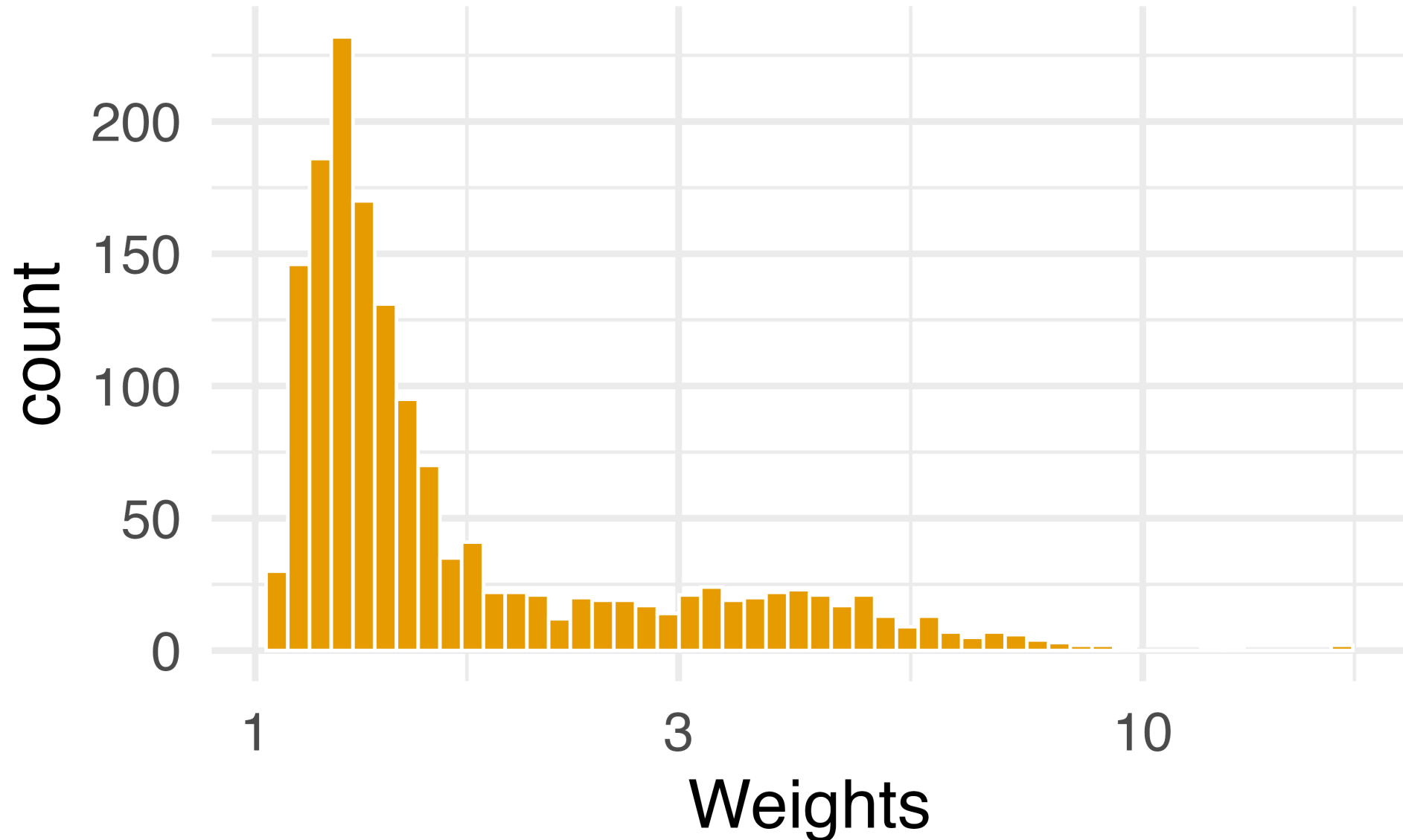
```
1 propensity_model <- glm(  
2   qsmk ~ sex +  
3     race + age + I(age^2) + education +  
4     smokeintensity + I(smokeintensity^2) +  
5     smokeyrs + I(smokeyrs^2) + exercise + active +  
6     wt71 + I(wt71^2),  
7   family = binomial(),  
8   data = nhefs_complete_uc  
9 )
```

Calculate inverse probability weights

```
1 library(propensity)
2 nhfs_complete_uc <- propensity_model |>
3   # predict whether quit smoking
4   augment(type.predict = "response", data = nhfs_complete_uc) |>
5   # calculate inverse probability
6   mutate(wts = wt_ate(.fitted, qsmk))
```

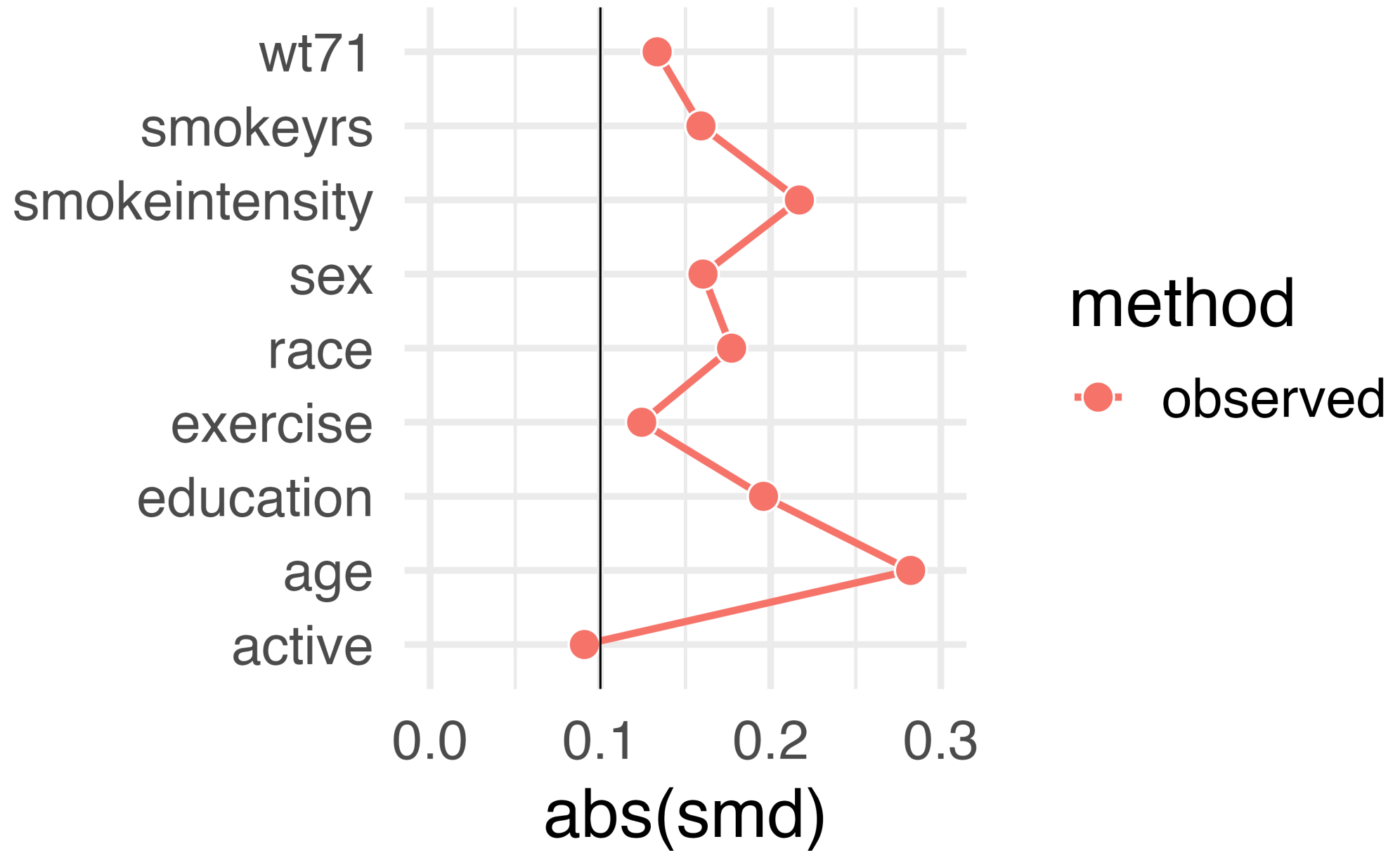
diagnose your model assumptions

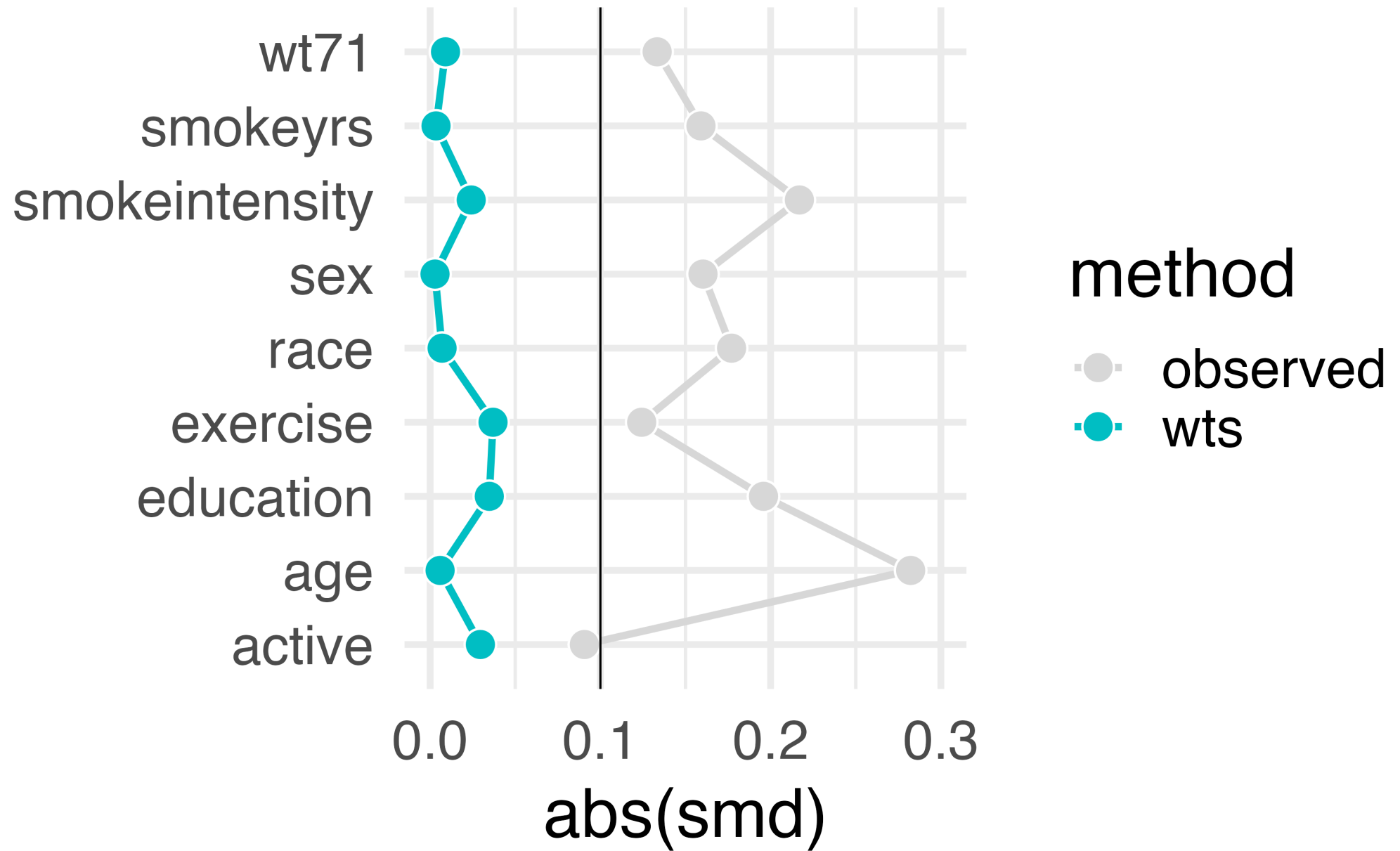
What's the distribution of weights?



What are the weights doing to the sample?

What are the weights doing to the sample?





estimate the causal effects

Estimate causal effect with IPW

```
1 ipw_model <- lm(  
2   wt82_71 ~ qsmk,  
3   data = nhefs_complete_uc,  
4   weights = wts  
5 )  
6  
7 ipw_estimate <- ipw_model |>  
8   tidy(conf.int = TRUE) |>  
9   filter(term == "qsmk")
```

Estimate causal effect with IPW

```
1 ipw_estimate
```

```
# A tibble: 1 × 7
  term      estimate std.error statistic  p.value conf.low
<chr>    <dbl>      <dbl>    <dbl>    <dbl>    <dbl>
1 qsmk      3.44      0.408      8.43 7.47e-17    2.64
# i 1 more variable: conf.high <dbl>
```

Let's fix our confidence intervals with robust SEs!

```
1 # also see robustbase, survey, gee, and others
2 library(estimatr)
3 ipw_model_robust <- lm_robust(
4   wt82_71 ~ qsmk,
5   data = nhefs_complete_uc,
6   weights = wts
7 )
8
9 ipw_estimate_robust <- ipw_model_robust |>
10   tidy(conf.int = TRUE) |>
11   filter(term == "qsmk")
```

Let's fix our confidence intervals with robust SEs!

```
1 as_tibble(ipw_estimate_robust)
```

```
# A tibble: 1 × 9
```

	term	estimate	std.error	statistic	p.value	conf.low
	<chr>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>
1	qsmk	3.44	0.526	6.54	8.57e-11	2.41

```
# i 3 more variables: conf.high <dbl>, df <dbl>,
```

```
# outcome <chr>
```

Let's fix our confidence intervals with the bootstrap!

```
1 # fit ipw model for a single bootstrap sample
2 fit_ipw_not_quite_rightly <- function(.split, ...) {
3   # get bootstrapped data frame
4   .df <- as.data.frame(.split)
5
6   # fit ipw model
7   lm(wt82_71 ~ qsmk, data = .df, weights = wts) |>
8     tidy()
9 }
```

```

1 fit_ipw <- function(.split, ...) {
2   # get bootstrapped data frame
3   .df <- as.data.frame(.split)
4
5   # fit propensity score model
6   propensity_model <- glm(
7     qsmk ~ sex +
8       race + age + I(age^2) + education +
9       smokeintensity + I(smokeintensity^2) +
10      smokeyrs + I(smokeyrs^2) + exercise + active +
11      wt71 + I(wt71^2),
12     family = binomial(),
13     data = .df
14   )
15
16   # calculate inverse probability weights
17   .df <- propensity_model |>
18     augment(type.predict = "response", data = .df) |>
19     mutate(wts = wt_ate(.fitted, qsmk))
20
21   # fit correctly bootstrapped ipw model
22   lm(wt82_71 ~ qsmk, data = .df, weights = wts) |>
23     tidy()
24 }

```

Using {rsample} to bootstrap our causal effect

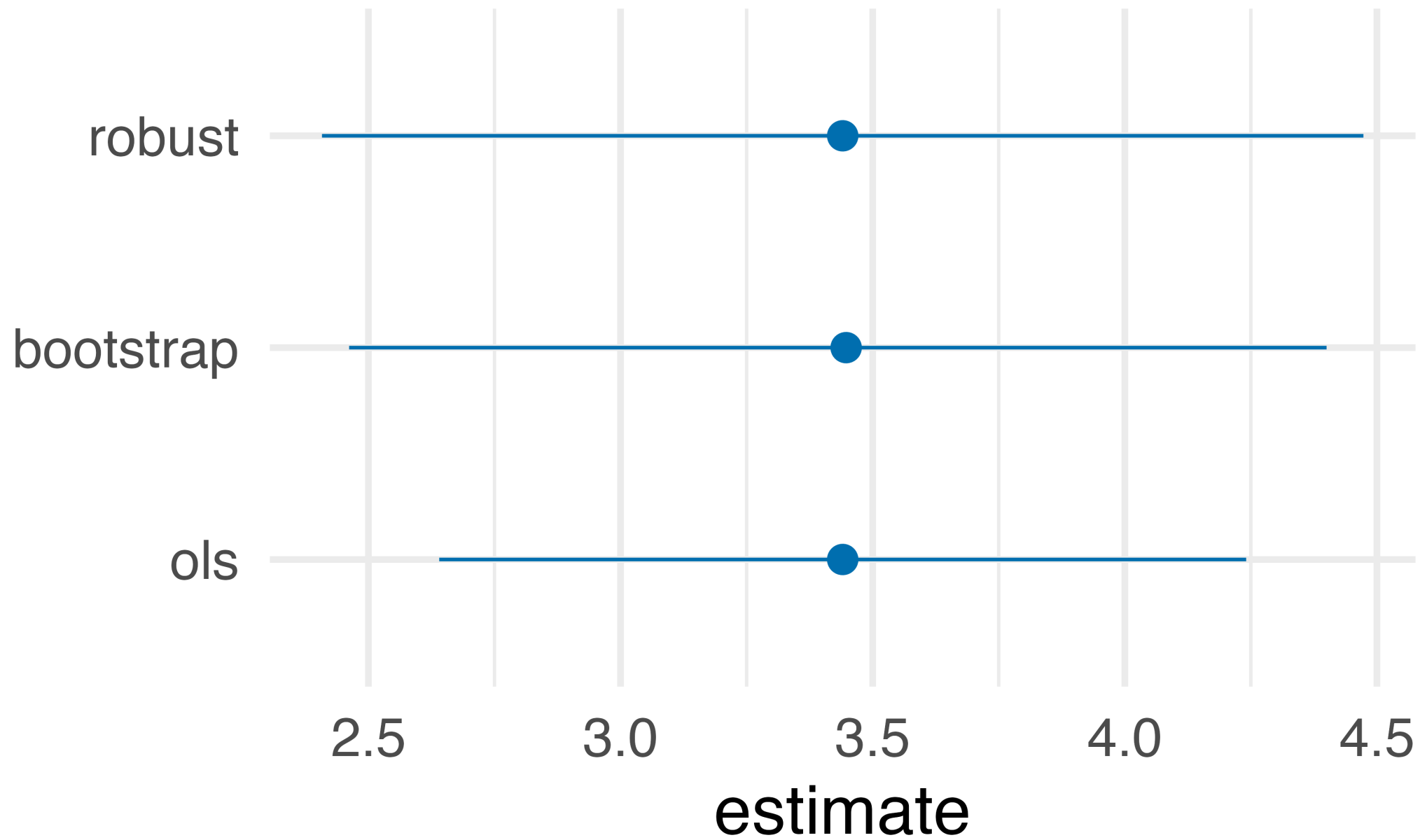
```
1 # fit ipw model to bootstrapped samples
2 ipw_results <- bootstraps(nhefs_complete_uc, 1000, apparent = TRUE) |>
3   mutate(results = map(splits, fit_ipw))
```


Using {rsample} to bootstrap our causal effect

```
1 # get t-statistic-based CIs
2 boot_estimate <- int_t(ipw_results, results) |>
3   filter(term == "qsmk")
4
5 boot_estimate
```

Using {rsample} to bootstrap our causal effect

```
# A tibble: 1 × 6
  term    .lower .estimate .upper .alpha .method
<chr>   <dbl>    <dbl>   <dbl> <dbl>  <chr>
1 qsmk    2.46      3.45    4.40  0.05  student-t
```



Our causal effect estimate: 3.5 kg (95% CI 2.4 kg, 4.4 kg)

Review the Quarto file... later!

Resources

Causal Inference: Comprehensive text on causal inference. Free online.

Bootstrap confidence intervals with {rsample}

R-causal: Our GitHub org with R packages and examples