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ABSTRACT

The Ecological Impact of Place-Based Economic Policies*

Does economic development have an unavoidable ecological cost? We examine the ecological impacts of one of India's signature place-based economic policies involving massive tax benefits for new industrial and infrastructure development following the creation of the new state of Uttarakhand. The policy, which had an explicit pro-environment mandate, resulted in no meaningful change in local forest cover. Our results suggest that even in settings with low levels of enforcement, place-based economic policies with pro-environment mandates can achieve sizeable economic expansion without major ecological costs.

JEL Classification: Q53, O40, Q56, H54

Keywords: place-based economic policies, agglomeration, deforestation

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1 Introduction

The central challenge of sustainable development is bridging the gap between rich and poor regions without lasting damage to the environment that could in turn undermine the goal of poverty alleviation (United Nations, 2015). Indeed, there has been a long-standing debate in both the conservation and economics literature on the effects of economic development and policies that encourage such development on the environment (Arrow et al., 1995; Grossman and Krueger, 1995; Stern, Common and Barbier, 1996; Andreoni and Levinson, 2001; Foster and Rosenzweig, 2003; Dasgupta, 2007; Alix-Garcia et al., 2013; Asher, Garg and Novosad, 2020). Increasingly, governments around the world are using place-based policies – policies that target tax breaks or infrastructure development to an underdeveloped region – as a means to close the rising gaps between regions within their borders (Felkner and Townsend, 2011; Busso, Gregory and Kline, 2013; Kline and Moretti, 2014; Shenoy, 2018). Yet even as these policies become ubiquitous, relatively little is known about their environmental impacts, particularly in developing countries (Greenstone and Jack, 2015).

We focus on a principal concern about such targeted development, the risk that forests will be cleared in the wake of infrastructure investments (Asher, Garg and Novosad, 2020) and rising incomes (Alix-Garcia et al., 2013). In the context of place-based economic policies, such land-use change is particularly relevant since these policies often target remote and previously underdeveloped regions with native vegetation. Furthermore, forest cover loss is an urgent concern, generating global greenhouse emissions (IPCC, 2014; Jayachandran et al., 2017) and local health externalities (Bauch et al., 2015; Garg, 2019; Masuda et al., 2019). The most recent report by the Intergovernmental Panel on Climate Change (IPCC) suggests that restoring and protecting forests could yield almost a sixth of the emissions mitigation required to prevent runaway climate change by 2030 (IPCC, 2019).

We exploit a spatial discontinuity in the introduction of one of the world's most generous place-based policies. In 2002, the Government of India provided tax breaks and infrastructure investments worth nearly $34 billion to the recently formed state of Uttarakhand. The policy had an important additional feature, an explicit pro-environment mandate that excluded certain environmentally detrimental industries from receiving any subsidies or tax-exemptions while favoring industries generally considered environmentally friendly.[1] Our setting is particularly important because Uttarakhand contains one of the only large contiguous tracts of forest in Northern India, with over 63% of the area in the state under forest cover. The region has also historically identified with the environmental conservation movement as the birthplace of the *Chipko* Movement that encouraged local residents to hug trees in order to dissuade logging efforts.

The introduction of large scale regional investment in infrastructure and production subsidies can have ambiguous effects on forest cover. Timber demand can increase either because rising incomes induce demand for land-intensive goods (Alix-Garcia et al., 2013) or highways and other infrastructure expand the scope for wood-using industry (Asher, Garg and Novosad, 2020). At the same time, increased industrial activity could be associated with exits from agriculture and affect demands on forested land from the agricultural sector (Assunção et al., 2017; Abman and Carney, 2019). Yet, other interventions such as alternative energy sources, even while ex-ante promising, have failed to reduce forest loss except when accompanied by complimentary policies (Meeks, Sims and Thompson, 2019). Overall, the effect of directed, geographically concentrated economic growth on forest cover is ambiguous.

Using a difference-in-discontinuities design, we find that the introduction of these subsidies had a small, statistically insignificant effect on forest cover, even 10 years after the introduction of the policy. By contrast, the same policy increased economic activity by at least 70% and as much as 300% (Shenoy, 2018). We find no evidence to suggest that the null effects are driven by spillovers across the border or within-borders. Ten years after the introduction of the policy, we show that the absolute increase in employment in wood-using firms is modest relative to the overall expansion in employment. Together, our results demonstrate that at least in terms of forest cover, place-based economic policies with pro-environment riders can achieve large economic expansion with relatively minimal environmental costs.

While a broad literature has documented the relationship between economic development and environmental quality – often characterized as the "Environmental Kuznets Curve" – to the best of our knowledge, none have considered the ecological effects of place-based economic policies.[2] Unlike other development policies, place-

[1]In the Appendix, we provide both the "positive" or encouraged environmentally friendly list and the "negative" or environmentally unfriendly list of industries.

[2]Other papers have considered cash transfers (Alix-Garcia et al., 2013; Wilebore et al., 2019), rural

based economic policies target an underdeveloped region rather than a segment of the population (e.g. the rural poor). One aim of these policies is to concentrate development in a region to generate a new center of agglomeration. These agglomerations could damage the environment by fostering industries that clear land and consume timber, or they could preserve it by concentrating people and economic activity within a few cities while leaving forests to regenerate. And by targeting firms rather than individuals, a place-based policy has the potential to shift production away from environmentally-intensive industries. The environmental damage done in developing countries by rapid industrialization continues to be a major source of controversy and therefore it is crucial to understand whether a carefully designed place-based policy can achieve major economic development without causing major ecological harm.

The rest of the paper is organized in the following sections. In Section 2, we provide background on the policy and describe our data sources. In Section 3 we outline the research design and in Section 4 we discuss the corresponding results. In Section 5 we offer concluding remarks.

2 Background and Data

2.1 The Policy

In 2002, the federal government initiated of a series of separate initiatives targeting the state of Uttarakhand (Shenoy, 2018). These included spending for new infrastructure, better access to existing infrastructure, and business tax exemptions. Though some of these funds were available ever since the state was formed in late 2000, it was only in 2002 that it began concentrating the funds in a handful of industrial estates along the border between Uttarakhand and the state of Uttar Pradesh to the south. These estates play a key role in the raft of tax exemptions that were specifically designed to spur growth without harming the environment.

credit (Assunção et al., 2019), agriculture (Assunção et al., 2017; Abman and Carney, 2019) and trade (Antweiler, Copeland and Taylor, 2001; Copeland and Taylor, 2004). There is also an extensive literature documenting the relationship between economic development and the environment. For a non-exhaustive list, see: Den Butter and Verbruggen (1994); Arrow et al. (1995); Grossman and Krueger (1995); Stern, Common and Barbier (1996); Andreoni and Levinson (2001); Dasgupta et al. (2002); Foster and Rosenzweig (2003); Stern (2004). For a through review on drivers of deforestation, see Busch and Ferretti-Gallon (2017).

These exemptions, titled the "Special Package Scheme for Himachal Pradesh and Uttarakhand," were first announced in March of 2002 with an effective date of 2003. The most generous include a complete exemption from federal income taxes for the first 5 years of production (and a 30 percent reduction for the next 5 years); a complete exemption from excise taxes for 10 years; and a 15 percent investment subsidy for new or expanded factories. For comparison, in 2003 the two exemptions bought relief from a statutory corporate tax rate of 36.75 percent and an excise tax of 16 percent.[3]

Firms can only exploit the investment subsidy and excise tax exemption if they build and produce within Uttarakhand, giving firms an incentive to move factories rather than just their nominal headquarters. Figure A.1, which shows the change in the number of factories, makes it clear that firms were responding in part to the tax incentives. Only factories registered by 2010 could claim the excise tax exemption. After the deadline the rate of new registrations drops sharply, suggesting that firms pushed forward their investment to exploit the policy.

The tax exemptions were designed to attract certain industries at the expense of others. The government published a "positive" list of industries that it considered "environmentally friendly" (Government of India, 2003). These include floriculture, honey, and goods related to tourism (especially "eco-tourism"). Unlike most firms, which got tax exemptions at establishments within approved industrial estates, firms in the positive industries were eligible throughout the state. There was likewise a "negative" list of industries denied any tax benefits regardless of their location. The negative list includes coal and oil-based power plants, wood pulp, and most paper products. The complete positive and negative lists are provided in the Appendix.

The explicit environmental focus of the policy is in part a consequence of Uttarakhand's history. The movement that ultimately led to its creation had its roots in environmentalist protests triggered by timber concessions many decades ago (Tillin, 2013). The policy was a calibrated attempt by the central government to win political support in the new state by promoting economic development without alienating the still-potent environmentalist movement.

The firms ultimately attracted to the industrial estates produce goods across all industries. Aside from information technology firms specifically courted by the IT Park

[3] As explained in Shenoy (2018), the effective rate is somewhat lower but still far from trivial.

at Dehradun's estate, nearly all registrants at the estates are in manufacturing. They produce everything from processed food to processed metals, Ayurvedic medicine to automobile parts, plastics to pharmaceuticals. Though paper products are supposedly excluded from the tax subsidies, there are still a non-trivial number of firms that produce boxes and packaging (possibly to supply the other firms). Given their presence it is not a foregone conclusion that the program caused little deforestation. That is an empirical question to which we devote the rest of the paper.

2.2 Data

Forest Cover: Detailed and reliable administrative records on forest cover and deforestation rarely exist, especially in developing countries. Instead, we obtain high resolution time series estimates of forest cover using a standardized publicly-available satellite-based dataset. Vegetation Continuous Fields (VCF) is available at 250m resolution and provides annual tree cover from 2000–2014 in the form of the percentage of each pixel under forest cover (Townshend et al., 2011).[4] For our primary specification, we define forest cover as the average percentage of forest cover in a pixel. Our results are robust to using the inverse hyperbolic sine transformation.

Firm Level Data: We obtain data on firms and employment from the the 1998 and 2013 Economic Census.[5] These data were merged to the Socioeconomic High-resolution Rural-Urban Geographic Dataset on India (SHRUG) and collapsed to a SHRUG location, which is the lowest identifiable census unit, either village or town (Asher et al., 2019). Our regressions thus give the impact on employment in the average census location.

Borders: We measure the discontinuous change in outcomes at the state boundaries by

[4]Some previous studies have used Global Forest Cover (GFC) dataset that describes baseline forest cover in the year 2000, and a binary indicator for the year of deforestation for each 30mX30m pixel. As noted in Asher, Garg and Novosad (2020), GFC is less useful for the study of forest cover in India because GFC does not capture forest gains in areas with positive baseline forest cover or partial forest loss. While GFC is an excellent source for other contexts such as Brazil and Indonesia, it is less suitable in the Indian context which saw overall increases in forest cover during our study period. For more information on the comparability of different forest cover datasets in India, see Asher, Garg and Novosad (2020).

[5]While there was an economic census conducted in 2005, employment figures for logging firms were combined with those engaged in afforestation practices and hence are unsuitable for the analysis in this paper.

linking the forest cover and firm-level data to shapefiles of administrative boundaries created by ML Infomap. These data give the border between Uttar Pradesh (control state) and Uttarakhand (treated state) as well as sub-districts, which we use as clusters in calculating standard errors.

3 Research Design

3.1 Forest Cover

Our design closely matches that of Shenoy (2018), which is based on the assumption that there are parallel trends at the border. Shenoy (2018) shows that although there are clear differential trends between Uttarakhand (the treated state) and Uttar Pradesh (the control state), these differences become statistically and economically insignificant at the border. We measure the impact of the policy on deforestation and other outcomes using three specifications that compare the difference in the discontinuity at the border across years, making this a difference-in-discontinuities approach.

The first specification uses a spatial polynomial in latitude and longitude to control for bias. Like Dell (2010) our control function is a third-order polynomial in the latitude and longitude of each observation. This control function absorbs all smooth variation in the outcome. The effect is measured by the coefficient on an indicator for being in the targeted state, which captures the discontinuous change at the border. Let i index each cell, let t be the year of observation, and let P^3 be a third-order polynomial in the latitude and longitude of the centroid of each cell. We estimate

$$\begin{aligned}[Tree\ Cover]_{i,t} = [Fixed\ Effect]_i + \sum_{t=2001}^{2014} \kappa_t [Year\ Dummy]_t \\ + \sum_{t=2001}^{2014} [Year\ Dummy]_t \times P_t^3([Lat]_i, [Lon]_i) \\ + \sum_{t=2001}^{2014} \beta_t^S [Year\ Dummy]_t \times [Targeted]_i + [Error]_{i,t}\end{aligned} \tag{1}$$

where $[Targeted]$ is an indicator for whether the cell is inside the targeted region. There is no direct term for the polynomial $P^3(\cdot)$ or the dummy $[Targeted]$ because they are absorbed into the fixed-effect. The coefficients $\{\beta_t^S\}$ measure the effect at the new border, relative to its effect in 2000, in each year before and after the policy.

The second approach uses the distance to the new border as a univariate running variable. Let $L_t([Distance]_i, [Targeted]_i) = \omega_{1,t}[Distance]_i + \omega_{2,t}[Distance]_i \times [Targeted]_i$. Following Imbens and Lemieux (2008) we estimate a local linear regression of the form

$$\begin{aligned}[Tree\ Cover]_{i,t} = [Fixed\ Effect]_i &+ \sum_{t=2001}^{2014} \kappa_t [Year\ Dummy]_t \\ &+ \sum_{t=2001}^{2014} [Year\ Dummy]_t \times L_t([Distance]_i, [Targeted]_i) \\ &+ \sum_{t=2001}^{2014} \beta_t^D [Year\ Dummy]_t \times [Targeted]_i + [Error]_{i,t}\end{aligned} \tag{2}$$

Similar to the first specification, the coefficients $\{\beta_t^D\}$ measure the effect at the new border.

The third specification is the simplest: a comparison of means very close to the border. Using only observations within 4 kilometers of the border we estimate

$$\begin{aligned}[Tree\ Cover]_{i,t} = [Fixed\ Effect]_i &+ \sum_{t=2001}^{2014} \kappa_t [Year\ Dummy]_t \\ &+ \sum_{t=2001}^{2014} \beta_t^C [Year\ Dummy]_t \times [Targeted]_i + [Error]_{i,t}\end{aligned} \tag{3}$$

to yield estimates $\{\beta_t^C\}$.

We also estimate average program impacts by pooling pre- and post-program years in all three specifications:

$$\begin{aligned}[Tree\ Cover]_{i,t} = [Fixed\ Effect]_i + \sum_{t=2001}^{2014} \kappa_t [Year\ Dummy]_t \\ + [Post]_t \times P_t^3([Lat]_i, [Lon]_i) + \beta^S [Post]_t \times [Targeted]_i + [Error]_{i,t}\end{aligned} \tag{4}$$

$$\begin{aligned}[Tree\ Cover]_{i,t} = [Fixed\ Effect]_i + \sum_{t=2001}^{2014} \kappa_t [Year\ Dummy]_t \\ + [Post]_t \times L_t([Distance]_i, [Targeted]_i) \\ + \beta^D [Post]_t \times [Targeted]_i + [Error]_{i,t}\end{aligned} \tag{5}$$

$$\begin{aligned}[Tree\ Cover]_{i,t} = [Fixed\ Effect]_i + \sum_{t=2001}^{2014} \kappa_t [Year\ Dummy]_t \\ + \beta^C [Post]_t \times [Targeted]_i + [Error]_{i,t}\end{aligned} \tag{6}$$

All specifications cluster standard errors by sub-district to account for arbitrary correlation in the error term across time and space. Shenoy (2018) shows using in Monte Carlo simulations that clustering by subdistrict yields hypothesis tests of the proper size. Since the number of clusters in the third specification is small, we show in Appendix Table A.2 that bootstrapped standard errors yield similar results to asymptotic errors. We use a bandwidth of 30 kilometers to estimate the first two specifications, and a bandwidth of 4 kilometers for the third.

3.2 Employment and Firm Growth

Since the 2005 Economic Census did not separate logging and tree-felling from other forestry industries (e.g. forest conservation), we must rely on only the 1998 and 2013 rounds. Since there are only two periods (pre and post), the specifications of Section 3.1 are not identified. We instead take the location-level change from 1998 to 2013 and run a local linear regression with a triangular kernel. Since the difference-in-discontinuities is now essentially a standard regression discontinuity design (but taking a difference as the outcome), we can follow the method of Calonico, Cattaneo and Titiunik (2014). We estimate

$$\Delta[Outcome]_i = \pi_0 + \pi_1[Distance]_i + \pi_2[Distance]_i \times [Targeted]_i + \omega[Targeted]_i + [Error]_i \tag{7}$$

again clustering by sub-district.

4 Results

We report two principal findings in this paper. First, across a number of specifications and robustness checks we find that the policy had a small and statistically insignificant effect on forest cover. The effect is especially small relative to the expansion of economic activity. Second, we find a precisely estimated impact on employment in logging and wood-using firms that, though positive, is small relative to the overall expansion of employment. Finally, we discuss potential threats to our research design, most notably the risk that forest loss is displaced from treatment to control areas.

Effect on Forest Cover: Figure 1 compares raw average night time luminosity (left panel) to average forest cover (right panel) within 10 kilometers on either side of the discontinuity. While average night time luminosity between treatment and control areas diverges substantially within a few years of the introduction of the policy (2002), average forest cover in treatment areas tracks closely with average forest cover in control areas showing no divergence in trends.

Figure 2 shows the discontinuity at the border in average forest cover in the years 2000 (left panel) and 2014 (right panel). Even 12 years after the introduction of the policy, and four years after the end of the policy, there is no discernible difference in forest cover at the border.

Figure 3 shows the year-by-year estimates corresponding to each of the Equations 1—3. In all three figures, each estimate provides the discontinuous change in tree cover at the boundary relative to the discontinuity in the year 2000. The red line indicates the year 2000 when the policy came into effect. Across all three specifications, we observe a small negative effect of the policy on forest cover.

We formally estimate the effect of the policy on tree cover and report the aggregate results of our difference-in-discontinuities design in Table 1. In Column (1) we employ a spatial polynomial estimator, in Column (2) we use a distance to border approach and in Column (3) we calculate a simple difference of means. Across all three specifications, we find that the shift in the estimate at the border before and after the implementation of policy was small and statistically insignificant at conventional levels. These null effects are unlikely to be the result of a lack of statistical power; indeed our results on employment reported subsequently show that our design has statistical power to pick up even small changes in forest cover/employment if they exist. Using our preferred specification in Column (1) we find a mean reduction of 0.49 percentage points or 2.98% of forest cover. Based on a 95% confidence interval, we can reject forest loss in excess of 1.37 percentage points or 8.3%. We are able to reject similar increases using alternative specifications (Columns 2 - 3). Our results are robust to using an inverse hyperbolic sine transformation of the dependent variable (Appendix Figure A.4, Appendix Table A.1).

Effect on Employment: Table 2 shows the effects of the policy on employment in all firms and specifically the subset of firms in the logging industry and more generally in industries where the primary input is raw lumber. We find there is a marked increase in overall employment. In Column (1) we show that employment increased by 104.36 persons in each census location and the effect is significant at the 1% level. Compared to a baseline treatment group mean of 64 employed persons per census location, this translates to a 130% increase in overall employment. By contrast, we see a precise but modest increase in employment in logging firms. The average census location saw an increase of 0.56 workers in this category (Column 2, Table 2). There was virtually no employment in this sector on either side of the discontinuity before the implementation of the policy. Logging firms represent 0.54% of total change in employment as a result of policy. When considering wood-using firms (Column 3, Table 2), we find that the policy increased employment in this category by nearly 7 workers per census location, or 6.56% of overall increase in employment.

Does displacement explain the null-result? One reason for our null-estimate could be that the effect of the policy led to increased forest loss in not only the treatment area but also the control area.[6] While it is not possible to test for displacement explicitly, in Appendix Figure A.2 we present maps of forest cover in 2000 and 2014 around the border. As is visually evident, there is no systematic change in the control region (south of the border) after the implementation of the policy. At endline in 2013, employment

[6]There is also the possibility of displacement from the border to locations in the treated state further away from the border. However, the policy was uniformly applied throughout the state so there is no reason to suspect that forest cover loss was displaced from one part of the state to another. Moreover, reasonable alterations in the bandwidth of our discontinuity design do not overturn our result suggesting that there is no reason to suspect spillovers to neighboring regions away from the border.

in logging is 0.07% of total employment near the border of the control region—not much of an increase from 0% in 1998. Moreover, we show in Figure 1 that forest cover in the treatment area closely tracks forest cover in the control areas, before, during and after the policy is in effect suggesting that displacement is unlikely to be the source of our null-finding.

5 Discussion and Conclusion

The rising concern of increasing, geographically-concentrated economic divisions within national borders has spurred the growth of place-based economic policies. These policies provide incentives for industrial development and infrastructure through subsidies and tax-breaks and typically target remote areas that are more likely to have native vegetation. While concern has been expressed over the short- and long-run ecological ramifications of such rapid development, the policy we study showed no such ramifications. Exploiting a spatial discontinuity in the policy, even ten years after its introduction and four years after its end we find no effect on forest cover. By contrast, the expansion of economic activity was massive. Finally, we find no evidence for spillovers across the border from the treatment to the control region.

One possible reason for this win-win result is that the policy had an explicit environmental rider that excluded tax-breaks to certain environmentally detrimental industries such as pulp, paper and mining while explicitly promoting others such as food, pharmaceuticals and non-timber forest-based products. In effect, the policy increased the relative costs of setting up environmentally detrimental industries.

An important caveat for our findings is that we focus on one measure of environmental quality - forest cover. Economic development can also affect air and water quality; however, the lack of detailed data during the relevant time period in our study region precludes us from estimating these effects. Future research should address other such potential external costs of policy-driven, geographically-concentrated economic development.

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Figures

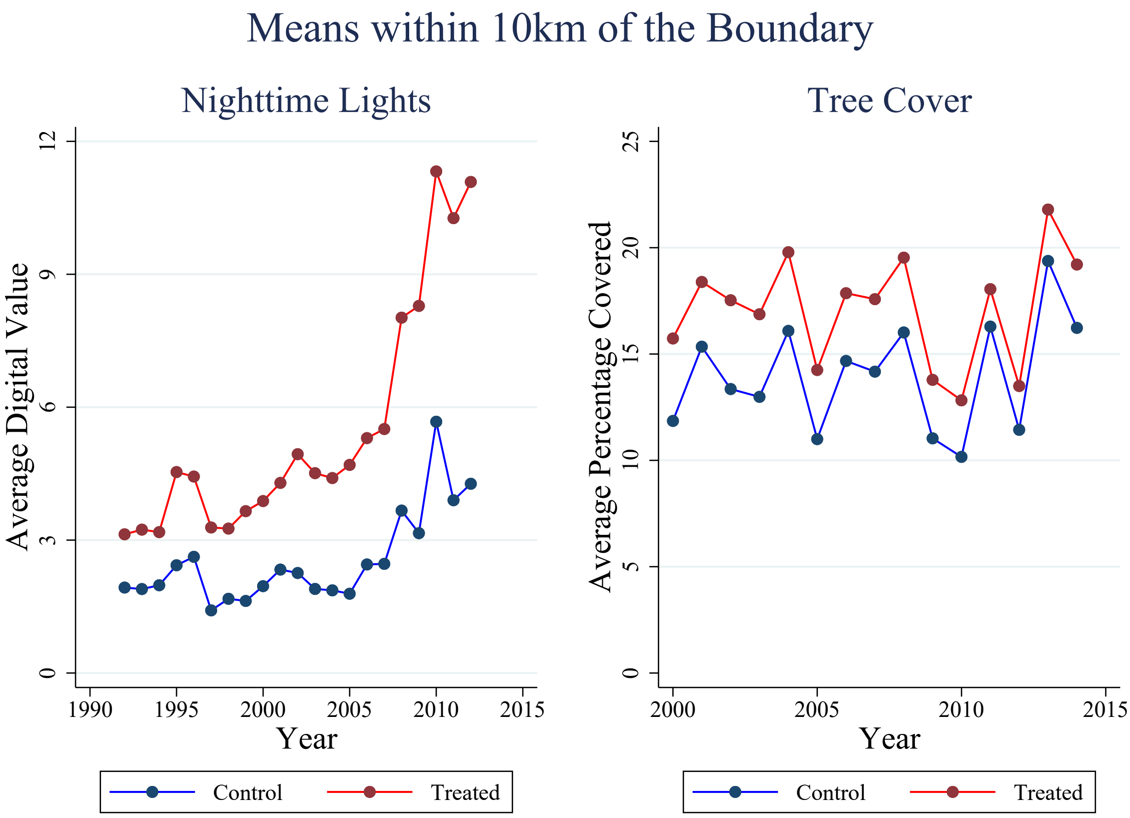

Figure 1: Comparison of Nighttime Luminosity and Deforestation Within 10KM of Border

We plot the mean of each outcome for cells that lie within 10 kilometers of the border.

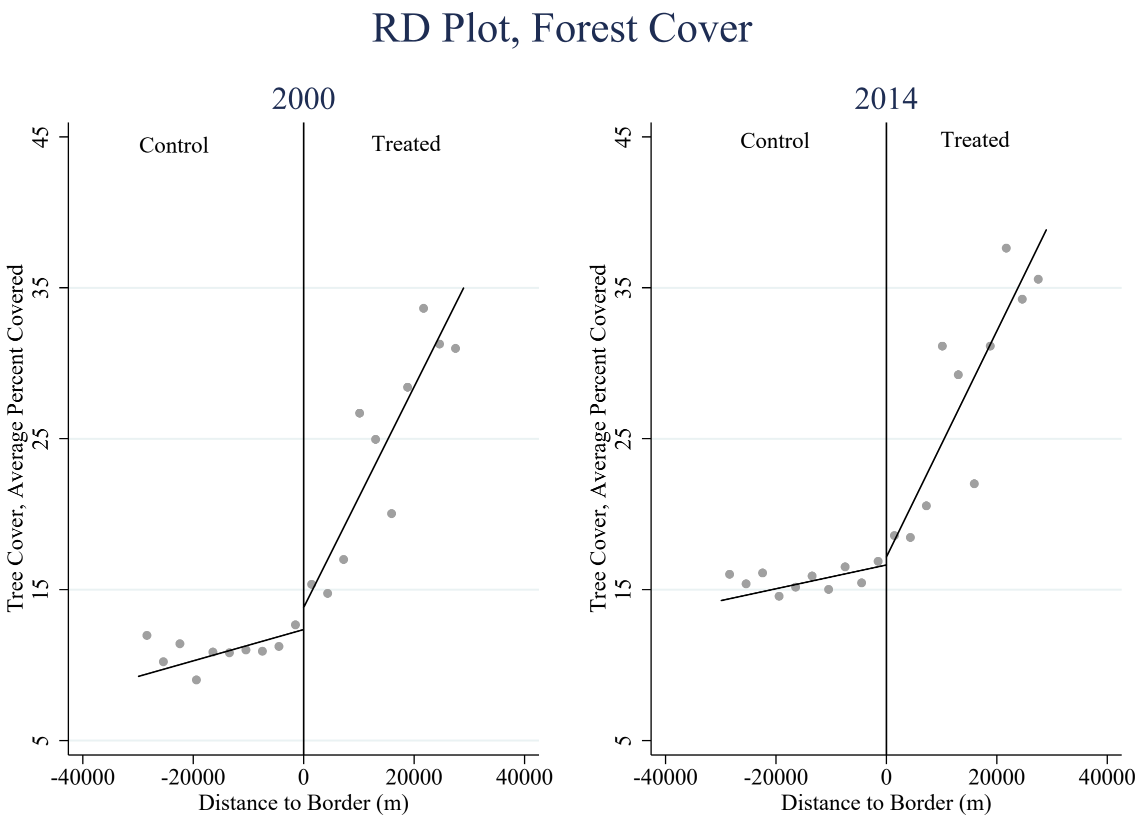

Figure 2: Regression Discontinuity at the Border in 2000 and 2014

We plot average tree cover against distance to the boundary (positive values are in the targeted state). Each dot shows average tree cover within a bin, where the bins are chosen by the variance evenly-spaced method estimated using code from Calonico, Cattaneo and Titiunik (2014).

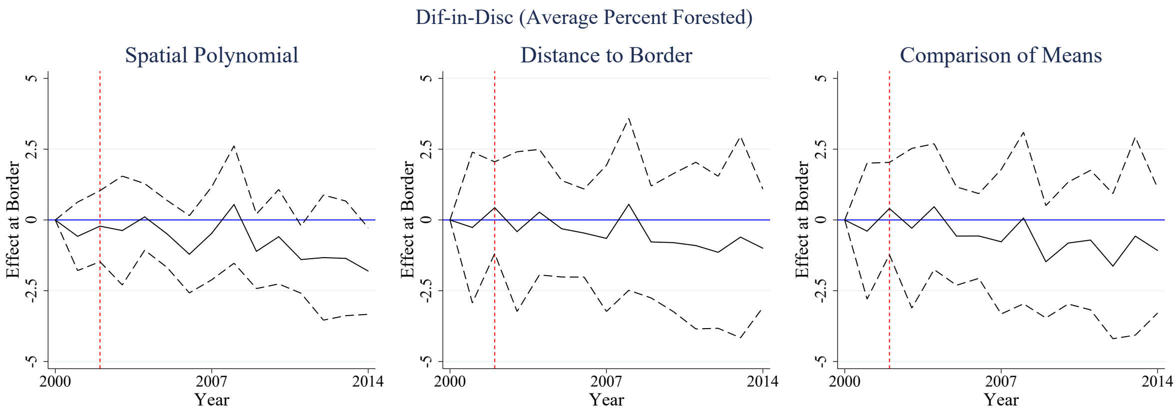

Figure 3: Difference-in-Discontinuities Estimate of Effect of PBP on Deforesation

We plot the estimates $\{\hat{\beta}_t^S\}$, $\{\hat{\beta}_t^D\}$, and $\{\hat{\beta}_t^C\}$ from estimating Equations 1—3. Each estimate gives discontinuous change in tree cover at the boundary relative to the discontinuity in the year 2000. The red dashed line shows the first year of the policy.

Tables

Table 1: Difference-in-Discontinuities Estimate of Place-Based Policies on Tree Cover

	Spatial Polynomial	Distance to Border	Comparison of Means
Post-PBP	-0.49	-0.31	-0.38
	(0.45)	(0.54)	(0.53)
Cell-Years	4320	4320	1350
Cells	288	288	90
Sub-districts	38	38	26
Mean at Baseline	16.4	16.4	16.4

Estimates of $\hat{\beta}^S, \hat{\beta}^D, \hat{\beta}^C$ from Equations 4—6. The outcome is the average tree cover within each cell. Standard errors are clustered by sub-district.
Significance levels denoted at conventional levels *** p<0.01, ** p<0.05, * p<0.1

Table 2: Regression Discontinuity Estimate of PBP on Employment and Firms

	All	Logging	Wood-Using
RD Estimate	104.36***	0.56**	6.85***
	(37.44)	(0.24)	(2.33)
Observations	25747	25747	25747
Sub-districts	67	67	54
Optimal BW	37.6	38.7	29.4
Control Mean, 1998	64.0	0.0	1.2
Treated Mean, 1998	80.0	0.0	3.2

We estimate Equation 7 for employment and the number of firms within each of the given industries ("all" is all employment measured in the Economic Census). The unit of observation is a census location (either a town or a village). Standard errors are clustered by sub-district.

Significance levels denoted at conventional levels *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Online Appendix

Additional Figures

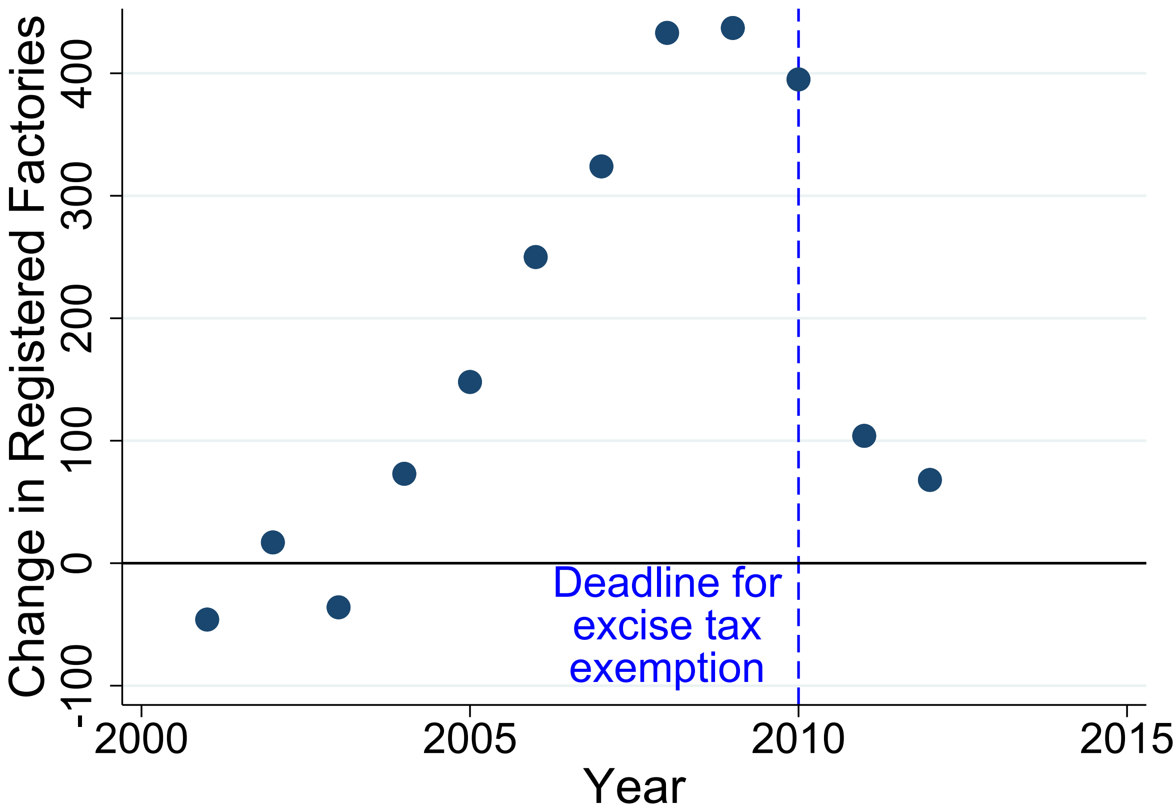

Figure A.1: Registration of Firms Before and After Subsidy Deadline

Replicated from Shenoy (2018). Based on aggregate data from the Annual Survey of Industries and the Economic Census.

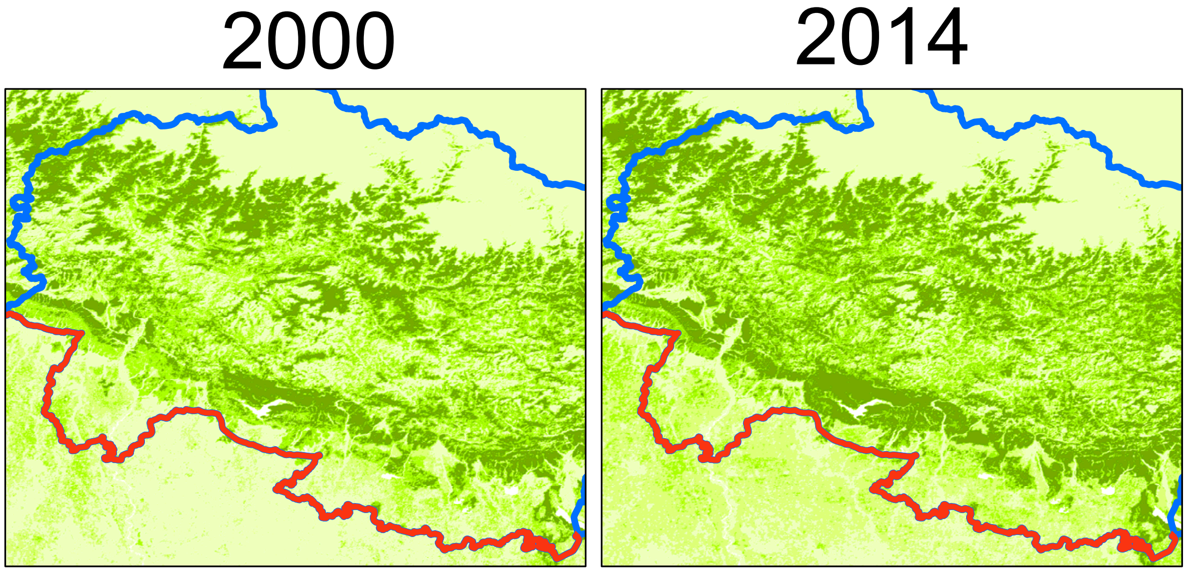

Figure A.2: Deforestation at the Border in 2000 and 2014

Each figure shows the raw tree cover in the area around the border between the targeted and control states (red line). The targeted state lies to the north of the boundary. Darker colors represent thicker tree cover.

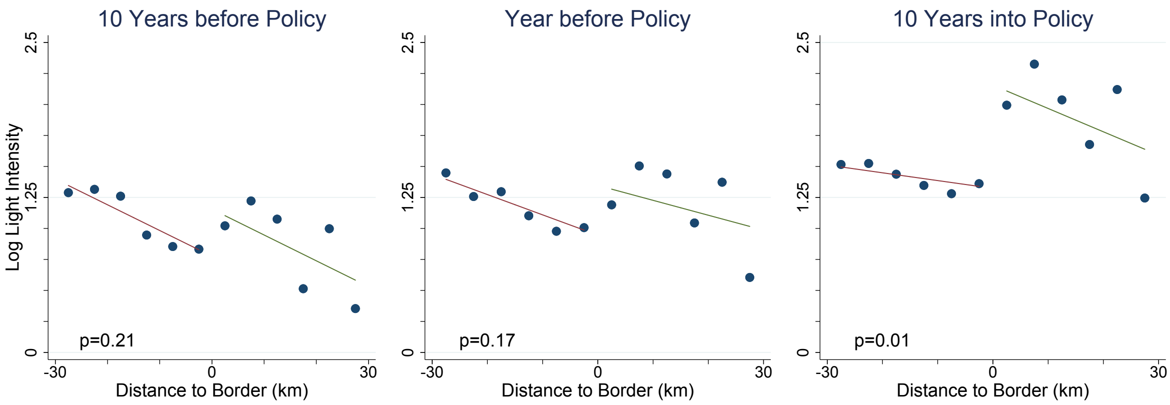

Figure A.3: Difference-in-Discontinuities Estimate of PBP on Night Lights (Replicated from Shenoy (2018))

Each dot represents the average of light intensity within a 5 kilometer bin. The specification is comparable to Equation 2. The p-value gives the significance of the border effect in the cross-sectional regression. P-values are computed from standard errors clustered by subdistrict.

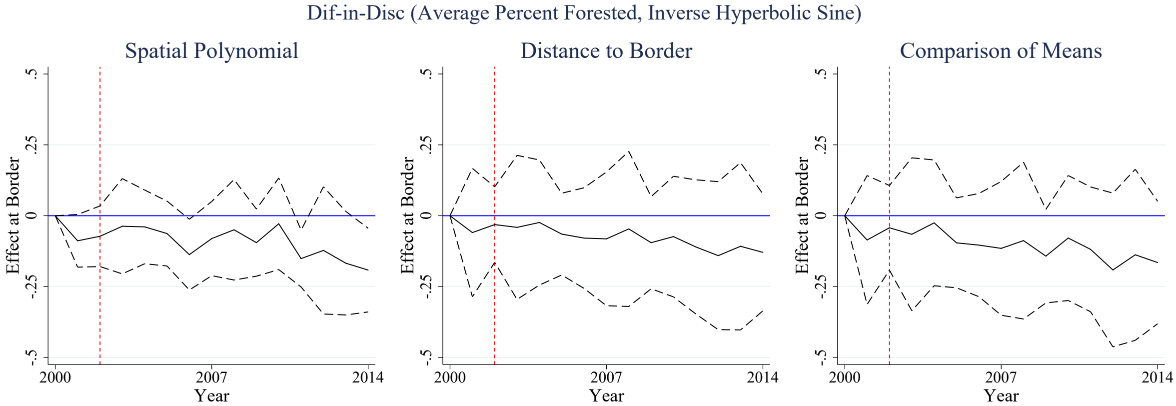

Figure A.4: Difference-in-Discontinuities Estimate of Effect of PBP on Deforesation(IHS)

This figure is comparable to Figure 3, but applies the inverse hyperbolic sine transformation to the measure of forest cover.

Additional Tables

Table A.1: Difference-in-Discontinuities Estimate of Place-Based Policies on Deforestation (IHS)

	Spatial Polynomial	Distance to Border	Comparison of Means
Post-PBP	-0.05	-0.05	-0.06
	(0.05)	(0.05)	(0.06)
Cell-Years	4320	4320	1350
Cells	288	288	90
Sub-districts	38	38	26

Outcome is the inverse hyperbolic sine of the average tree cover. The specifications are comparable to Table 1. All standard errors are clustered by sub-district.
Significance levels denoted at conventional levels *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table A.2: Difference-in-Discontinuities Estimate of Deforestation, Bootstrapped Standard Errors

	Spatial Polynomial	Distance to Border	Comparison of Means
Post-PBP	-0.49	-0.31	-0.38
	(0.45)	(0.57)	(0.50)
Cell-Years	4320	4320	1350
Cells	288	288	90
Sub-districts	38	38	26
Mean at Baseline	16.4	16.4	16.4

Similar to Table 1, but Columns 2 and 3 use bootstrapped standard errors. We cannot estimate bootstrapped errors for (1) because there are too many parameters. Significance levels denoted at conventional levels *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Policy Details

Positive "Thrust" Industries

- Floriculture
- Medicinal herbs and aromatic herbs etc. - processing
- Honey
- Horticulture and Agro based industries such as
  - Sauces, Ketchup, etc.
  - Fruit Juices & fruit pulp
  - Jams, Jellies, vegetable juices, puree, pickles etc.
  - Preserved fruits and vegetables
  - Processing of fresh fruits and vegetables including packaging
  - Processing, preservation, packaging of mushrooms.
- Food Processing Industry excluding those included in the negative list
- Sugar and its by products
- Silk and silk products
- Wool and wool products
- Woven fabrics (Excisable garments)
- Sports goods and articles and equipment for general physical exercise and equipment for adventure sports/activities, tourism (to be separately specified)
- Paper & paper products excluding those in negative list (as per excise classification)
- Pharma products
- Information & Communication Technology Industry
- Computer hardware Call centres
- Bottling of mineral water
- Eco-tourism
- Hotels, resorts, spa, entertainment/amusement parks and ropeways
- Industrial gases (based on atmospheric fraction)
- Handicrafts
- Non-timber forest-based product industries

Negative List

- Tobacco and tobacco products including cigarettes and pan masala
- Thermal Power Plant(coal/oil based)
- Coal washeries/dry coal processing
- Inorganic Chemicals excluding medicinal grade oxygen, medicinal grade hydrogen peroxide, compressed air
- Organic chemicals excluding Provitamins/vitamins, Hormones , Glycosides, sugars
- Tanning and dyeing extracts, tanins and their derivatives, dyes, colours, paints and varnishes; putty, fillers and other mastics; inks
- Marble and mineral substances not classified elsewhere
- Flour mills/rice mill
- Foundries using coal
- Minerals fuels, mineral oils and products of their distillation;
- Bituminous substances : mineral waxes
- Synthetic rubber products
- Cement clinkers and asbestos, raw including fibre.
- Explosive (including industrial explosives, detonators & fuses, fireworks, matches, propellant powders etc.)
- Mineral or chemical fertilisers
- Insecticides, fungicides, herbicides & pesticides (basic manufacture and formulation)
- Fibre glass & articles thereof
- Manufacture of pulp - wood pulp, mechanical or chemical (including dissolving pulp)
- Branded aerated water/soft drinks (non-fruit based)
- Paper
  - Writing or printing paper, etc.
  - Paper or paperboard, etc.
  - Maplitho paper, etc.
  - Newsprint, in rolls or sheets
  - Craft paper, etc.
  - Sanitary towels, etc.
  - Cigarette paper
  - Grease-proof paper
  - Toilet or facial tissue, etc.
  - Paper & paper board, laminated internally with bitumen, tar or asphalt

  - Carbon or similar copying paper
  - Products consisting of sheets of paper or paperboard, impregnated, coated or covered with plastics, etc.
  - Paper and paperboard, coated impregnated or covered with wax, etc.

- Plastics and articles thereof