Gov 50: 13. Midterm Review + Prediction

Matthew Blackwell

Harvard University

Roadmap

1. Midterm Review: Estimating effects
2. Prediction
3. Evaluating the predictions

1/ Midterm Review: Estimating effects

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- RCT or observational study?

Data

Name	Description
`chain`	Name of the fast-food restaurant chain
`location`	Location of the restaurant
`wageBefore`	Average wage at the restaurant before NJ minimum wage law
`wageAfter`	Average wage at the restaurant after NJ minimum wage law
`fullBefore`	Number of full-time employees before NJ minimum wage law
`fullAfter`	Number of full-time employees after NJ minimum wage law
`partBefore`	Number of full-time employees before NJ minimum wage law
`partAfter`	Number of full-time employees after NJ minimum wage law

Loading the data

```
library(tidyverse)
library(qss)
data(minwage)
minwage <- as_tibble(minwage)
minwage
```

```
## # A tibble: 358 x 8
##    chain  location wageBefore wageAfter fullBefore fullAfter
##    <chr>  <chr>         <dbl>     <dbl>      <dbl>     <dbl>
##  1 wendys PA             5         5.25       20           0
##  2 wendys PA             5.5       4.75        6          28
##  3 burge~ PA             5         4.75       50          15
##  4 burge~ PA             5         5          10          26
##  5 kfc    PA             5.25      5           2           3
##  6 kfc    PA             5         5           2           2
##  7 roys   PA             5         4.75        2.5         1
##  8 burge~ PA             5         5          40           9
##  9 burge~ PA             5         4.5         8           7
## 10 burge~ PA             5.5       4.75       10.5        18
## # i 348 more rows
## # i 2 more variables: partBefore <dbl>, partAfter <dbl>
```

Creating a treatment vector

```r
minwage |>
  count(location)
```

```
## # A tibble: 5 x 2
##   location     n
##   <chr>    <int>
## 1 PA          67
## 2 centralNJ   45
## 3 northNJ    146
## 4 shoreNJ     33
## 5 southNJ     67
```

```r
minwage <- minwage |>
  mutate(
    state = if_else(location == "PA", "PA", "NJ"), ## PA is control
    full_prop_after = fullAfter / (fullAfter + partAfter) ## proportion ful
  )
```

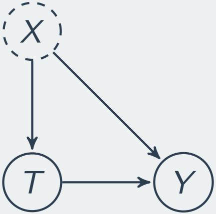
Cross-sectional estimate

```r
ate_cs <- minwage |>
  group_by(state) |>
  summarize(full_mean = mean(full_prop_after)) |>
  pivot_wider(
    names_from = state,
    values_from = full_mean
  ) |>
  mutate(ATE = NJ - PA)
ate_cs
```

```
## # A tibble: 1 x 3
##      NJ    PA    ATE
##   <dbl> <dbl>  <dbl>
## 1 0.320 0.272 0.0481
```

Interpretation: The minimum wage law increased the percent of full-time employment by 4.81 percentage points if the cross sectional assumptions hold.

Confounders



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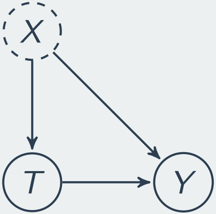

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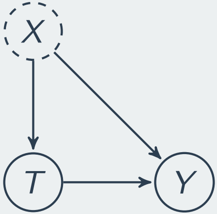

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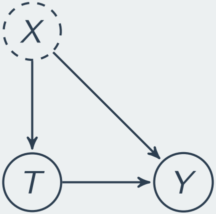

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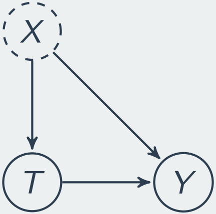

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    - Then the difference we see in employment might be due to the differece in BKs rather than the MW law.

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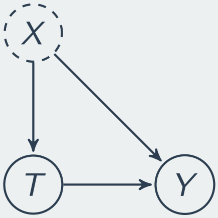

- Could there be **confounders** between having a minimum wage law at \$5.05 and employment?
    - A confounder is a pre-treatment variable that affects both treatment and the outcome.
- One possibility: different chain types.
    - Imagine if Burger King requires fewer workers to operate than other chains and if for historical reasons there are more BKs in PA than in NJ.
    - Then the difference we see in employment might be due to the differece in BKs rather than the MW law.
    - We can check this by comparing chain distribution across states.

Balance of chains across states

```
minwage |>
  group_by(state, chain) |>
  summarize(n = n(), .groups = "drop_last") |>
  mutate(prop = n / sum(n)) |>
  pivot_wider(
    id_cols = chain,
    names_from = state,
    values_from = prop
  )
```

```
## # A tibble: 4 x 3
##   chain        NJ    PA
##   <chr>     <dbl> <dbl>
## 1 burgerking 0.405 0.463
## 2 kfc       0.223 0.149
## 3 roys      0.251 0.224
## 4 wendys    0.120 0.164
```

Some differences here: more BK in PA and more KFC in NJ. What to do? We can perform **statistical control** by estimating ATEs within groups.

ATE by chain

```r
minwage |>
  group_by(state, chain) |>
  summarize(full_mean = mean(full_prop_after)) |>
  pivot_wider(
    names_from = state,
    values_from = full_mean
  ) |>
  mutate(ATE = NJ - PA)
```

```
## # A tibble: 4 x 4
##   chain          NJ    PA    ATE
##   <chr>       <dbl> <dbl>  <dbl>
## 1 burgerking 0.358 0.321 0.0364
## 2 kfc        0.328 0.236 0.0918
## 3 roys       0.283 0.213 0.0697
## 4 wendys     0.260 0.248 0.0117
```

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    - Called **unmeasured confounding**
- Before and after design compares NJ before the law to after the law.
    - Anything fixed about NJ cannot be causing the the differences.

Estimating ATE with before-and-after

```r
minwage <- minwage |>
  mutate(full_prop_before = fullBefore / (fullBefore + partBefore))

minwage |>
  filter(state == "NJ") |>
  summarize(ATE = mean(full_prop_after) - mean(full_prop_before))
```

```
## # A tibble: 1 x 1
##      ATE
##    <dbl>
## 1 0.0239
```

Interpretation: we estimate the MW law increase the full-time employment percentage by 2.39% if there are no **time-varying confounders**.

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- Before and after designs could be affected by time-varying confounders.

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- Before and after designs could be affected by time-varying confounders.
- If the whole US economy is shifting to full time employment due to a good economy, then it's not the MW law that is driving things.
- We can account for trends that are affecting all units by comparing the trends in the treated group to the trends in the control group.

Difference-in-differences estimate

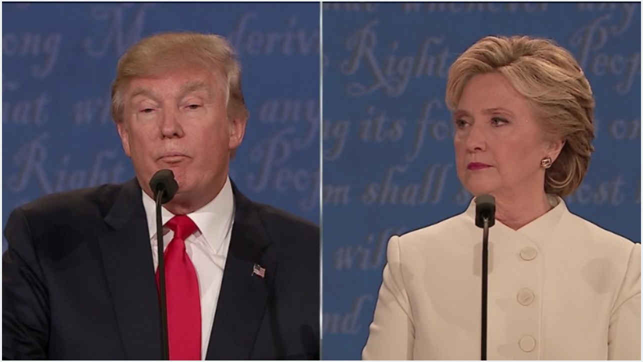
```
minwage |>
  group_by(state) |>
  summarize(trend = mean(full_prop_after) - mean(full_prop_before)) |>
  pivot_wider(
    names_from = state,
    values_from = trend
  ) |>
  mutate(DID = NJ - PA)
```

```
## # A tibble: 1 x 3
##       NJ      PA    DID
##    <dbl>   <dbl>  <dbl>
## 1 0.0239 -0.0377 0.0616
```

Interpretation: minimum wage laws increased percent full-time in NJ by 6.16 percentage points if trends in PA are a good proxy for trends in NJ if it didn't enact a MW law.

2/ Prediction

2016 US Presidential Election



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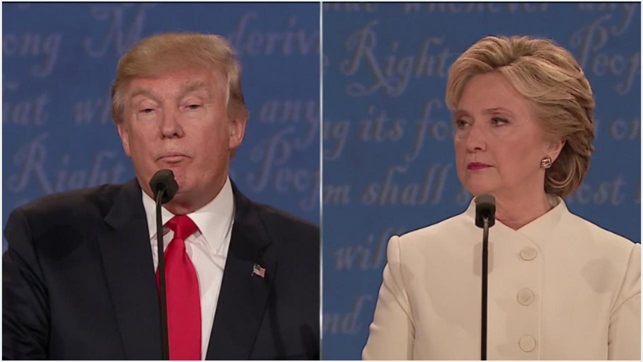

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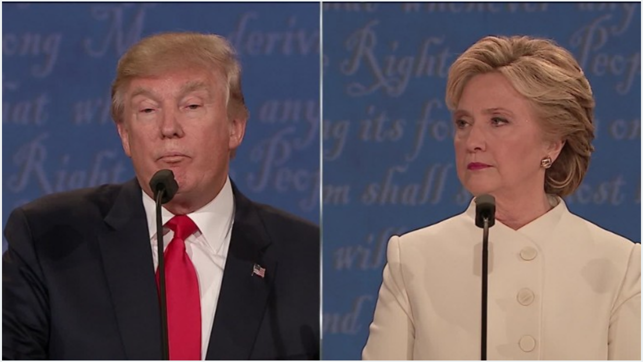

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    - Clinton: 65,853,516 (48.2%)

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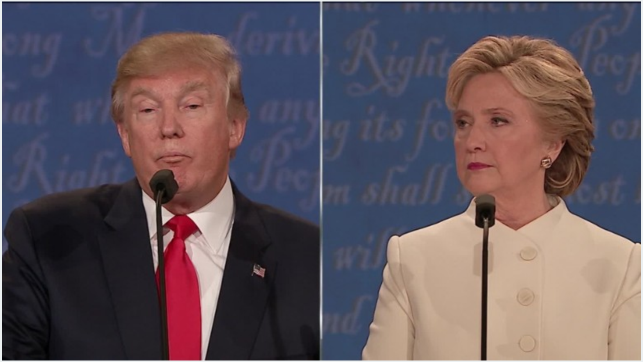

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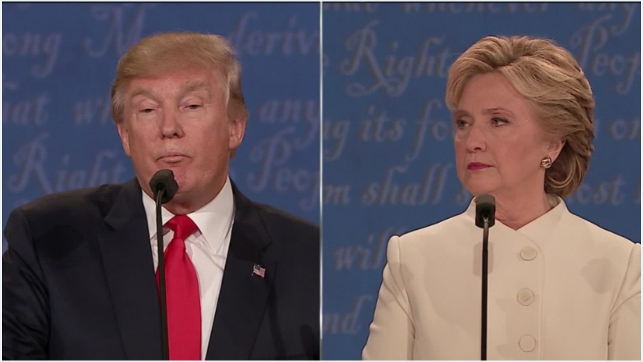

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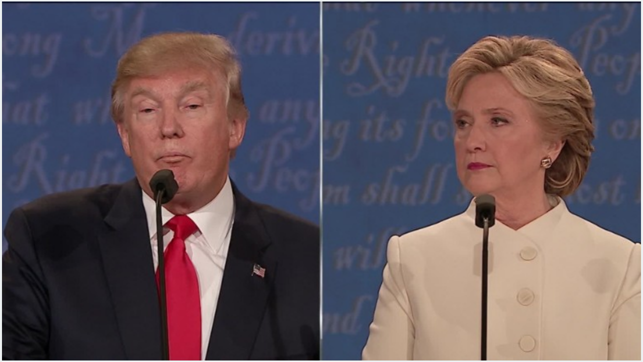

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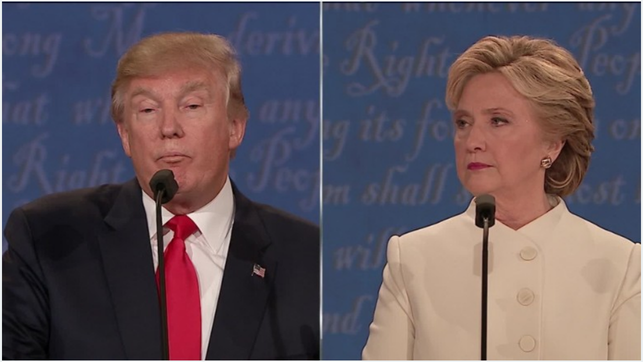

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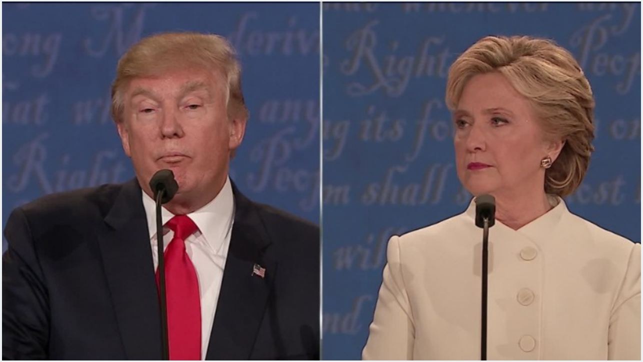

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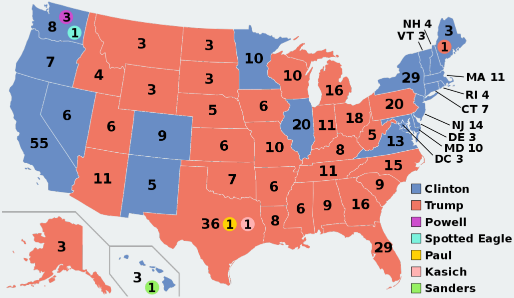
- Election determined by 77,744 votes (margins in WI, MI, and PA)
    - 0.056% of the electorate (~136 million)

Predicting US Presidential Elections



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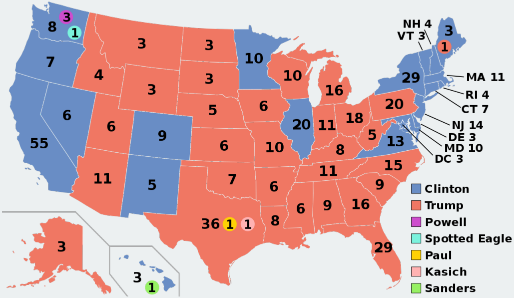

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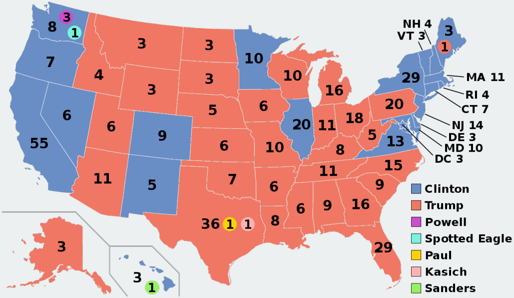

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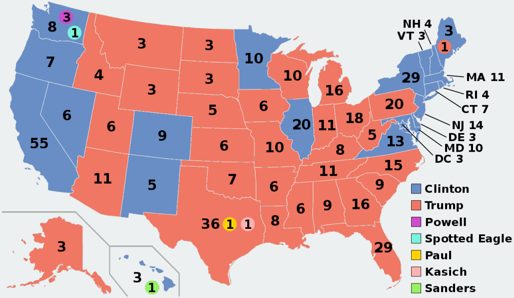

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  - Must win at least 270 votes

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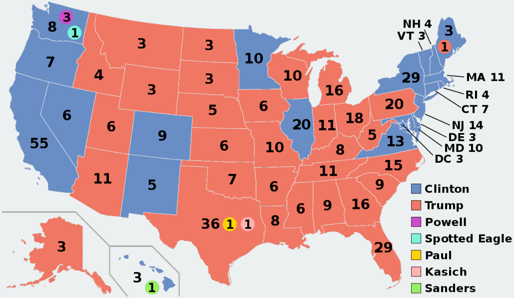

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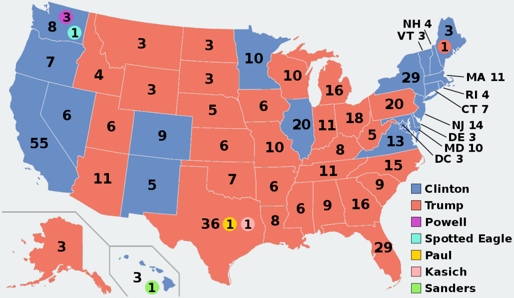

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- Must predict winner of each state

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    2. Further subset the latest polls
    3. Average the latest polls to estimate support for each candidate
    4. Allocate the electoral votes to the candidate who has greatest support
    5. Repeat this for all states and aggregate the electoral votes

2020 polling prediction

Election data: `pres20`

Name	Description
`state`	abbreviated name of state
`biden`	Biden's vote share (percentage)
`trump`	Trump's vote share (percentage)
`ev`	number of electoral college votes for the state

Polling data `polls20`:

Name	Description
`state`	state in which poll was conducted
`end_date`	end date the period when poll was conducted
`daysleft`	number of days between end date and election day
`pollster`	name of organization conducting poll
`sample_size`	name of organization conducting poll
`biden`	predicted support for Biden (percentage)
`trump`	predicted support for Trump (percentage)

Some preprocessing

```r
library(gov50data)
glimpse(polls20)
```

```
## Rows: 2,445
## Columns: 7
## $ end_date    <date> 2020-11-02, 2020-11-02, 2020-11-02, 2~
## $ state       <chr> "FL", "PA", "FL", "FL", "NV", "GA", "S~
## $ days_left   <dbl> 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,~
## $ pollster    <chr> "The Political Matrix/The Listener Gro~
## $ sample_size <dbl> 966, 499, 400, 1054, 1024, 1041, 817, ~
## $ biden       <dbl> 44.2, 48.4, 47.0, 47.3, 48.4, 45.4, 39~
## $ trump       <dbl> 48.0, 49.2, 48.2, 49.4, 49.1, 49.7, 51~
```

Easy to iterate with tidyverse

```
poll_pred <- polls20 |>
  group_by(state) |>
  filter(days_left == min(days_left)) |>
  summarize(margin_pred = mean(biden - trump))
poll_pred
```

```
## # A tibble: 51 x 2
##    state margin_pred
##    <chr>       <dbl>
##  1 AK         -9
##  2 AL        -26
##  3 AR        -23
##  4 AZ          4.25
##  5 CA         26
##  6 CO         11
##  7 CT         22
##  8 DC         89
##  9 DE         22
## 10 FL          0.0800
## # i 41 more rows
```

3/ Evaluating the predictions

Polling errors

Prediction error = actual outcome − predicted outcome

```
poll_pred <- poll_pred |>
  left_join(pres20) |>
  mutate(margin = biden - trump) |>
  mutate(errors = margin - margin_pred)
poll_pred
```

```
## # A tibble: 51 x 8
##    state margin_pred    ev biden trump  other  margin errors
##    <chr>       <dbl> <dbl> <dbl> <dbl>  <dbl>   <dbl>  <dbl>
##  1 AK         -9         3  42.8 52.8  0.732  -10.1   -1.06
##  2 AL        -26         9  36.6 62.0  0.699  -25.5    0.538
##  3 AR        -23         6  34.8 62.4  0.257  -27.6   -4.62
##  4 AZ          4.25     11  49.4 49.1  0.263    0.309 -3.94
##  5 CA         26        55  63.5 34.3  0.244   29.2    3.16
##  6 CO         11         9  55.0 41.6  0.161   13.4    2.41
##  7 CT         22         7  59.3 39.2  0.129   20.1   -1.93
##  8 DC         89         3  92.1  5.40 0.491   86.8   -2.25
##  9 DE         22         3  58.7 39.8  0.0780  19.0   -3.03
## 10 FL          0.0800   29  47.9 51.2  0.0835  -3.36  -3.44
## # i 41 more rows
```

Assessing the prediction error

Bias: average prediction error

```
mean(poll_pred$errors)
```

```
## [1] -3.98
```

Assessing the prediction error

Bias: average prediction error

```
mean(poll_pred$errors)
```

```
## [1] -3.98
```

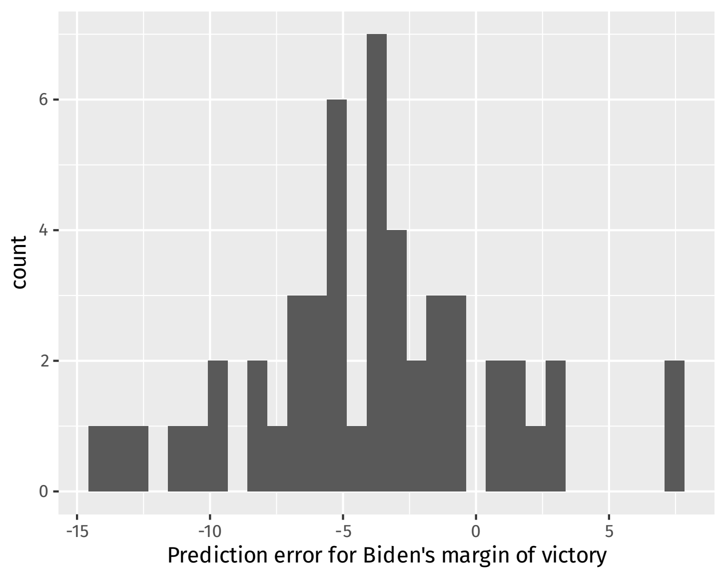
Root mean-square error: average magnitude of the prediction error

```
sqrt(mean(poll_pred$errors^2))
```

```
## [1] 6.07
```

Histogram of the errors

```r
ggplot(poll_pred, aes(x = errors)) +
  geom_histogram() +
  labs(
    x = "Prediction error for Biden's margin of victory"
  )
```



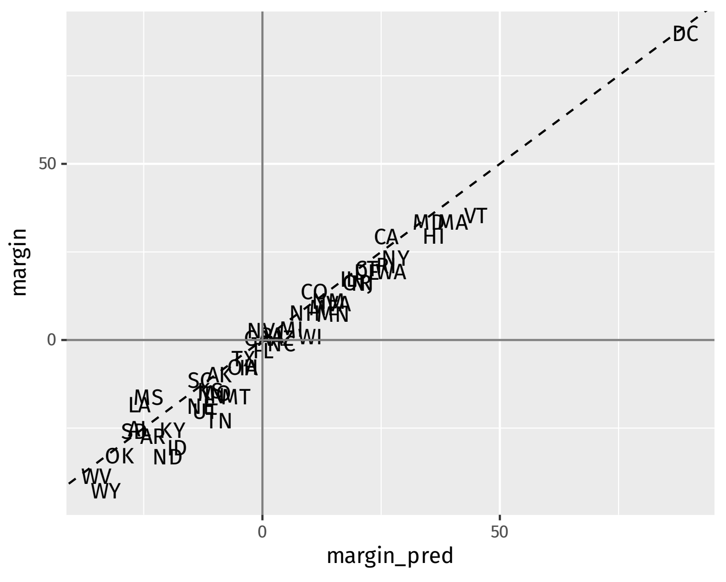
count
6
4
2
0
-15
-10
-5
0
5
Prediction error for Biden's margin of victory

Comparing polls to outcome

Sometimes we want plot text labels instead of point and we use `geom_text` and the `label` aesthetic:

```
## merge the actual results
ggplot(poll_pred, aes(x = margin_pred, y = margin)) +
  geom_text(aes(label = state)) +
  geom_abline(xintercept = 0, slope = 1, linetype = 2) +
  geom_hline(yintercept = 0, color = "grey50") +
  geom_vline(xintercept = 0, color = "grey50")
```

Comparing polls to outcome



Classification

Election prediction: need to predict winner in each state:

```r
poll_pred |>
  filter(margin > 0) |>
  summarize(sum(ev)) |> pull()
```

```
## [1] 306
```

```r
poll_pred |>
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  summarize(sum(ev)) |> pull()
```

```
## [1] 328
```

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- Prediction of binary outcome variable = **classification problem**

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- Prediction of binary outcome variable = **classification problem**
- Wrong prediction $\rightsquigarrow$ misclassification

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- Prediction of binary outcome variable = **classification problem**
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  1. **true positive**: predict Trump wins when he actually wins.

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- Prediction of binary outcome variable = **classification problem**
- Wrong prediction $\rightsquigarrow$ misclassification
    1. **true positive**: predict Trump wins when he actually wins.
    2. **false positive**: predict Trump wins when he actually loses.

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- Prediction of binary outcome variable = **classification problem**
- Wrong prediction $\rightsquigarrow$ misclassification
  1. **true positive**: predict Trump wins when he actually wins.
  2. **false positive**: predict Trump wins when he actually loses.
  3. **true negative**: predict Trump loses when he actually loses.
  4. **false negative**: predict Trump loses when he actually wins.
- Sometimes false negatives are more/less important: e.g., civil war.

Classification based on polls

Accuracy: `sign()` returns 1 for a positive number, `-1` for a negative number, and `0` for 0.

```
poll_pred |>
  summarize(prop_correct = mean(sign(margin_pred) == sign(margin))) |>
  pull()
```

```
## [1] 0.922
```

Classification based on polls

Accuracy: `sign()` returns 1 for a positive number, `-1` for a negative number, and `0` for 0.

```
poll_pred |>
  summarize(prop_correct = mean(sign(margin_pred) == sign(margin))) |>
  pull()
```

```
## [1] 0.922
```

Which states did polls call wrong?

```
poll_pred |>
  filter(sign(margin_pred) != sign(margin))
```

```
## # A tibble: 4 x 8
##   state margin_pred    ev biden trump  other margin errors
##   <chr>       <dbl> <dbl> <dbl> <dbl>  <dbl>  <dbl>  <dbl>
## 1 FL         0.0800    29  47.9  51.2 0.0835 -3.36   -3.44
## 2 GA        -1.15      16  49.5  49.2 0.0759  0.236   1.39
## 3 NC         3.95      15  48.6  49.9 0.296  -1.35   -5.30
## 4 NV        -0.350      6  50.1  47.7 0.759   2.39    2.74
```