Policy Evaluation

4. Child and Family Policies

Introduction to RDD

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Child Penalties

Kleven, Landais, et al. (2018, AEJ: AE) study the impacts of children on gender inequality in the labor market

The analysis is based on admin data for the full population in Denmark between 1980–2013 (going back to 1964)

The data contain rich information on children, earnings, labor supply, occupation, firms, education, and many other variables $\Rightarrow$ control for these effects (economic cycle, age,...)

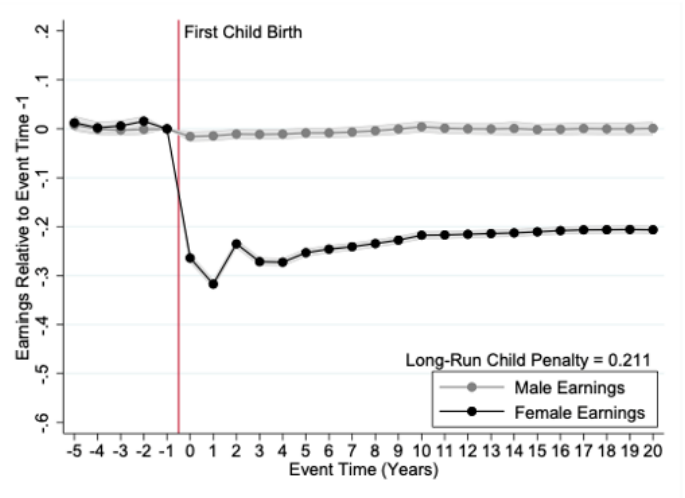
For each parent in the data, denote the year in which the individual has his/her first child by $t = 0$, and index all years relative to that year

It may be problematic to use men as a control group in a diff-in-diff given that they are also treated by the event, even if smoothness of male outcomes $\Rightarrow$ use those who never have children

Figure 2: Impacts of Children in the Very Long Run

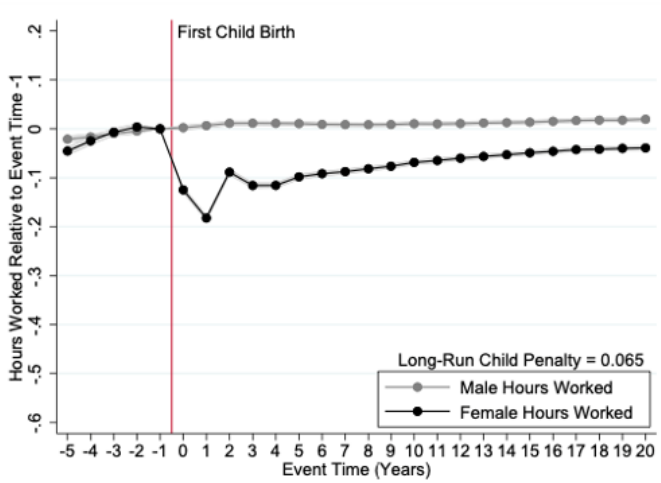
A: Earnings

20 Years After Child Birth



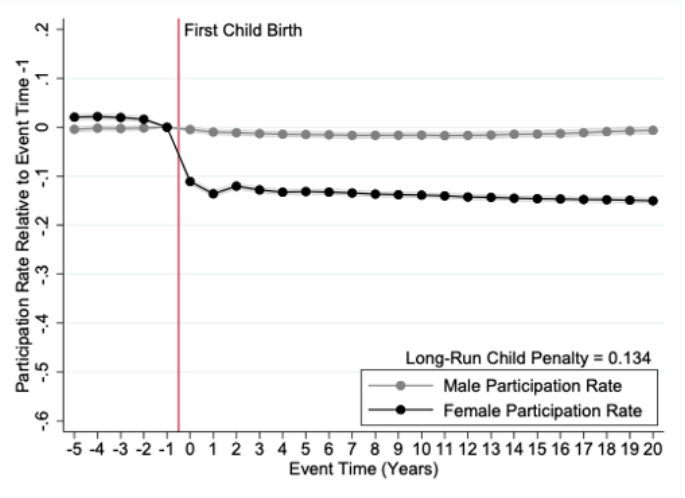
B: Hours Worked

20 Years After Child Birth



C: Participation Rates

20 Years After Child Birth



D: Wage Rates

20 Years After Child Birth

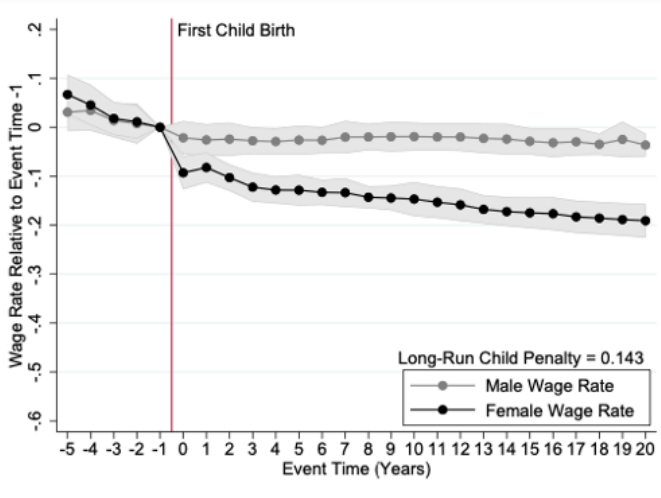
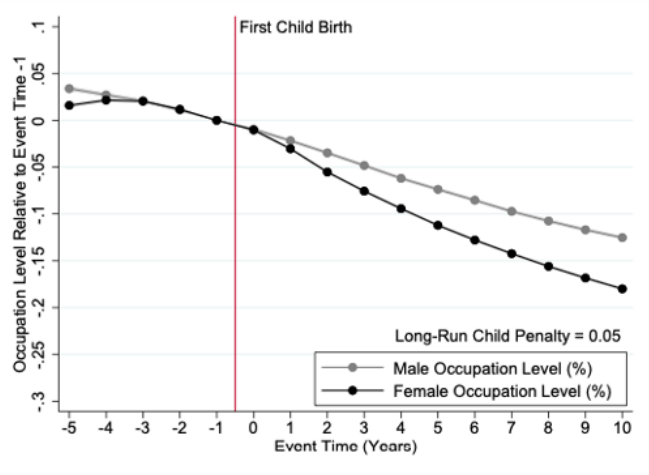


Figure 3: Anatomy of Child Impacts

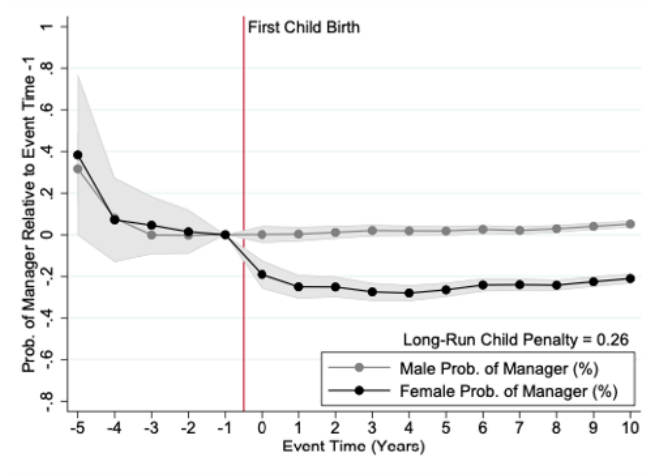
A: Occupational Rank

Levels 1-5 from Unskilled Labor to Manager



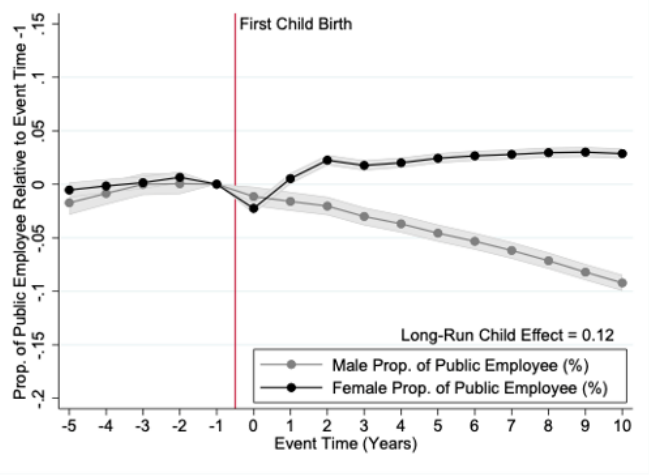
B: Probability of Being Manager

Manager Dummy



C: Probability of Public Sector Job

Public Sector Dummy



D: Probability of Having a Female Manager with Children

Female Manager with Children Dummy

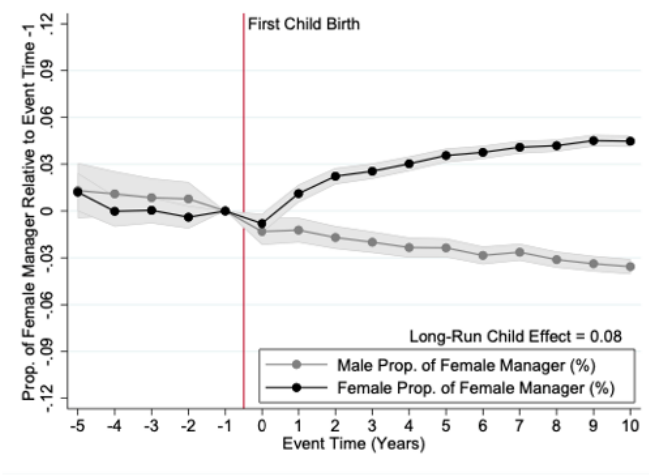


Figure 2: Child Penalties in Earnings in English-Speaking Countries

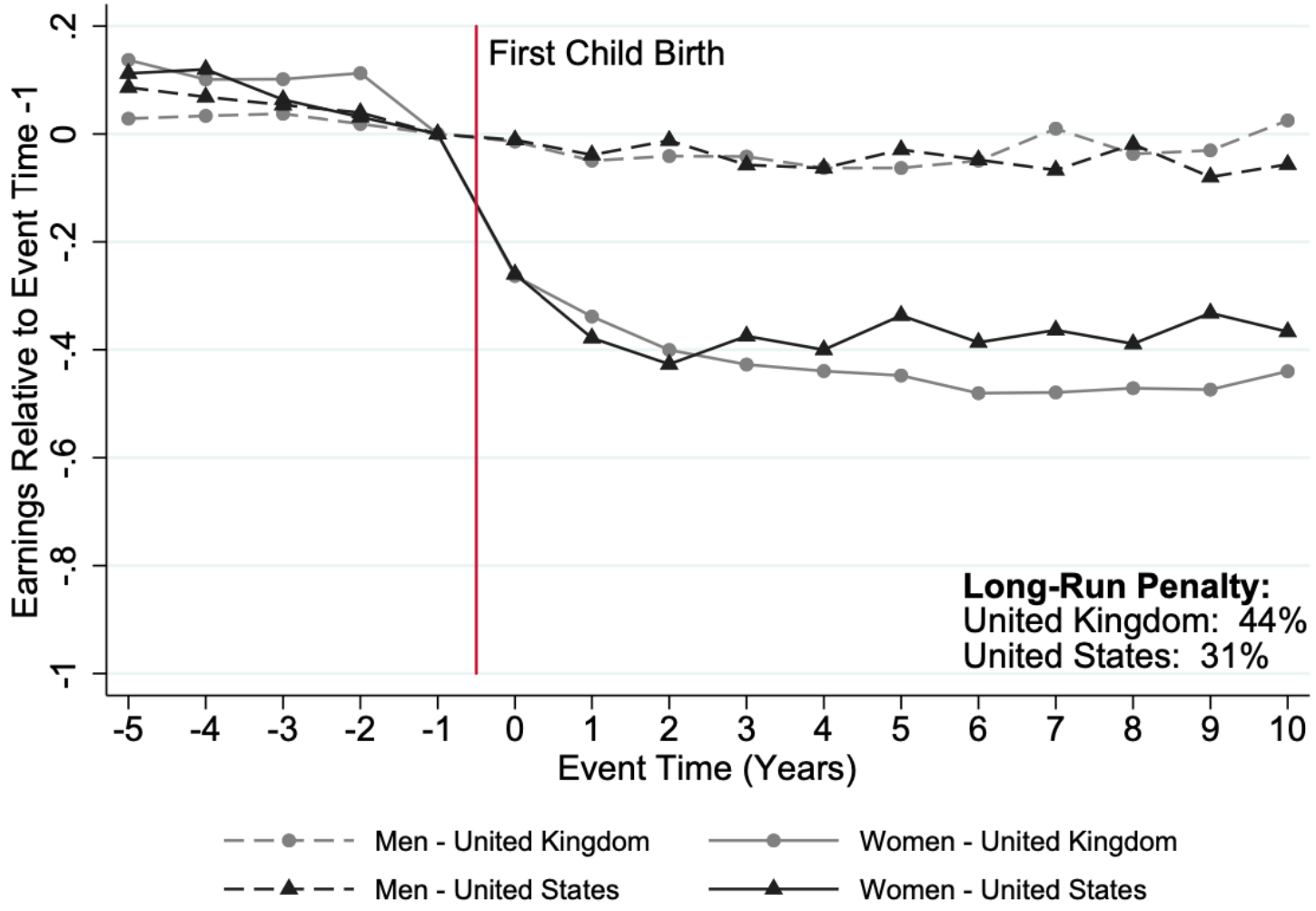
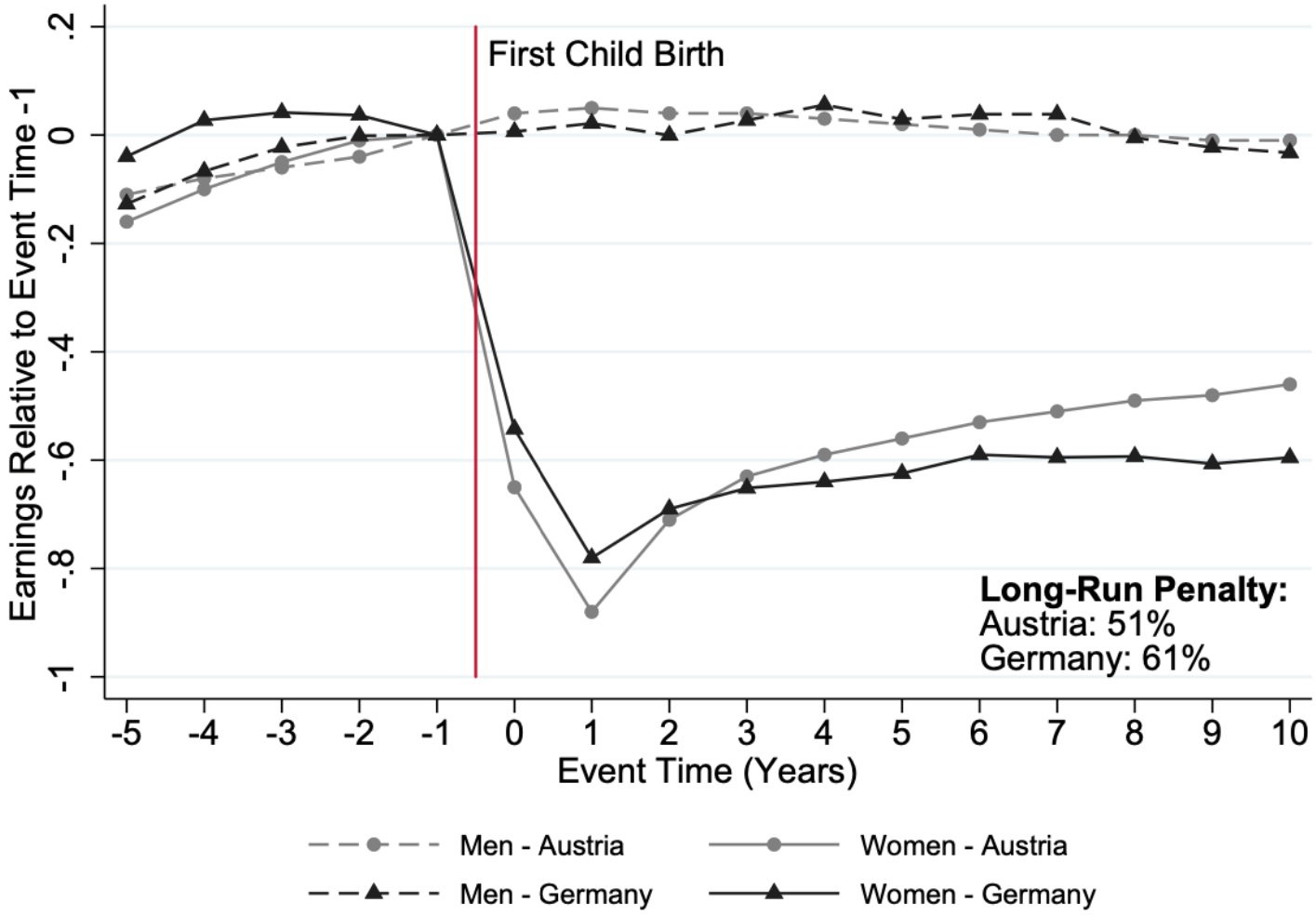


Figure 3: Child Penalties in Earnings in German-Speaking Countries



Possible explanations

1. Biology

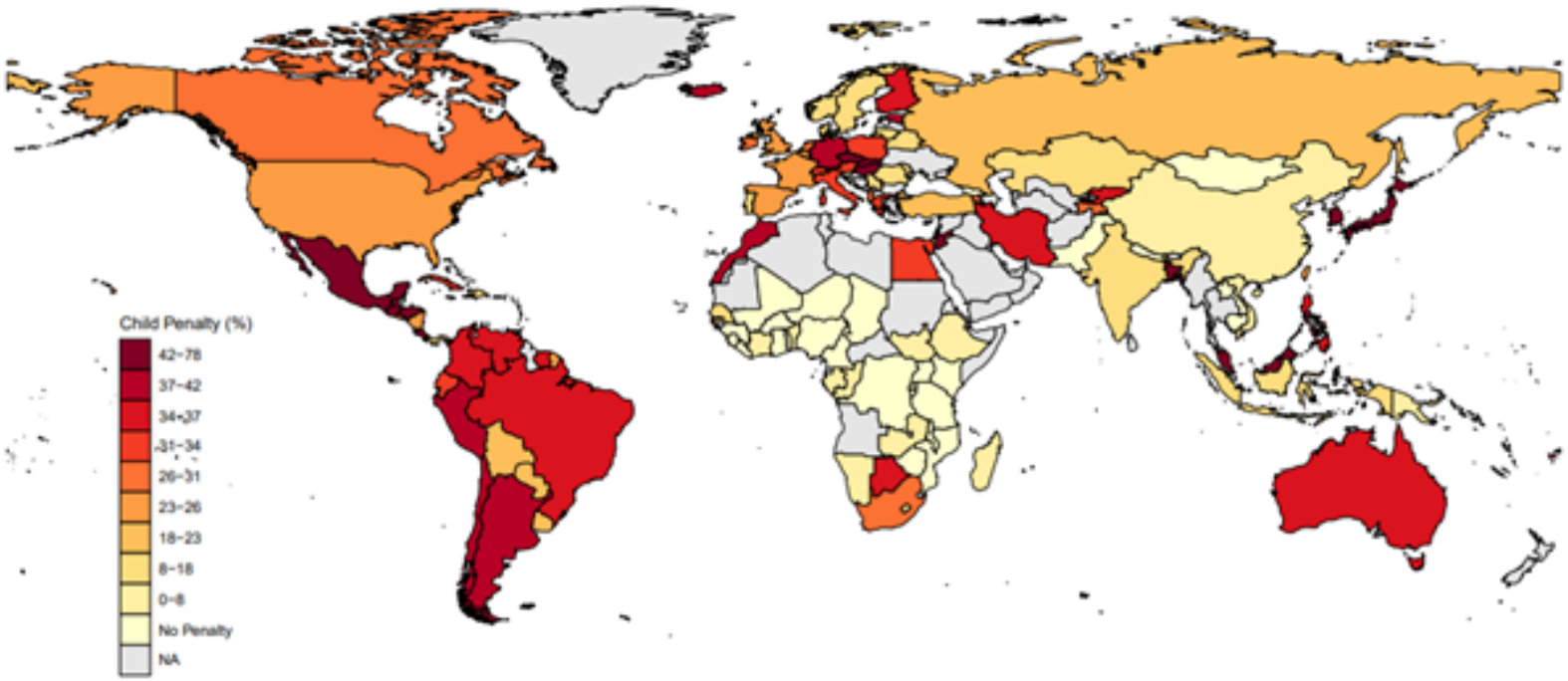
• Hard-wired (but then why so many regional disparities?)

• Birth-related: pregnancy changing hormone levels and then there are labor-market dynamic effects...

How can we test that?

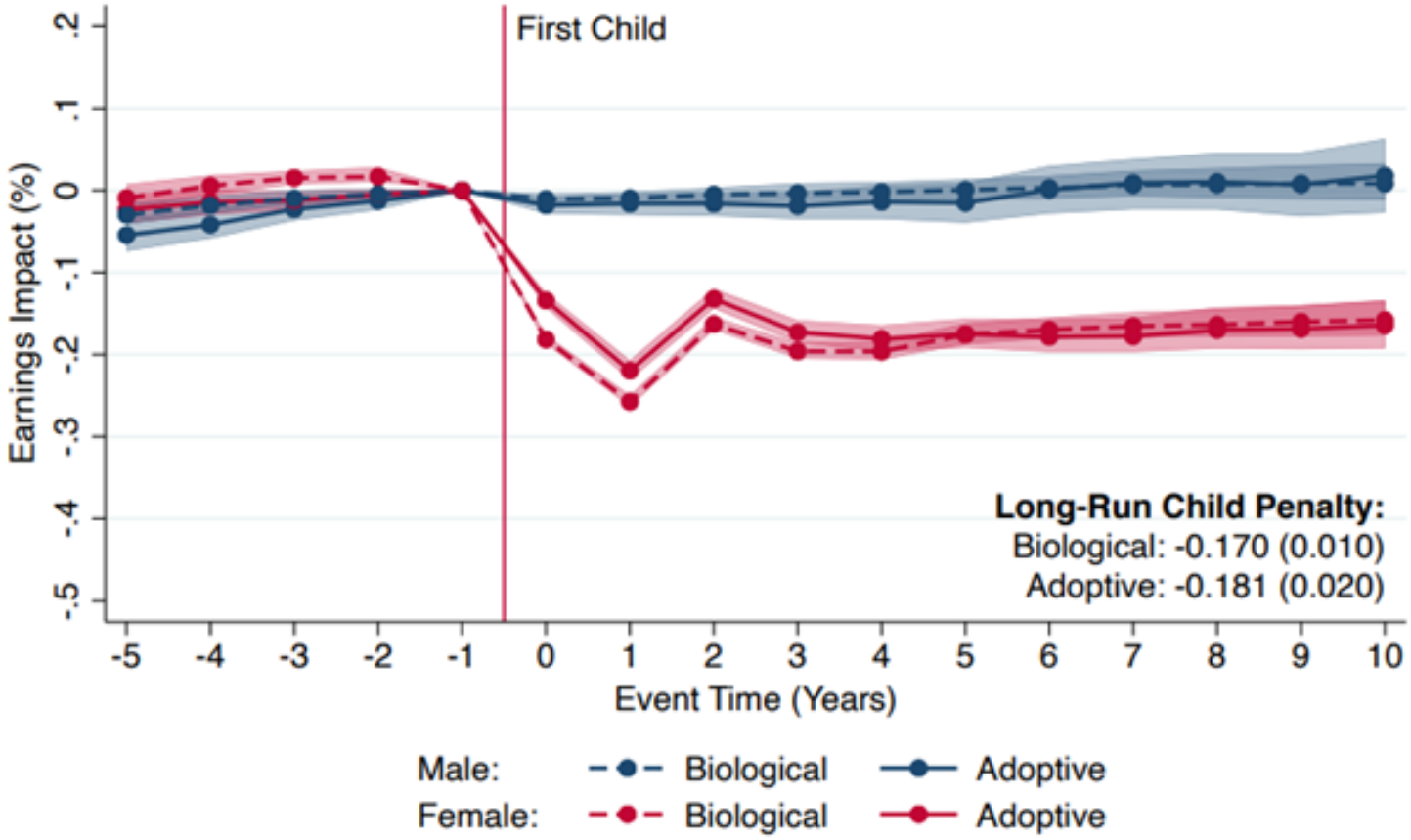
World Map of Child Penalties

Employment Penalties



Biological vs Adoptive Families in Denmark

Earnings Penalties



Possible explanations

1. Biology

- Hard-wired (but then why so many regional disparities?)
- Birth-related

2. Comparative Advantage and specialisation

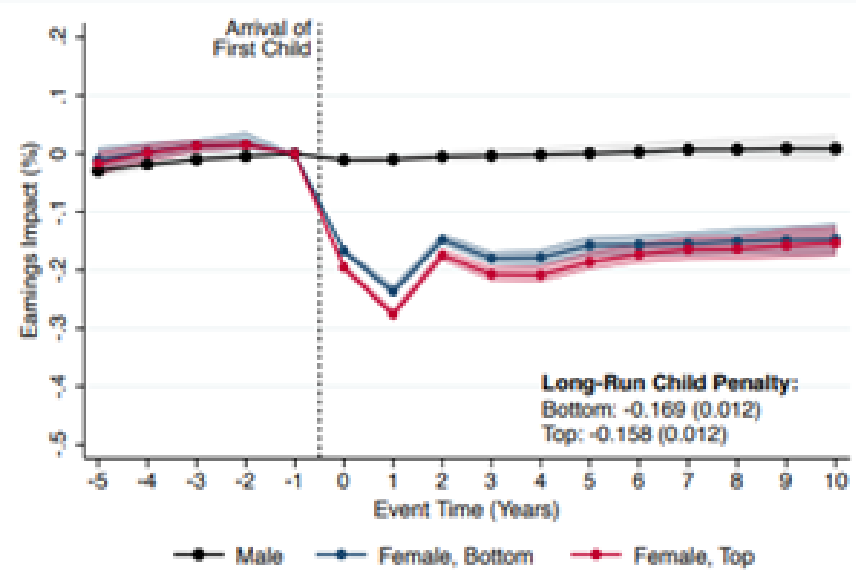
- Education and earnings capacity

How can we test that?

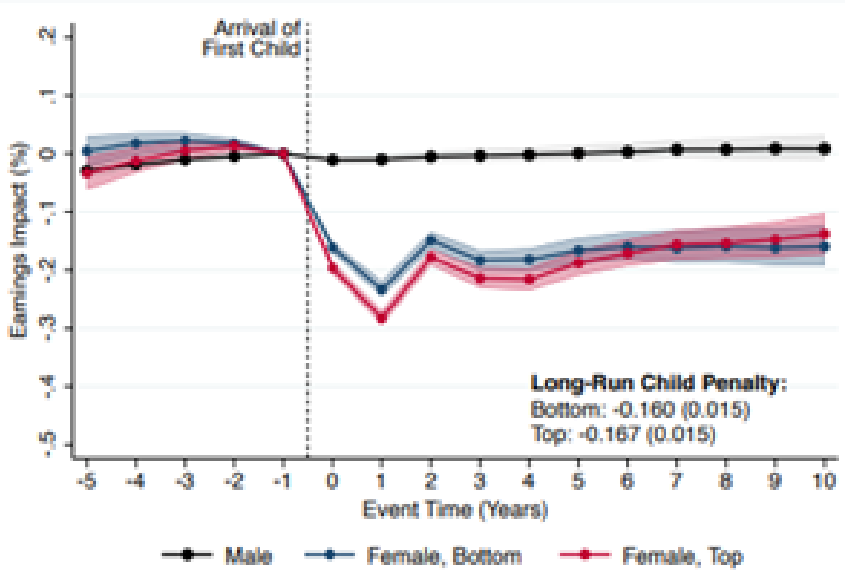
Child Penalties by Female Earnings Capacity

Using Education Degree/Field to Predict Earnings Capacity (Danish Data)

Top vs Bottom Half of
Female Earnings Capacity (Relative to Males)



Top vs Bottom Quartile of
Female Earnings Capacity (Relative to Males)



Possible explanations

1. Biology

2. Comparative Advantage and specialisation

3. Public Policy (survey Olivetti and Petrongolo (2017, JEP))
- Parental leave
- Child care
- Welfare

4. Employer Discrimination

5. Gender Norms and Culture

6. General Equilibrium
- Child care: family network (informal), market-provision
- Job flexibility: industrial composition, family friendliness

Is the child penalty also a (self-reported) Happiness penalty?

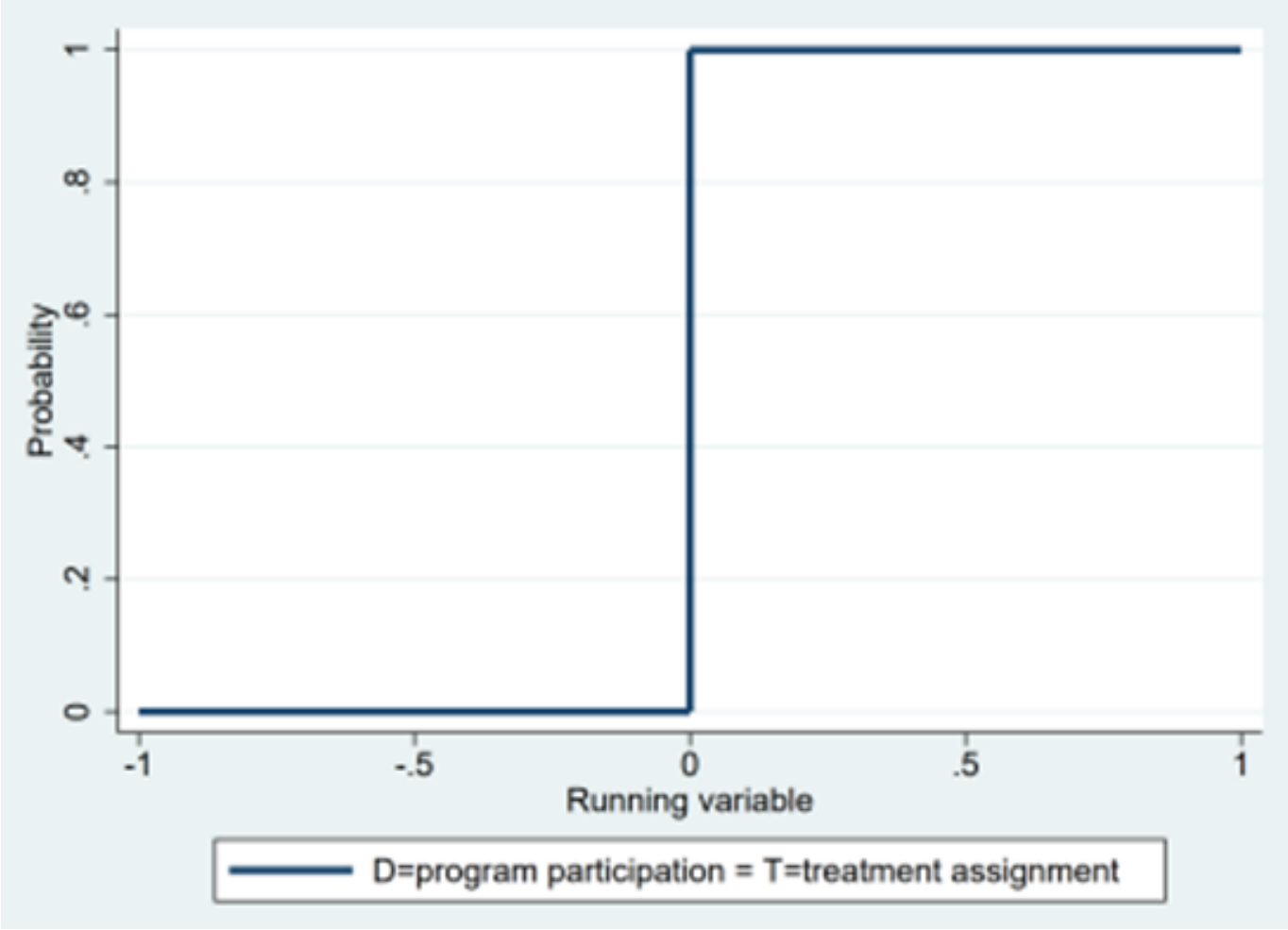
Regression discontinuity - basic idea

A precise rule based on a continuous characteristic determines participation in a program. Some examples, but surely more:

- Academic test scores: scholarships or prizes, higher education admission, certificates of merit
- Poverty scores: (proxy-)means-tested anti-poverty programs
- Any program targeting that features rounding or cutoffs
- Land area: fertilizer program or debt relief initiative for owners of plots below a certain area
- Date: age cutoffs for pensions; dates of birth for starting school with different cohorts; date of loan to determine eligibility for debt relief
- Elections: fraction that voted for a candidate/ party

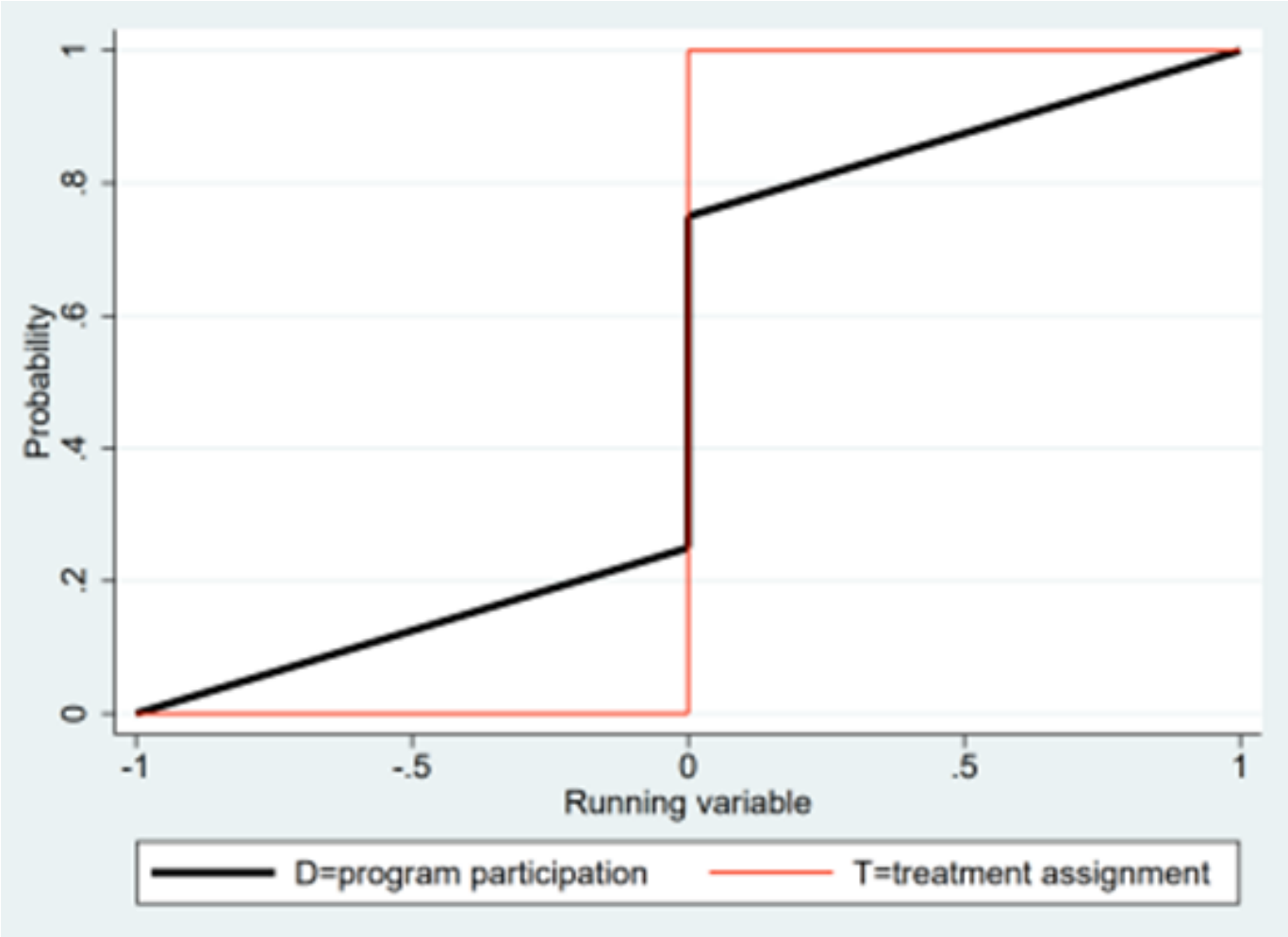
Assuming treatment offered above a certain threshold:

Sharp RDD



Everyone follows treatment assignment rule (all are compliers)

Fuzzy RDD



Partial compliance around cutoff

Attending a good university

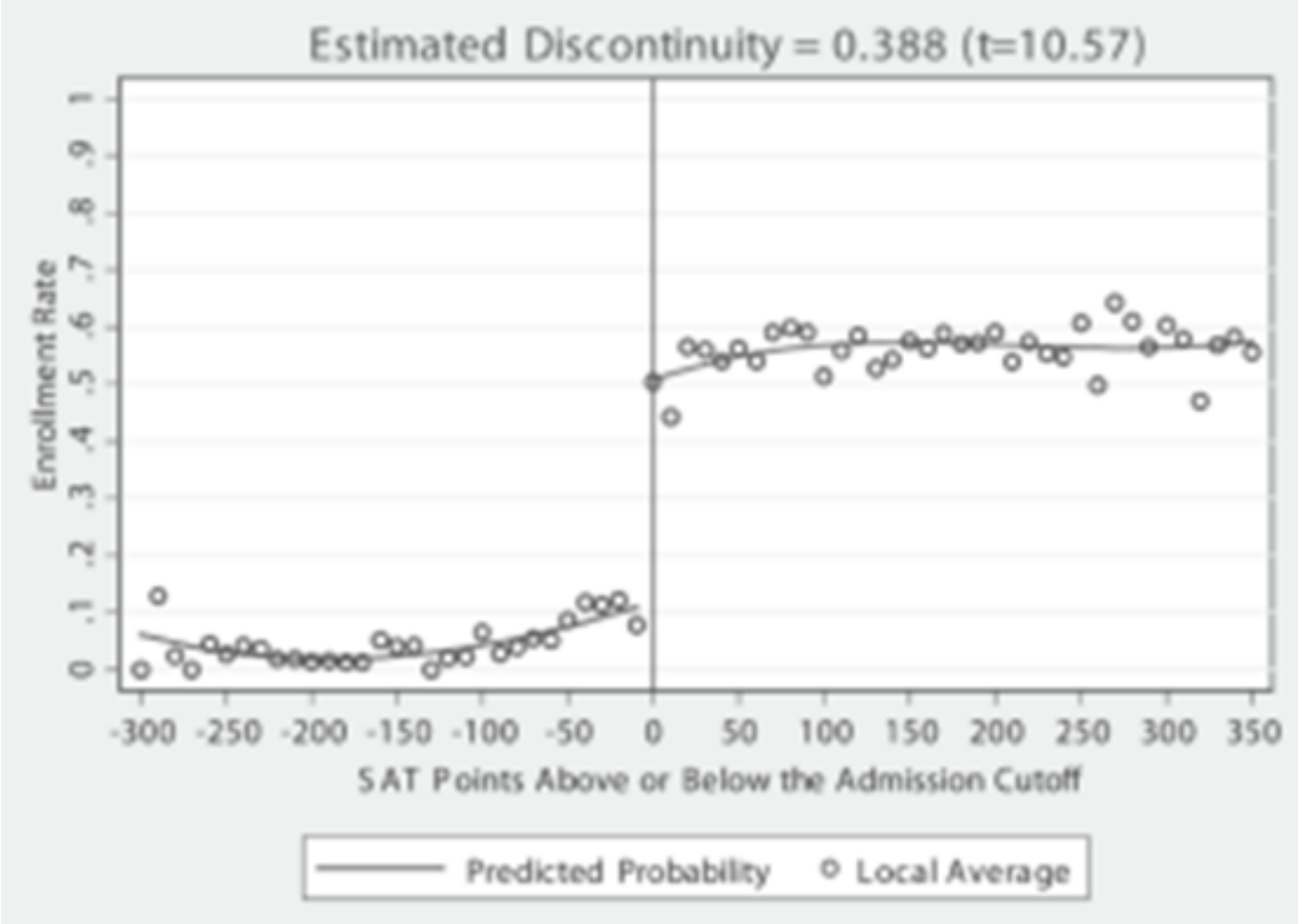
Hoekstra (2009) "The Effect of Attending the Flagship State University on Earnings: A Discontinuity-Based Approach", REStat

The paper demonstrates RD idea by examining the economic return of attending the most selective public state university in the US

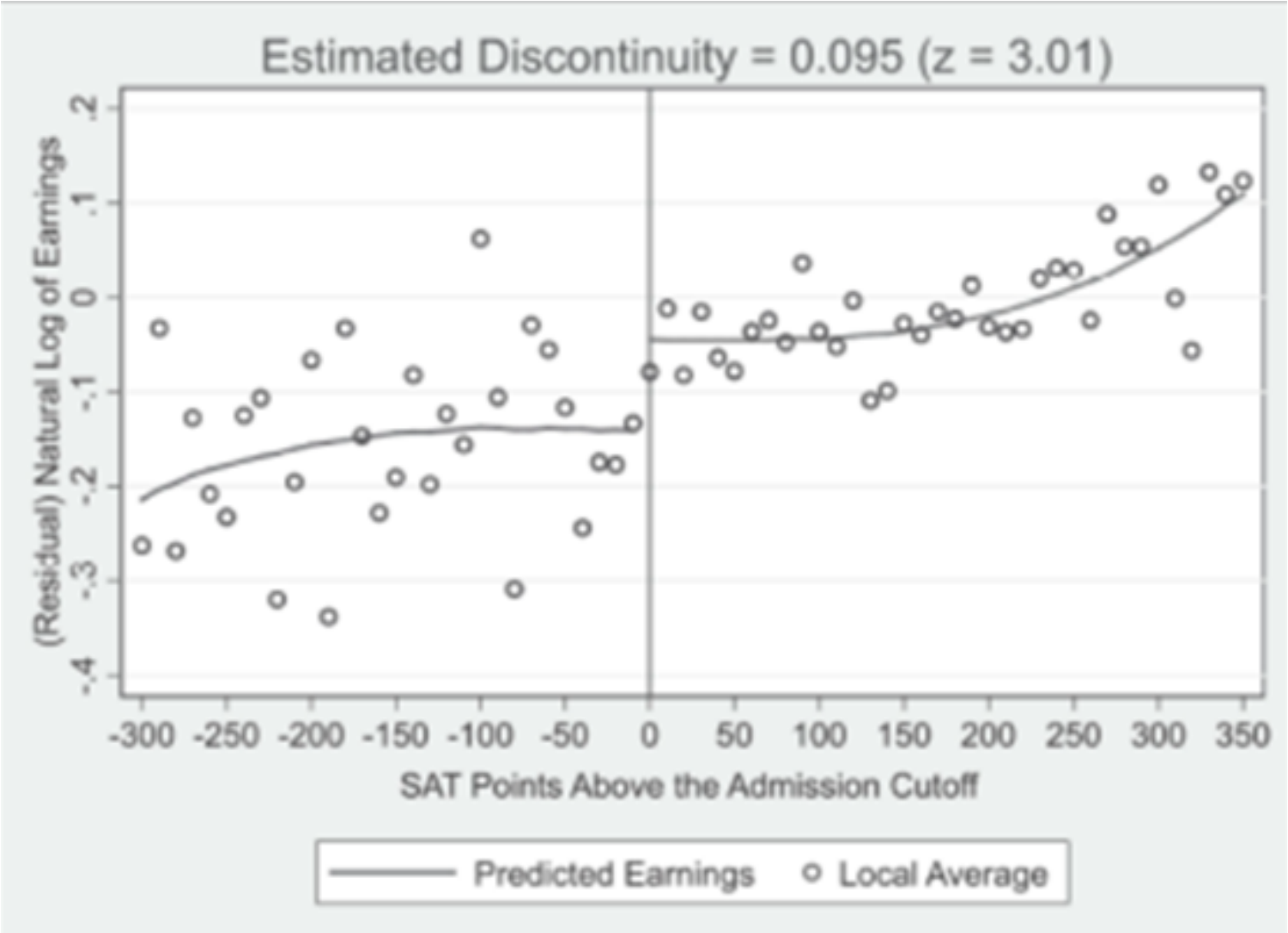
The flagship state university considered in this paper uses a strict cutoff based on SAT score

The author matched (using social security numbers) students applying to the flagship university in 1986-89 to their administrative earnings data for 1998 to 2005

1st stage: Enrollment



2nd stage: Future earnings



Some decisions

1. How to select the bandwidth? Usually we use the optimal bandwidth proposed by CCT considering the trade-off between precision and accuracy
Larger bandwidth $\Rightarrow$ more precise treatment effect estimates since more data points are used in the regression. But the specification is less likely to be accurate and the estimated treatment effect could be biased

2. Linear? Quadratic? Higher polynomials?
Show robustness. There are some criteria (Akaike). Check CCT RDD papers

Parental Leave Reforms in Sweden

Persson and Rossin-Slater (2019) study impact of paternal leave on maternal health

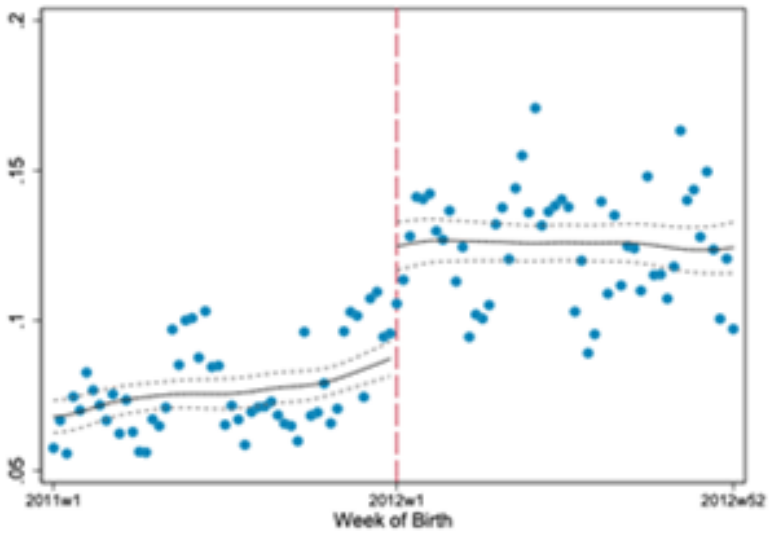
Prior to reform, parents given 16 months paid leave to be shared across both parents
However, parents were not allowed to both be on leave at the same time

"Double days" reform in Sweden allowed fathers to choose whether to claim paid leave on a day-to-day basis, independent of whether the mother was on leave

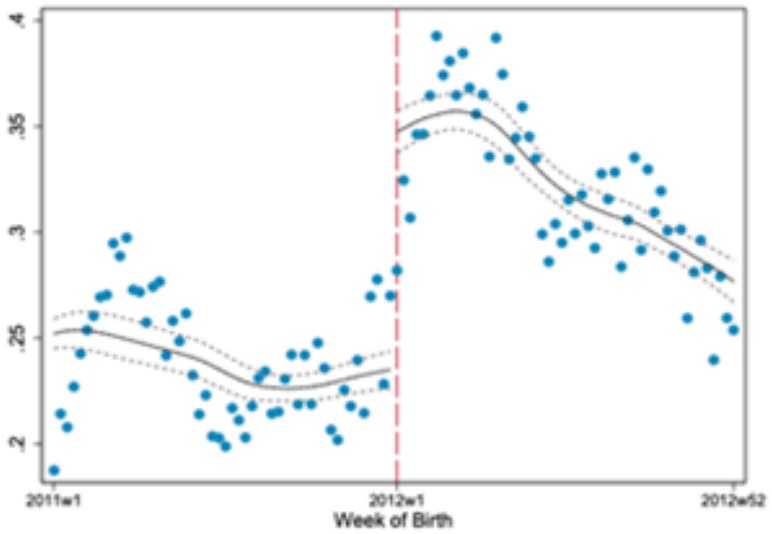
Again, a threshold so they compute a RDD

Figure 3: Effects of 2012 "Double Days" Reform on Paternity Leave Take-Up

(a) Any Post-Baseline Leave in First 60 Days



(b) Any Post-Baseline Leave in First 180 Days



(c) Tot. # Leave Days in First 180 Days

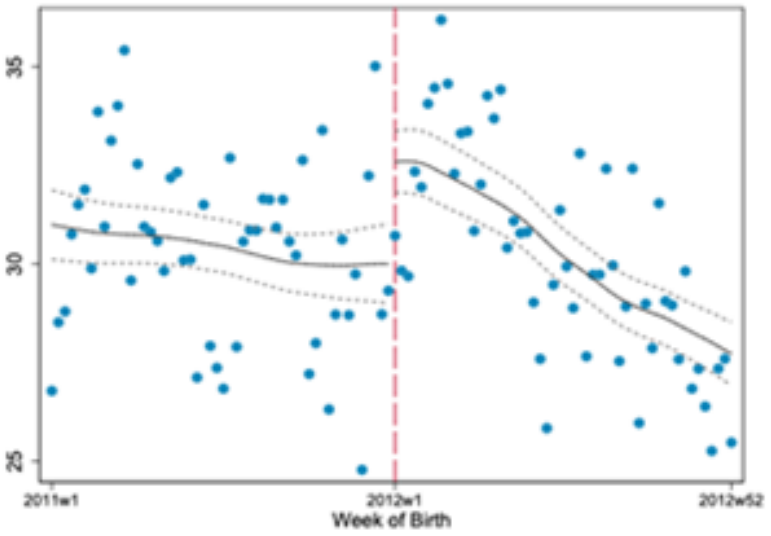
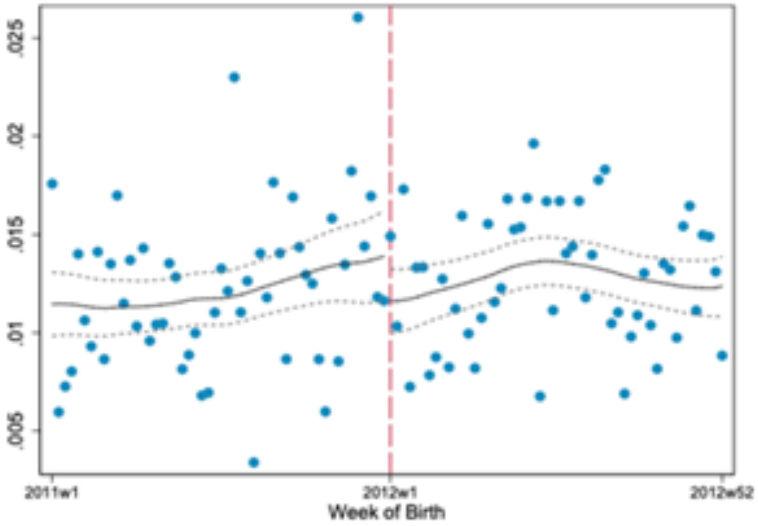
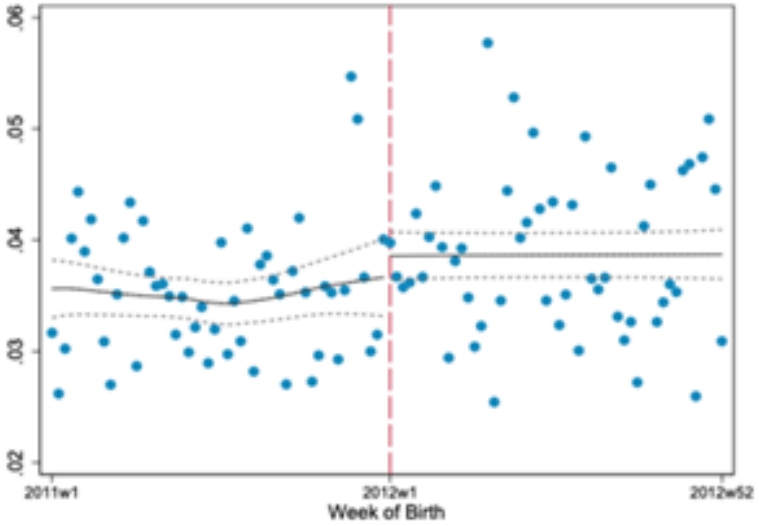


Figure 5: Effects of 2012 "Double Days" Reform on Maternal Health Outcomes in First 180 Days Post-Childbirth, Prescription Drug Data

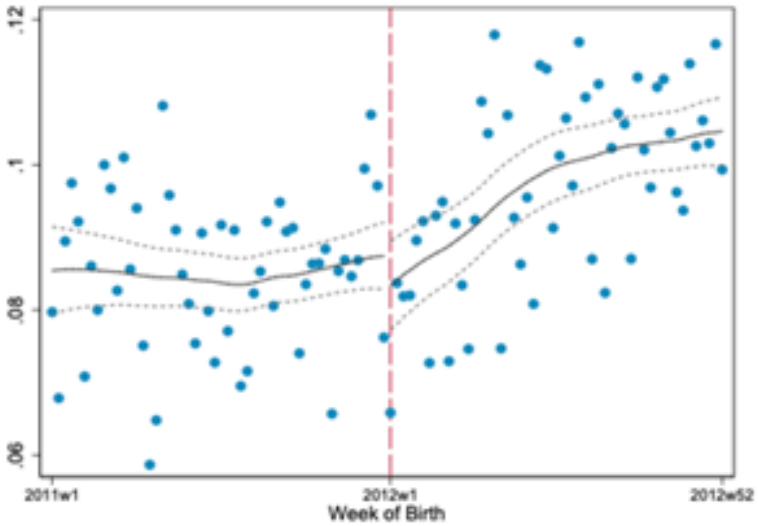
(a) Any Anti-Anxiety Drug



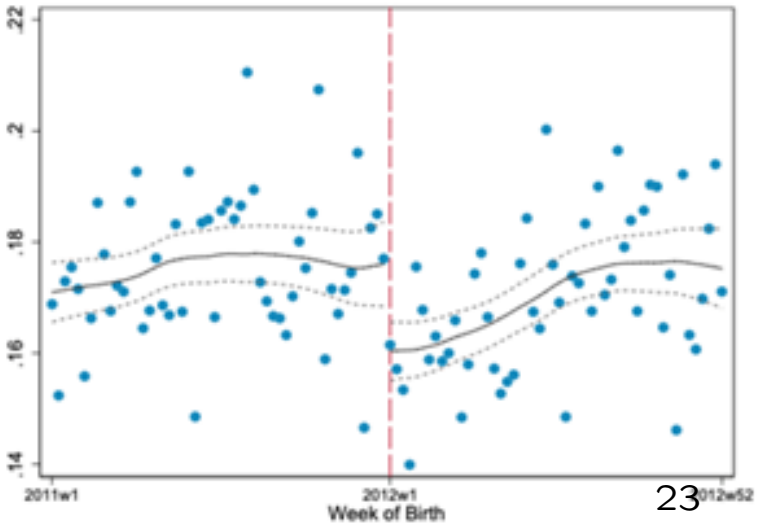
(b) Any Anti-Depressant Drug



(c) Any Painkiller Drug



(d) Any Antibiotic Drug



Main assumption

The Continuity assumption can be violated if:

1. There are differences between the individuals who are just below and above the cutoff that are NOT explained by the treatment.
The same cutoff is used to assign some other treatment.
Other factors also change at cutoff.

One example...

"Can Close Election Regression Discontinuity Designs Identify Effects of Winning Politician Characteristics?"

A particularly popular version of the RDD uses close elections to estimate effects of a specific characteristic of elected politicians on policy and constituent outcomes

Marshall (2022, AJPS) shows that RDD identify the effect of the specific characteristic of interest and all compensating differentials, i.e. candidate-level characteristics that ensure elections remain close between candidates who differ in the characteristic of interest

Estimates are not biased if the characteristic of interest does not affect candidate vote shares or if no compensating differential (e.g., competence) affects the outcome

"Gender is a particularly challenging example." The relevant counterfactual for isolating the effect of gender is equally competent men who win elections against women

Main assumption

The Continuity assumption can be violated if:

1. There are differences between the individuals who are just below and above the cutoff that are NOT explained by the treatment.
The same cutoff is used to assign some other treatment.
Other factors also change at cutoff.

2. Sorting: Individuals can fully manipulate the running variable in order to gain access to the treatment or to avoid it.

How can we test this? McCrary (2008, ECMA) test

One example...

Sorting/ bunching effects

Camacho and Conover (2011) "Manipulation of Social Program Eligibility" AEJ: Economic Policy

A poverty index is used to decide eligibility for social programs in Colombia

The algorithm to create the poverty index becomes public during the second half of 1997

In this case, RDD does not give the treatment effect of receiving the program

1994
1995
1996
1997
Percent
0
1
2
3
4
5
6
0 7 14 21 28 35 42 49 56 63 70 77 84 91 98
Poverty index score

1998
Percent
0
1
2
3
4
5
6
0 7 14 21 28 35 42 49 56 63 70 77 84 91 98
Poverty index score

1999
Percent
0
1
2
3
4
5
6
0 7 14 21 28 35 42 49 56 63 70 77 84 91 98
Poverty index score

2000
Percent
0
1
2
3
4
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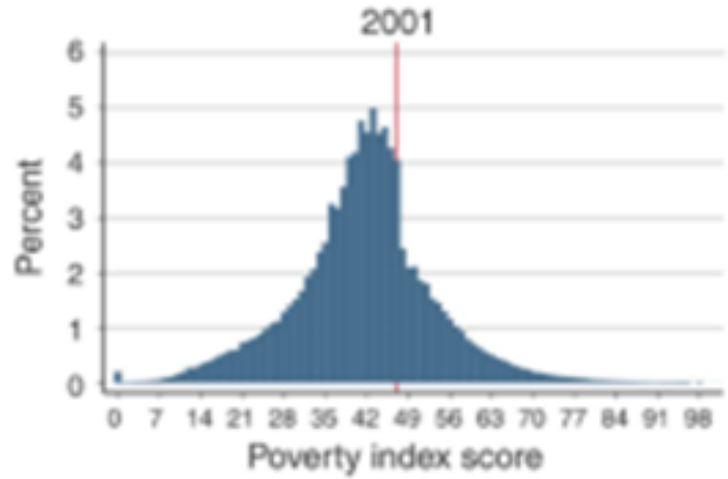
0 7 14 21 28 35 42 49 56 63 70 77 84 91 98
Poverty index score


2001
Percent
0
1
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0 7 14 21 28 35 42 49 56 63 70 77 84 91 98
Poverty index score