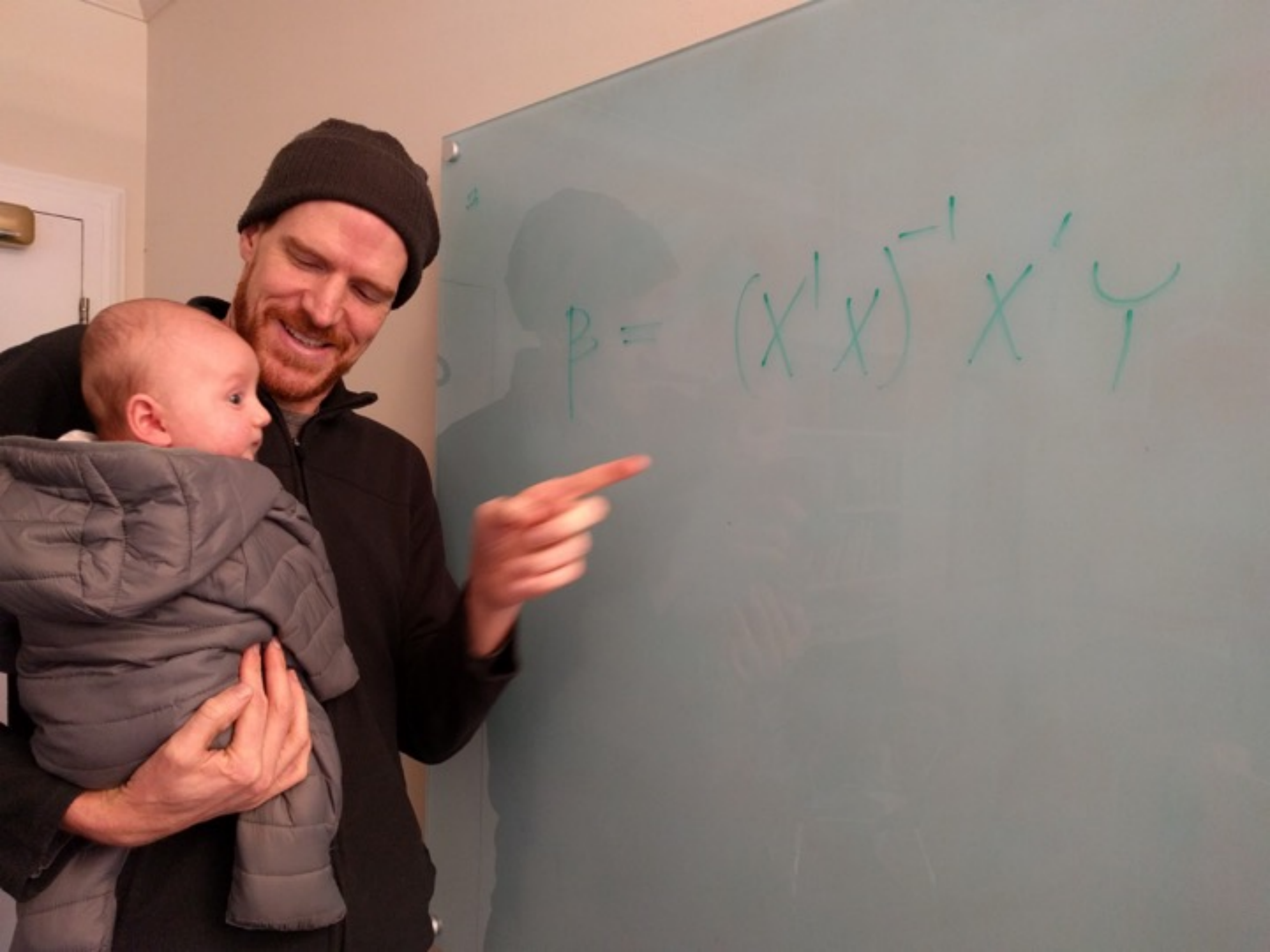
Panel data for causal inference

Intermediate Social Statistics
Week 5 (14 February 2017)
Andy Eggers


$\beta = (X'X)^{-1}X'Y$

Causal inference: the big picture

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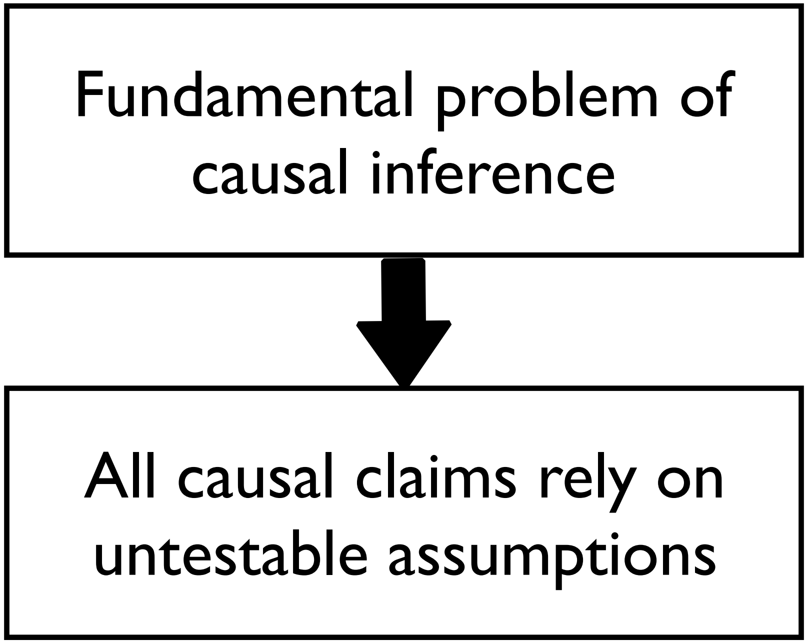
Fundamental problem of causal inference

Causal inference: the big picture



Fundamental problem of causal inference

All causal claims rely on untestable assumptions

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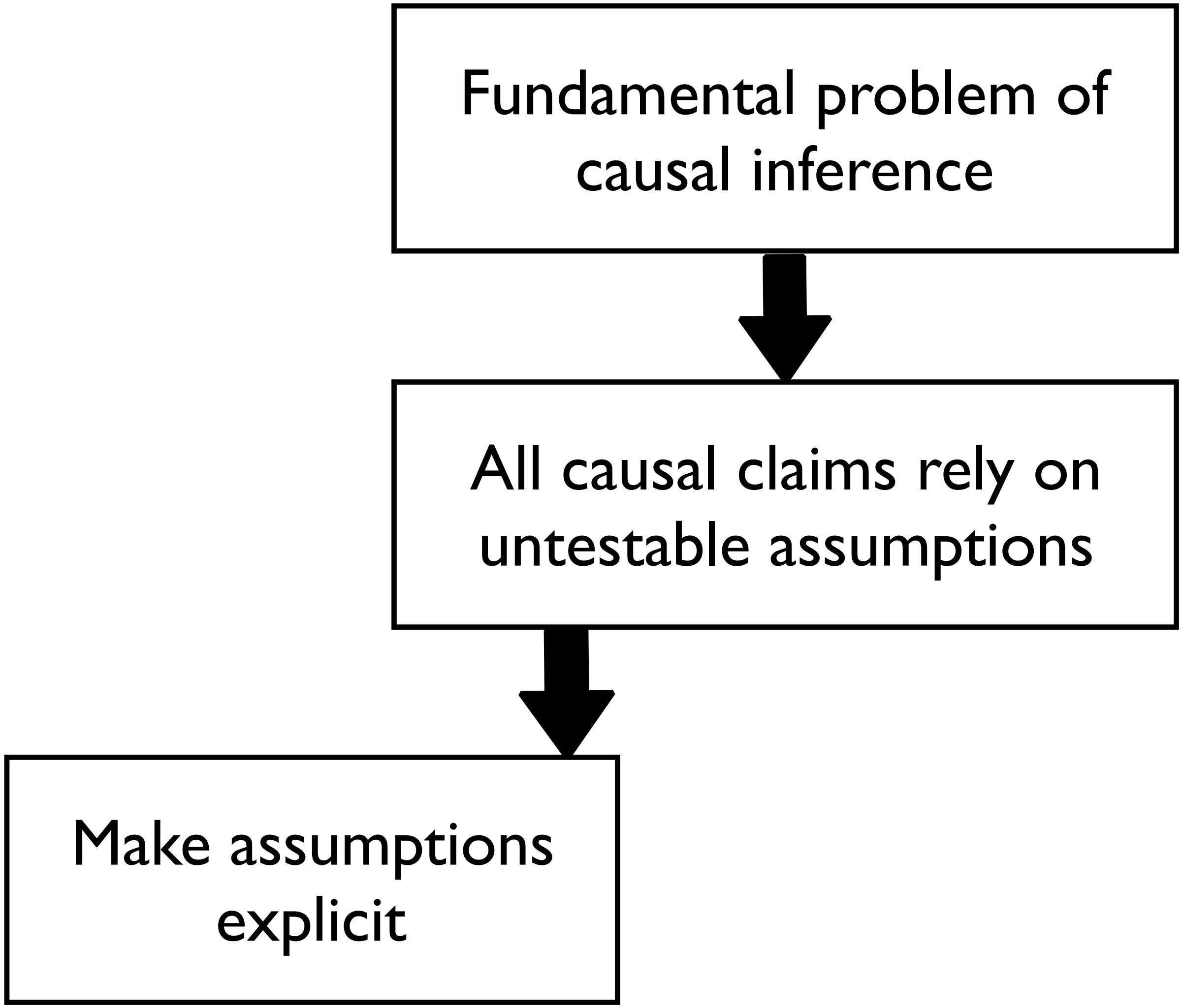

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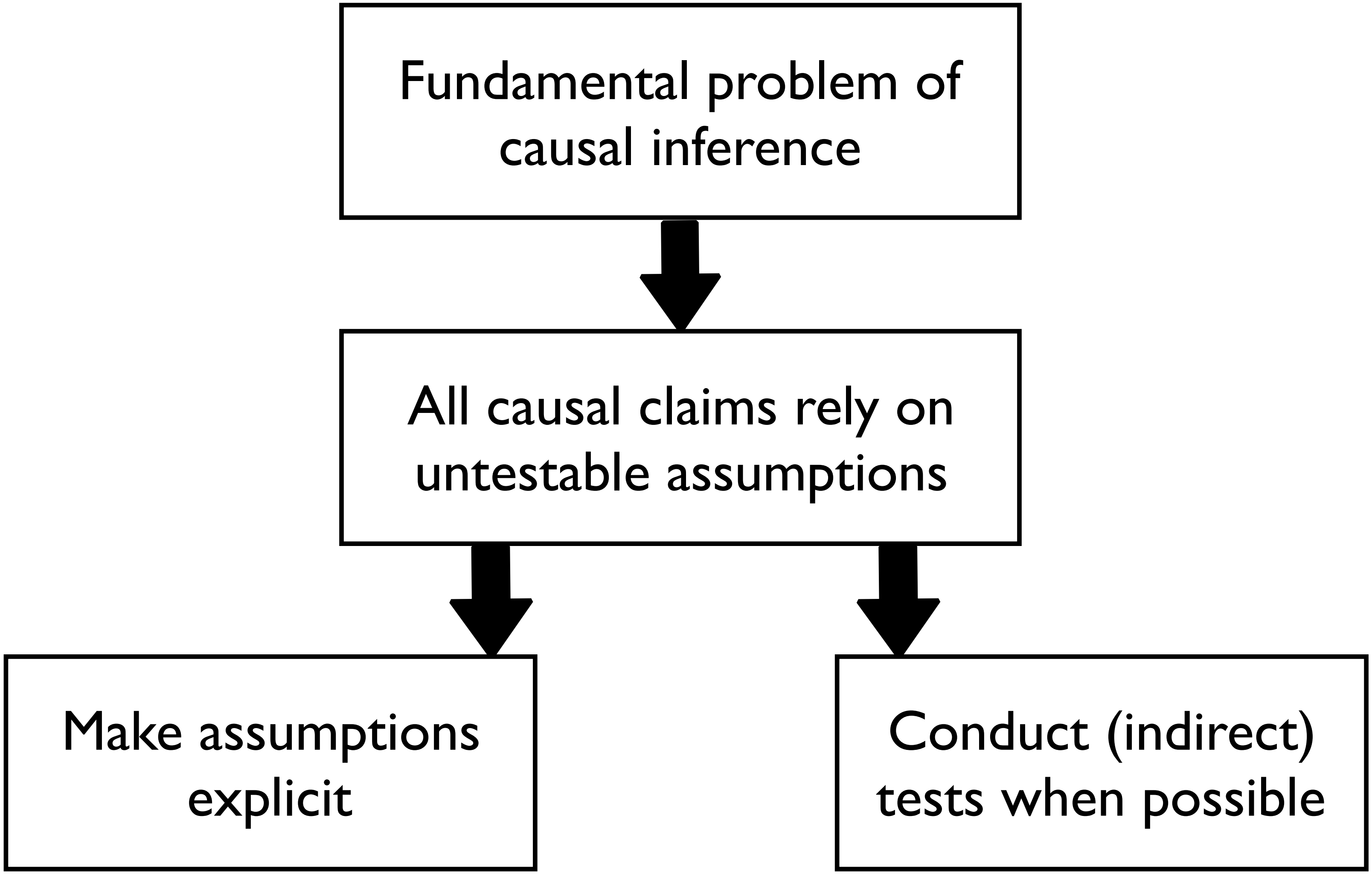

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Make assumptions explicit

Conduct (indirect) tests when possible

Causal inference: the big picture (2)

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Causal inference: the big picture (2)

What are the assumptions? What indirect tests?

- Regression
- Matching
- IV
- Diff-in-diff

Today's plan

- Big picture on importance of assumptions (done)
- Brief diff-in-diff review
- Generalizing in panel data
  - "First differences" approach
  - "Dummy variables" approach
  - "Fixed effects" approach ("within" regression)
- An example from the reading
- General guidelines: when is panel data useful for causal inference?

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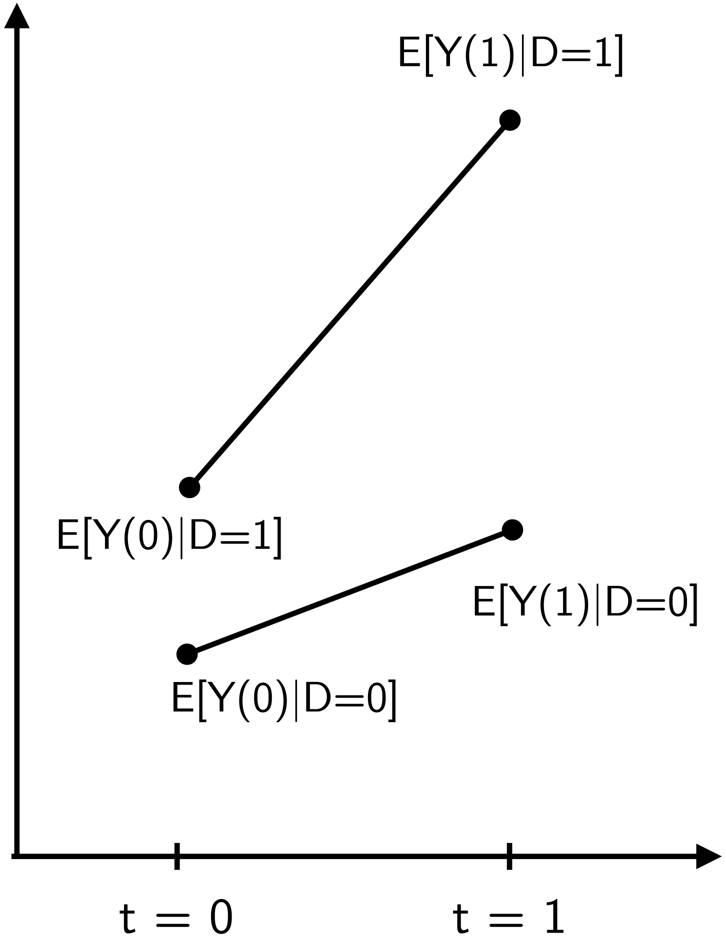

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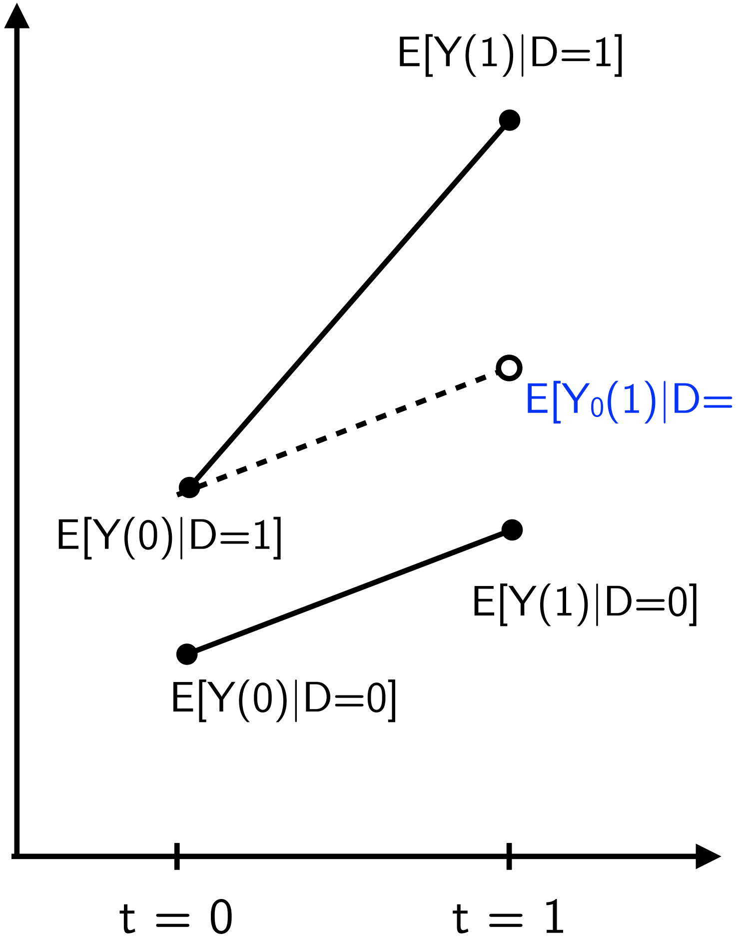

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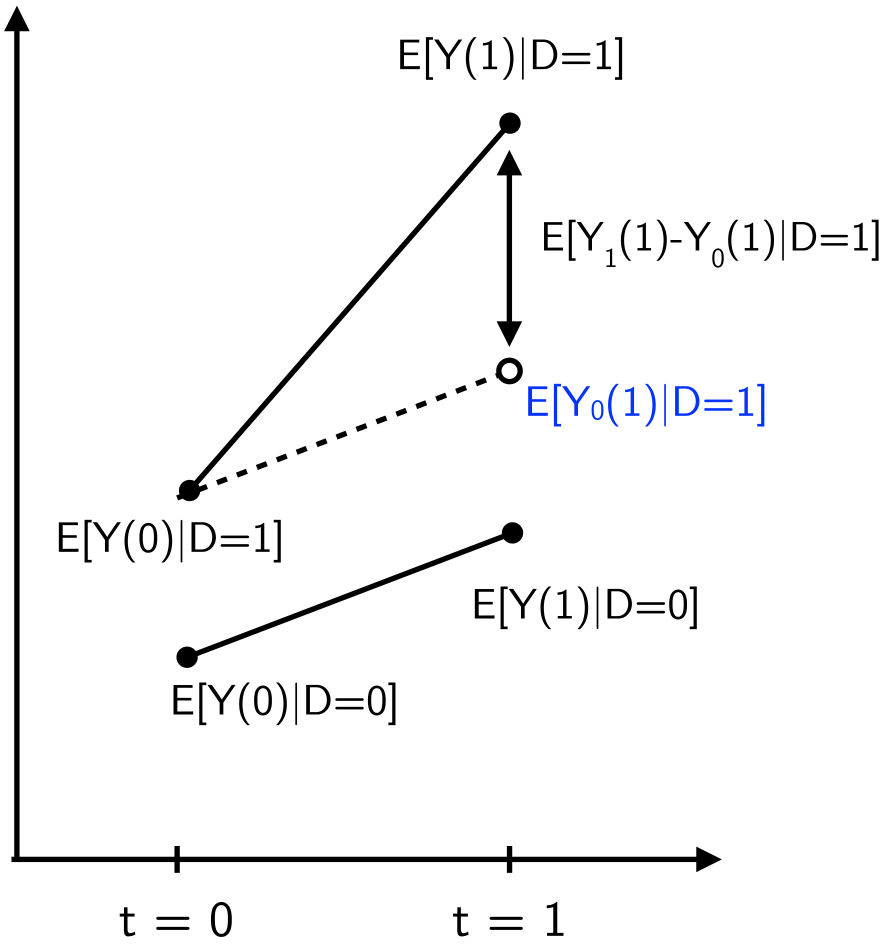

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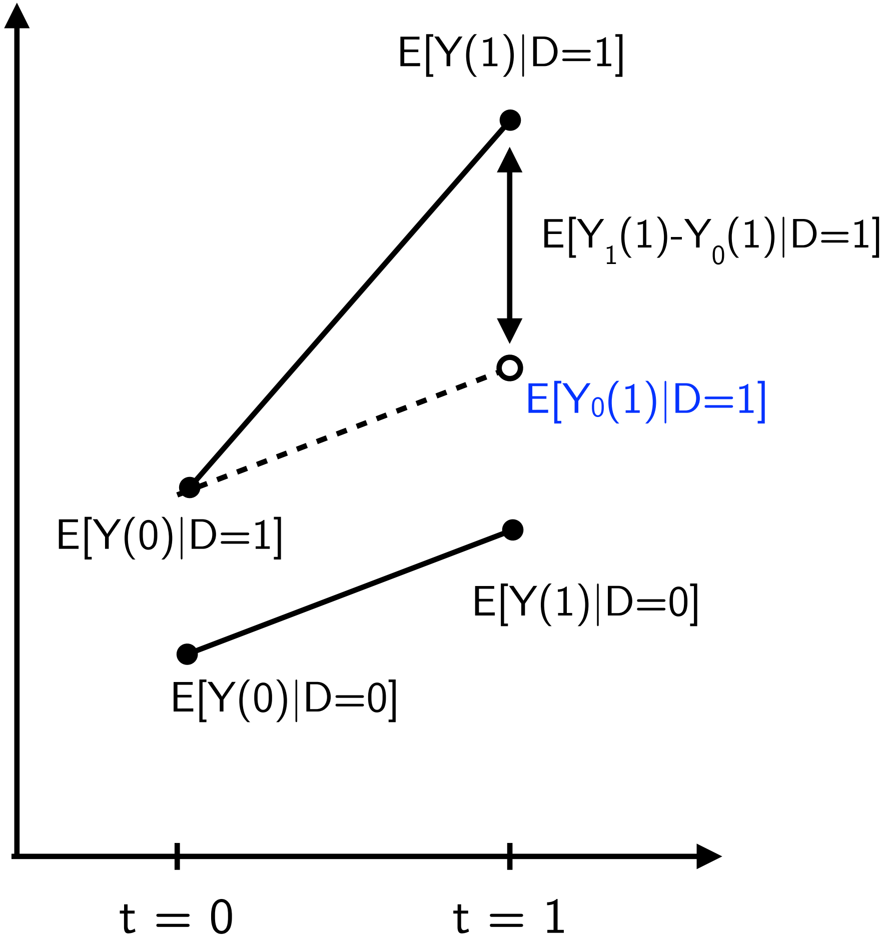

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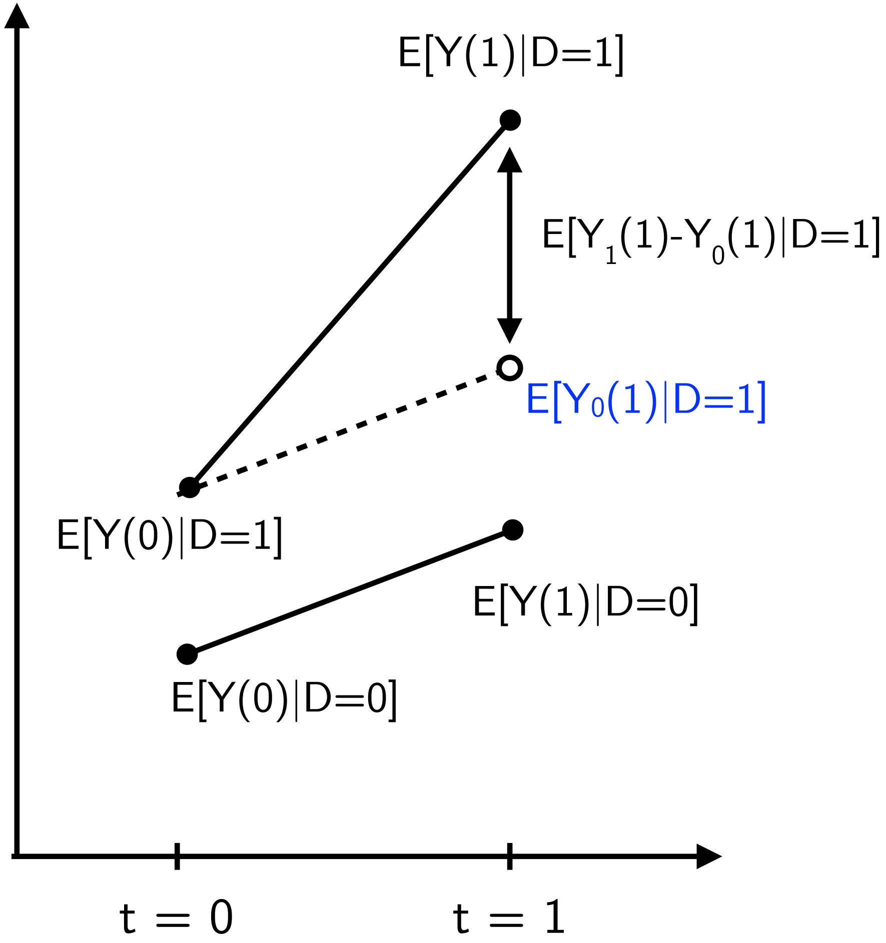

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If assumption holds, ATT given by diff-in-diff, i.e.

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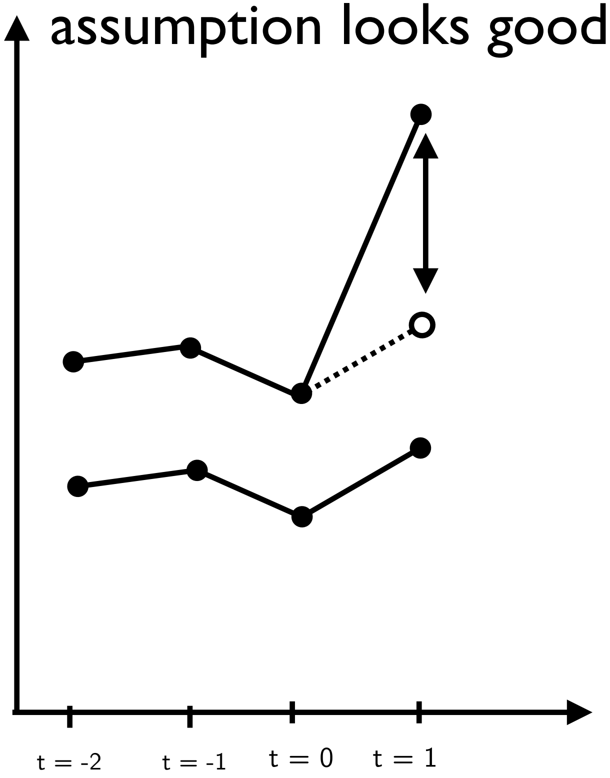
Testing the parallel trends assumption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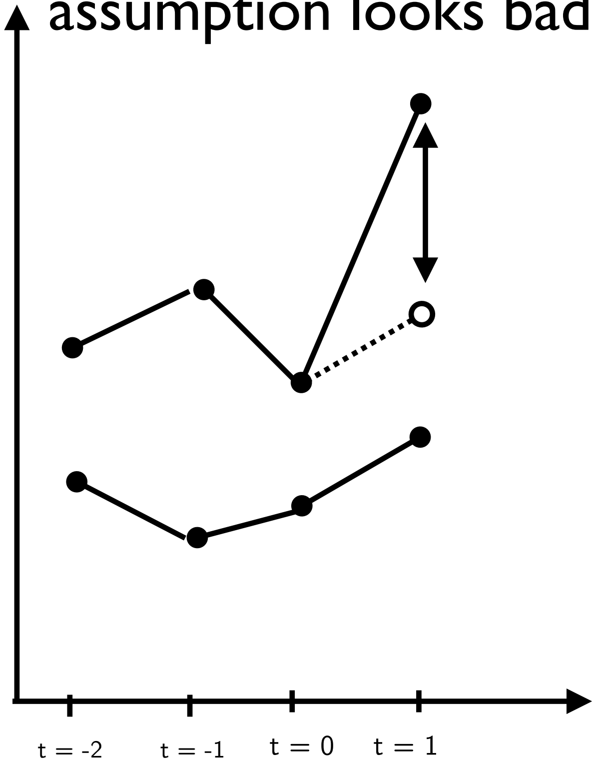
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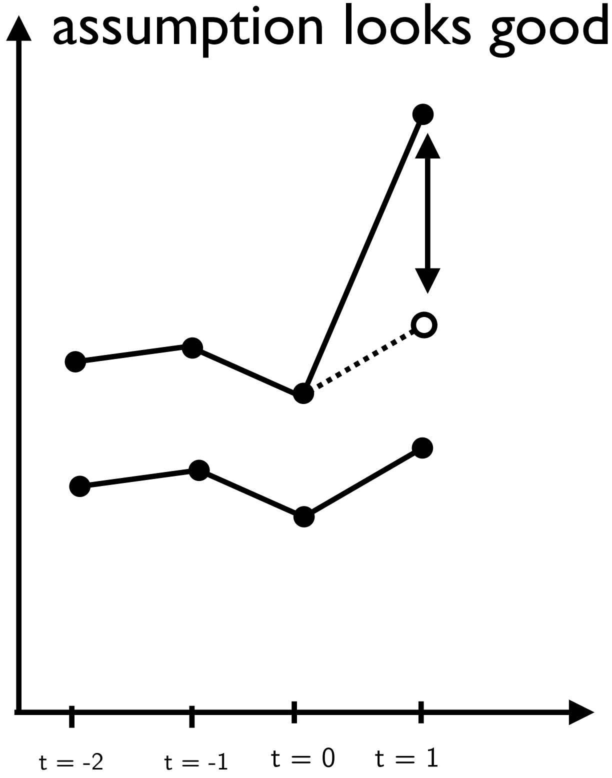

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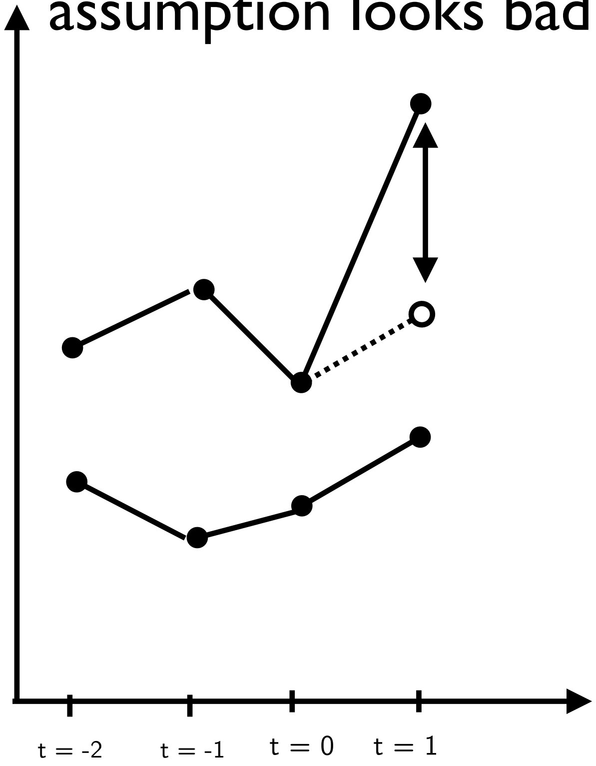

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Can we test it?

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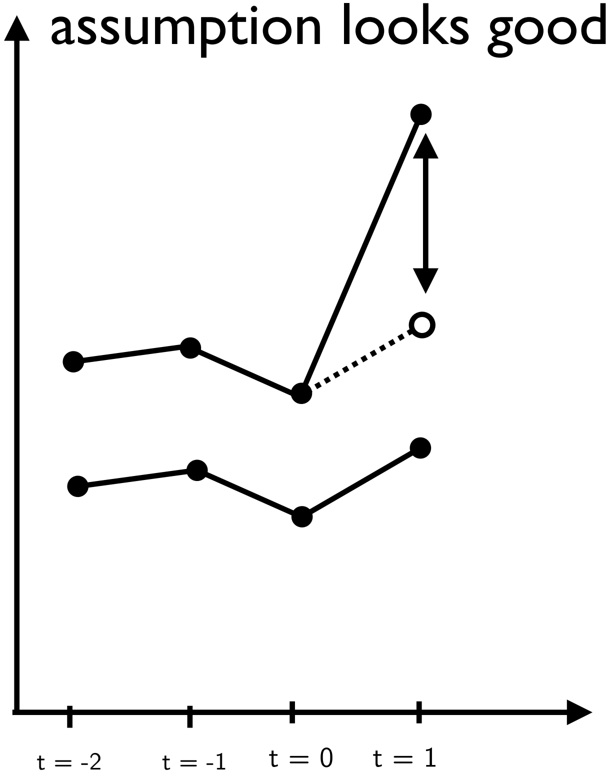

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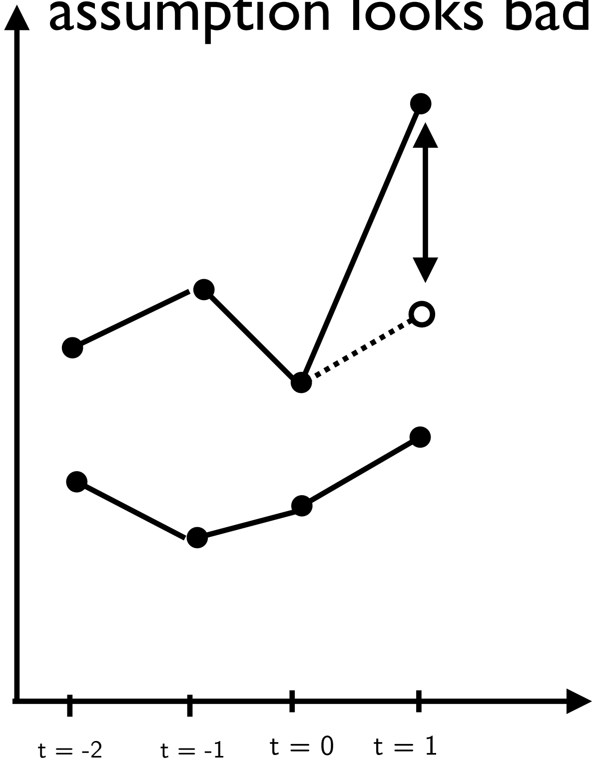

The beauty of the diff-in-diff: selection on unobservables

The key assumption in regression & matching can be stated as *selection on observables:*

- All covariates (factors that differ between treatment and control and affect the outcome) are observed (and properly controlled for).
- Or, *no unobserved confounding variables*.

With diff-in-diff (and today's panel methods, and IV), we can make a weaker assumption — these allow *selection on unobservables*.

Key (in diff-in-diff):

- All confounders are unchanging over time.
- Or, *no time-invariant confounding variables*.
- In other words, *unobserved okay if unchanging*.

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(Note that diff-in-diff does **not** require panel data! Repeated cross-section could work.)

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- non-binary treatment?

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You can estimate τ even though u_i is unobserved!

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Idea, continued: There may be many important unobserved covariates that affect outcome and treatment. Any time-invariant covariates are controlled for by the unit-specific dummy variable. Any common time trends are controlled for by the time period dummy variables.

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Also referred to as “within” (vs “between”) regression.

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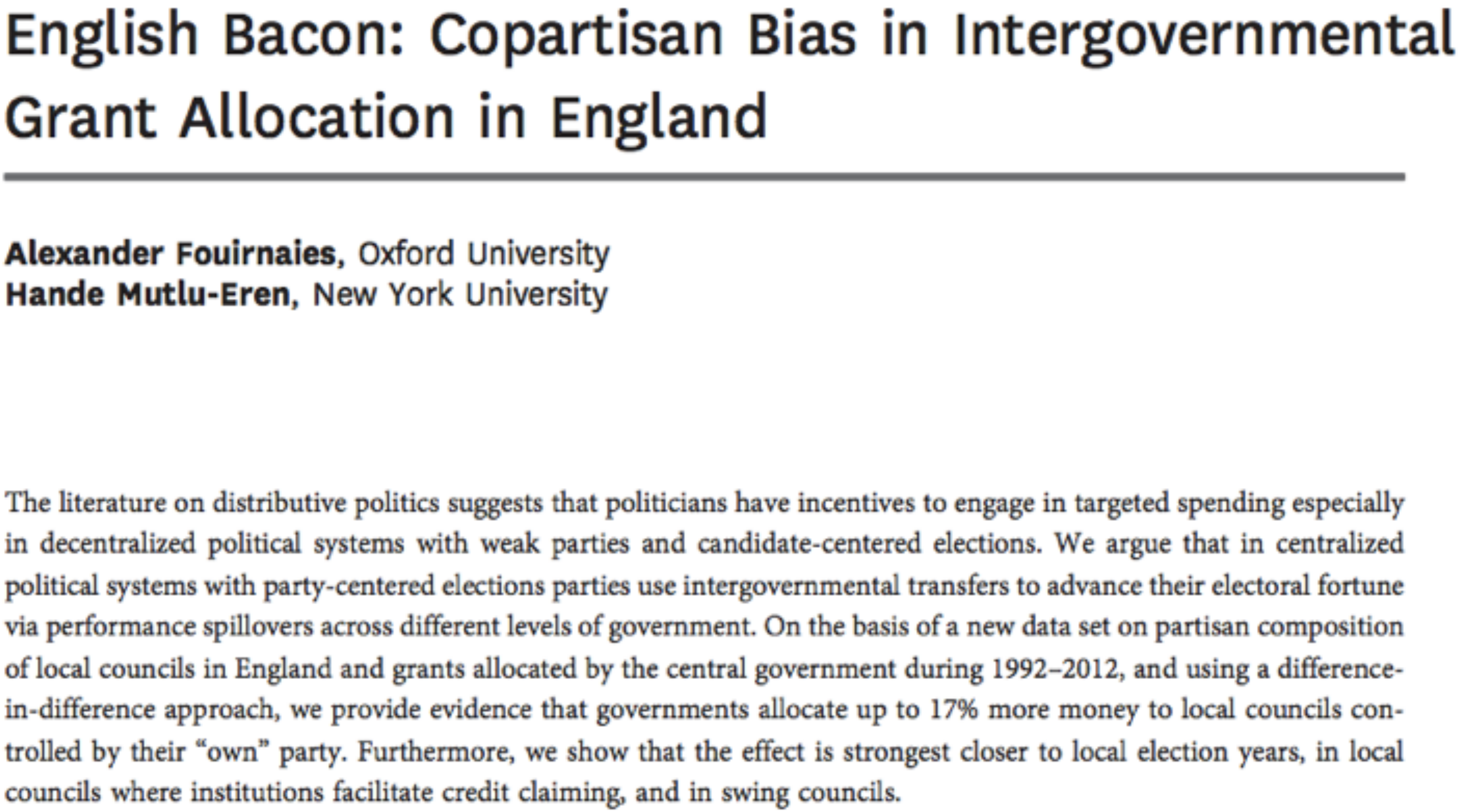
- key assumption: no time-variant unit-specific confounders
- your job: think about what could violate this assumption

Example

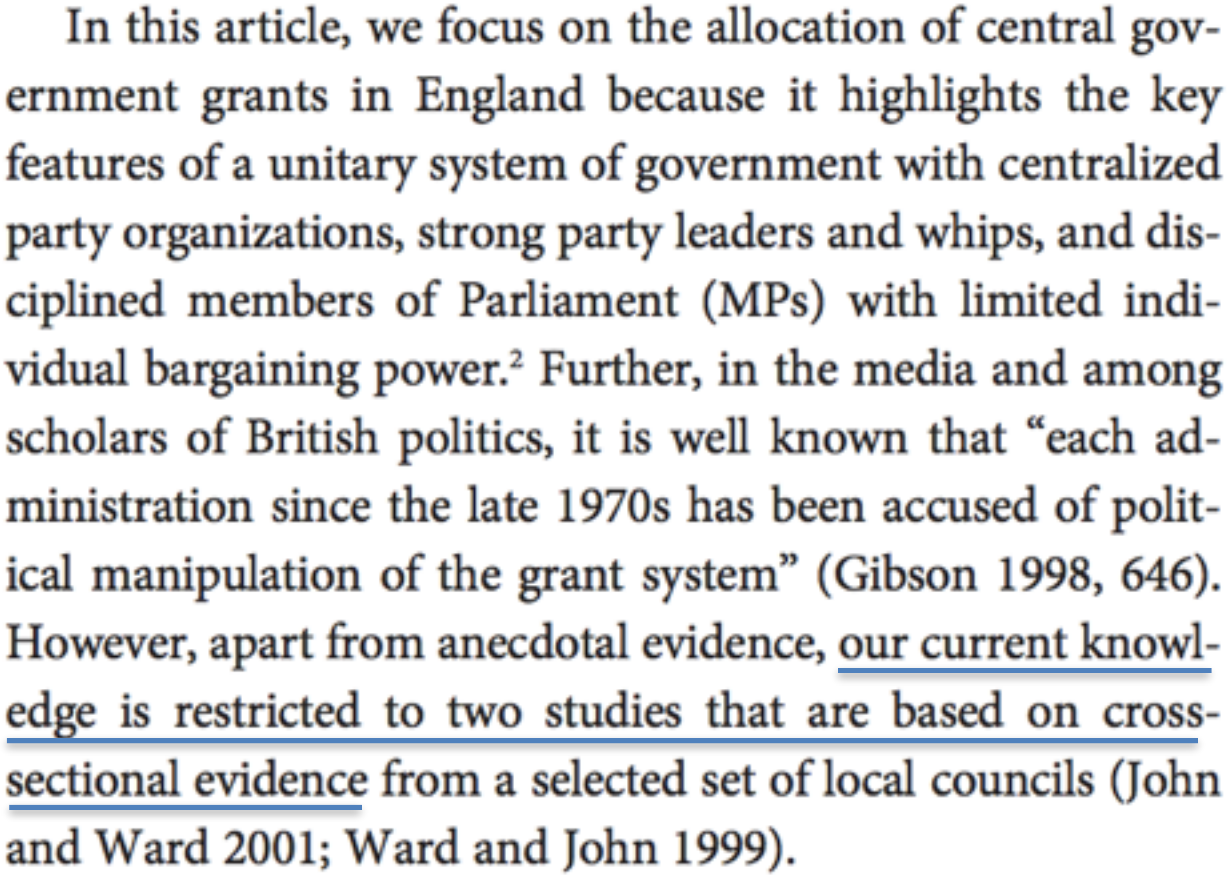


English Bacon: Copartisan Bias in Intergovernmental Grant Allocation in England

Alexander Fouirnaies, Oxford University
Hande Mutlu-Eren, New York University

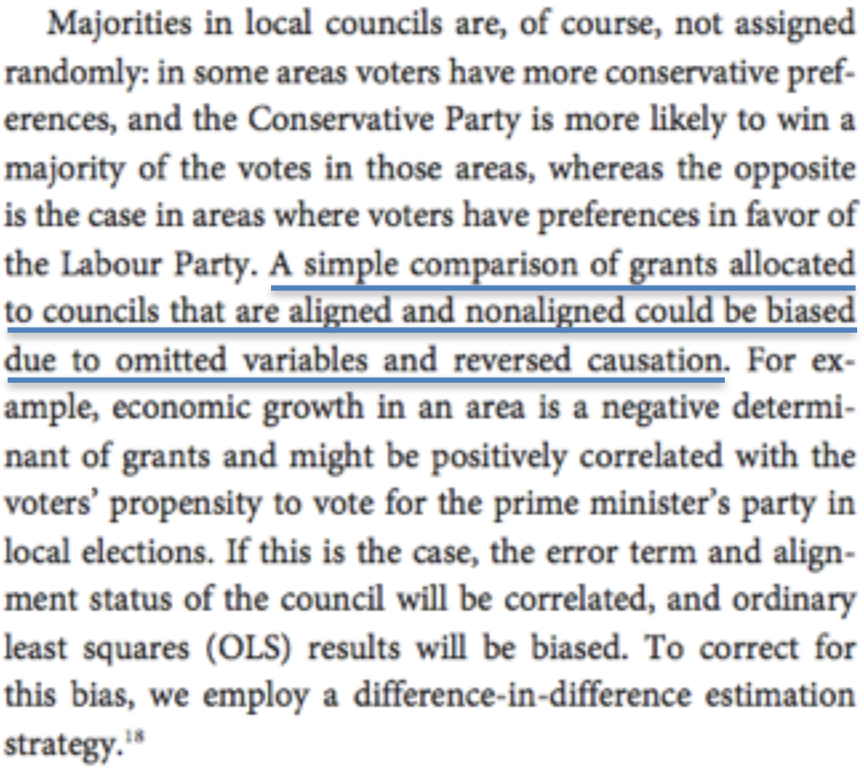
The literature on distributive politics suggests that politicians have incentives to engage in targeted spending especially in decentralized political systems with weak parties and candidate-centered elections. We argue that in centralized political systems with party-centered elections parties use intergovernmental transfers to advance their electoral fortune via performance spillovers across different levels of government. On the basis of a new data set on partisan composition of local councils in England and grants allocated by the central government during 1992–2012, and using a difference-in-difference approach, we provide evidence that governments allocate up to 17% more money to local councils controlled by their "own" party. Furthermore, we show that the effect is strongest closer to local election years, in local councils where institutions facilitate credit claiming, and in swing councils.

Example: motive

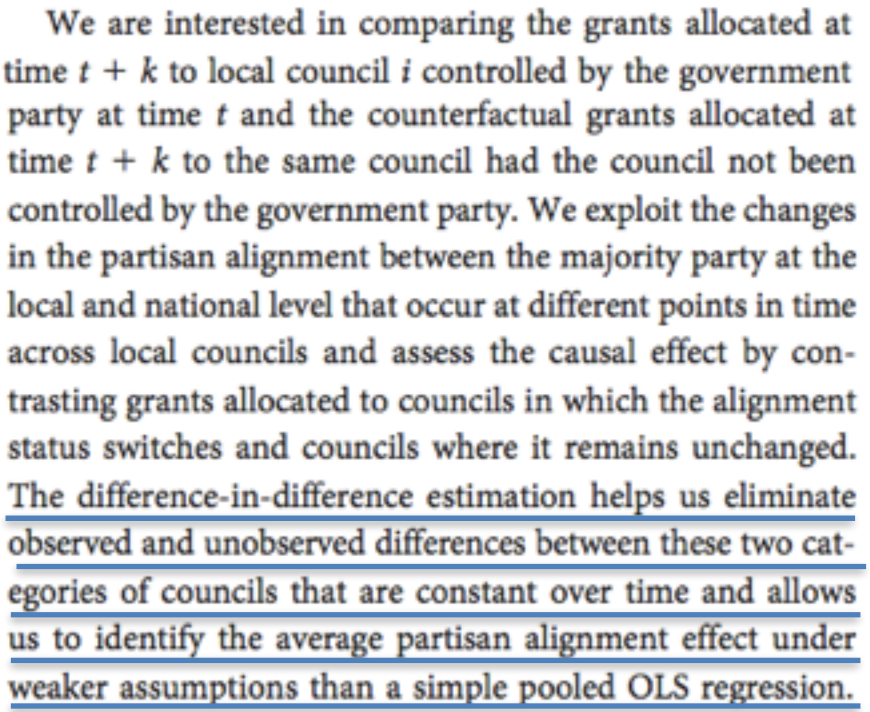


In this article, we focus on the allocation of central government grants in England because it highlights the key features of a unitary system of government with centralized party organizations, strong party leaders and whips, and disciplined members of Parliament (MPs) with limited individual bargaining power.[2] Further, in the media and among scholars of British politics, it is well known that "each administration since the late 1970s has been accused of political manipulation of the grant system" (Gibson 1998, 646). However, apart from anecdotal evidence, our current knowledge is restricted to two studies that are based on cross-sectional evidence from a selected set of local councils (John and Ward 2001; Ward and John 1999).

Example: design and assumptions

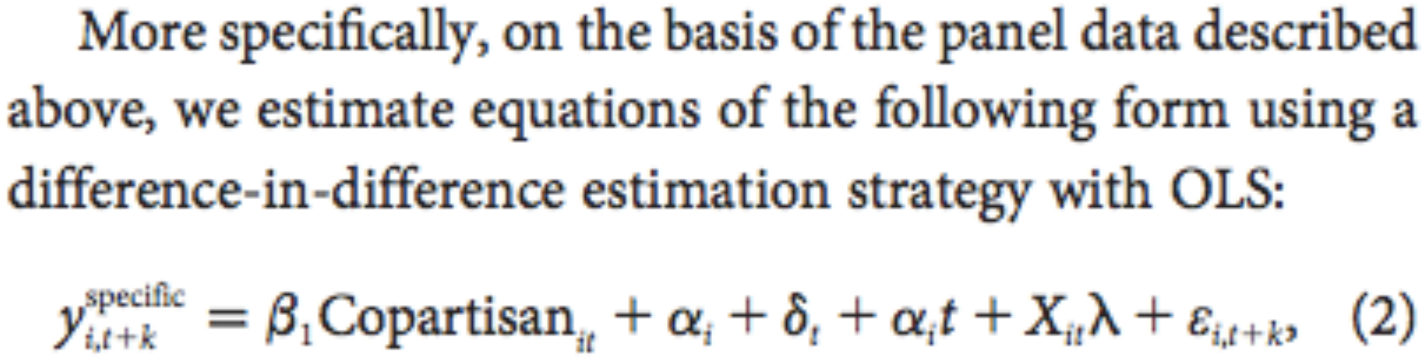


Majorities in local councils are, of course, not assigned randomly: in some areas voters have more conservative preferences, and the Conservative Party is more likely to win a majority of the votes in those areas, whereas the opposite is the case in areas where voters have preferences in favor of the Labour Party. A simple comparison of grants allocated to councils that are aligned and nonaligned could be biased due to omitted variables and reversed causation. For example, economic growth in an area is a negative determinant of grants and might be positively correlated with the voters' propensity to vote for the prime minister's party in local elections. If this is the case, the error term and alignment status of the council will be correlated, and ordinary least squares (OLS) results will be biased. To correct for this bias, we employ a difference-in-difference estimation strategy.[18]



We are interested in comparing the grants allocated at time $t + k$ to local council i controlled by the government party at time t and the counterfactual grants allocated at time $t + k$ to the same council had the council not been controlled by the government party. We exploit the changes in the partisan alignment between the majority party at the local and national level that occur at different points in time across local councils and assess the causal effect by contrasting grants allocated to councils in which the alignment status switches and councils where it remains unchanged. The difference-in-difference estimation helps us eliminate observed and unobserved differences between these two categories of councils that are constant over time and allows us to identify the average partisan alignment effect under weaker assumptions than a simple pooled OLS regression.

Example: specification



More specifically, on the basis of the panel data described above, we estimate equations of the following form using a difference-in-difference estimation strategy with OLS:

$$y^{\text{specific}}_{i,t+k} = \beta_1 \text{Copartisan}_{it} + \alpha_i + \delta_t + \alpha_i t + X_{it}\lambda + \varepsilon_{i,t+k}, \quad (2)$$

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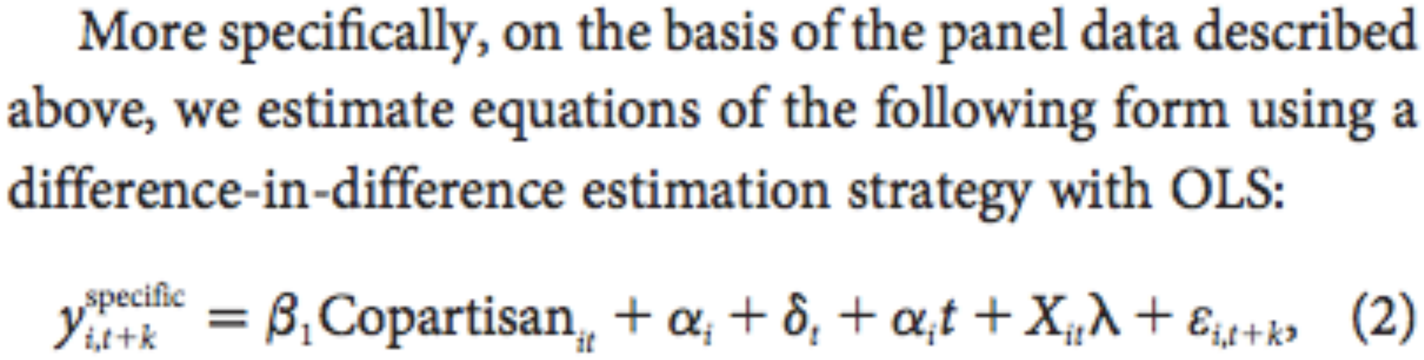

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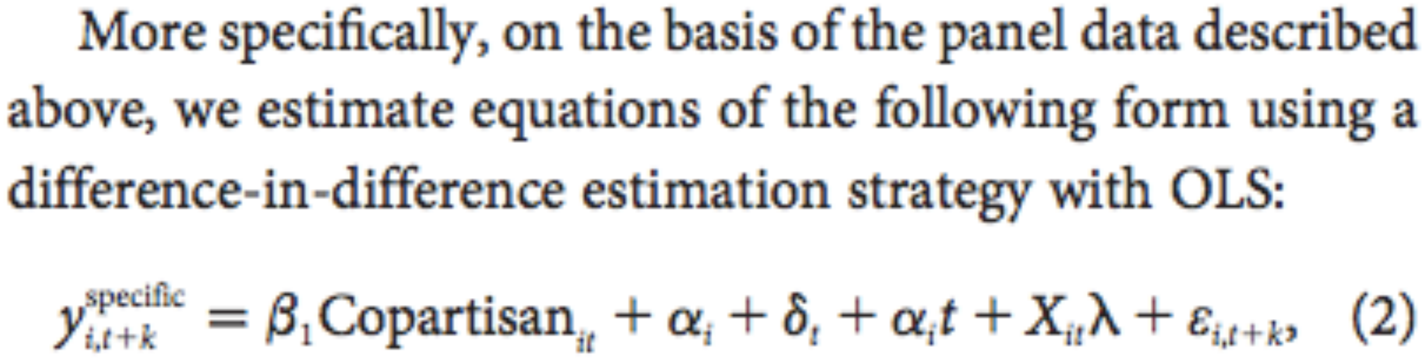

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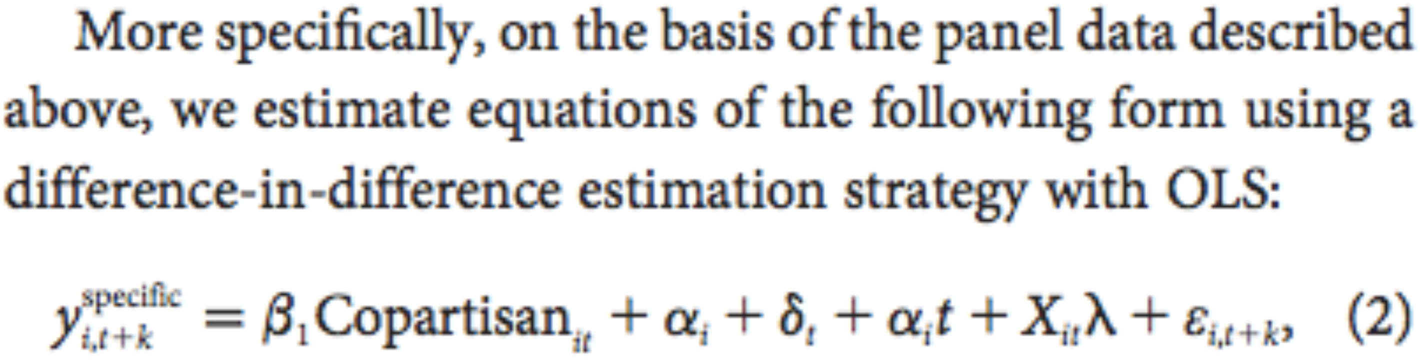

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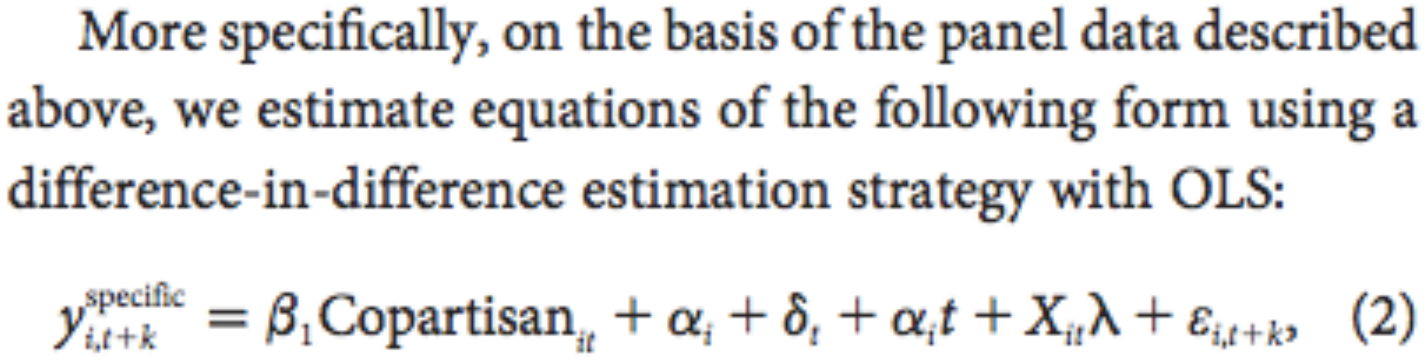

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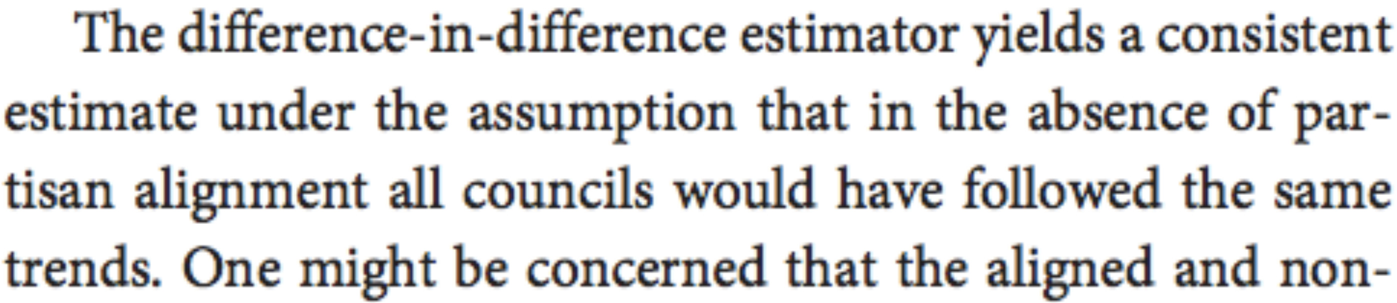
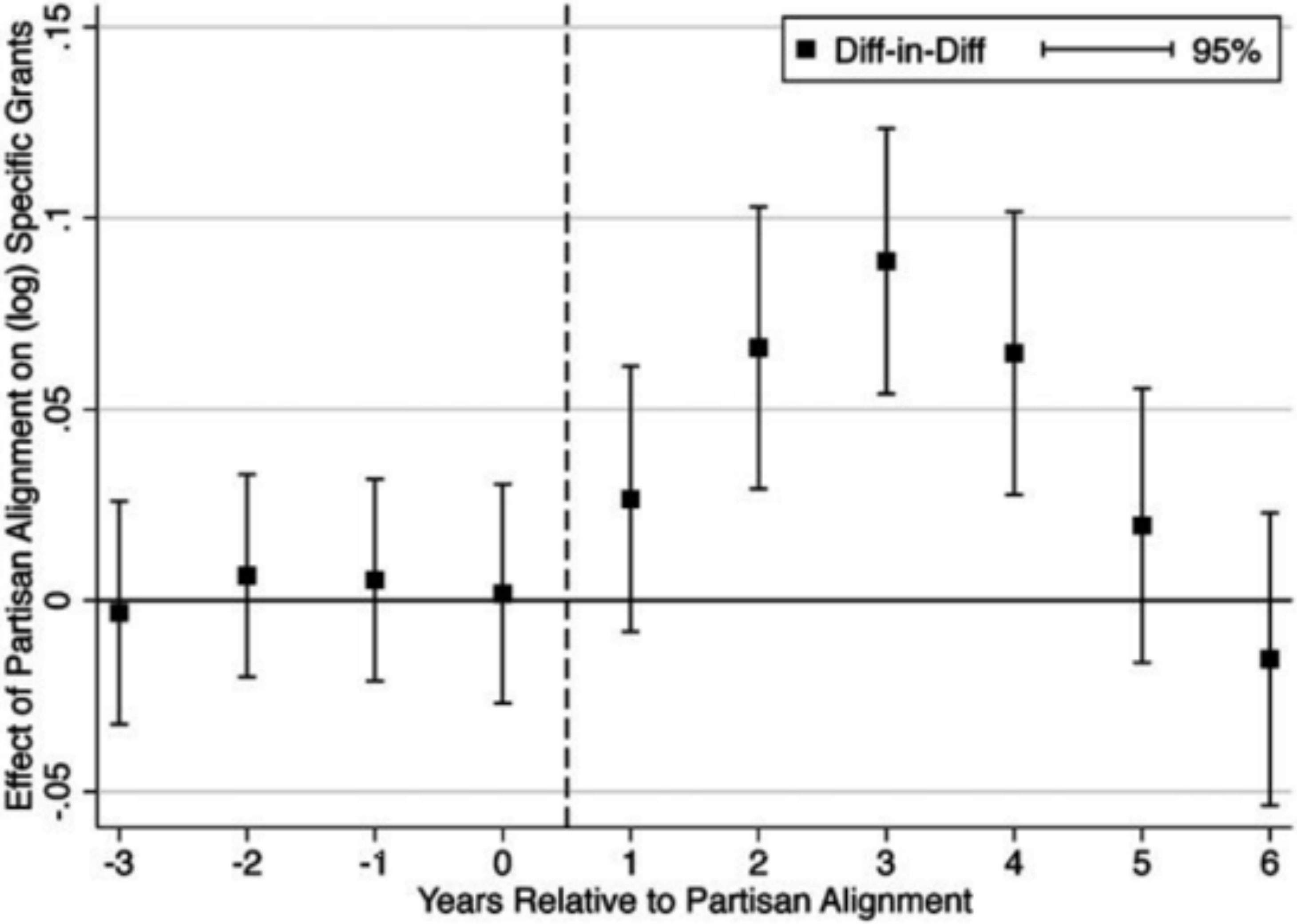
Statement of assumptions under which this gives the right answer (and possible violations of those assumptions):

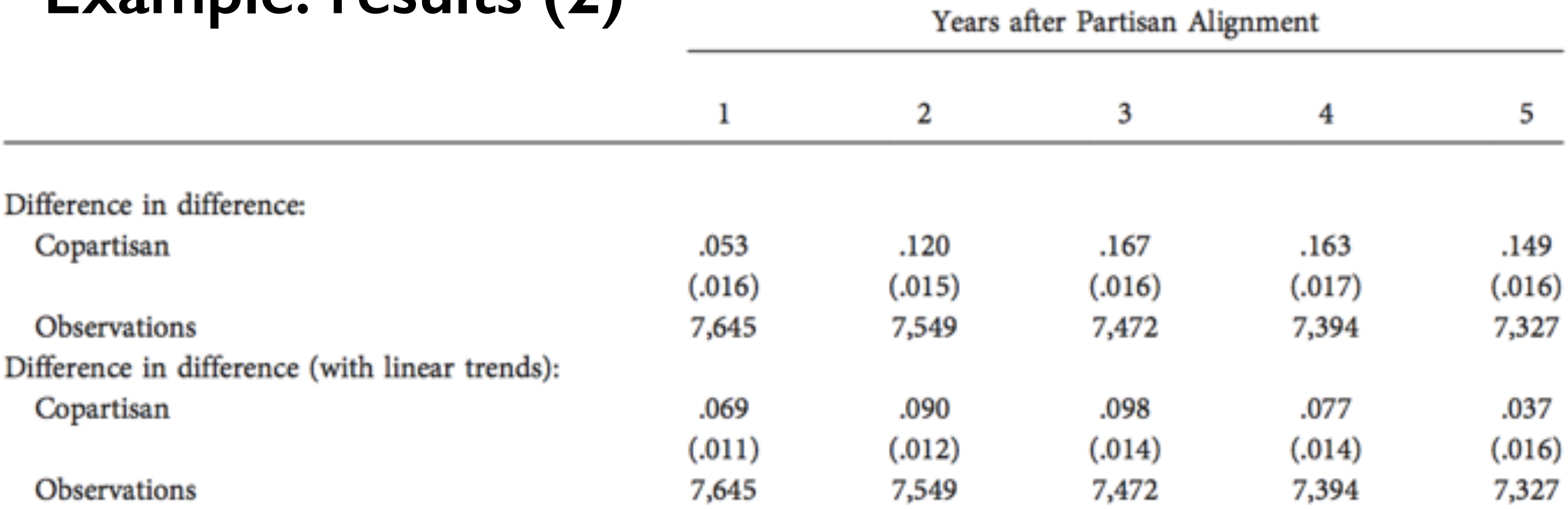


The difference-in-difference estimator yields a consistent estimate under the assumption that in the absence of partisan alignment all councils would have followed the same trends. One might be concerned that the aligned and non-

Example: results



Example: results (2)



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	1	2	3	4	5
Difference in difference:					
Copartisan	.053	.120	.167	.163	.149
	(.016)	(.015)	(.016)	(.017)	(.016)
Observations	7,645	7,549	7,472	7,394	7,327
Difference in difference (with linear trends):					
Copartisan	.069	.090	.098	.077	.037
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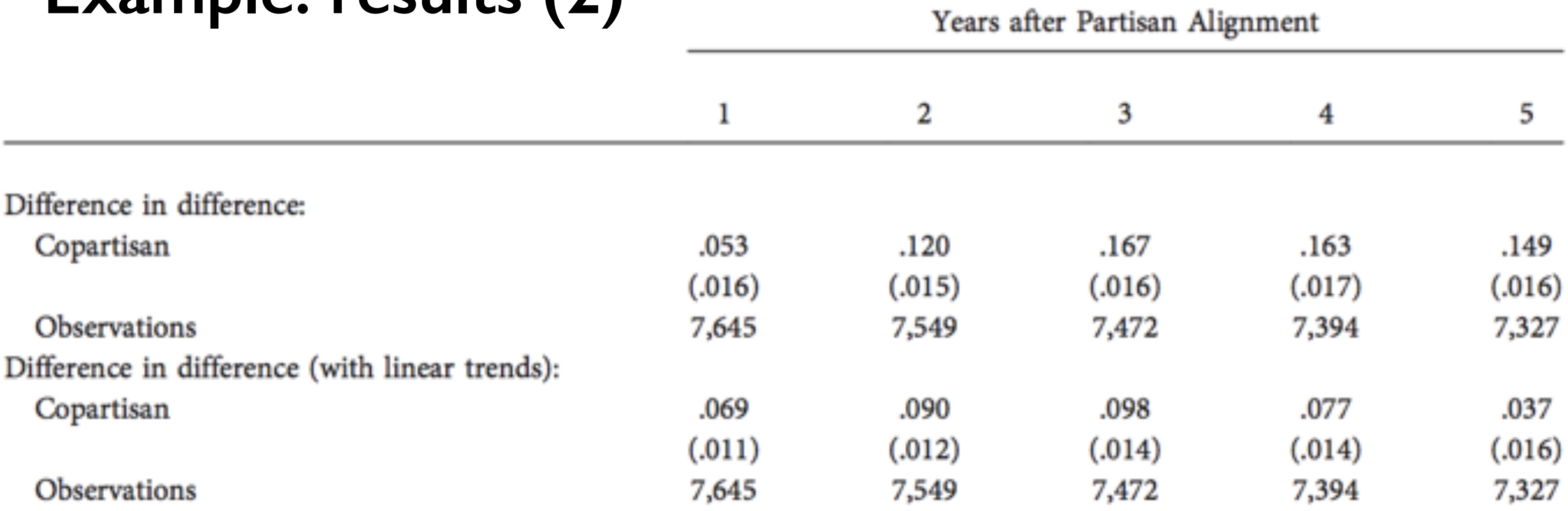

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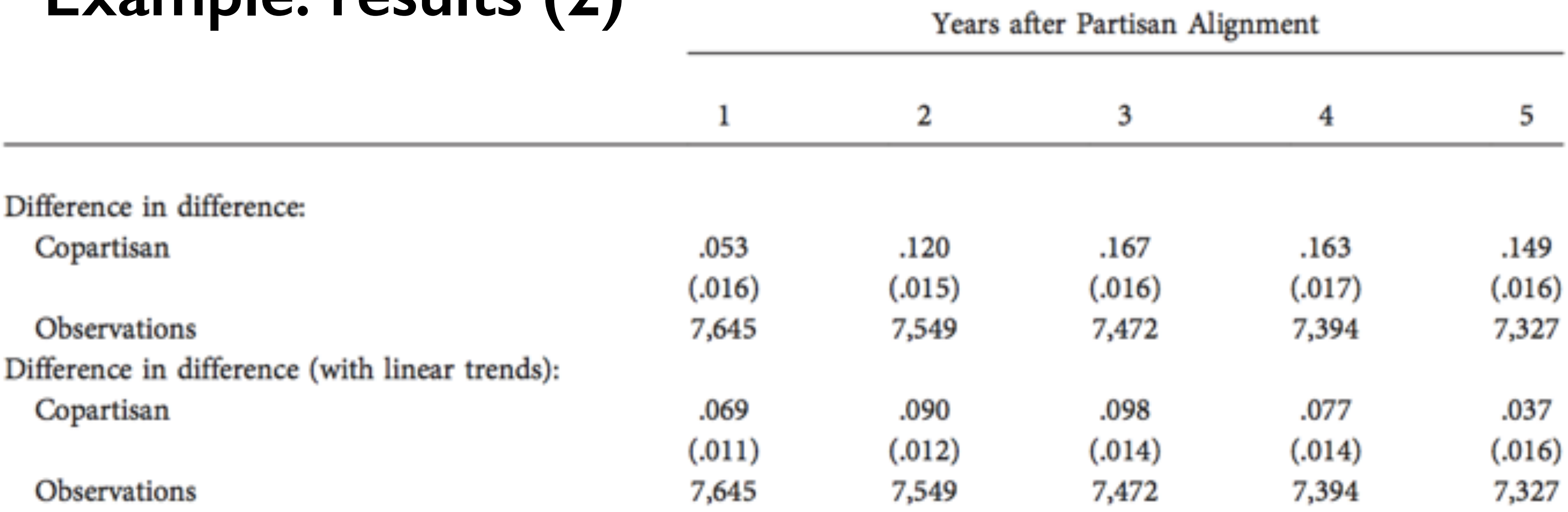

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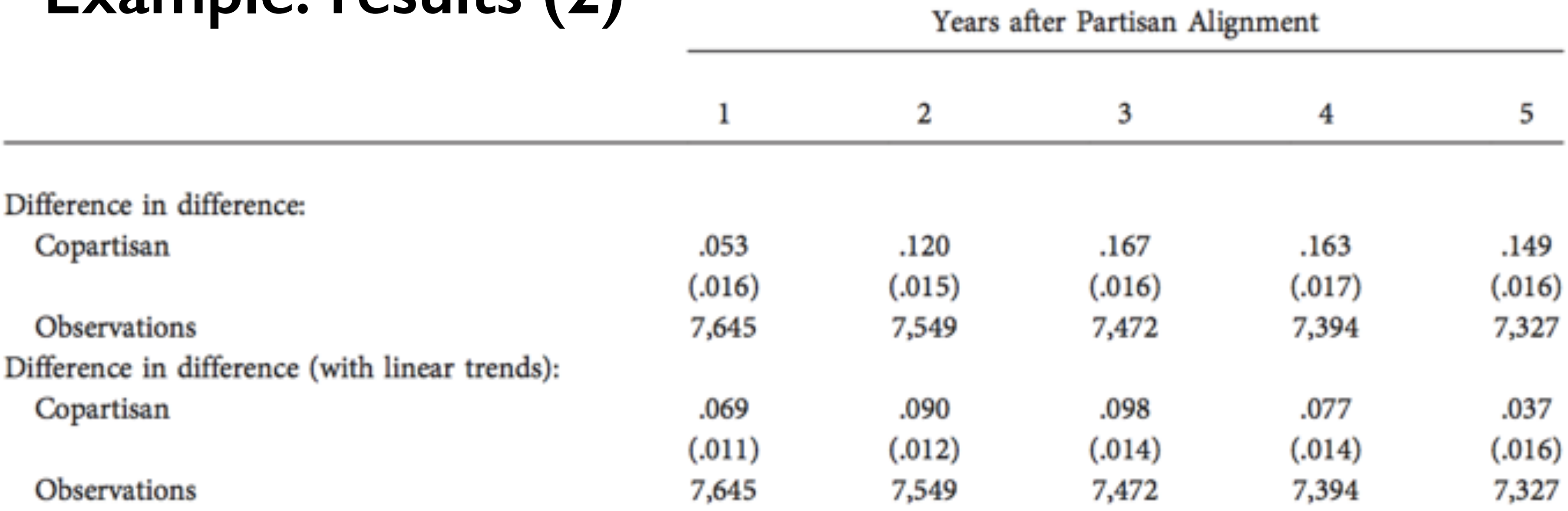

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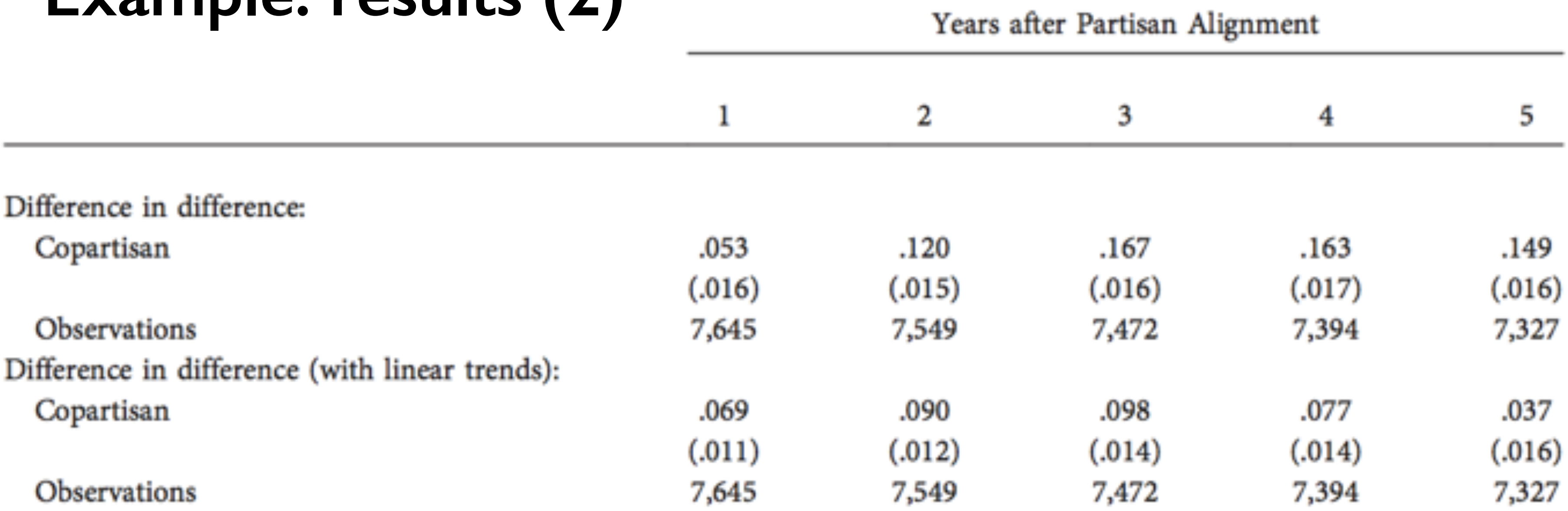

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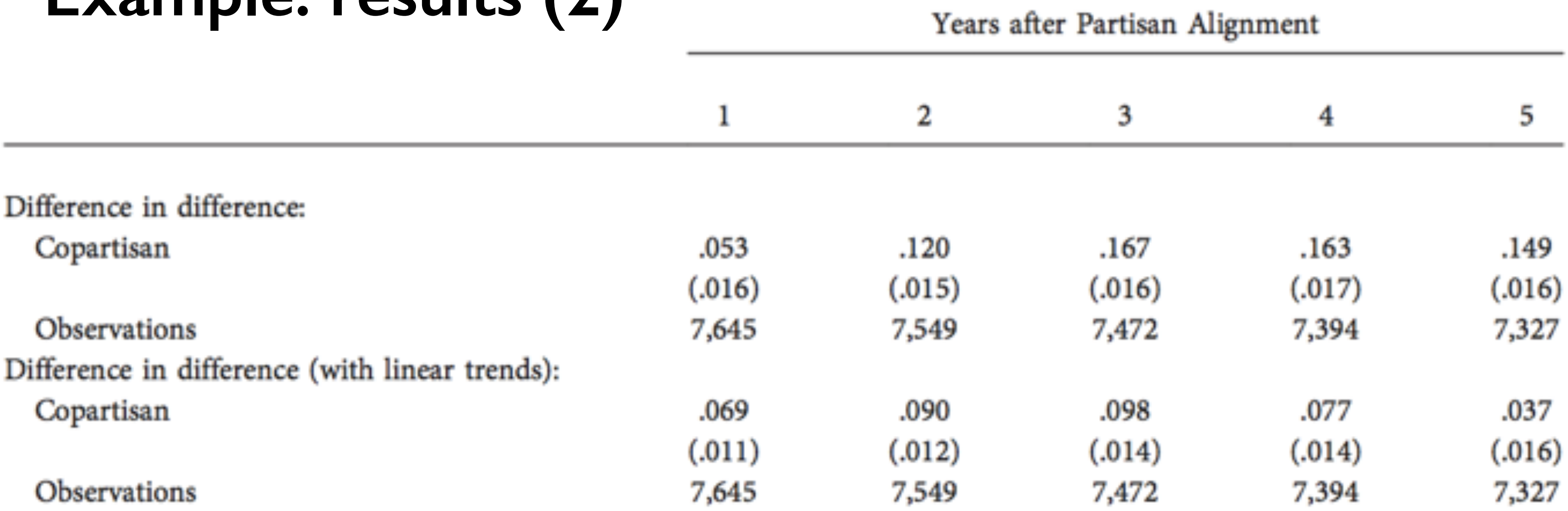

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They also do a “triple-difference” analysis, but this is not what people usually call a “triple-difference”.

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Suppose you do a classic diff-in-diff, but you know the parallel trends assumption probably doesn't hold.

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Example: bicycles offered to girls in Bihar to help them get to school. What about using diff-in-diff to estimate effect of program, using boys as control group? (Muralidharan and Prakash 2017)

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To deal with likely violation of parallel trends assumption, could do diff-in-diff in neighboring state (without program) and subtract first DiD from second DiD => triple-diff.

In what circumstances is this better than using girls in neighboring state as control group instead of boys in Bihar?

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- when the treatment’s effects are not too delayed, or are delayed in a consistent manner