Regression Discontinuity Designs

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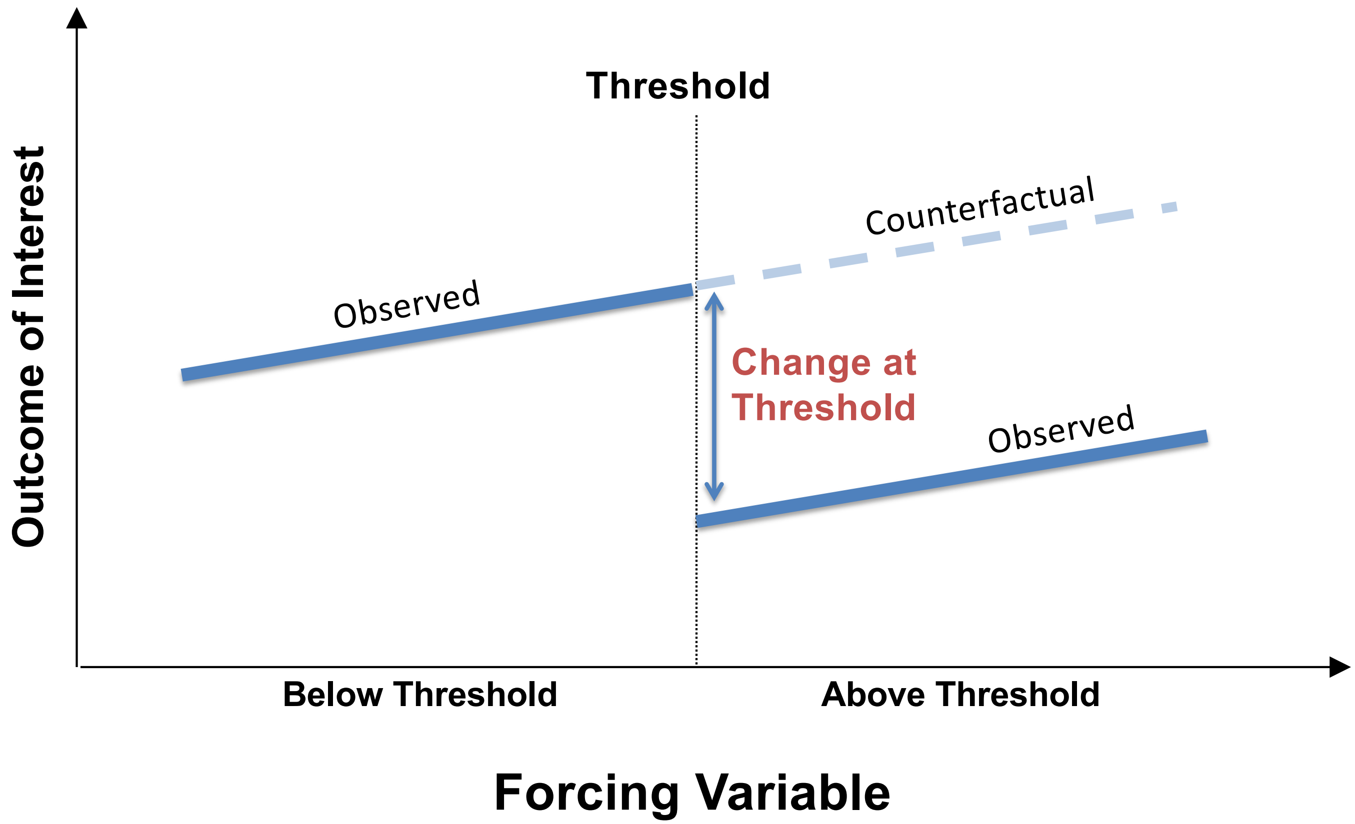
Presentation Overview

- Introduction to RD
- An Example Study on BC’s Fair Pharmacare Program
- How to model an RD

Regression Discontinuity (RD)

- Design
  - Compare trends in an outcome above and below a threshold in a forcing variable
- Counterfactual Assumption
  - The existing trend in the outcome above/below the threshold would have been smooth absent the change at the threshold

Regression Discontinuity



RD Estimates

- RDs estimate what's known as a local average treatment effect (LATE)

- Interpretation:
  - The effect of the receipt of the intervention for those who would not have received it absent the change in eligibility at 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

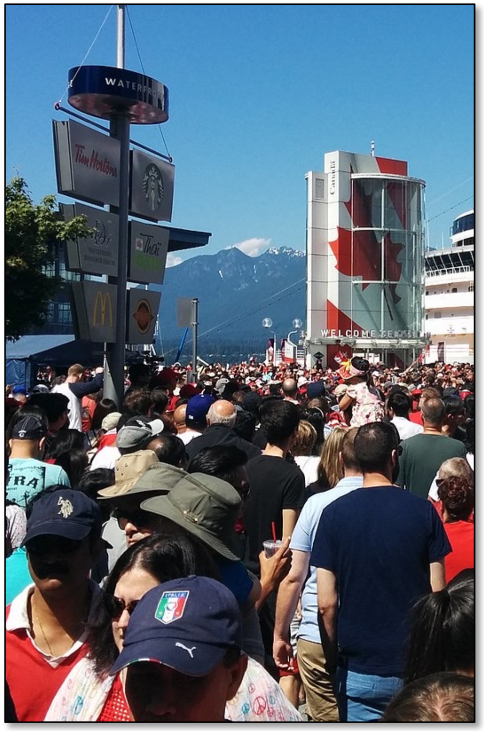
3. Ascertainment
   – Individuals are differentially included in the sample on either side of the threshold

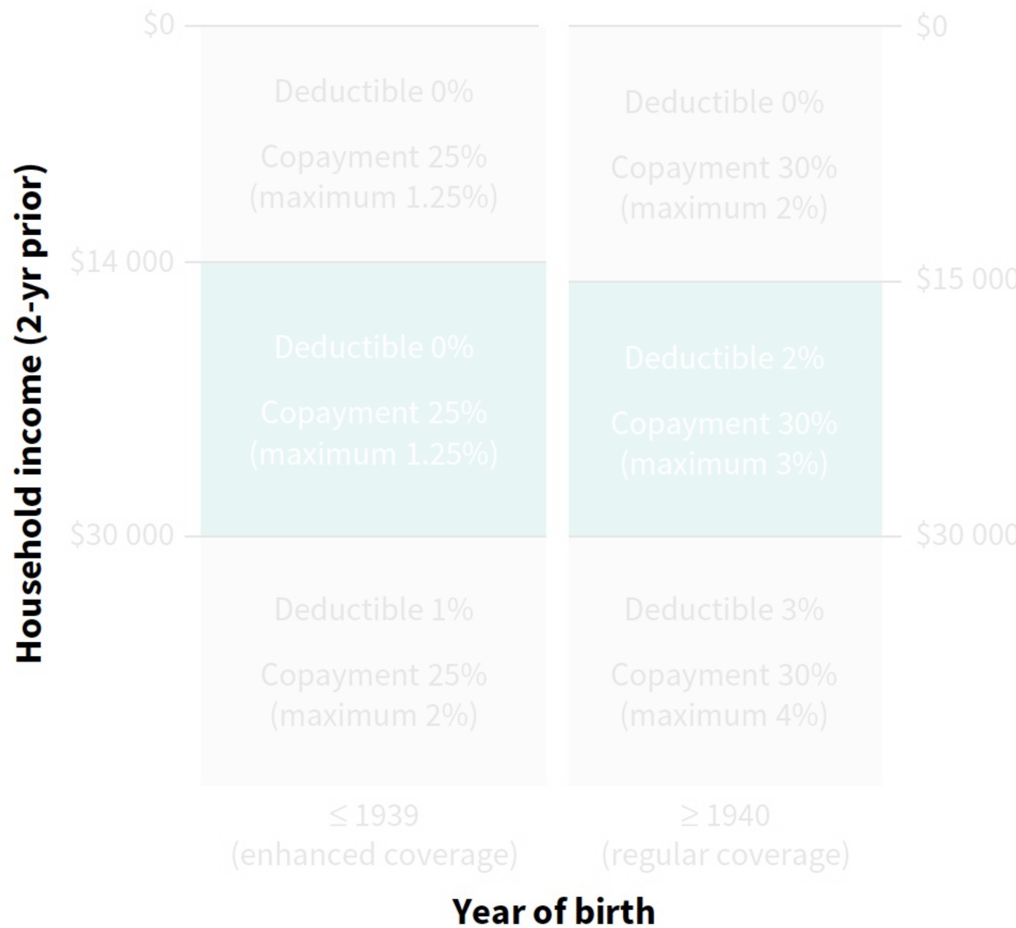
Example from BC Fair Pharmacare

- Several Canadian public drug plans charge income-based deductibles before coverage starts
  - In BC, 3-4% of household income

- Question: What is the impact of these deductibles on drug use and use of other health care services?

Methods




$0
$14 000
$30 000
$0
$15 000
$30 000
Deductible 0%
Copayment 25% (maximum 1.25%)
Deductible 0%
Copayment 25% (maximum 1.25%)
Deductible 1%
Copayment 25% (maximum 2%)
Deductible 0%
Copayment 30% (maximum 2%)
Deductible 2%
Copayment 30% (maximum 3%)
Deductible 3%
Copayment 30% (maximum 4%)
≤ 1939 (enhanced coverage)
≥ 1940 (regular coverage)
Household income (2-yr prior)
Year of birth

RESEARCH

Impact of income-based deductibles on drug use and health care utilization among older adults

Michael R. Law PhD, Lucy Cheng MSc, Heather Worthington MSc, Muhammad Mamdani PharmD MPH, Kimberlyn M. McGrail PhD, Fiona K.I. Chan BSc (Pharm), Sumit R. Majumdar MD MPH

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See related article at www.cmaj.ca/lookup/doi/10.1503/cmaj.170169

ABSTRACT

BACKGROUND: Income-based deductibles are present in several provincial public drug plans in Canada and have been the subject of extensive debate. We studied the impact of such deductibles in British Columbia's Fair PharmaCare plan on drug and health care utilization among older adults.

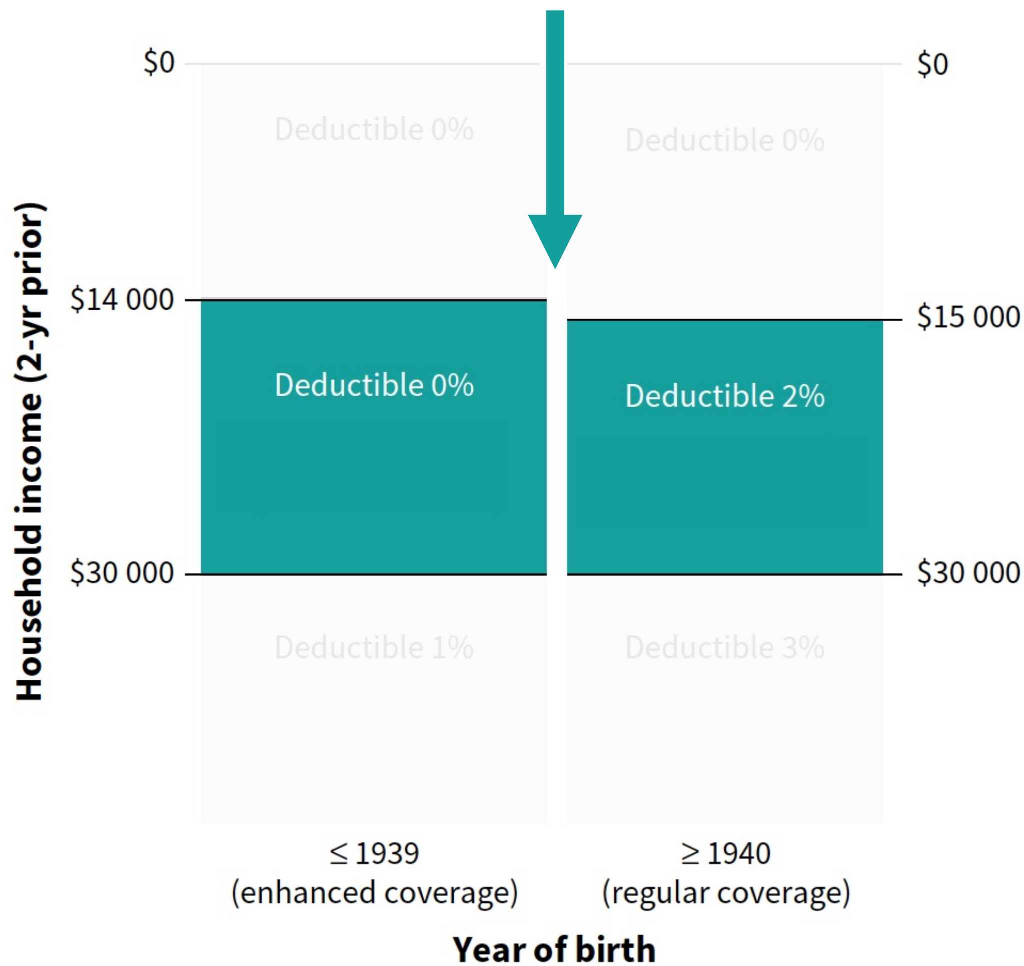
METHODS: We used a quasi-experimental

2% of household income). We used 1.2 million person-years of data between 2003 and 2015 to study public drug plan expenditures, overall drug use, and physician and hospital resource utilization in these 2 groups.

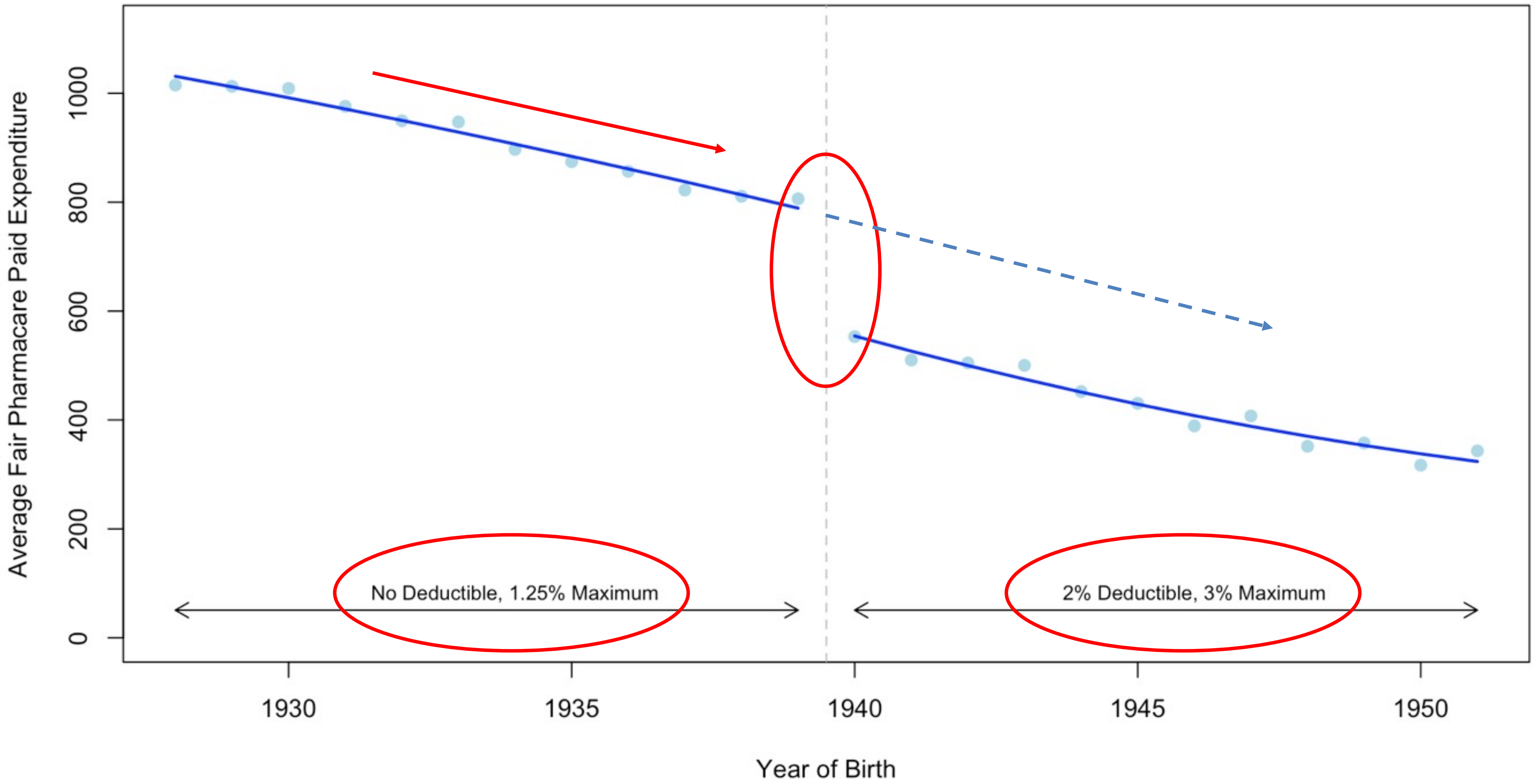
RESULTS: The income-based deductible led to a 28.6% decrease in person-years in which public drug plan benefits were

total drug spending once privately paid amounts were accounted for (p = 0.4 and 0.8, respectively). Further, we found only small or nonexistent changes in health care resource utilization at the 1939 threshold.

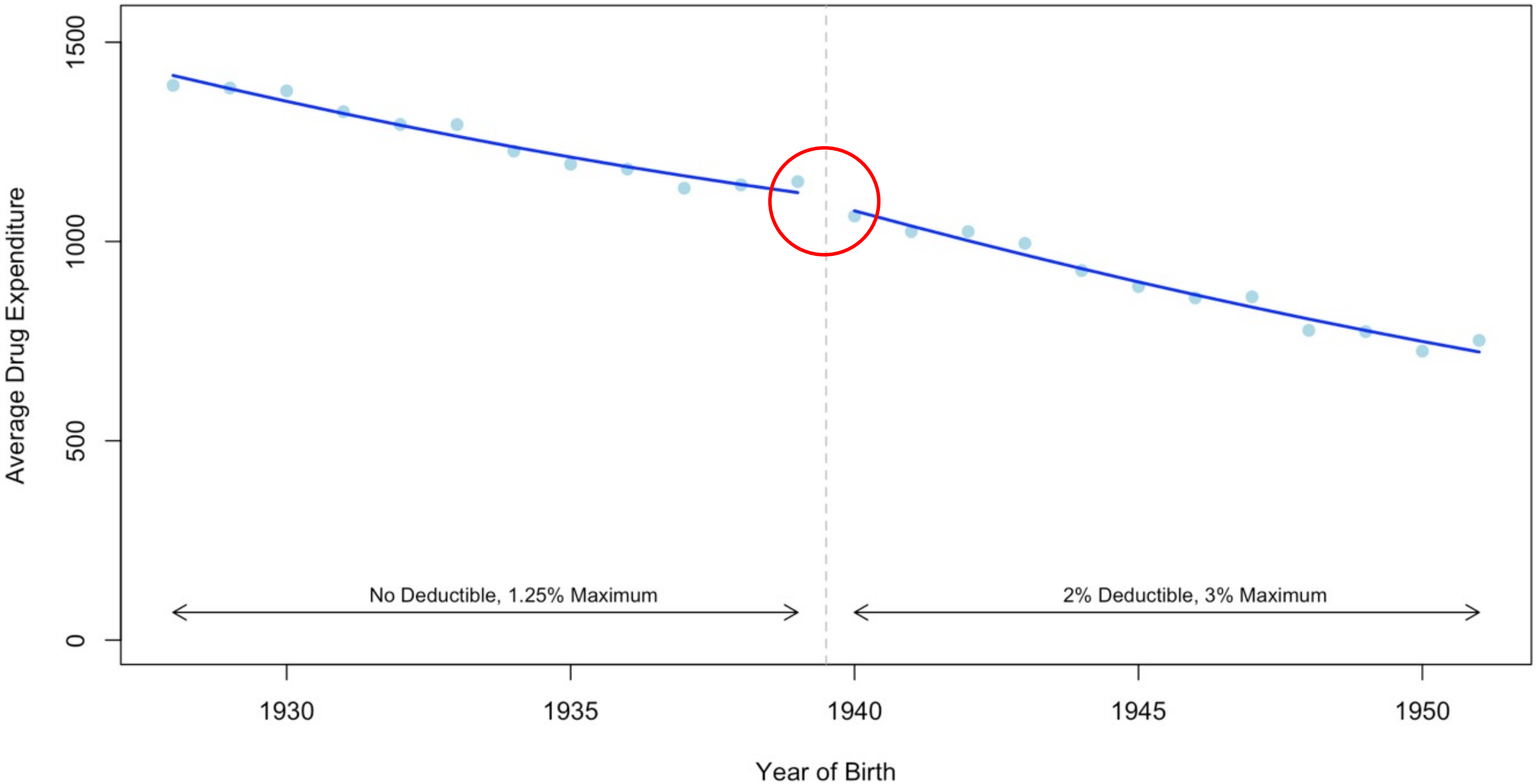
INTERPRETATION: A modest income-based deductible had a considerable impact on the extent of public subsidy



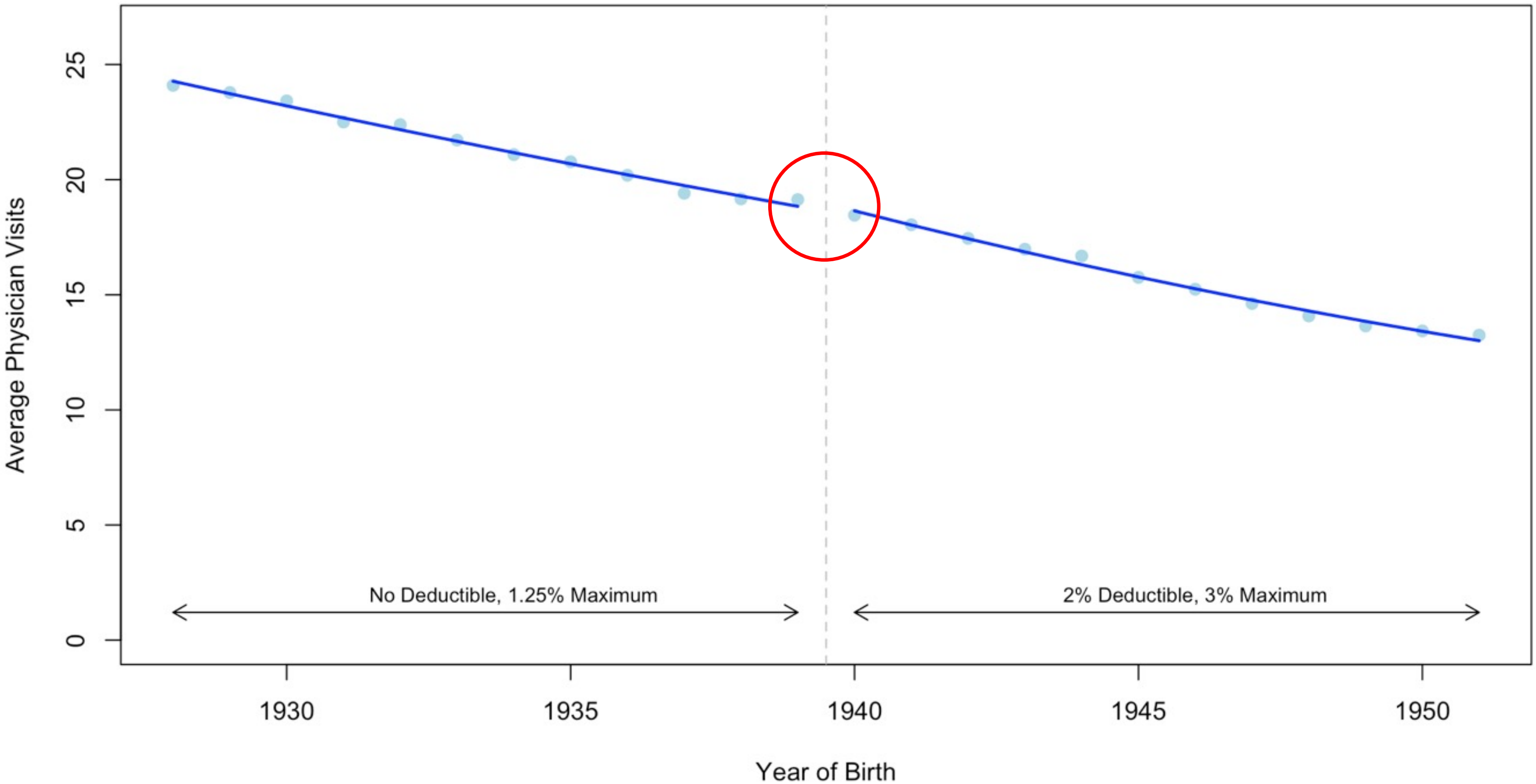
$0
$0
Deductible 0%
Deductible 0%
$14 000
$15 000
Deductible 0%
Deductible 2%
$30 000
$30 000
Deductible 1%
Deductible 3%
Household income (2-yr prior)
≤ 1939 (enhanced coverage)
≥ 1940 (regular coverage)
Year of birth



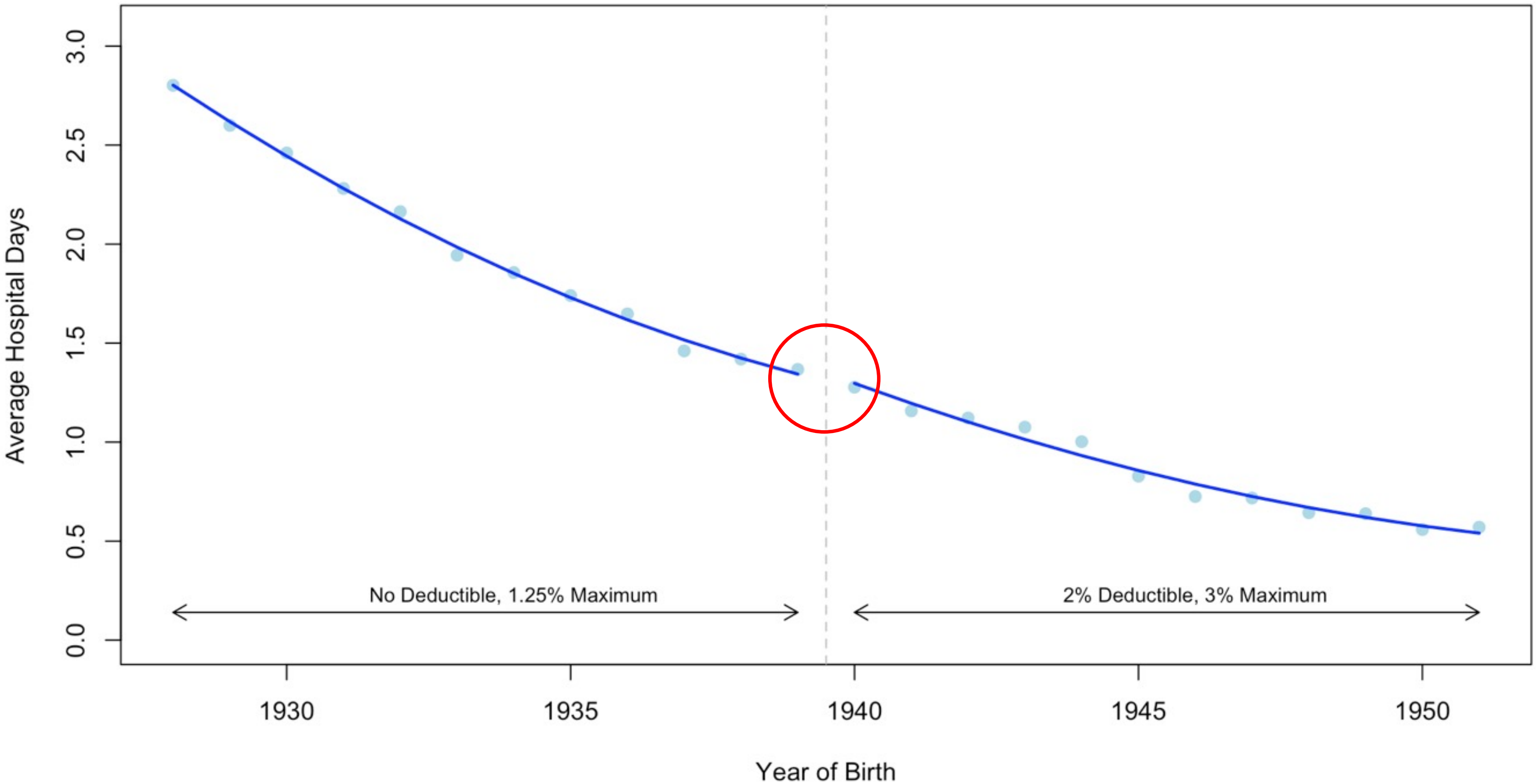
Average Fair Pharmacare Paid Expenditure
0
200
400
600
800
1000
1930
1935
1940
1945
1950
Year of Birth
No Deductible, 1.25% Maximum
2% Deductible, 3% Maximum



1500
1000
500
0
Average Drug Expenditure
No Deductible, 1.25% Maximum
2% Deductible, 3% Maximum
1930
1935
1940
1945
1950
Year of Birth



Average Physician Visits
0
5
10
15
20
25
No Deductible, 1.25% Maximum
2% Deductible, 3% Maximum
1930
1935
1940
1945
1950
Year of Birth


Average Hospital Days
3.0
2.5
2.0
1.5
1.0
0.5
0.0
No Deductible, 1.25% Maximum
2% Deductible, 3% Maximum
1930
1935
1940
1945
1950
Year of Birth

Local Average Treatment Effect

- LATE: the impact of a 2% of household income deductible on individuals born in 1939/1940 with household incomes between $15,000 and $30,000.

- How useful is this estimate?

cmajOPEN

Research

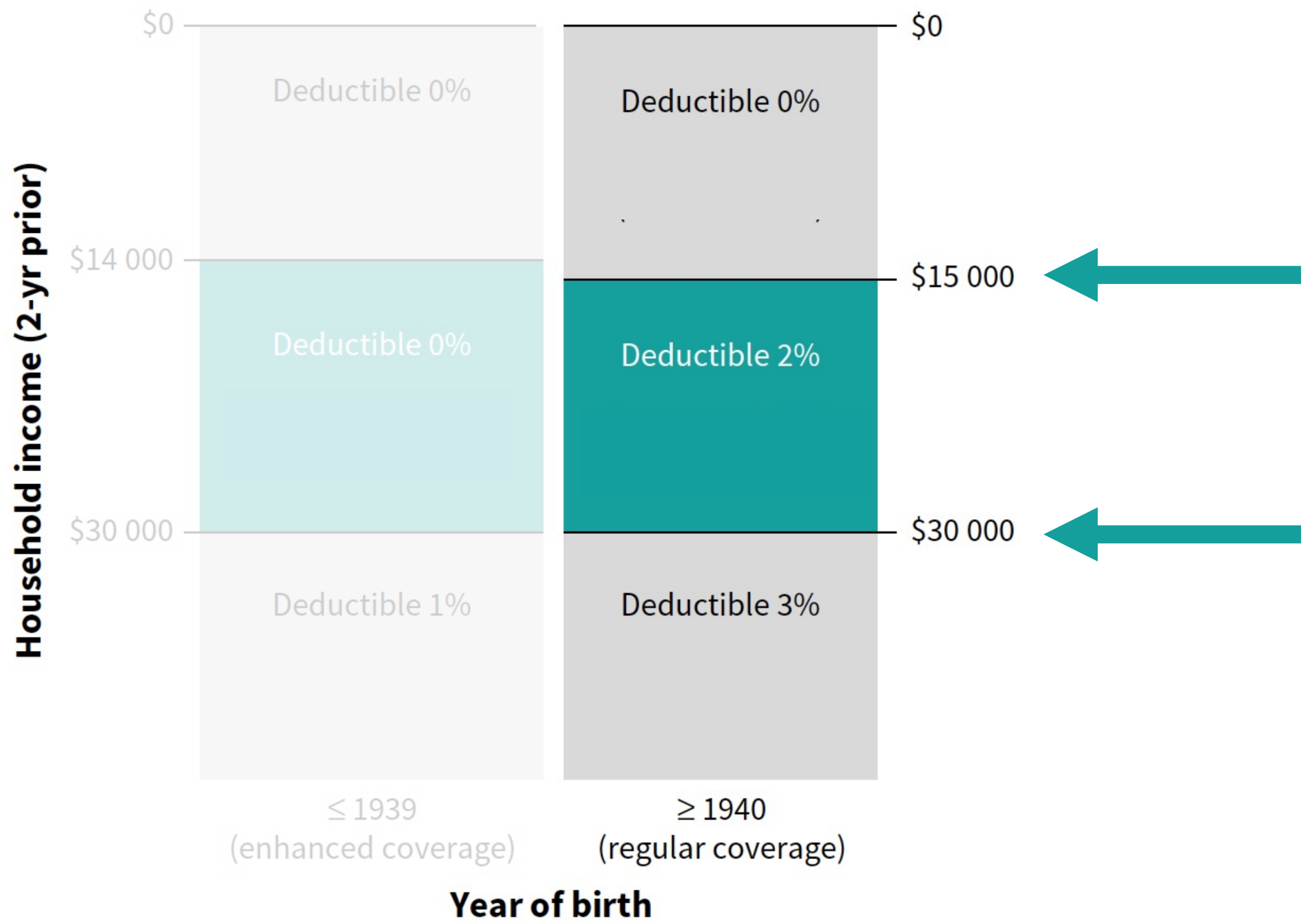
Impact of a household-level deductible on prescription drug use among lower-income adults: a quasi-experimental study

Michael R. Law PhD, Lucy Cheng MSc, Heather Worthington MSc, Sumit R. Majumdar MD MPH, Kimberlyn M. McGrail PhD, Fiona Chan MSc, Tracey-Lea Laba PhD, Muhammad Mamdani PharmD MPH

Abstract

Background: Several Canadian public drug plans have income-based deductibles, but we have limited data on their impact, particularly for vulnerable populations. Therefore, we studied the impact of deductibles in British Columbia's Fair PharmaCare program on drug use among lower-income adults.

Methods: We used a quasi-experimental regression discontinuity design to study the impact of BC rules that impose no deductible before receiving public coverage on households with incomes less than $15 000, a deductible of 2% of household income on those with incomes between $15 000 and $30 000, and a deductible of 3% of household income on those with incomes above $30 000. We studied the impact of these thresholds on public and total drug expenditures between 2003 and 2015 using 24 million person-



$0
Deductible 0%
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Deductible 0%
$30 000
Deductible 1%
$0
Deductible 0%
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Deductible 2%
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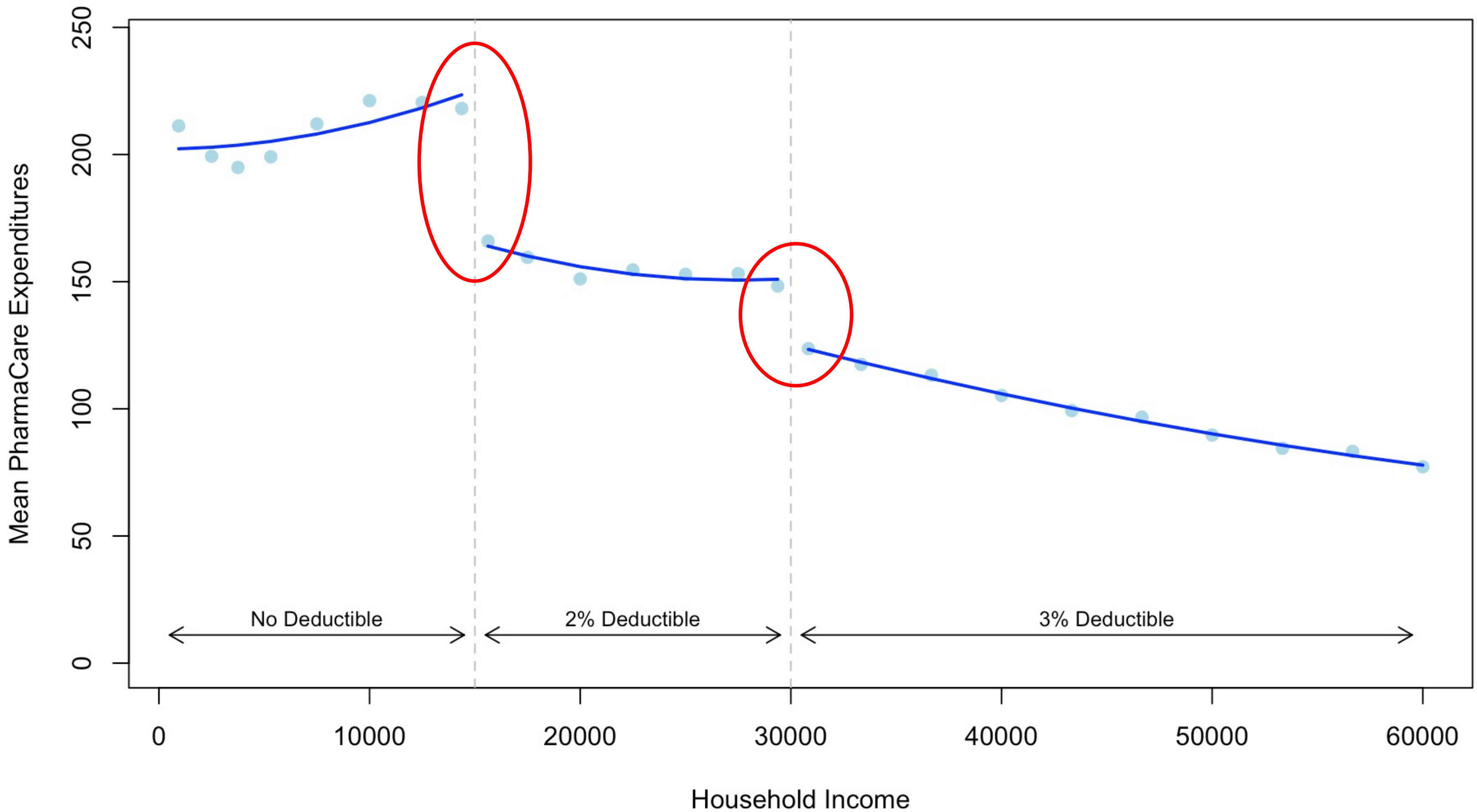
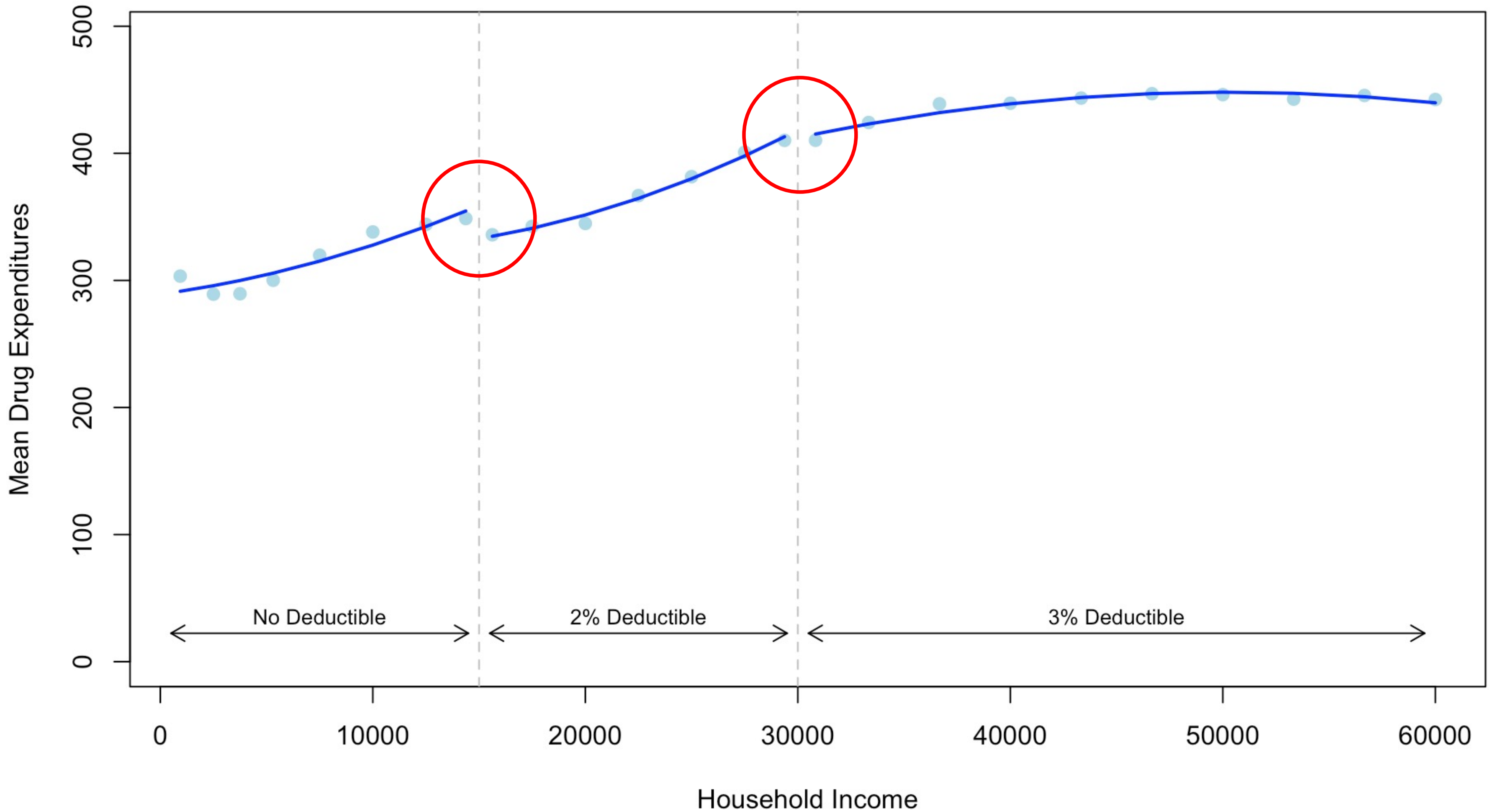
Household income (2-yr prior)
≤ 1939
(enhanced coverage)
≥ 1940
(regular coverage)
Year of birth



Mean PharmaCare Expenditures
250
200
150
100
50
0
No Deductible
2% Deductible
3% Deductible
0
10000
20000
30000
40000
50000
60000
Household Income



Mean Drug Expenditures
0
100
200
300
400
500
No Deductible
2% Deductible
3% Deductible
0
10000
20000
30000
40000
50000
60000
Household Income

Sub-analyses

- Results persist across:
  - Age groups (< 65 vs. > 65)
  - Household size (kids vs. no kids)
  - Sex (male vs. female)
  - Drug type (generic vs. brand)
  - Drug importance (“essential” vs. “non-essential”)

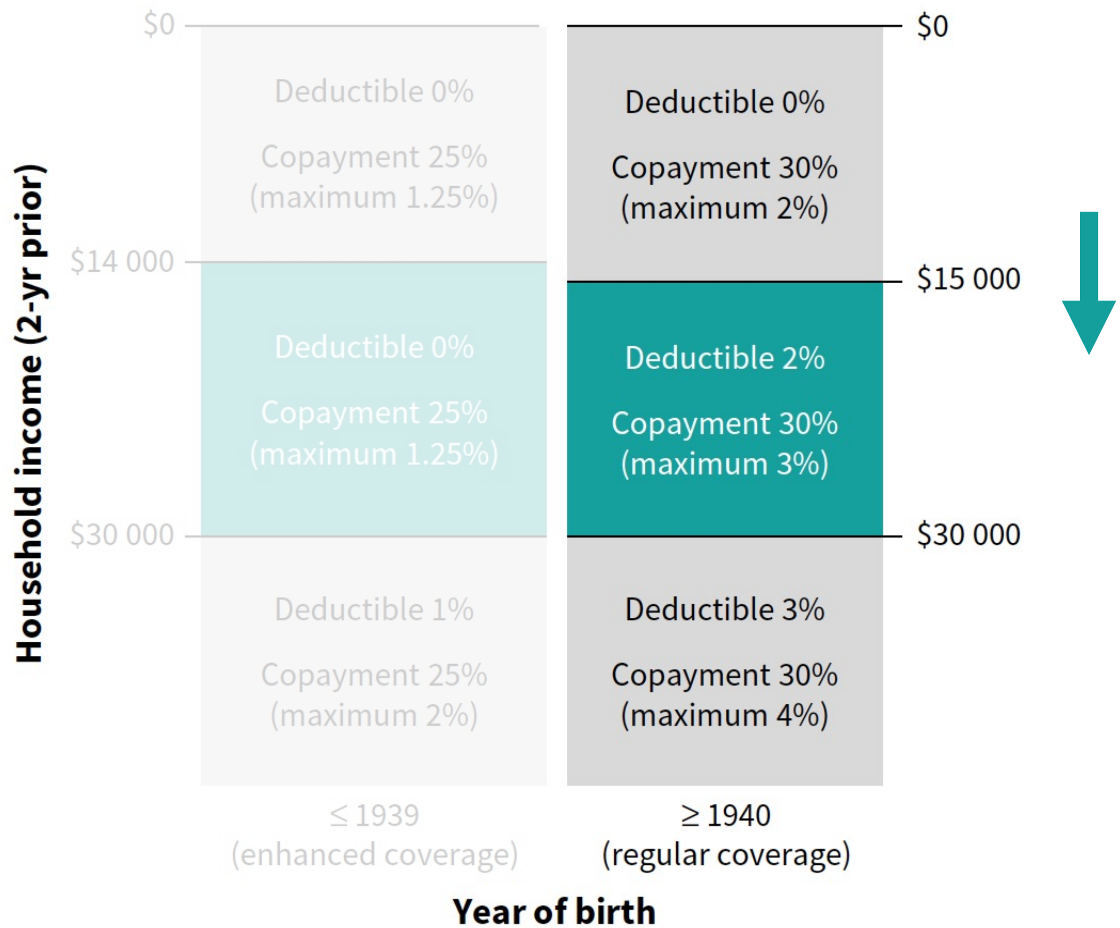
Local Average Treatment Effect

- LATE: the impact of a 2% of household income deductible on individuals with household incomes around $15,000

- How useful is this estimate?

Overall Interpretation

- Deductibles
  - Substantially reduced public drug spending
  - Reduced overall drug use, but only at lower incomes
- Limitations
  - LATEs limited to existing thresholds
  - No information on private drug coverage



Household income (2-yr prior)
$0
$14 000
$30 000
Deductible 0%
Copayment 25%
(maximum 1.25%)
Deductible 0%
Copayment 25%
(maximum 1.25%)
Deductible 1%
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$0
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Deductible 0%
Copayment 30%
(maximum 2%)
Deductible 2%
Copayment 30%
(maximum 3%)
Deductible 3%
Copayment 30%
(maximum 4%)
≤ 1939
(enhanced coverage)
≥ 1940
(regular coverage)
Year of birth

BRINGING DOWN THE COST OF PRESCRIPTION DRUGS

- People shouldn't have to choose between paying for their medications and putting food on the table. For many, the cost of prescription drugs and medical supplies has put serious strains on household budgets. The $105 million investment in the **FAIR PHARMACARE** program will expand coverage for 240,000 B.C. families.
- All families with household net incomes under $45,000 will benefit from this investment.
- Deductibles will also be eliminated entirely for families with net annual incomes between $15,000 and $30,000.

240,000 B.C. FAMILIES BENEFIT

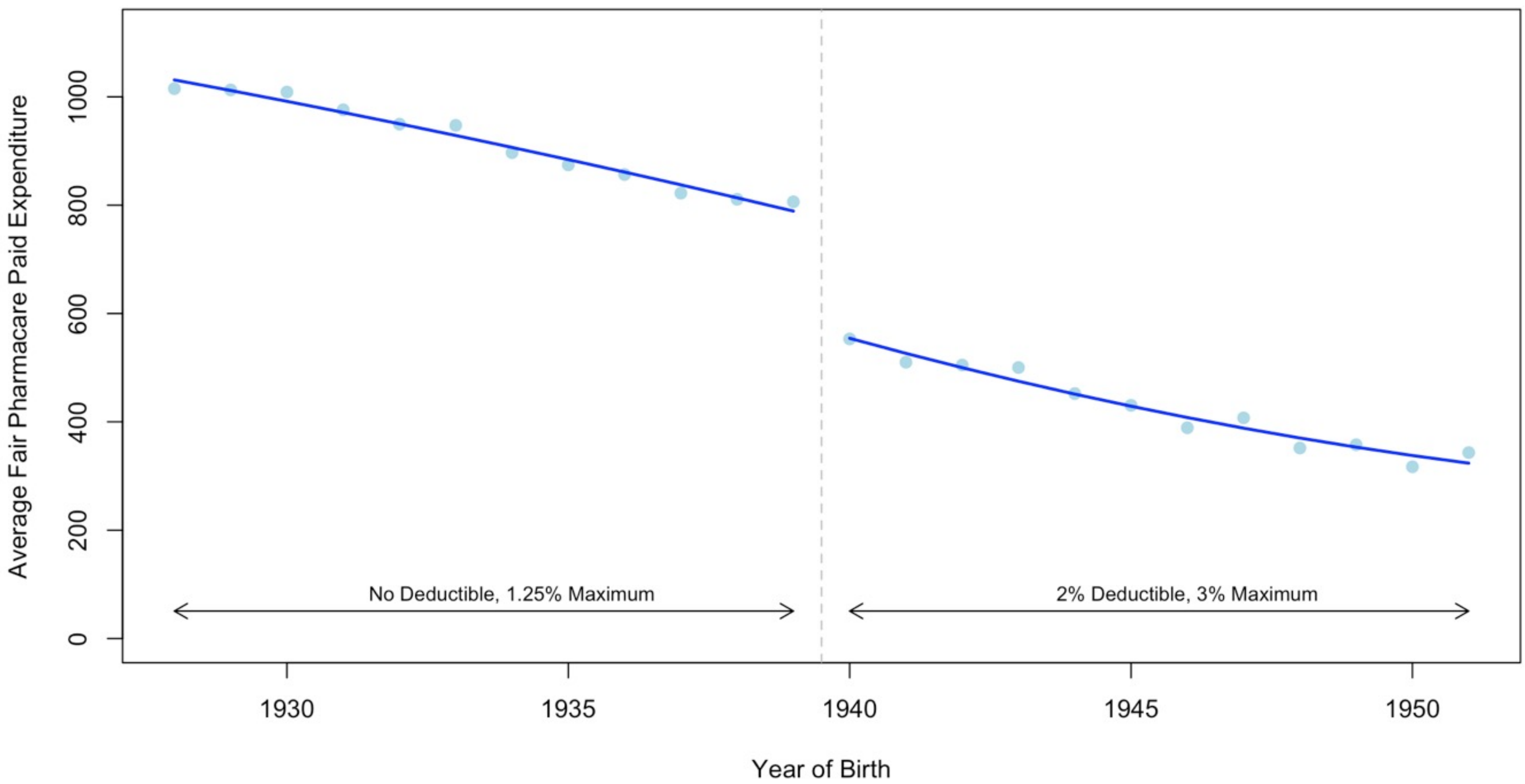
DEDUCTIBLES ELIMINATED

- Families with net incomes below $30,000.

DEDUCTIBLES REDUCED

- Families with net incomes below $45,000.

Performing an RD Analysis



Average Fair Pharmacare Paid Expenditure
0
200
400
600
800
1000
No Deductible, 1.25% Maximum
2% Deductible, 3% Maximum
1930
1935
1940
1945
1950
Year of Birth

Data setup

ID	Forcing (Year-1928)	Threshold (>=1940)	Forcing*Threshold	Outcome ($)
1	11	0	0	456
2	2	0	0	523
3	24	1	24	34
4	19	1	19	37
5	5	0	0	20
6	10	0	0	54
7	14	1	14	902
…	…	…	…	…

Basic RD model

- For individual *i* with 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

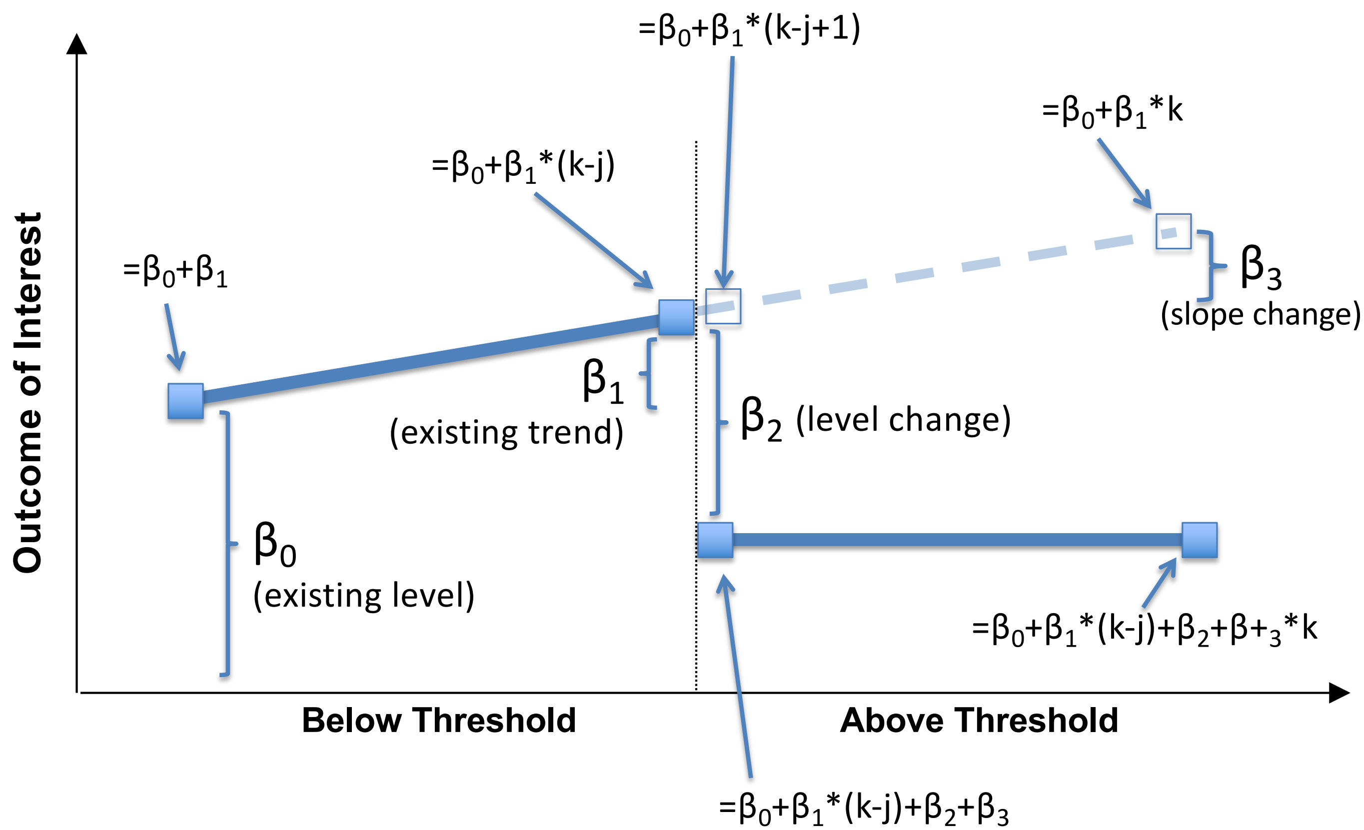
Pre-existing slope in the outcome of interest

Change in the level above the threshold
* Variable of interest

Change in the slope above the threshold

- This allows you to predict 2 line segments
  - Some RDs do not use slope variables
  - Some use quadratic terms and other model modifications

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



Problems with RD

- Often requires more data than comparable RCT
- Relies on smoothness over threshold
  - Not testable, can do falsification test
  - Concern: something like retirement age
- Requires technical skill to properly fit from a statistical standpoint
  - Many options for modeling technique, weighting, etc.

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Methods Readings

- Bor J, Moscoe E, Mutevedzi P, Newell ML, Barnighausen T. Regression discontinuity designs in epidemiology: causal inference without randomized trials. Epidemiology. Sep 2014;25(5):729-737.

- Venkataramani AS, Bor J, Jena AB. Regression discontinuity designs in healthcare research. BMJ (2016): 352:i1216.

Law MR, Cheng L, Worthington HC, Mamdani M, McGrail KM, Chan F, Majumdar SR. Impact of Income-based Deductibles on Drug Use and Health Care Utilization in Older Adults. CMAJ 2017; 189(19): E690-E696.

Law MR, Cheng L, Worthington HC, Majumdar SR, McGrail KM, Chan F, Laba T, Mamdani M. The Impact of a Household-level Deductible on Drug Use among Lower Income Adults. CMAJ Open 2019; 7(1): E167-E173.

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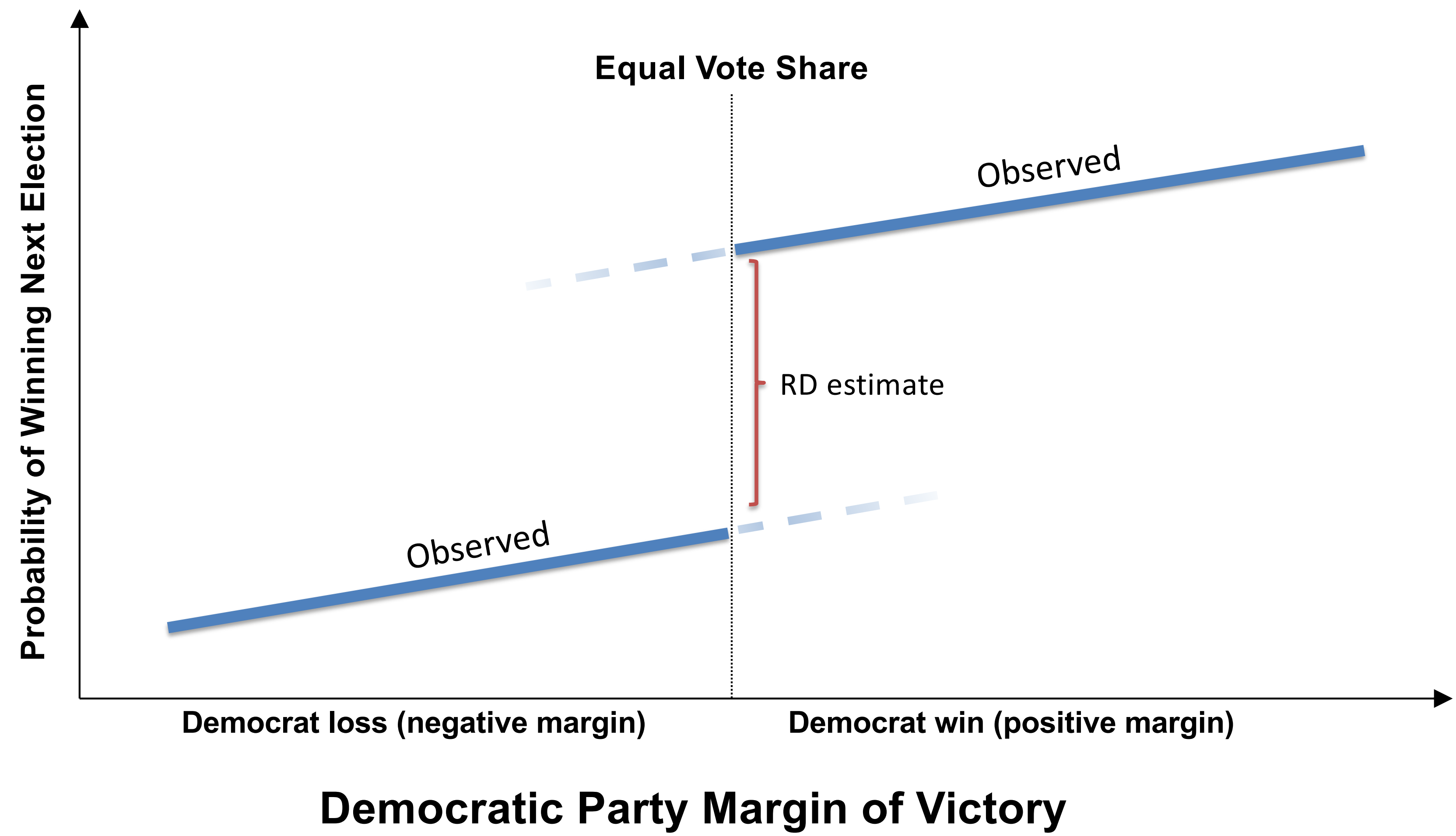
ANOTHER MODELING EXAMPLE

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 term for forcing variable
dataset$dmargin2 <- dataset$dmargin^2

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

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

Preliminary Plot

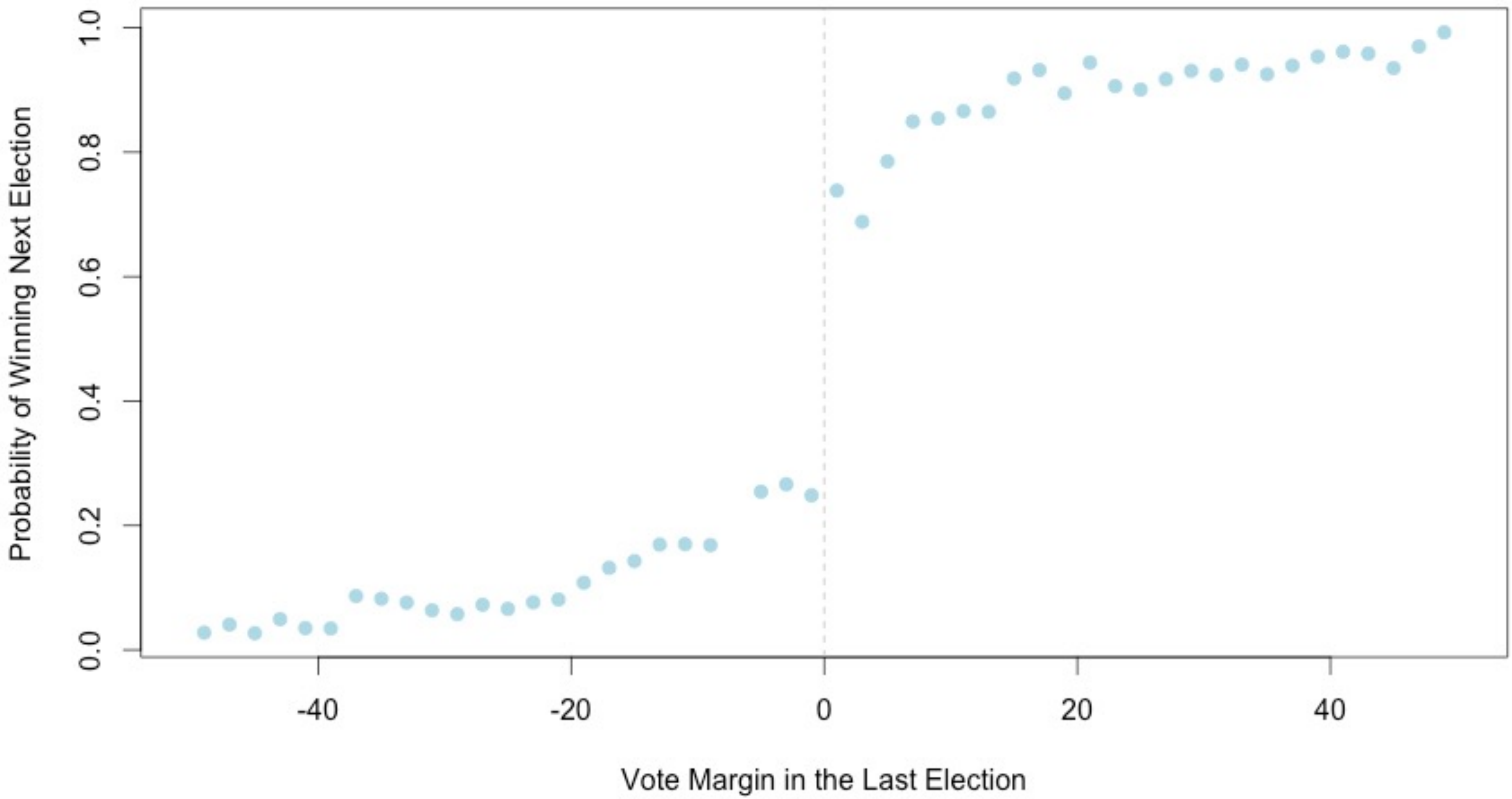
```
###################################
# Preliminary Plot
###################################

# 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

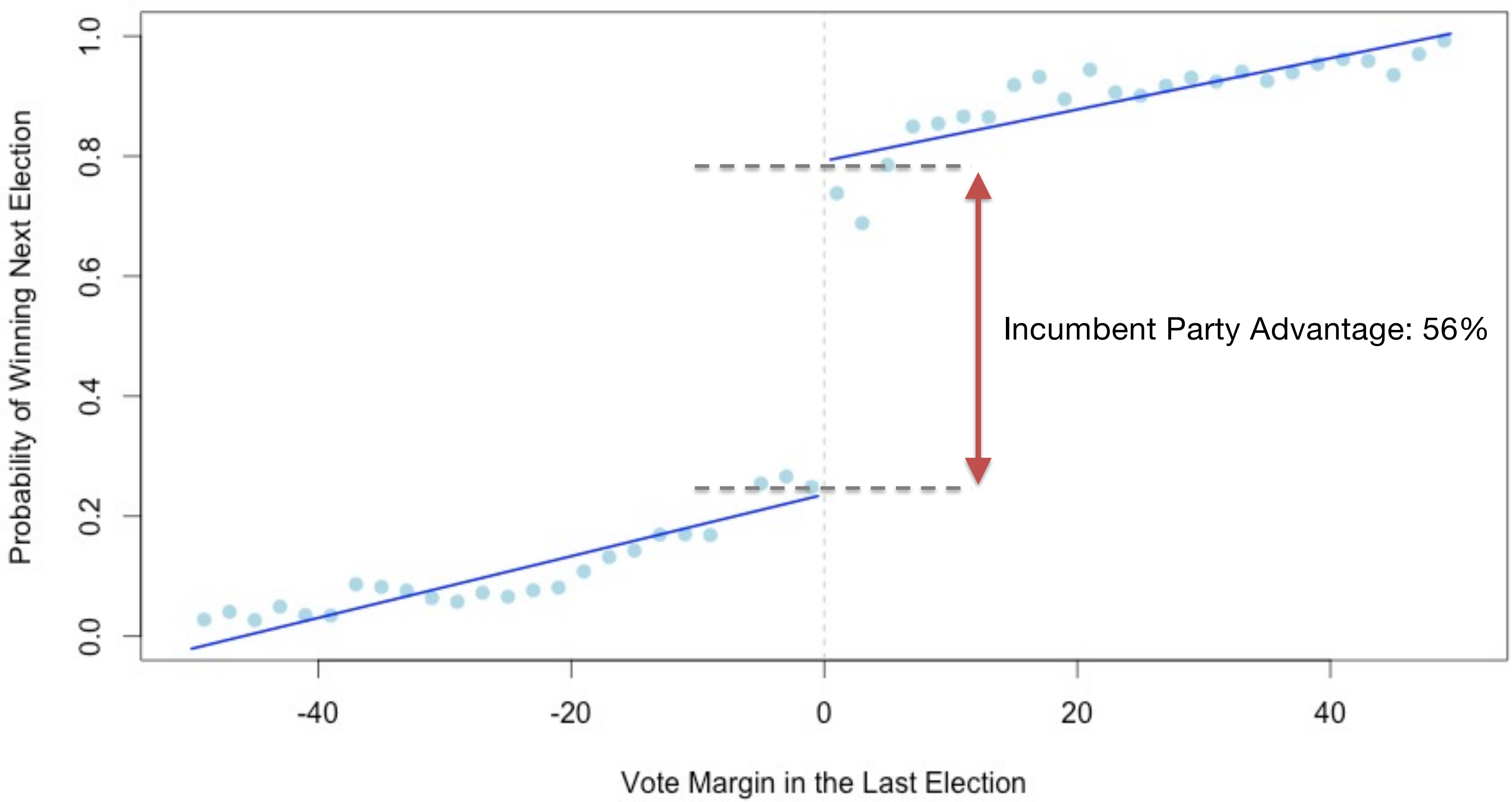
```
###################################
# Modeling
###################################

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)
```

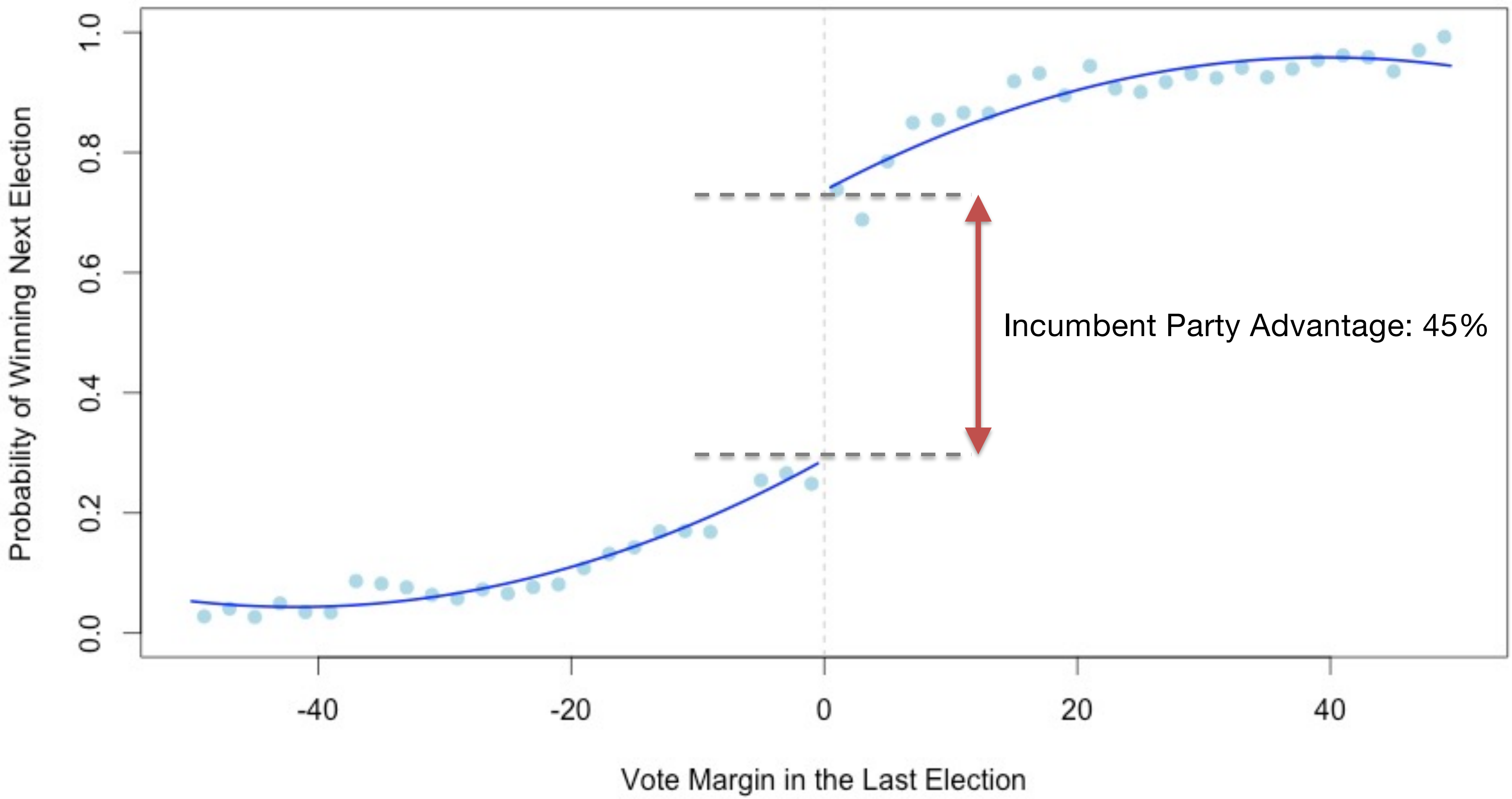
Model 2 Results

```
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