Replication of "Titling community land to prevent deforestation: An evaluation of a best-case program in Morona-Santiago, Ecuador"

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Abstract[1]

Buntaine, et al (2015) find that donor-financed, government-implemented land tenure legalization efforts in forested areas have a negligible effect on the rate of deforestation versus that found in areas not subject to such an intervention. The major results of their analysis was successfully replicated in this study. In the present paper, I explore how spatial autocorrelation in both the treatment and the outcome affects the treatment effect found by the original authors. This illustrates the importance of including spatial relationships into models attempting to explain causality within explicitly spatial datasets.

[1]* All analysis and data for this paper is available here

Introduction

"Titling community land to prevent deforestation: An evaluation of a best-case program in Morona-Santiago, Ecuador" (Buntaine, Hamilton, and Millones 2015) is an evaluation of the impact of a donor-funded land titling and land management program for indigenous communities in Morona-Santiago, Ecuador. They claim that the presence of all the known contextual factors that lead to successful land legalization-led deforestation efforts makes this a best-case policy intervention. The data for the model was generated from spatial data on intervention areas and title boundaries provided by USAID and NGOs and publicly available spatial raster data such as population density (Landscan) and forest cover (Hansen, et al's (2013) Global Forest Change (GFC) dataset). The change in GFC value in an area is used as the metric for deforestation. Areas receiving the program treatment were matched with areas that did not receive the treatment using a genetic matching algorithm. The treatment effect over the five years after is then estimated with a difference-in-difference OLS model. They find that treatment does not have a significant effect on deforestation rates.

I successfully replicated all of the paper's major results. The authors made their raw data and code available on Harvard's Dataverse; matched data was made available upon request to the corresponding author. All analysis, both for the original paper and this one, were done in the R statistical programming language (R Core Team 2019).

Paper Review

Following the lead of the property right evangelist Hernando de Soto, over the past two decades governments, international institutions, and academics have looked to land titling as a solution for a range of vexing land-based problems. Reframed as market failures, challenges like deforestation are addressed by legitimizing the land tenure claims of otherwise unrecognized landholders. Recognizing their claims, the reasoning goes, means that landholders will be better able to exclude competing users while also incentivizing more sustainable forest management in order to maximize long-term benefits. However, evidence in support of this line of reasoning is mixed, since analyses often do not isolate the causal effects of land titling programs on forest loss from the factors that motivate the targeting of such programs in the first place.

Buntaine, et al (2013) draw on a combination of parcel-level data from a USAID-funded land titling program and a range of geospatial data to produce a more robust analysis of the causal effects of land titling on deforestation. The *Programa de Sostenibilidad y Unión Regional Sur* (PSUR) was a US $27 million program implemented for 170,000 hectares of indigenous land in the heavily forested province of Morona-Santiago, Ecuador from 2002-2007. Under PSUR, communities of the Shaur indigenous people were able to codify exclusive claims over their customary lands and, hopefully, prevernt the encroachment of non-indigenous colonizers. The end result of the legalization process was a Land Legalization Plan (*Plan de Manejo para Legalización*, PML). Every participating community completed a PML as part of the program. Starting in 2003, the second year of the PSUR, all communities (80% of the eventual total) also completed supplementary management plans (*Plan de Manejo Integral*, PMI) which were co-designed with USAID partner organizations and delineated a roadmap for sustainable resource management in the area.

To begin their analysis, the authors divided the province into 27,984 0.87 square kilometer grid cells (this being the size of the coarsest input dataset used). The outcome measure was the amount of forest loss in each grid cell following legalization, using data from Hansen, et al's (2013) Global Forest Cover (GFC) dataset. To isolate the treatment effect of legalization, grid cells within the PSUR areas were matched with grid cells outside with similar pre-treatment characteristics to create a set of control cells. This is done using a genetic matching algorithm with twelve covariates that have strong associations with deforestation in the literature. Three are measures of forest loss; four are distances to features or land use disturbance; three are demographic or institutional variables; and two are geophysical—elevation and slope. Two iterations of matching were done—one for plots receiving the PML-only treatment from 2002, and one for those receiving the PML + PMI intervention from 2003–2007.

These same covariates were then used, along with the treatment variable, to estimate difference-in-differences between treatment and control plots for PML-only and PMI treatment groups.

Replication

I was able to successfully replicate all of the major results from their paper, including coefficients for PML-only and PMI plots both before and after matching. Their tests for lagged effects over the five years after the start of the intervention were also successfully replicated.

Extension

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## longlat argument overrides object

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## longlat argument overrides object

## Warning in knearneigh(spatial_PMI_prematch, k = 6, longlat = TRUE): knearneigh:
## identical points found
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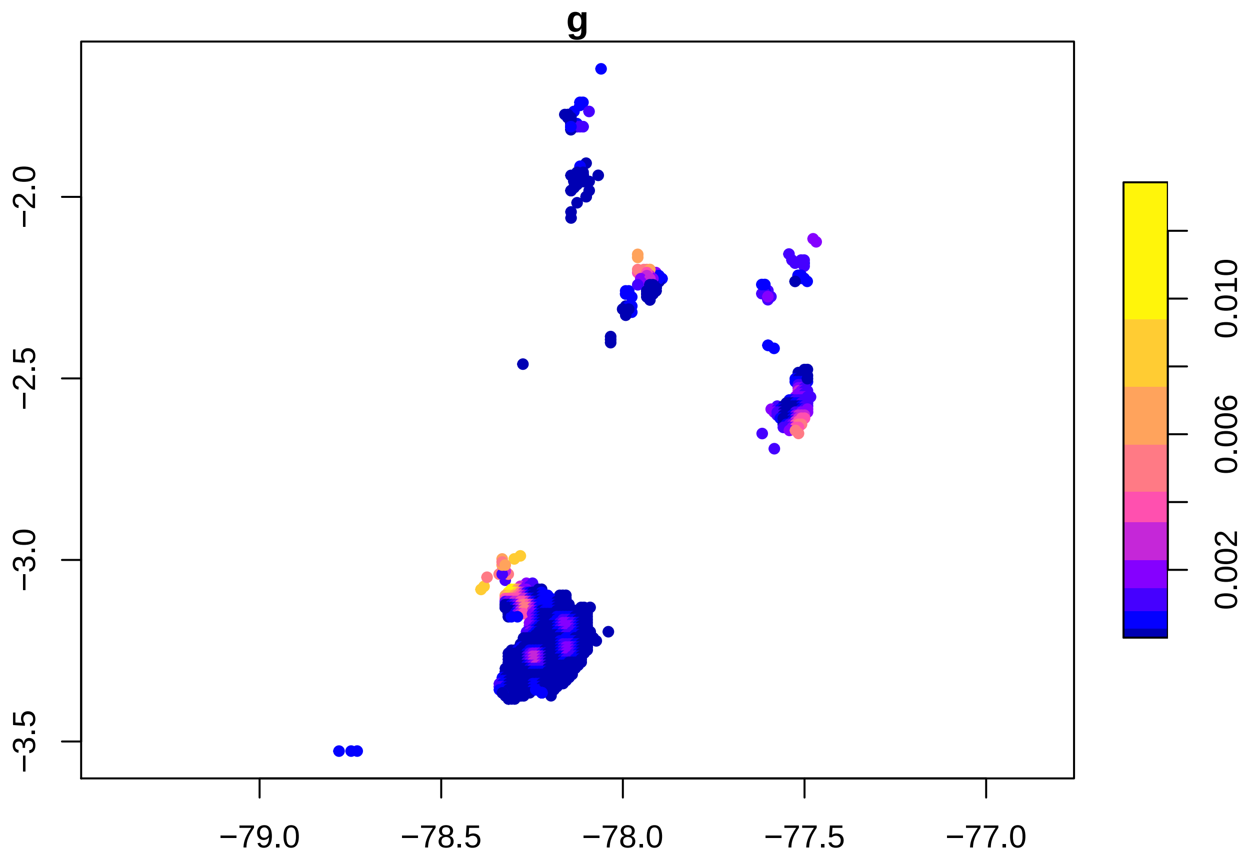
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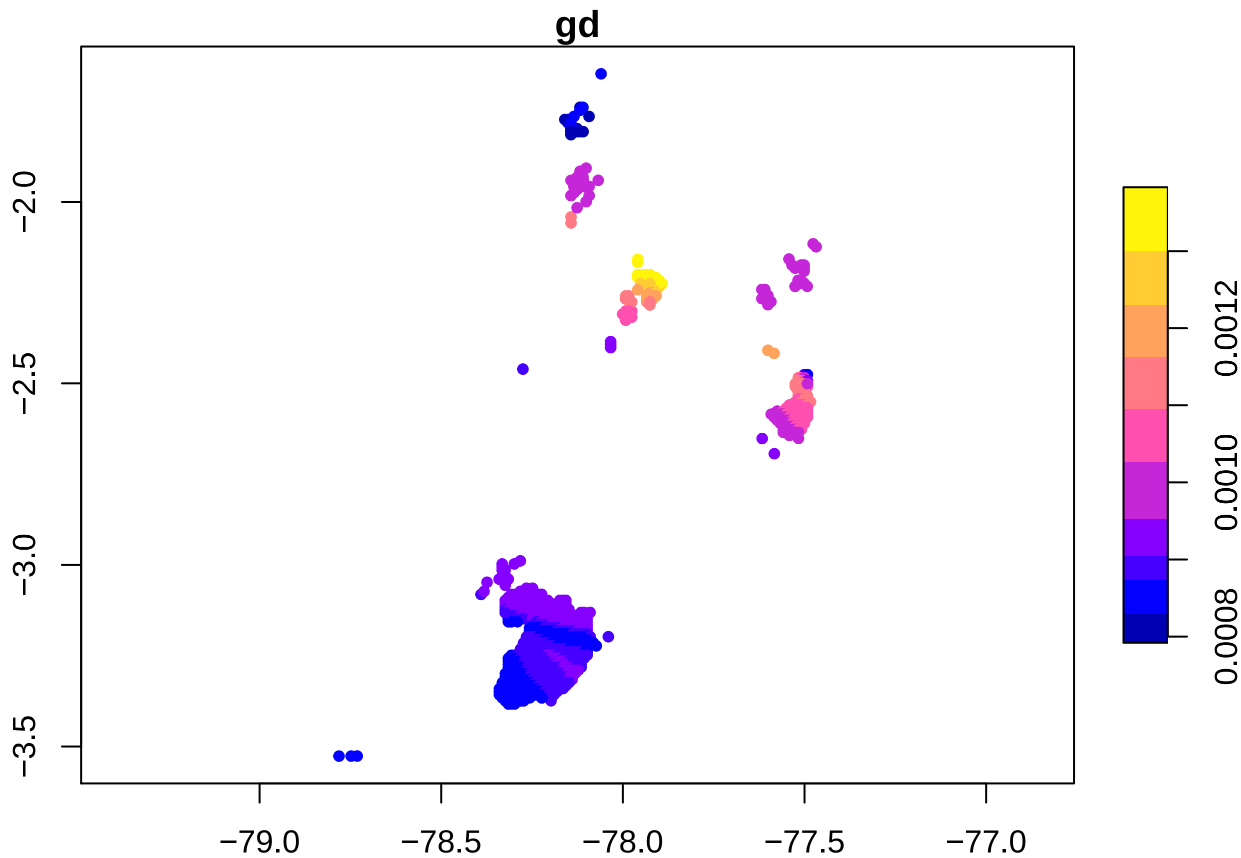
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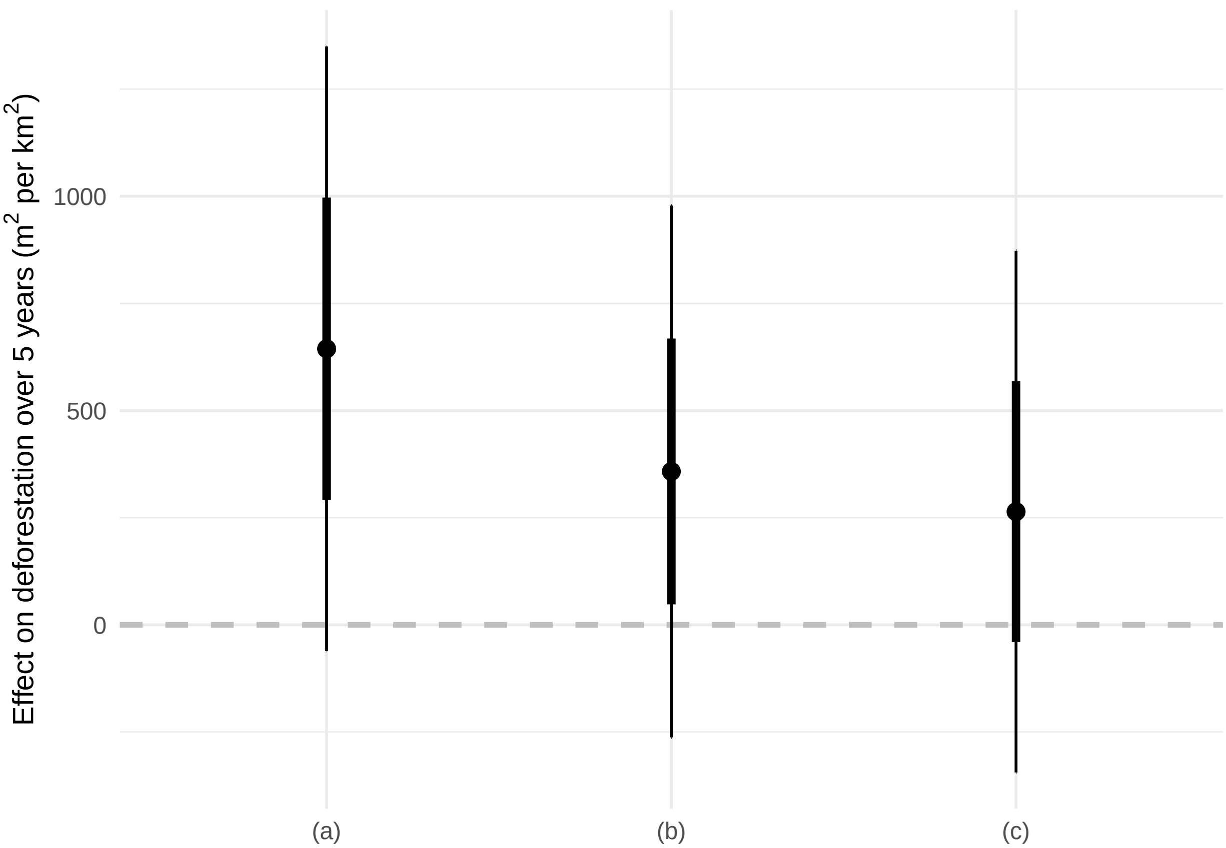


Conclusion

References

Buntaine, M.T., S.E. Hamilton, and M. Millones. 2015. "Titling Community Land to Prevent Deforestation: An Evaluation of a Best-Case Program in Morona-Santiago, Ecuador." *Global Environmental Change*, no. 33: 32–43.

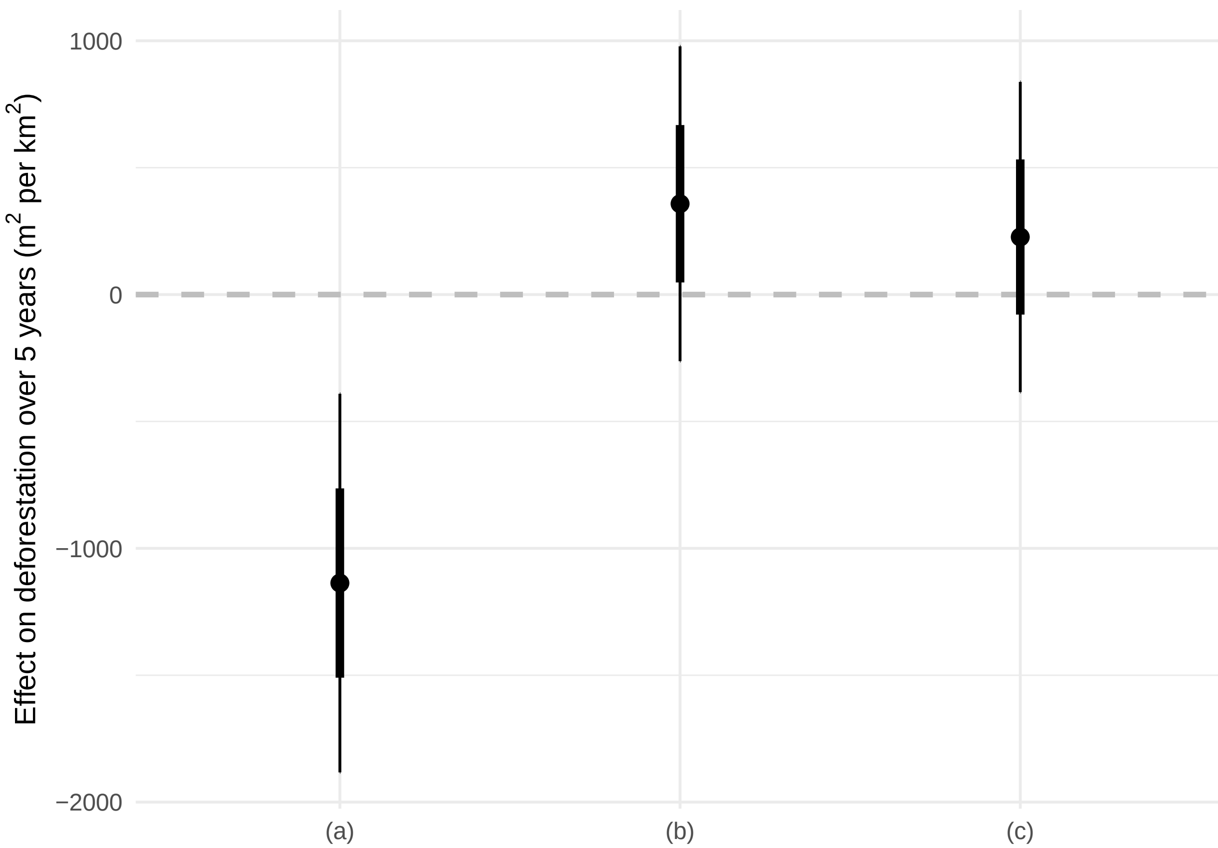
Hansen, M C, P V Potapov, R Moore, M Hancher, S A Turubanova, A Tyukavina, D Thau, et al. 2013. "High-Resolution Global Maps of 21st-Century Forest Cover Change." *Science*, no. 342: 850–53.

R Core Team. 2019. *R: A Language and Environment for Statistical Computing*. Vienna, Austria: R Foundation for Statistical Computing. https://www.R-project.org/.

Appendix: Replication of Key Results

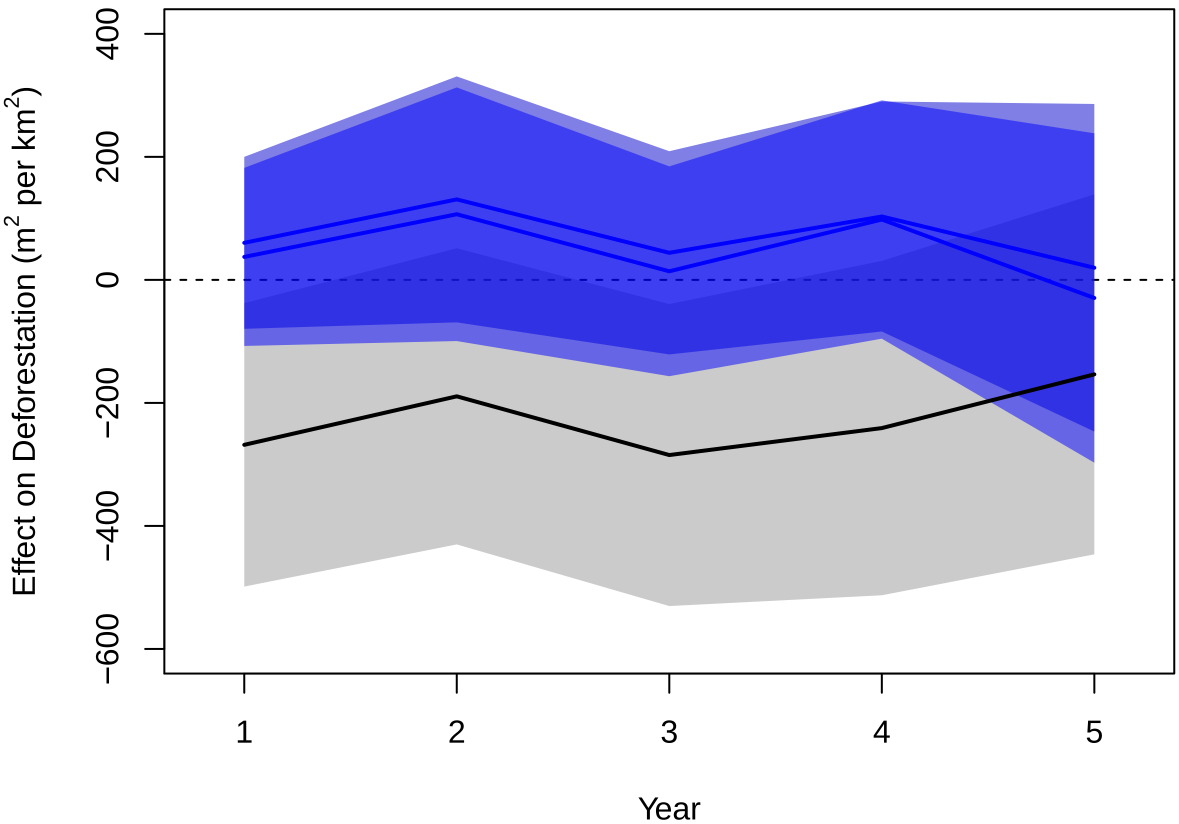
Since this paper is, in the end, a relatively straightforwardly evaluative difference-in-differences model, the key result is the treatment effect of land tenure legalization. In the paper, this is the only result presented—all of the non-treatment variables in the four main regressions were a non-representative set of observations created to isolate the effect of the treatment variable. In this appendix, I have reproduced the four most important graphics in the paper (figures 4 to 7).

The first is figure 4 from the paper (this is the same as was produced for Milestone 5). It shows the treatment effect of legalization on the first set of treated plots, i.e. those that received only the PML legalization, without any other community development planning.



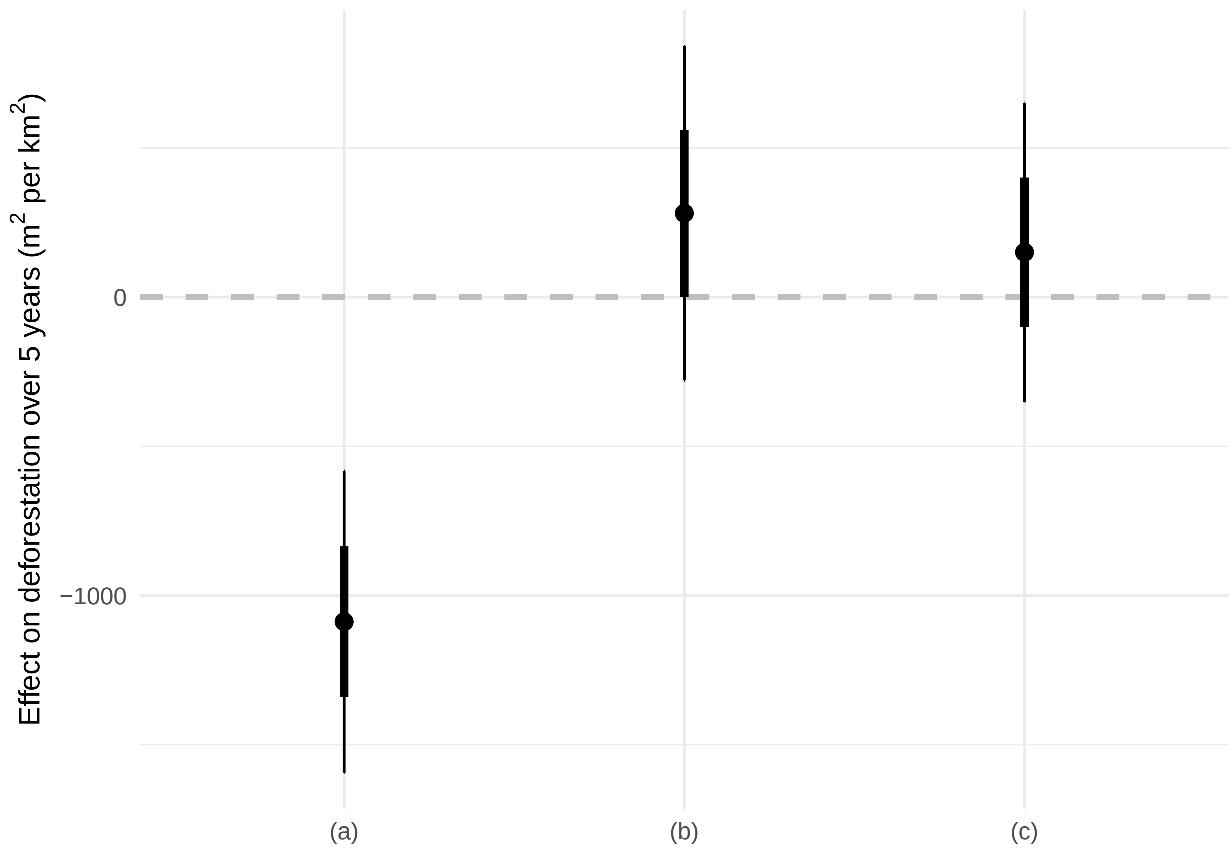
Difference in differences over five years for PSUR plots with legalization plan (PML) and title versus non-PSUR plots with no plan or title, 2002–2012. Notes: Figure shows treatment effect of tenure status for models as follows: (a) covariates, no pre-matching; (b) no covariates, pre-matching; (c) covariates, pre-matching.

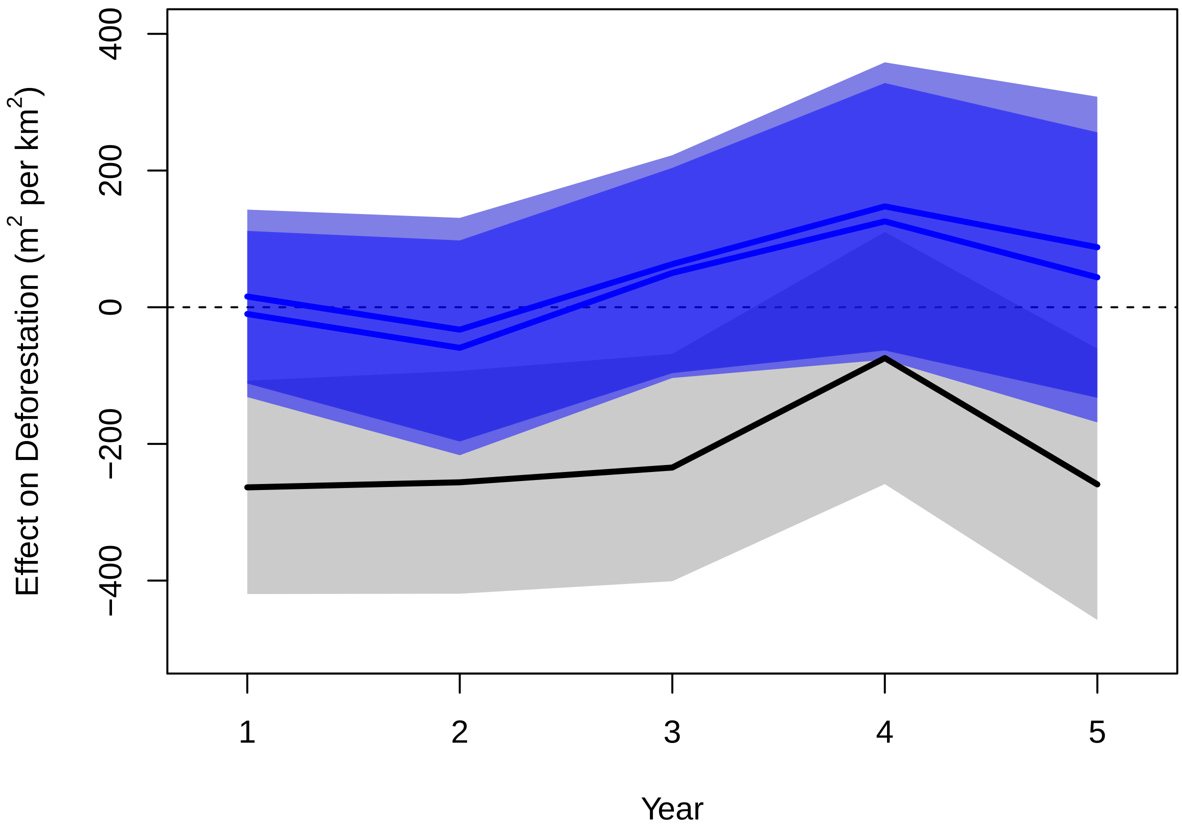
The authors wanted to consider the possibility of variable lag in the effects of land titling on deforestation; they do so by looking at the treatment effects in each year after the PSUR intervention in 2002. The results are largely the same as in the preceding figure: before matching, there appears to be a reduction in deforestation, but after matching the effect disappears.



PML-only effects on an annual basis following treatment. The black line/gray error bars are regression without pre-matching; the blue lines and error bars are regression estimates with pre-matching both with (dark blue) and without (light blue) covariates. The error bars show two standard errors.

After 2003, the PSUR included an additional set of management and training programming to supplement the legalization process. They run the same analysis for these plots as the legalization-only ones: match, model, decompose, compare. The results are displayed in figures 6 and 7 in the original paper.


Effect on deforestation over 5 years (m^2 per km^2)
0
−1000
(a)
(b)
(c)



Appendix: All code for this report