Section 1: Hospital Pricing and Selection on Observables

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Econ 470 & HLTH 470

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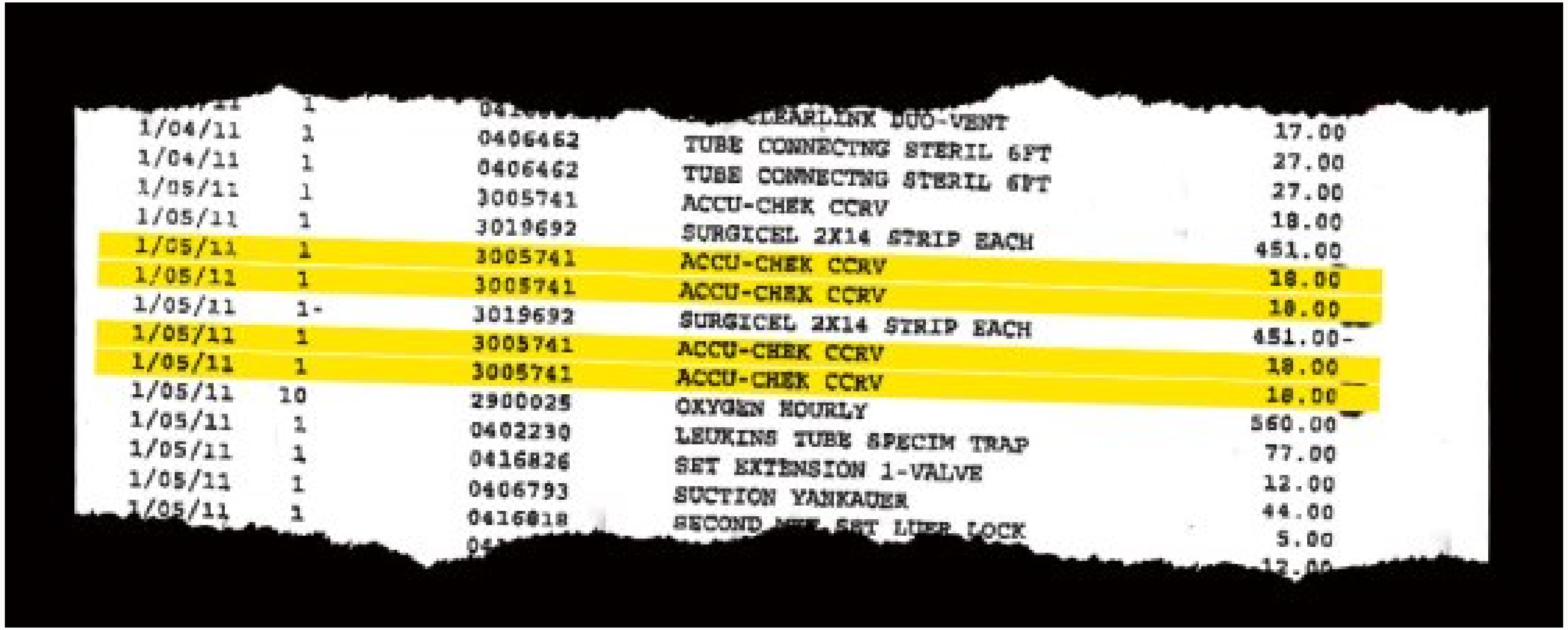
Background on Hospital Pricing

What is a hospital price?

Defining characteristic of hospital services: *it's complicated!*



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1/04/11	1	0406462	TUBE CONNECTNG STERIL 6FT	27.00
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1/05/11	1	3005741	ACCU-CHEK CCRV	18.00
1/05/11	1	3019692	SURGICEL 2X14 STRIP EACH	451.00
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1/05/11	1	0416826	SET EXTENSION 1-VALVE	12.00
1/05/11	1	0406793	SUCTION YANKAUER	44.00
1/05/11	1	0416818	SECOND [illegible] SET LUER LOCK	5.00

Brill, Steven. 2013. "Bitter Pill: Why Medical Bills are Killing Us." *Time Magazine*.

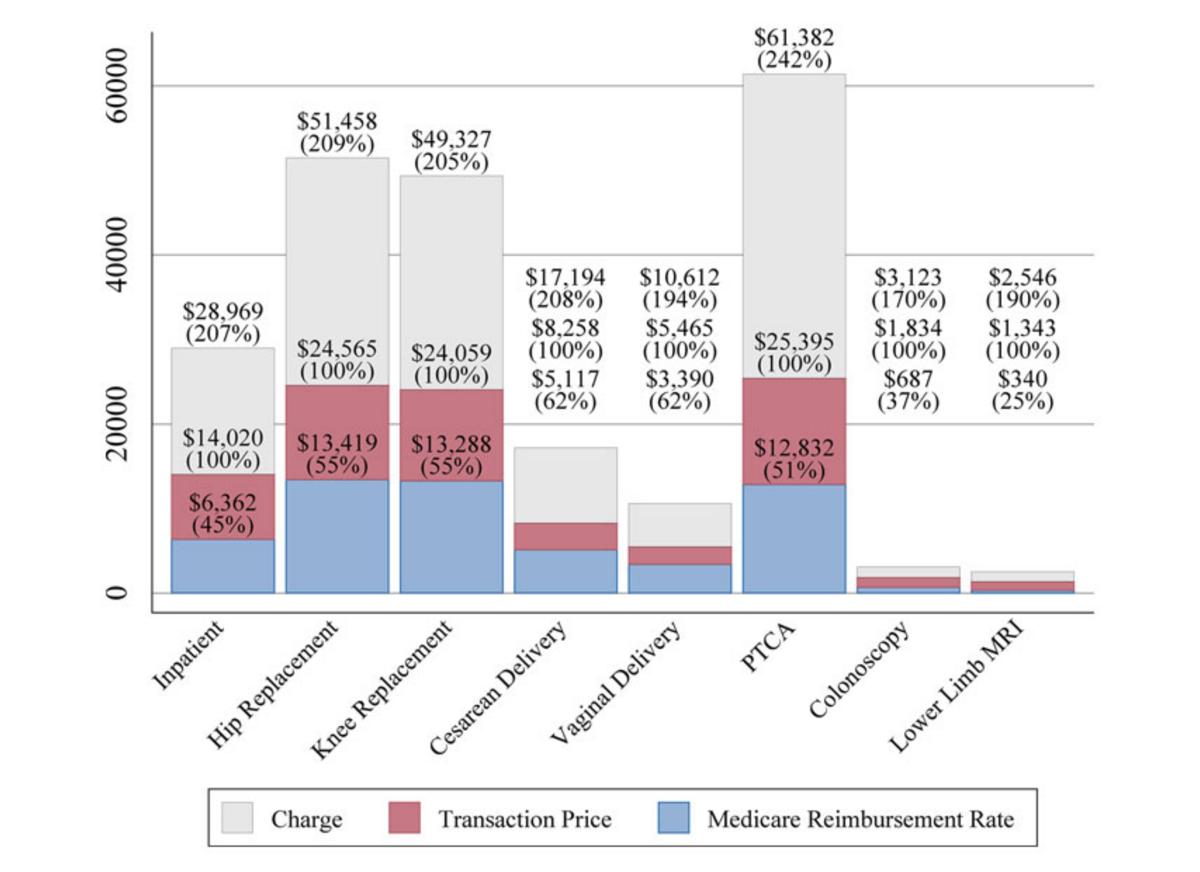
What is a hospital price?

Lots of different payers paying lots of different prices:

- Medicare fee-for-service prices
- Medicaid payments
- Private insurance negotiations (including Medicare Advantage)
- But what about the price to patients?

$$\text{Price} \neq \text{charge} \neq \text{cost} \neq \text{patient out-of-pocket spending}$$

What is a hospital price?



Source: Health Care Pricing Project

What is a hospital price?

Not clear what exactly is negotiated...

Fee-for-service

- price per procedure
- percentage of charges
- markup over Medicare rates

Capitation

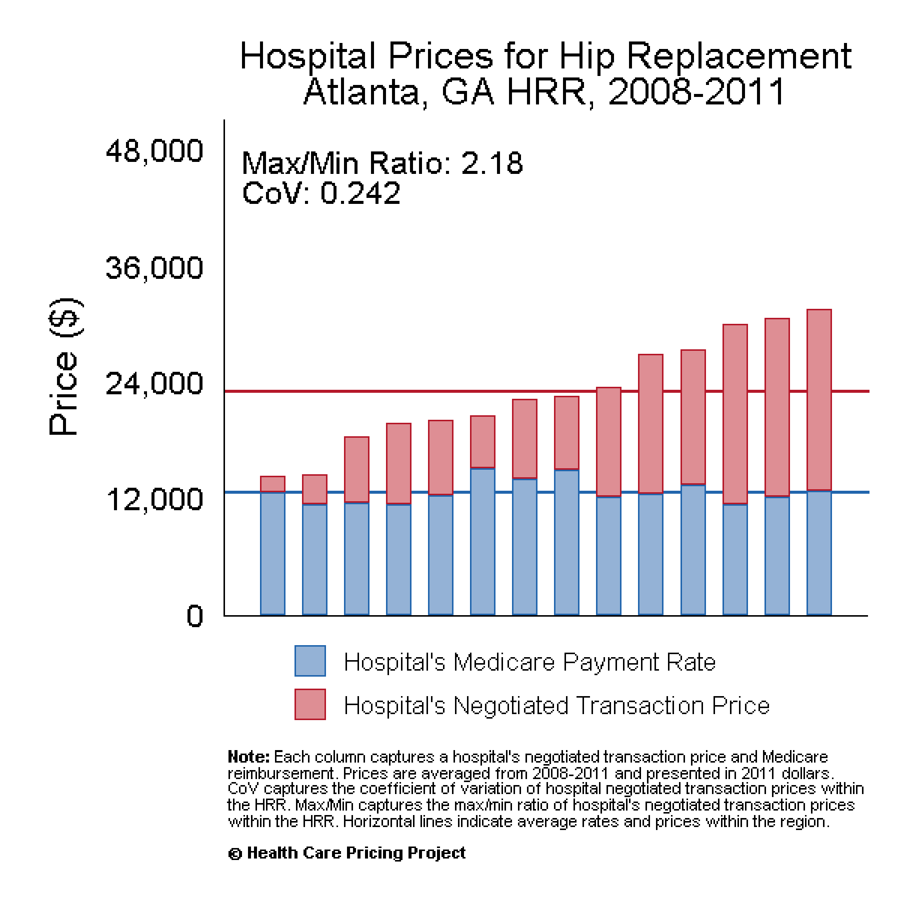
- payment per patient
- pay-for-performance
- shared savings

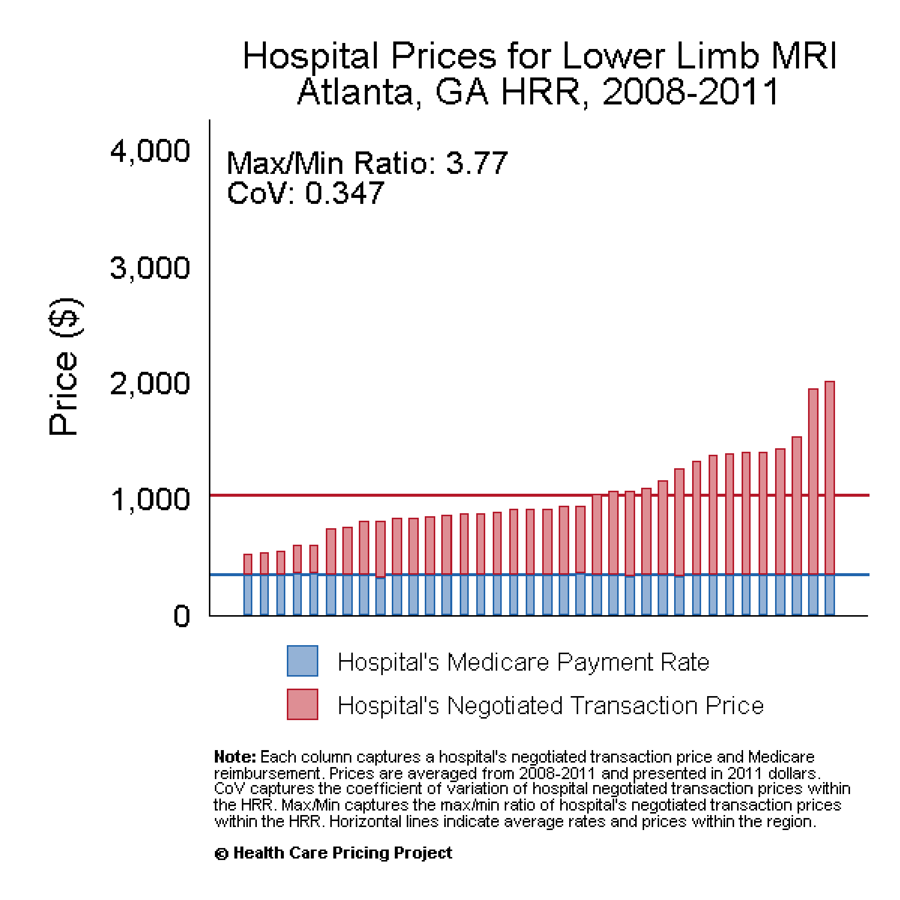
Hospital prices in real life

A few empirical facts:

1. Hospital services are expensive
2. Prices vary dramatically across different areas
3. Lack of competition is a major reason for high prices

Hospital prices in real life





Source: Health Care Pricing Project

Understanding HCRIS Data

What is HCRIS?

Healthcare Cost Report Information System ('cost reports')

- Nursing Homes (SNFs)
- Hospice
- Home Health Agencies
- Hospitals

Hospital Cost Reports

10-12 FORM CMS-2552-10 4090 (Cont.)

STATEMENT OF PATIENT REVENUES AND OPERATING EXPENSES	PROVIDER CCN:	PERIOD: FROM ____ TO ____	WORKSHEET G-2, PARTS I & II

PART I - PATIENT REVENUES

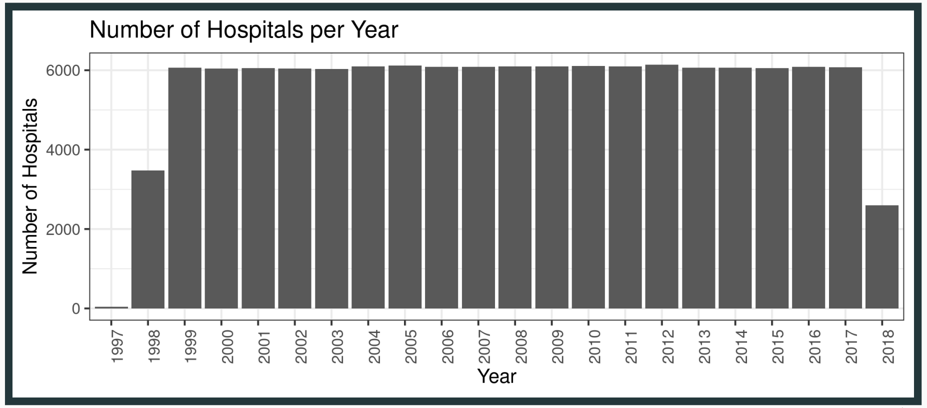
	REVENUE CENTER	INPATIENT	OUTPATIENT	TOTAL	
		1	2	3	
	GENERAL INPATIENT ROUTINE CARE SERVICES				
1	Hospital				1
2	Subprovider IPF				2
3	Subprovider IRF				3
4	Subprovider (Other)				4
5	Swing bed - SNF				5
6	Swing bed - NF				6
7	Skilled nursing facility				7
8	Nursing facility				8
9	Other long term care				9
10	Total general inpatient care services (sum of lines 1-9)				10
	INTENSIVE CARE TYPE INPATIENT HOSPITAL SERVICES				
11	Intensive care unit				11
12	Coronary care unit				12
13	Burn intensive care unit				13
14	Surgical intensive care unit				14
15	Other special care (specify)				15
16	Total intensive care type inpatient hospital services (sum of of lines 11-15)				16
17	Total inpatient routine care services (sum of lines 10 and 16)				17
18	Ancillary services				18
19	Outpatient services				19
20	Rural Health Clinic (RHC)				20
21	Federally Qualified Health Center (FQHC)				21
22	Home health agency				22

The Data

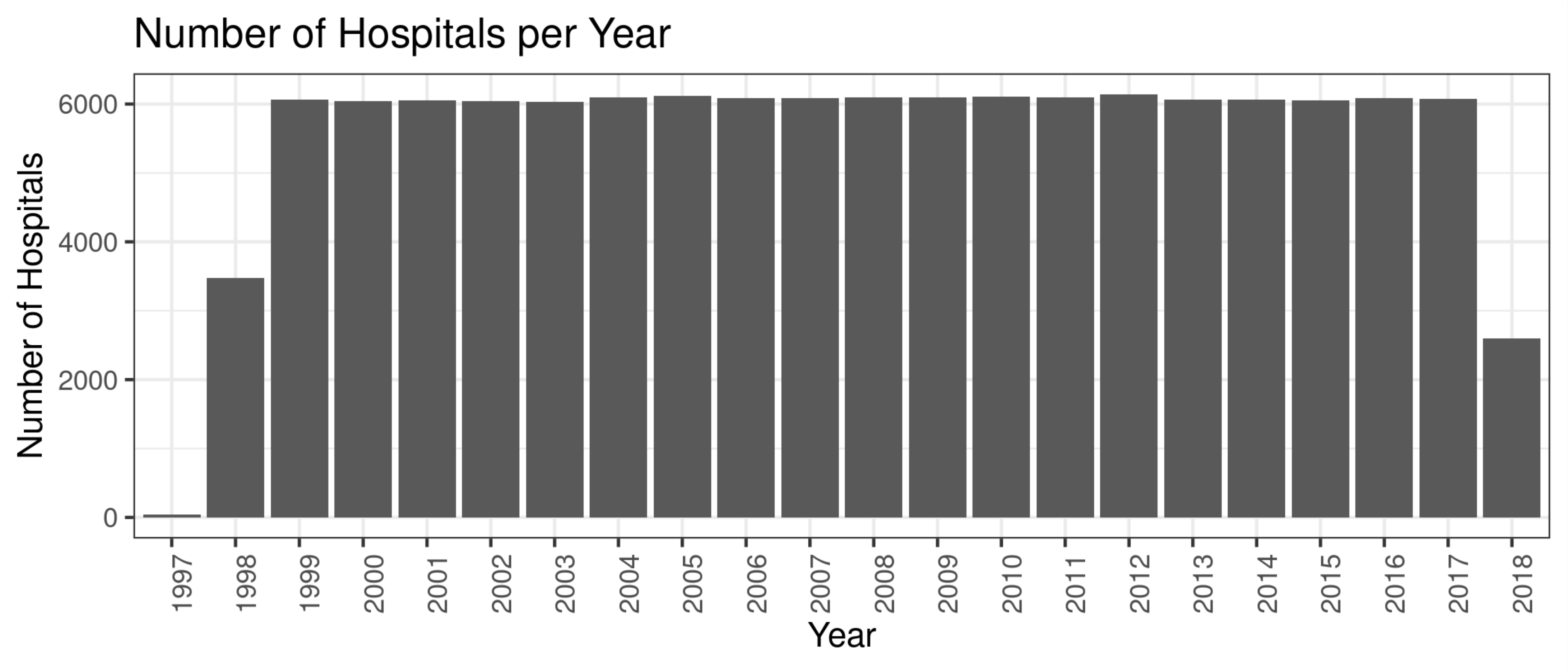
Let's work with the HCRIS GitHub repository. But forming the dataset is up to you this time.

The Data

```
hcris.data %>%
  ggplot(aes(x=as.factor(year))) +
  geom_bar() +
  labs(
    x="Year",
    y="Number of Hospitals",
    title="Number of Hospitals per Year"
  ) + theme_bw() +
  theme(axis.text.x = element_text(angle = 90, hjust=1))
```



Number of hospitals

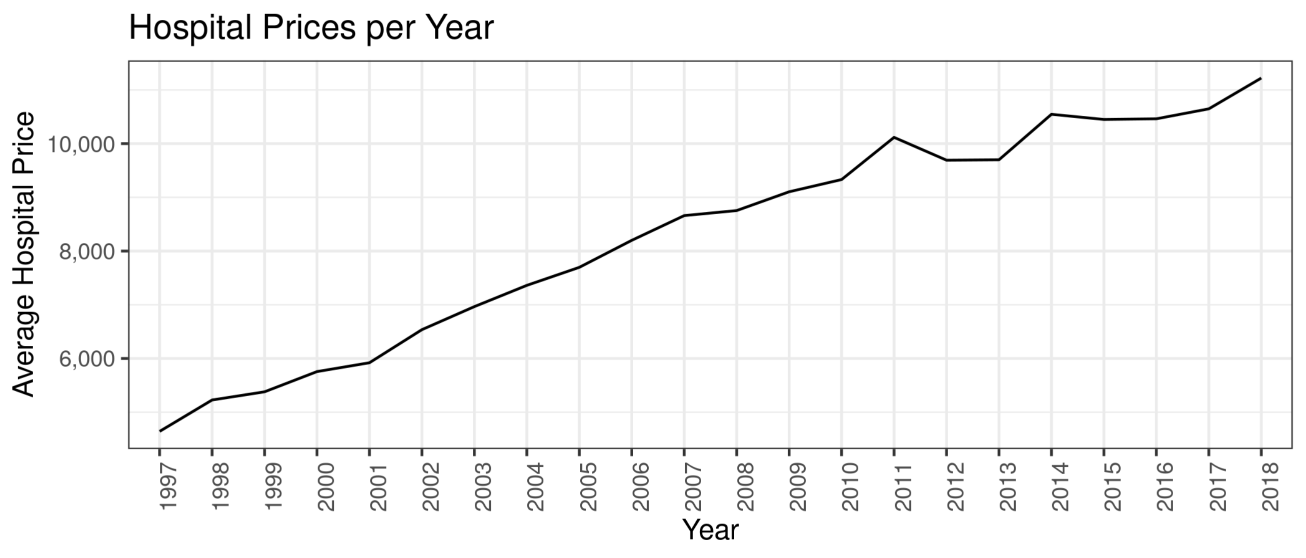


Estimating hospital prices

```
hcris.data <- hcris.data %>%
  mutate( discount_factor = 1-tot_discounts/tot_charges,
          price_num = (ip_charges + icu_charges + ancillary_charges)*discount_factor - tot_mcare_payment,
          price_denom = tot_discharges - mcare_discharges,
          price = price_num/price_denom)
```

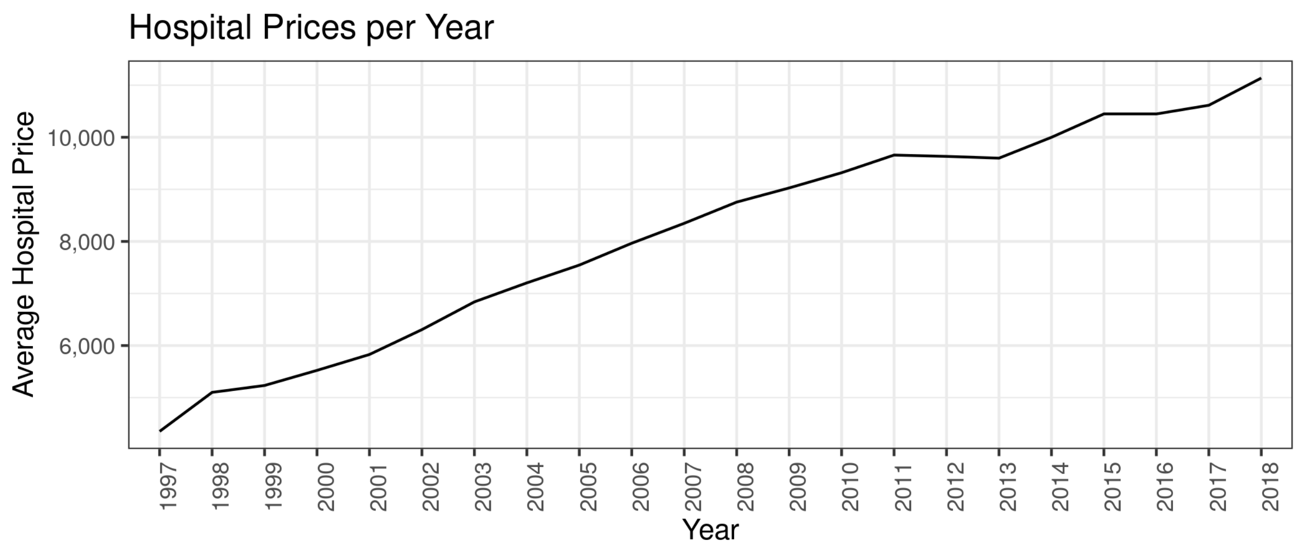
Estimating hospital prices

```
hcris.data %>% group_by(year) %>%
  filter(price_denom>10, !is.na(price_denom),
         price_num>0, !is.na(price_num)) %>%
  select(price, year) %>%
  summarize(mean_price=mean(price, na.rm=TRUE
  ggplot(aes(x=as.factor(year), y=mean_price)
  geom_line(aes(group=1)) +
  labs(
    x="Year",
    y="Average Hospital Price",
    title="Hospital Prices per Year"
  ) + scale_y_continuous(labels=comma) +
  theme_bw() + theme(axis.text.x = element_te
```



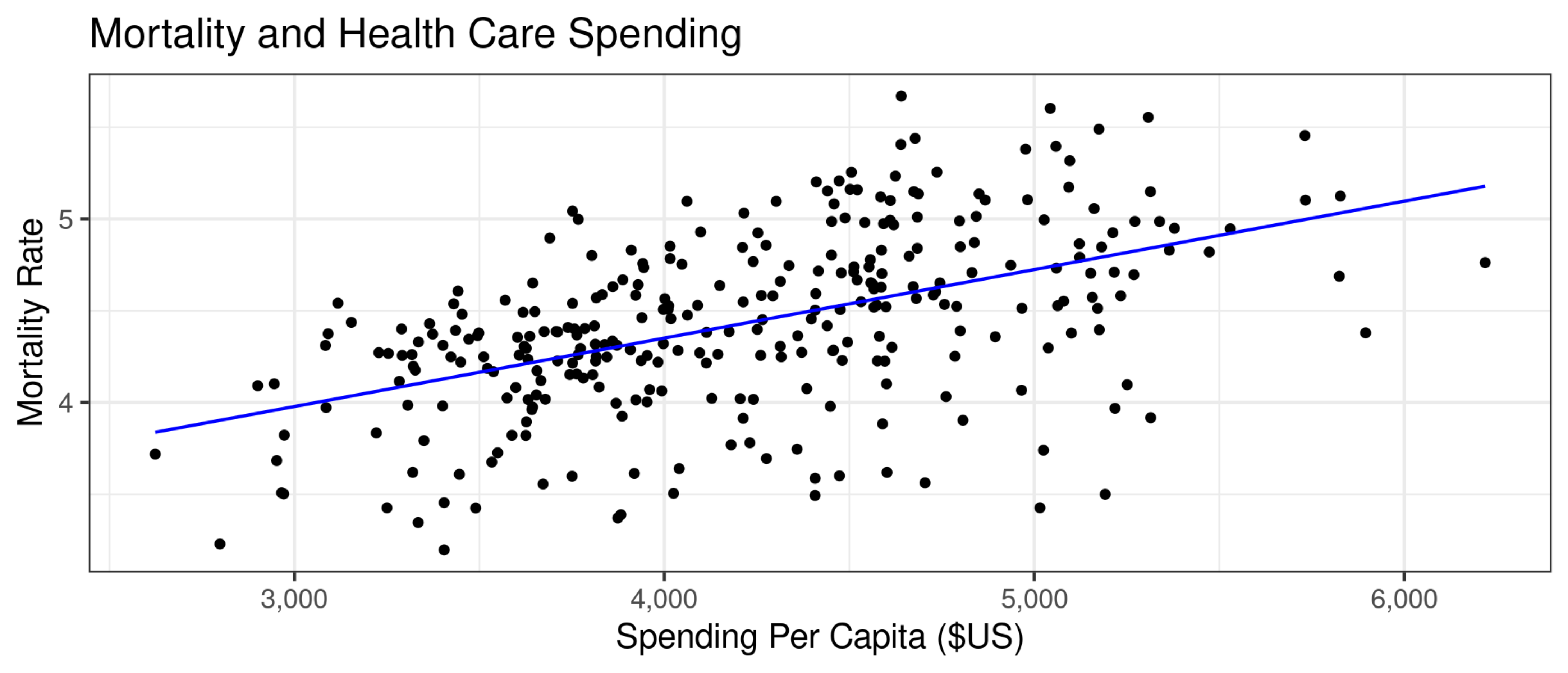
Estimating hospital prices

```
hcris.data %>% group_by(year) %>%
  filter(price_denom>100, !is.na(price_denom)
         price_num>0, !is.na(price_num),
         price<100000) %>%
  select(price, year) %>%
  summarize(mean_price=mean(price, na.rm=TRUE
  ggplot(aes(x=as.factor(year), y=mean_price)
  geom_line(aes(group=1)) +
  labs(
    x="Year",
    y="Average Hospital Price",
    title="Hospital Prices per Year"
  ) + scale_y_continuous(labels=comma) +
  theme_bw() + theme(axis.text.x = element_te
```



Causal Inference and Potential Outcomes

Why causal inference?



Why causal inference?

Another example: **What price should we charge for a night in a hotel?**

Machine Learning

- Focuses on prediction
- High prices are strongly correlated with higher sales
- Increase prices to attract more people?

Causal Inference

- Focuses on **counterfactuals**
- What would sales look like if prices were higher?

Goal of Causal Inference

- **Goal:** Estimate effect of some policy or program
- Key building block for causal inference is the idea of **potential outcomes**

Some notation

Treatment D_i

$$D_i = \begin{cases} 1 \text{ with treatment} \\ 0 \text{ without treatment} \end{cases}$$

Some notation

Potential outcomes

- Y_{1i} is the potential outcome for unit i with treatment
- Y_{0i} is the potential outcome for unit i without treatment

Some notation

Observed outcome

$$Y_i = Y_{1i} \times D_i + Y_{0i} \times (1 - D_i)$$

or

$$Y_i = \begin{cases} Y_{1i} \text{ if } D_i = 1 \\ Y_{0i} \text{ if } D_i = 0 \end{cases}$$

Assumes **SUTVA** (stable unit treatment value assumption)…no interference across units

Example of "Potential Outcomes"

Y_1 = \$75,000

Y_0 = \$60,000

Example of "Potential Outcomes"

Y_1 = $75,000

Y_0 = $60,000

Earnings due to Emory = $Y_1 - Y_0$ = $15,000

Example of "Potential Outcomes"

Y_1 = $75,000

Y_0 = ?

Example of "Potential Outcomes"

Y_1 = $75,000

Y_0 = ?

Earnings due to Emory = $Y_1 - Y_0$ = ?

Do we ever observe the potential outcomes?

Without a time machine…not possible to get *individual* effects.

Fundamental Problem of Causal Inference

- We don't observe the counterfactual outcome...what would have happened if a treated unit was actually untreated.

- *ALL* attempts at causal inference represent some attempt at estimating the counterfactual outcome. We need an estimate for Y_0 among those that were treated, and vice versa for Y_1.

Average Treatment Effects

Different treatment effects

Tend to focus on **averages**[1]:

- **ATE**: $\delta_{ATE} = E[Y_1 - Y_0]$
- **ATT**: $\delta_{ATT} = E[Y_1 - Y_0|D = 1]$
- **ATU**: $\delta_{ATU} = E[Y_1 - Y_0|D = 0]$

[1] or similar measures such as medians or quantiles

Average Treatment Effects

- **Estimand**:

$$\delta_{ATE} = E[Y_1 - Y_0] = E[Y|D = 1] - E[Y|D = 0]$$

- **Estimate**:

$$\hat{\delta}_{ATE} = \frac{1}{N_1} \sum_{D_i=1} Y_i - \frac{1}{N_0} \sum_{D_i=0} Y_i,$$

where N_1 is number of treated and N_0 is number untreated (control)

- With random assignment and equal groups, inference/hypothesis testing with standard two-sample t-test

Selection Bias

Selection bias

- Assume (for simplicity) constant effects, $Y_{1i} = Y_{0i} + \delta$
- Since we don't observe Y_0 and Y_1, we have to use the observed outcomes, Y_i

$$
\begin{aligned}
E[Y_i|D_i = 1] - E[Y_i|D_i = 0] \\
&= E[Y_{1i}|D_i = 1] - E[Y_{0i}|D_i = 0] \\
&= \delta + E[Y_{0i}|D_i = 1] - E[Y_{0i}|D_i = 0] \\
&= \text{ATE} + \text{ Selection Bias}
\end{aligned}
$$

Selection bias

- Selection bias means $E[Y_{0i}|D_i = 1] - E[Y_{0i}|D_i = 0] \neq 0$
- In words, the potential outcome without treatment, Y_{0i}, is different between those that ultimately did and did not receive treatment.
- e.g., treated group was going to be better on average even without treatment (higher wages, healthier, etc.)

Selection bias

- How to "remove" selection bias?
- How about random assignment?
- In this case, treatment assignment doesn't tell us anything about Y_{0i}

$$E[Y_{0i}|D_i = 1] = E[Y_{0i}|D_i = 0],$$

such that

$$E[Y_i|D_i = 1] - E[Y_i|D_i = 0] = \delta_{ATE} = \delta_{ATT} = \delta_{ATU}$$

Selection bias

- Without random assignment, there's a high probability that

$$E[Y_{0i}|D_i = 1] \neq E[Y_{0i}|D_i = 0]$$

- i.e., outcomes without treatment are different for the treated group

Omitted variables bias

- In a regression setting, selection bias is the same problem as omitted variables bias (OVB)

- Quick review: Goal of OLS is to find $\hat{\beta}$ to "best fit" the linear equation $y_i = \alpha + x_i\beta + \epsilon_i$

Regression review

$$\min_{\beta} \sum_{i=1}^{N} (y_i - \alpha - x_i\beta)^2 = \min_{\beta} \sum_{i=1}^{N} (y_i - (\bar{y} - \bar{x}\beta) - x_i\beta)^2$$

$$0 = \sum_{i=1}^{N} \left(y_i - \bar{y} - (x_i - \bar{x})\hat{\beta}\right)(x_i - \bar{x})$$

$$0 = \sum_{i=1}^{N} (y_i - \bar{y})(x_i - \bar{x}) - \hat{\beta} \sum_{i=1}^{N} (x_i - \bar{x})^2$$

$$\hat{\beta} = \frac{\sum_{i=1}^{N} (y_i - \bar{y})(x_i - \bar{x})}{\sum_{i=1}^{N} (x_i - \bar{x})^2} = \frac{Cov(y, x)}{Var(x)}$$

Omitted variables bias

- Interested in estimate of the effect of schooling on wages

$$Y_i = \alpha + \beta s_i + \gamma A_i + \epsilon_i$$

- But we don't observe ability, A_i, so we estimate

$$Y_i = \alpha + \beta s_i + u_i$$

- What is our estimate of β from this regression?

Omitted variables bias

$$
\begin{aligned}
\hat{\beta} &= \frac{Cov(Y_i, s_i)}{Var(s_i)} \\
&= \frac{Cov(\alpha + \beta s_i + \gamma A_i + \epsilon_i, s_i)}{Var(s_i)} \\
&= \frac{\beta Cov(s_i, s_i) + \gamma Cov(A_i, s_i) + Cov(\epsilon_i, s_i)}{Var(s_i)} \\
&= \beta \frac{Var(s_i)}{Var(s_i)} + \gamma \frac{Cov(A_i, s_i)}{Var(s_i)} + 0 \\
&= \beta + \gamma \times \theta_{as}
\end{aligned}
$$

Removing selection bias without RCT

- The field of causal inference is all about different strategies to remove selection bias
- The first strategy (really, assumption) in this class: **selection on observables** or **conditional indpendence**

Intuition

- Example: Does having health insurance, $D_i = 1$, improve your health relative to someone without health insurance, $D_i = 0$?
- Y_{1i} denotes health with insurance, and Y_{0i} health without insurance (these are **potential** outcomes)
- In raw data, $[Y_i|D_i = 1] > E[Y_i|D_i = 0]$, but is that causal?

Intuition

Some assumptions:

- $Y_{0i} = \alpha + \eta_i$
- $Y_{1i} - Y_{0i} = \delta$
- There is some set of "controls", x_i, such that $\eta_i = \beta x_i + u_i$ and $E[u_i|x_i] = 0$ (conditional independence assumption, or CIA)

$$\begin{aligned} Y_i &= Y_{1i} \times D_i + Y_{0i} \times (1 - D_i) \\ &= \delta D_i + Y_{0i} D_i + Y_{0i} - Y_{0i} D_i \\ &= \delta D_i + \alpha + \eta_i \\ &= \delta D_i + \alpha + \beta x_i + u_i \end{aligned}$$

ATEs versus regression coefficients

- Estimating the regression equation,

$$Y_i = \alpha + \delta D_i + \beta x_i + u_i$$

  provides a causal estimate of the effect of D_i on Y_i

- But what does that really mean?

ATEs vs regression coefficients

- *Ceteris paribus* ("with other conditions remaining the same"), a change in D_i will lead to a change in Y_i in the amount of $\hat{\delta}$
- But is *ceteris paribus* informative about policy?

ATEs vs regression coefficients

- $Y_{1i} = Y_{0i} + \delta_i D_i$ (allows for heterogeneous effects)
- $Y_i = \alpha + \beta D_i + \gamma X_i + \epsilon_i$, with $Y_{0i}, Y_{1i} \perp\!\!\!\perp D_i | X_i$
- Aronow and Samii, 2016, show that:

$$\hat{\beta} \rightarrow_p \frac{E[w_i \delta_i]}{E[w_i]},$$

where $w_i = (D_i - E[D_i|X_i])^2$

ATEs vs regression coefficients

- Simplify to ATT and ATU
- $Y_{1i} = Y_{0i} + \delta_{ATT} D_i + \delta_{ATU}(1 - D_i)$
- $Y_i = \alpha + \beta D_i + \gamma X_i + \epsilon_i$, with $Y_{0i}, Y_{1i} \perp\!\!\!\perp D_i | X_i$

$$\beta = \frac{P(D_i = 1) \times \pi(X_i|D_i = 1) \times (1 - \pi(X_i|D_i = 1))}{\sum_{j=0,1} P(D_i = j) \times \pi(X_i|D_i = j) \times (1 - \pi(X_i|D_i = j))}\delta_{ATU}$$
$$+ \frac{P(D_i = 0) \times \pi(X_i|D_i = 0) \times (1 - \pi(X_i|D_i = 0))}{\sum_{j=0,1} P(D_i = j) \times \pi(X_i|D_i = j) \times (1 - \pi(X_i|D_i = j))}\delta_{ATT}$$

ATEs vs regression coefficients

What does this mean?

- OLS puts more weight on observations with treatment D_i "unexplained" by X_i
- "Reverse" weighting such that the proportion of treated units are used to weight the ATU while the proportion of untreated units enter the weights of the ATT
- This is *an* average effect, but probably not the average we want

Matching and Weighting

Goal

Find covariates X_i such that the following assumptions are plausible:

1. Selection on observables:

$$Y_{0i}, Y_{1i} \perp\!\!\!\perp D_i | X_i$$

2. Common support:

$$0 < \Pr(D_i = 1 | X_i) < 1$$

Then we can use X_i to group observations and use expectations for control as the predicted counterfactuals among treated, and vice versa.

Assumption 1: Selection on Observables

$$E[Y_1|D,X] = E[Y_1|X]$$

In words...nothing unobserved that determines treatment selection and affects your outcome of interest.

Assumption 1: Selection on Observables

- Example of selection on observables from *Mastering Metrics*

Assumption 2: Common Support

Someone of each type must be in both the treated and untreated groups

$$0 < \Pr(D = 1|X) < 1$$

Causal inference with observational data

With selection on observables and common support:

1. Subclassification
2. Matching estimators
3. Reweighting estimators
4. Regression estimators

Subclassification

Sum the average treatment effects by group, and take a weighted average over those groups:

$$ATE = \sum_{i=1}^{N} P(X = x_i) \left(E[Y|X, D = 1] - E[Y|X, D = 0] \right)$$

Subclassification

- Difference between treated and controls
- Weighted average by probability of given group (proportion of sample)
- What if outcome is unobserved for treatment or control group for a given subclass?

- This is the *curse of dimensionality*

Matching: The process

1. For each observation i, find the m "nearest" neighbors, $J_m(i)$.

2. Impute $\hat{Y}_{0i}$ and $\hat{Y}_{1i}$ for each observation:

$$\hat{Y}_{0i} = \begin{cases} Y_i & \text{if} \quad D_i = 0 \\ \frac{1}{m} \sum_{j \in J_m(i)} Y_j & \text{if} \quad D_i = 1 \end{cases}$$

$$\hat{Y}_{1i} = \begin{cases} Y_i & \text{if} \quad D_i = 1 \\ \frac{1}{m} \sum_{j \in J_m(i)} Y_j & \text{if} \quad D_i = 0 \end{cases}$$

3. Form "matched" ATE:
$\hat{\delta}^{\text{match}} = \frac{1}{N} \sum_{i=1}^{N} \left(\hat{Y}_{1i} - \hat{Y}_{0i} \right)$

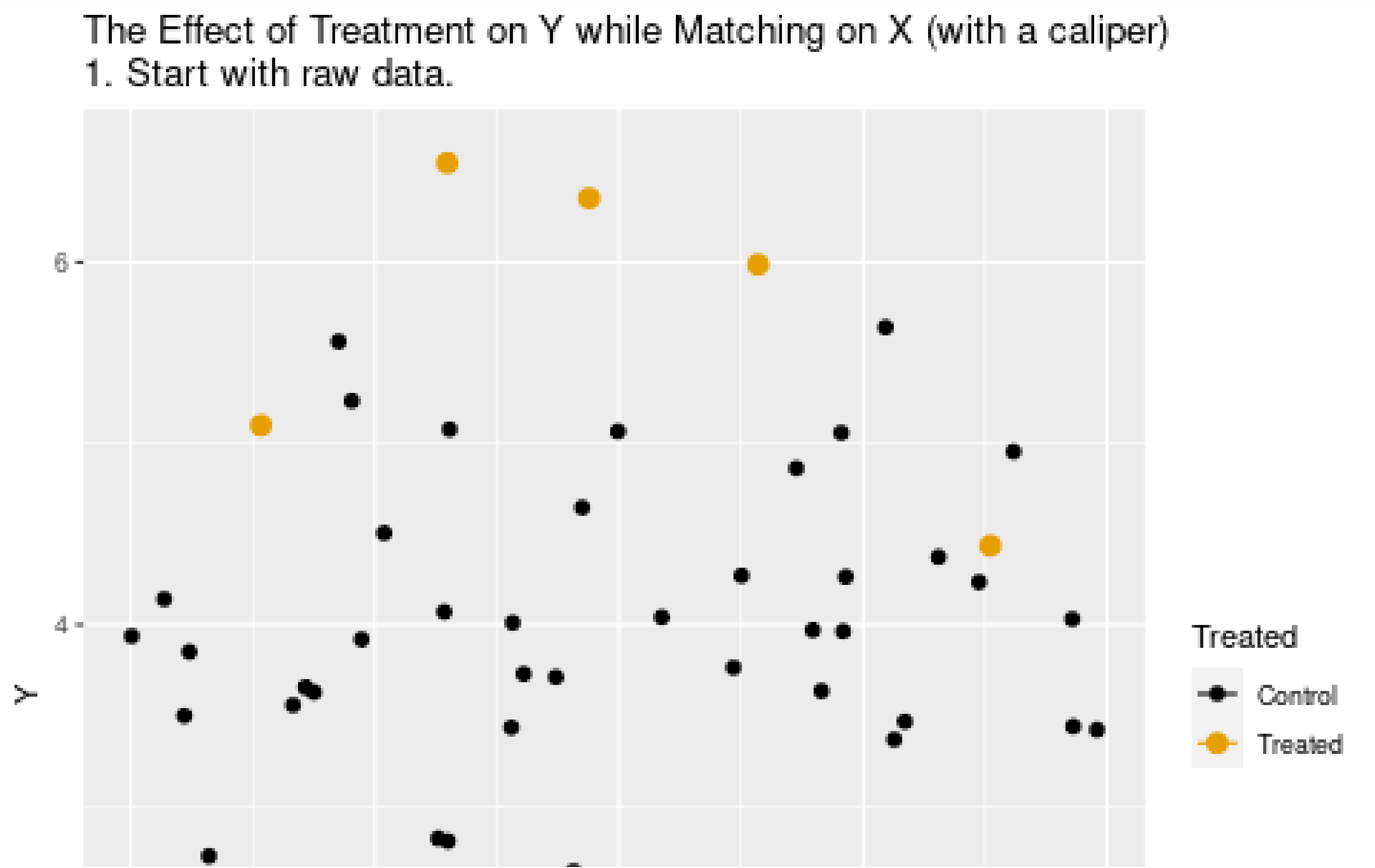
Matching: Defining "nearest"

1. Euclidean distance:
   $\sum_{k=1}^{K}(X_{ik} - X_{jk})^2$

2. Scaled Euclidean distance:
   $\sum_{k=1}^{K} \frac{1}{\sigma^2_{X_k}}(X_{ik} - X_{jk})^2$

3. Mahalanobis distance:
   $(X_i - X_j)'\Sigma_X^{-1}(X_i - X_j)$

Animation for matching



Matching: Defining "nearest"

- But are observations really the same in each group?
- Potential for "matching discrepancies" to introduce bias in estimates

- "Bias correction" based on

$$\hat{\mu}(x_i) - \hat{\mu}(x_{j(i)})$$

(i.e., difference in fitted values from regression of y on x, with the difference between observed Y_{1i} and imputed Y_{0i})

Weighting

1. Estimate propensity score `ps <- glm(D~X, family=binomial, data)`, denoted $\hat{\pi}(X_i)$
2. Weight by inverse of propensity score

$$\hat{\mu}_1 = \frac{\sum_{i=1}^{N} \frac{Y_i D_i}{\hat{\pi}(X_i)}}{\sum_{i=1}^{N} \frac{D_i}{\hat{\pi}(X_i)}} \text{ and } \hat{\mu}_0 = \frac{\sum_{i=1}^{N} \frac{Y_i(1-D_i)}{1-\hat{\pi}(X_i)}}{\sum_{i=1}^{N} \frac{1-D_i}{1-\hat{\pi}(X_i)}}$$

3. Form "inverse-propensity weighted" ATE:

$$\hat{\delta}^{IPW} = \hat{\mu}_1 - \hat{\mu}_0$$

Regression

1. Regress Y_i on X_i among $D_i = 1$ to form $\hat{\mu}_1(X_i)$
2. Regress Y_i on X_i among $D_i = 0$ to form $\hat{\mu}_0(X_i)$
3. Form difference in predictions:

$$\hat{\delta}^{reg} = \frac{1}{N} \sum_{i=1}^{N} (\hat{\mu}_1(X_i) - \hat{\mu}_0(X_i))$$

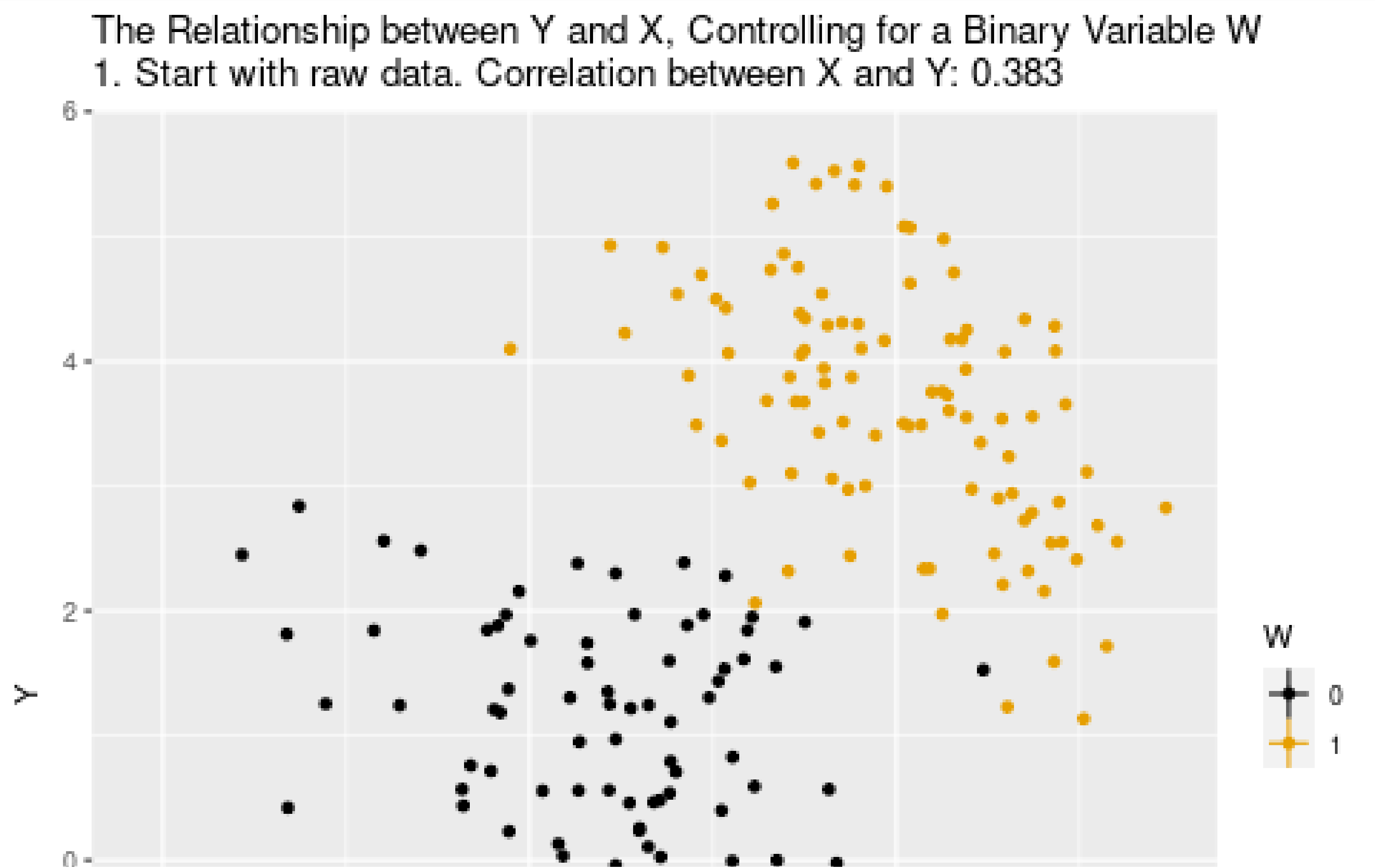
Regression

Or estimate in one step,

$$Y_i = \delta D_i + \beta X_i + D_i \times \left(X_i - \bar{X}\right)\gamma + \varepsilon_i$$

- Note the $\left(X_i - \bar{X}\right)$. What does this do?

Animation for regression



Simulated data

Now let's do some matching, re-weighting, and regression with simulated data:

```
n <- 5000
select.dat <- tibble(
  x = runif(n, 0, 1),
  z = rnorm(n, 0, 1),
  w = (x>0.65),
  y = -2.5 + 4*w + 1.5*x + rnorm(n,0,1),
  w_alt = ( x + z > 0.35),
  y_alt = -2.5 + 4*w_alt + 1.5*x + 2.25*z + rnorm(n,0,1)
)
```

Simulation: nearest neighbor matching

```r
nn.est1 <- Matching::Match(Y=select.dat$y,
                            Tr=select.dat$w,
                            X=select.dat$x,
                            M=1,
                            Weight=1,
                            estimand="ATE")
summary(nn.est1)
```

```
##
## Estimate...  4.0175
## AI SE......  0.52954
## T-stat.....  7.5869
## p.val......  3.2863e-14
##
## Original number of observations..............  5000
## Original number of treated obs...............  1732
## Matched number of observations...............  5000
## Matched number of observations  (unweighted).  5016
```

Simulation: nearest neighbor matching

```
nn.est2 <- Matching::Match(Y=select.dat$y,
                           Tr=select.dat$w,
                           X=select.dat$x,
                           M=1,
                           Weight=2,
                           estimand="ATE")
summary(nn.est2)
```

```
##
## Estimate...  4.0175
## AI SE......  0.52954
## T-stat.....  7.5869
## p.val......  3.2863e-14
##
## Original number of observations..............  5000
## Original number of treated obs...............  1732
## Matched number of observations...............  5000
## Matched number of observations  (unweighted).  5016
```

Simulation: regression

```r
reg1.dat <- select.dat %>% filter(w==1)
reg1 <- lm(y ~ x, data=reg1.dat)

reg0.dat <- select.dat %>% filter(w==0)
reg0 <- lm(y ~ x, data=reg0.dat)
pred1 <- predict(reg1,new=select.dat)
pred0 <- predict(reg0,new=select.dat)
mean(pred1-pred0)
```

```
## [1] 4.076999
```

Violation of selection on observables

NN Matching

```
nn.est3 <- Matching::Match(Y=select.dat$y_alt,
                          Tr=select.dat$w_alt,
                          X=select.dat$x,
                          M=1,
                          Weight=2,
                          estimand="ATE")
summary(nn.est3)
```

```
##
## Estimate...  7.6642
## AI SE......  0.052903
## T-stat.....  144.87
## p.val......  < 2.22e-16
##
## Original number of observations..............  5000
## Original number of treated obs...............  2748
## Matched number of observations...............  5000
## Matched number of observations  (unweighted).  23014
```

Regression

```
reg1.dat <- select.dat %>% filter(w_alt==1)
reg1 <- lm(y_alt ~ x, data=reg1.dat)

reg0.dat <- select.dat %>% filter(w_alt==0)
reg0 <- lm(y_alt ~ x, data=reg0.dat)
pred1_alt <- predict(reg1,new=select.dat)
pred0_alt <- predict(reg0,new=select.dat)
mean(pred1_alt-pred0_alt)
```

```
## [1] 7.646532
```

What covariates to use?

- There are such things as "bad controls"
- We want to avoid control variables that are:

- Outcomes of the treatment
- Also endogenous (more generally)

Pricing and Hospital Penalties

Penalized hospitals

```
final.hcris <- hcris.data %>% ungroup() %>%
  filter(price_denom>100, !is.na(price_denom),
         price_num>0, !is.na(price_num),
         price<100000,
         beds>30, year==2012) %>%
  mutate( hvbp_payment = ifelse(is.na(hvbp_payment),0,hvbp_payment),
          hrrp_payment = ifelse(is.na(hrrp_payment),0,abs(hrrp_payment)),
    penalty = (hvbp_payment-hrrp_payment<0))
```

Summary stats

Always important to look at your data before doing any formal analysis. Ask yourself a few questions:

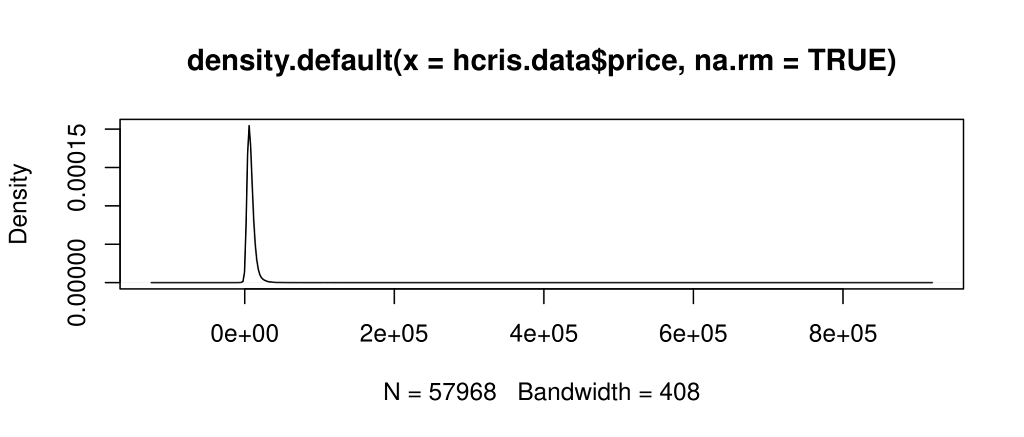
1. Are the magnitudes reasonable?
2. Are there lots of missing values?
3. Are there clear examples of misreporting?

Summary stats

```
summary(hcris.data$price)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's 
## -123697    4783    7113     Inf   10230     Inf   63662 
```

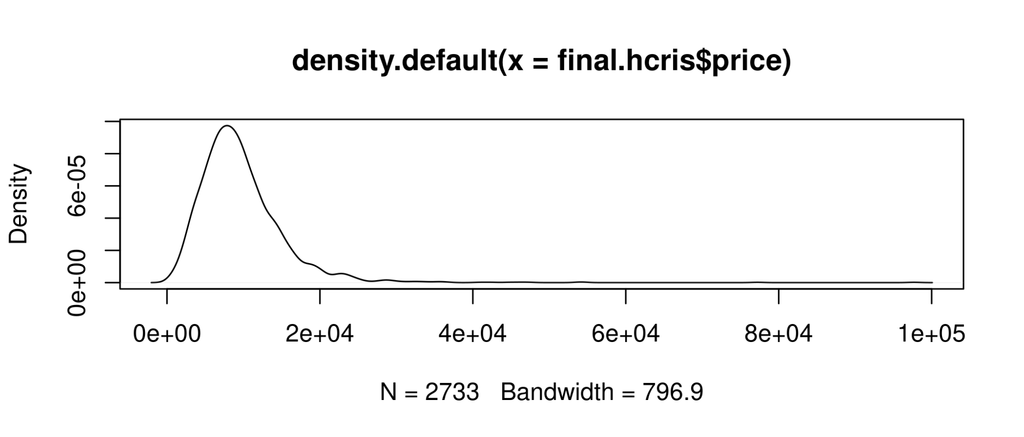
```
plot(density(hcris.data$price, na.rm=TRUE))
```




```
summary(final.hcris$price)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max. 
##   340.8  6129.9  8705.4  9646.9 11905.4 97688.8 
```

```
plot(density(final.hcris$price))
```



Dealing with problems

We've adopted a very brute force way to deal with outlier prices. Other approaches include:

1. Investigate very closely the hospitals with extreme values
2. Winsorize at certain thresholds (replace extreme values with pre-determined thresholds)
3. Impute prices for extreme hospitals

Differences among penalized hospitals

- Mean price among penalized hospitals: 9,896.31
- Mean price among non-penalized hospitals: 9,560.41
- Mean difference: 335.9

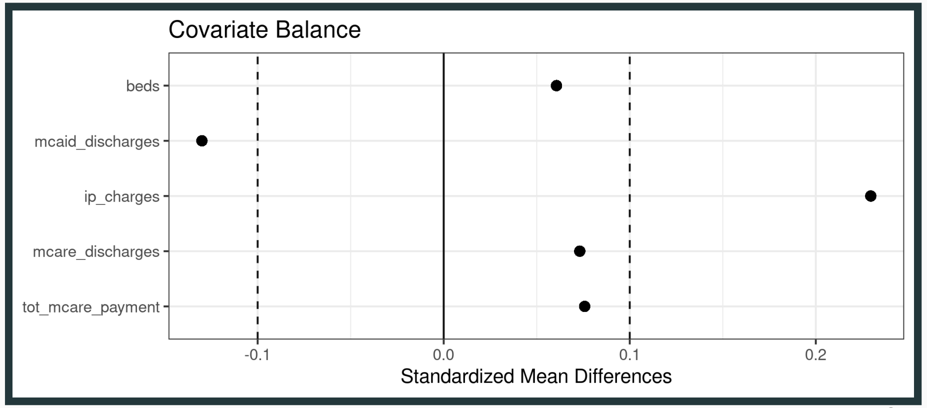
Comparison of hospitals

Are penalized hospitals sufficiently similar to non-penalized hospitals?

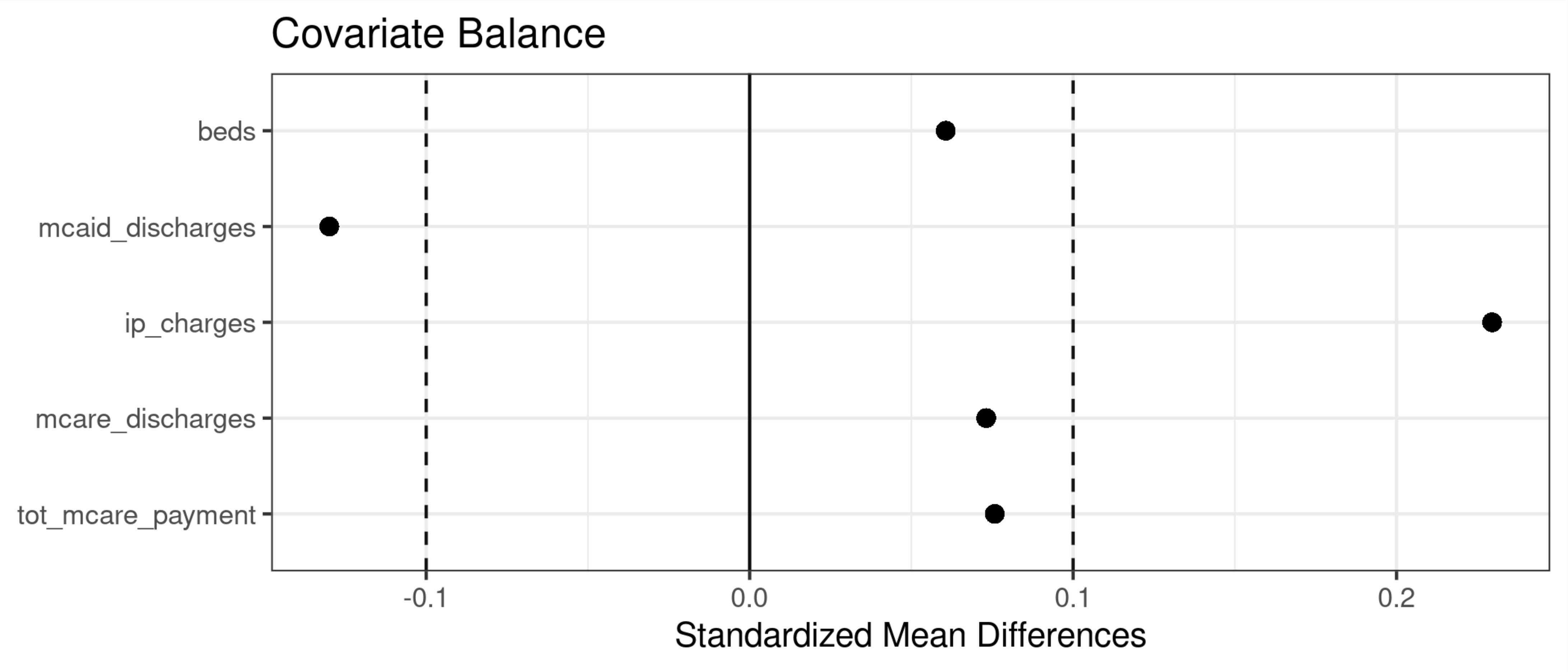
Let's look at covariate balance using a love plot, part of the `library(cobalt)` package.

Love plots without adjustment

```
love.plot(bal.tab(lp.covs,treat=lp.vars$penalty), colors="black", shapes="circle", threshold=0.1) +
  theme_bw() + theme(legend.position="none")
```



Love plots without adjustment



Using matching to improve balance

Some things to think about:

- exact versus nearest neighbor
- with or without ties (and how to break ties)
- measure of distance

1. Exact Matching

```
m.exact ← Matching::Match(Y=lp.vars$price,
                           Tr=lp.vars$penalty,
                           X=lp.covs,
                           M=1,
                           exact=TRUE)
print(m.exact)
```

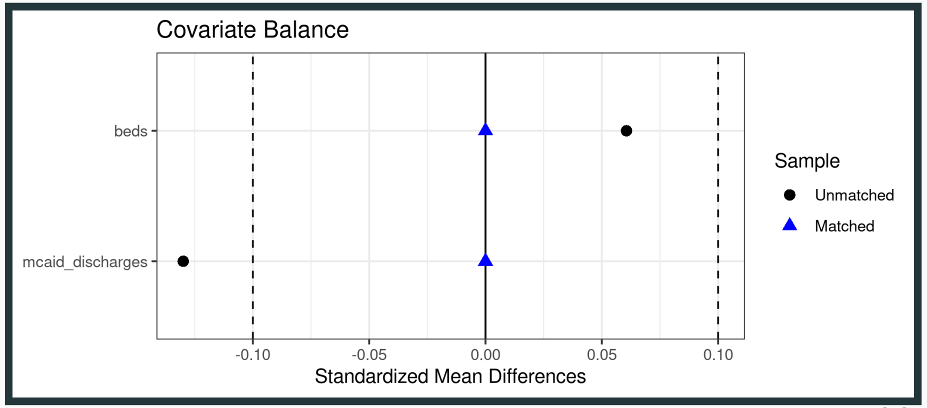
```
## [1] NA
## attr(,"class")
## [1] "Match"
```

1. Exact Matching (on a subset)

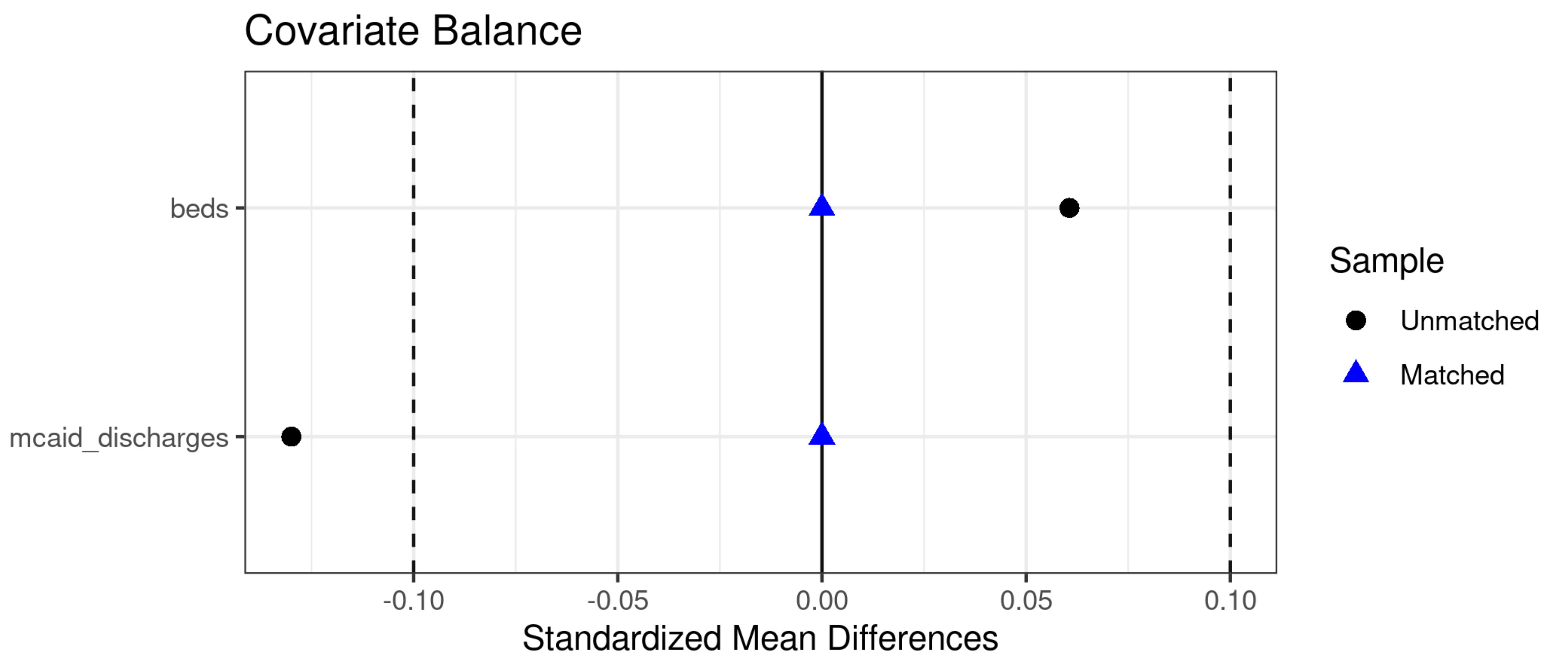
```
lp.covs2 ← lp.covs %>% select(beds, mcaid_discharges)
m.exact ← Matching::Match(Y=lp.vars$price,
                          Tr=lp.vars$penalty,
                          X=lp.covs2,
                          M=1,
                          exact=TRUE,
                          estimand="ATE")
```

1. Exact Matching (on a subset)

```
love.plot(bal.tab(m.exact, covs = lp.covs2, treat = lp.vars$penalty),
          threshold=0.1,
          grid=FALSE, sample.names=c("Unmatched", "Matched"),
          position="top", shapes=c("circle","triangle"),
          colors=c("black","blue")) +
  theme_bw()
```



1. Exact Matching (on a subset)

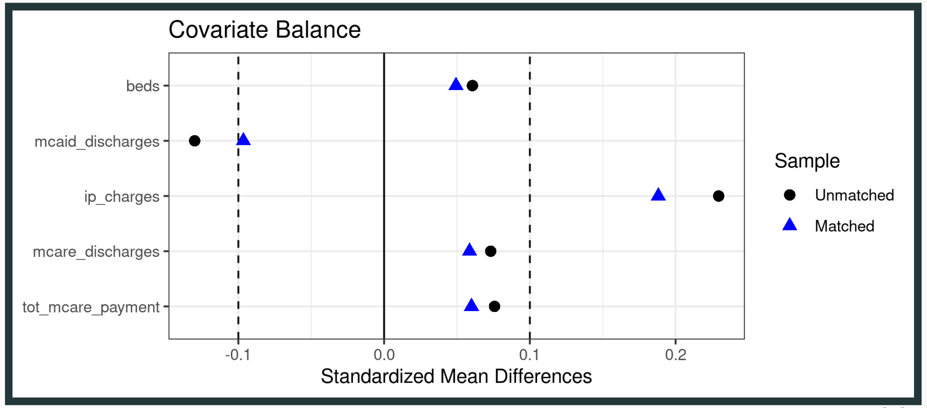


2. Nearest neighbor matching (inverse variance)

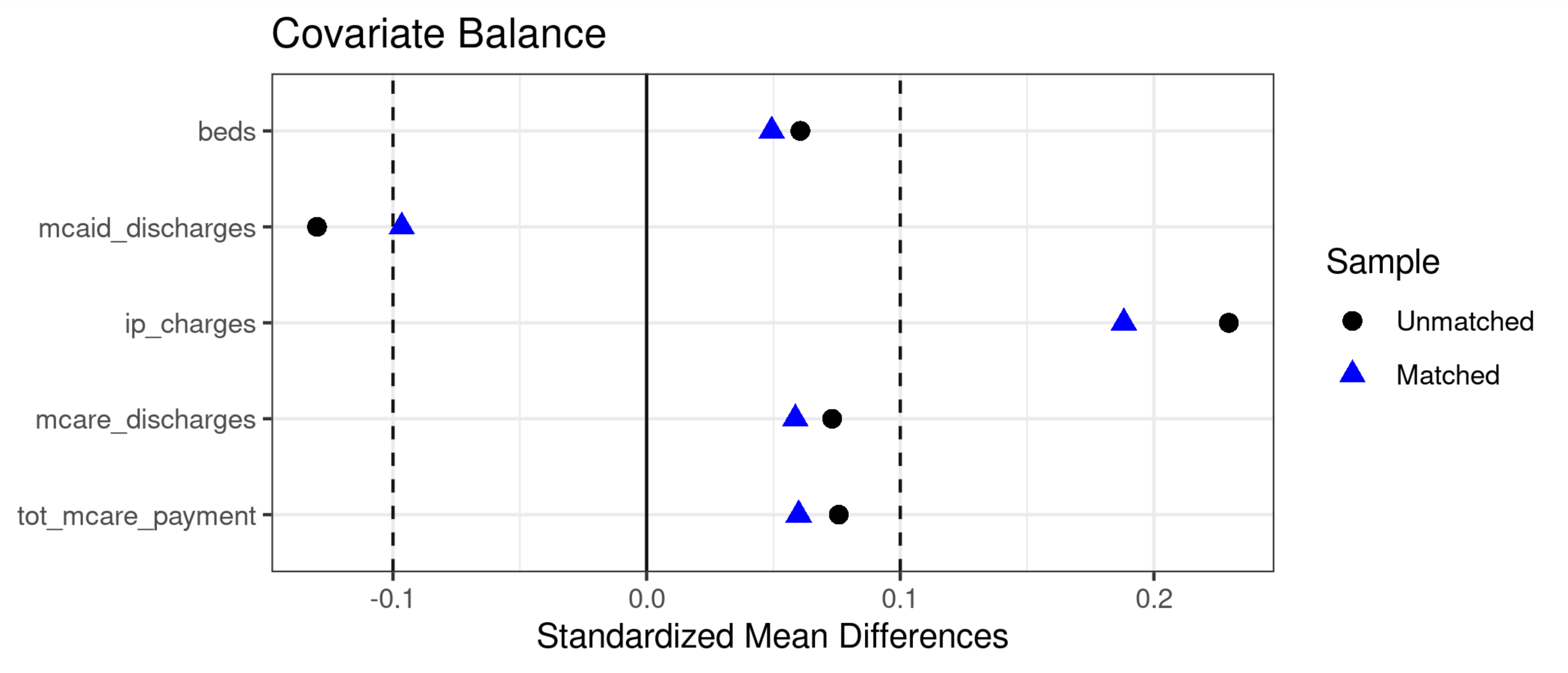
```
m.nn.var ← Matching::Match(Y=lp.vars$price,
                           Tr=lp.vars$penalty,
                           X=lp.covs,
                           M=4,
                           Weight=1,
                           estimand="ATE")

v.name=data.frame(new=c("Beds","Medicaid Discharges", "Inaptient Charges",
                   "Medicare Discharges", "Medicare Payments"))
```

2. Nearest neighbor matching (inverse variance)

```
love.plot(bal.tab(m.nn.var, covs = lp.covs, treat = lp.vars$penalty),
          threshold=0.1,
          var.names=v.name,
          grid=FALSE, sample.names=c("Unmatched", "Matched"),
          position="top", shapes=c("circle","triangle"),
          colors=c("black","blue")) +
  theme_bw()
```



2. Nearest neighbor matching (inverse variance)

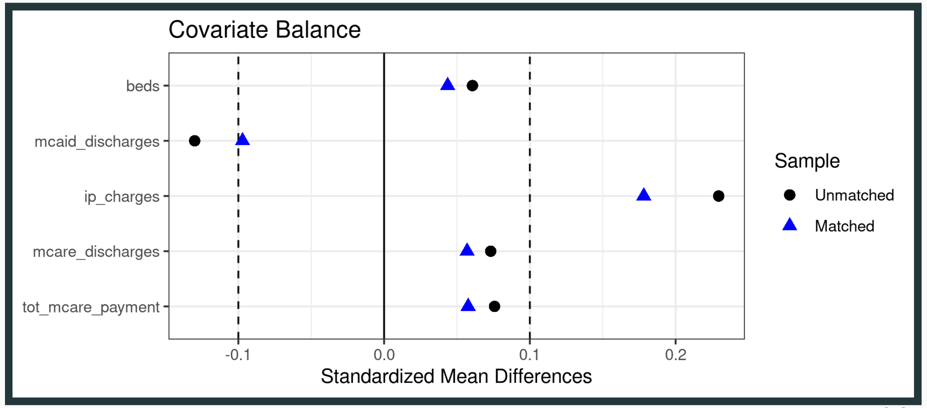


2. Nearest neighbor matching (inverse variance)

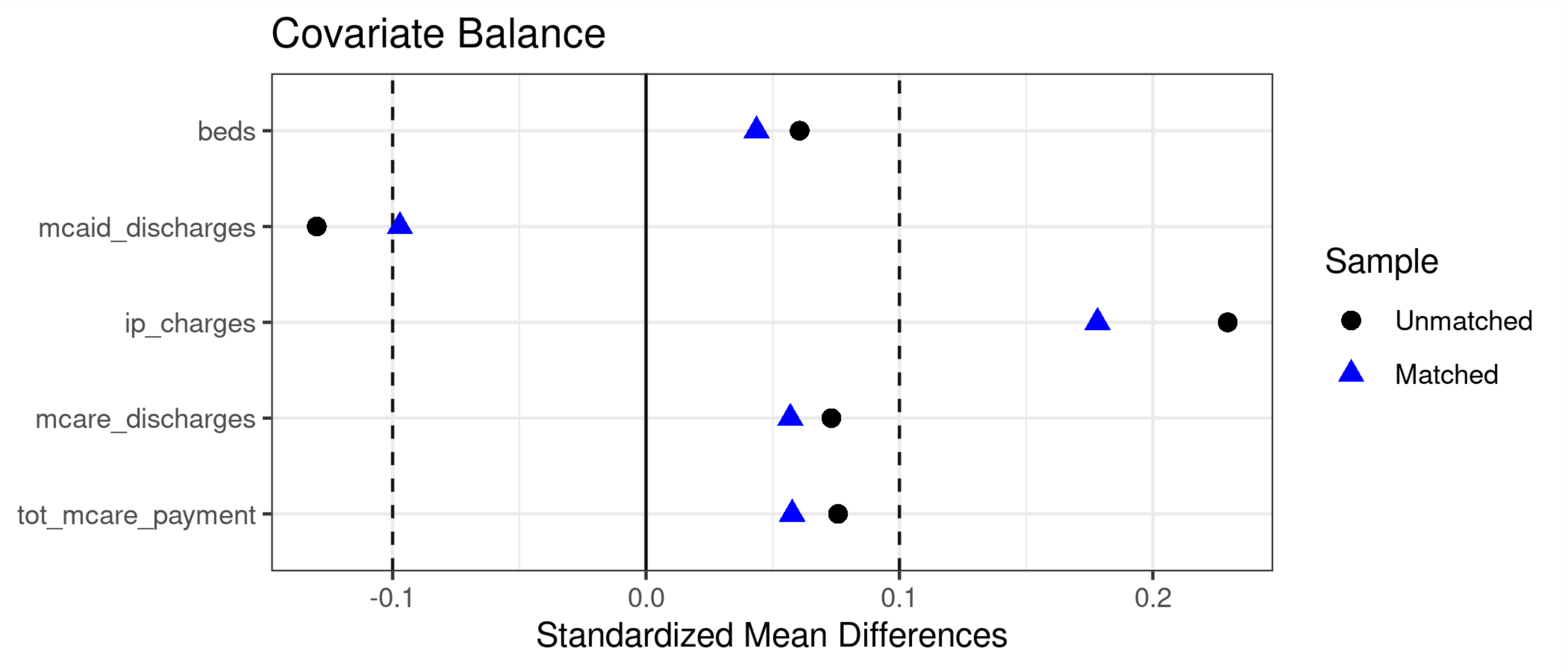
```
m.nn.var2 <- Matching::Match(Y=lp.vars$price,
                             Tr=lp.vars$penalty,
                             X=lp.covs,
                             M=1,
                             Weight=1,
                             estimand="ATE")
```

2. Nearest neighbor matching (inverse variance)

```
love.plot(bal.tab(m.nn.var2, covs = lp.covs, treat = lp.vars$penalty),
          threshold=0.1,
          var.names=v.name,
          grid=FALSE, sample.names=c("Unmatched", "Matched"),
          position="top", shapes=c("circle","triangle"),
          colors=c("black","blue")) +
  theme_bw()
```



2. Nearest neighbor matching (inverse variance)

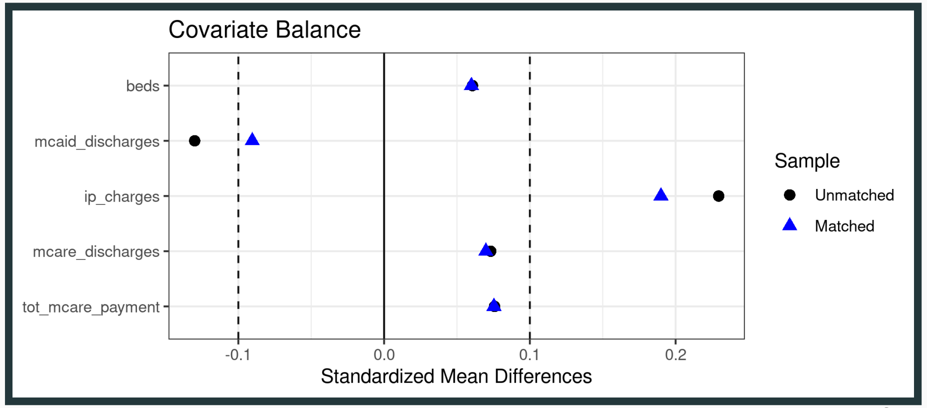


2. Nearest neighbor matching (Mahalanobis)

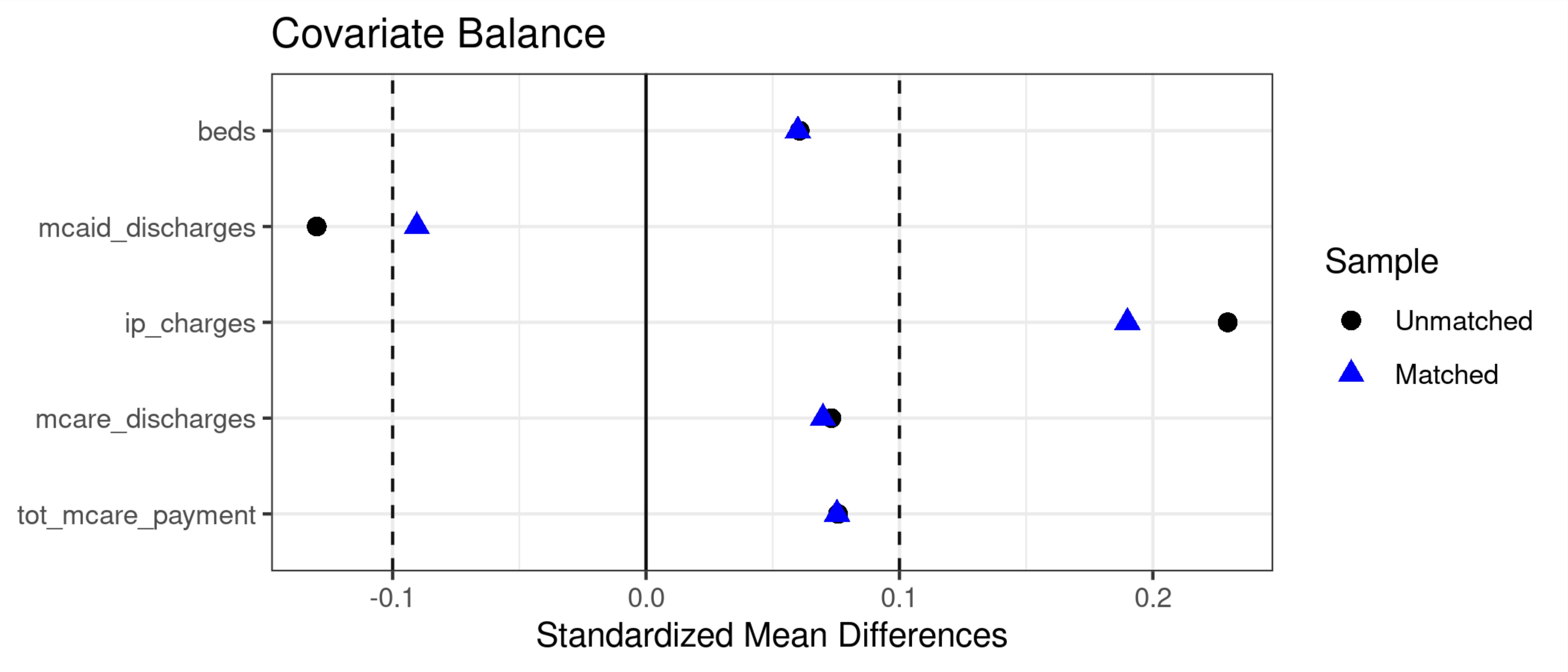
```
m.nn.md <- Matching::Match(Y=lp.vars$price,
                           Tr=lp.vars$penalty,
                           X=lp.covs,
                           M=1,
                           Weight=2,
                           estimand="ATE")
```

2. Nearest neighbor matching (Mahalanobis)

```
love.plot(bal.tab(m.nn.md, covs = lp.covs, treat = lp.vars$penalty),
          threshold=0.1,
          var.names=v.name,
          grid=FALSE, sample.names=c("Unmatched", "Matched"),
          position="top", shapes=c("circle","triangle"),
          colors=c("black","blue")) +
  theme_bw()
```



2. Nearest neighbor matching (Mahalanobis)

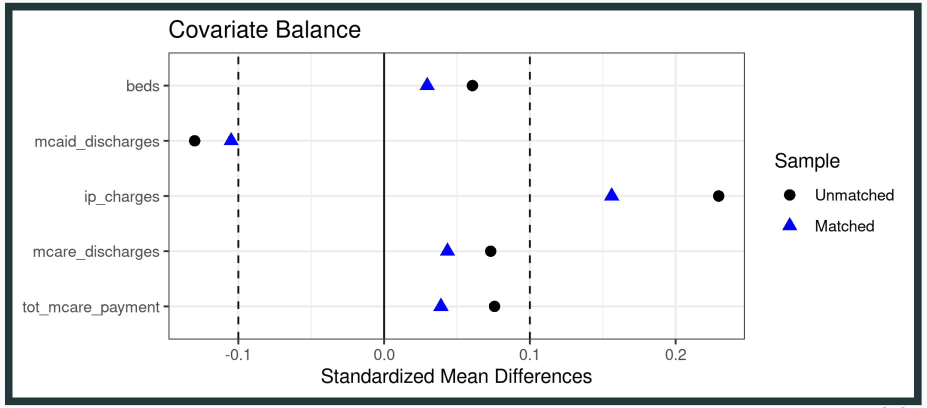


2. Nearest neighbor matching (propensity score)

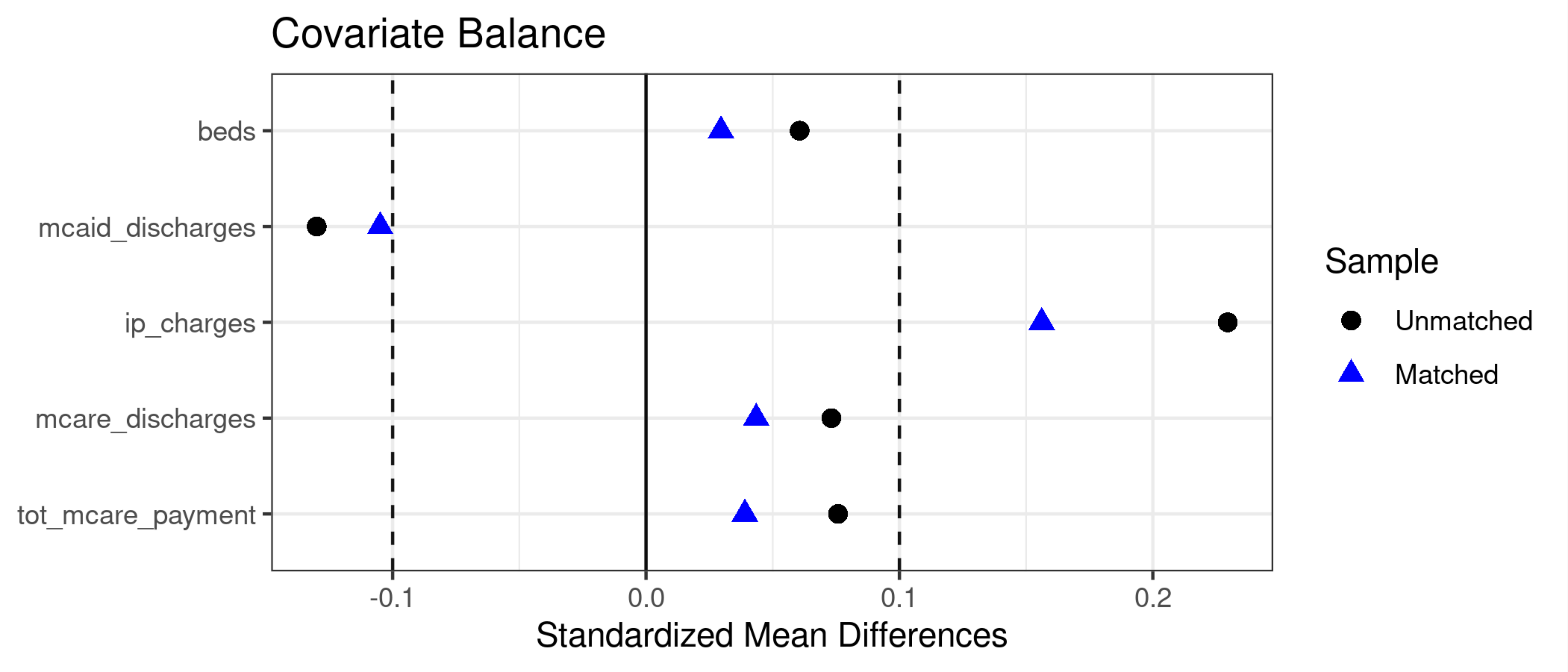
```
logit.model <- glm(penalty ~ beds + mcaid_discharges + ip_charges + mcare_discharges +
            tot_mcare_payment, family=binomial, data=lp.vars)
ps <- fitted(logit.model)
m.nn.ps <- Matching::Match(Y=lp.vars$price,
                           Tr=lp.vars$penalty,
                           X=ps,
                           M=1,
                           estimand="ATE")
```

2. Nearest neighbor matching (propensity score)

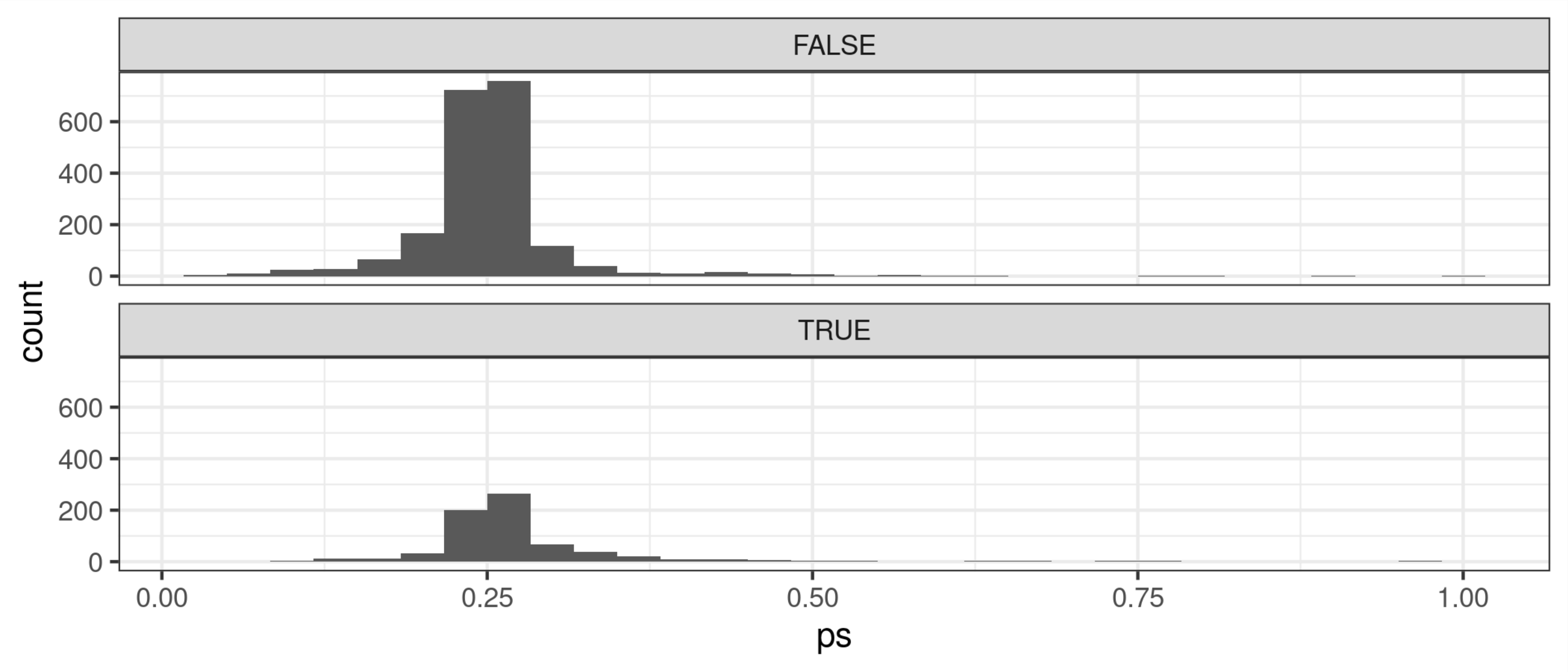
```
love.plot(bal.tab(m.nn.ps, covs = lp.covs, treat = lp.vars$penalty),
          threshold=0.1,
          var.names=v.name,
          grid=FALSE, sample.names=c("Unmatched", "Matched"),
          position="top", shapes=c("circle","triangle"),
          colors=c("black","blue")) +
  theme_bw()
```



2. Nearest neighbor matching (propensity score)



3. Weighting



Results: Exact matching

```
##
## Estimate...  1777.6
## AI SE......  34.725
## T-stat.....  51.191
## p.val......  < 2.22e-16
##
## Original number of observations..............  2707
## Original number of treated obs...............  698
## Matched number of observations...............  12
## Matched number of observations  (unweighted).  12
##
## Number of obs dropped by 'exact' or 'caliper'  2695
```

Results: Nearest neighbor

- Inverse variance

```
##
## Estimate...  -526.95
## AI SE......  223.06
## T-stat.....  -2.3623
## p.val......  0.01816
##
## Original number of observations..............  2707
## Original number of treated obs...............  698
## Matched number of observations...............  2707
## Matched number of observations  (unweighted).  2711
```

Results: Nearest neighbor

- Mahalanobis

```
##
## Estimate...  -492.82
## AI SE......  223.55
## T-stat.....  -2.2046
## p.val......  0.027485
##
## Original number of observations..............  2707
## Original number of treated obs...............  698
## Matched number of observations...............  2707
## Matched number of observations  (unweighted).  2708
```

Results: Nearest neighbor

- Propensity score

```
##
## Estimate...  -201.03
## AI SE......  275.76
## T-stat.....  -0.72898
## p.val......  0.46601
##
## Original number of observations..............  2707
## Original number of treated obs...............  698
## Matched number of observations...............  2707
## Matched number of observations  (unweighted).  14795
```

Results: IPW weighting

```r
lp.vars <- lp.vars %>%
  mutate(ipw = case_when(
    penalty==1 ~ 1/ps,
    penalty==0 ~ 1/(1-ps),
    TRUE ~ NA_real_
  ))
mean.t1 <- lp.vars %>% filter(penalty==1) %>%
  select(price, ipw) %>% summarize(mean_p=weighted.mean(price,w=ipw))
mean.t0 <- lp.vars %>% filter(penalty==0) %>%
  select(price, ipw) %>% summarize(mean_p=weighted.mean(price,w=ipw))
mean.t1$mean_p - mean.t0$mean_p
```

```
## [1] -196.8922
```

Results: IPW weighting with regression

```
ipw.reg <- lm(price ~ penalty, data=lp.vars, weights=ipw)
summary(ipw.reg)
```

```
##
## Call:
## lm(formula = price ~ penalty, data = lp.vars, weights = ipw)
##
## Weighted Residuals:
##    Min     1Q Median     3Q    Max
## -18691  -4802  -1422   2651  94137
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)   9876.4      147.8  66.808   <2e-16 ***
## penaltyTRUE   -196.9      211.2  -0.932    0.351
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 7829 on 2705 degrees of freedom
## Multiple R-squared:  0.0003211,    Adjusted R-squared:  -4.85e-05
## F-statistic: 0.8688 on 1 and 2705 DF,  p-value: 0.3514
```

Results: Regression

```r
reg1.dat <- lp.vars %>% filter(penalty==1, complete.cases(.))
reg1 <- lm(price ~ beds+ mcaid_discharges + ip_charges + mcare_discharges +
            tot_mcare_payment, data=reg1.dat)

reg0.dat <- lp.vars %>% filter(penalty==0, complete.cases(.))
reg0 <- lm(price ~ beds + mcaid_discharges + ip_charges + mcare_discharges +
            tot_mcare_payment, data=reg0.dat)
pred1 <- predict(reg1,new=lp.vars)
pred0 <- predict(reg0,new=lp.vars)
mean(pred1-pred0)
```

```
## [1] -5.845761
```

Results: Regression in one step

```
reg.dat <- lp.vars %>% ungroup() %>% filter(complete.cases(.)) %>%
  mutate(beds_diff = penalty*(beds - mean(beds)),
         mcaid_diff = penalty*(mcaid_discharges - mean(mcaid_discharges)),
         ip_diff = penalty*(ip_charges - mean(ip_charges)),
         mcare_diff = penalty*(mcare_discharges - mean(mcare_discharges)),
         mpay_diff = penalty*(tot_mcare_payment - mean(tot_mcare_payment)))
reg <- lm(price ~ penalty + beds + mcaid_discharges + ip_charges + mcare_discharges + tot_mcare_payment +
            beds_diff + mcaid_diff + ip_diff + mcare_diff + mpay_diff,
          data=reg.dat)
```

Results: Regression in one step

```
##
## Call:
## lm(formula = price ~ penalty + beds + mcaid_discharges + ip_charges +
##     mcare_discharges + tot_mcare_payment + beds_diff + mcaid_diff +
##     ip_diff + mcare_diff + mpay_diff, data = reg.dat)
##
## Residuals:
##    Min     1Q Median     3Q    Max
## -38175  -2900   -597   2105  67409
##
## Coefficients:
##                    Estimate Std. Error t value Pr(>|t|)
## (Intercept)       8.466e+03  1.711e+02  49.482  < 2e-16 ***
## penaltyTRUE      -5.846e+00  2.124e+02  -0.028  0.97804
## beds              1.107e+00  1.421e+00   0.779  0.43618
## mcaid_discharges -4.714e-01  7.296e-02  -6.462 1.23e-10 ***
## ip_charges        6.426e-06  1.285e-06   5.002 6.04e-07 ***
## mcare_discharges -8.122e-01  9.257e-02  -8.774  < 2e-16 ***
## tot_mcare_payment  9.502e-05  6.858e-06  13.857  < 2e-16 ***
## beds_diff         2.517e+00  2.986e+00   0.843  0.39931
## mcaid_diff        1.058e-01  1.570e-01   0.674  0.50050
## ip_diff          -4.534e-06  2.027e-06  -2.237  0.02539 *
## mcare_diff        4.806e-01  1.809e-01   2.657  0.00793 **
## mpay_diff        -5.452e-05  1.321e-05  -4.128 3.78e-05 ***
## ---
```

Summary of ATEs

1. Exact matching: 1777.63
2. NN matching, inverse variance: -526.95
3. NN matching, mahalanobis: -492.82
4. NN matching, pscore: -201.03
5. Inverse pscore weighting: -196.89
6. IPW regression: -196.89
7. Regression: -5.85
8. Regression 1-step: -5.85

Summary of ATEs

Why such large differences between linear (unweighted) regression and other approaches?

Problem is due to common support. Without weighting, the treated group looks very different than the control group, and standard OLS (without weights) doesn't do anything to account for this.

So what have we learned?

Key assumptions for causal inference

1. Selection on observables
2. Common support

These become more nuanced but the intuition is the same in almost all questions of causal inference.

Causal effect assuming selection on observables

If we assume selection on observables holds, then we only need to condition on the relevant covariates to identify a causal effect. But we still need to ensure common support...

1. Matching
2. Reweighting
3. Regression