Conservation impact evaluation using remotely sensed data

Alberto Garcia and Robert Heilmayr

CRCS workshop on AI-Assisted Decision-Making for Conservation

10.21.2022

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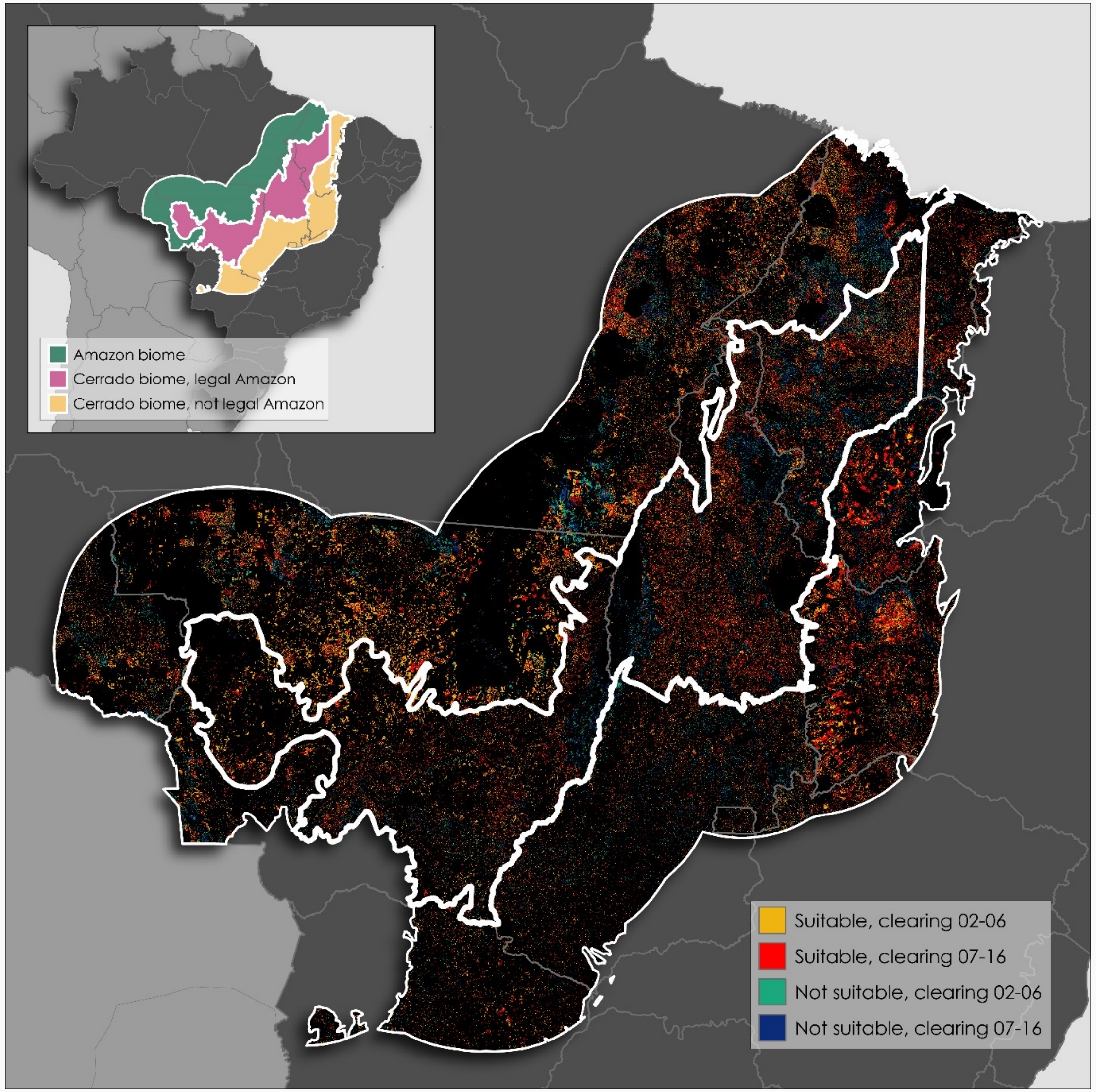
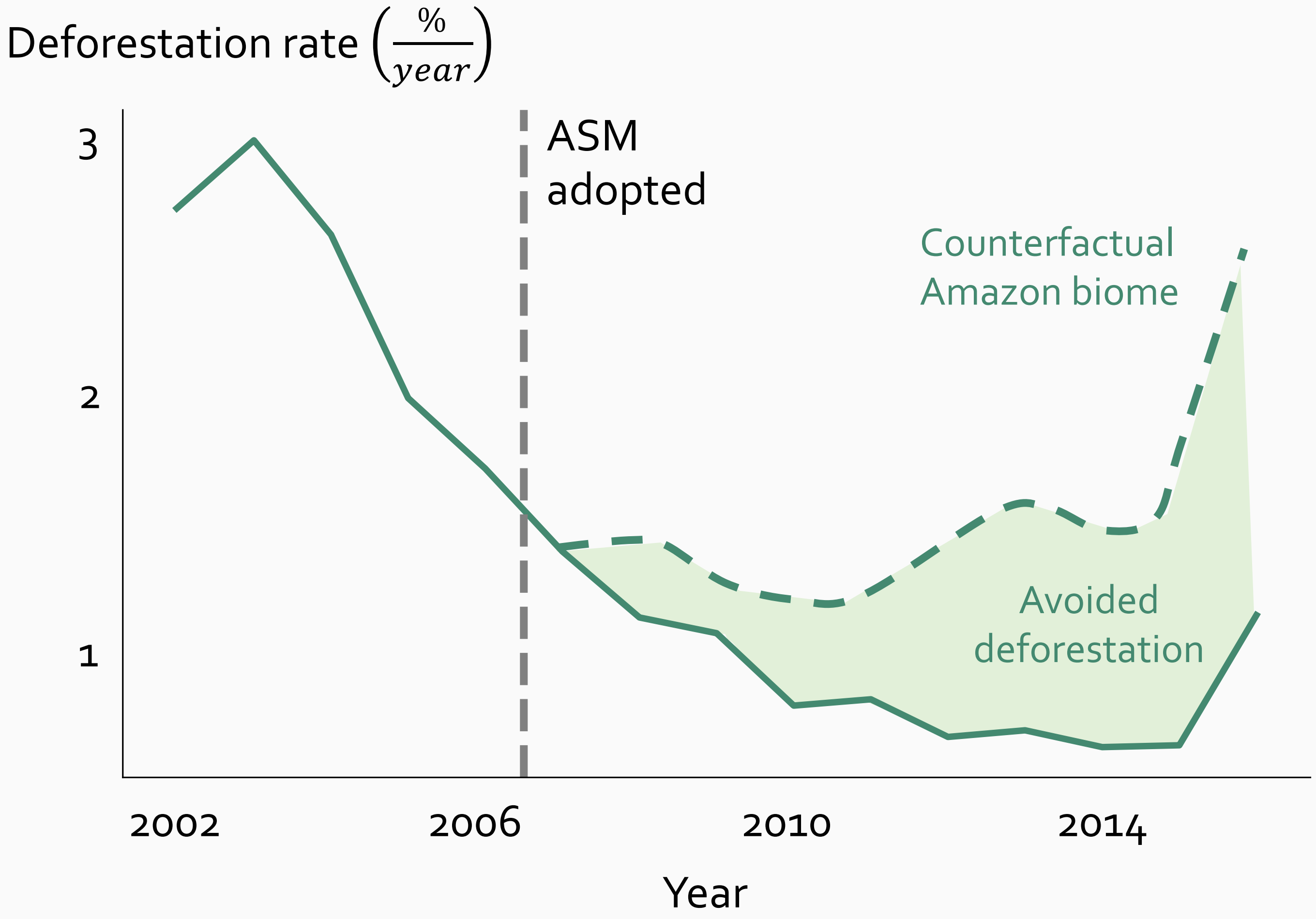
Impacts of the Amazon Soy Moratorium

Photo credit: CIFOR

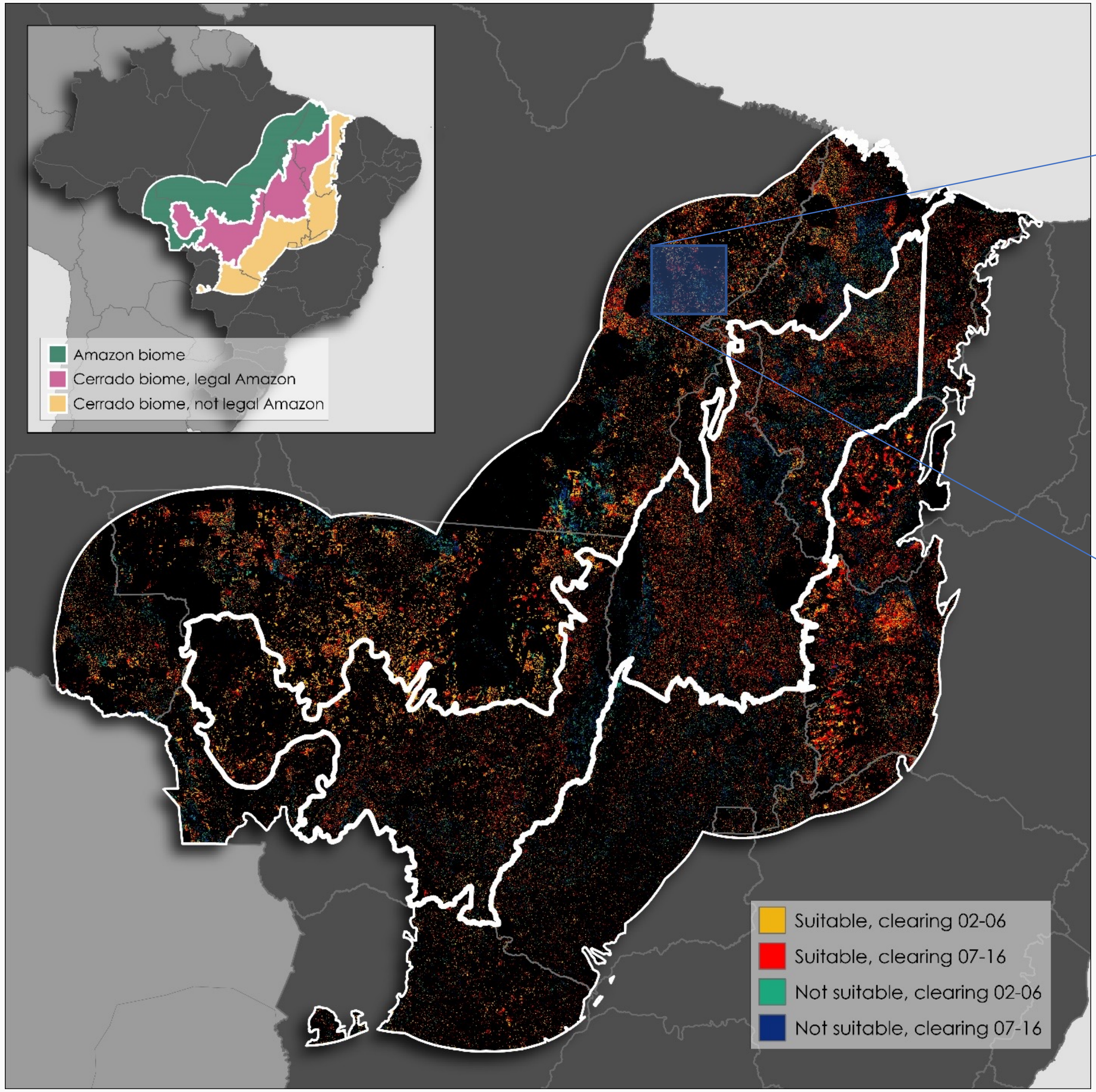
Impacts of the Amazon Soy Moratorium



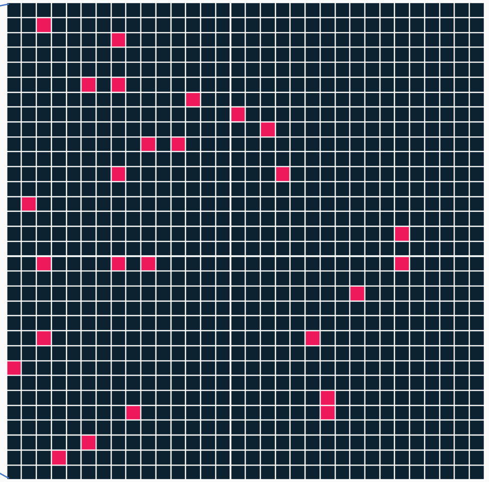


Heilmayr, Rausch, Munger and Gibbs, 2020

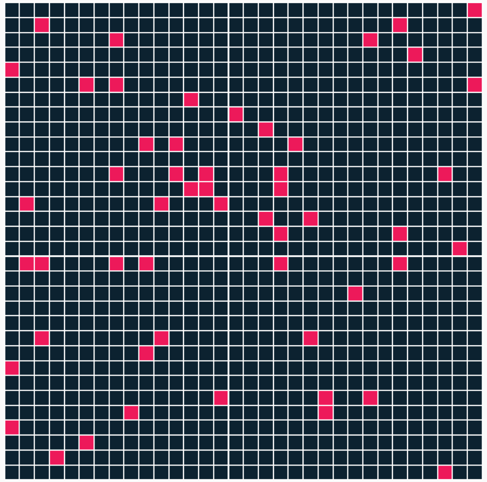
Impacts of the Amazon Soy Moratorium



What happened with the policy: $y_i(1)$



Potential outcome of what would've happened without the policy: $y_i(0)$



The pixel-level *treatment effect* can be expressed as:

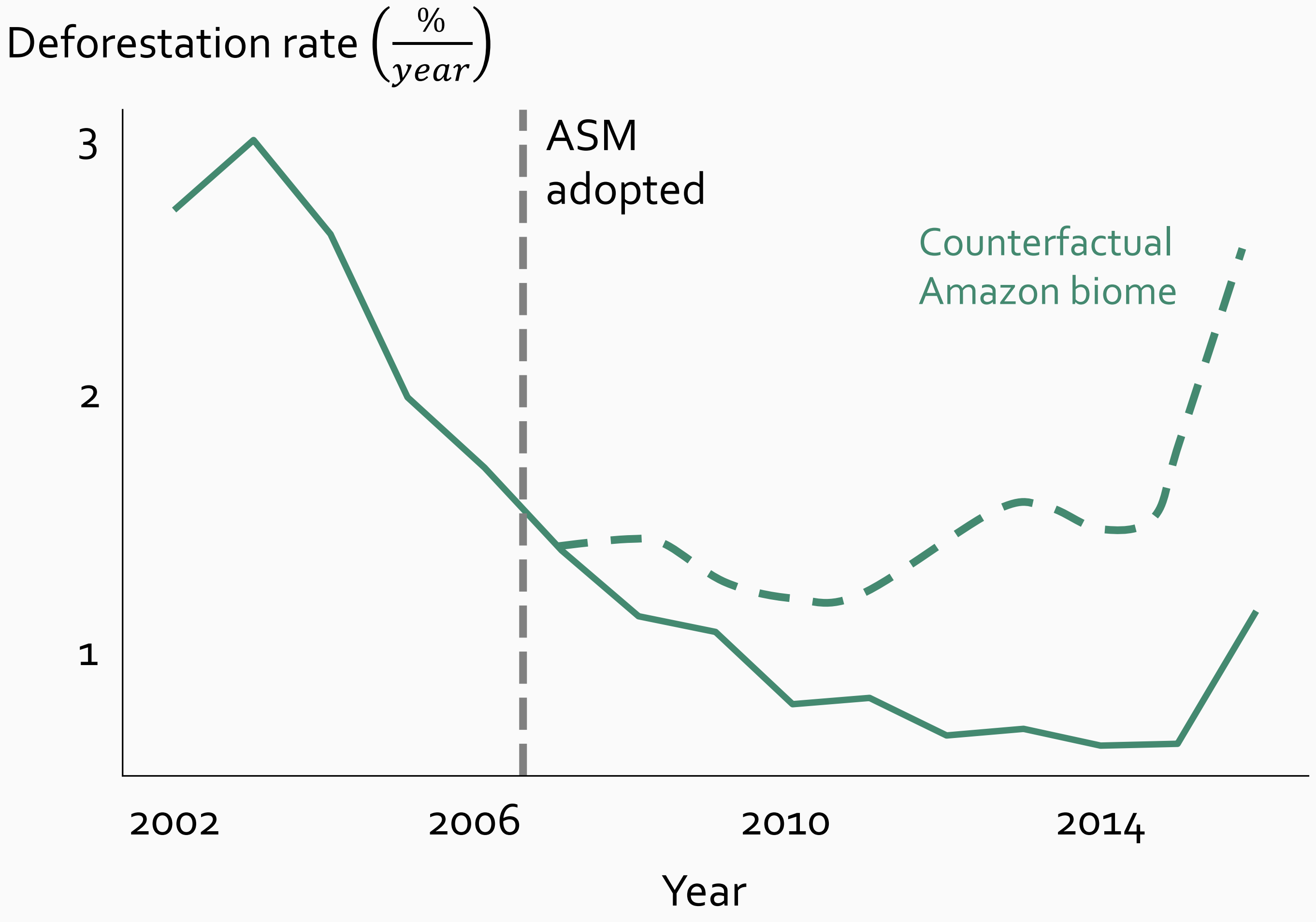
$$E_i = y_i(1) - y_i(0)$$

We want to measure the **Average Treatment Effect on the Treated** (ATT):

$$ATT = \frac{1}{n_{i:D_i=1}} \sum_{i;D_i=1}^{N} y_i(1) - y_i(0)$$

Methods for estimating counterfactual

- Experiments
  Jayachandran et al., 2017
- Difference in differences / event study
  Alix-Garcia and Gibbs, 2017
- Propensity score matching
  Heilmayr and Lambin, 2016
- Instrumental variables
  MacDonald and Mordecai, 2019
- Synthetic control
  West et al., 2020
- Regression discontinuity design
  Jordán and Heilmayr, 2021
- Double machine learning
  Sanford, 2021

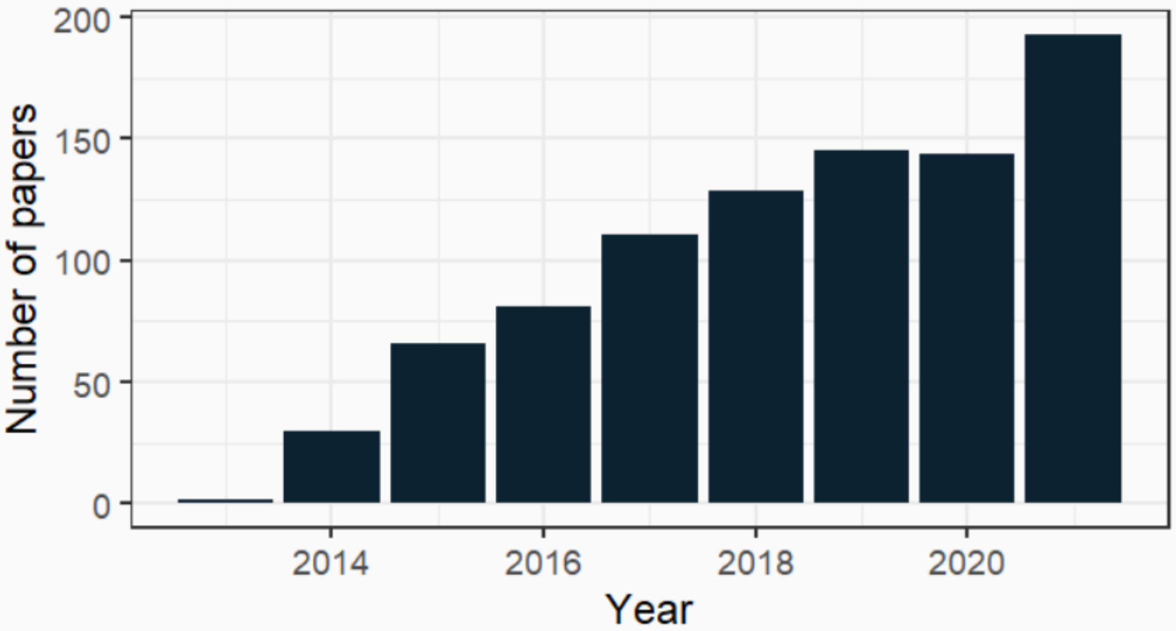


Reviews

Blackman, 2013; Van Butsic et al., 2017

Enthusiasm for remote sensing + econometrics

~1000 papers using econometric methods† that cite Hansen et al., 2013

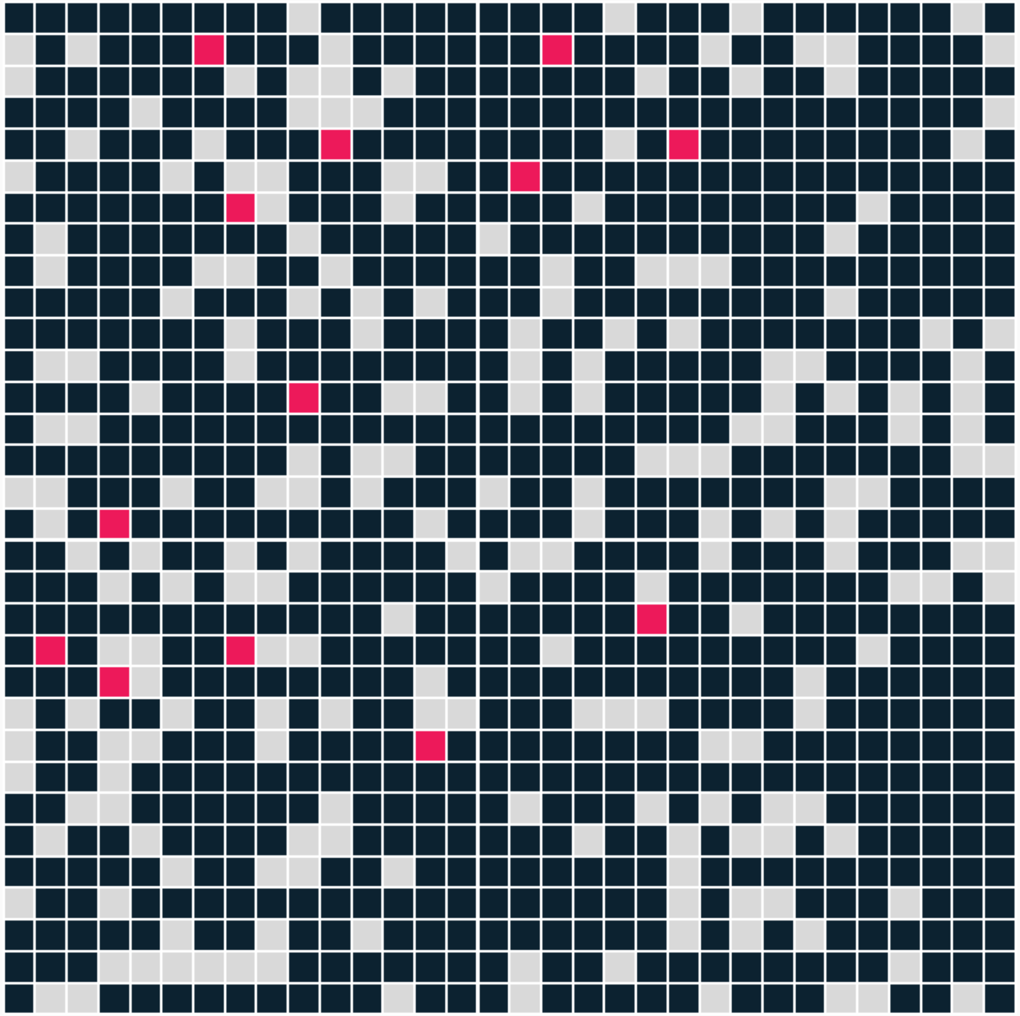


† Google scholar search for (econometric* or "causal inference" or "impact evaluation" or "fixed effects" or "regression discontinuity" or "instrumental variable")

Causal inference + remote sensing has facilitated new insights into:

- Protected areas
  Andam et al., 2008; Herrera, Pfaff and Robalino, 2019
- Payments for ecosystem services
  Ramirez-Reyes et al., 2018; Heilmayr, Echeverría and Lambin, 2020
- Indigenous tenure reform
  Baragwanath and Bayi, 2020; Jordán and Heilmayr, 2021
- Zero-deforestation commitments
  Alix-Garcia and Gibbs, 2017; Heilmayr, Rausch, Munger and Gibbs, 2020

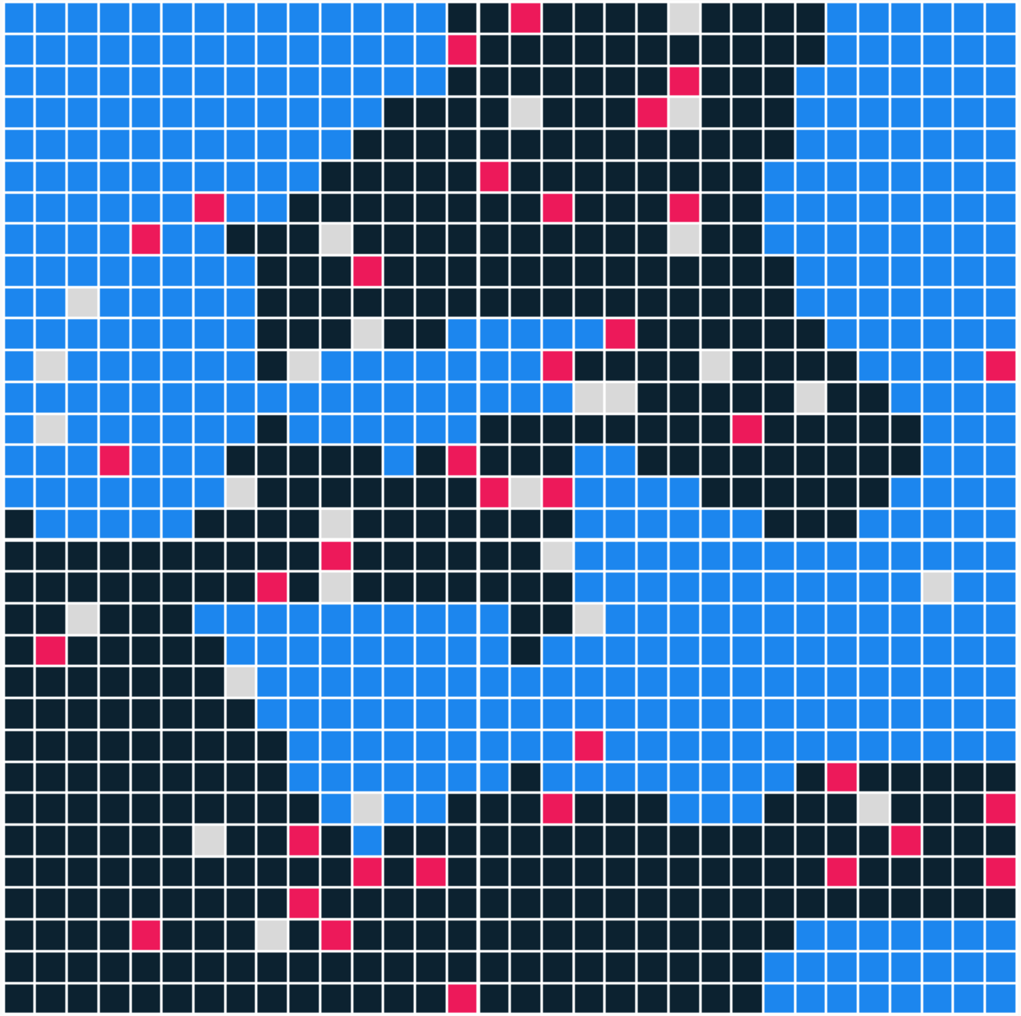
Appeal of remotely sensed data for causal inference



Data characteristics

- Wall to wall data
- Fine spatial scales
- Relatively long time series

However, remotely sensed data are different…



Question: Does applying standard econometric methods to remotely sensed data generate accurate estimates of the impacts of conservation policies?

Answer: Frequently not. Many previous estimates may be biased. However, careful model design can solve this problem.

Garcia and Heilmayr, 2022

Roadmap

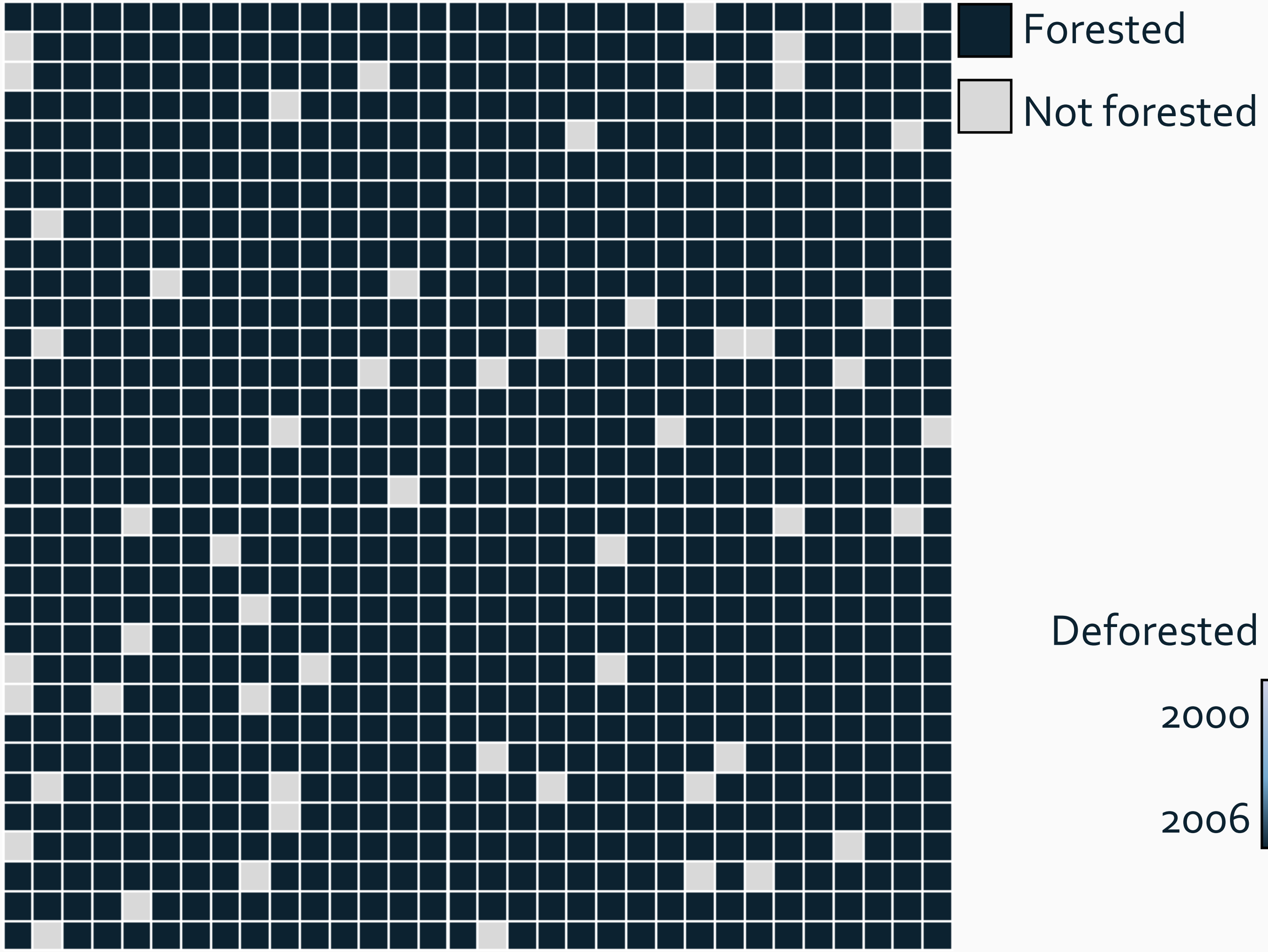
- Foundation
  - Remotely sensed **data** on deforestation
  - Panel, econometric **methods** for impact evaluation
- Testing alternate models
- Insights
  - A big problem
  - A simple solution
  - A better solution

Data setting

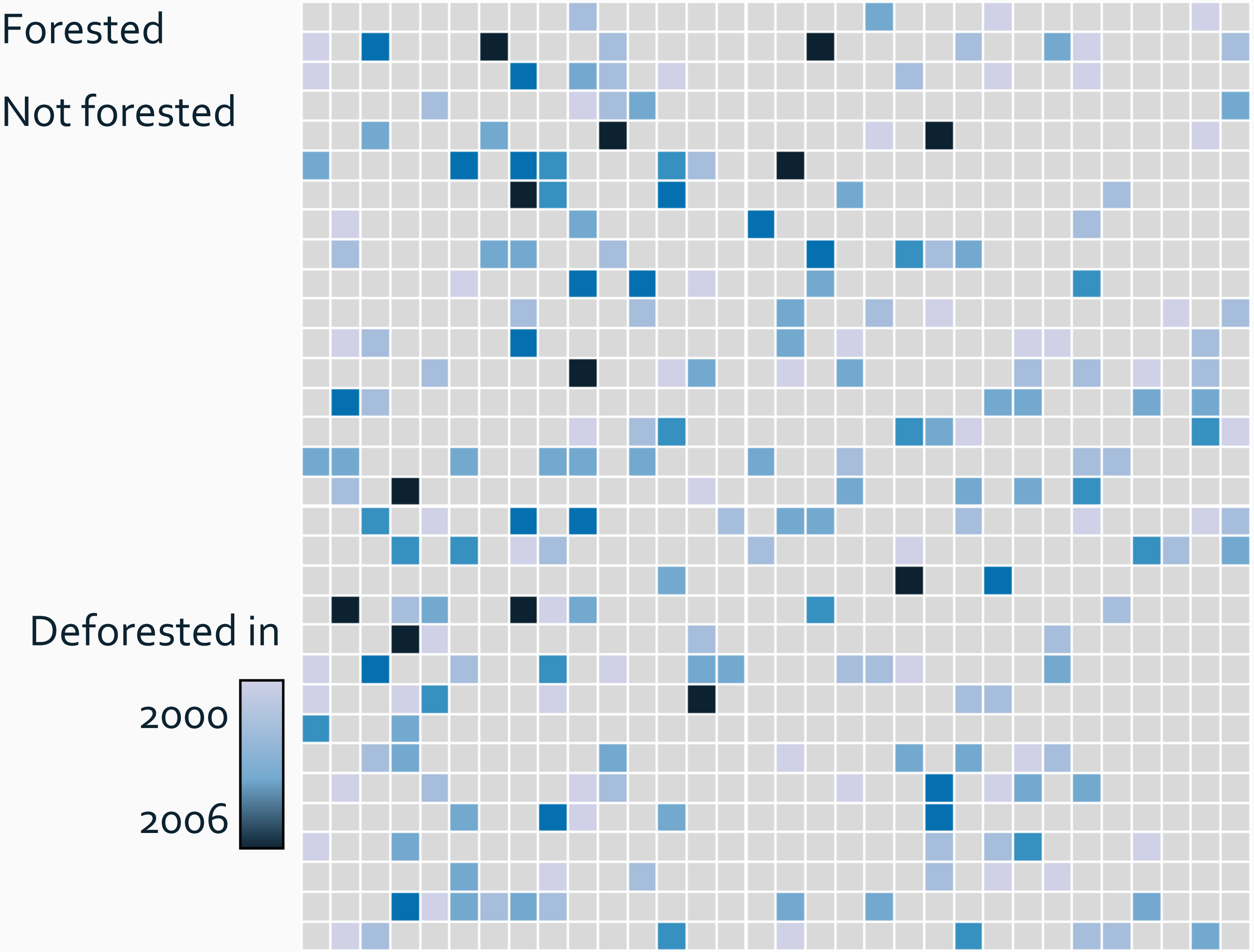
Remotely sensed maps of deforestation

Data setting

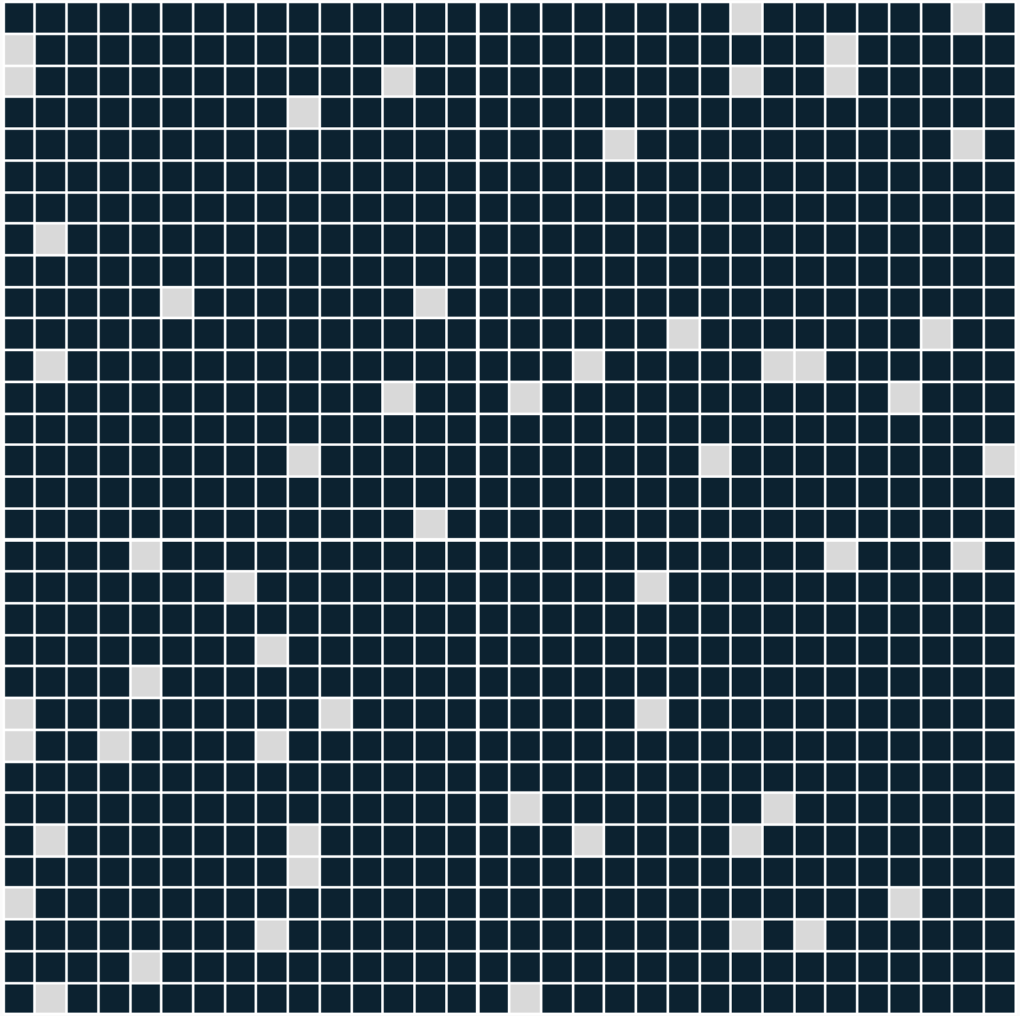
Initial forest cover



Year of deforestation



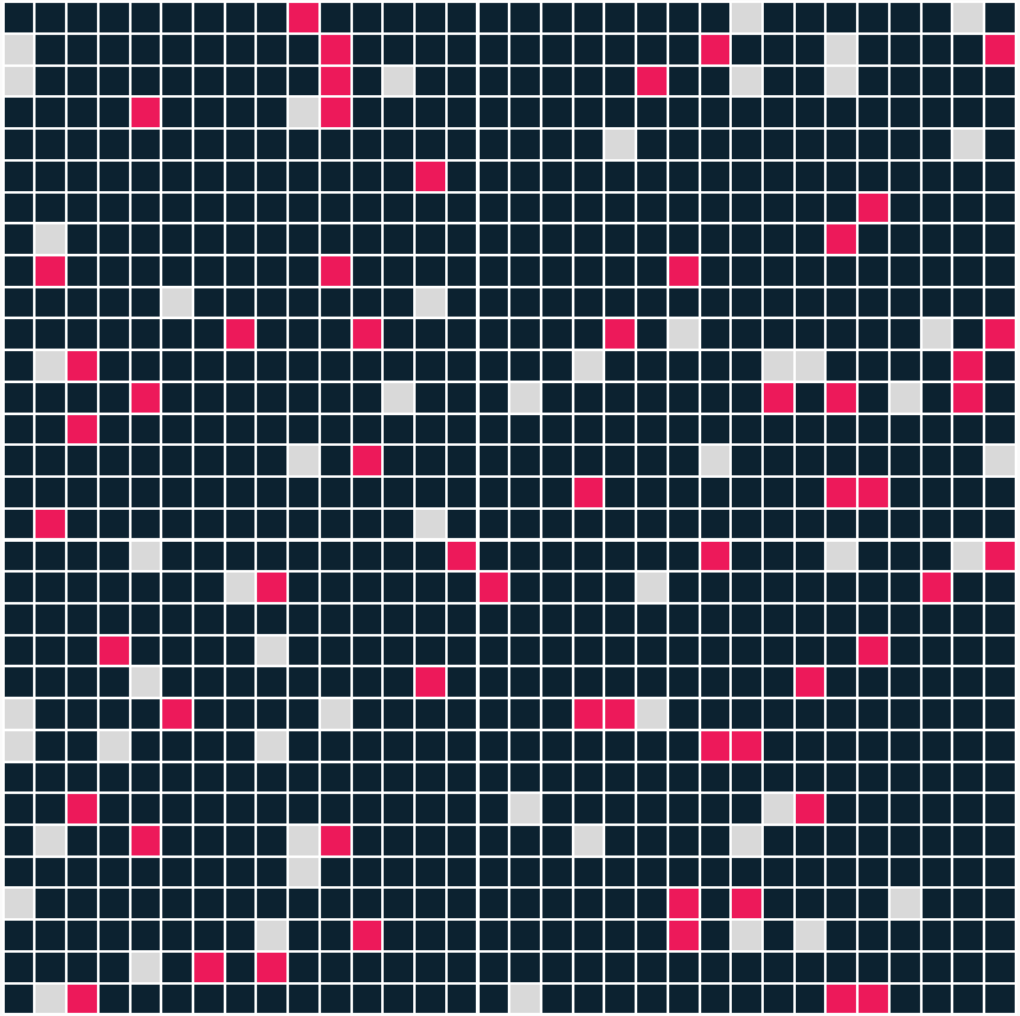
Data setting



Initial forested landscape in 2000

- Previously deforested
- Not deforested

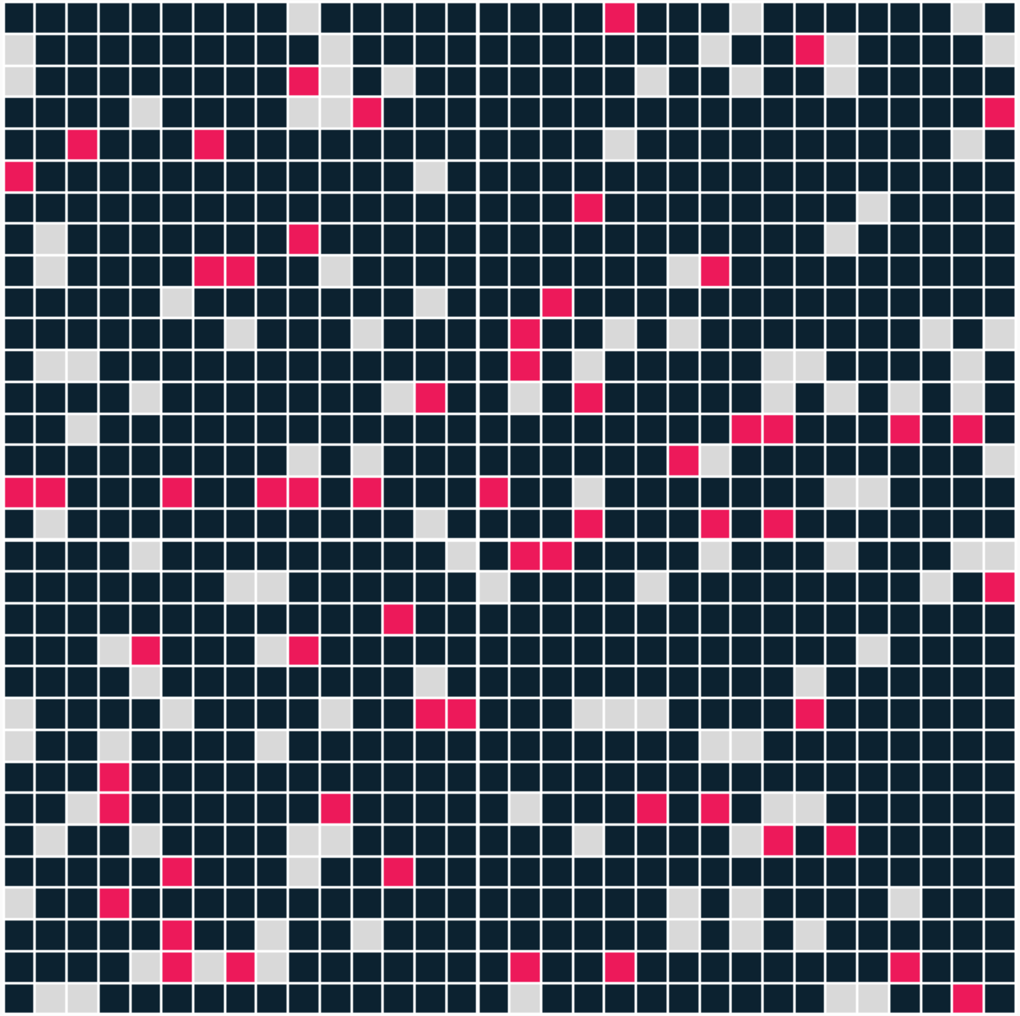
Data setting



Deforestation in 2001

$$y_{i,2001} = \begin{cases} 0 \text{ if persistent forest} \\ 1 \text{ if deforested} \\ NA \text{ if previously deforested} \end{cases}$$

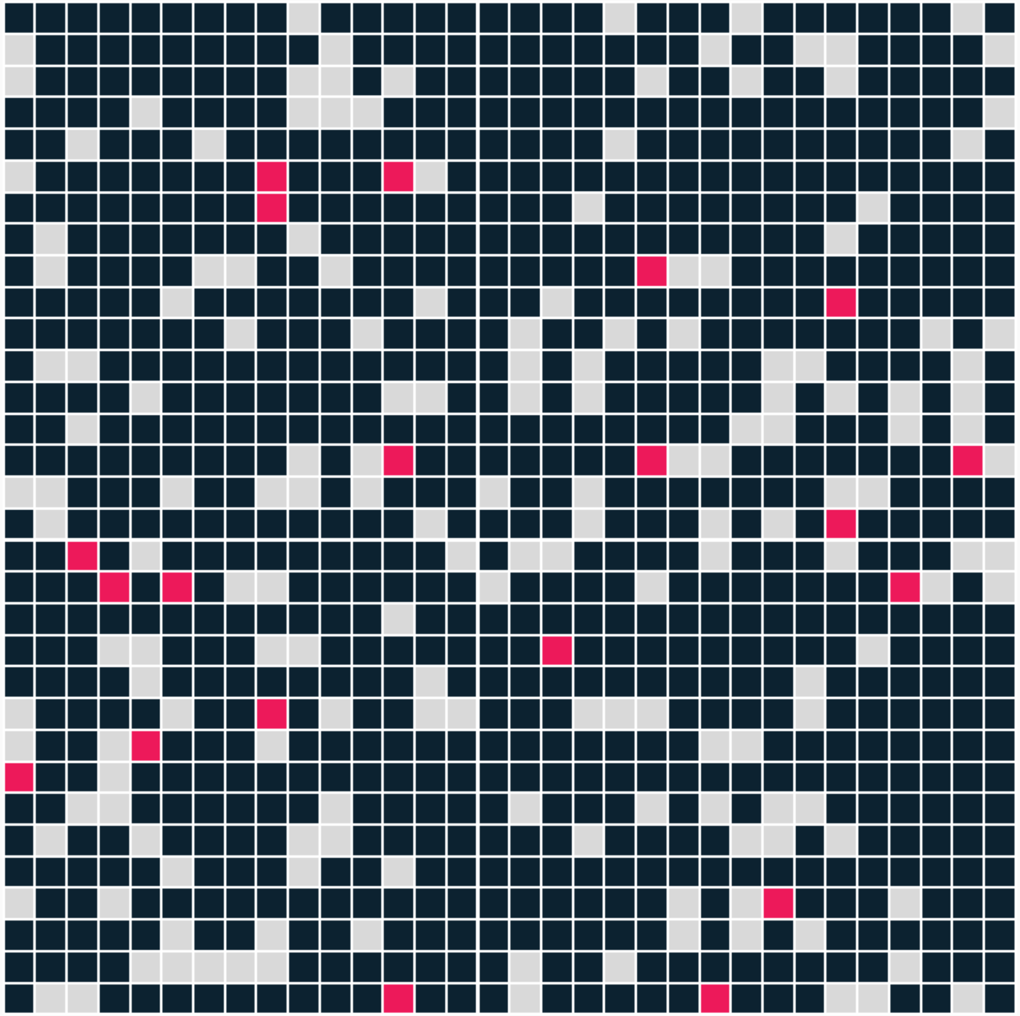
Data setting



Deforestation in 2002

$$y_{i,2002} = \begin{cases} 0 \text{ if persistent forest} \\ 1 \text{ if deforested} \\ NA \text{ if previously deforested} \end{cases}$$

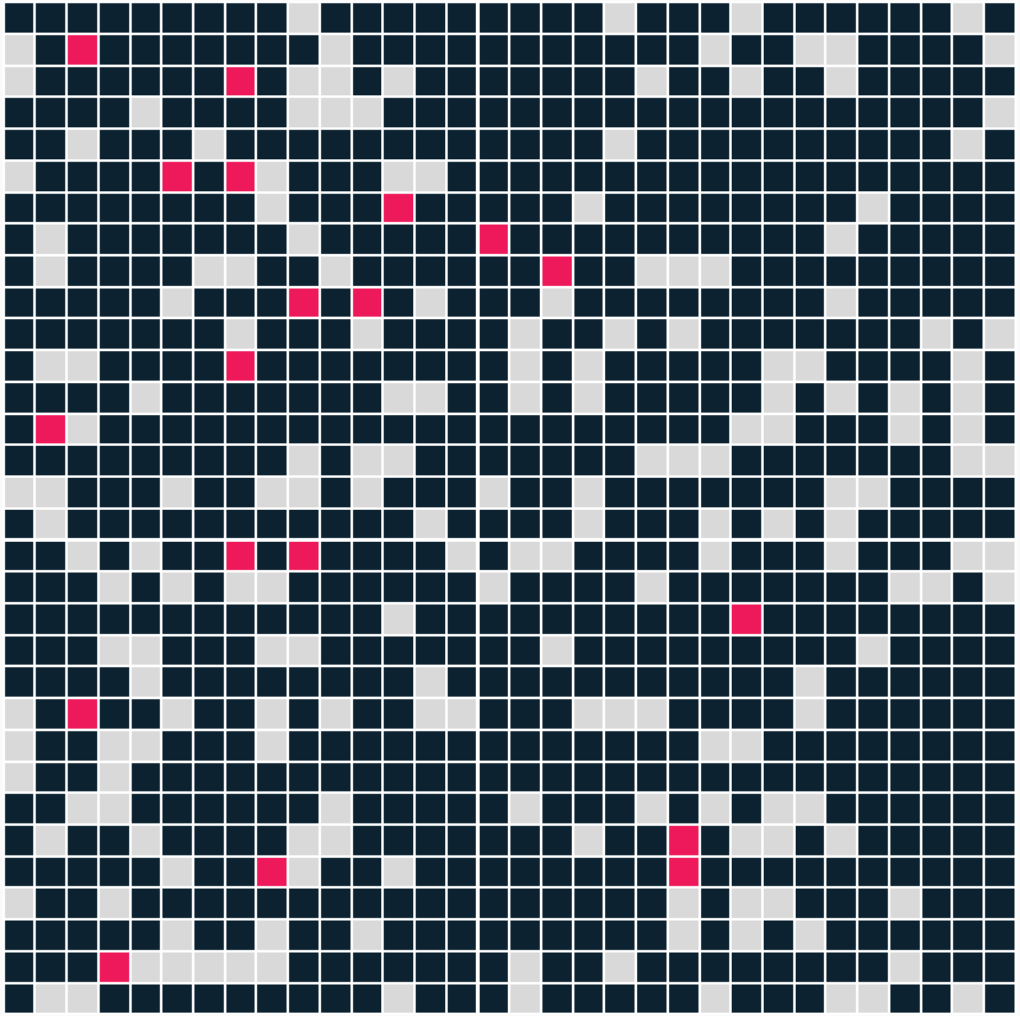
Data setting



Deforestation in 2003

$$y_{i,2003} = \begin{cases} \blacksquare\ 0 \text{ if persistent forest} \\ \blacksquare\ 1 \text{ if deforested} \\ \square\ NA \text{ if previously deforested} \end{cases}$$

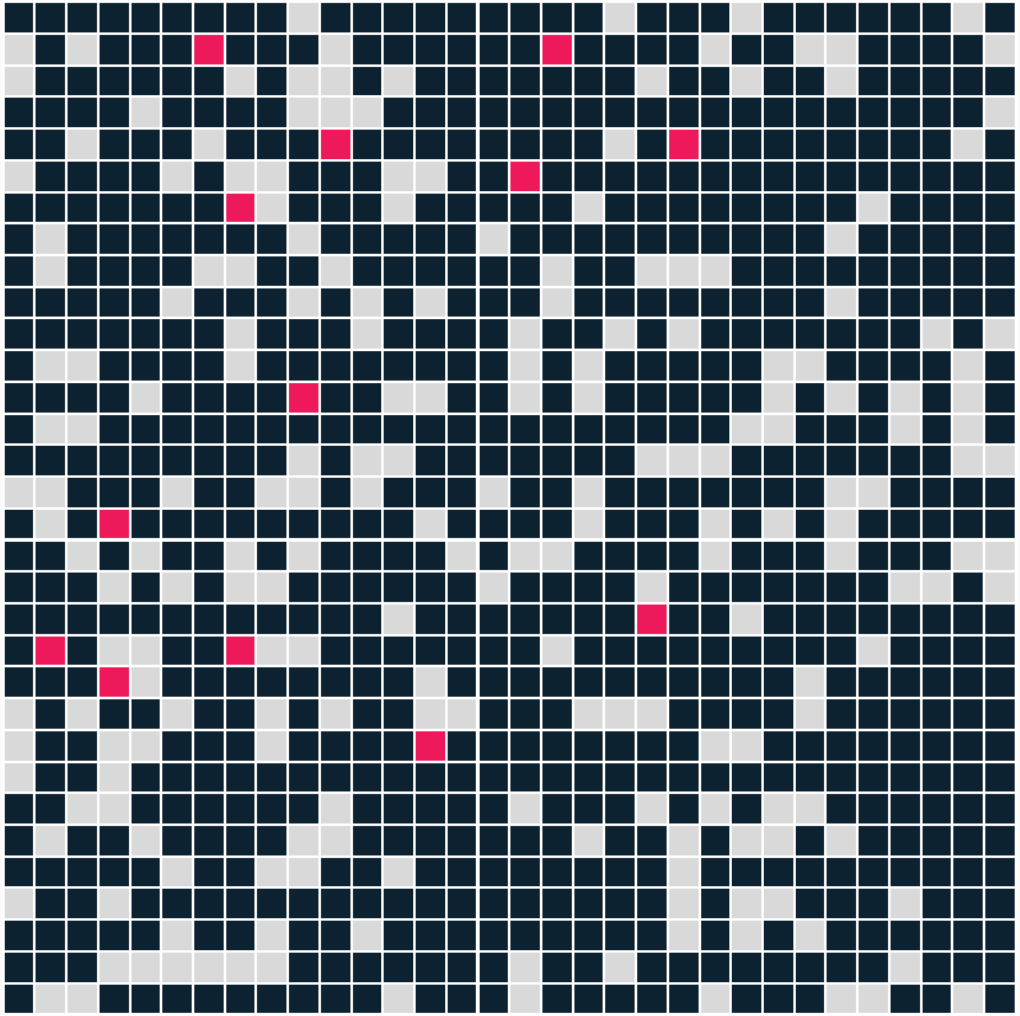
Data setting



Deforestation in 2004

$$y_{i,2004} = \begin{cases} \blacksquare\ 0 \text{ if persistent forest} \\ \blacksquare\ 1 \text{ if deforested} \\ \square\ NA \text{ if previously deforested} \end{cases}$$

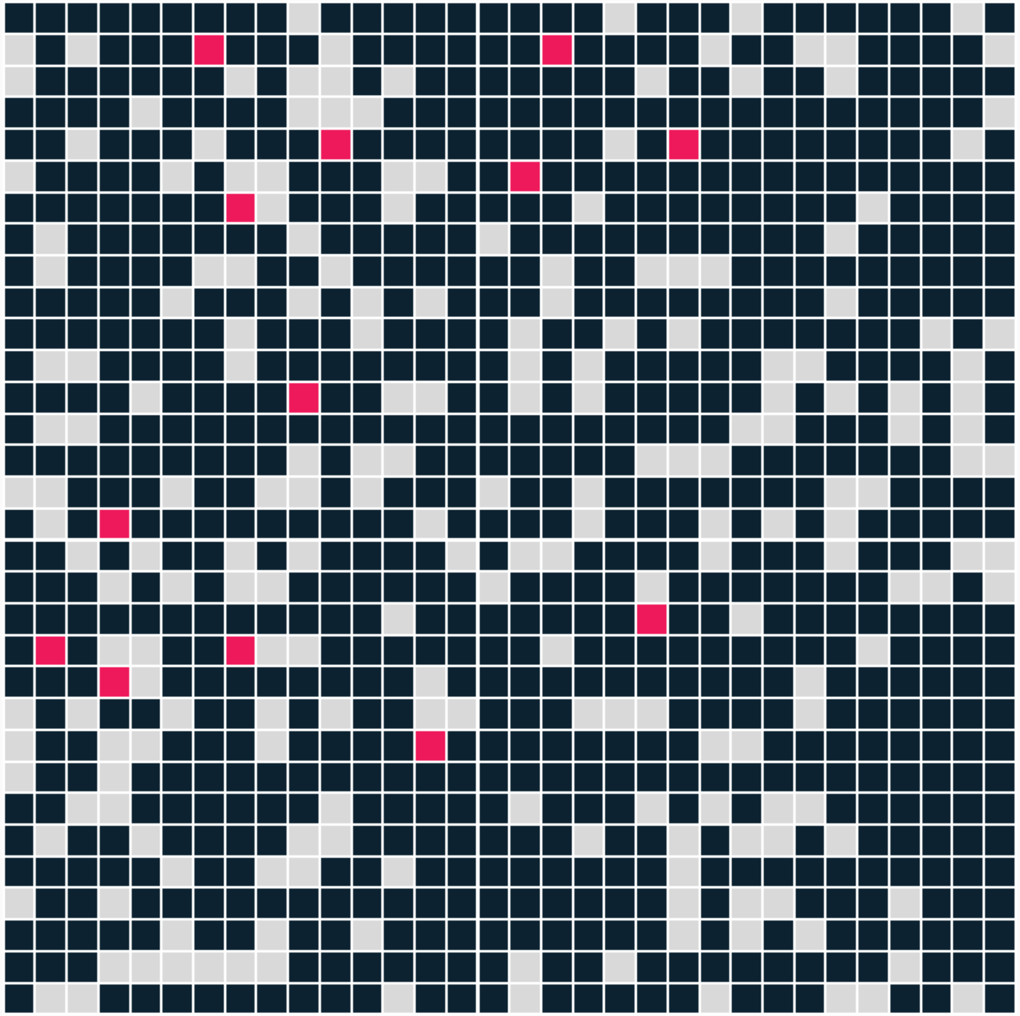
Data setting



Deforestation in 2005

$$y_{i,2005} = \begin{cases} \blacksquare\ 0 \text{ if persistent forest} \\ \blacksquare\ 1 \text{ if deforested} \\ \square\ NA \text{ if previously deforested} \end{cases}$$

Data setting



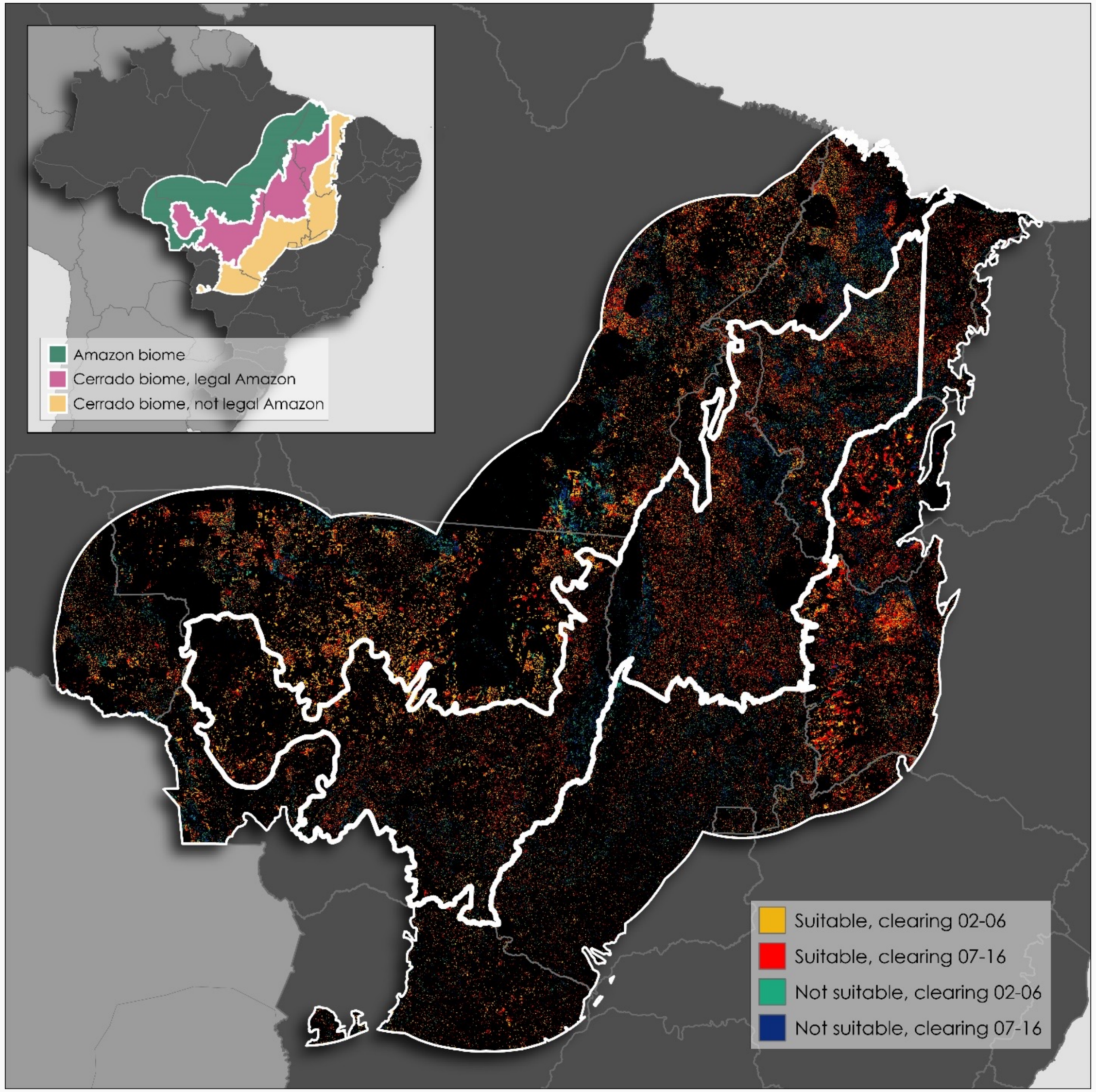
Data characteristics

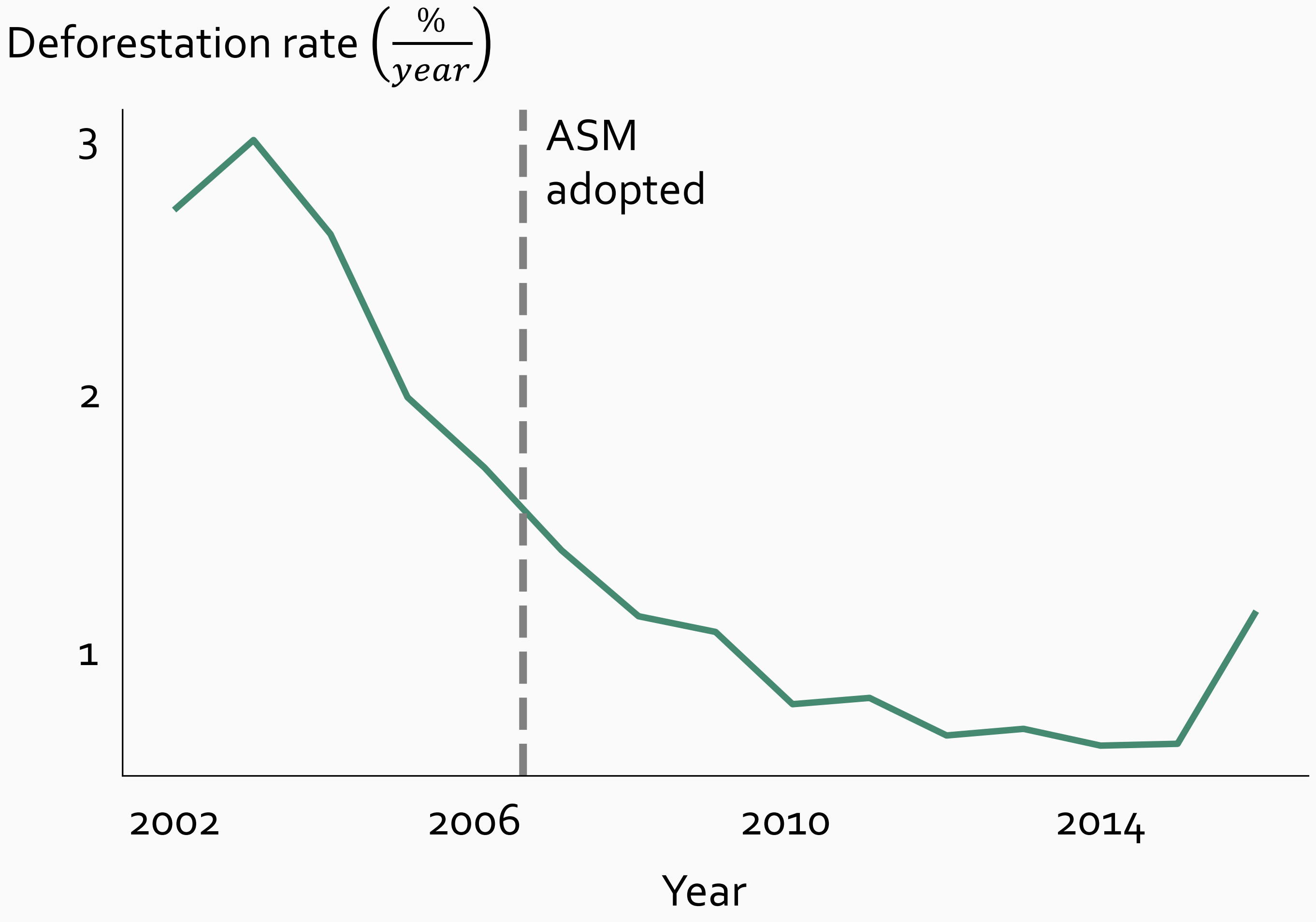
- Wall to wall data
- Fine spatial scales
- Relatively long time series
- Binary
- Irreversible

Econometric methods

Panel approaches to impact evaluation

Impacts of the Amazon Soy Moratorium





Heilmayr, Rausch, Munger and Gibbs, 2020

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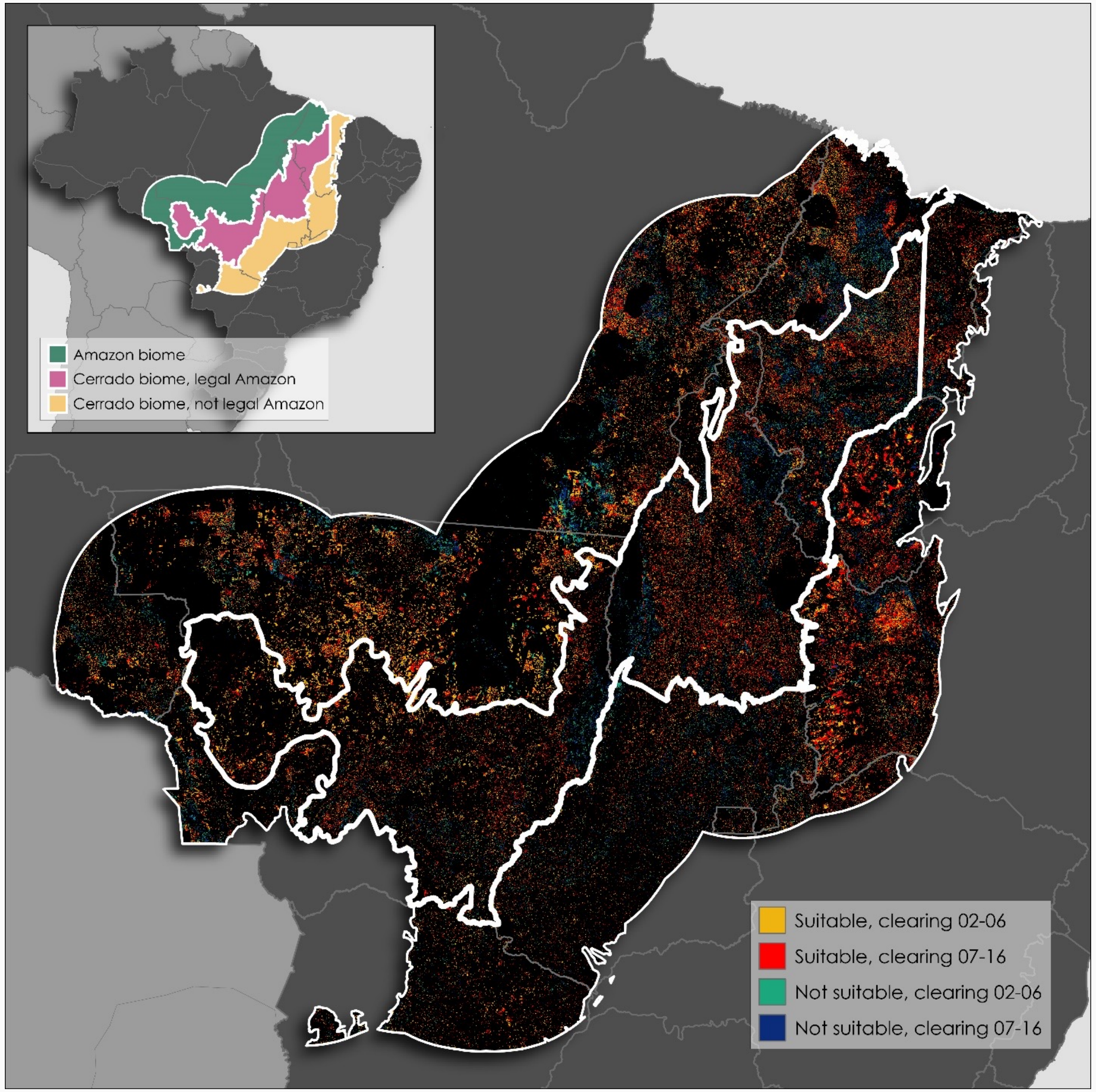

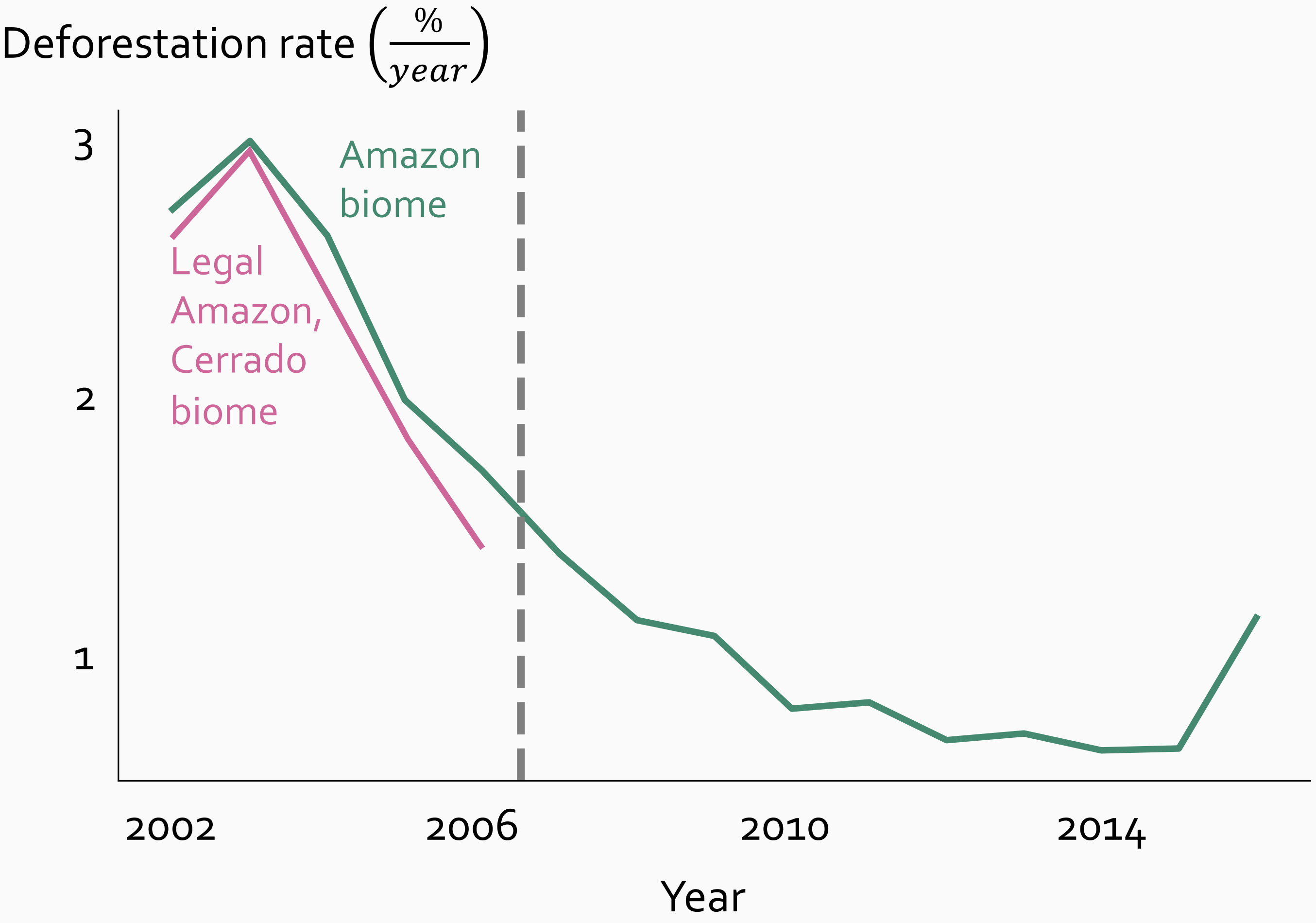

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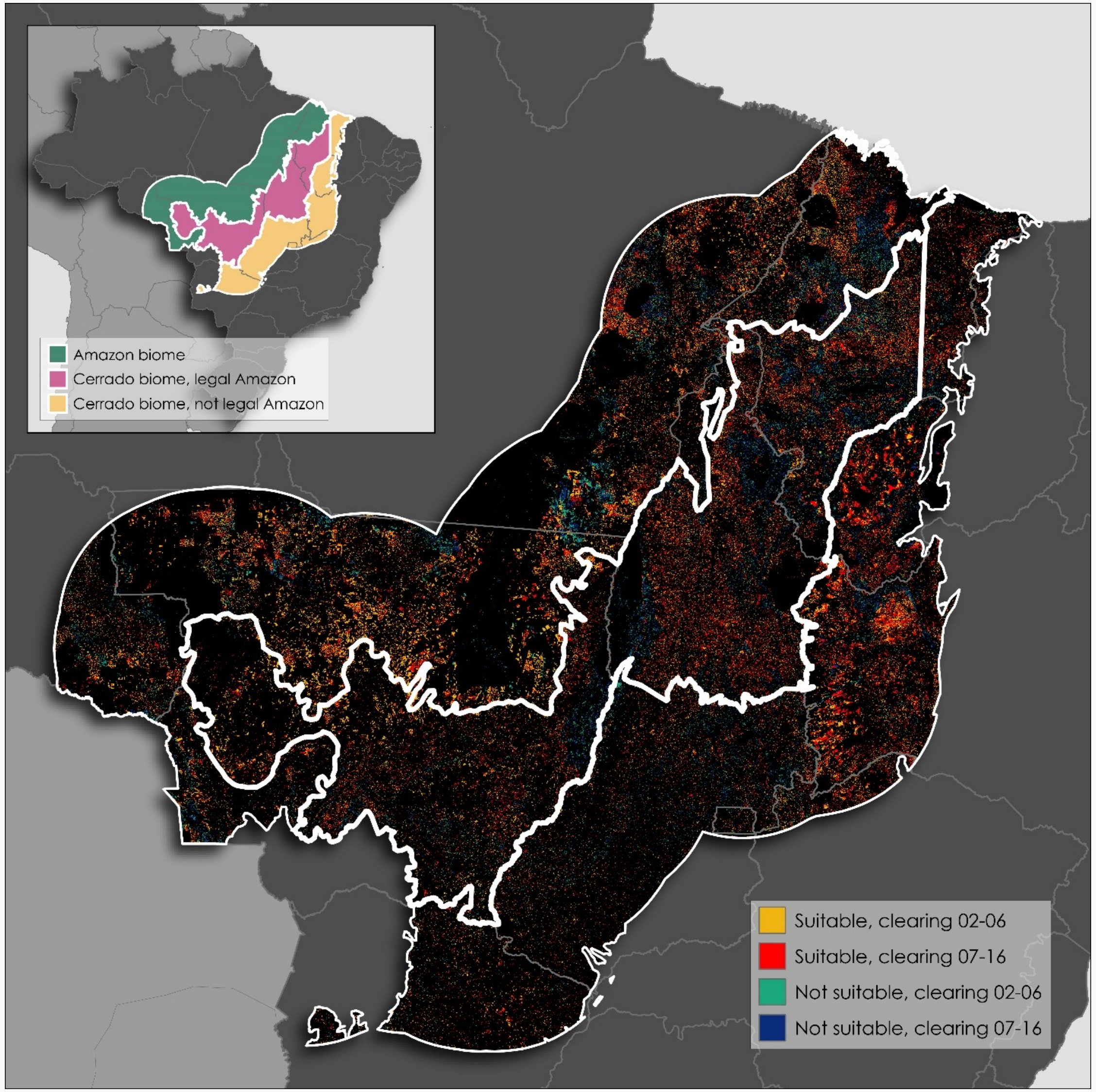
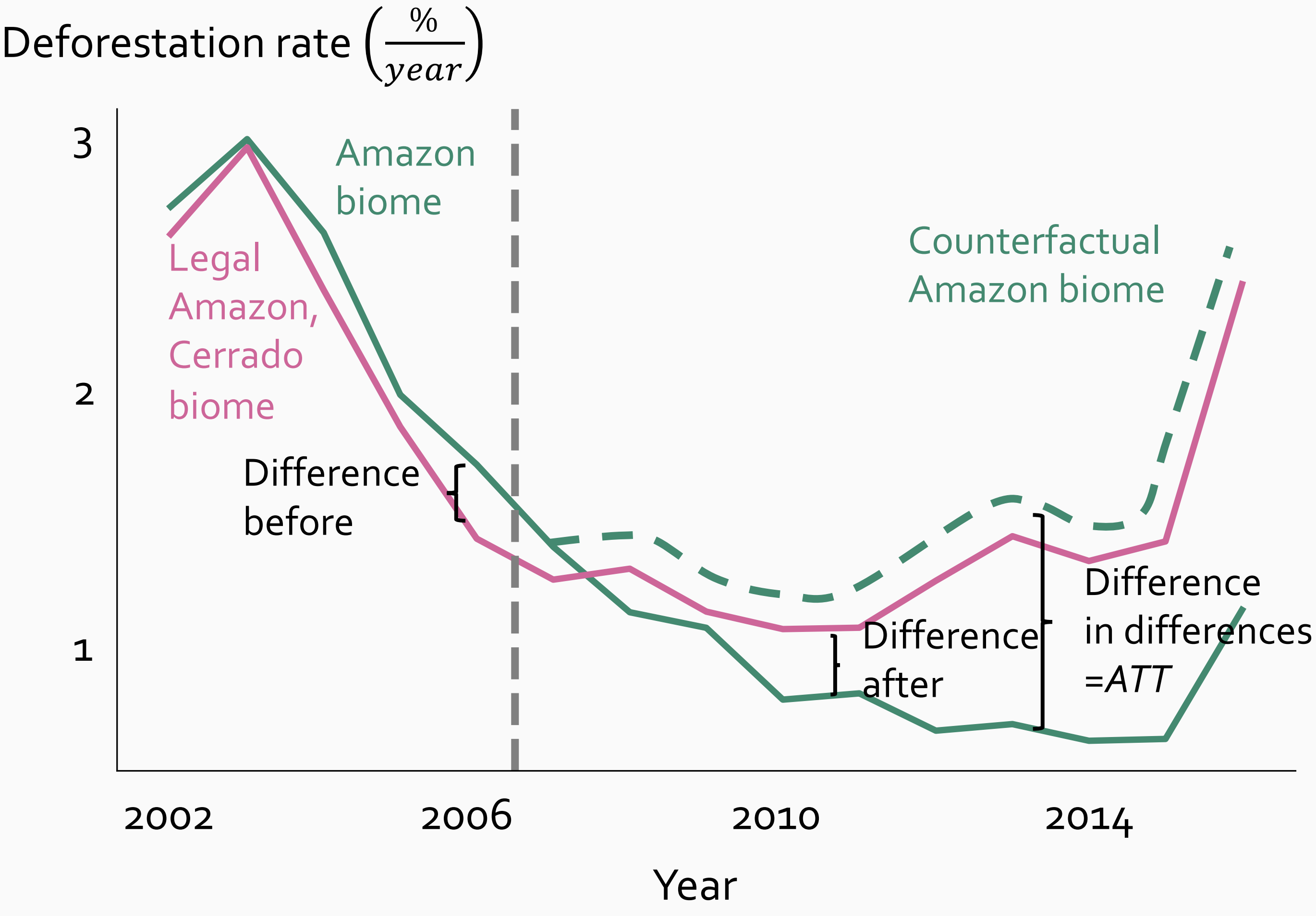




Heilmayr, Rausch, Munger and Gibbs, 2020

Impacts of the Amazon Soy Moratorium

Difference in differences regression:

$$y_{i,t} = \boldsymbol{\beta_{DID} \times D_i \times T_t} + \gamma D_i + \eta T_t + \mu_{i,t}$$

$$D_i = \text{Points inside Amazon Biome}$$

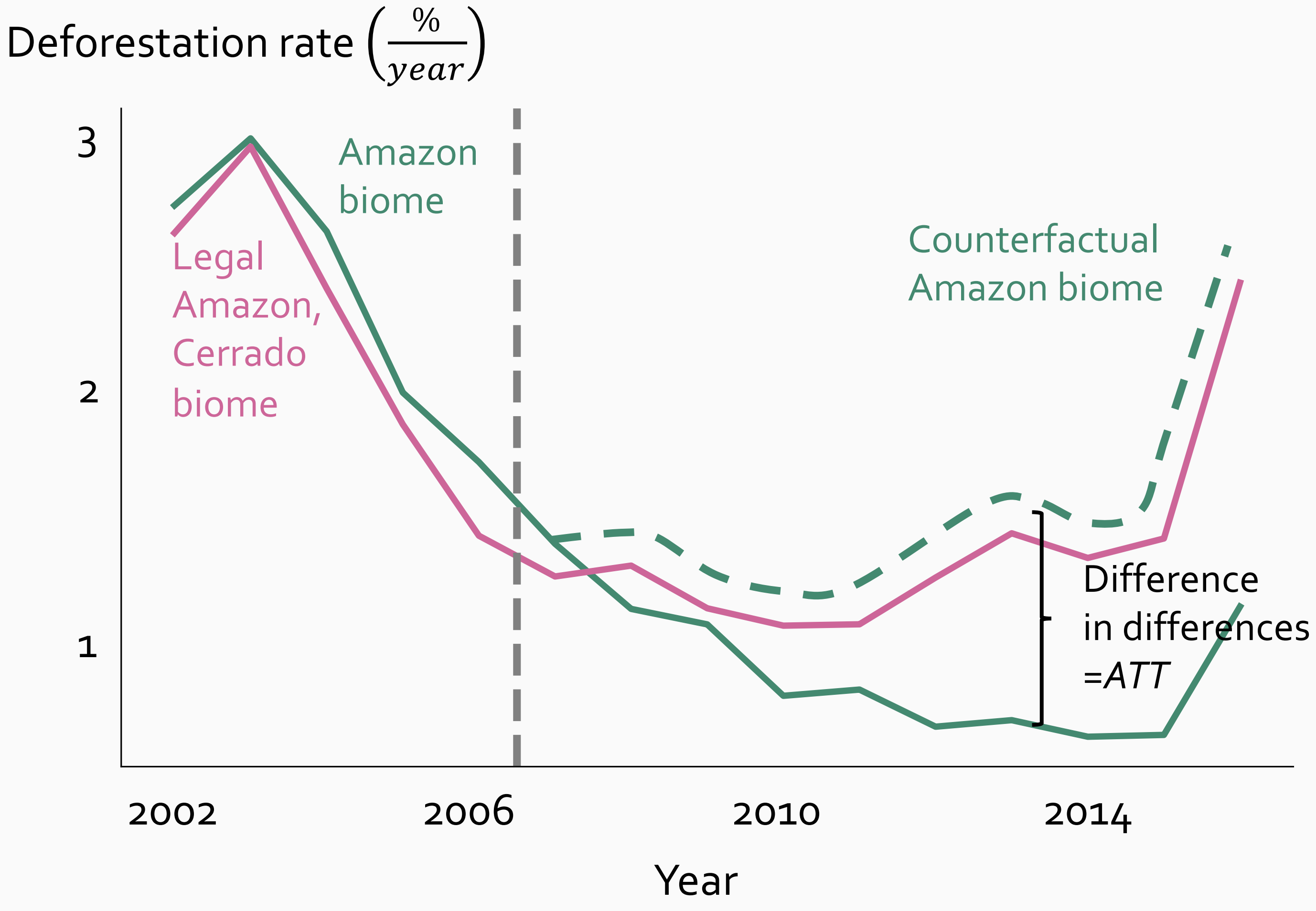
$$T_t = \text{Years after adoption (2006)}$$

$\hat{\beta}_{DID}$ is an estimate of ATT

Two-way, fixed effects regression (Generalized difference in differences):

$$y_{i,t} = \beta_{TWFE} \times D_i \times T_t + \gamma_i + \eta_t + \mu_{i,t}$$

Which model is right?



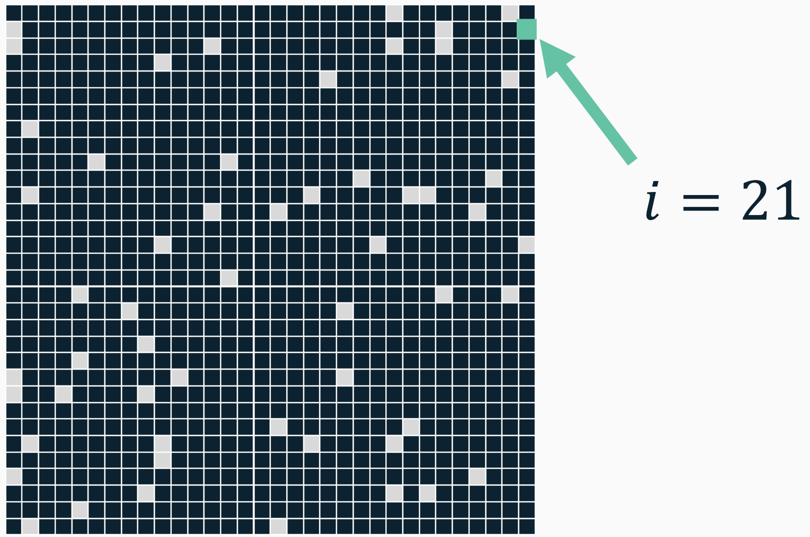
Heilmayr, Rausch, Munger and Gibbs, 2020

Monte Carlo simulations

Testing alternate models for impact evaluation.

Simulating forested landscapes

We generate a landscape of i pixels



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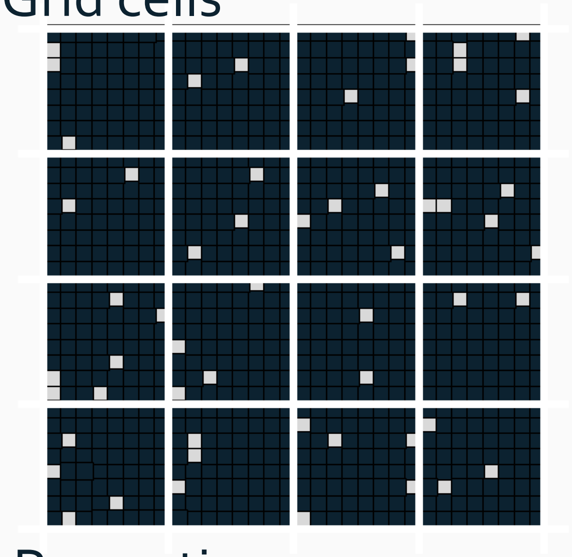
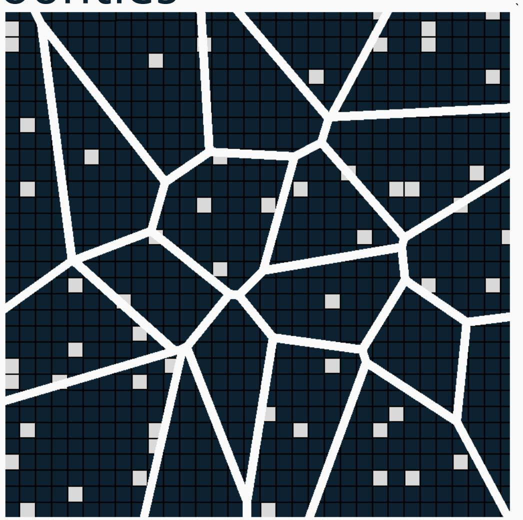
Simulating forested landscapes

Pixels can be grouped into different scales of geographic or management units (e.g. grid cells, counties or properties)

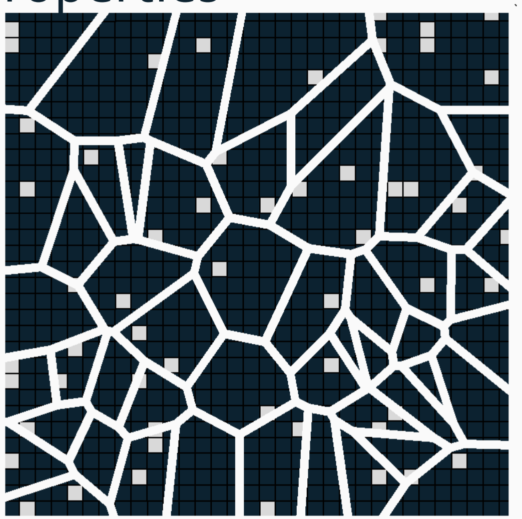
Grid cells



Counties



Properties



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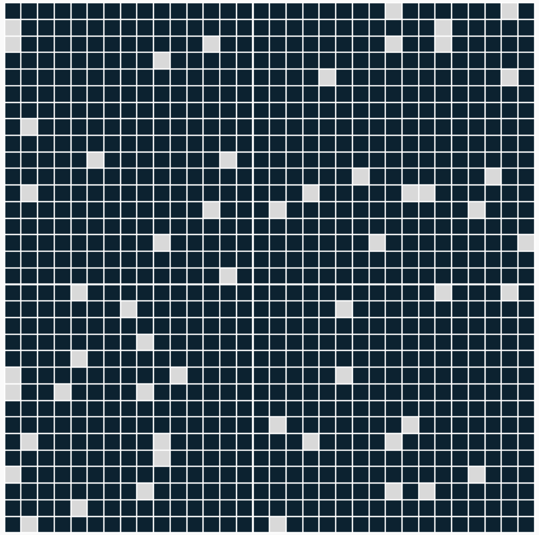
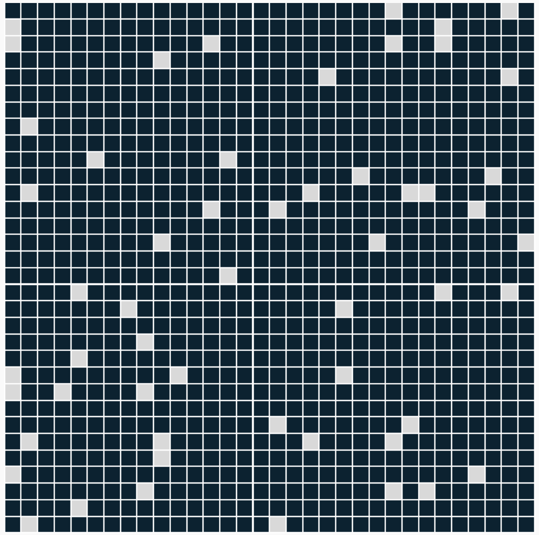
Simulating forested landscapes

We observe the landscape across t time periods

$t = 1$

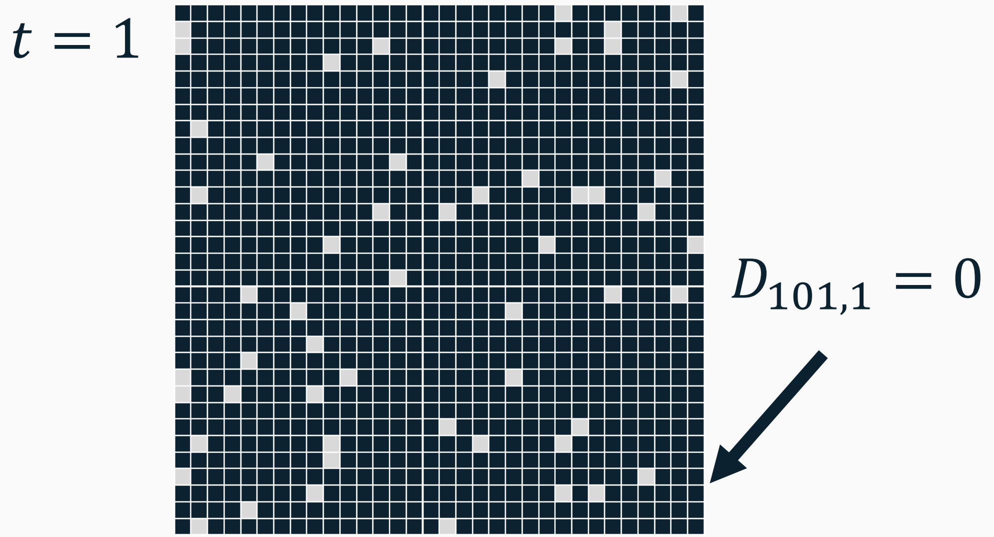


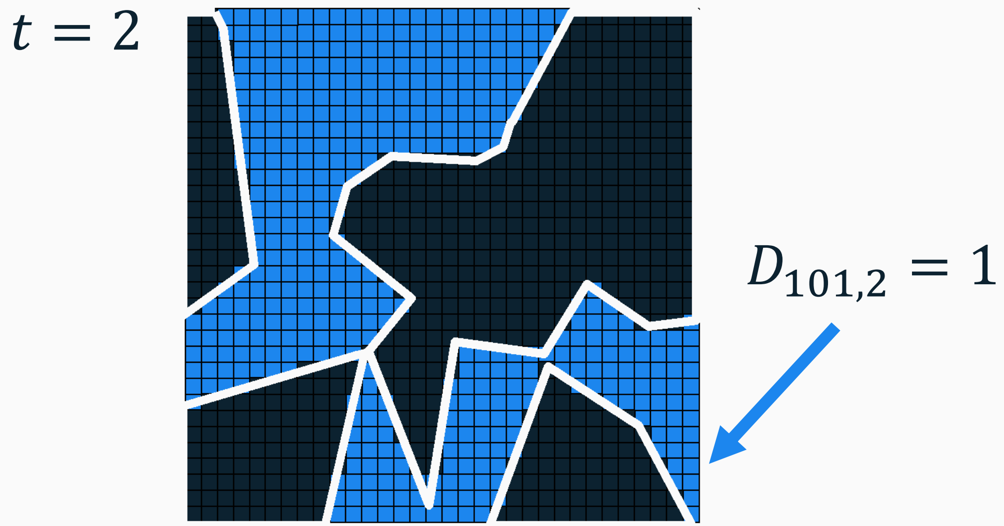
$t = 2$



Simulating forested landscapes

Some units are randomly assigned to a policy treatment in second period $\left(D_{i,t=2} = 1\right)$





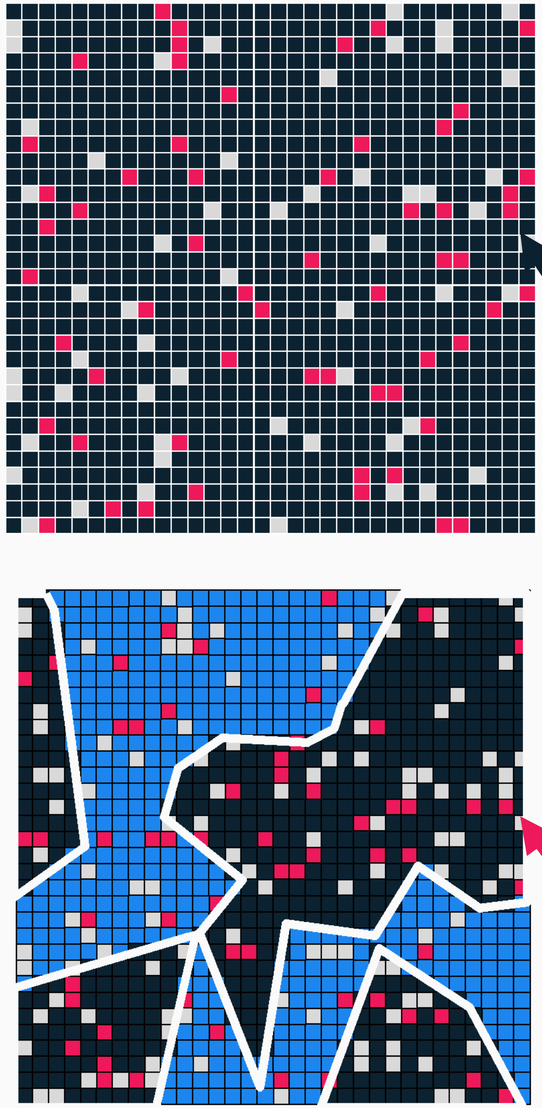
Simulating forested landscapes

Deforestation $(y_{i,t})$ is simulated as a binary irreversible outcome

$$y_{i,t} = \begin{cases} 0 \text{ if not deforested} \\ 1 \text{ if deforested} \\ NA \text{ if previously deforested} \end{cases}$$

$t = 1$

$y_{60,1} = 0$



$t = 2$

$y_{60,2} = 1$

What models yield good estimates of ATT?

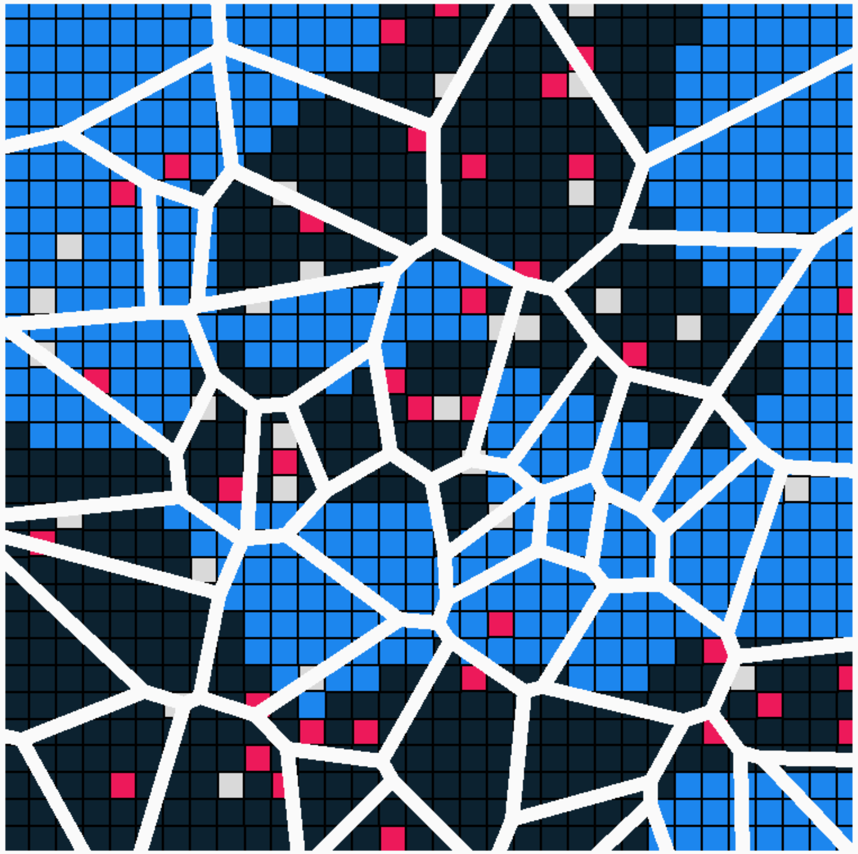
Scale of fixed effects or units of observatio

- Pixel (e.g. Alix-Garcia et al., 2018)
- Treatment (e.g. Arriagada et al., 2012)
- County (e.g. Blackman, 2015)
- Grid cell (e.g. BenYishay et al., 2017)
- Property (e.g. Heilmayr and Lambin, 2016)

Functional form

Calculation of deforestation rate

Calculation of standard errors



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Insight 1: A big problem

Pixel-level, two-way fixed effects model does not estimate the ATT

Difference in differences or two-way fixed effects?

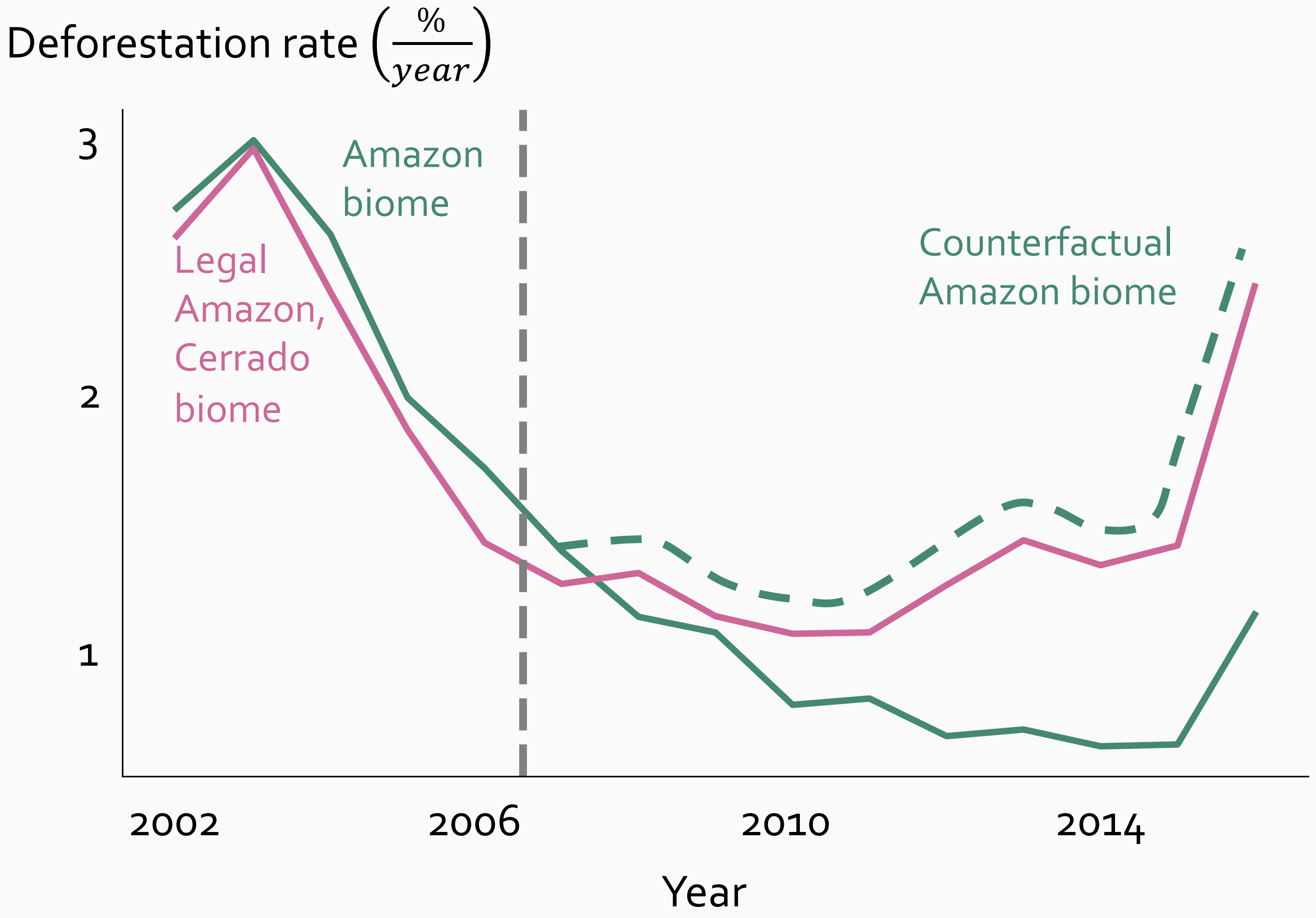
Difference in differences regression:

$$y_{i,t} = \beta_{DID} \times D_i \times T_t + \gamma D_i + \eta T_t + \mu_{i,t}$$

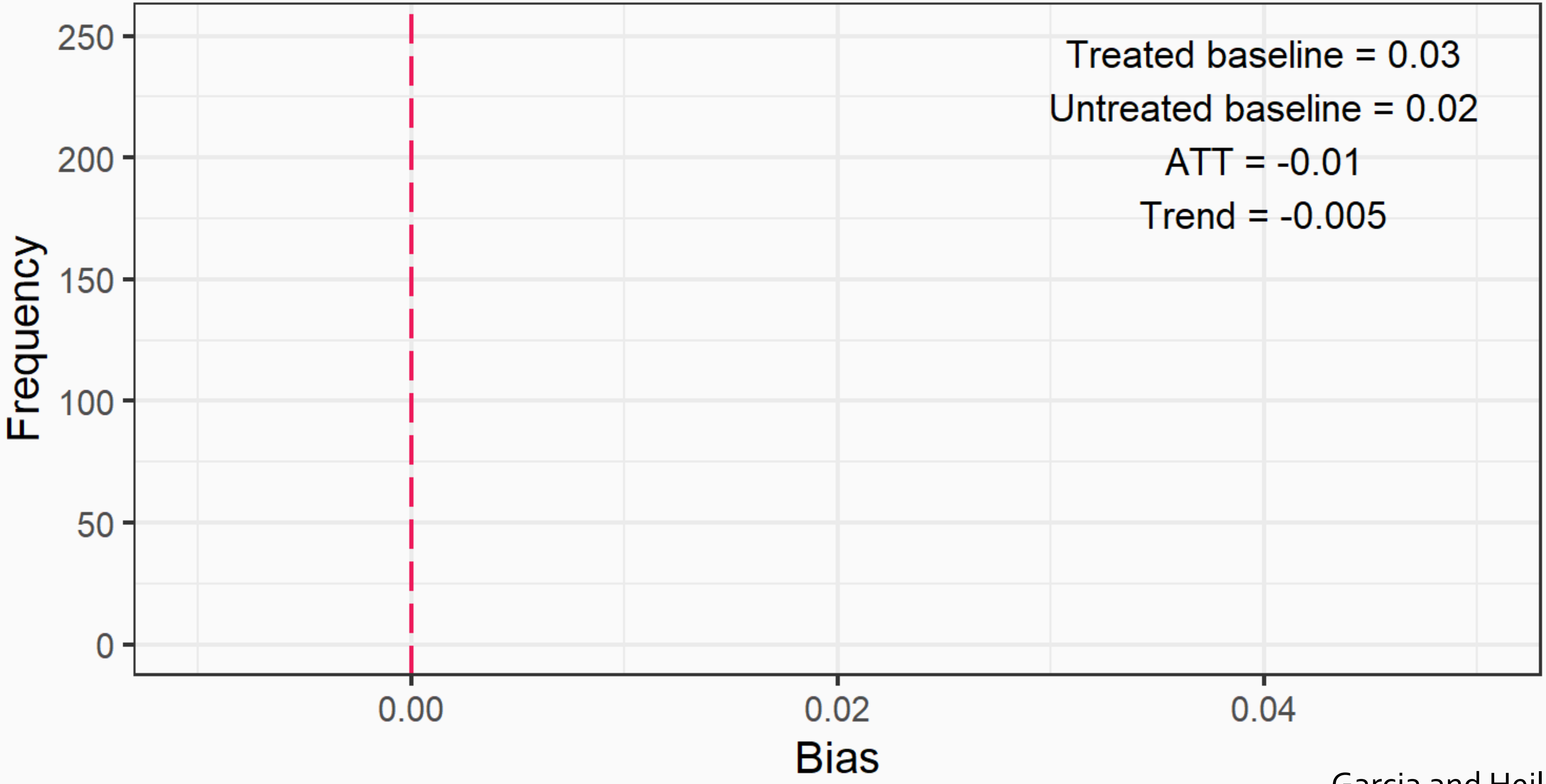
Two-way, fixed effects regression (Generalized difference in differences):

$$y_{i,t} = \beta_{TWFE} \times D_i \times T_t + \gamma_i + \eta_t + \mu_{i,t}$$

Which model is right?



Difference in differences or two-way fixed effects?



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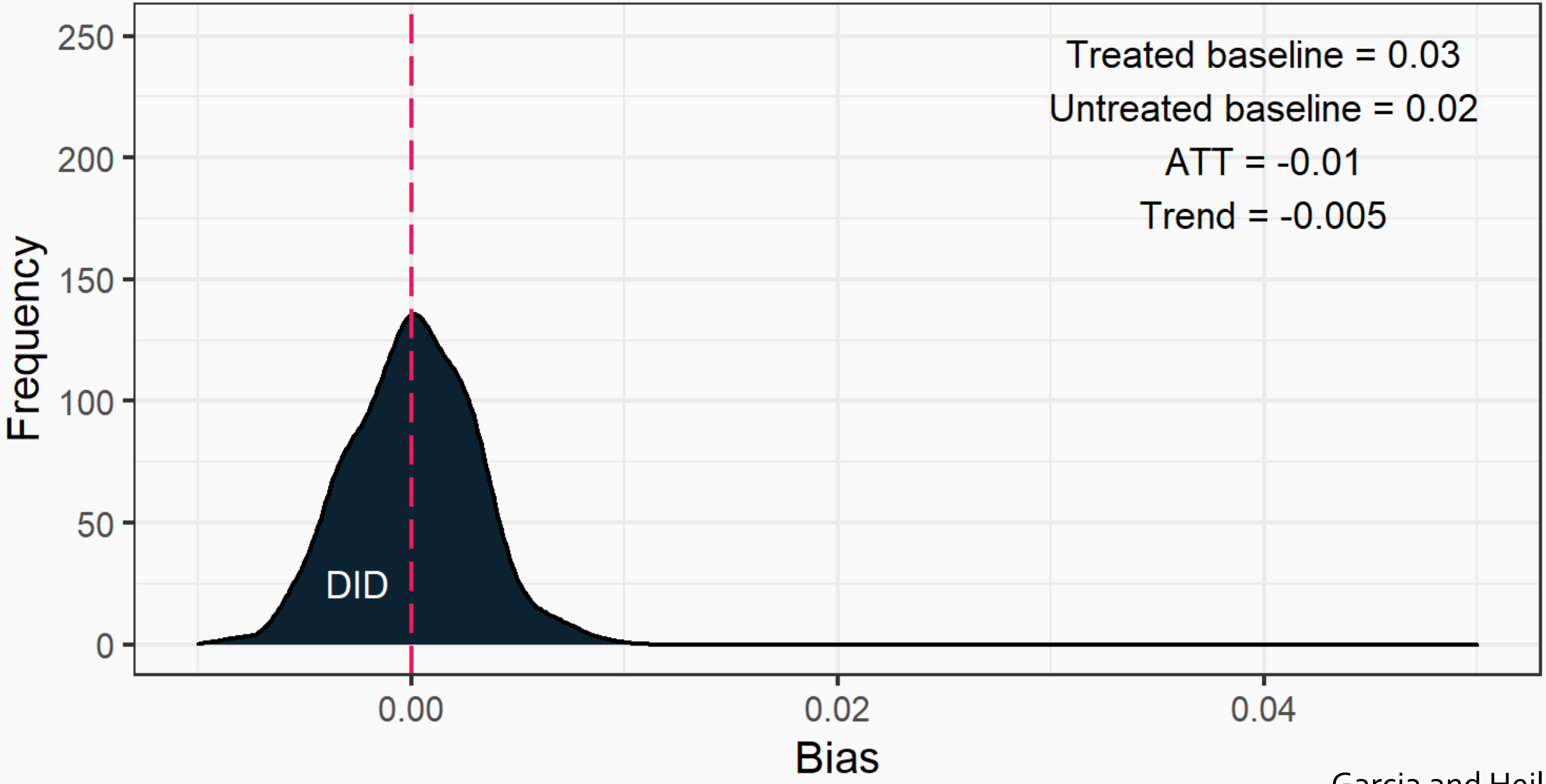
Difference in differences or two-way fixed effects?



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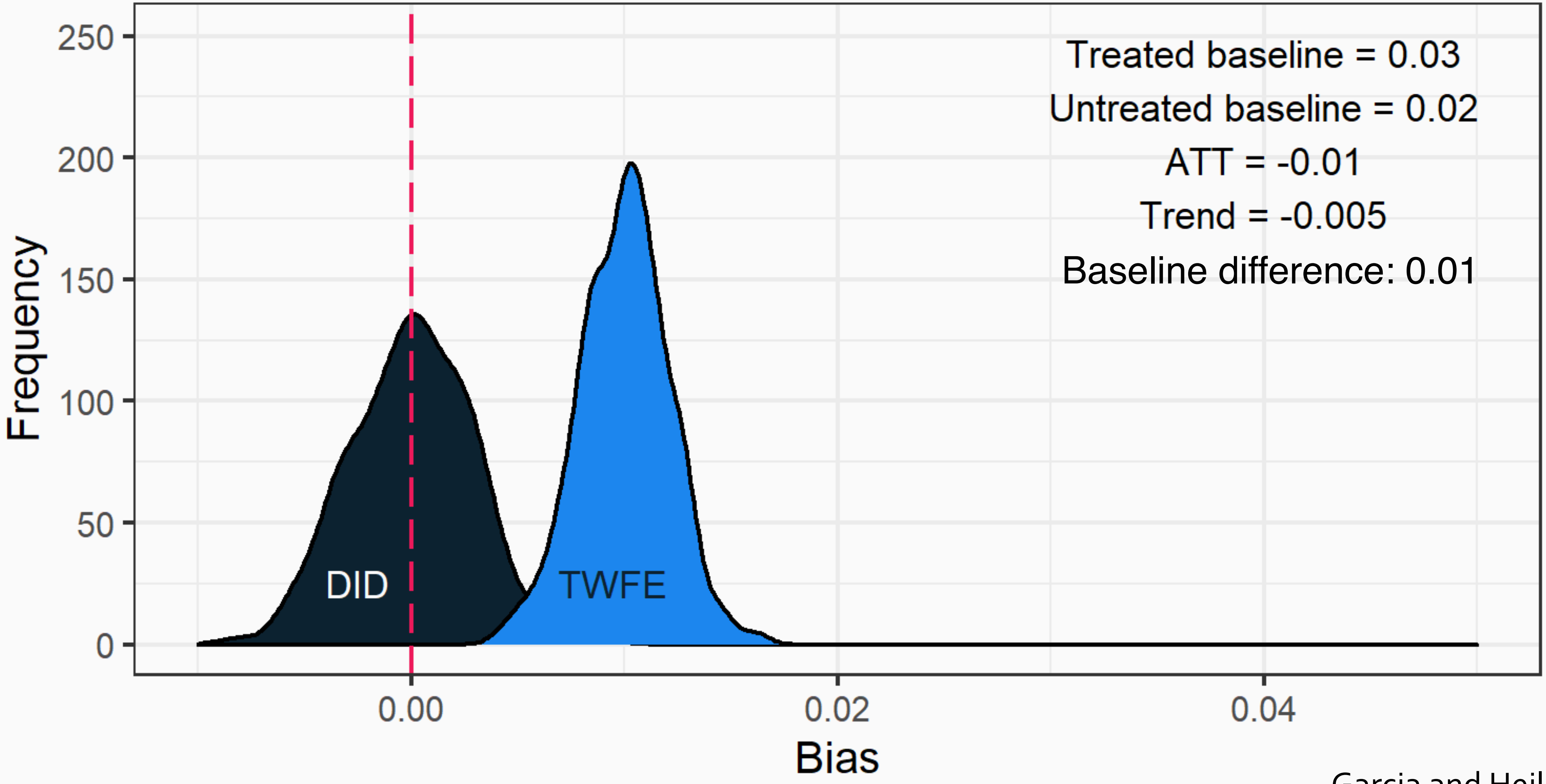
Difference in differences or two-way fixed effects?



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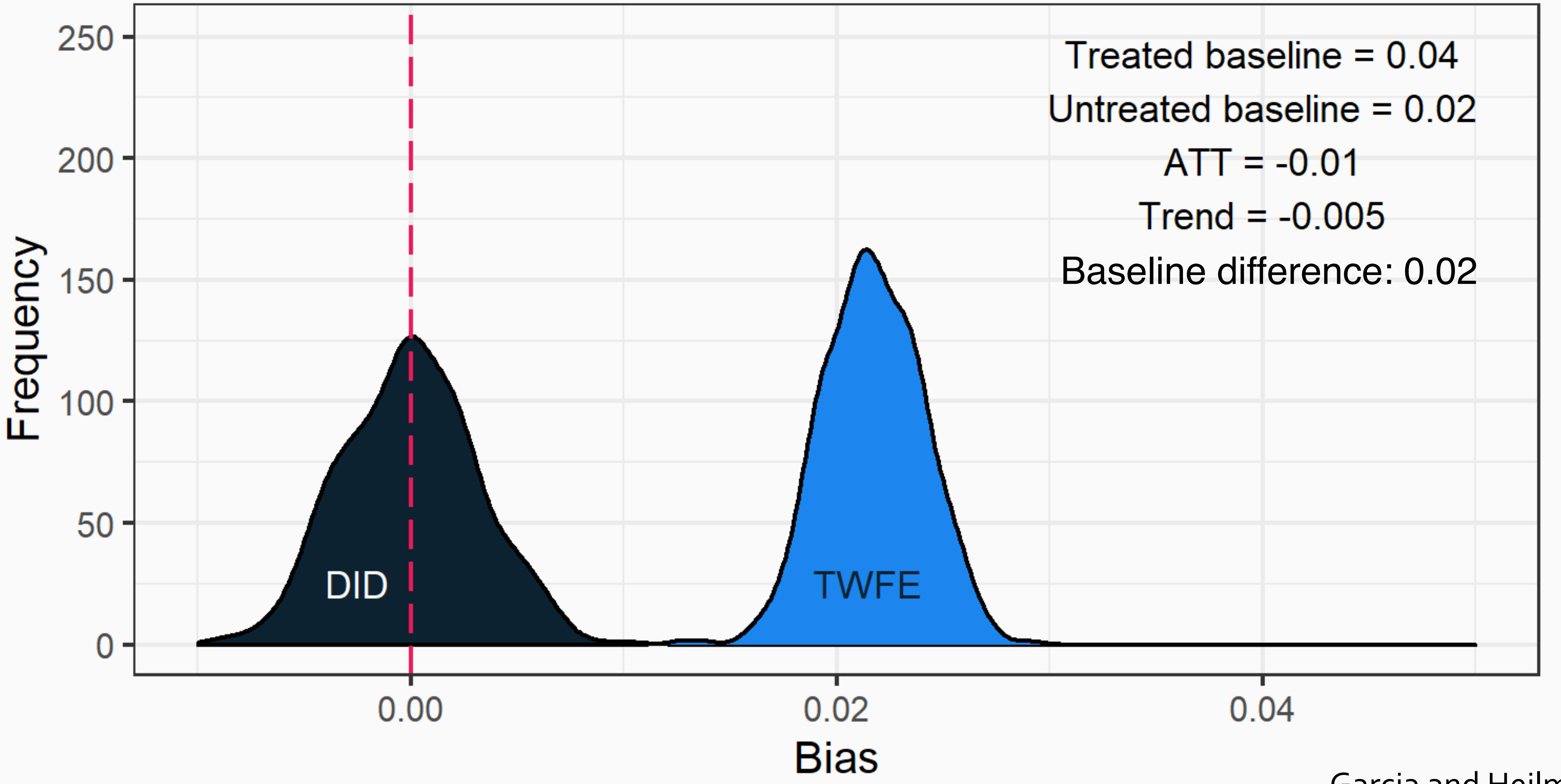
Difference in differences or two-way fixed effects?



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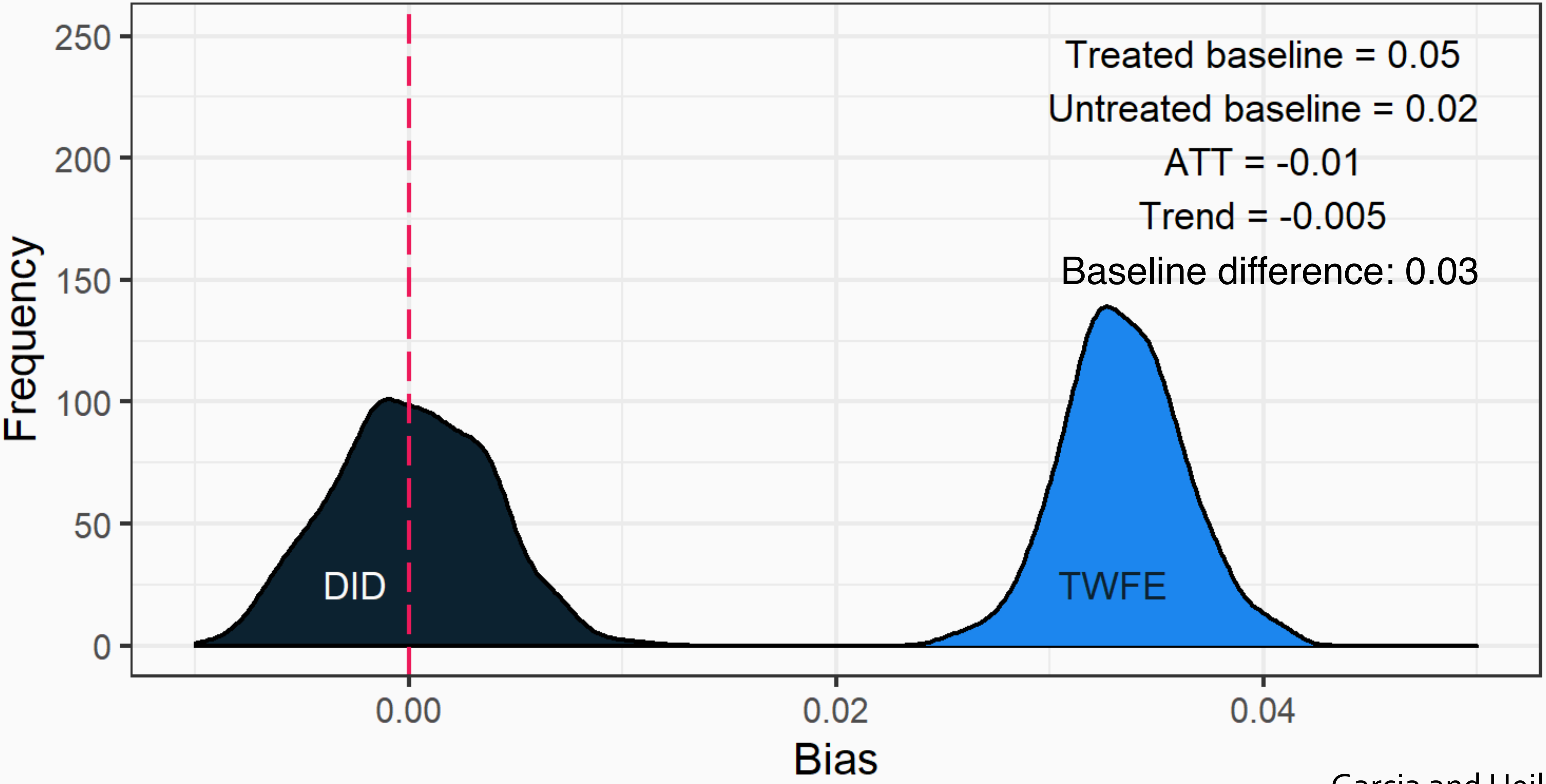
Difference in differences or two-way fixed effects?



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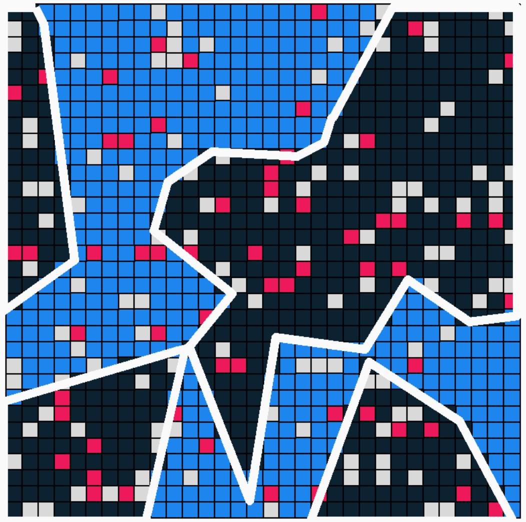
TWFE yields biased estimate of ATT



Two-way fixed effects regression:

$$y_{i,t} = \beta_{TWFE} \times D_i \times T_t + \gamma_i + \eta_t + \mu_{i,t}$$

$$\hat{\beta}_{TWFE} = \underbrace{\frac{1}{n_{i:D_i=1}} \sum_{i;D_i=1}^{N} y_{i,2}(1) - y_{i,2}(0)}_{ATT} + \underbrace{\left(\frac{1}{n_{i:D_i=1}} \sum_{i;D_i=1}^{N} y_{i,2}(0) - \frac{1}{n_{i:D_i=1}} \sum_{i;D_i=1}^{N} y_{i,2}(0) \right)}_{\text{Baseline difference in deforestation rate}}$$

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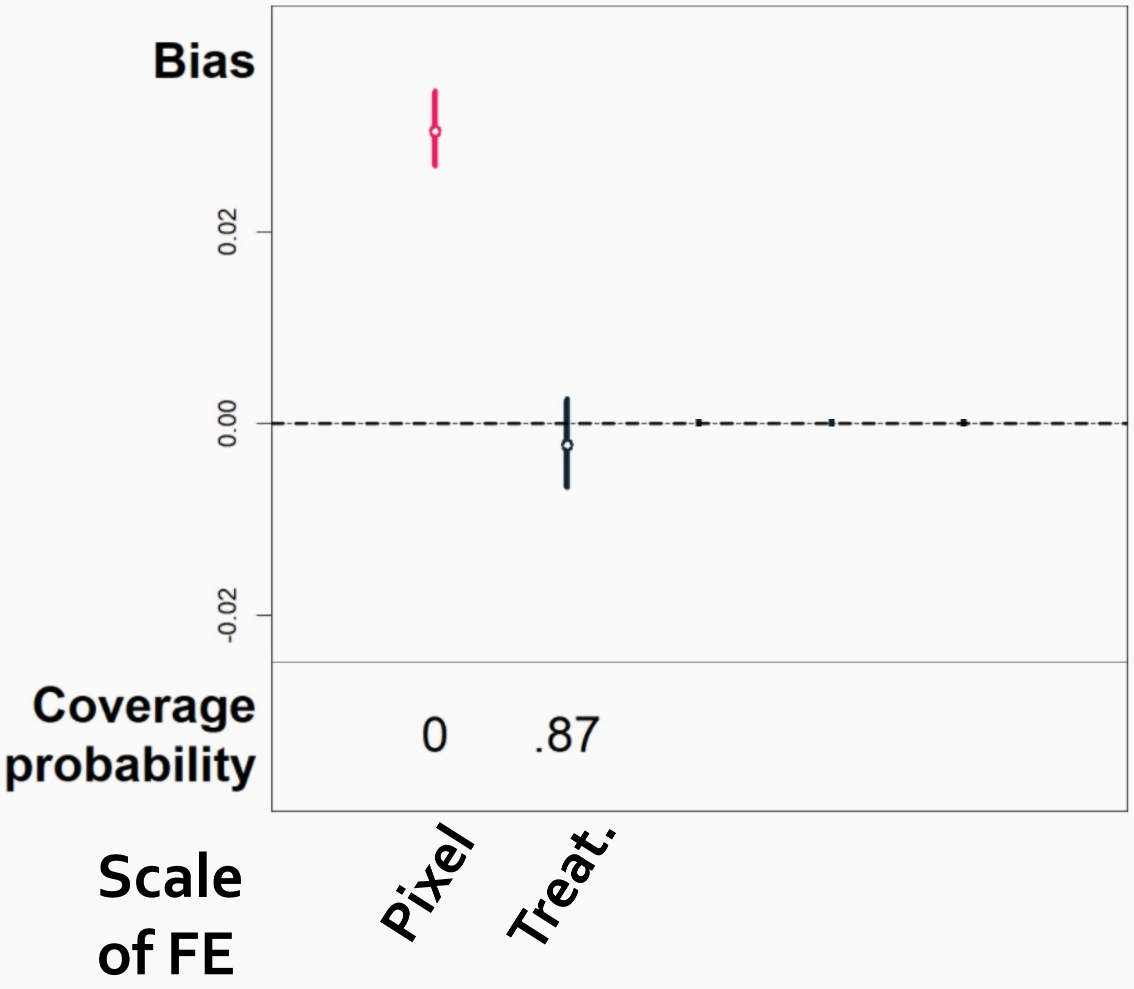
Insight 2: A simple solution

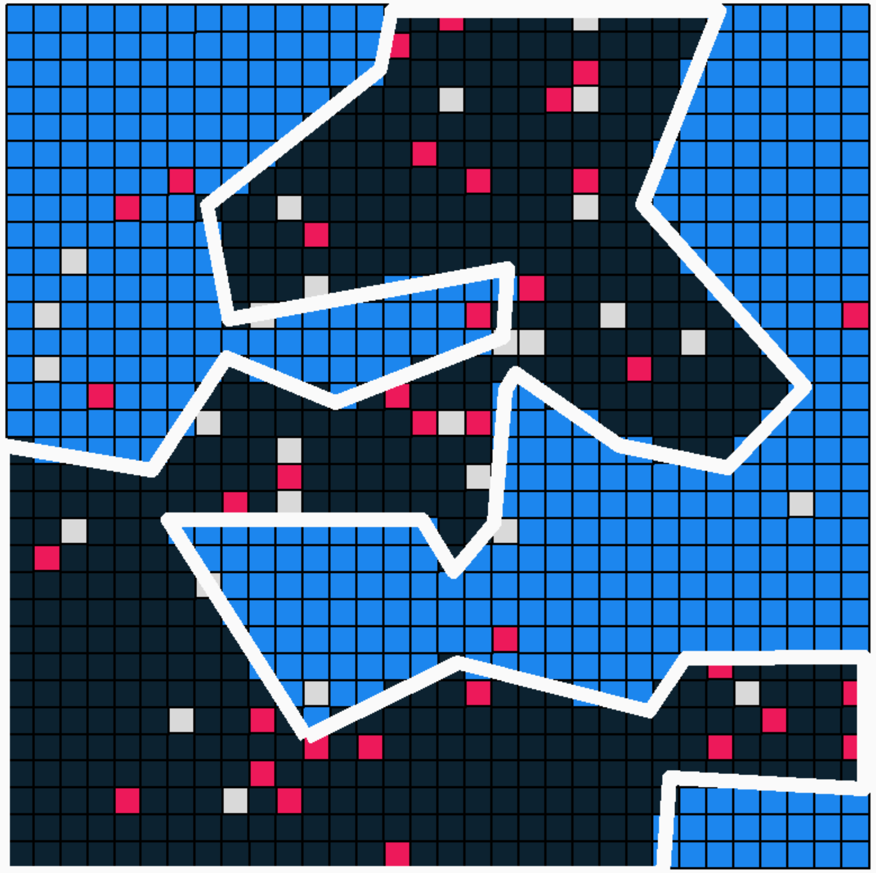
Aggregation can yield unbiased estimates of the ATT.

Aggregation as a solution

Varying scale of fixed effects



Treatment (i.e. DiD)



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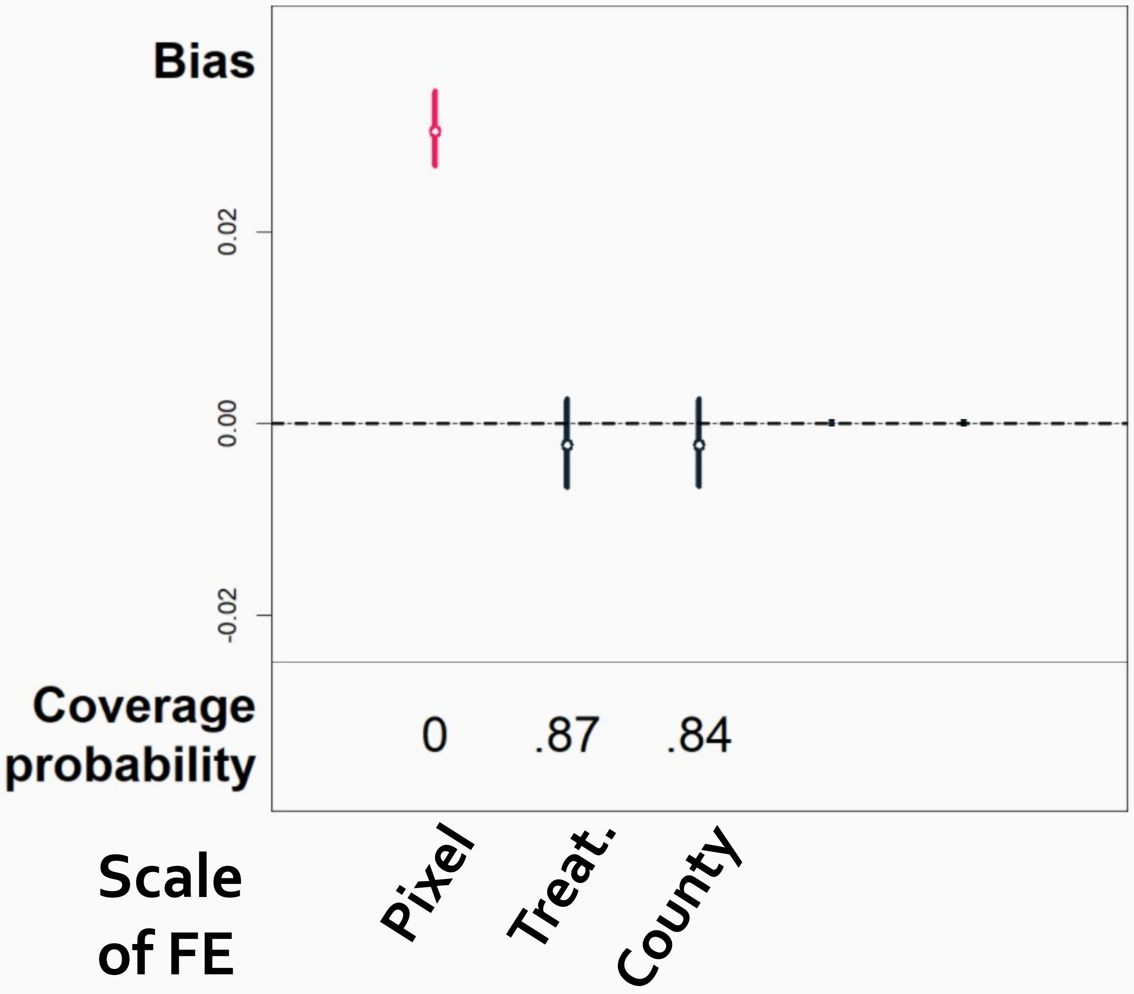
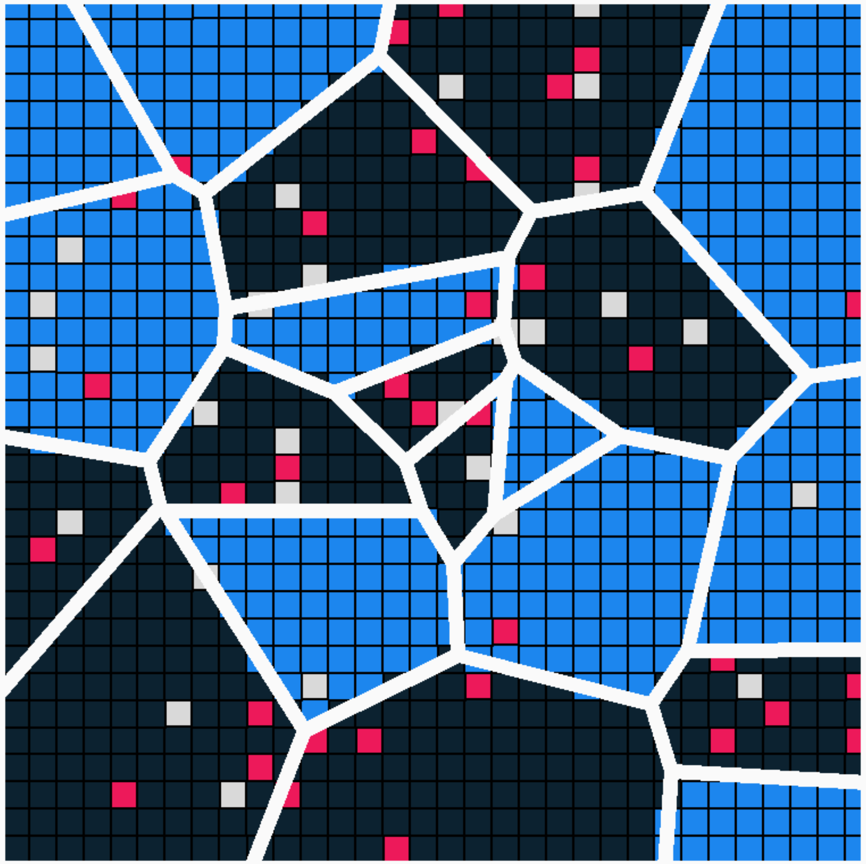
Aggregation as a solution

Varying scale of fixed effects



Counties



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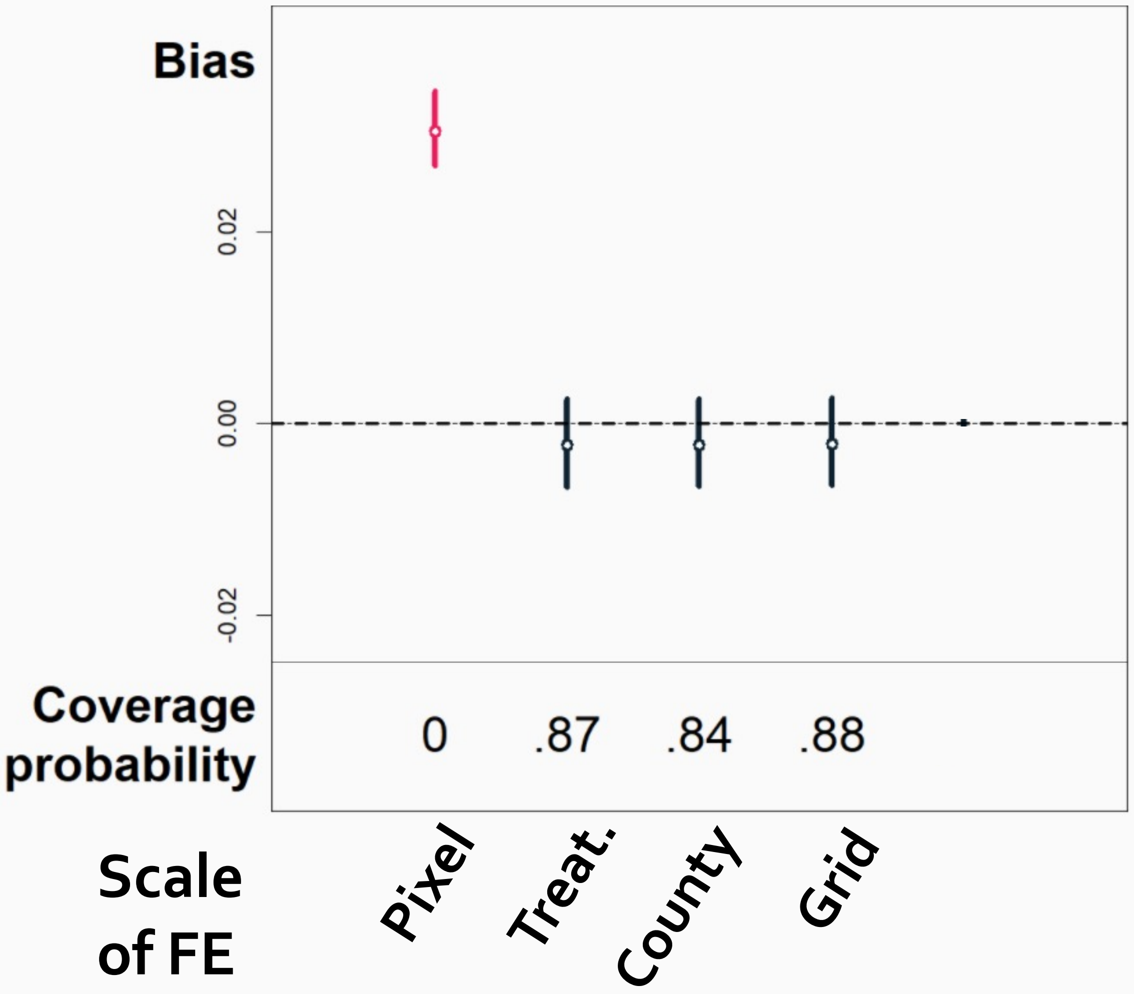
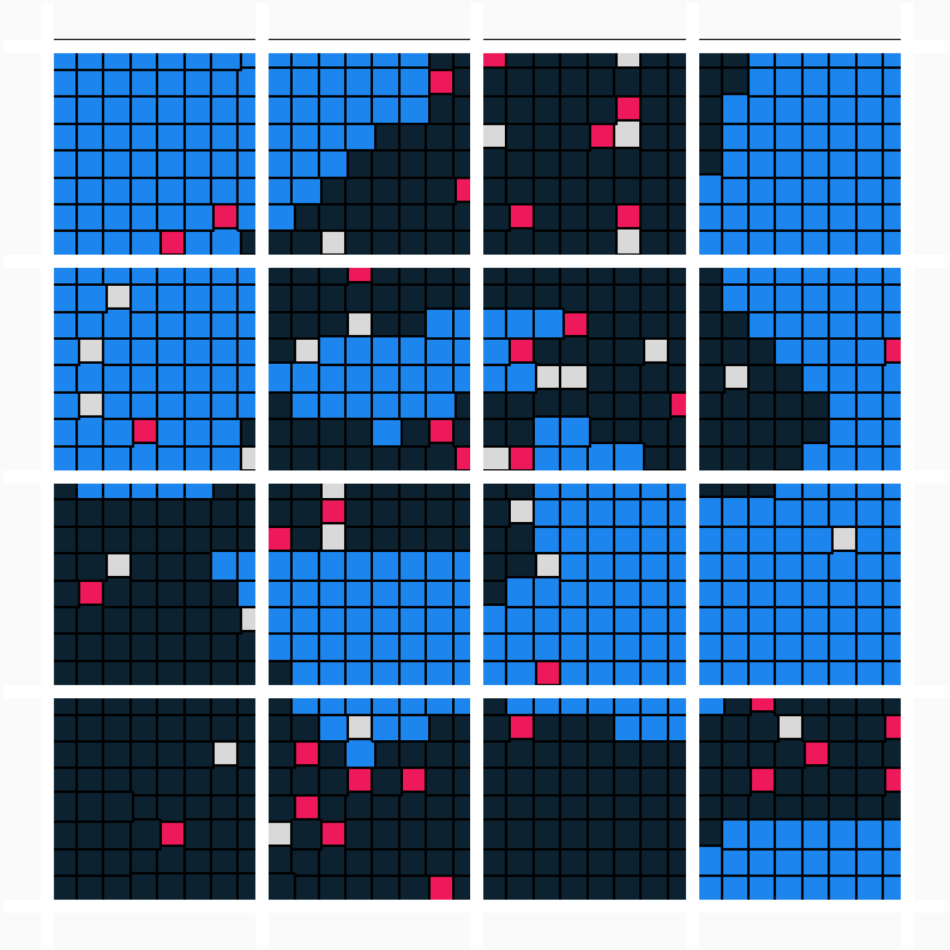
Aggregation as a solution

Varying scale of fixed effects



Grid cell



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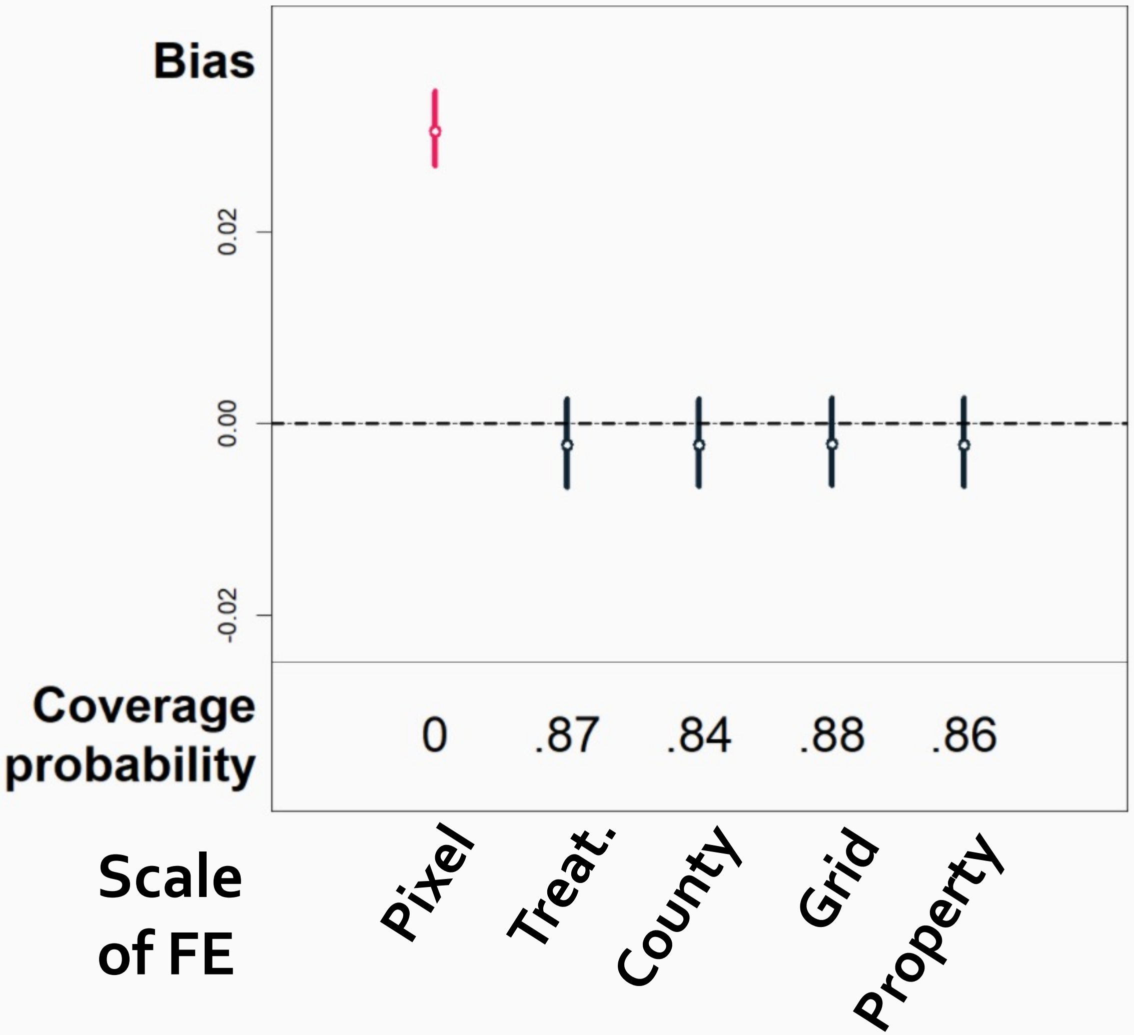
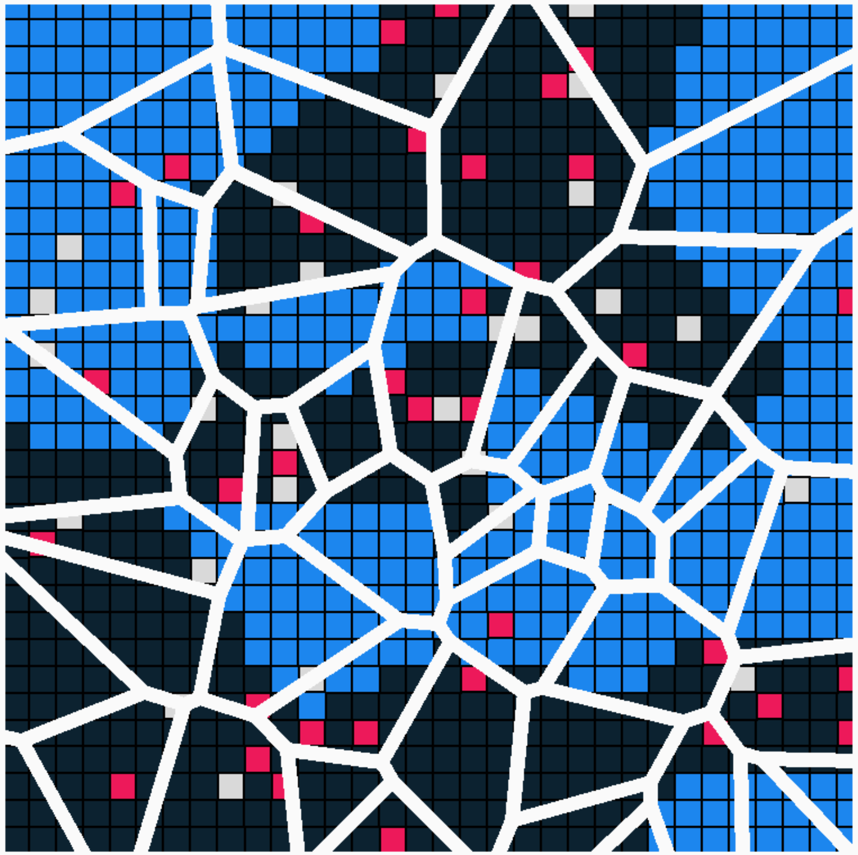
Aggregation as a solution

Varying scale of fixed effects



Property



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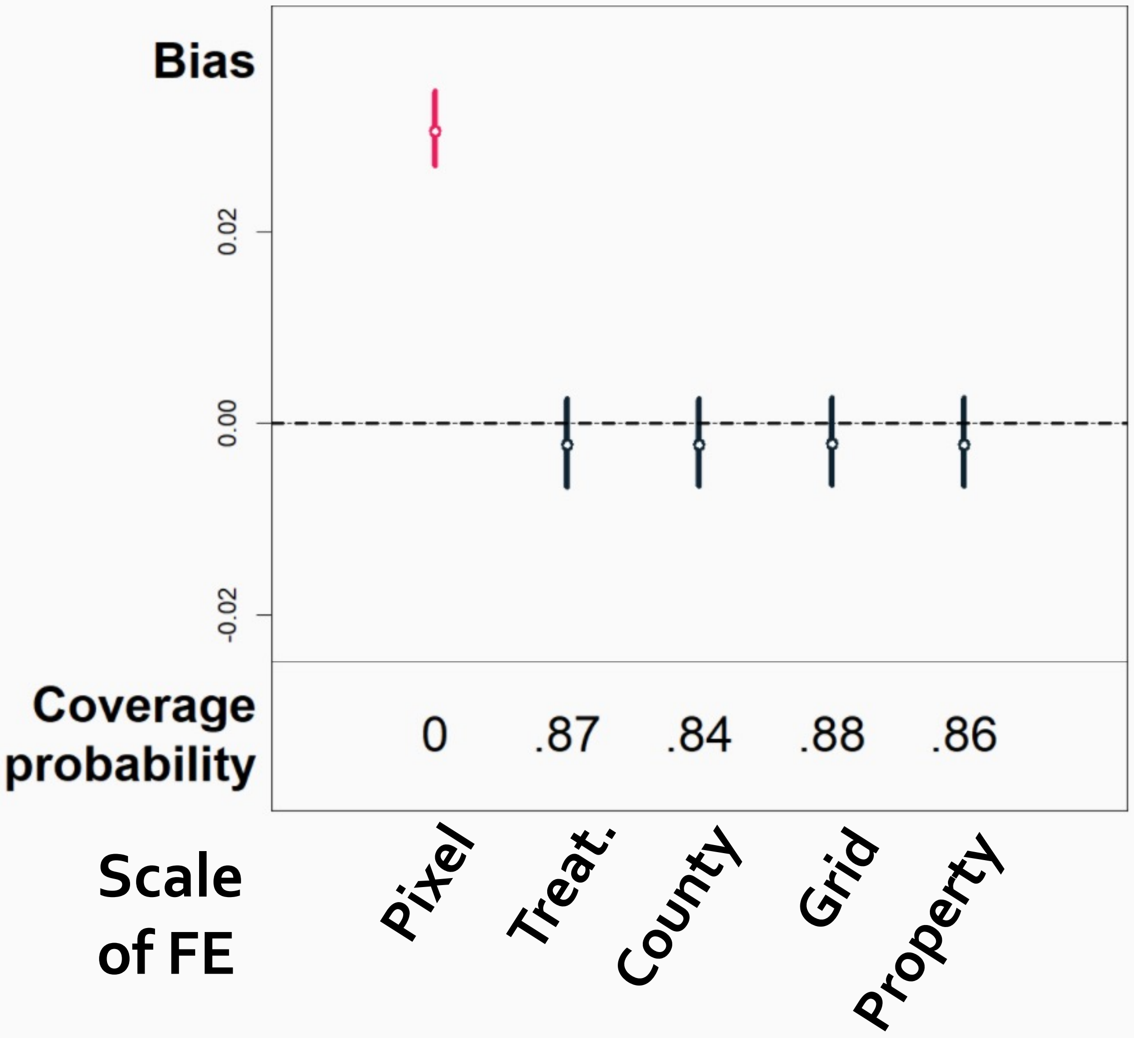
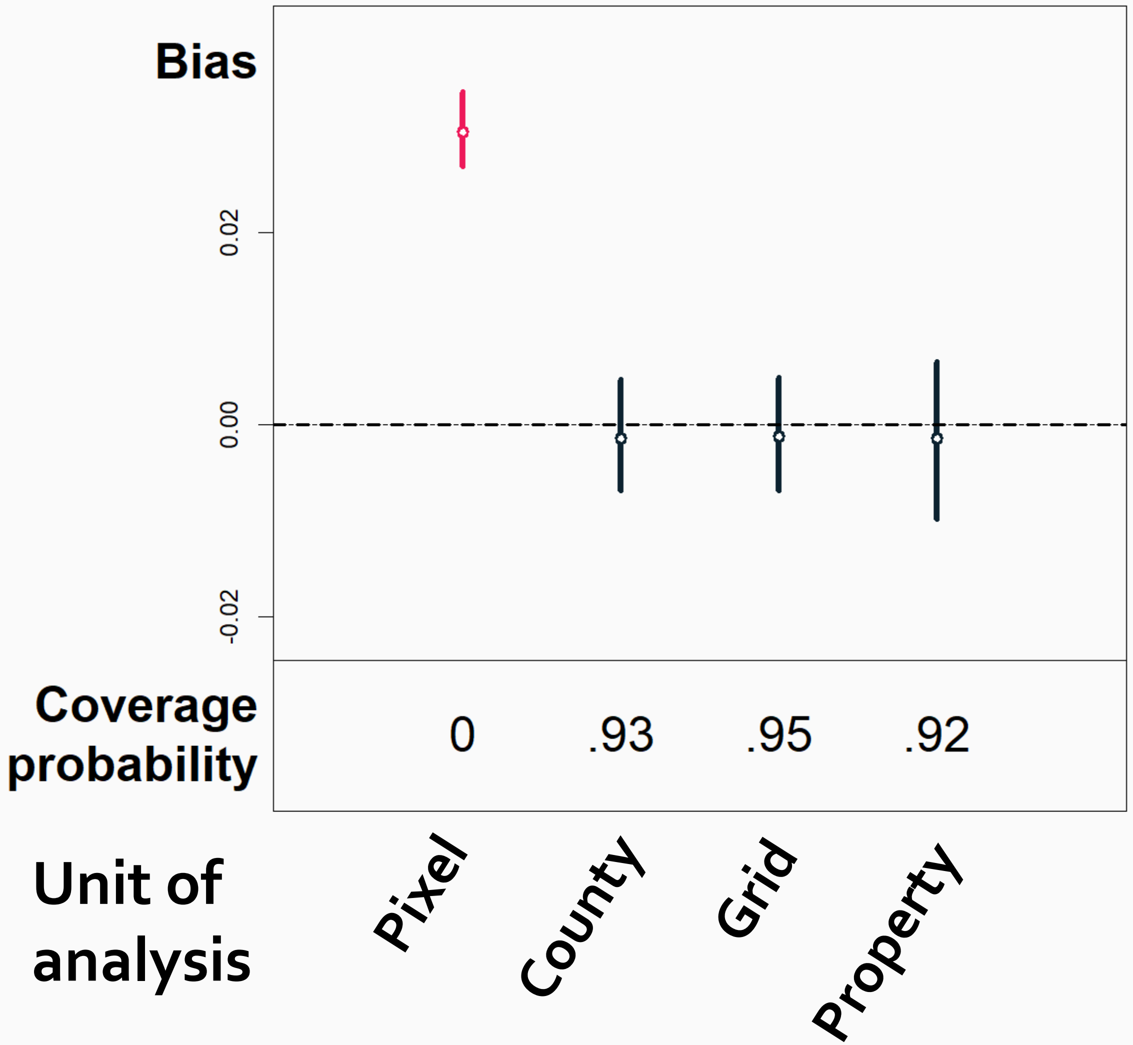
Aggregation as a solution

Varying scale of fixed effects



Varying scale of units of observation

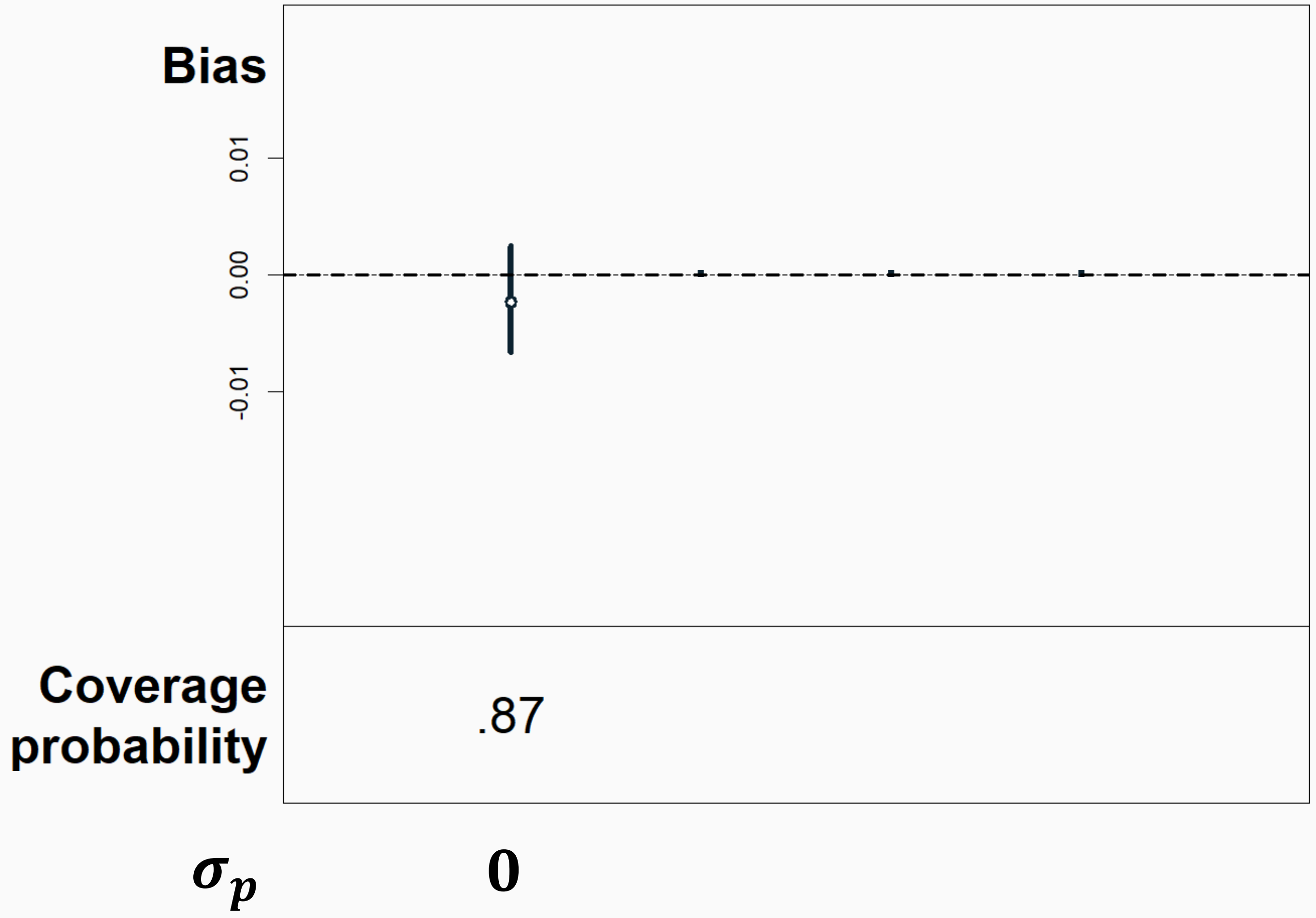


Insight 3: A better solution

Matching model structure to scale of real-world decisionmaking yields a better model.

Effect of property-level disturbances

Increasing property-scale disturbances



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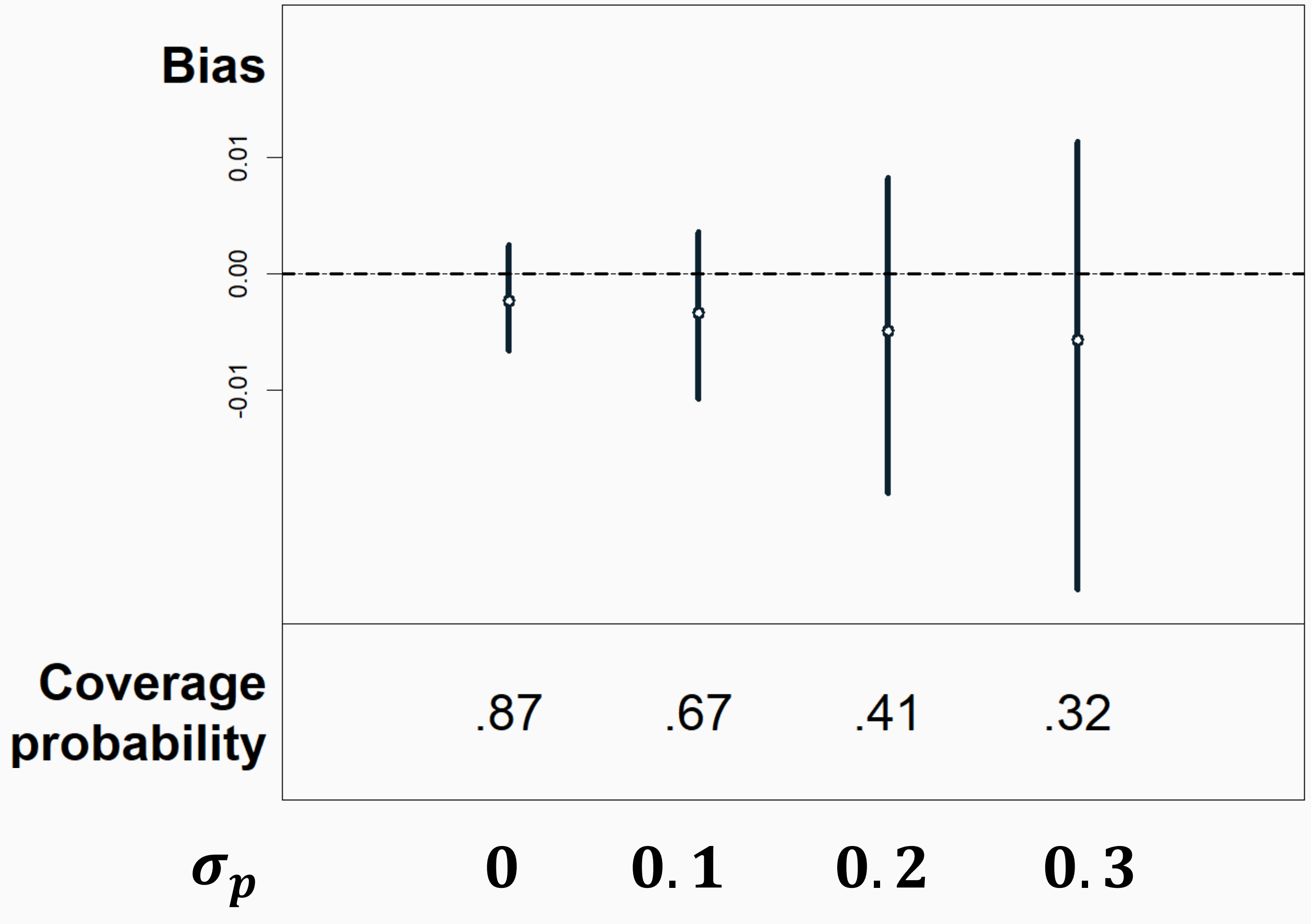
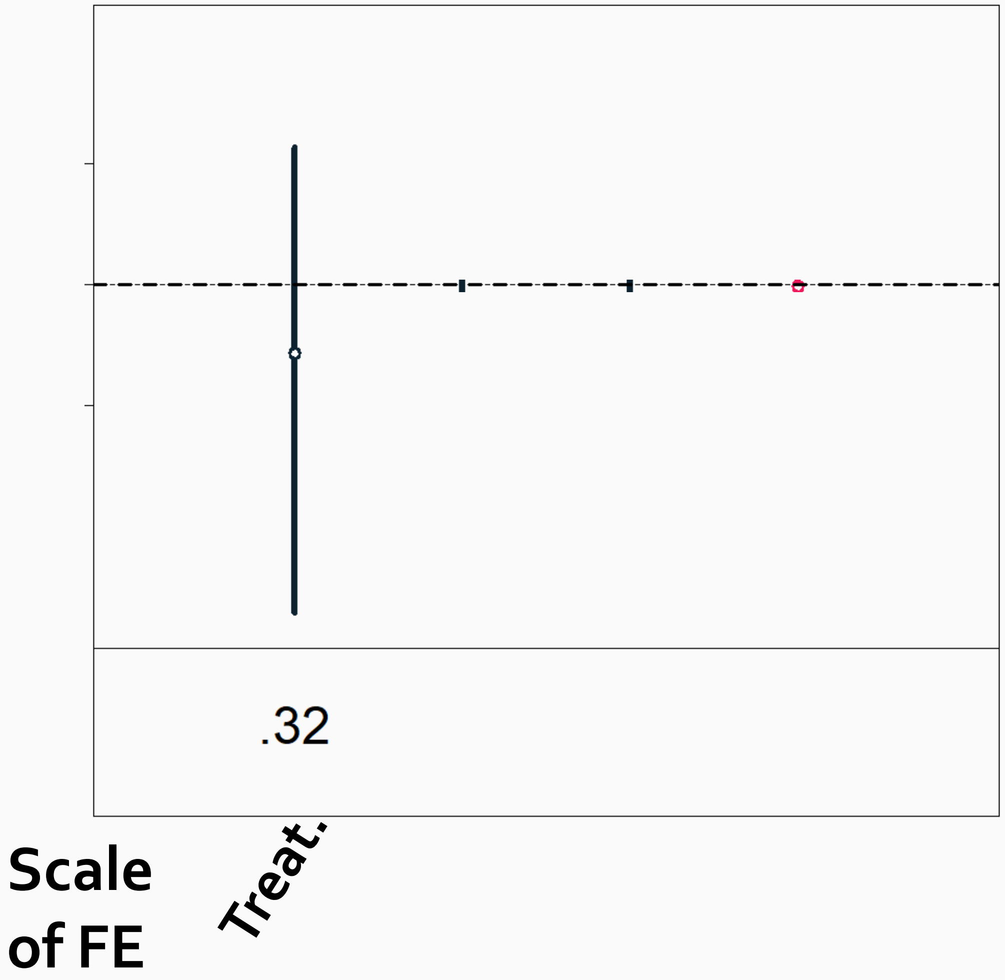
Effect of property-level disturbances

Increasing property-scale disturbances within difference in differences model



Varying units of observation with high property-level disturbances ($\sigma_p = 0.3$)



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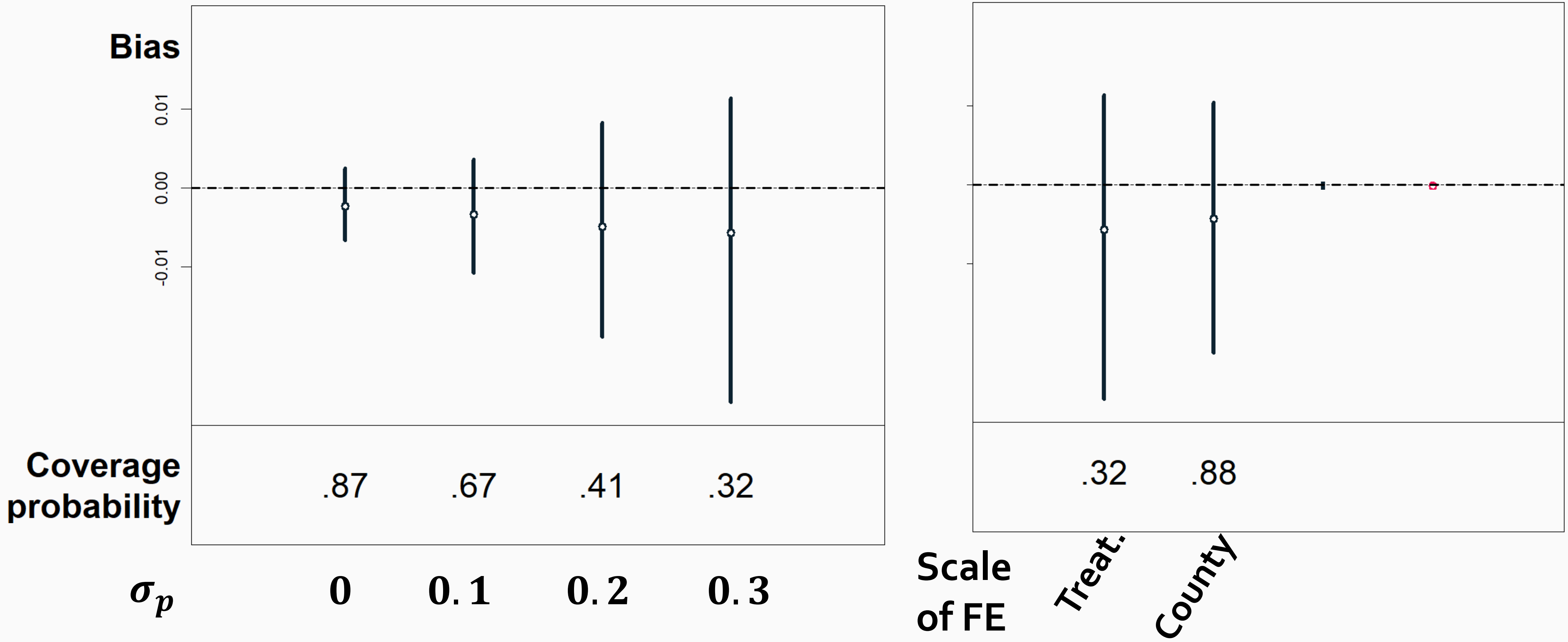

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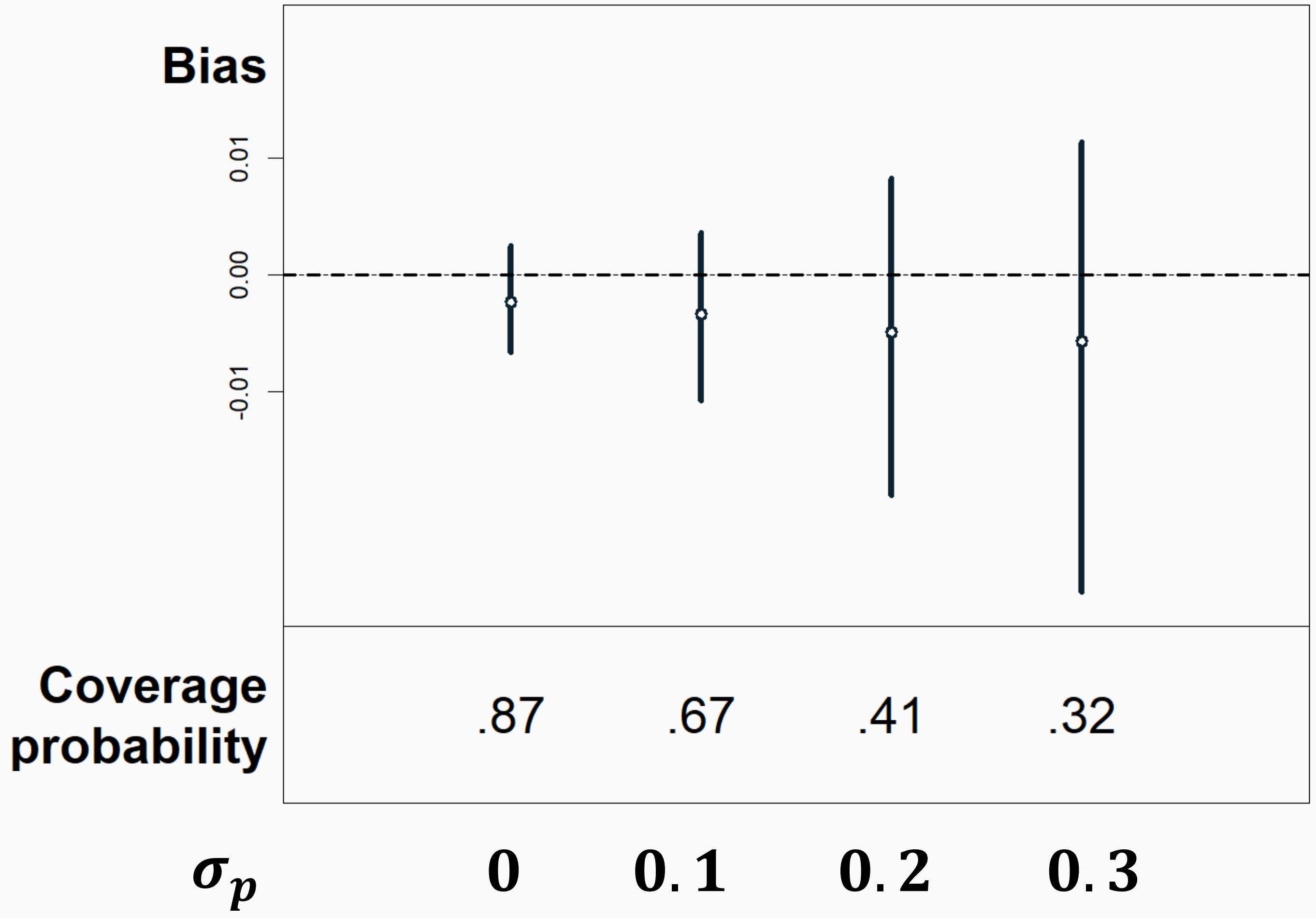

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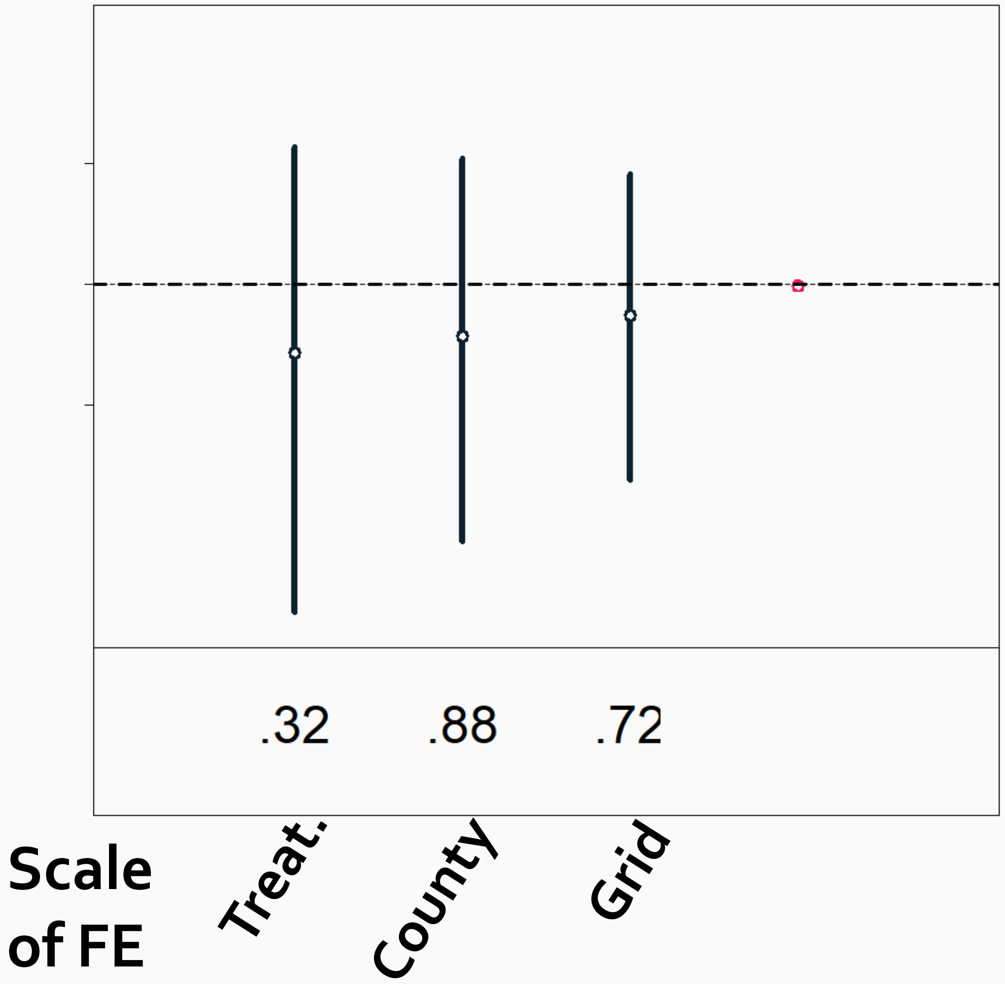

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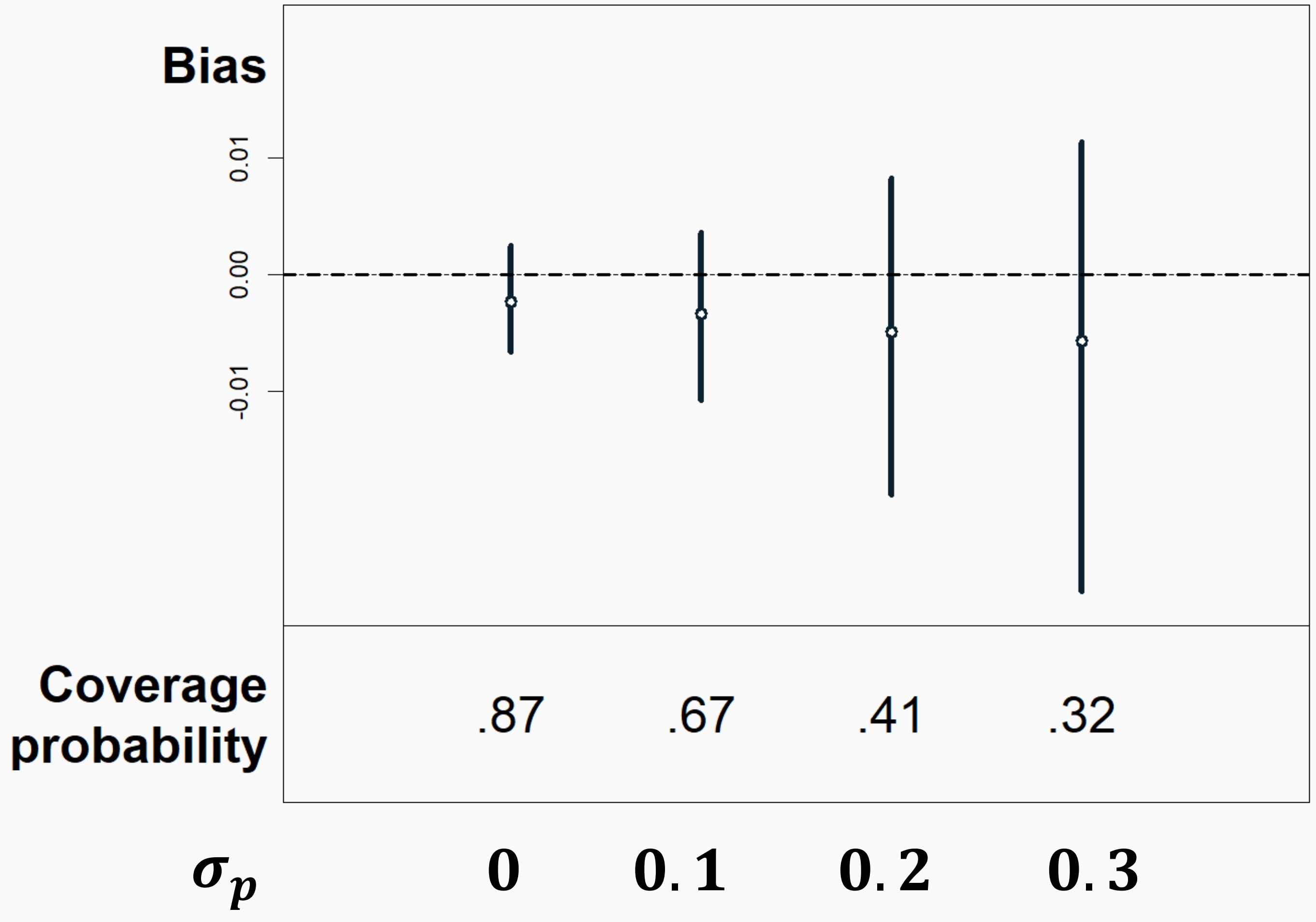

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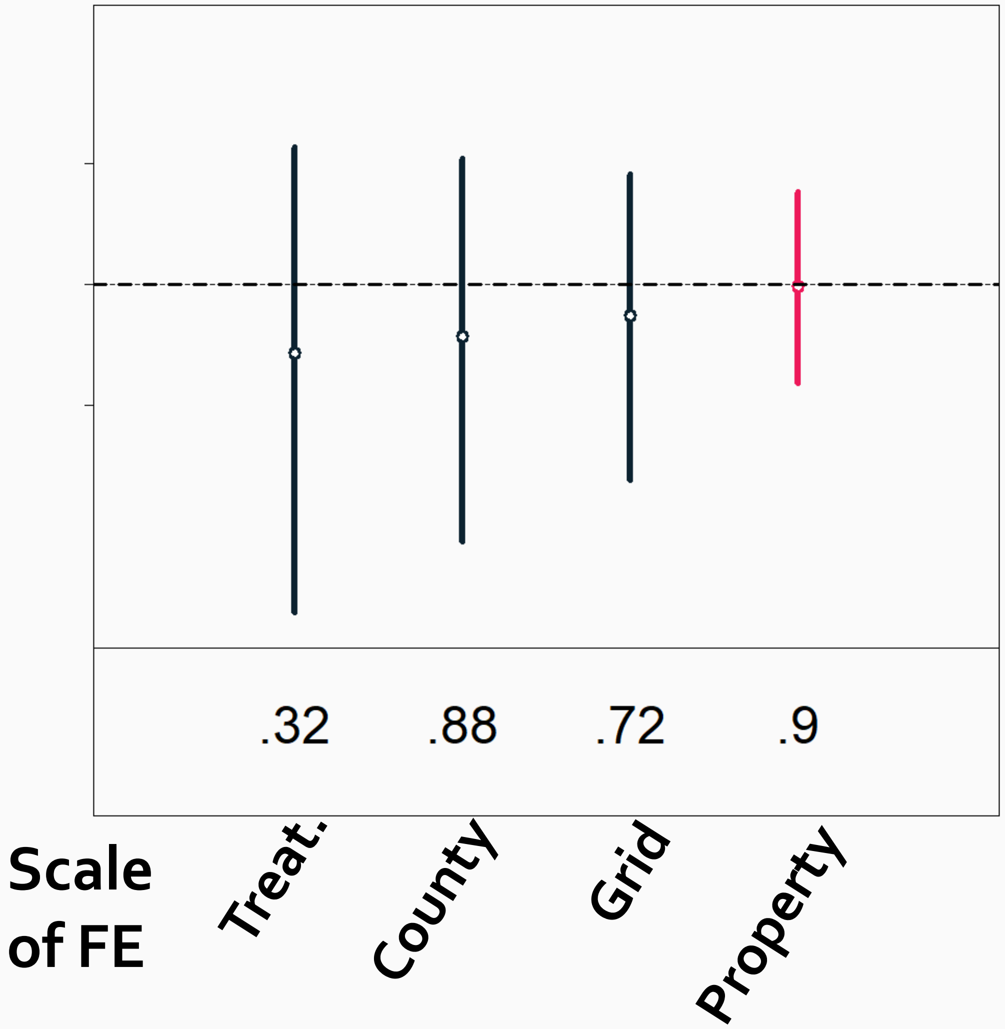
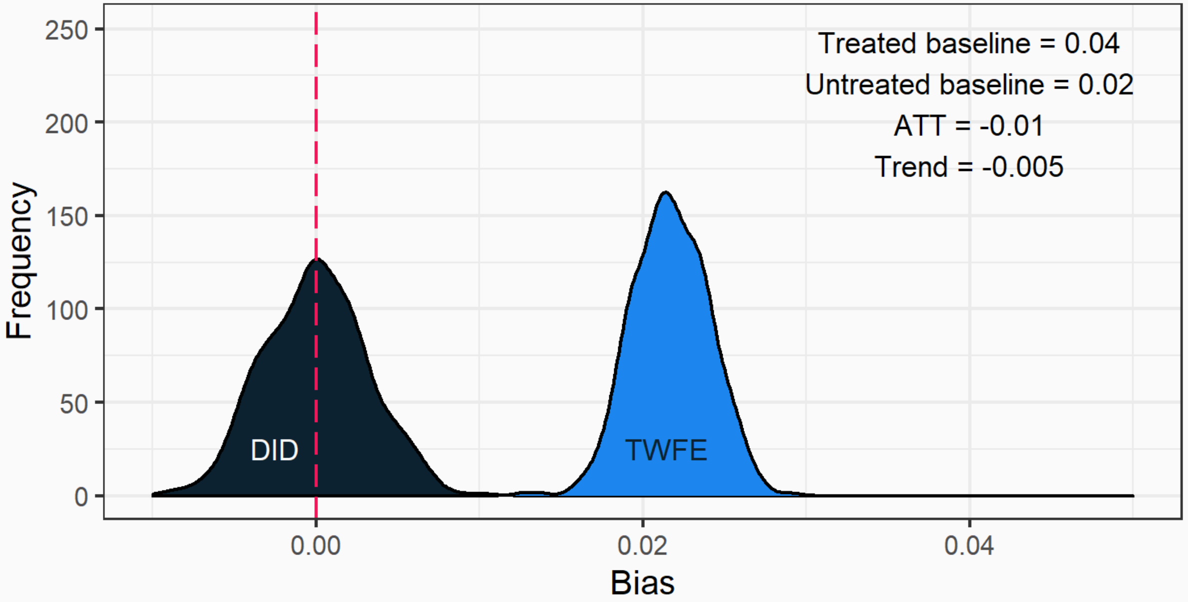
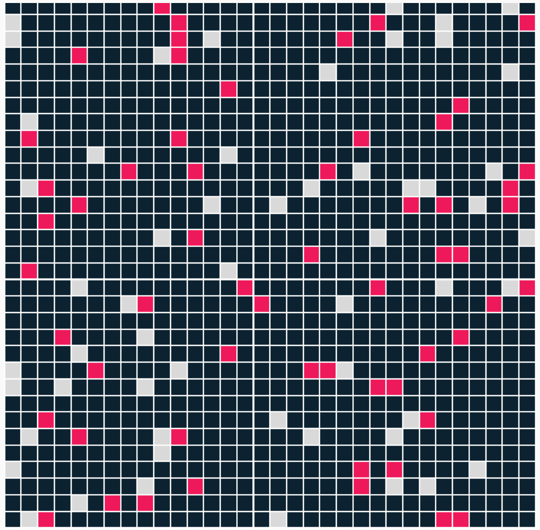
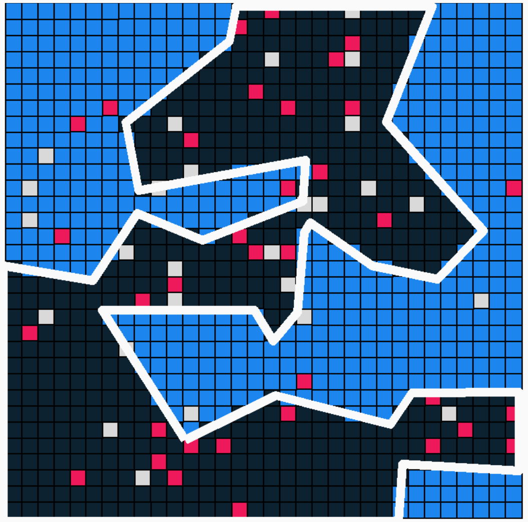


Opportunities and challenges







- Interdisciplinary collaboration opens doors to new data and methods
- Causal inference + remote sensing has yielded critical insights to guide more effective ecosystem management
- *But*, requires caution – standard tools from one field may need modification for others
- What opportunities, and challenges, emerge as we begin to quantify impact using novel biodiversity data?

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Full paper covers…

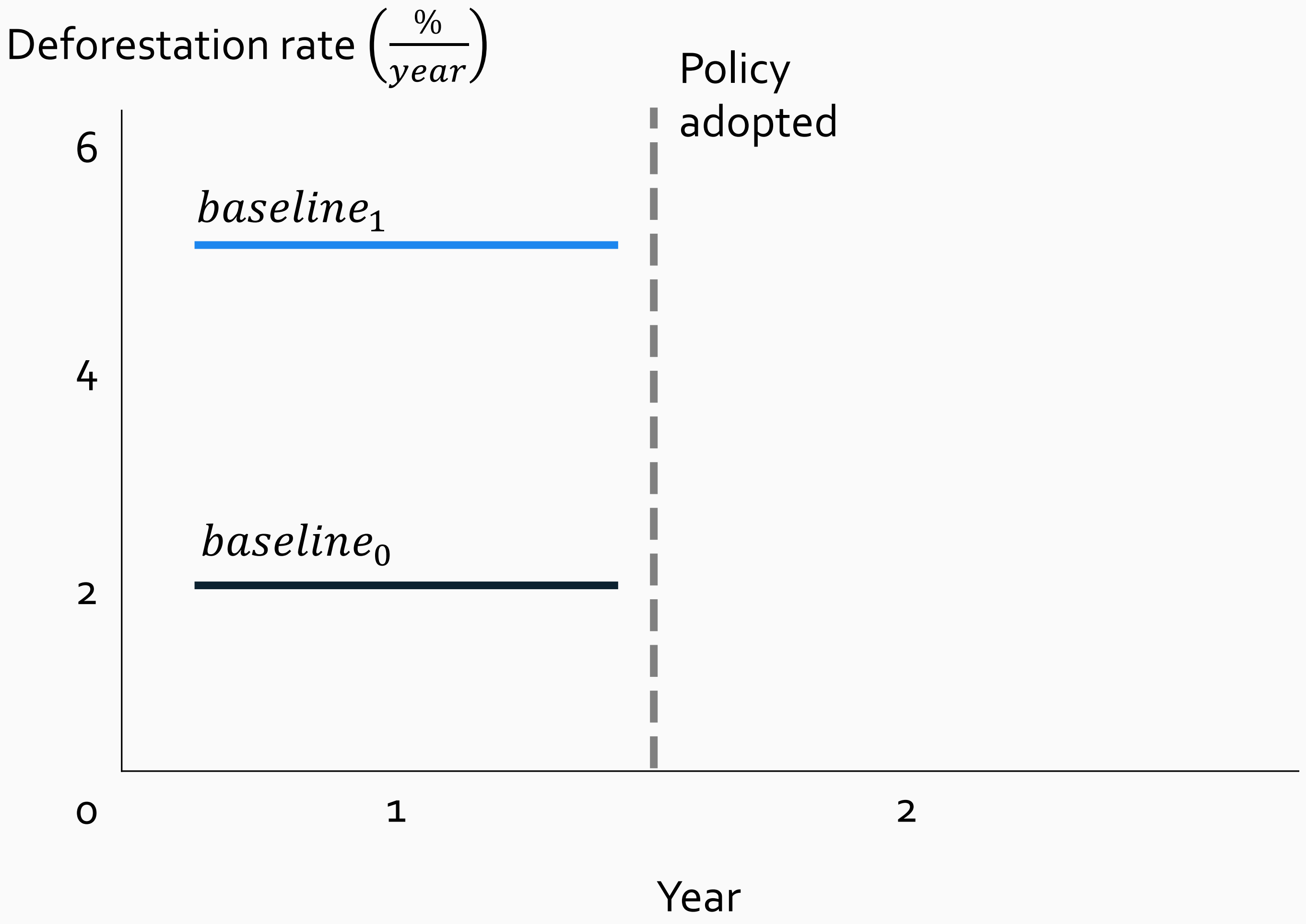
- Selection bias due to attrition
- Survival model designs
- Impact of different measures of deforestation
- Staggered adoption
- Heterogeneous treatment effects


Photo credit: CIFOR

Simulating forested landscapes

Deforestation ($y_{i,t}$) is simulated as a function of seven parameters:

- $baseline_0$: Pre-treatment deforestation rate outside of treatment area
- $baseline_1$: Pre-treatment deforestation rate inside of treated area



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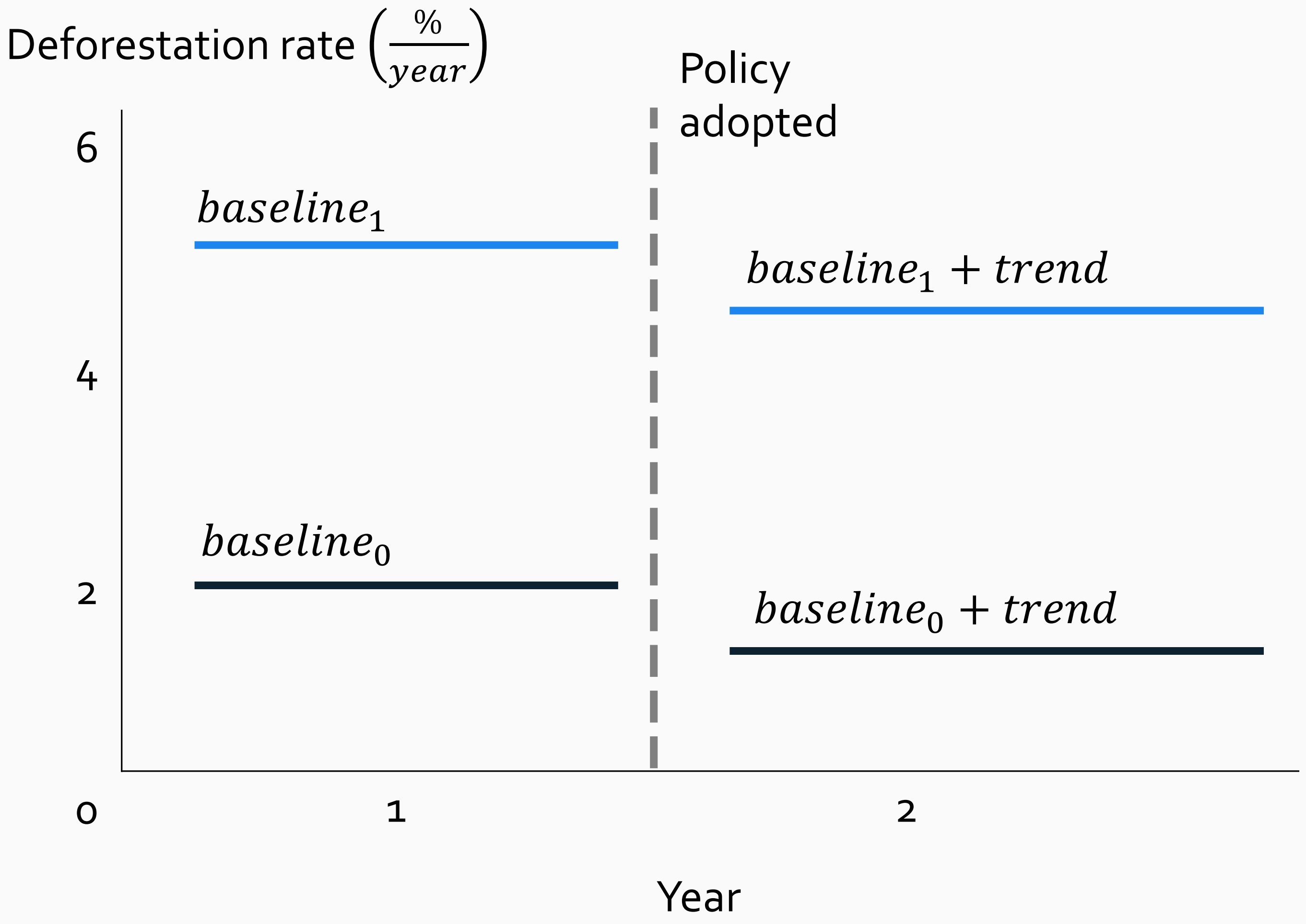
- $trend$: Common trend in deforestation rates across the two time periods



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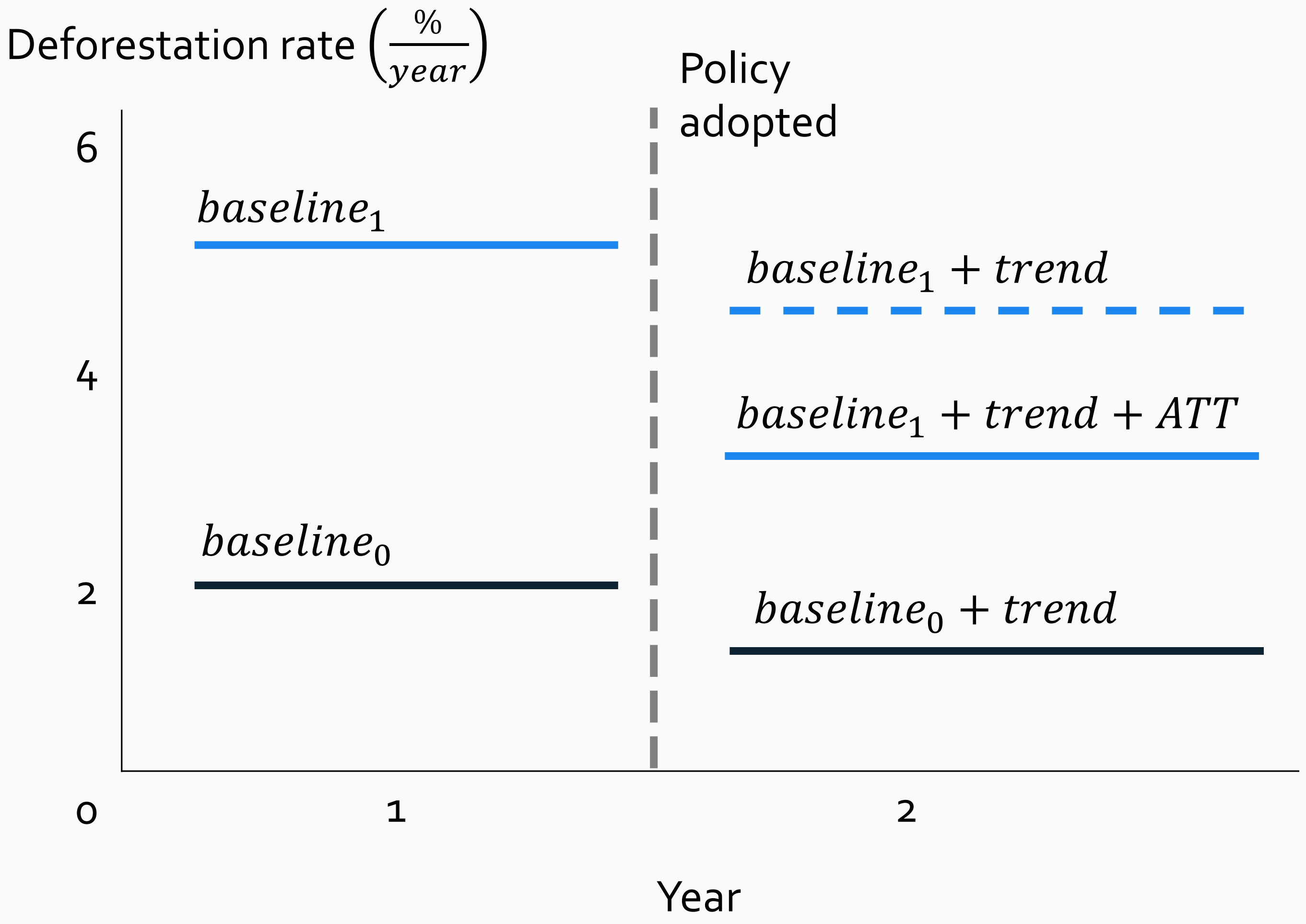

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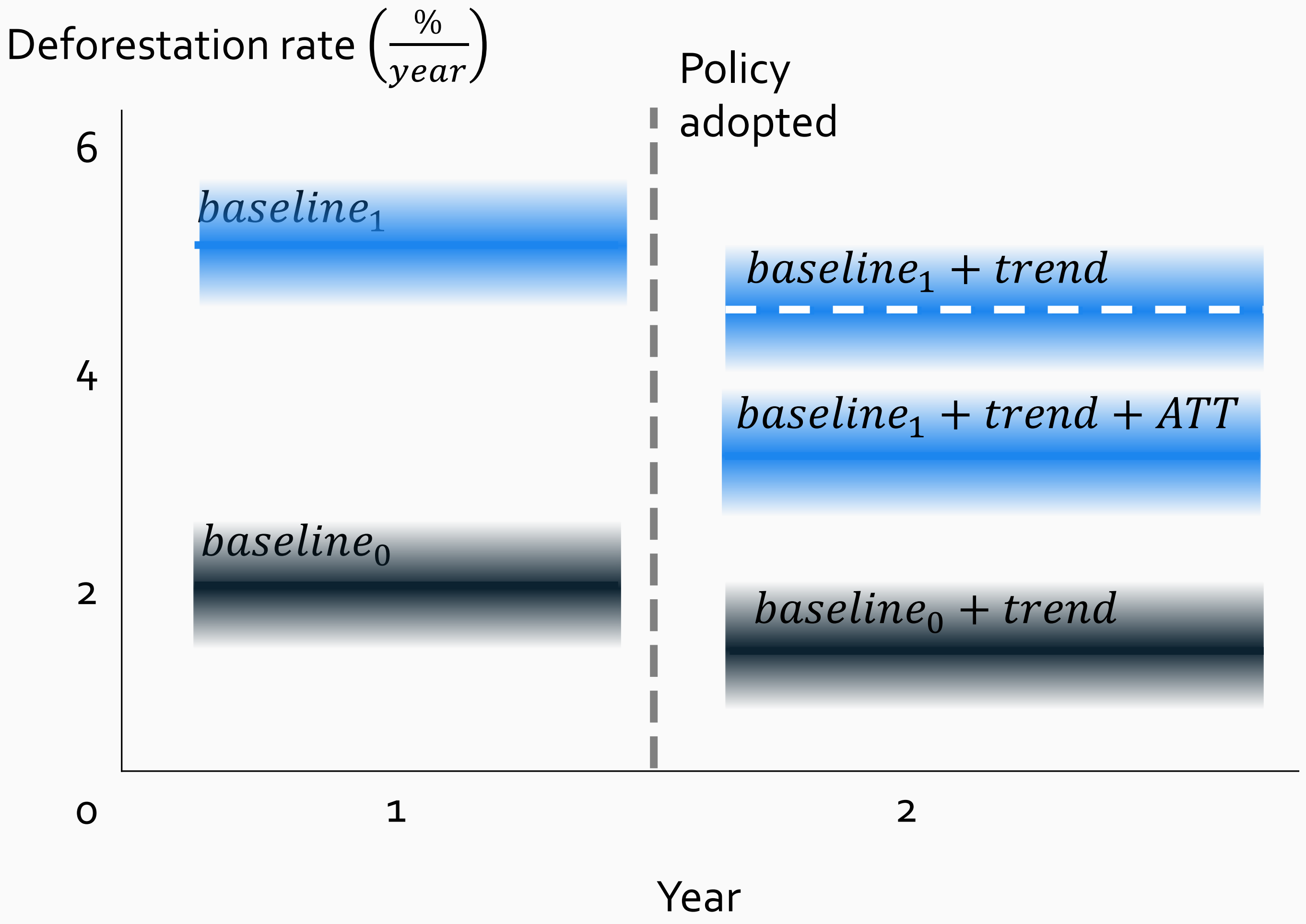
- $\alpha_i, \rho_v, \mu_{i,t}$: Normally distributed, random variables representing pixel, property and pixel-by-year random disturbances



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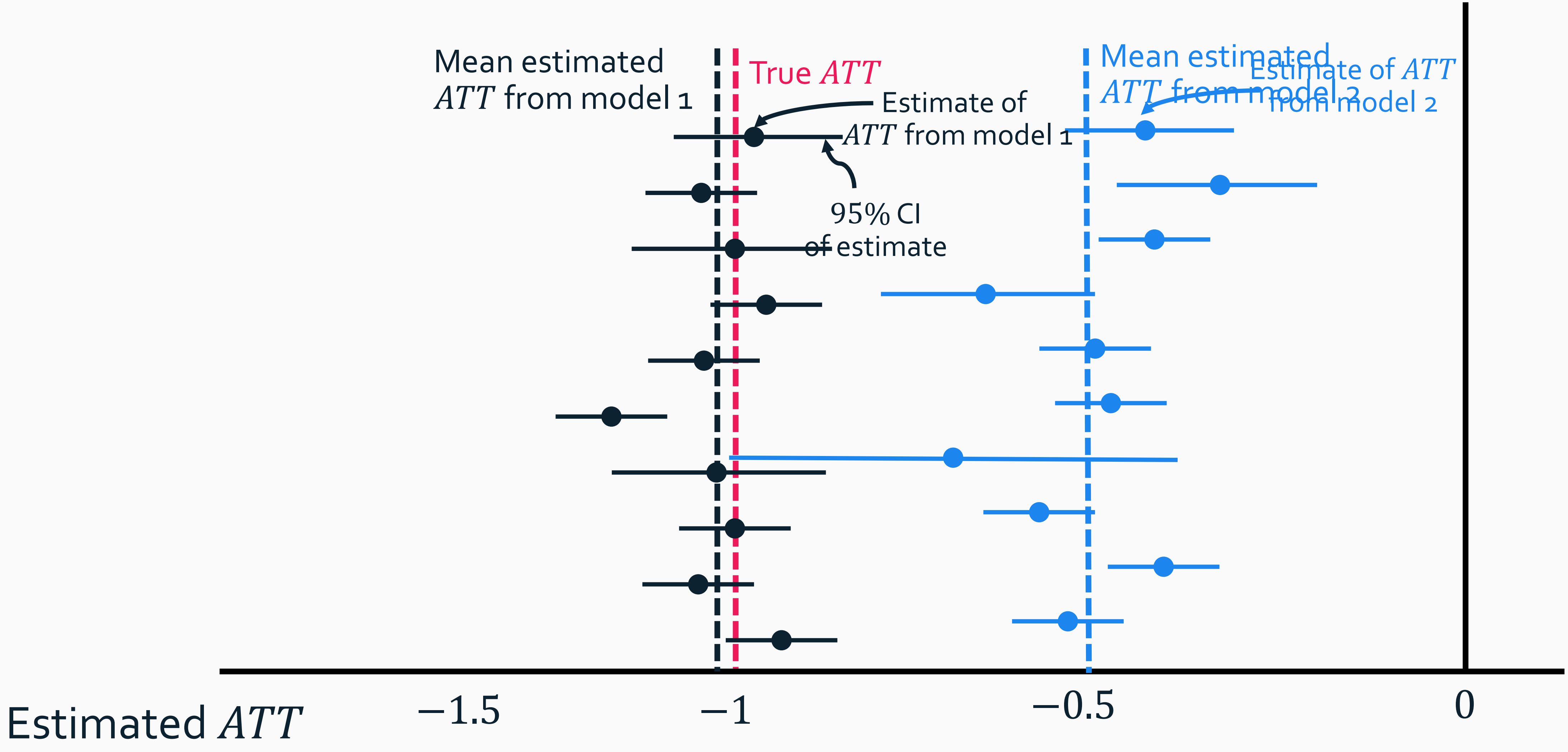
Evaluation of candidate models



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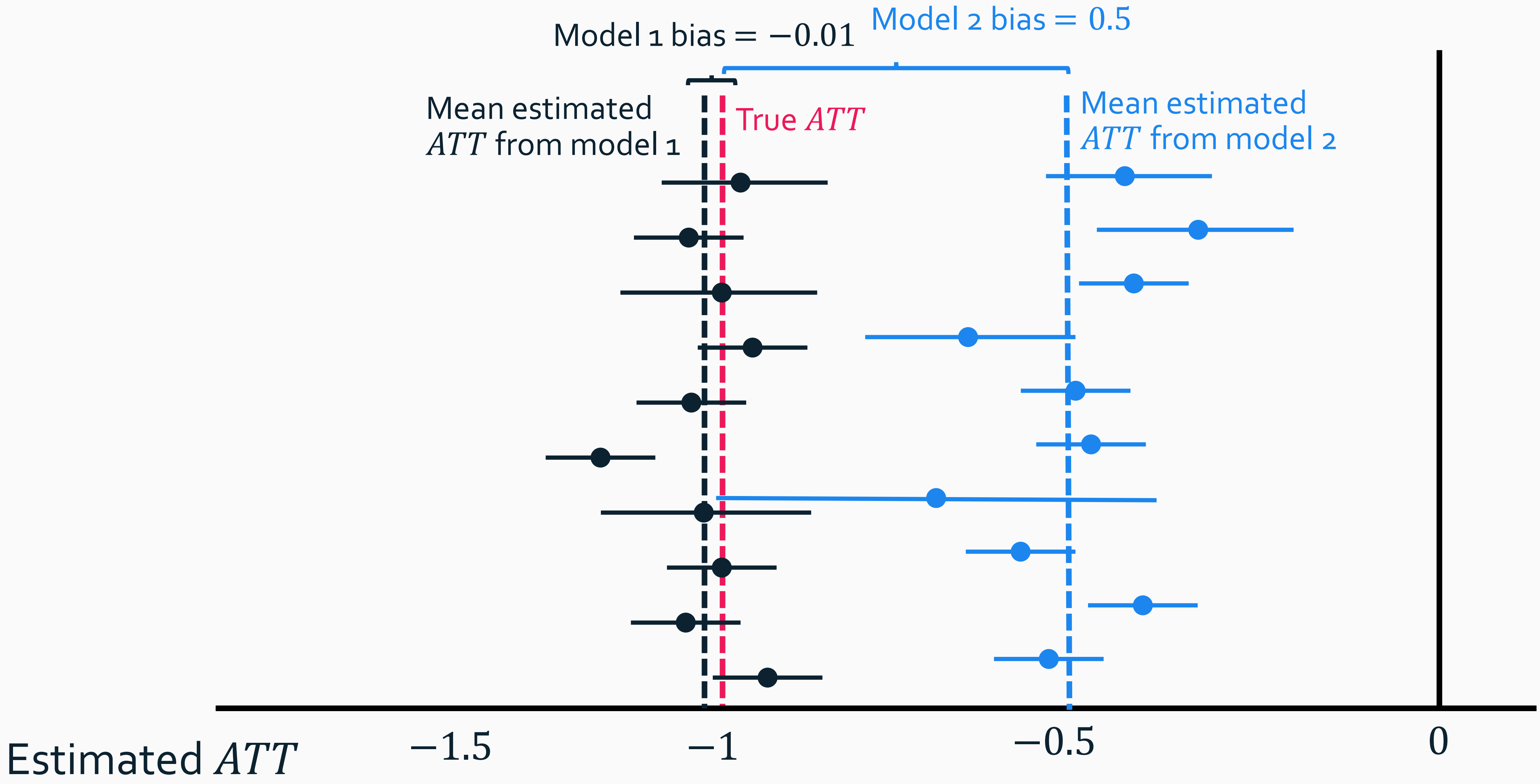
Evaluation of candidate models – Bias



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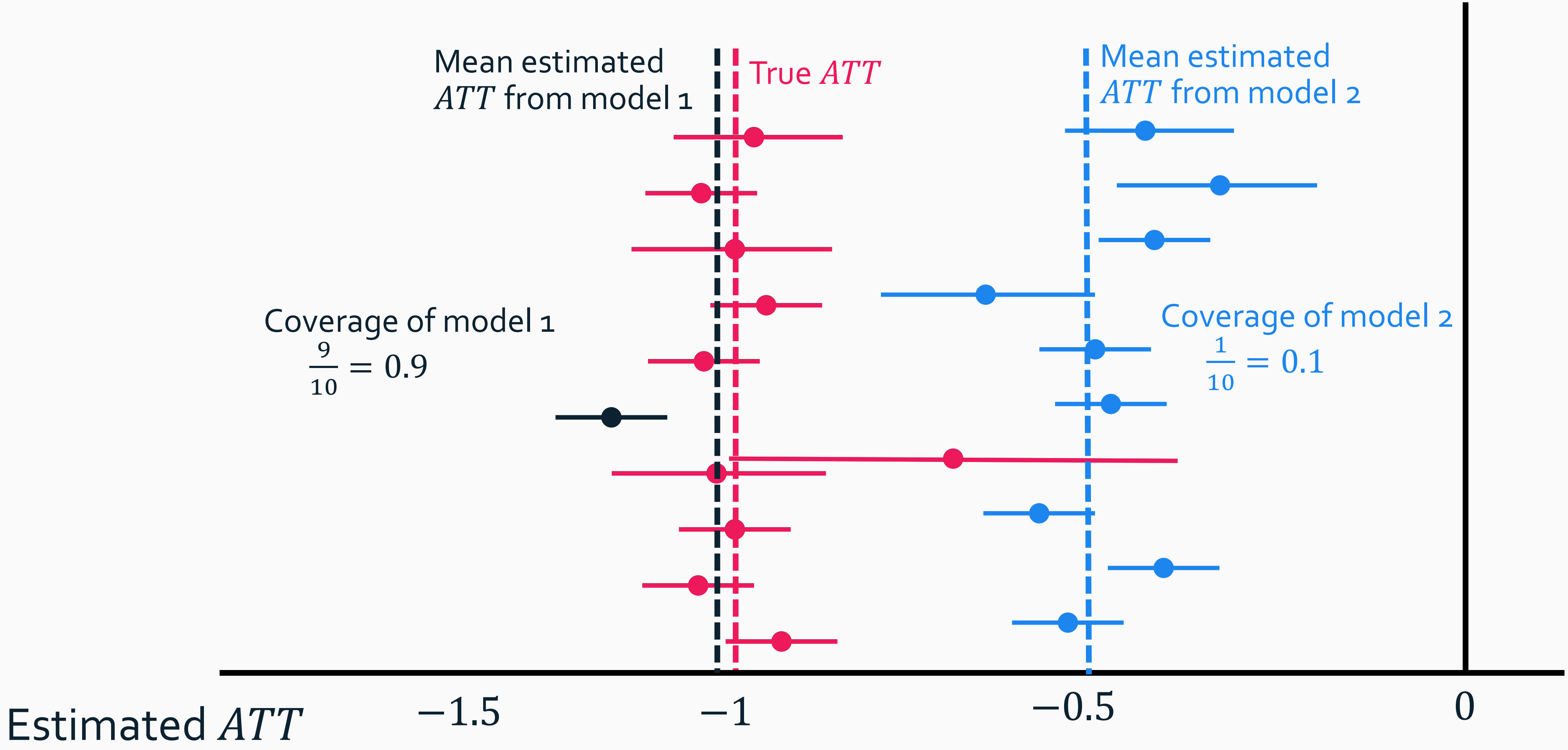
Evaluation of candidate models – Coverage



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