Regression Discontinuity

EC 425/525, Set 9

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Prologue

Schedule

Last time

- Introduction to selection-on-unobservables designs
- Instrumental variables
- Two-stage least squares

Today

Regression discontinuity [†]

Upcoming

Problem set

† These notes largely follow notes from Michael Anderson, Imbens and Lemieux (2008), and notes from Teppei Yamamoto.

Regression discontinuity

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Regression discontinuity (**RD**) offers a particularly clear/clean research design based upon an arbitrary threshold (the *discontinuity*).

That said, most RDs boil down to an implementation of IV.

In addition, while RD is all the rage in modern applied econometrics, Thistlewaite and Campbell wrote about it back in 1960.

Regression discontinuity

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The variable $\mathbf{X}_i$ need not be randomly assigned—we will assume it is not (*i.e.*, $\mathbf{X}_i$ correlates with $\mathbf{Y}_{0i}$ and $\mathbf{Y}_{1i}$).

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The variable $\mathbf{X}_i$ need not be randomly assigned—we will assume it is not (*i.e.*, $\mathbf{X}_i$ correlates with $\mathbf{Y}_{0i}$ and $\mathbf{Y}_{1i}$).

We will assume that $\mathbf{Y}_{0i}$ and $\mathbf{Y}_{1i}$ vary smoothly in $\mathbf{X}_i$.

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Regression discontinuity

Examples

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- Election runoffs are triggered if "winner" is below 50%.
- Antidiscrimination laws only apply to firms with >15 employees.
- Prisoners are eligible for early parole if some score exceeds a threshold.
- An individual is eligible for Medicare if her age is at least 65.
- You get a ticket if your speed exceeds the speed limit.
- Fifteen-percent discount at Sizzler if your age exceeds 60.
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In some cases, "treatment" is definite once we exceed the threshold.

Regression discontinuity

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E.g., crossing some GRE threshold discontinuously increases your chances of getting into some grad schools (but doesn't guarantee admittance).

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$$\mathbf{D}_i = \mathbb{I}\{\mathrm{X}_i \geq \boldsymbol{c}\}$$

To estimate the causal effect of $\mathbf{D}_i$ on $\mathbf{Y}_i$, we compare the mean of $\mathbf{Y}_i$ just *above* the threshold to the mean of $\mathbf{Y}_i$ just *below* the threshold.

Sharp RDs

More formally

We can write the comparison of means at the threshold as

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I.e., Because we don't observe Y_{0i} for treated individuals, we extrapolate $E[\mathrm{Y}_{0i} \mid \mathrm{X}_i = c - \varepsilon]$ to $E[\mathrm{Y}_{0i} \mid \mathrm{X}_i = x + \varepsilon]$ for small ε.

Sharp RDs

Estimation

Thus, we estimate

$$\tau_{\mathrm{SRD}} = \lim_{x \downarrow c} E[\mathrm{Y}_i - \mathrm{X}_i = x] - \lim_{x \uparrow c} E[\mathrm{Y}_i \mid \mathrm{X}_i = x]$$

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as the diffrence between two regression functions estimated "near" c.

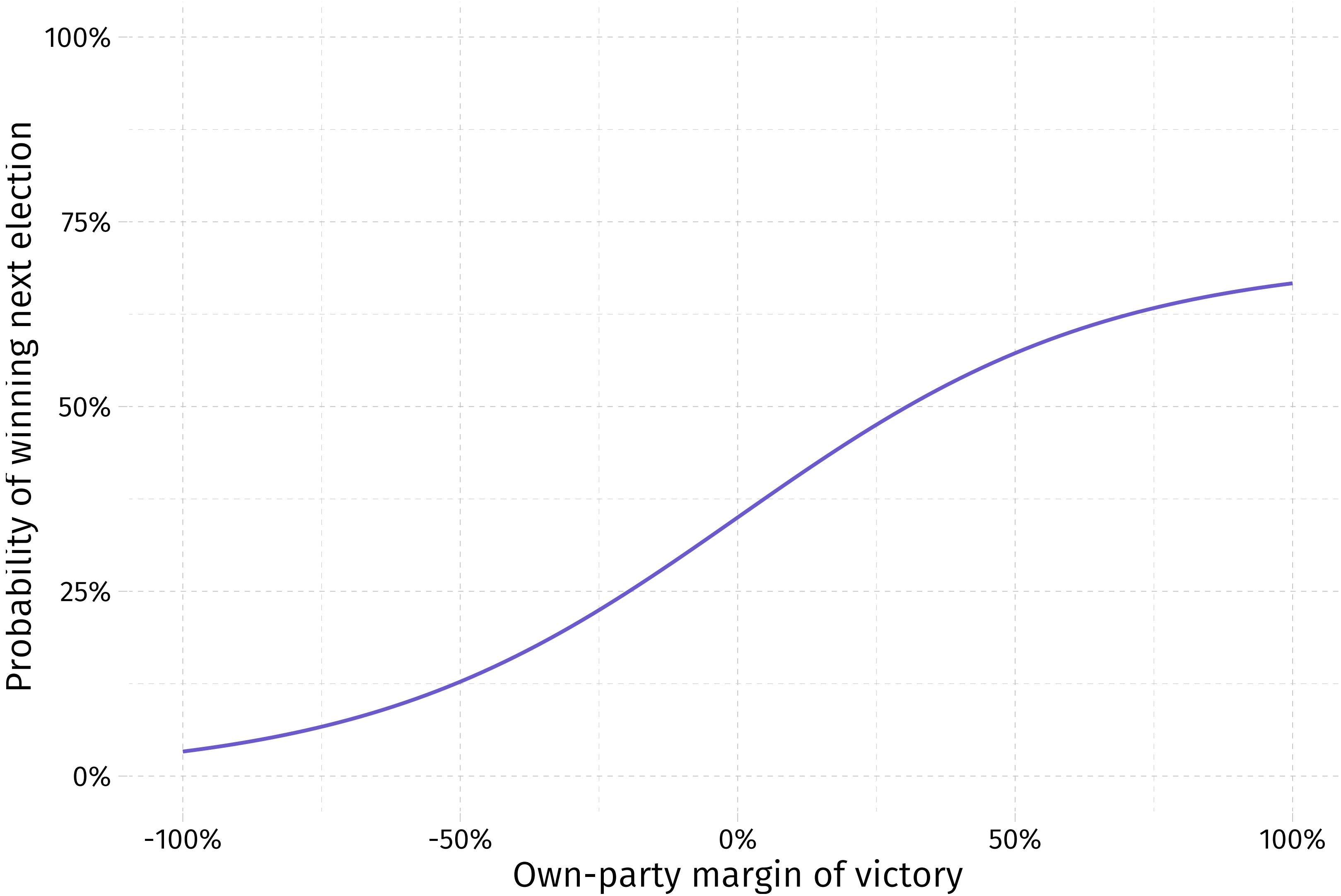
We must stay "near" to c to minimize the bias from extrapolating $E[\mathrm{Y}_{0i} \mid \mathrm{X}_i = c - \varepsilon]$ to $E[\mathrm{Y}_{0i} \mid \mathrm{X}_i = c + \varepsilon]$ (and assuming continuity).

Ex. Is there effect of a political party winning an election on that party's likelihood of winning the following election?

Is there a benefit of incumbency (at the party level)?†

† Lee (2008) addresses this question via RD. Caughey and Sekhon (2011) discuss RD in this setting.

Let's start with $E[\mathrm{Y}_{0i} \mid \mathrm{X}_i]$



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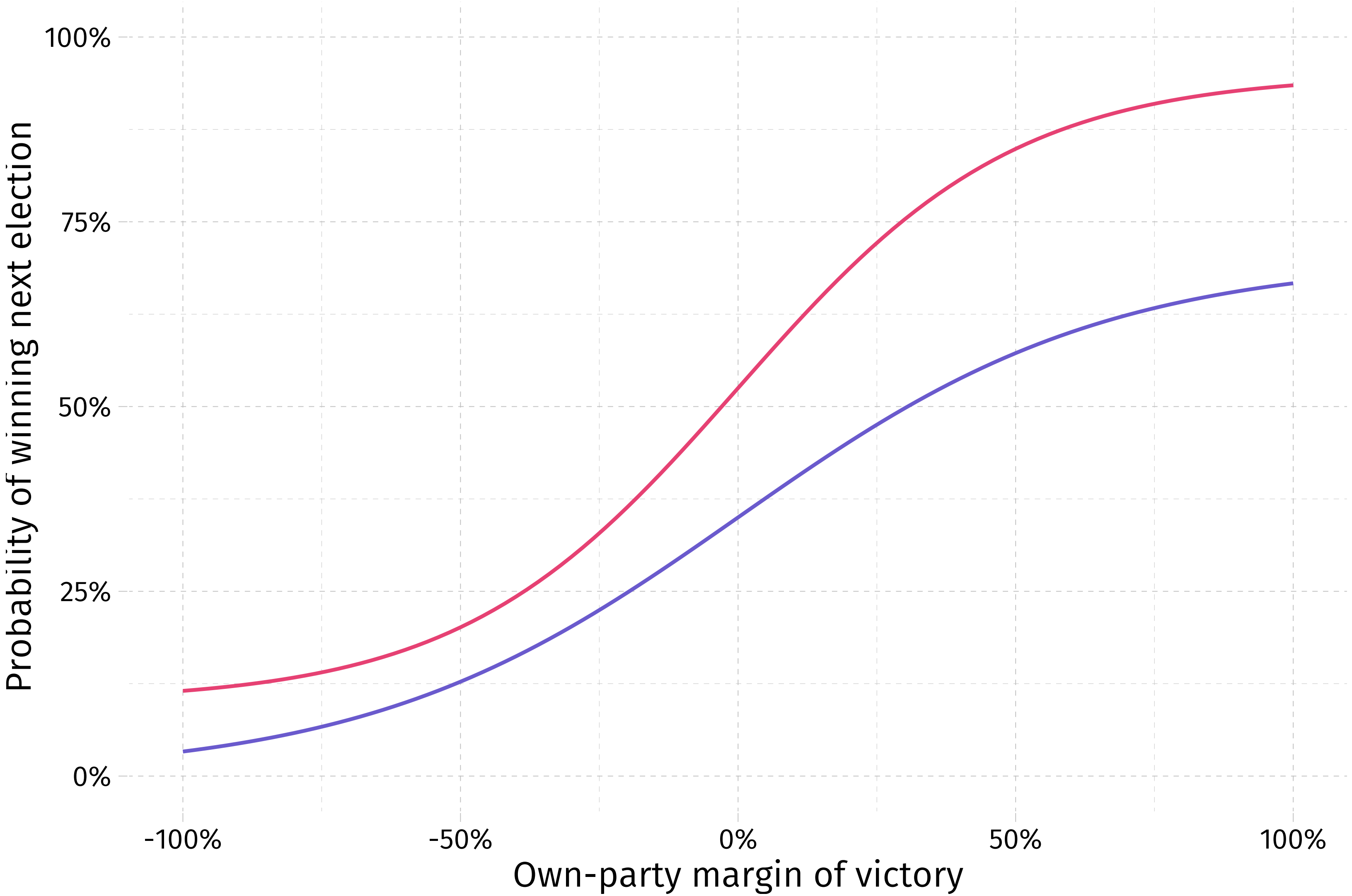
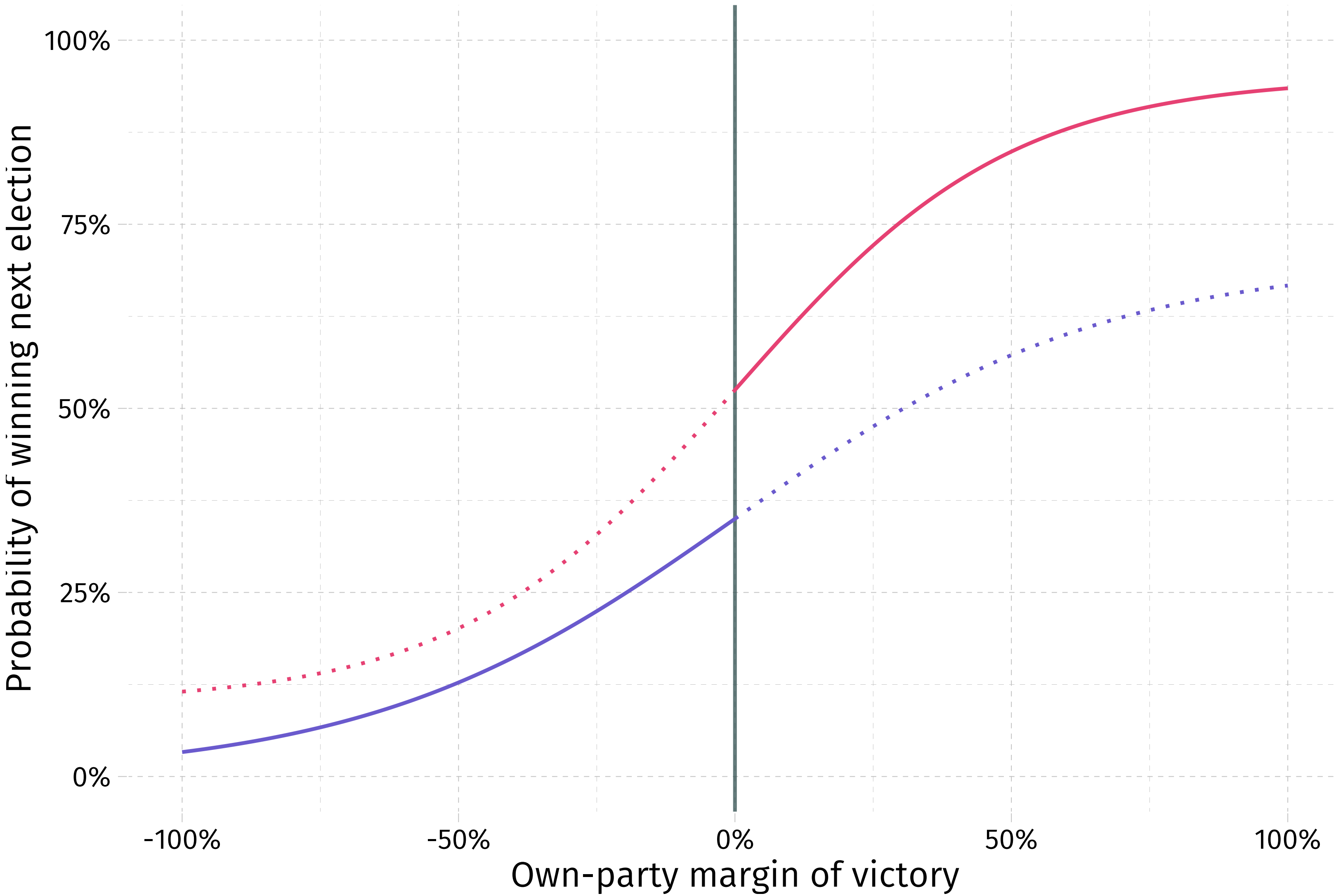
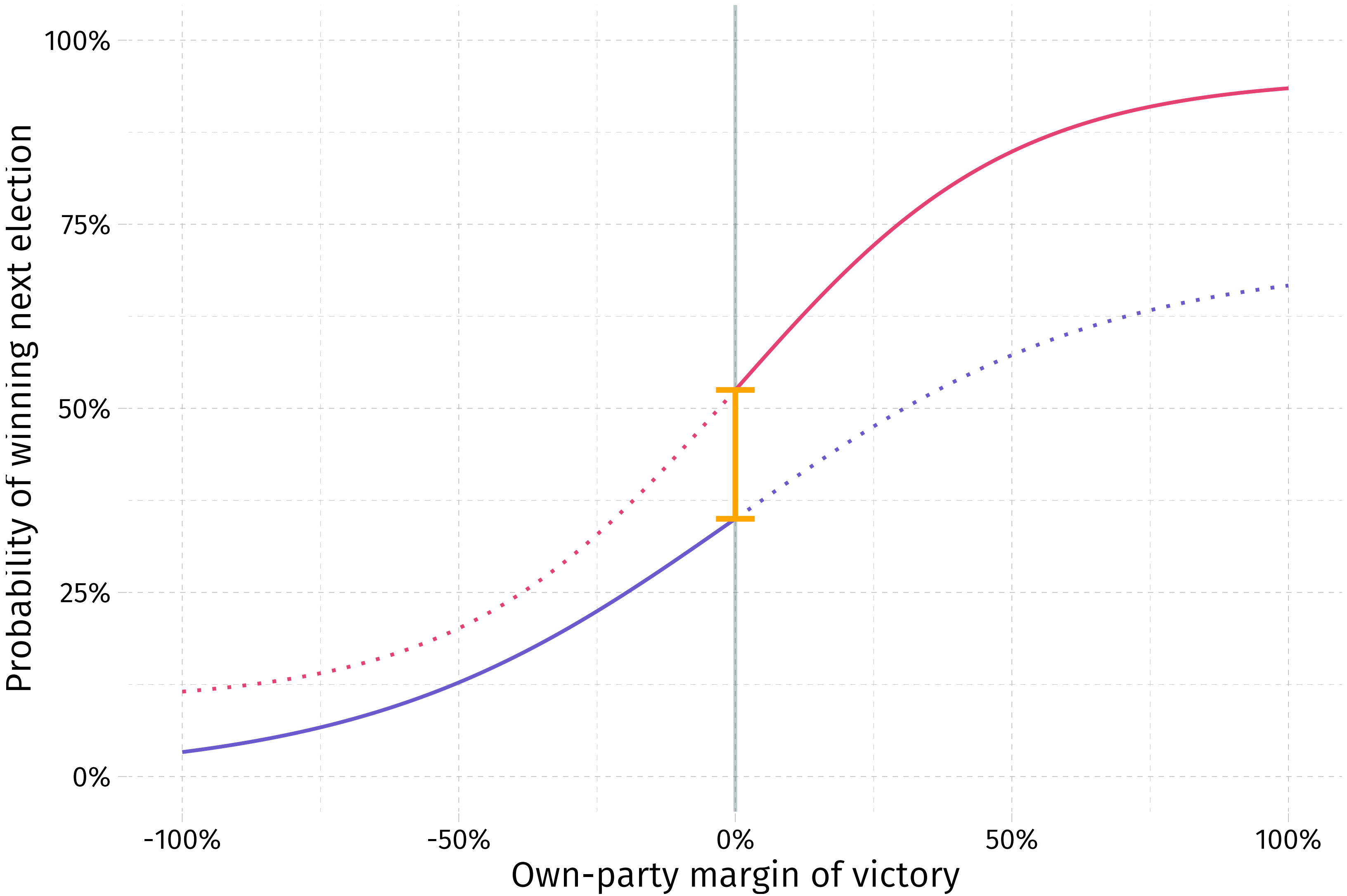


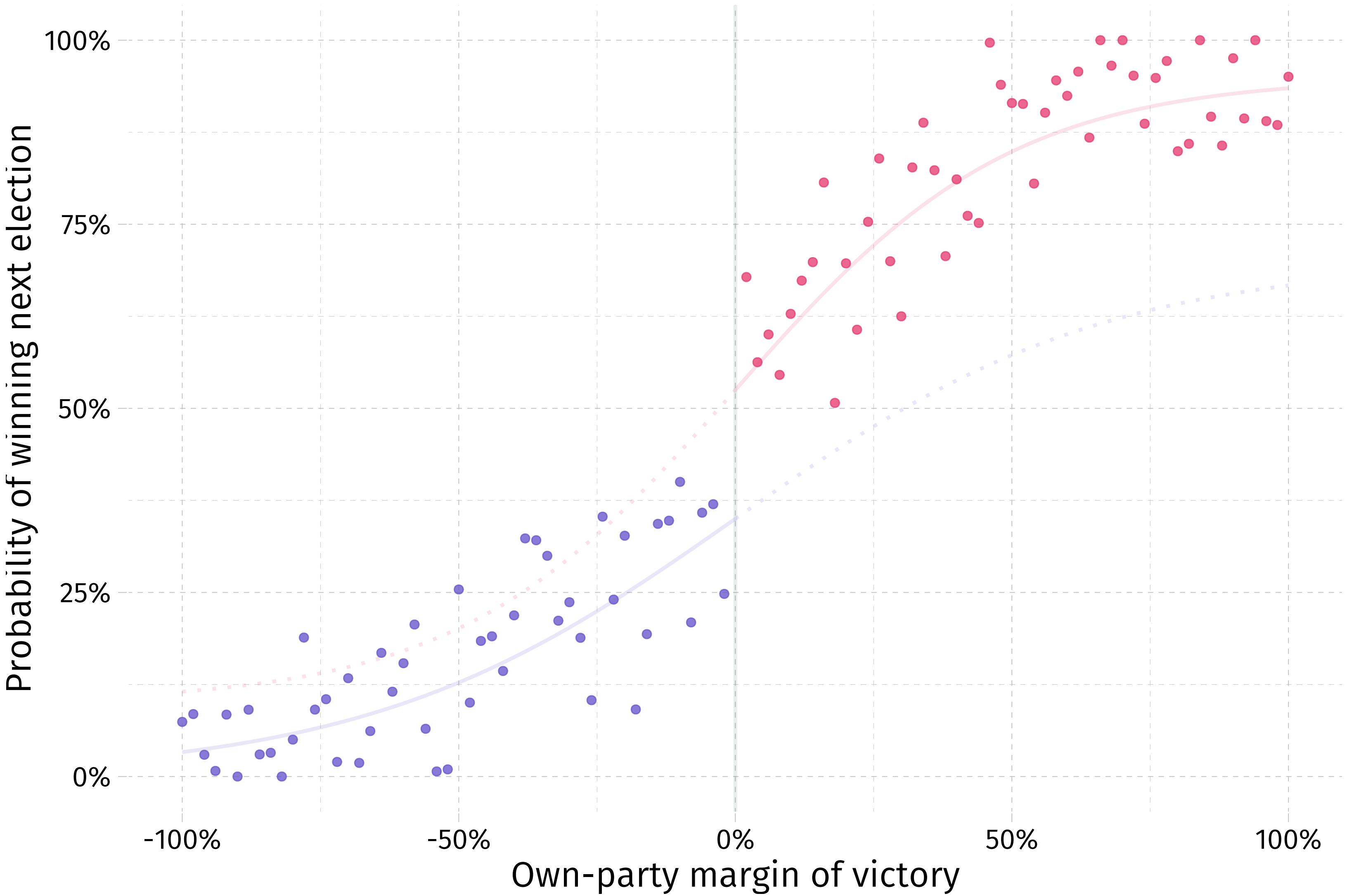
You only win an election if your **margin of victory exceeds zero**.



$E[\mathrm{Y}_{1i} \mid \mathrm{X}_i] - E[\mathrm{Y}_{0i} \mid \mathrm{X}_i]$ **at the discontinuity** gives τ_{SRD}.



Real data are a bit trickier. We must estimate $E[\mathrm{Y}_{1i} \mid \mathrm{X}_i]$ and $E[\mathrm{Y}_{0i} \mid \mathrm{X}_i]$.

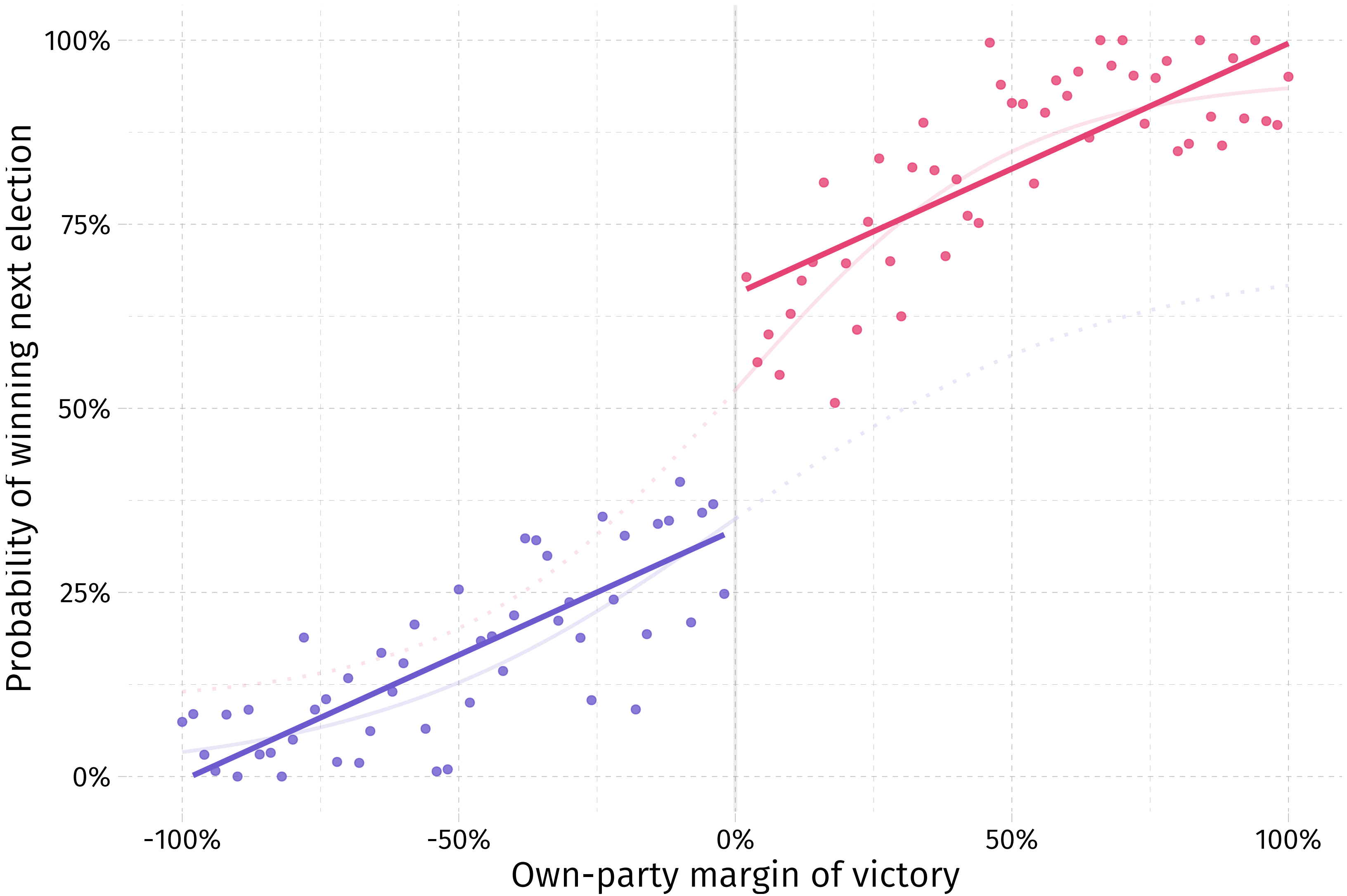


Questions

1. How should we estimate $E[\mathbf{Y}_{1i} \mid \mathbf{X}_i]$ and $E[\mathbf{Y}_{0i} \mid \mathbf{X}_i]$?

2. How much data should we use—*i.e.*, what is the right **bandwidth** size?

Option 1a Linear regression with constant slopes (and all data)



Option 1a Linear regression with constant slopes (and all data)

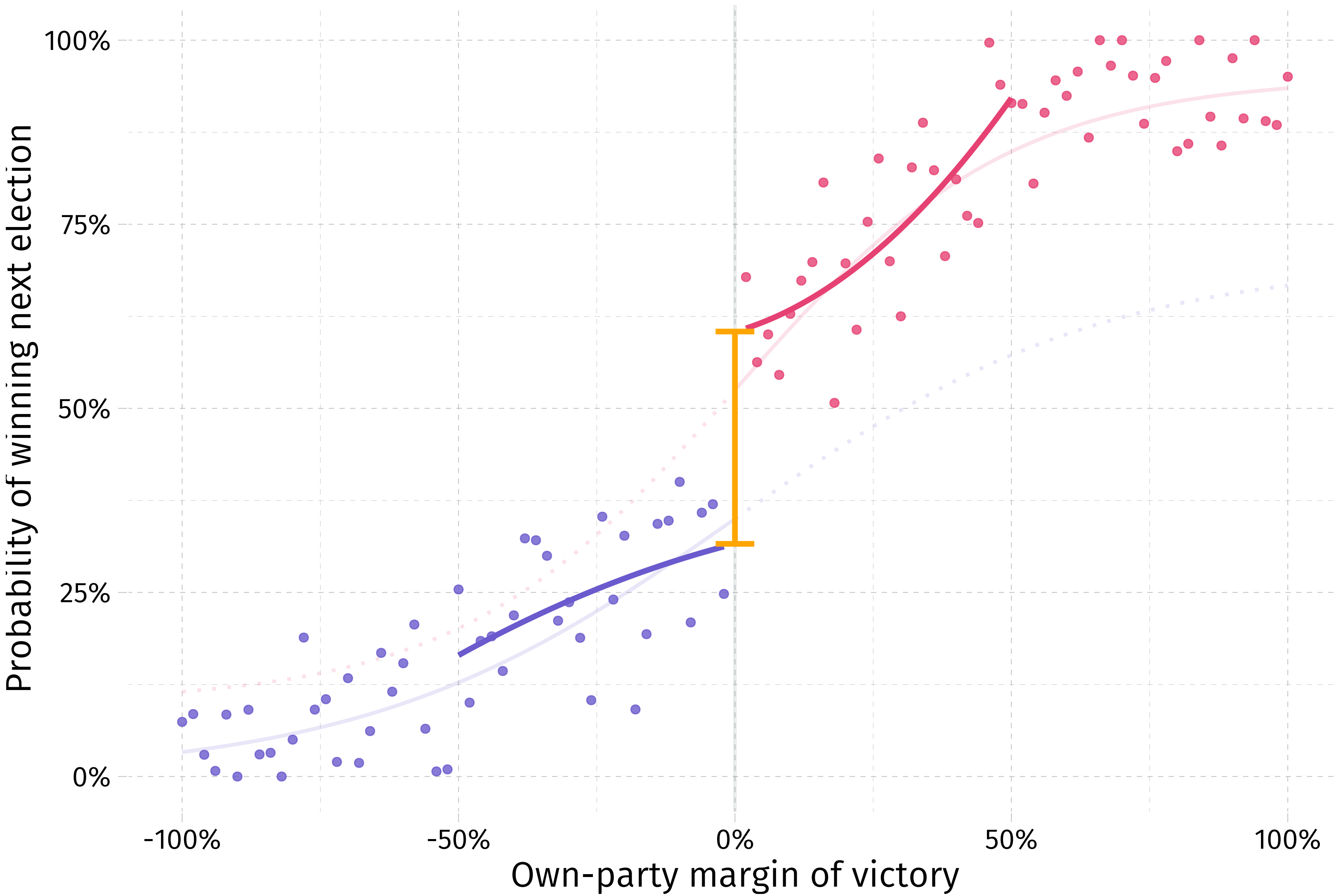
Option 1b Linear regression with constant slopes; limited to +/- 50%.

Option 2a Linear regression with differing slopes (and all data)

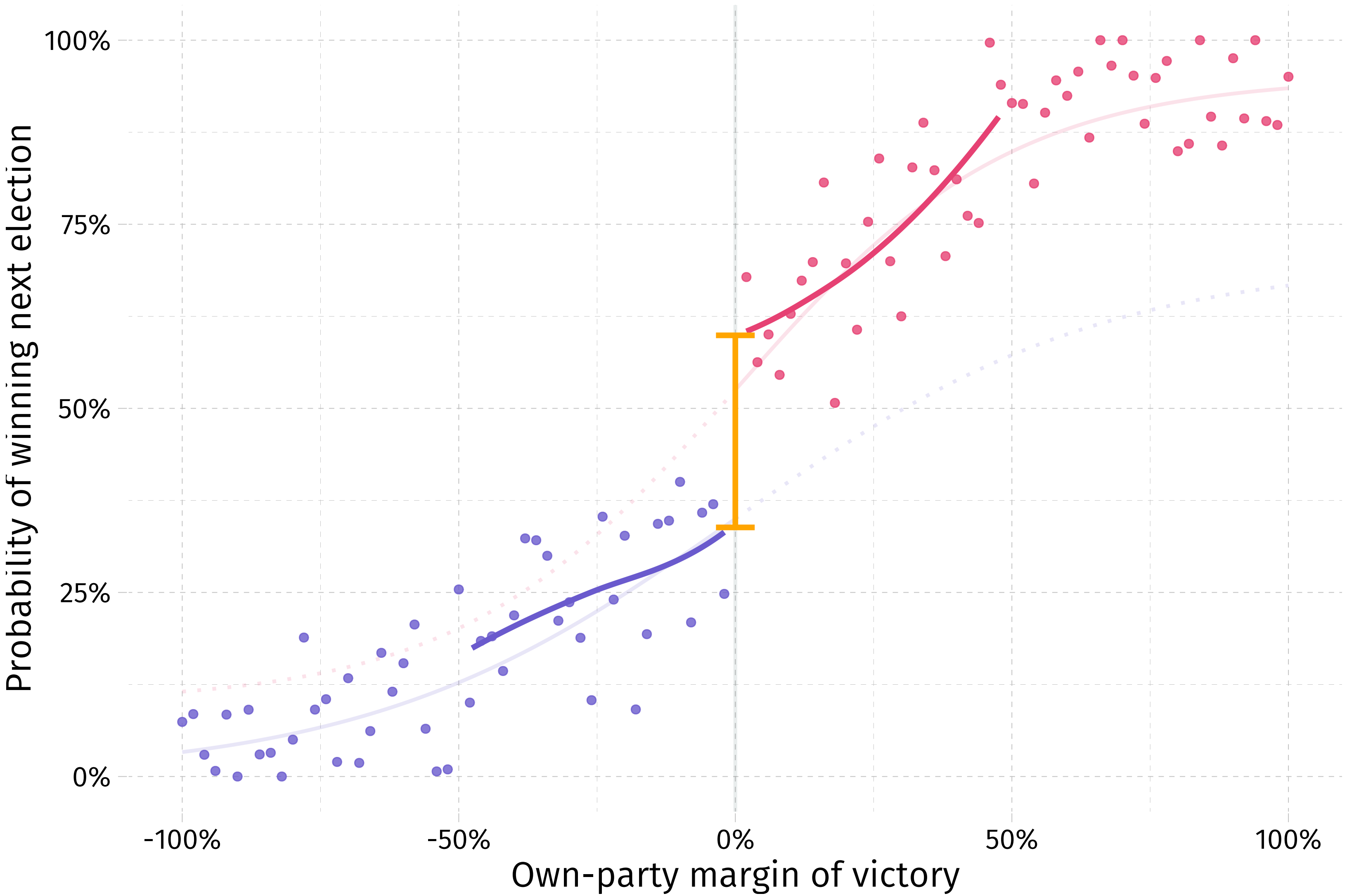
Option 2b Linear regression with differing slopes; limited to +/- 50%.

Option 2c Linear regression with differing slopes; limited to +/- 25%.

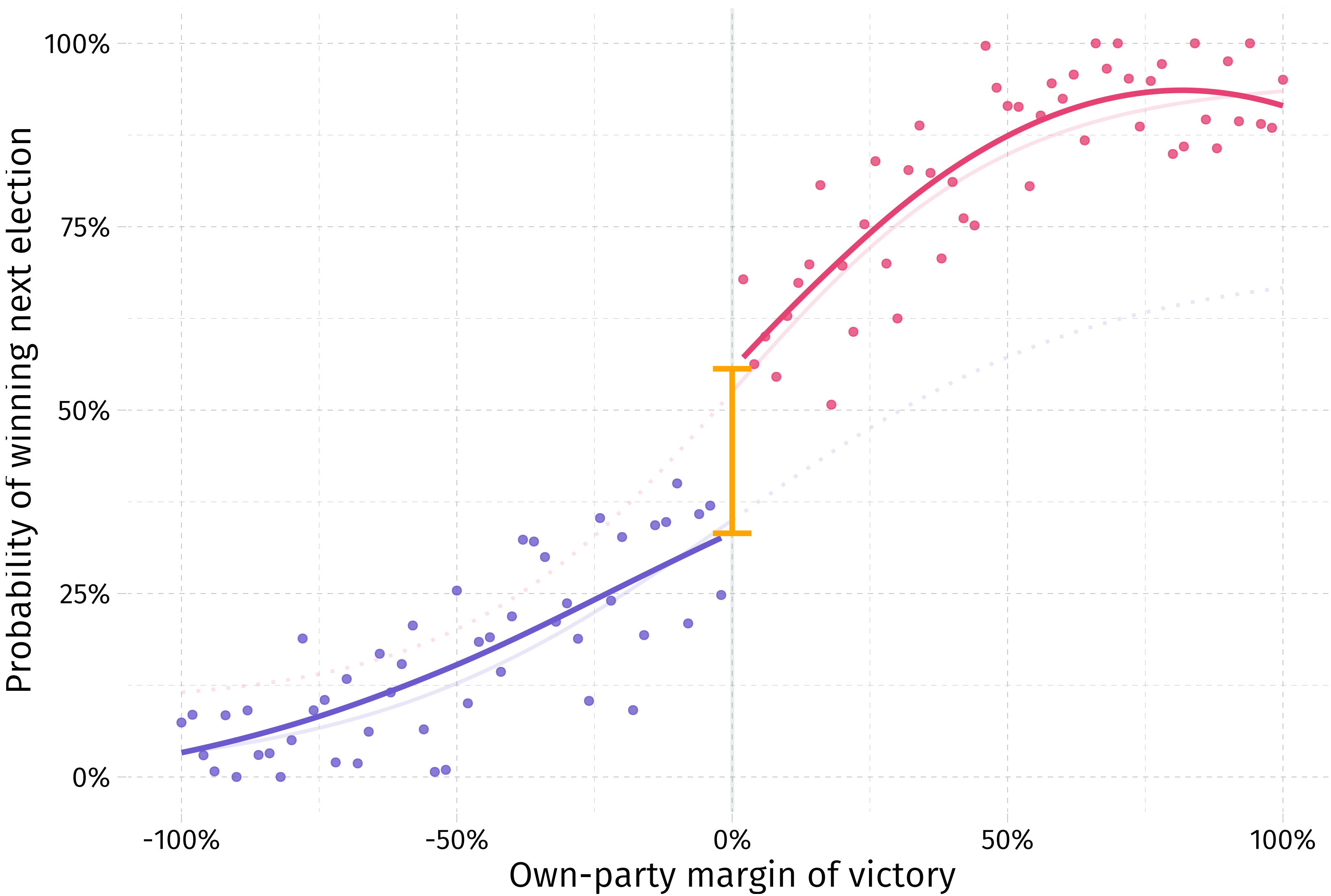
Option 3 Differing quadratic regressions (limited to +/- 50%).



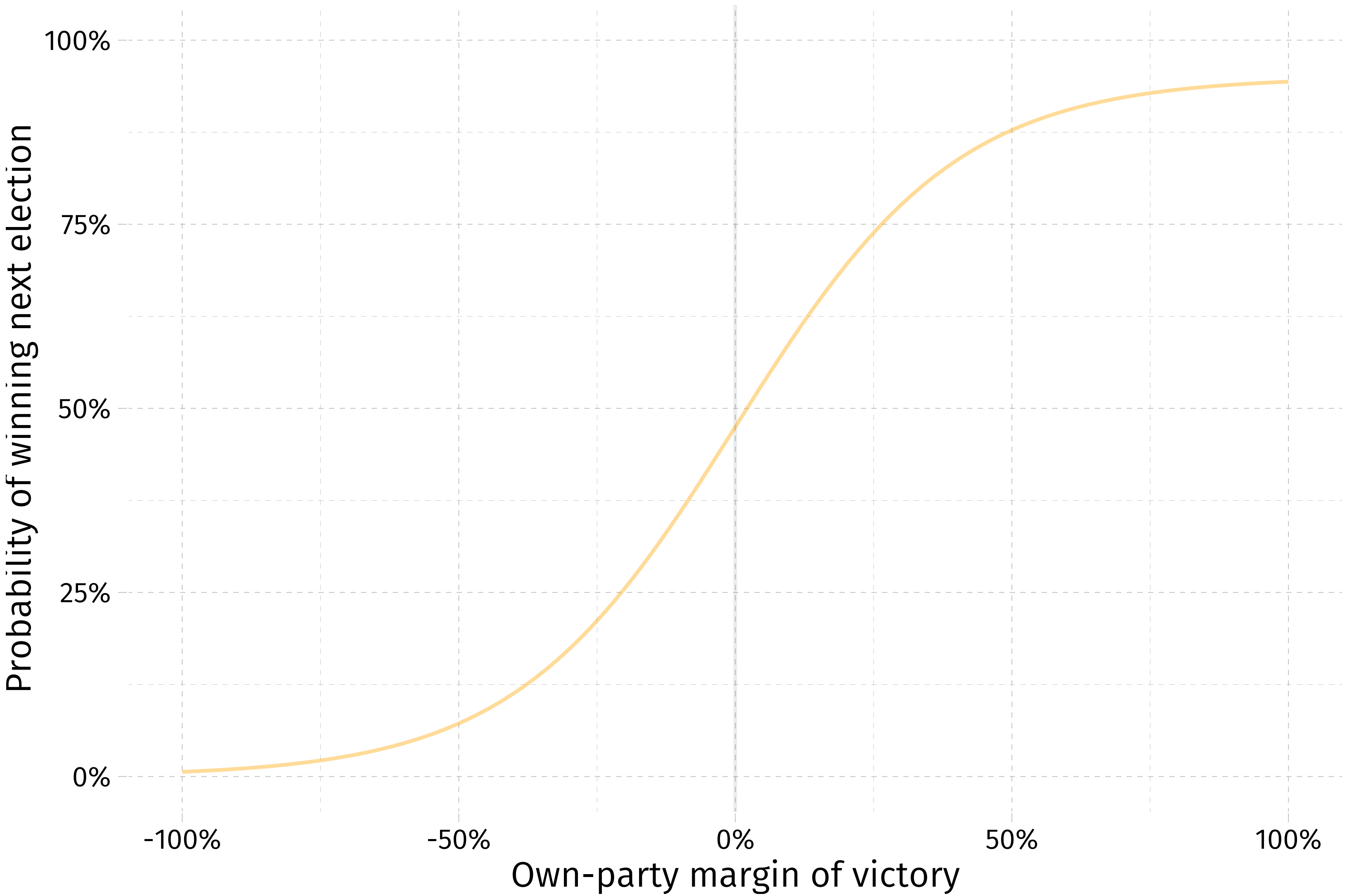
Option 4a Differing local (LOESS) regressions (limited to +/- 50%).



Option 4b Differing local (LOESS) regressions (all data).



Note Functional form can be very important.



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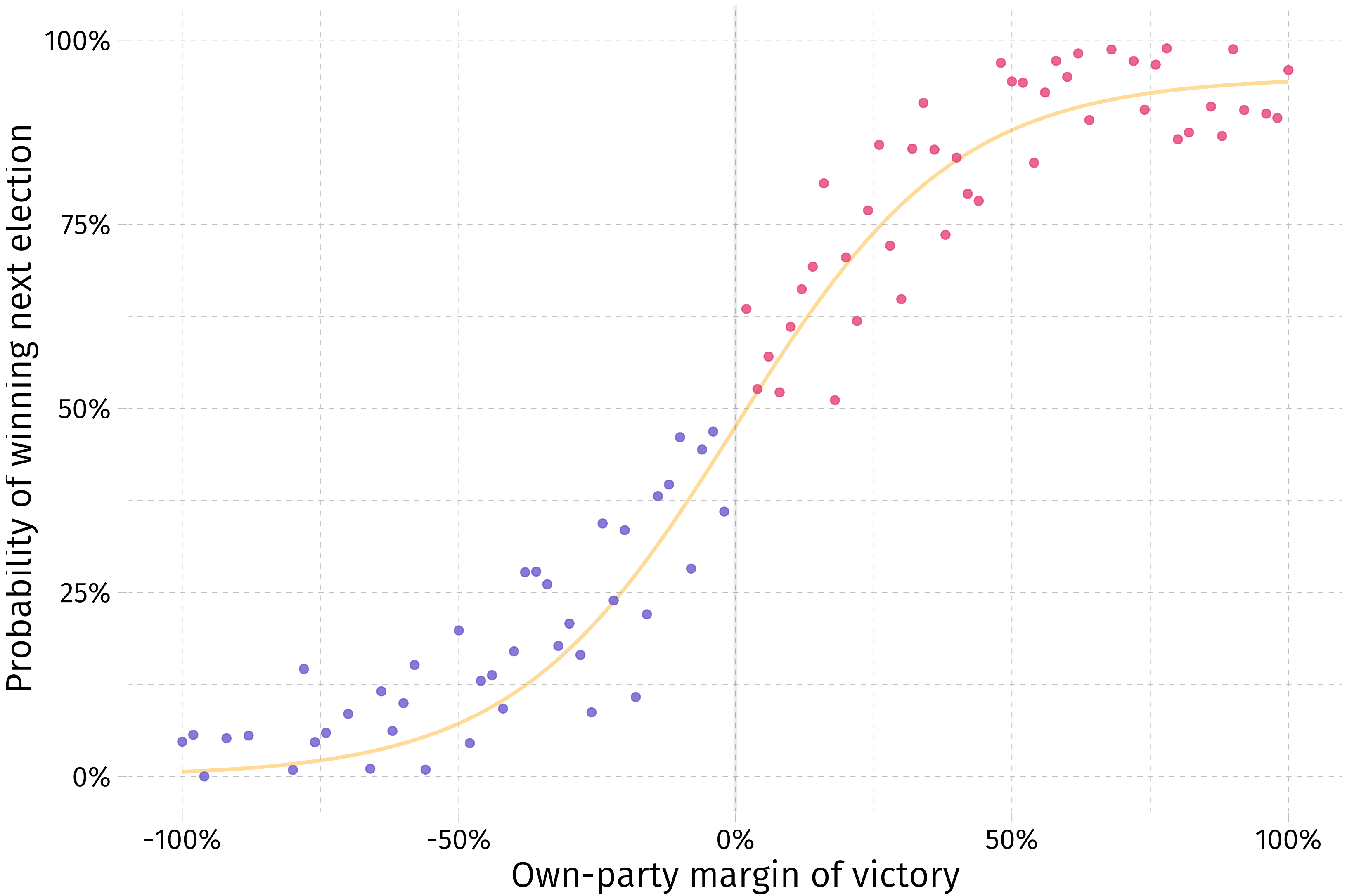

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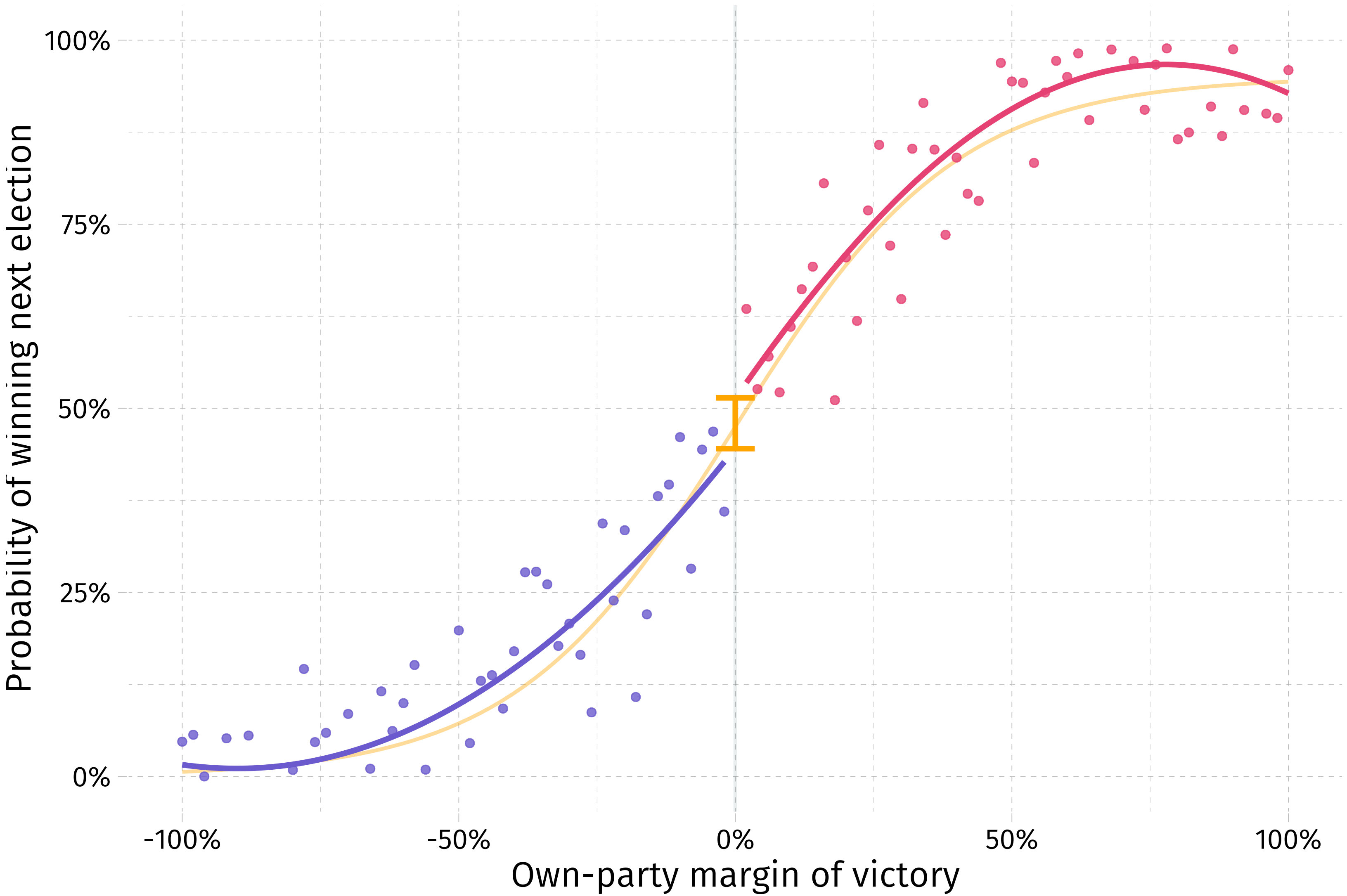
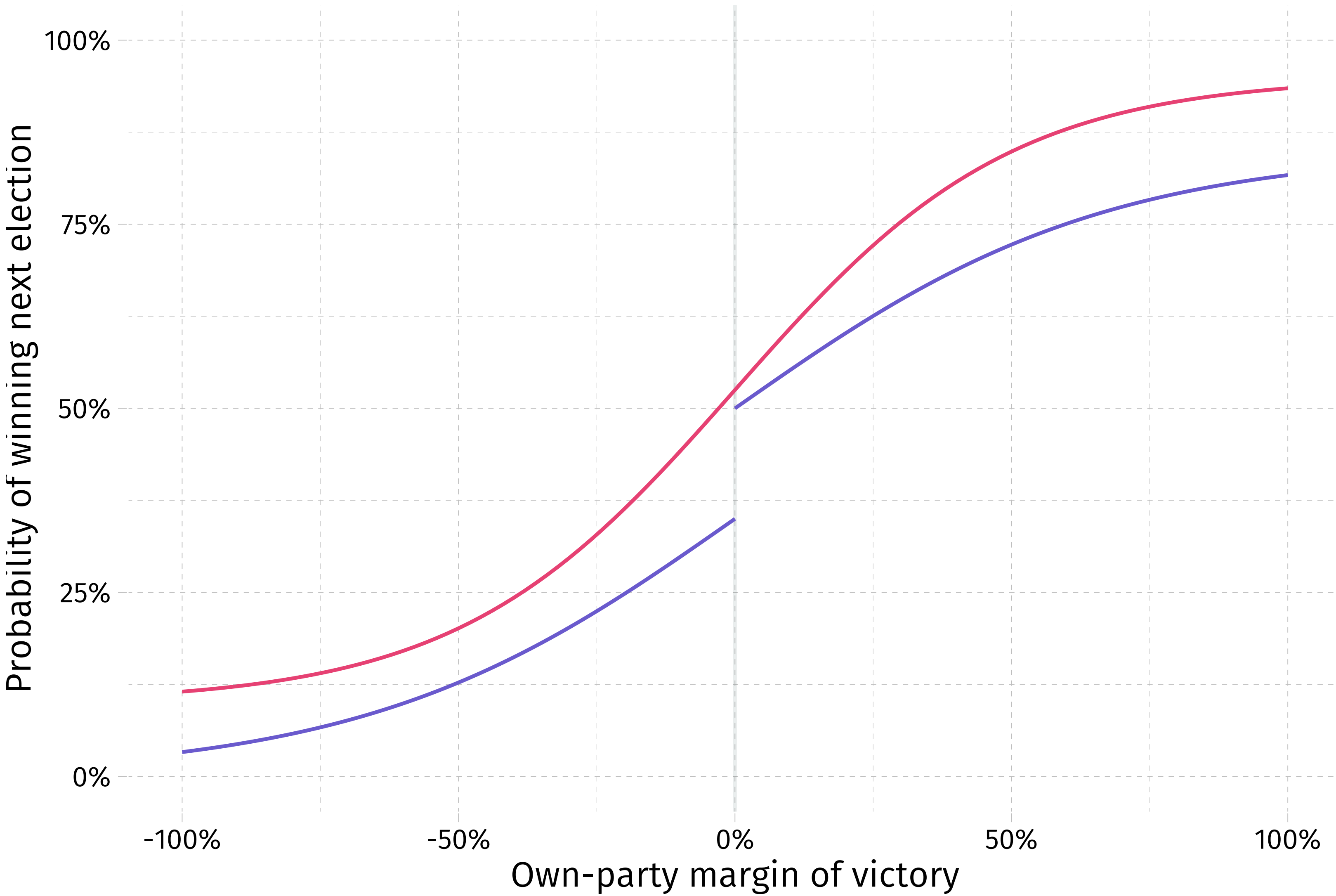


The continuity of $E[\mathrm{Y}_{0i} \mid \mathrm{X}_i = x]$ (in x) is also very important. No sorting.



Sharp RDs

In practice

Gelman and Imbens (2018) on functional form:

> We argue that controlling for global high-order polynomials in regression discontinuity analysis is a flawed approach with three major problems: it leads to noisy estimates, sensitivity to the degree of the polynomial, and poor coverage of confidence intervals. We recommend researchers instead use estimators based on local linear or quadratic polynomials or othersmooth functions.

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See Imbens and Kalyanaraman (2012) for optimal bandwidth selection.

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   - $\widetilde{\text{X}}_i < 0$ if $\text{X}_i < c$ and thus $\text{D}_i = 0$
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3. Determine a model to **estimate** $E\left[\text{Y}_i \mid \widetilde{\text{X}}_i\right]$ for $\widetilde{\mathbf{X}}_i$ above and below 0

    - Linear with common slopes for $E\left[\mathbf{Y}_i \mid \widetilde{\mathbf{X}}_i < 0\right]$ and $E\left[\mathbf{Y}_i \mid \widetilde{\mathbf{X}}_i > 0\right]$
    - Linear/quadratic/polynomial with differing slopes
    - LOESS, kernel regression, *etc.*

Estimation: Linear, common slope

Assumptions

1. $E[\mathrm{Y}_{0i}|\mathrm{X}_i = x]$ is linear in x, *i.e.*, $E[\mathrm{Y}_{0i} \mid \mathrm{X}_i] = \alpha + \beta \mathrm{X}_i$
2. Treatment effect does not depend upon τ, *i.e.*, $E[\mathbf{Y}_{1i} - \mathbf{Y}_{0i} \mid \mathbf{X}_i] = \tau$

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$$\begin{aligned} E[\text{Y}_i \mid \text{X}_i,\, \text{D}_i] &= \text{D}_i \, E[\text{Y}_{1i} \mid \text{X}_i] + (1 - \text{D}_i) \, E[\text{Y}_{0i} \mid \text{X}_i] \\ &= \alpha + \tau \text{D}_i + \beta \text{X}_i \end{aligned}$$

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$$\implies E[\text{Y}_{1i} \mid \text{X}_i] = \tau + E[\text{Y}_{0i} \mid \text{X}_i] = \tau + \alpha + \beta \text{X}_i$$

Recall our definition of $\text{Y}_i = \text{D}_i \text{Y}_{1i} + (1 - \text{D}_i)\text{Y}_{0i}$.

$$\begin{aligned} E[\text{Y}_i \mid \text{X}_i, \text{D}_i] &= \text{D}_i \, E[\text{Y}_{1i} \mid \text{X}_i] + (1 - \text{D}_i) \, E[\text{Y}_{0i} \mid \text{X}_i] \\ &= \alpha + \tau \text{D}_i + \beta \text{X}_i = \alpha + \tau \text{D}_i + \beta \left(\widetilde{\text{X}}_i + c \right) \end{aligned}$$

Estimation: Linear, common slope

Assumptions

1. $E[\mathrm{Y}_{0i}|\mathrm{X}_i = x]$ is linear in x, *i.e.*, $E[\mathrm{Y}_{0i} \mid \mathrm{X}_i] = \alpha + \beta \mathrm{X}_i$
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Sharp RDs

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which we can estimate by regressing Y_i on D_i and $\widetilde{\mathrm{X}}_i$.

Sharp RDs

Estimation: Linear, differing slopes

Assumption $E[\text{Y}_{0i}|\text{X}_i = x]$ and $E[\text{Y}_{1i}|\text{X}_i = x]$ are linear in x, *i.e.*,
$E[\text{Y}_{0i} \mid \text{X}_i] = \alpha_0 + \beta_0 \text{X}_i$ and $E[\text{Y}_{0i} \mid \text{X}_i] = \alpha_1 + \beta_1 \text{X}_i$

Now treatment effects can vary with $\mathbf{X}_i$.

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τ is the LATE at $\widetilde{\mathrm{X}}_i = \mathbf{0}$ $(\mathrm{X}_i = c)$.

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τ is the LATE at $\widetilde{\mathrm{X}}_i = 0$ ($\mathrm{X}_i = c$). Estimate: Regress Y_i in $\widetilde{\mathrm{X}}_i$, D_i, *and* $\mathrm{D}_i\widetilde{\mathrm{X}}_i$.†

† See Appendix for omitted steps.

Sharp RDs

Estimation: Additional

Fuzzy RDs

Fuzzy RDs

Setup

As with their sharp-RD relatives, **fuzzy RDs** take advantage of a discontinuous change in treatment assignment across some threshold c.

Fuzzy RDs

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Formally,

$$0 < \lim_{x \downarrow c} \Pr(\text{D}_i = 1 \mid \text{X}_i = x) - \lim_{x \uparrow c} \Pr(\text{D}_i = 1 \mid \text{X}_i = x) < 1$$

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Ex., Exceeding a minimum GRE requirement for graduate school.

Fuzzy RDs

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2. The effect of X_i crossing c on the probability of treatment

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$$\lim_{x \downarrow c} E[\text{D}_i \mid \text{X}_i = x] - \lim_{x \uparrow c} E[\text{D}_i \mid \text{X}_i = x]$$

The treatment effect defined by a fuzzy RD is the ratio of (1) to (2)

$$\tau_{\text{FRD}} = \frac{\lim_{x \downarrow c} E[\text{Y}_i \mid \text{X}_i = x] - \lim_{x \uparrow c} E[\text{Y}_i \mid \text{X}_i = x]}{\lim_{x \downarrow c} E[\text{D}_i \mid \text{X}_i = x] - \lim_{x \uparrow c} E[\text{D}_i \mid \text{X}_i = x]}$$

Fuzzy RDs

An old friend

This definition of the fuzzy-RD treatment effect

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should remind you of something—**IV**, where $\mathbf{Z}_i = \mathbb{I}\left\{\text{X}_i \geq c\right\}$.

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should remind you of something—**IV**, where $\mathbf{Z}_i = \mathbb{I}\left\{\mathbf{X}_i \geq \boldsymbol{c}\right\}$.

Accordingly, fuzzy RDs are going to have the **same requirements and interpretation as IV**.

More formally

Let $\mathrm{D}_i\left(x^*\right)$ denote the **potential treatment status** of i **with threshold** x^*.

Why write potential treatment status D_i a function of the threshold?

Fuzzy RDs

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Assumption $\text{D}_i\left(x^*\right)$ is non-increasing in x^* at $x^* = c$.

This is our monotonicity assumption for fuzzy RDs. If we raise x^* from c to $c + \epsilon$, no one joins treatment—no defiers.

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Fuzzy RDs

Compliance

Our compliers in this setting are individuals such that

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Back to the fuzzy RD treatment effect

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$$= E[\mathrm{Y}_{1i} - \mathrm{Y}_{0i} | i \text{ is a complier and } \mathbf{X}_i = c].$$

Thus, τ_{FRD} can be a *very local* LATE.

Graphical analysis

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General

RD analyses hinge on their graphical analyses.

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If the discontinuity is not graphically apparent, most people are not going to care about the results of a few tortured regressions.

You're arguing you know that treatment assignment changes across the threshold. If your reader/viewer cannot see it, they're likely not going to believe your regression tables.†

† This skepticism may be well founded. We know RDs are sensitive to functional form—and researchers have been known to *p-hack*.

Graphical analysis

Three figures

Most RD analyses will have some subset of three types of figures.

1. **Outcomes** by the running/forcing variable] (X_i)
   Do we observe a treatment effect across the discontinuity?

2. **Covariates** by the running/forcing variable (X_i)
   Are covariates smooth/balanced across the discontinuity?

3. **Density** of running/forcing variable (X_i)
   Is there evidence of sorty into treatment (across the threshold)?

Appendix

Estimation: Linear, differing slopes

Definitions of terms that magically appear

- $\widetilde{\alpha} = \alpha_0 + \beta_0 c$
- $\tau = (\alpha_1 - \alpha_0) + (\beta_1 - \beta_0)\, c$
- $\tilde{\beta} = (\beta_1 - \beta_0)$

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