Lecture 11

Deforestation // Regression discontinuity

Ivan Rudik
AEM 6510

Roadmap

- Can we exploit situations when we know the mechanism for treatment assignment?
  - Can we exploit situations where some units are just above some threshold to get treatment, and others are just below the threshold?
  - Do deforestation policies work?

Regression discontinuity

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Here we will understand one way we can break this bias by exploiting **discontinuities**

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If a county goes above one of these thresholds, call them c_0, it is deemed to be in **non-attainment**

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Non-attainment counties had **much** greater pollution reductions during the 1970s and 1980s compared to attainment counties (Chay and Greenstone, 2005)

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In the absence of this policy we might expect counties with $c_0 + \epsilon$ levels of pollution to be similar to counties with $c_0 - \epsilon$ in terms of **all other factors** (on average)

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Thus any differences in property values is likely due to the NAAQS-induced decline in pollution in non-attainment counties

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The subsequent difference in other outcomes we may consider **as good as random**

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In RDD the jump is the chance of being put into treatment (in our example, under more regulatory scrutiny)

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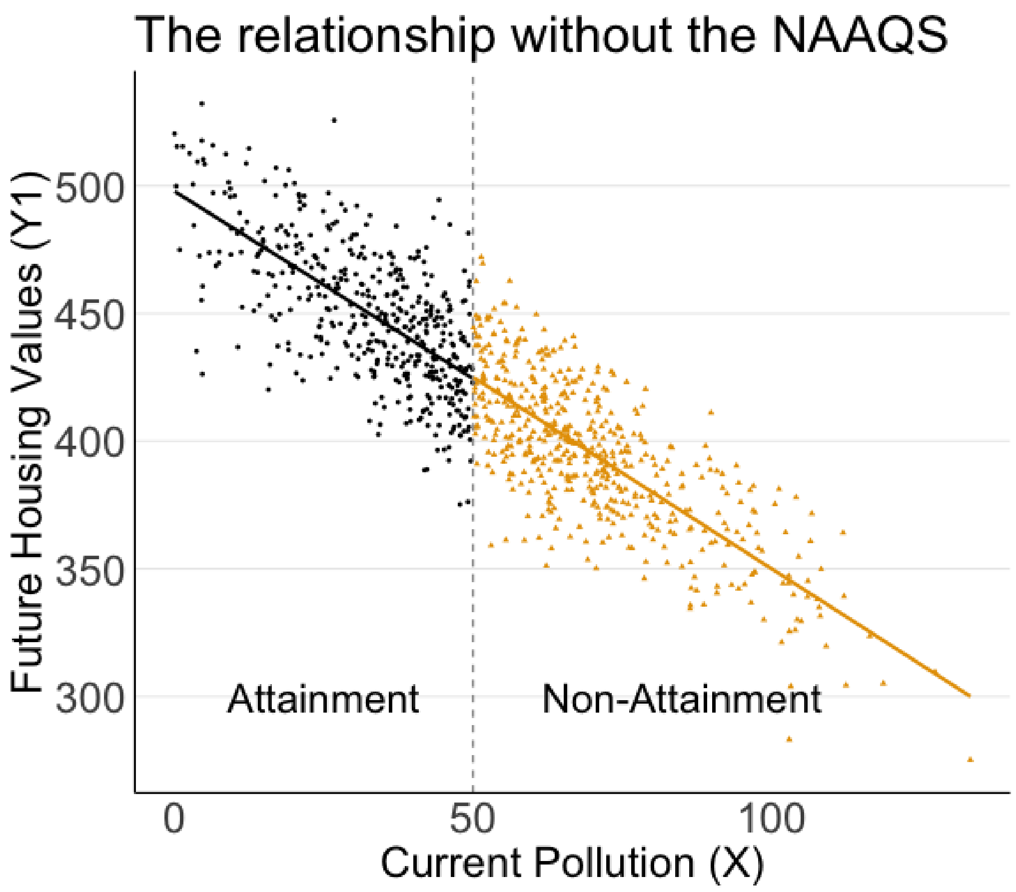
Here's what we're doing in pictures

Regression discontinuity design: graphs

```r
set.seed(12345)
late <- 0 # local average treatment effect
n_obs <- 1000 # number of observations
rdd_df <- tibble(
  state = seq(1, n_obs)) %>%  # control/untreated potential outcome
  mutate(
    X = rnorm(n(), 50, 25), # running variable
    D = X > 50,
    Y1 = 500 + late*D - 1.5*X + rnorm(n(), 0, 20)
  ) %>%
  filter(X > 0) %>%
  select(
    state, D, X, Y1
  )
```

Regression discontinuity design: graphs



Suppose the pollution threshold is at 50

In the absence of the NAAQS, we expect a smooth/continuous transition in housing values above vs below the threshold

Next, suppose we implement the NAAQS

Regression discontinuity design: graphs

```
set.seed(12345)
late ← 40 # local average treatment effect (NOW 40)
n_obs ← 1000 # number of observations
rdd_df ← tibble(
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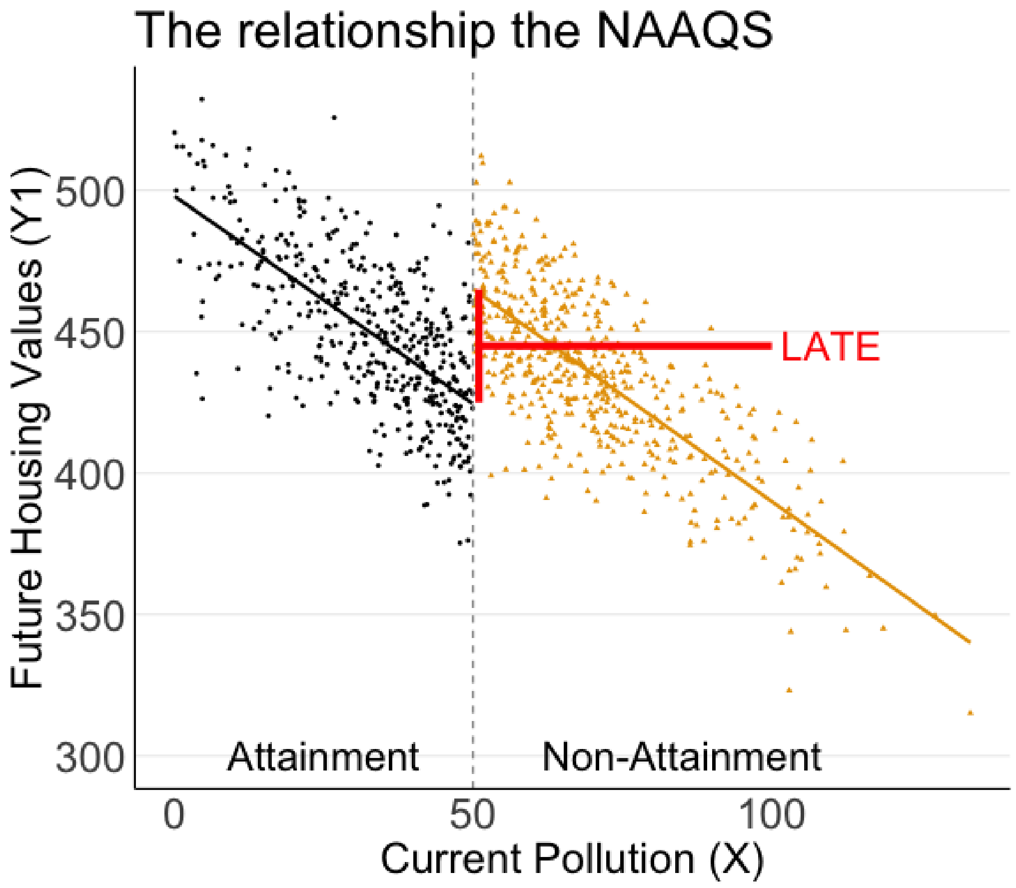

The policy induced greater pollution reductions in the non-attainment counties

Housing prices shift up for those counties

The vertical distance between the two groups at 50 is our **local average treatment effect**

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RDD is about finding these **jumps** in the probability of treatment as we move along some other variable X

How do we find these jumps?

For environmental topics they're often embedded in rules (e.g. the NAAQS), or across space (e.g. deforestation policy)

Regression discontinuity design: the data

Good and plausible RDDs often involve Xs having a 'hair trigger' that's not tightly related to the outcome

- e.g. being 10 meters on either side of the Bolivia/Brazil border is pretty arbitrary in the grand scheme of things, but a massive discontinuity in deforestation policy

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We will need to be focused on the area right around this hair trigger threshold: that means we will need a lot of data near c_0 in order to have precise estimates of the LATE

Regression discontinuity design: the types

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Sharp designs are where the probability of treatment increases from 0 to 1 at the threshold c_0

Fuzzy designs are where the probability of treatment increases discontinuously at c_0, but not necessarily from 0 to 1

We will be focusing on sharp designs to keep it simple

Sharp RDD: set up

A sharp RDD has treatment D being a deterministic function of the running variable X

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In a sharp RDD treatment is given by:

$$D_i = \begin{cases} 1 & X_i \geq c_0 \\ 0 & X_i < c_0 \end{cases}$$

If we know X_i we know treatment with certainty

Sharp RDD: set up

In potential outcomes terms we then have:

$$Y_i^0 = \alpha + \beta X_i$$

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Which gives us our regression is:

$$\begin{aligned}
Y_i &= D_i Y_i^1 + (1 - D_i) Y_i^0 && \text{(Rubin model)} \\
Y_i &= Y_i^0 + (Y_i^1 - Y_i^0) D_i && \text{(Rearranged)} \\
Y_i &= \alpha + \beta X_i + \delta D_i + \underbrace{\varepsilon_i}_{\text{Error}} && \text{(Plug in above terms)}
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What is the mathematical definition of δ?

Sharp RDD: treatment effects

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$$\begin{aligned}
\delta &= \lim_{X_i \rightarrow c_0} E[Y_i^1 | X_i = c_0] - \lim_{c_0 \leftarrow X_i} E[Y_i^0 | X_i = c_0] \\
&= \lim_{X_i \rightarrow c_0} E[Y_i | X_i = c_0] - \lim_{c_0 \leftarrow X_i} E[Y_i | X_i = c_0]
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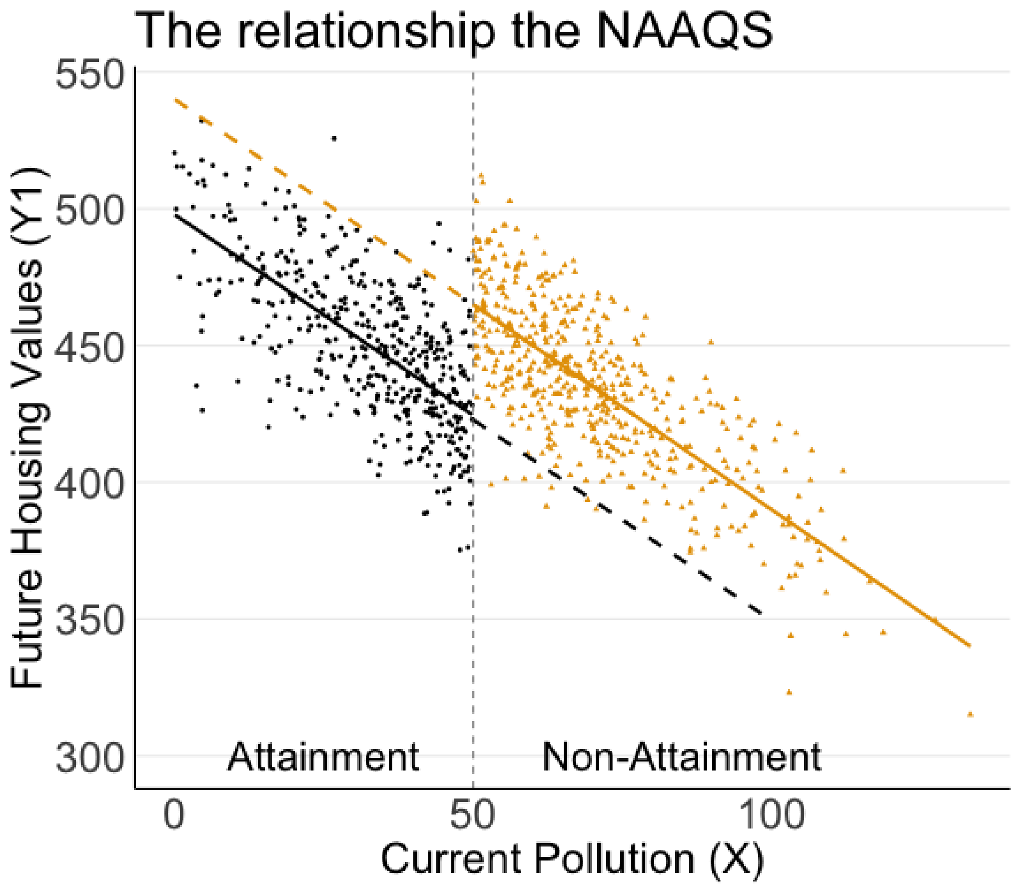
The sharp RDD gives us an average causal effect of treatment **at the discontinuity,** which is why it is called a local average treatment effect (LATE):

$$\delta_{SRDD} = E[Y_i^1 - Y_i^0 | X_i = c_0]$$

Sharp RDD: treatment effects



Notice that extrapolation plays a key role: there is no X where we have some units with $D_i = 1$ and others with $D_i = 0$

We are extrapolating (locally around c_0) using the dashed lines to estimate the difference in the two means

Sharp RDD: identifying assumption

The identifying assumption for RDD is called the **continuity assumption:**

> $E[Y_i^0|X = c_0]$ and $E[Y_i^1|X = c_0]$ are continuous (smooth) in X at c_0

It means that the expected potential outcomes should remain continuous at the threshold in the absence of treatment: they would not have jumped

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If this is true, then all other determinants of Y are thus continuously related to X and the jump is completely due to treatment

The Brazilian Amazon’s Double Reversal of Fortune

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Why is this important?

1. The Amazon rainforest is incredibly important
2. The Amazon is largely undeveloped, unclear if deforestation regulation can be adequately enforced to matter
3. Understanding whether the regulation works is important for future policy

How does the paper do it?

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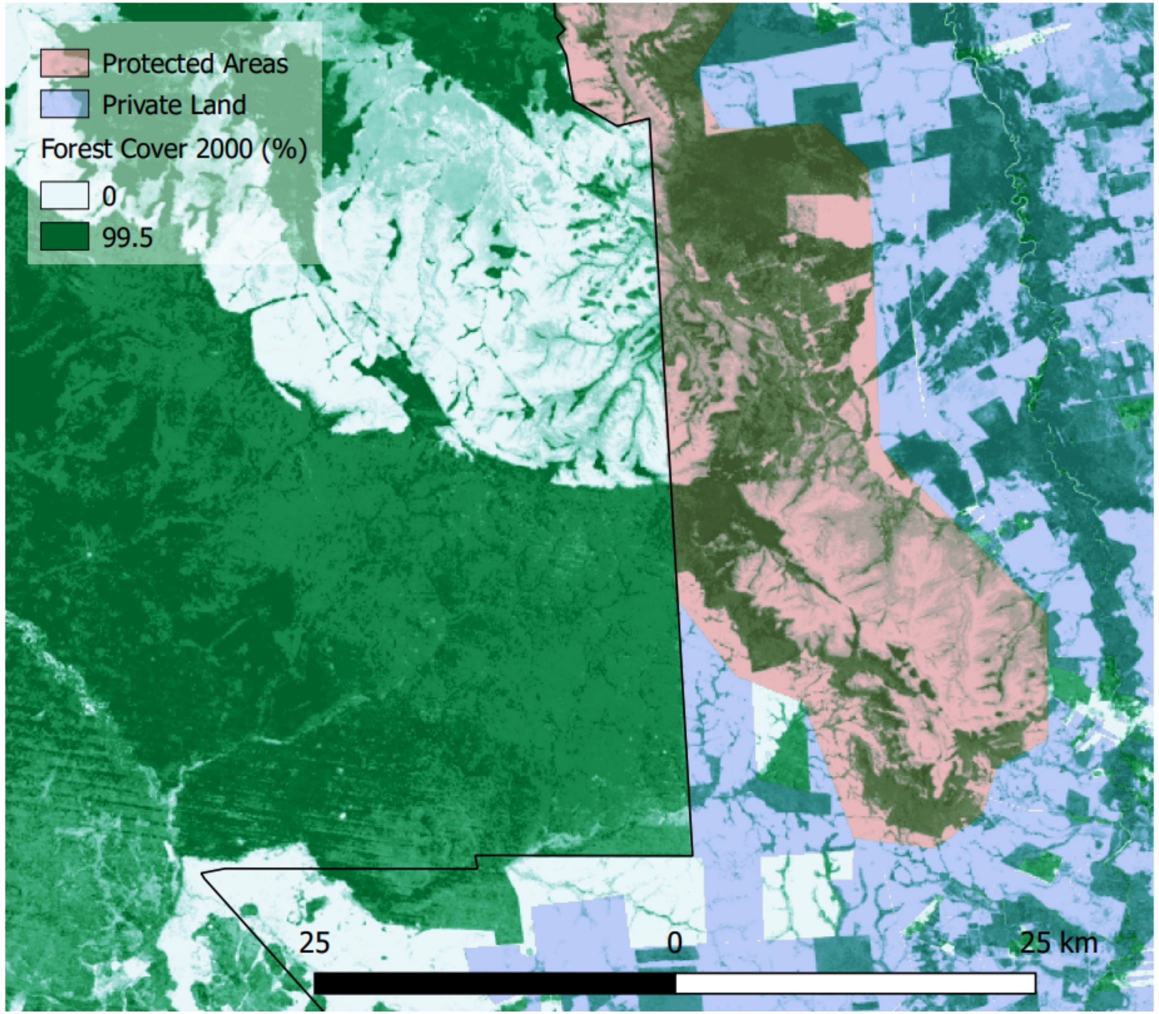
They compare deforestation outcomes in Brazil, to those in other countries, close to the country border

How does the paper do it?

Bolivia is on the left, Brazil is on the right



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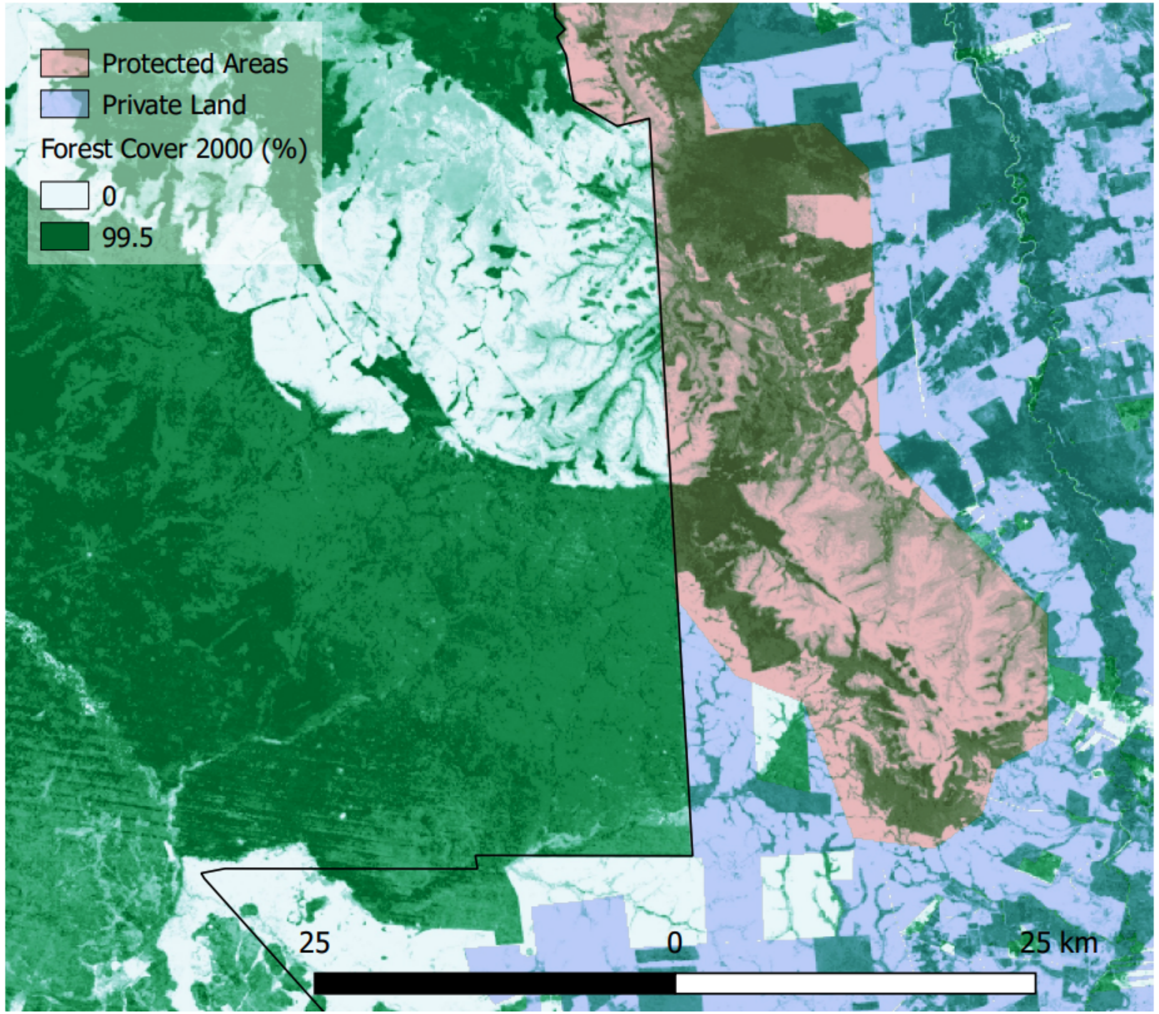
Darker green is more forested



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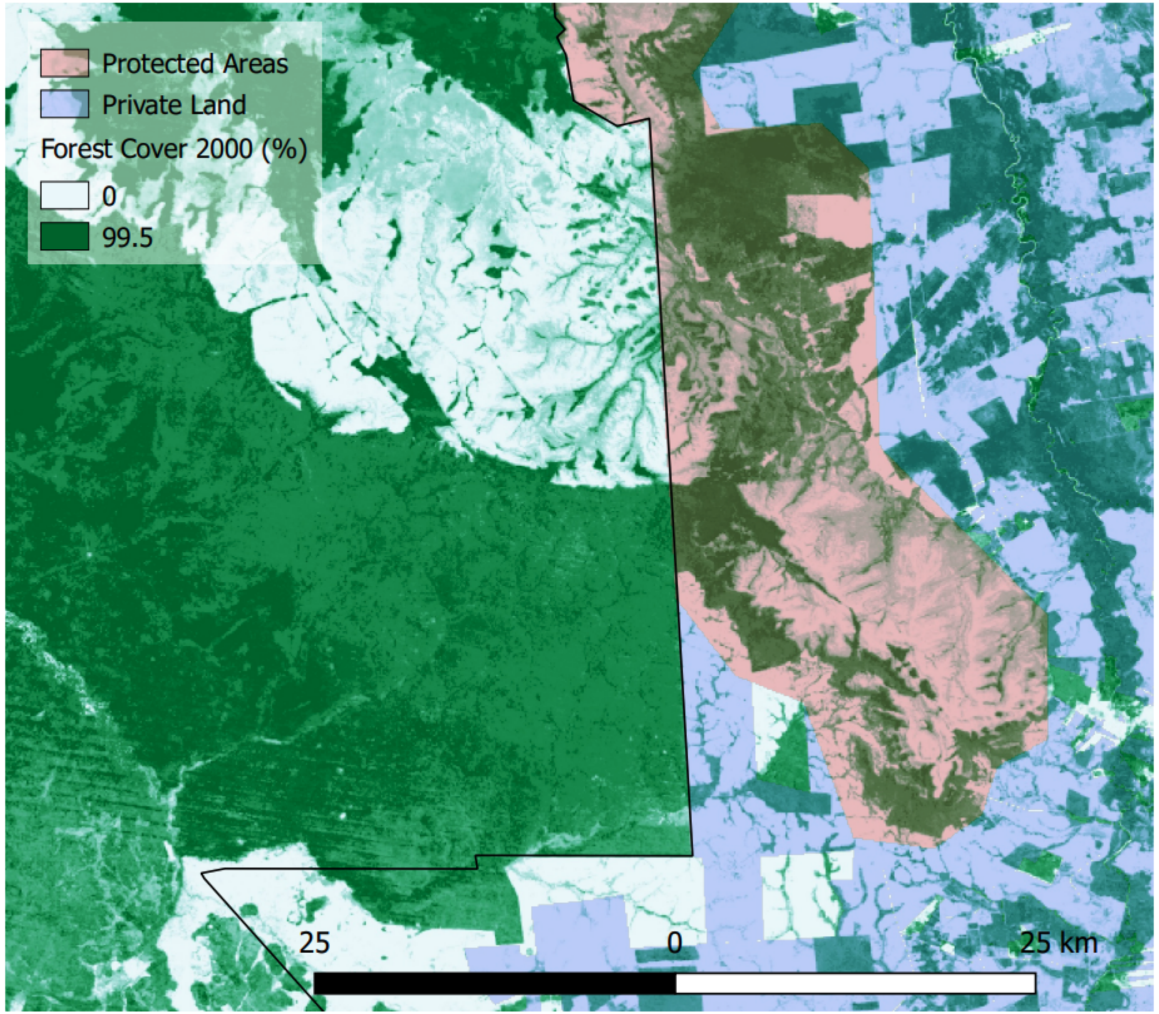

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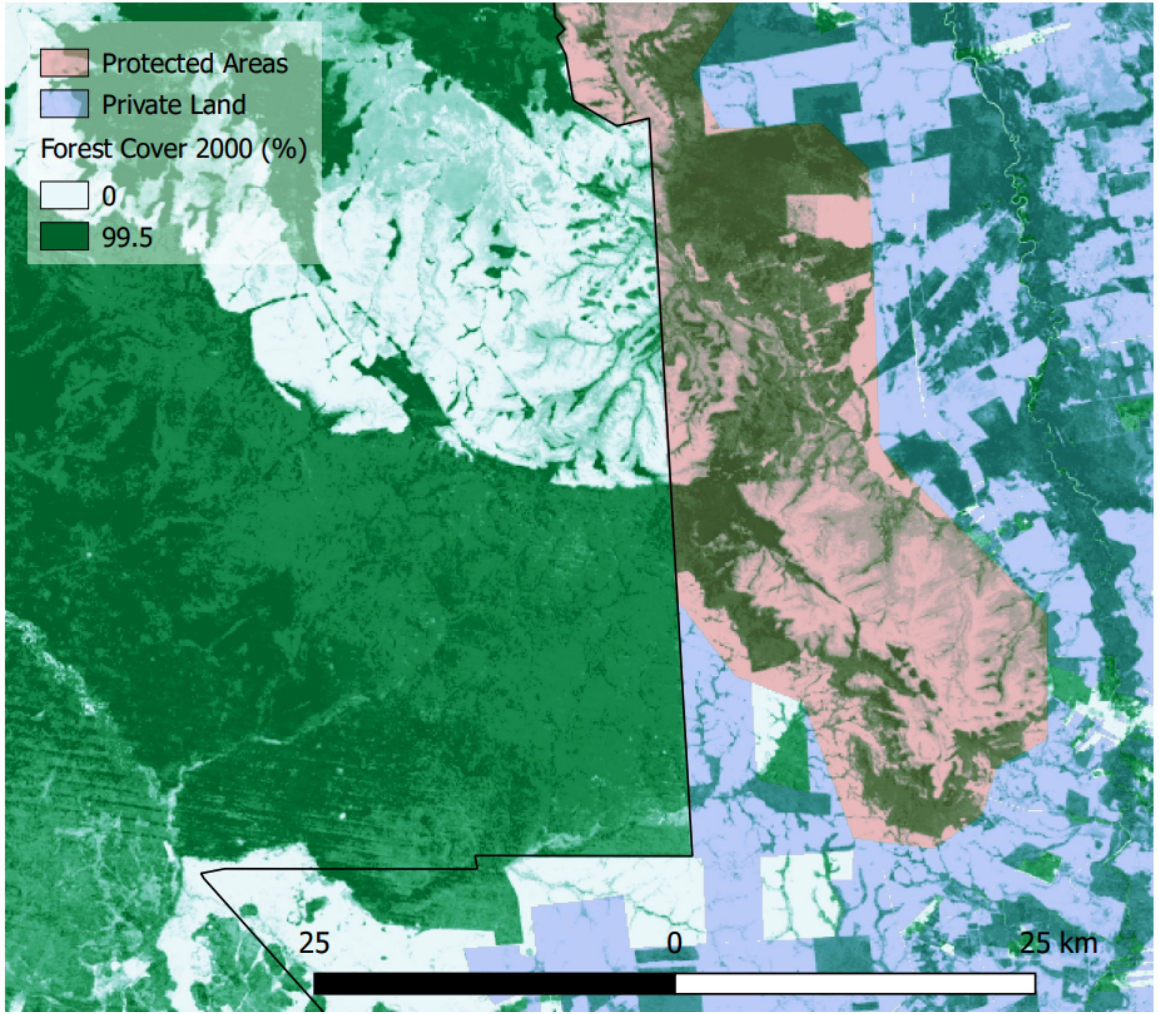
Sharp discontinuities in forest cover are very clear all along the border (black)



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Their model is similar to what we just went over with sharp RDD:

$$Y_i = \delta \text{Brazil}_i + f(\text{distance to border}_i) + \text{controls} + \varepsilon_i$$

Here:

- $\text{Brazil}_i \equiv D_i$
- $f(\text{distance to border}_i) \equiv X_i$

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This is likely reasonable: the borders were arbitrarily set in 1750 when the area was virtually unexplored: where the border is **locally** is effectively random

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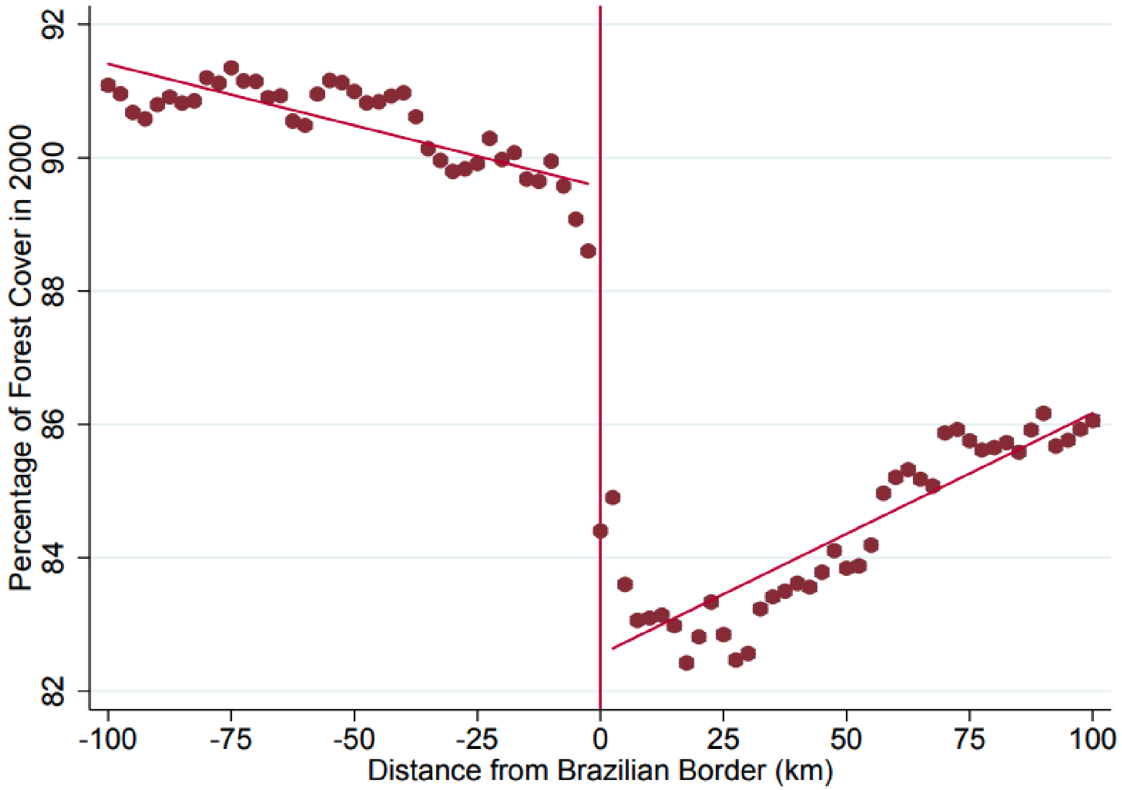
They also find no discontinuities in other things that may be important for deforestation: roads, slope, distance to cities, etc

What they get

The forest data are very, very large (120 meter pixels!) so we won't be doing this hands on

What they get

0 is the border, to the right is Brazil, to the left is other countries, the year is 2000



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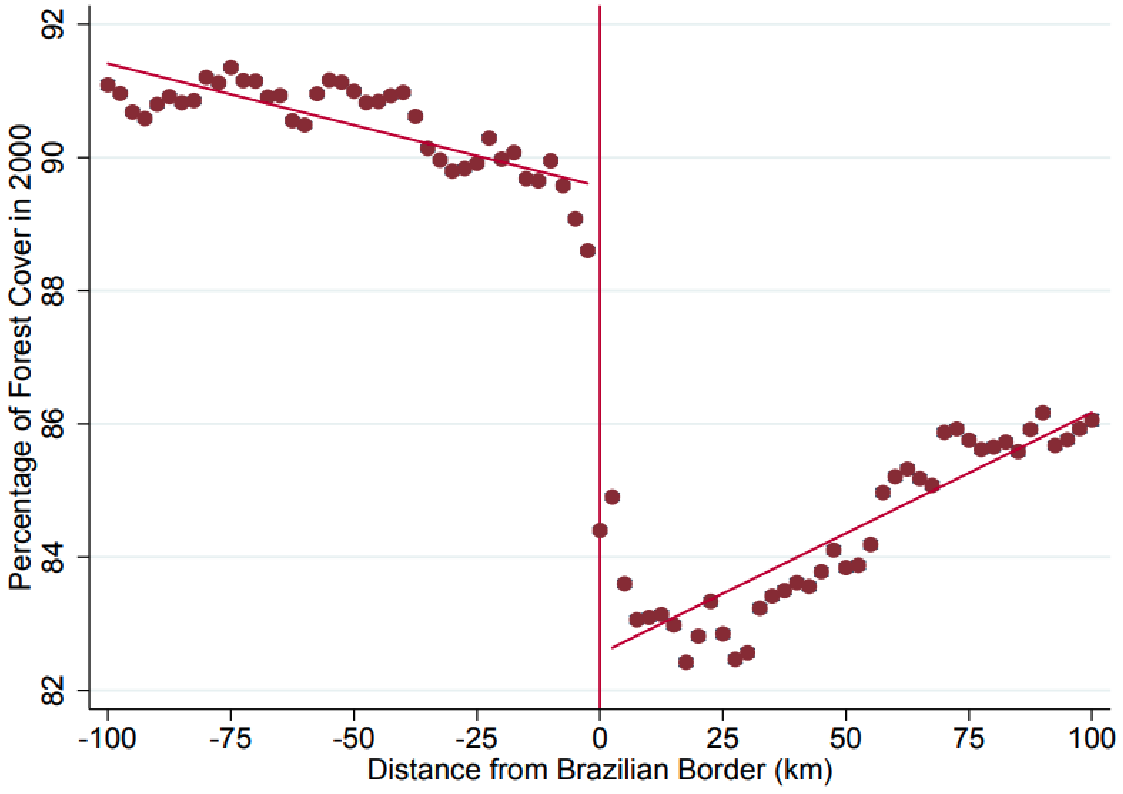
Other countries have greater forest cover than Brazil, but with a slight decline as you move to the Brazil border



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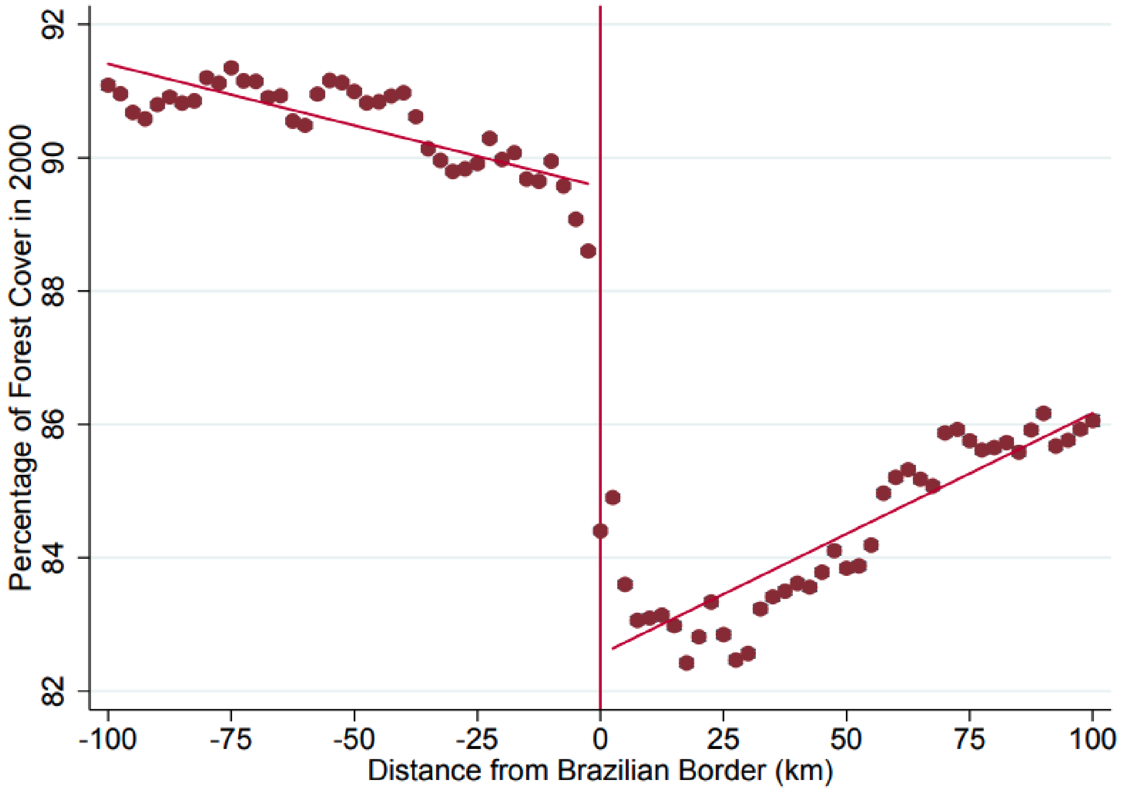
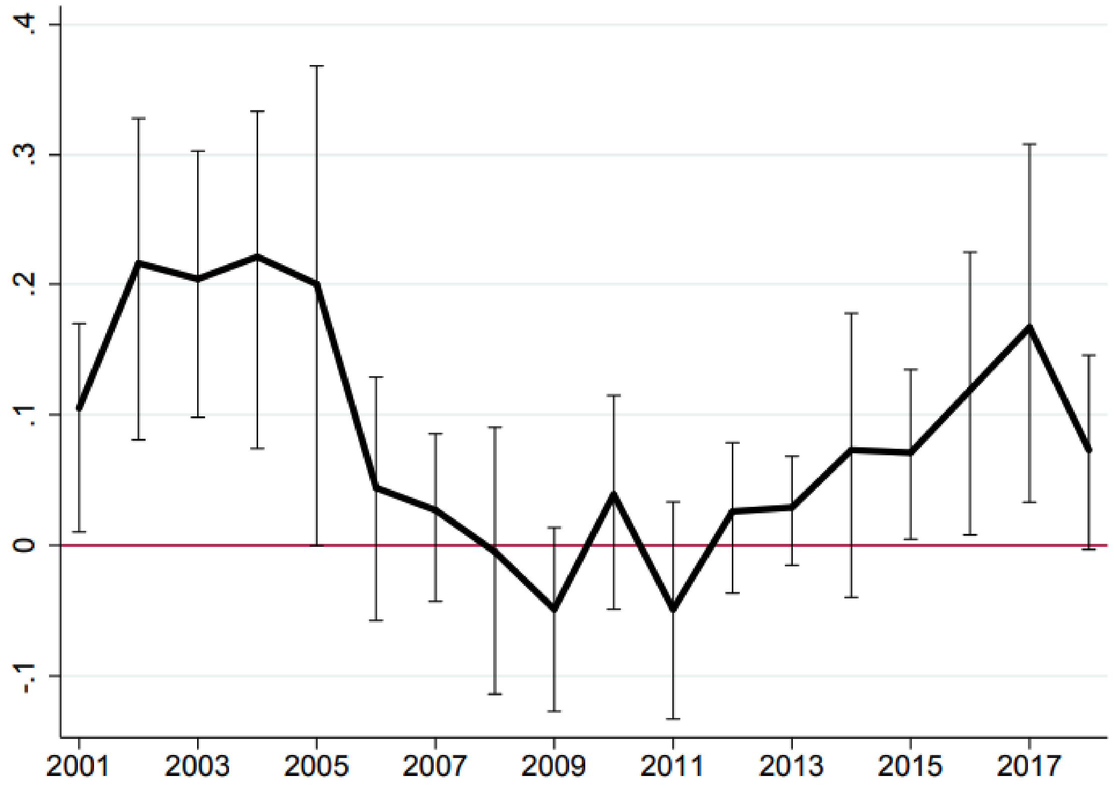
Brazil has discontinuously lower forest cover near the border



What they get

BCO also runs the RDD year-by-year so we can see how the LATE changes over time



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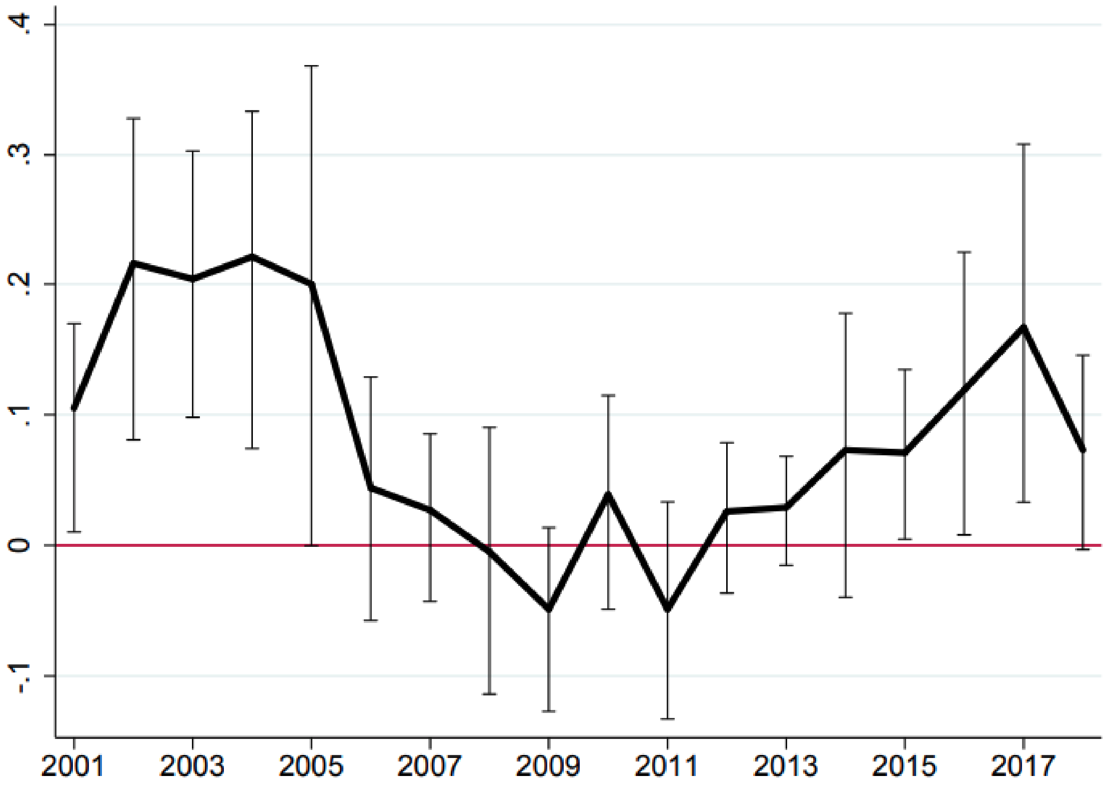

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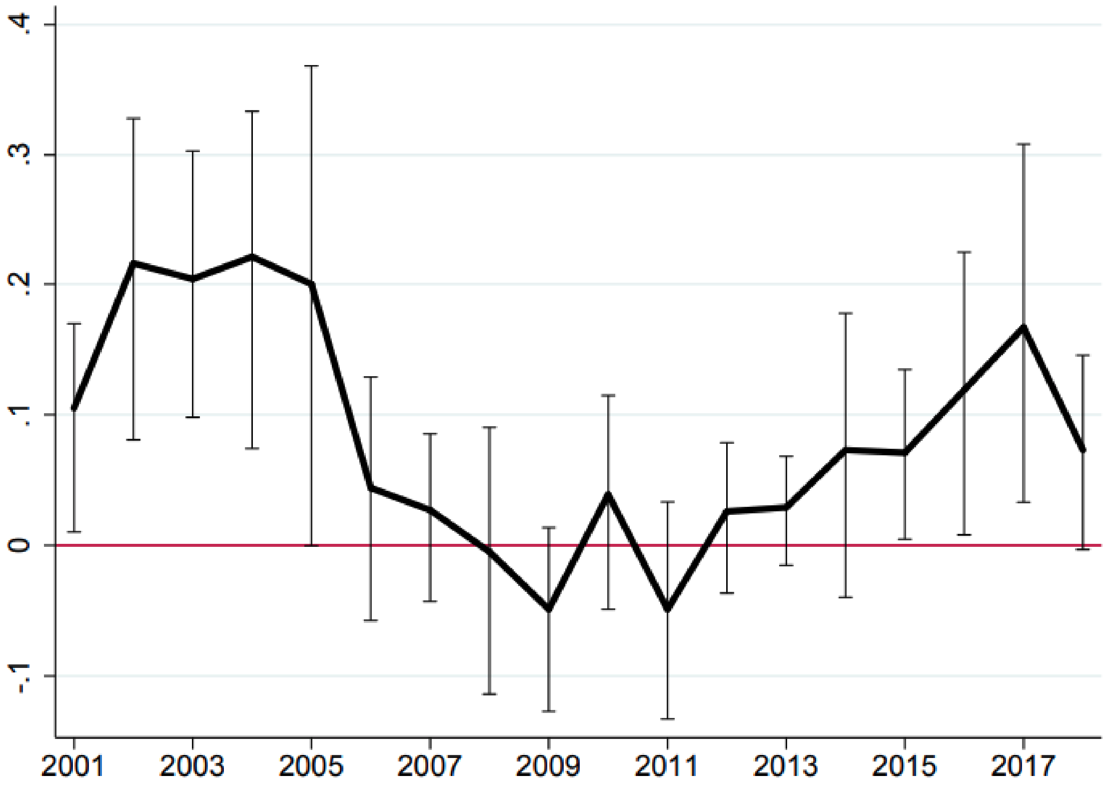
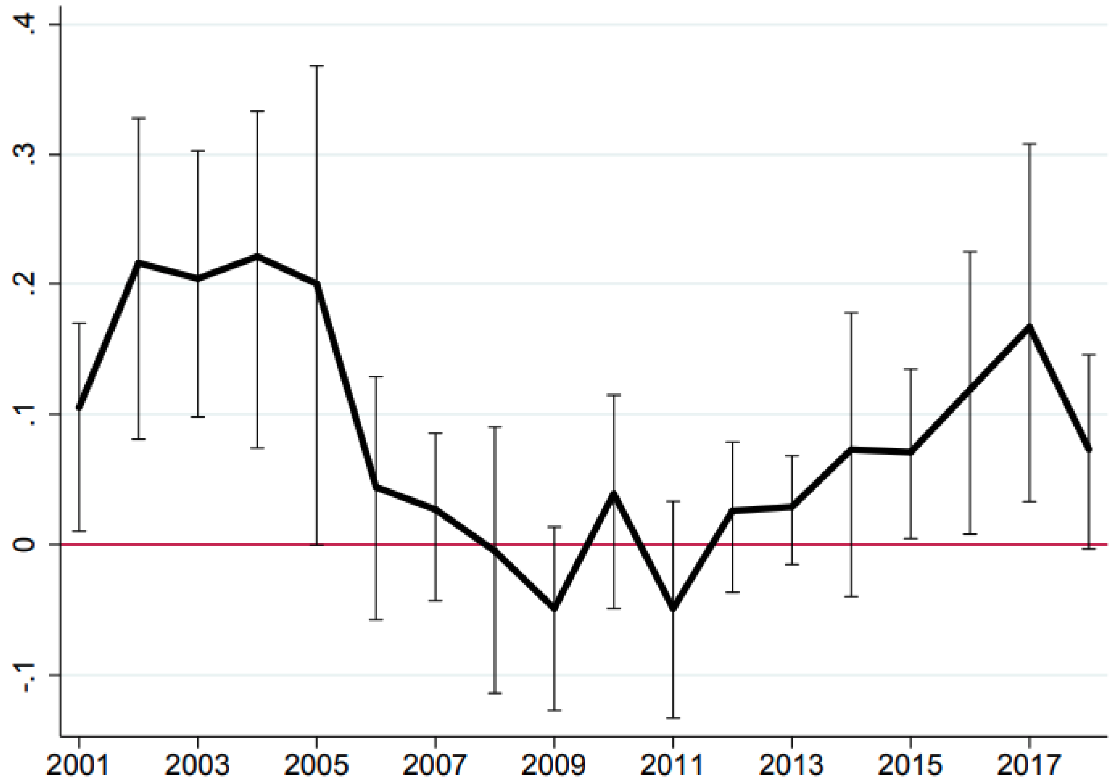


This is about when Brazil implemented tougher national deforestation policies: *Action Plan for the Prevention and Control of Deforestation in the Legal Amazon, Law on Public Forest Management, etc*

What they get: deforestation LATE by year

The effect of the tougher policies seems to have gone away after 2014



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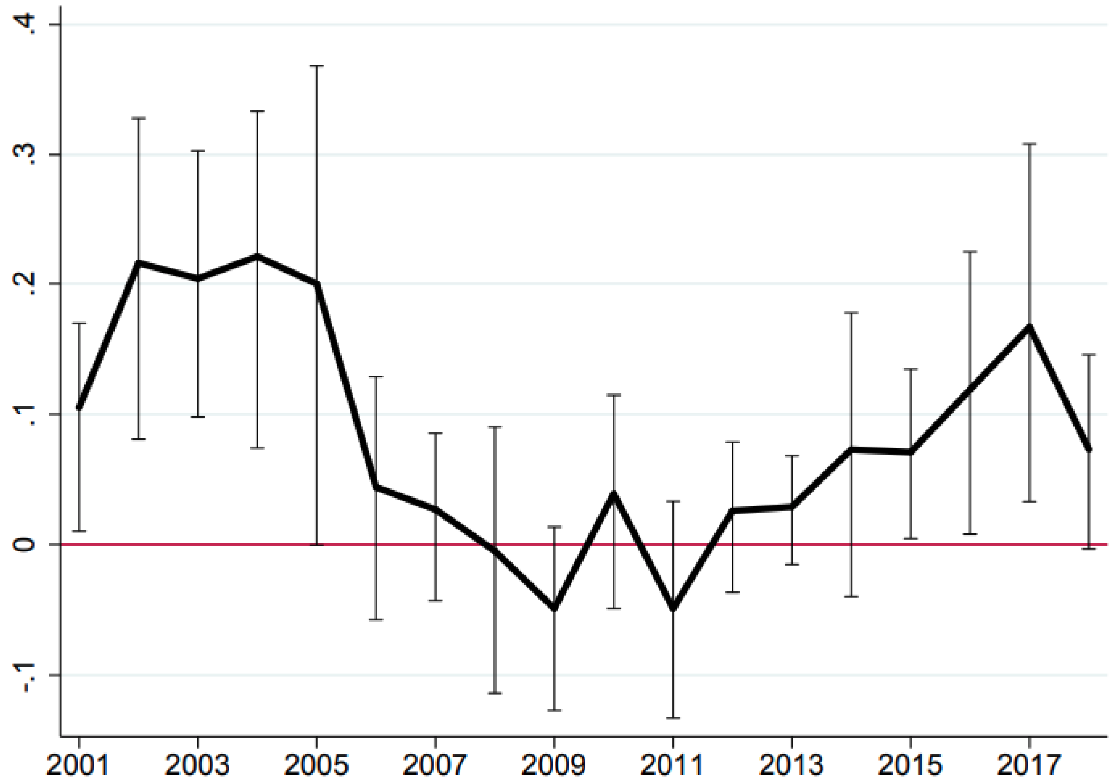

What they get: deforestation LATE by year

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Why?

Economic crises decreased enforcement of environmental regulations, and lead to weakening of the regulations