ITSx: Policy Analysis Using Interrupted Time Series

Week 5 Slides

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COURSE OVERVIEW

Layout of the weeks

1. Introduction, setup, data sources
2. Single series interrupted time series analysis
3. ITS with a control group
4. ITS Extensions
5. Regression discontinuities & Wrap-up

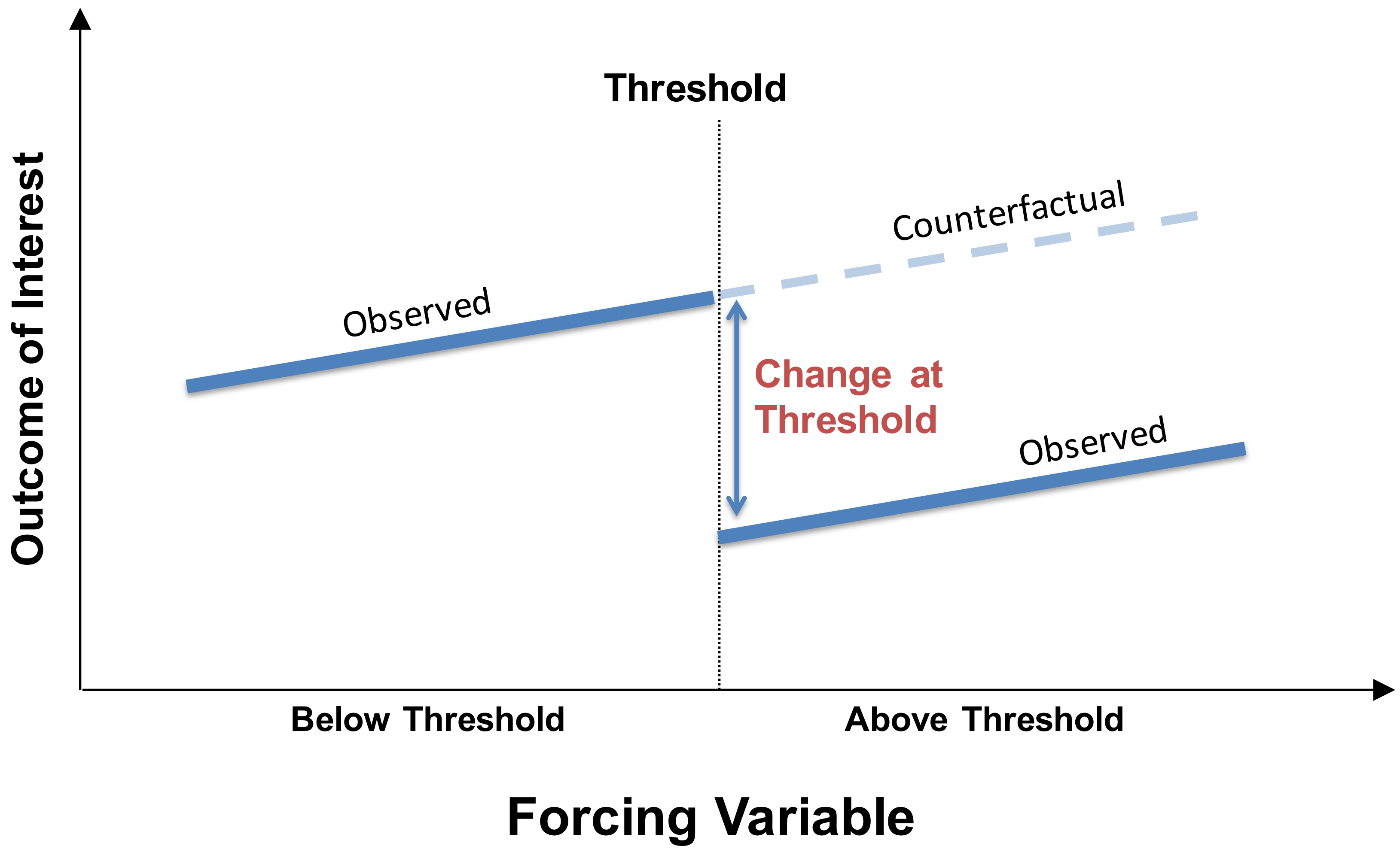
REGRESSION DISCONTINUITIES

Regression Discontinuity (RD)

- Design
  - Compare trends in an outcome across an exposure variable below and above a threshold

- Major Assumption
  - The level and trend in the outcome above/below the threshold would have continued absent the threshold

The Counterfactual



Estimates

- RD estimates what's known as a local average treatment effect (LATE)
  - Comparing people just below to just above the threshold

Forcing Variable Examples

- Student Achievement
- Vote Margin
- Birth Year
- Minute of birth
- Many others…

Integrity of the Forcing Variable

- Institutional integrity
  - Describe the process of assigning variables, and how access to the intervention was assigned
  - Should not be subject to potential manipulation

- Statistical integrity
  - There should not be a discontinuity in the density of cases at the threshold

Testing Assumptions

- Other variables should be smooth through the threshold

Potential RD Biases

1. Co-intervention / Non-smooth curve
   - Something aside from the intervention affects the outcome and changes at the same threshold as the intervention
2. Instrumentation
   - The method of measurement differs above and below the threshold
3. Attrition
   - Individuals are differentially included in the sample on either side of the threshold
4. Manipulation of threshold

PERFORMING AN RD ANALYSIS

Basic data setup

Person ID	Forcing	Threshold	Forcing_Threshold	Outcome
1	3	0	0	4
2	6	1	6	5
3	8	1	8	8
4	9	1	9	4
5	1	0	0	5
6	2	0	0	5
7	4	0	0	3
8	7	1	7	2
9	4	0	0	6
…	…	…	…	…

Basic RD model

- For threshold *j* and forcing variable *k:*

$$outcome_{jk} = \beta_0 + \beta_1 \cdot (k - j) + \beta_2 \cdot [k > j] + \beta_3 \cdot [k > j] \cdot k + \varepsilon_{jk}$$

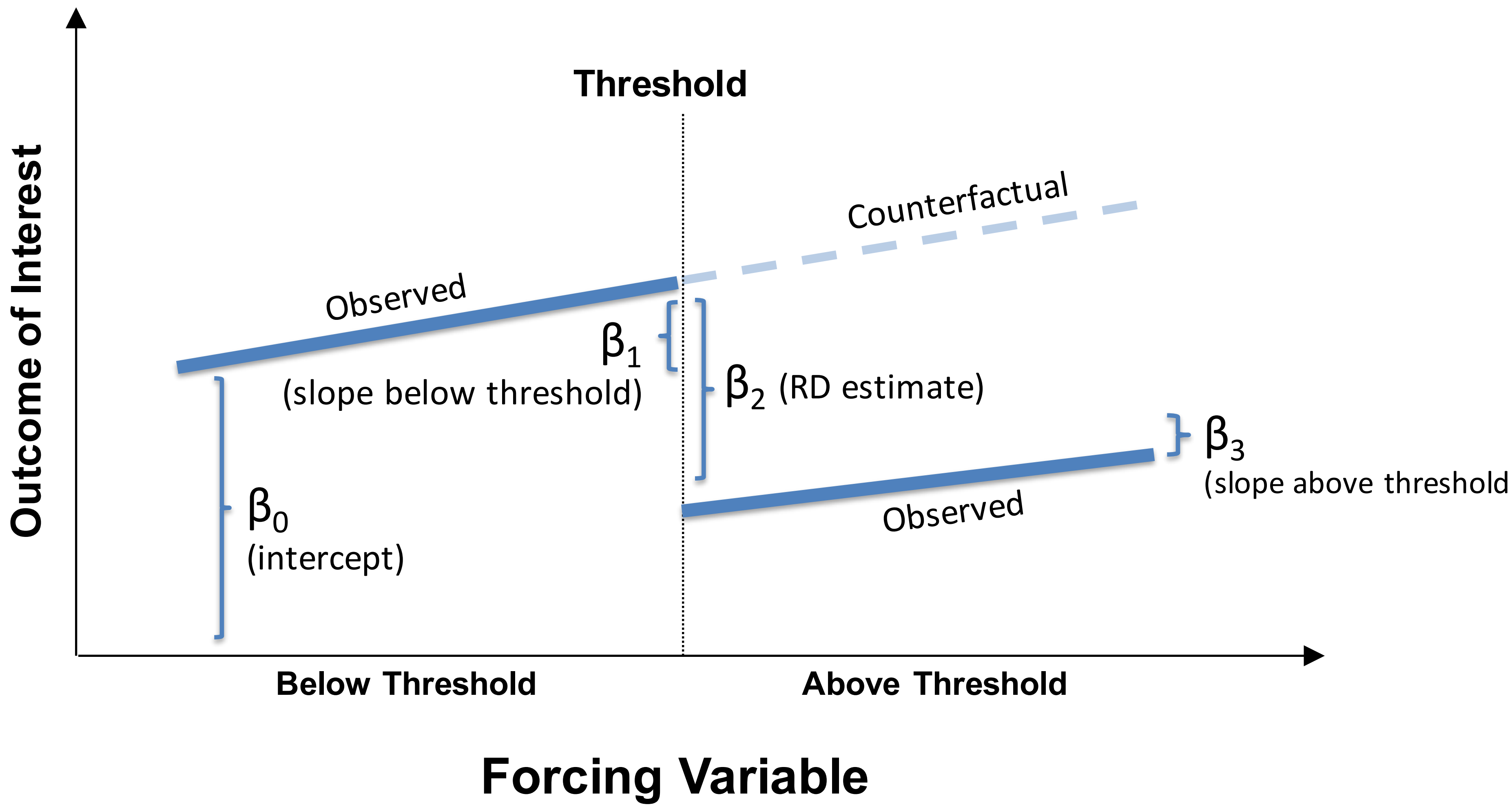
Predicted level at smallest forcing variable value

Pre-existing slope in the outcome of interest

Change in the level above the threshold
* Variable of interest

Change in the slope above the threshold

$$outcome_{jk} = \beta_0 + \beta_1 \cdot (k - j) + \beta_2 \cdot [k > j] + \beta_3 \cdot [k > j] \cdot k + \varepsilon_{jk}$$



Running an RD Model

```
#########################
# Modeling an RD
#########################

# Fit the standard regression model
rd_model <- gls(outcome ~ forcing + threshold +
                forcing_threshold,
                data=data,
                method="ML")

summary(rd_model)
```

Higher-order Polynomials

- Often the relationship between the forcing variable and the outcome on either side of the threshold will be non-linear
  - Solution: model in polynomial terms

- Similar in structure and form to using a quadratic trend in a time series analysis

Running an RD Model

```
######################################
# Modeling an RD with square terms
######################################

# Construct a square term on either side of the threshold
data$forcing_sq <- data$forcing^2
data$forcing_threshold_sq <- data$forcing_threshold^2

# Fit the standard regression model
rd_model <- gls(outcome ~ forcing + forcing_sq + threshold +
                 forcing_threshold + forcing_threshold_sq,
                data=dataset,
                method="ML")

summary(rd_model)
```

Modeling

- Have to make decisions about range
  - Trade-off between linearity and data, or “precision and bias” as Lee and Lemieux refer to it

- Other considerations
  - Local linear regression
  - Kernel densities
  - “Fuzzy” RD designs

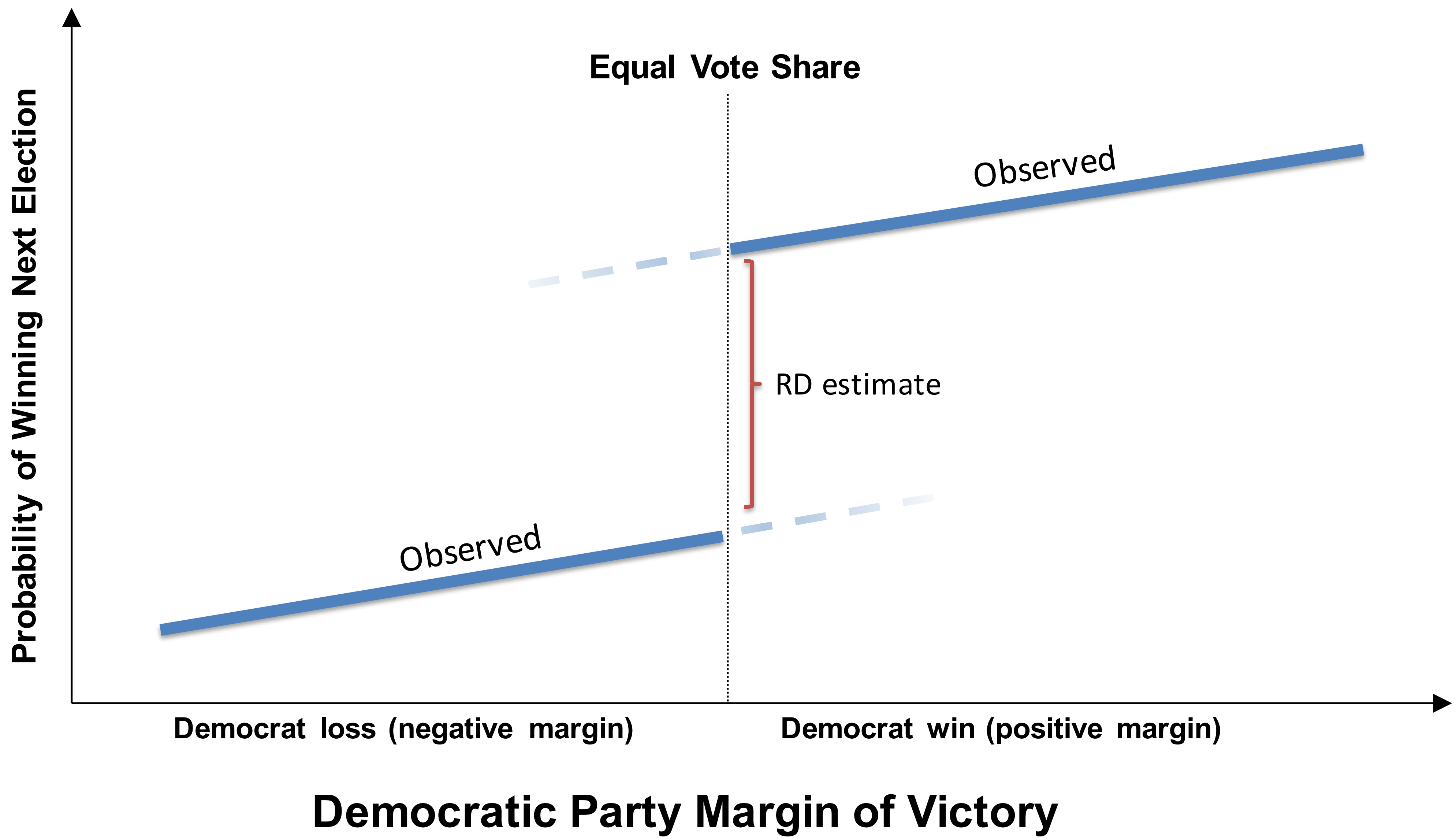
Presenting an RD Analyis

- Common to present two figures:
  - Forcing variable and exposure to the intervention
  - Forcing variable and outcome

RD EXAMPLE: INCUMBENCY

Lee (2008)

- Interested in the effect of incumbent party advantage
- Uses data from US House of Representatives elections
- Our data are from a replication by Caughey and Sekhon
  - Includes 7,598 elections from 1942 through 2006


Equal Vote Share
Observed
RD estimate
Observed
Probability of Winning Next Election
Democrat loss (negative margin)
Democrat win (positive margin)
Democratic Party Margin of Victory

Data Setup

state	year	dmargin	demwin	dwinnext	bin
...	...	...	...	...	...
5	1946	-6.218	0	0	22
5	1950	-4.146	0	0	23
5	1954	-5.118	0	1	23
5	1956	6.148	1	1	29
...	...	...	...	...	...

Setup Variables

```
# Setup square and cubic terms for forcing variable
dataset$dmargin2 <- dataset$dmargin^2
dataset$dmargin3 <- dataset$dmargin^3

# Setup interaction between forcing variable and threshold
dataset$dmargin_demwin <- dataset$dmargin * dataset$demwin

# Setup square and cubic terms for forcing variable * threshold
interactions
dataset$dmargin_demwin2 <- dataset$dmargin_demwin^2
dataset$dmargin_demwin3 <- dataset$dmargin_demwin^3
```

Preliminary Plot

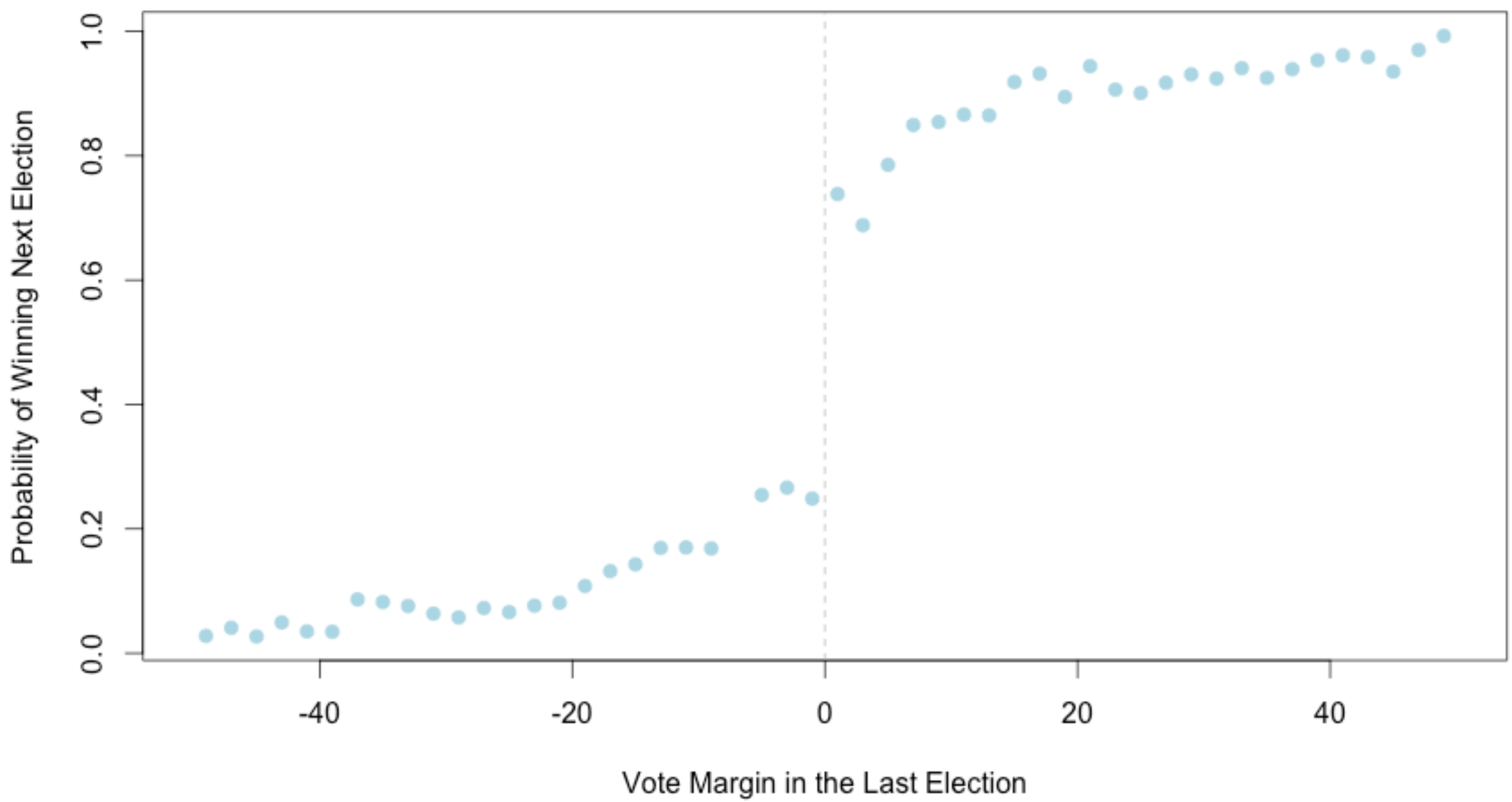
```
###################################
# Preliminary Plot
###################################

# Setup bins for plotting
bins <- seq(-49,49,2)

# Get the mean within each bin
means <- tapply(dataset$dwinnext,dataset$bin,mean)

# Plot the results
plot(bins,means,
     pch=19,
     ylab="Probability of Winning Next Election",
     xlab="Vote Margin in the Last Election",
     xlim=c(-50,50),
     col="lightblue")

# Add line at zero
abline(v=0,lty=2,col="grey")
```


Probability of Winning Next Election
0.0
0.2
0.4
0.6
0.8
1.0
-40
-20
0
20
40
Vote Margin in the Last Election

Run Basic Model

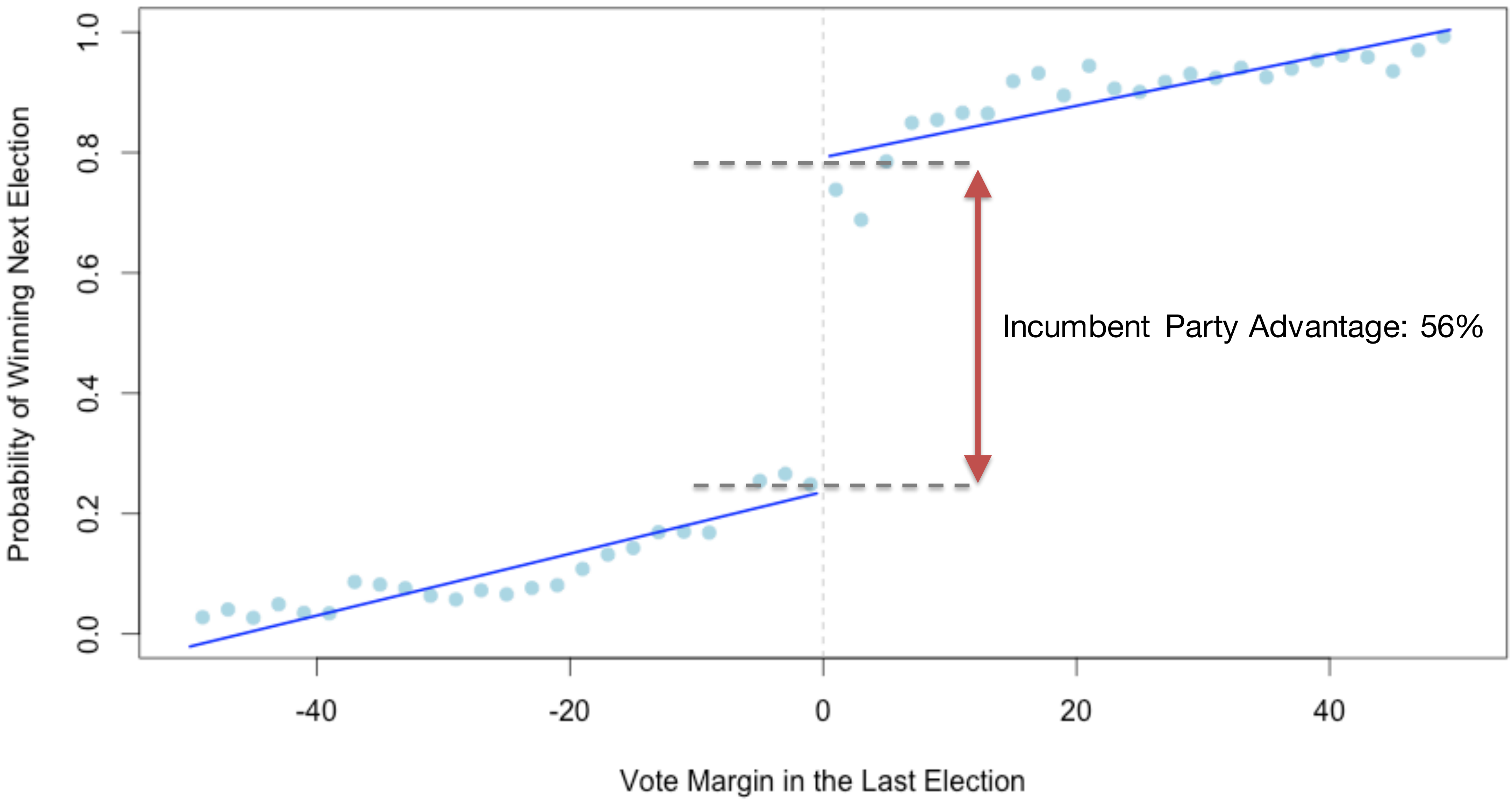
```
####################################
# Modeling
####################################

model <- lm(dwinnext  ~ dmargin + demwin + dmargin_demwin,
            data=dataset)

summary(model)
```

Model 1 Results

```
Coefficients:
                  Estimate  Std. Error t value  Pr(>|t|)
(Intercept)      0.2362171   0.0096311  24.526    <2e-16 ***
dmargin          0.0051402   0.0003727  13.790    <2e-16 ***
demwin           0.5558085   0.0139324  39.893    <2e-16 ***
dmargin_demwin  -0.0008619   0.0005163  -1.669    0.0951 .
```



Incumbent Party Advantage: 56%
Probability of Winning Next Election
Vote Margin in the Last Election
0.0
0.2
0.4
0.6
0.8
1.0
-40
-20
0
20
40

Add square terms

```
# Add square terms
model2 <- lm(dwinnext ~ dmargin + dmargin2 +
               demwin + dmargin_demwin + dmargin_demwin2,
               data=dataset)
summary(model2)

# Compare versus model 1
anova(model1, model2)
```

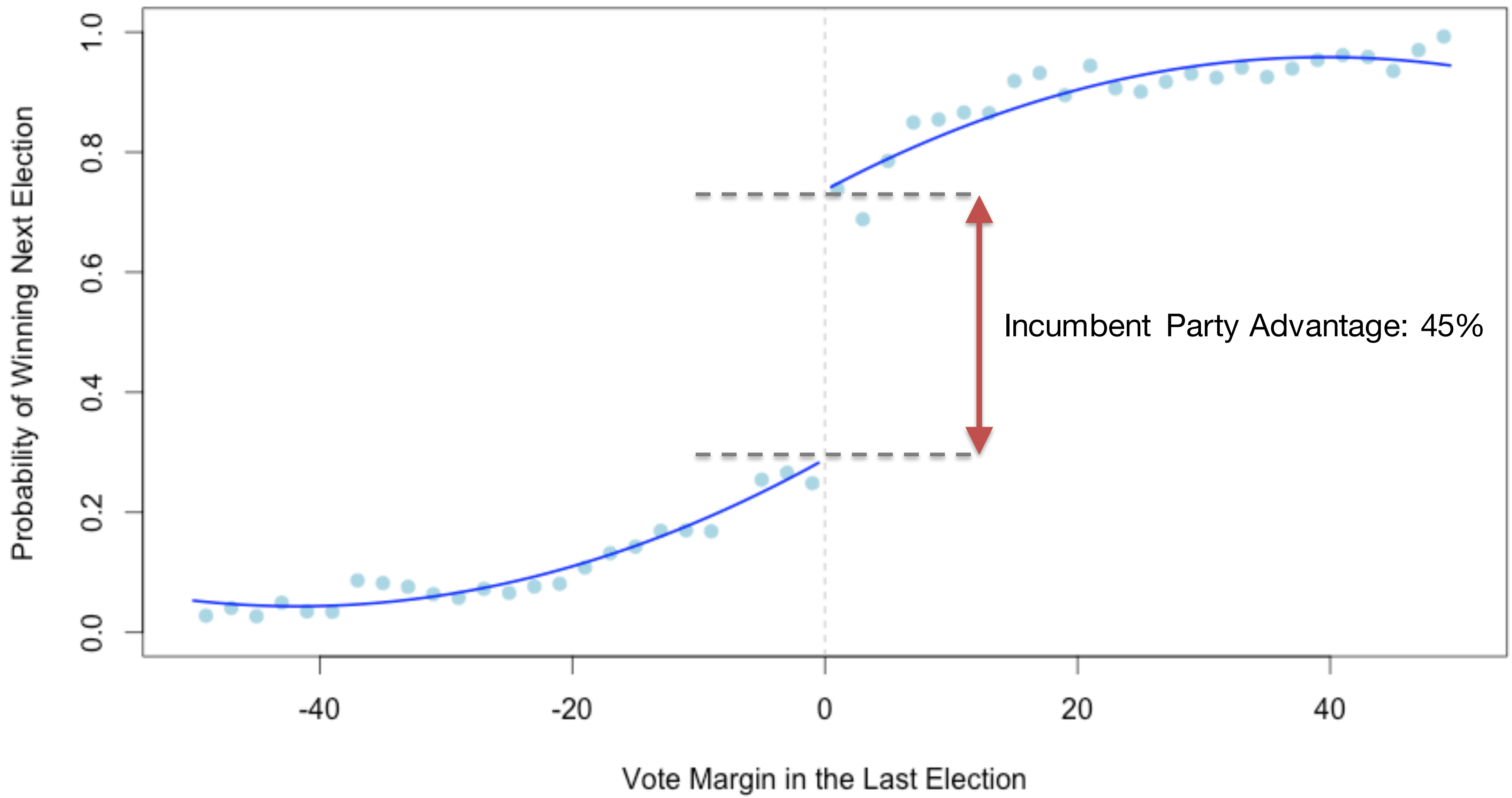
Model 2 Results

```
Coefficients:
                    Estimate   Std. Error t value  Pr(>|t|)
(Intercept)       0.28847535   0.01425106   20.242  < 2e-16 ***
dmargin           0.01172643   0.00137841    8.507  < 2e-16 ***
dmargin2          0.00014036   0.00002829    4.962 7.14e-07 ***
demwin            0.44811150   0.02054055   21.816  < 2e-16 ***
dmargin_demwin   -0.00053605   0.00196543   -0.273    0.785
dmargin_demwin2  -0.00028161   0.00003958   -7.114 1.23e-12 ***
```

Model 1 vs. Model 2

```
Analysis of Variance Table

Model 1: dwinnext ~ dmargin + demwin + dmargin_demwin
Model 2: dwinnext ~ dmargin + dmargin2 + demwin +
dmargin_demwin + dmargin_demwin2
  Res.Df    RSS Df Sum of Sq     F    Pr(>F)
1   7593 732.19
2   7591 727.33  2    4.8522 25.32 1.096e-11 ***
```


Incumbent Party Advantage: 45%
Probability of Winning Next Election
0.0
0.2
0.4
0.6
0.8
1.0
-40
-20
0
20
40
Vote Margin in the Last Election

Add cubic terms

```
# Run full specified model
model3 <- lm(dwinnext ~ dmargin + dmargin2 + dmargin3 + demwin
            + dmargin_demwin + dmargin_demwin2 +
            dmargin_demwin3,
            data=dataset)
summary(model3)

# Compare versus model 2
anova(model2, model3)
```

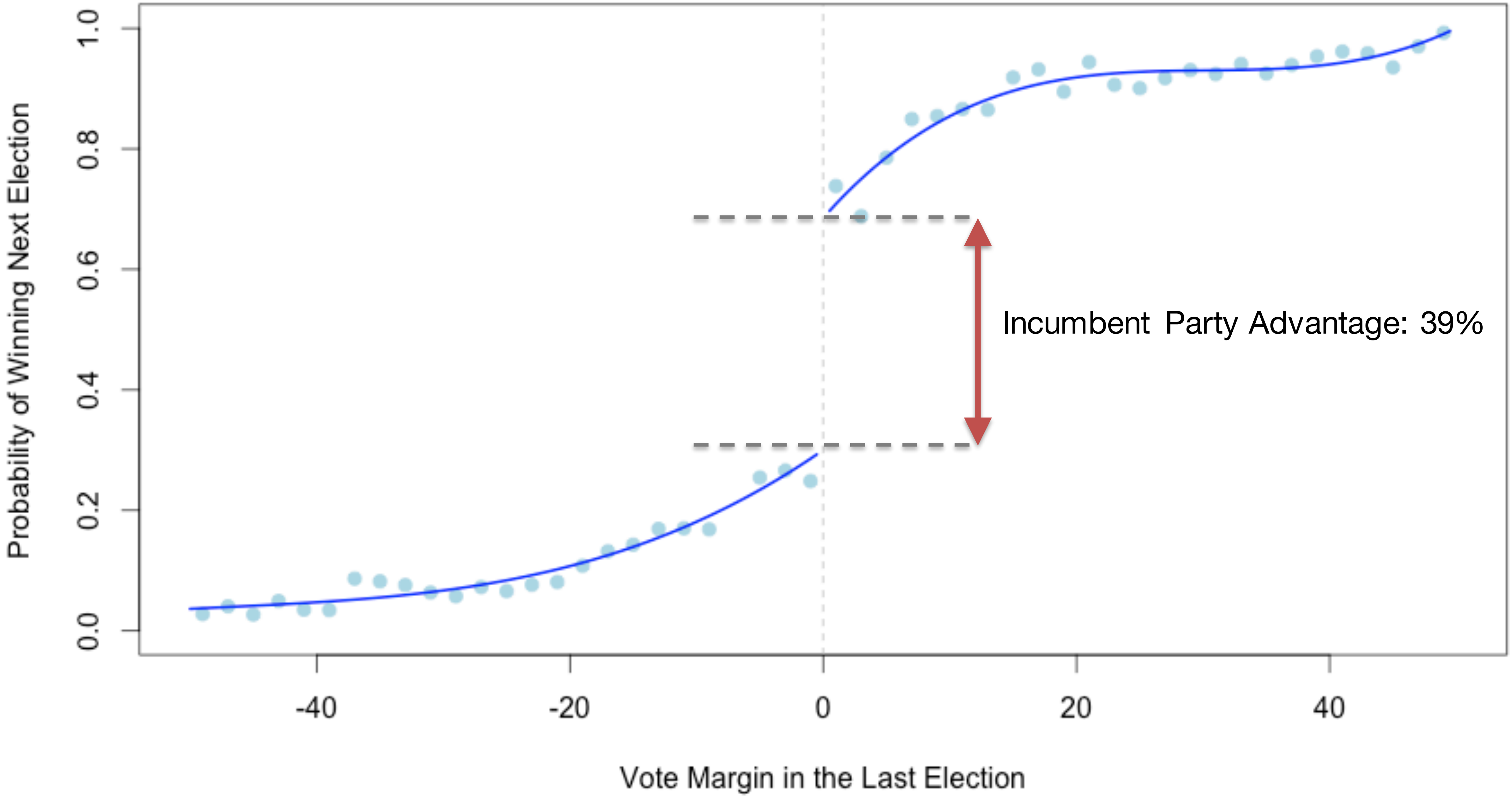
Model 3 Results

```
Coefficients:
                    Estimate   Std. Error t value    Pr(>|t|)
(Intercept)      0.300040593  0.018943445  15.839     < 2e-16 ***
dmargin          0.014578041  0.003374783   4.320  0.00001582 ***
dmargin2         0.000288379  0.000162408   1.776      0.0758 .
dmargin3         0.000002045  0.000002209   0.926      0.3547
demwin           0.385243821  0.027359614  14.081     < 2e-16 ***
dmargin_demwin   0.009250574  0.004872682   1.898      0.0577 .
dmargin_demwin2 -0.001068132  0.000231675  -4.610  0.00000408 ***
dmargin_demwin3  0.000006539  0.000003111   2.102      0.0356 *
```

Model 2 vs. Model 3

```
Analysis of Variance Table

Model 1: dwinnext ~ dmargin + dmargin2 + demwin +
dmargin_demwin + dmargin_demwin2
Model 2: dwinnext ~ dmargin + dmargin2 + dmargin3 + demwin +
dmargin_demwin + dmargin_demwin2 + dmargin_demwin3
  Res.Df    RSS Df Sum of Sq      F    Pr(>F)
1   7591 727.33
2   7589 725.78  2    1.5515 8.1114 0.0003027 ***
```



Probability of Winning Next Election
0.0
0.2
0.4
0.6
0.8
1.0
-40
-20
0
20
40
Vote Margin in the Last Election
Incumbent Party Advantage: 39%

A note on the example…

- I have modeled a discrete (win / loss) outcome using linear regression

- I have also posted code to perform the same analysis using logistic regression