

Public Policy Under Limited State Capacity: Evidence from Deforestation Control in the Brazilian Amazon

Supporting Information

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A1 A Formal Model of Spatial Spillovers in Deforestation Monitoring

Consider a $[0, 1]$ continuum of possible locations for forest clearing. The value (product price) of clearing land at location d is $\alpha > 0$, a constant set such that supply (endogenously derived) and demand (downward slope) meet. The cost of traveling to location d is d^2 , so that the net profit from land clearing decreases as the produced moves away from the central location, $d = 0$.

The producer's problem is to choose all location $d \in [0, 1]$ for production. In the absence of monitoring, the producer's profit from location d can be written as $\alpha - d^2$. Thus, the producer optimally selects a closed and continuous interval $[0, d_0]$ for production, where d_0 meets $\alpha = d_0^2$. Let α_0 denote the price that clears the market.

In the presence of monitoring, we assume that there is a penalty $\beta > 0$ for clearing land at any location d . Deforestation activity is undetected at location d with probability $p(d)$, an increasing and strictly concave function on the $[0, 1]$ interval. Let $\lim_{d \rightarrow 0} p = 0$ and $p' \rightarrow \infty$ as $d \rightarrow 0$. Thus, $1 - p(d)$ is the probability of being caught.

In the presence of monitoring, the producer's profit from location d is $p(d)\alpha - (1 - p(d))\beta - d^2$. The marginal profit from increasing d is $p'(d)\alpha + p'(d)\beta - 2d$. Given strict concavity and the Inada condition in the neighborhood of zero for $p(d)$, this function is strictly increasing for sufficiently low values of d . If α is high enough and β low enough, the function obtains a non-negative value for some closed interval $[\underline{d}, \bar{d}]$. If α is low enough and β high enough, the producer does not clear land anywhere.

We can now compare the area deforested under monitoring. For any fixed α , monitoring shrinks the area deforested, as $[\underline{d} > 0]$ and $[\bar{d} < d_0]$. As α increases, however, \underline{d} decreases and \bar{d} increases. Therefore, the effect of monitoring on forest clearing depends on the elasticity of demand.

When elasticity of demand is very high, α remains approximately unchanged. In this case, monitoring reduces deforestation, as shown above.

When elasticity of demand is very low, the total interval deforested must remain unchanged. The measure of $[\underline{d}, \bar{d}]$ approximates the measure of $[0, d_0]$, but deforestation begins away from the center, as $\underline{d} > 0$.

Thus, positive spillovers from hot spot monitoring are always present in that deforestation close to the center decreases. But as the elasticity of demand increases, negative spillovers grow.

These dynamics are illustrated in Figure A1. For these graphs, we assume the functional form $p(d) = \sqrt{d/2}$. The figure shows how deforestation at different distances from the priority municipality responds to monitoring. When monitoring yields a high equilibrium price (right panel), deforestation away from the center becomes profitable. Monitoring is not a major threat as long as the location is far away from the center, and the higher market price encourages deforestation that was previously unprofitable because of transportation costs.

A1.1 Model Variant: Fixed Price

We now consider a variant of the model in which the price is fixed. In this case, $\alpha = \alpha_0$ is fixed, but otherwise the analysis above continues to hold. In this variant of the model, monitoring shrinks the area deforested, as $[\underline{d} > 0]$ and $[\bar{d} < d_0]$. The deforested interval shrinks monotonically. from both ends.

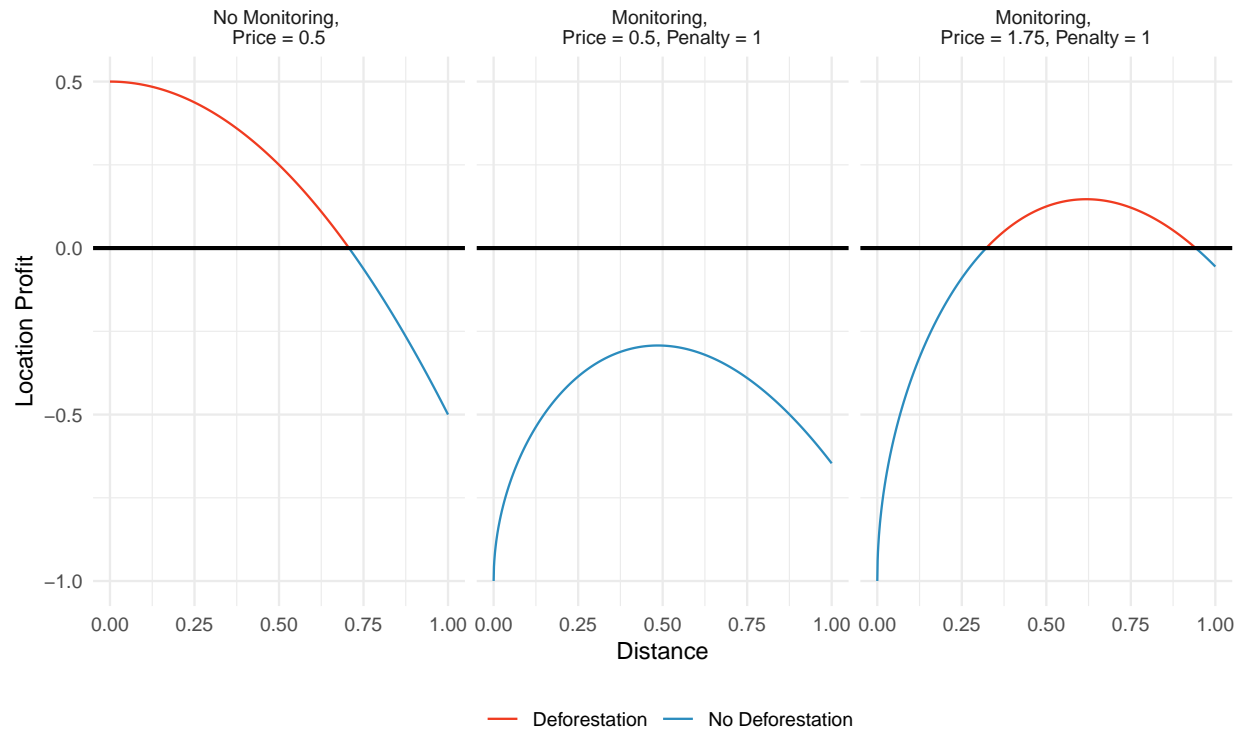


Figure A1: Graphical illustration of a formal model of forest clearing with and without monitoring. The red color of the profit function indicates the area that will be deforested because the profit from doing so is positive at market-clearing price. As the left panel shows, the cleared area begins at the center in the absence of monitoring. If demand for forest clearing is inelastic so that monitoring does not change the price of the product, as in the middle panel, deforestation may disappear entirely because of positive spatial spillovers. If demand for forest clearing is sufficiently elastic and monitoring increases the equilibrium price of the product, deforestation decreases close to the center (positive spillovers) but increases away from the center (negative spillovers), as shown in the right corner.

A2 Municipality Summary Statistics

- Table A1 shows the summary of all municipalities targeted by the PM program and their mapping into the gridded units.

A3 Research Design Visualization

A3.1 Visualization of Clustering

We provide a visualization of the clustered treatment assignment in the following map. The grid cells are cluster assigned to treatment with the nearest Priority Municipality ($n = 52$). This defines both the treatment indicator and serves as the clustering variable for the purpose of variance estimation. The colors here are arbitrary and are intended solely to show how the clusters are defined geographically.

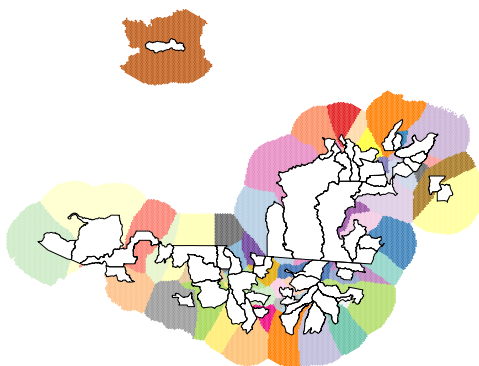


Figure A2: Definition of geographic clusters for the purpose of treatment assignment. Each color corresponds to one cluster.

A3.2 Visualization of Treatment Status, Outcomes

Incorporating the dataset reported in Table A1 and the assignment of buffer area to Priority Municipalities reported in Figure A2, there are nine distinct configurations of treatment, defined over time and space. Figure A3 visualizes these patterns. Figure A4 overlays our outcome data on deforestation events outside of priority municipalities (PMs) onto the graphical depiction of our treatment indicator in Figure A3. Each black point represents a deforestation event. The points are not drawn to scale. Note that due to the variation in the duration of each pattern of treatment in addition to the seasonal patterns described at more length in Section A4, it is quite difficult to make inferences about the spillover effects of the Priority Municipality program from the raw data alone.

Priority Municipality	Treatment Dates			Source: Portaria		<i>n</i>	Months per Treatment		
Municipality	State	Start	End	Designation	“Graduation”	Cells	Control	Treatment	Graduated
Paragominas	PA	1/2008	3/2010	#28/2008	#67/2010	1270	17	25	65
Querência	MT	1/2008	4/2011	#28/2008	#139/2011	627	17	38	52
Santa do Araguaia	PA	1/2008	6/2012	#28/2008	#187/2012	373	17	52	38
Alta Floresta	MT	1/2008	6/2012	#28/2008	#187/2012	166	17	52	38
Dom Eliseu	PA	1/2008	7/2012	#28/2008	#324/2012	76	17	53	37
Ulianópolis	PA	1/2008	7/2012	#28/2008	#324/2012	77	17	53	37
Brasil Novo	PA	1/2008	10/2013	#28/2008	#412/2013	768	17	68	22
Brasnorte	MT	1/2008	10/2013	#28/2008	#412/2013	467	17	68	22
Marcelândia	MT	1/2008	10/2013	#28/2008	#412/2013	62	17	68	22
Machadinho D'oeste	RO	1/2008		#28/2008		447	17	90	0
Pimenta Bueno	RO	1/2008		#28/2008		1084	17	90	0
Porto Velho	RO	1/2008		#28/2008		1021	17	90	0
Nova Mamoré	RO	1/2008		#28/2008		820	17	90	0
Lábrea	AM	1/2008		#28/2008		2155	17	90	0
Altamira	PA	1/2008		#28/2008		1499	17	90	0
Cumaru do Norte	PA	1/2008		#28/2008		295	17	90	0
Novo Progresso	PA	1/2008		#28/2008		1000	17	90	0
Novo Repartimento	PA	1/2008		#28/2008		69	17	90	0
Rondon do Pará	PA	1/2008		#28/2008		194	17	90	0
Santa Maria Das Barreiras	PA	1/2008		#28/2008		888	17	90	0
São Félix do Xingu	PA	1/2008		#28/2008		180	17	90	0
Aripuan†	MT	1/2008		#28/2008		106	17	90	0
Colniza	MT	1/2008		#28/2008		851	17	90	0
Confresa	MT	1/2008		#28/2008		120	17	90	0
Cotriguaçu	MT	1/2008		#28/2008		468	17	90	0
Gaúcha do Norte	MT	1/2008		#28/2008		815	17	90	0
Juína	MT	1/2008		#28/2008		456	17	90	0
Nova Bandeirantes	MT	1/2008		#28/2008		148	17	90	0
Nova Ubiratã	MT	1/2008		#28/2008		770	17	90	0
Paranaíta	MT	1/2008		#28/2008		224	17	90	0
Peixoto de Azevedo	MT	1/2008		#28/2008		239	17	90	0
Porto Dos Gaúchos	MT	1/2008		#28/2008		153	17	90	0
São Félix do Araguaia	MT	1/2008		#28/2008		1085	17	90	0
Vila Rica	MT	1/2008		#28/2008		191	17	90	0
Nova Maringá	MT	1/2008		#28/2008		825	17	90	0
Tailândia	PA	3/2009	10/2013	#102/2009	#412/2013	56	31	54	22
Feliz Natal	MT	3/2009	10/2013	#102/2009	#412/2013	39	31	54	22
Mucajá	RR	3/2009		#102/2009		2646	31	76	0
Itupiranga	PA	3/2009		#102/2009		13	31	76	0
Marabá	PA	3/2009		#102/2009		763	31	76	0
Pacajá	PA	3/2009		#102/2009		199	31	76	0
Amarante do Maranhão	MA	3/2009		#102/2009		777	31	76	0
Juara	MT	3/2009		#102/2009		89	31	76	0
Boca do Acre	AM	5/2011		#175/2011		1874	56	51	0
Moju	PA	5/2011		#175/2011		1091	56	51	0
Grajaú	MA	5/2011		#175/2011		1548	56	51	0
Alto Boa Vista	MT	5/2011		#175/2011		34	56	51	0
Cláudia	MT	5/2011		#175/2011		125	56	51	0
Santa Carmem	MT	5/2011		#175/2011		66	56	51	0
Tapurah	MT	5/2011		#175/2011		155	56	51	0
Anapu	PA	7/2012		#323/2012		235	70	37	0
Senador Jose Porfirio	PA	7/2012		#323/2012		463	70	37	0

Table A1: This table shows the PMs, their dates of designation as PMs, the source documents (Portarias) that document designation, the number of hexagon cells in the cross-section that are assigned to each PM, and the number of months in each treatment condition. “Graduation” signifies that the PM designation was lifted.

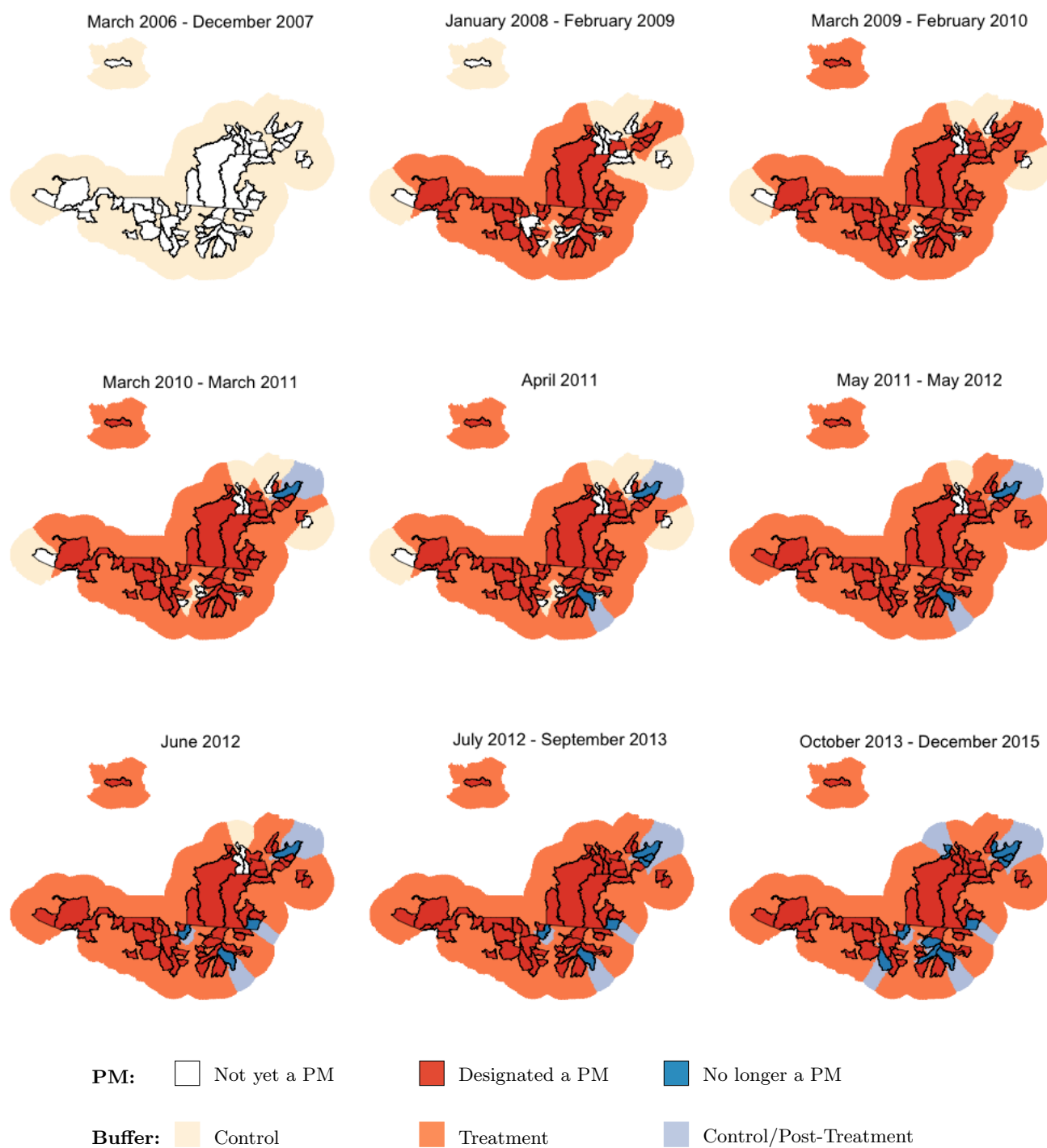


Figure A3: Visualization of the geographic and temporal variation in the treatment indicator. Our analysis focuses only on the buffer areas outside of priority municipalities (PMs).

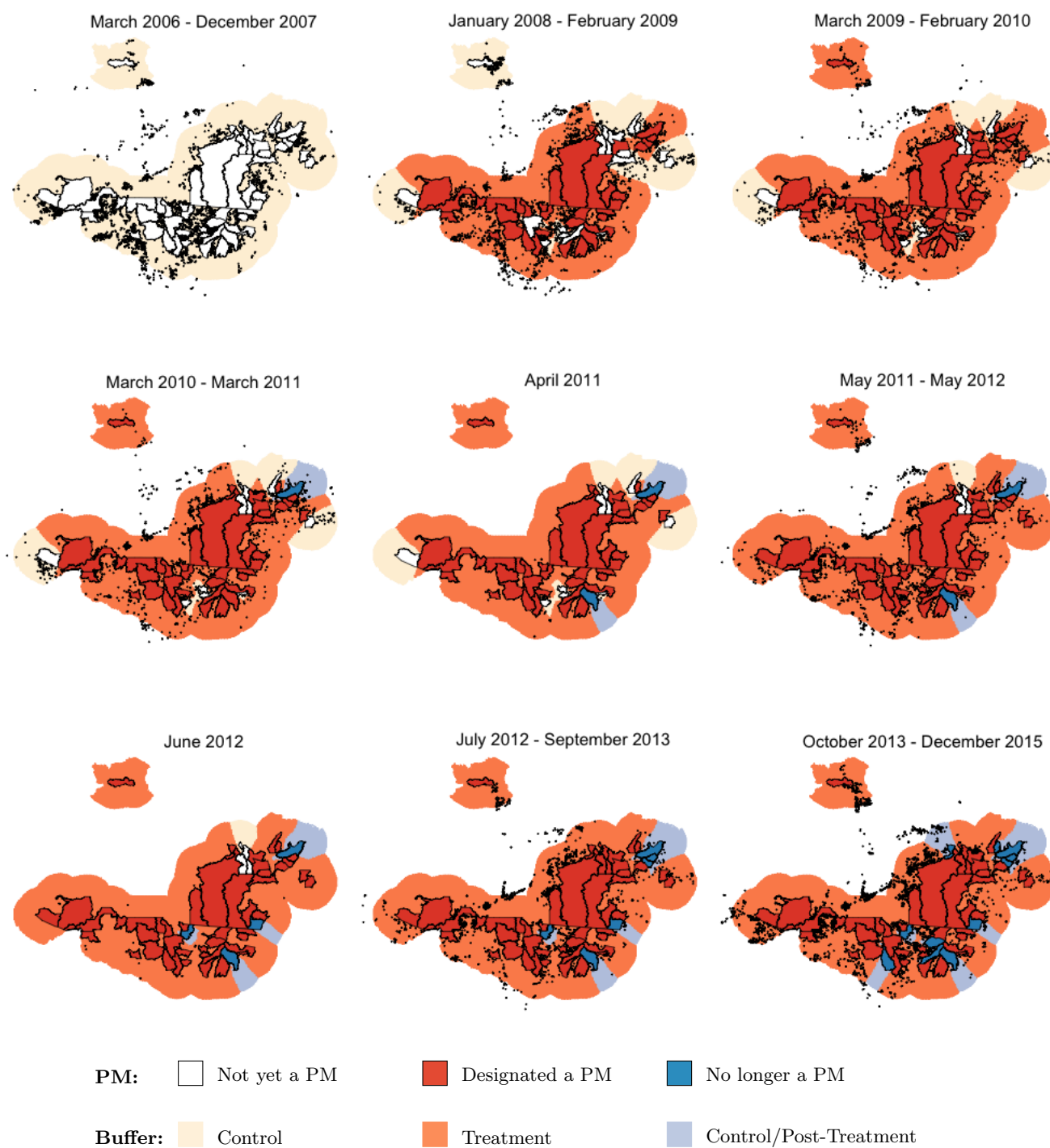


Figure A4: Visualization of the deforestation events outside of priority municipalities (our dependent variable) by location and treatment assignment status. Each black point represents a deforestation event. Note that points are not drawn to scale.

A4 Deforestation Data: Seasonality

Deforestation patterns are highly seasonal. The seasonality is evident by simple graphical examination of patterns in the deforestation data over time. Figure A5 suggests that deforestation peaks in approximately June through October.

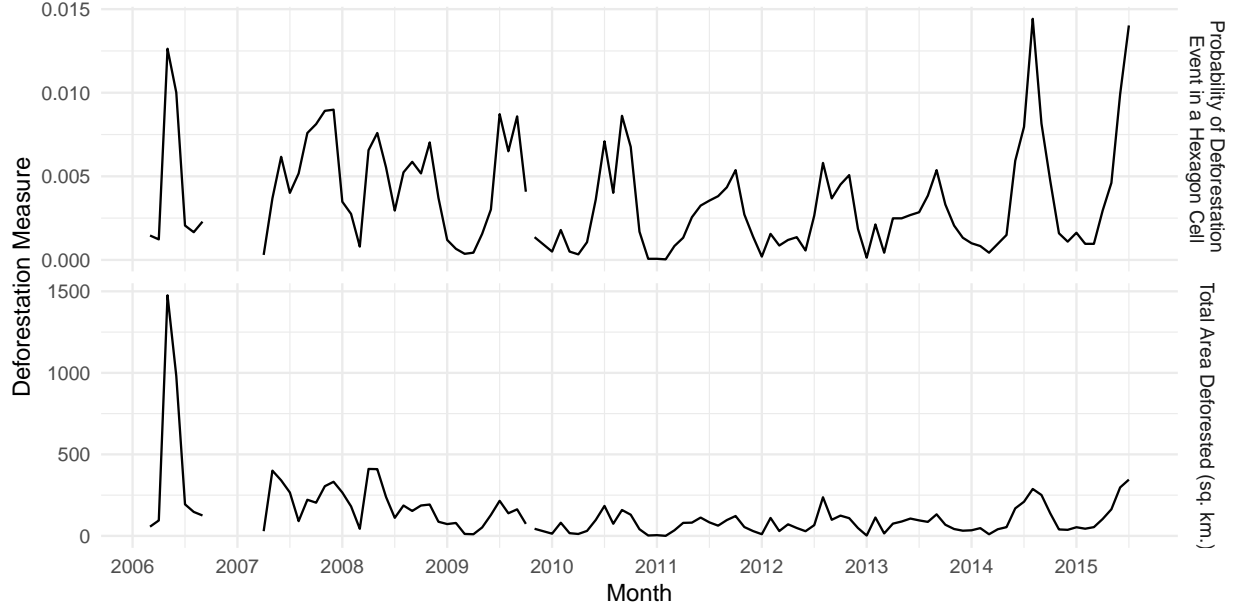


Figure A5: The top panel graphs the probability of a deforestation event in a given hexagon cell by month from 2006-2015. The bottom panel graphs the log area deforested by month from 2006-2015. The geographic scope is all events in the 200-km bandwidth surrounding (eventual) Priority Municipalities. Data from DETER. Missing segments indicate months with missing data.

To test these patterns more rigorously, we estimate the specification:

$$Y_t = \beta_0 + \sum_{m=2}^{12} \gamma_m I[\text{Month}_t = m] + \epsilon_t \quad (1)$$

where Y_t is the outcome aggregated at the monthly level across all hexagons (as in Figure A5), $I[\cdot]$ is an indicator function, and ϵ_t is an error term. We test for seasonality by evaluating the null hypothesis that $\gamma_m = 0 \forall m \in \{2, \dots, 12\}$ using an F -test. All specifications suggest that deforestation levels are predicted by month dummies, providing evidence of seasonal patterns. For this reason, our preferred specification includes grid cell (hexagon)-month fixed effects to partial out hexagon-specific temporal patterns in deforestation.

A5 Identifying Assumptions

- Figure A6 provides a non-parametric test of the parallel trends assumption.

	Probability of Deforestation Event		Total Area Deforested (sq. km.)	
	(1)	(2)	(3)	(4)
F-statistic, $H_0 : \gamma_m = 0 \forall m$	4.82	5.66	3.132	3.315
p -value	< 0.001	<0.001	0.001	0.001
Time trend (cubic)		✓	✓	
Observations	107	107	107	107

Table A2: Test for seasonality in the deforestation data. This table reports the F -statistics estimated from the specification reported in 1, with and without a time trend. Rejecting the null hypothesis provides evidence of that deforestation patterns are highly seasonal.

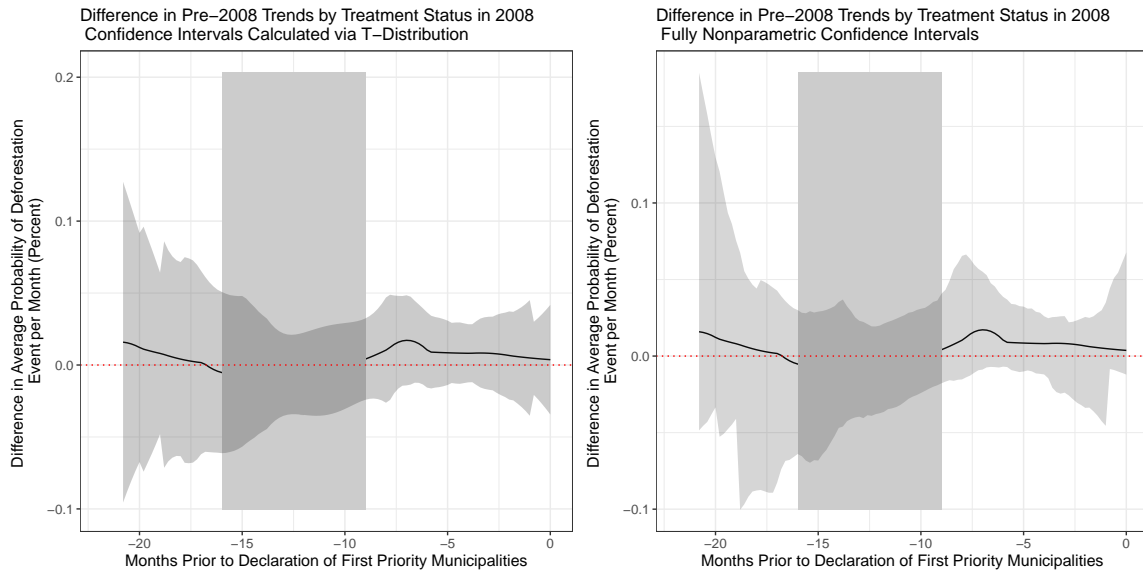


Figure A6: This figure provides a non-parametric test of the parallel trends assumption. The graphs show the difference in slope from a Loess regression between hexagons assigned to become Priority Municipalities in 2008 and those that became Priority Municipalities in subsequent years over the course of 2006-2007. The gray box indicates the months for which outcome data is missing. Standard errors are calculated via bootstrapping.

A6 Graph of Estimates from “First Assignment”

This graph parallels Figure 4 but depicts results from the “First Assignment” subsample of the data. The graphs provide visualizations of: Table 2 Column [5] in Panels A (upper left) and C (lower left) and Table 3 Panel A, Column [3] (upper right) and Panel B, Column [3] (lower right). In this sample, we do not find negative spillovers that are distinguishable from 0, though the pattern is otherwise qualitatively similar to the results from the full sample. Our interpretation is that the deforestation frontier expands gradually; the negative spillovers may take time to emerge. Nevertheless, there is strong evidence of positive spillovers in areas proximate to PMs.

First Treatment Assignment: Conditional ATT of a Neighbor's Designation as a Priority Municipality on:

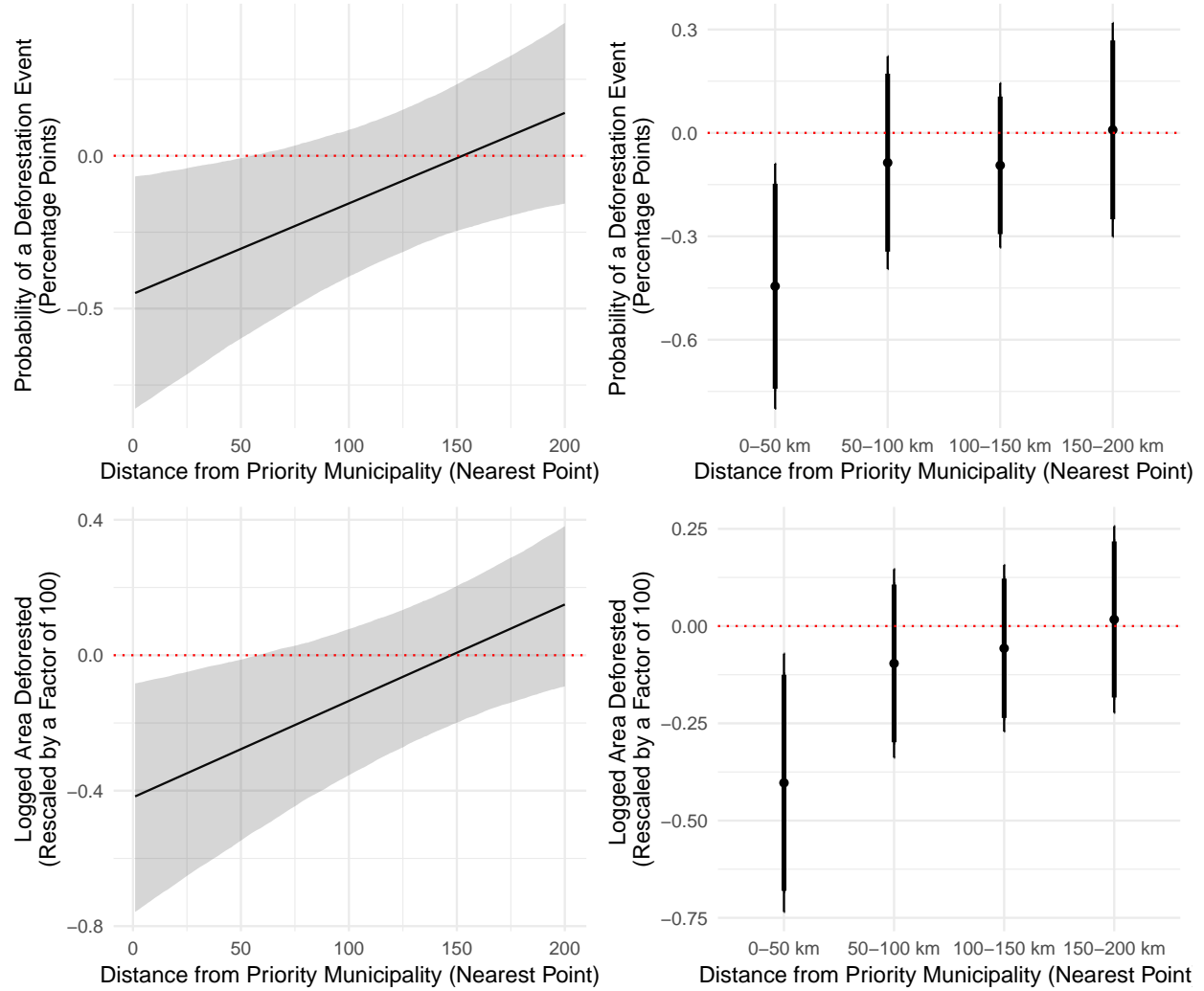


Figure A7: Conditional ATT estimates of a neighbor's status as a priority municipality on deforestation outcomes. The conditional ATT is the sum of the coefficient for neighbor's PM status and the interaction coefficient for the distance bin of interest. Graphed estimates depict specifications on the "First Assignment" sample in Table 2 Column [5] in Panels A (upper left) and C (lower left) and Table 3 Panel A, Column [3] (upper right) and Panel B, Column [3] (lower right). 95% confidence intervals around point estimate are estimated using by standard errors clustered at the priority municipality level.

A7 Robustness Tests

A7.1 Polynomial Distance Specifications

While we probe the assumption of linearity underlying the estimates in Table 2 in Table 3, we further probe the robustness of the conditional ATT estimates to quadratic and cubic functional forms on the distance variable. The estimation equations for the quadratic and cubic specifications are as follows:

$$Y_{ijktm} = \beta_0 Z_{jt} + \beta_1 Z_{jt} \text{Distance}_{ij} + \beta_2 Z_{jt} \text{Distance}_{ij}^2 + \phi_t + \gamma_i + \nu_{im} + \epsilon_{ijkt} \quad (2)$$

$$Y_{ijktm} = \beta_0 Z_{jt} + \beta_1 Z_{jt} \text{Distance}_{ij} + \beta_2 Z_{jt} \text{Distance}_{ij}^2 + \beta_3 Z_{jt} \text{Distance}_{ij}^3 + \phi_t + \gamma_i + \nu_{im} + \epsilon_{ijkt} \quad (3)$$

The ATTs, conditional on distance are plotted in the graph below, with the linear model from Table 2 and depicted in 4 superimposed. The differences in conditional ATTs (difference in the estimates at specific distance) across the three models are generally not statistically significant.

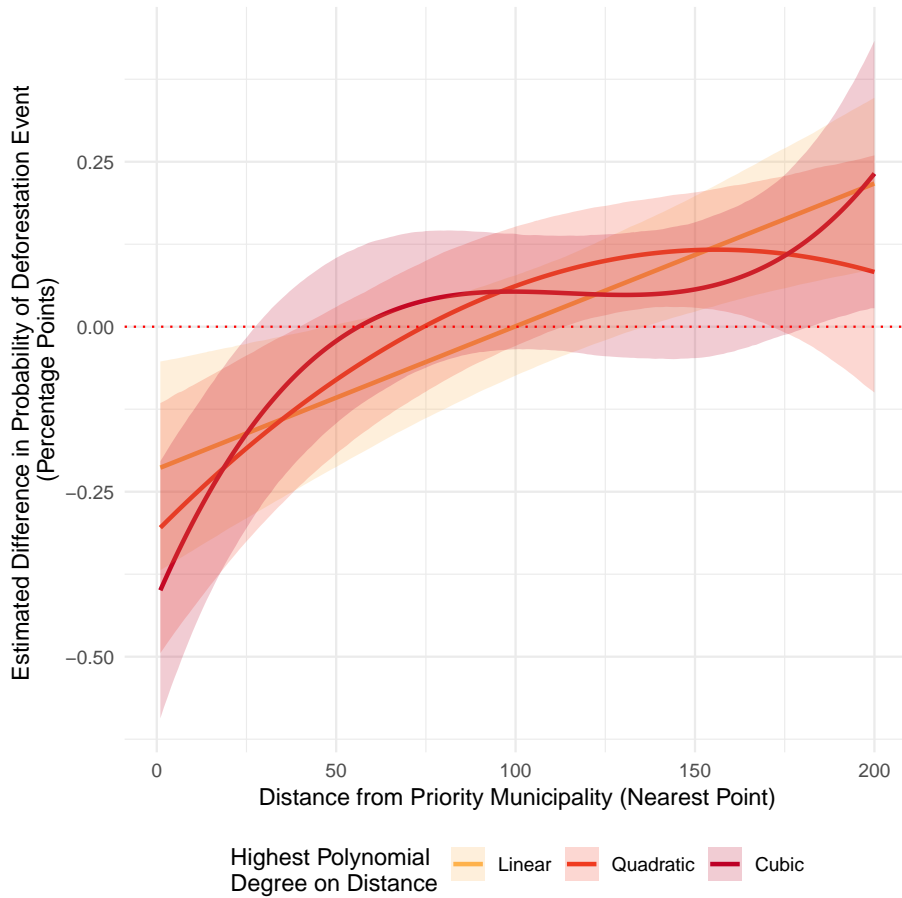


Figure A8: Conditional ATT estimates using linear, quadratic, and cubic polynomials on the Distance variable. 95% confidence intervals about each point estimate are estimated using by standard errors clustered at the priority municipality level.

A7.2 Jackknife-Style Test

In this test, we reestimate the main specification from Table 2, Column 5 dropping priority municipalities and their associated grid cells one by one. The x -axis arranges municipalities by ascending size of cluster (i.e. increasing number of grid cells). The estimates and associated inferences are not sensitive to the dropping of any cluster.

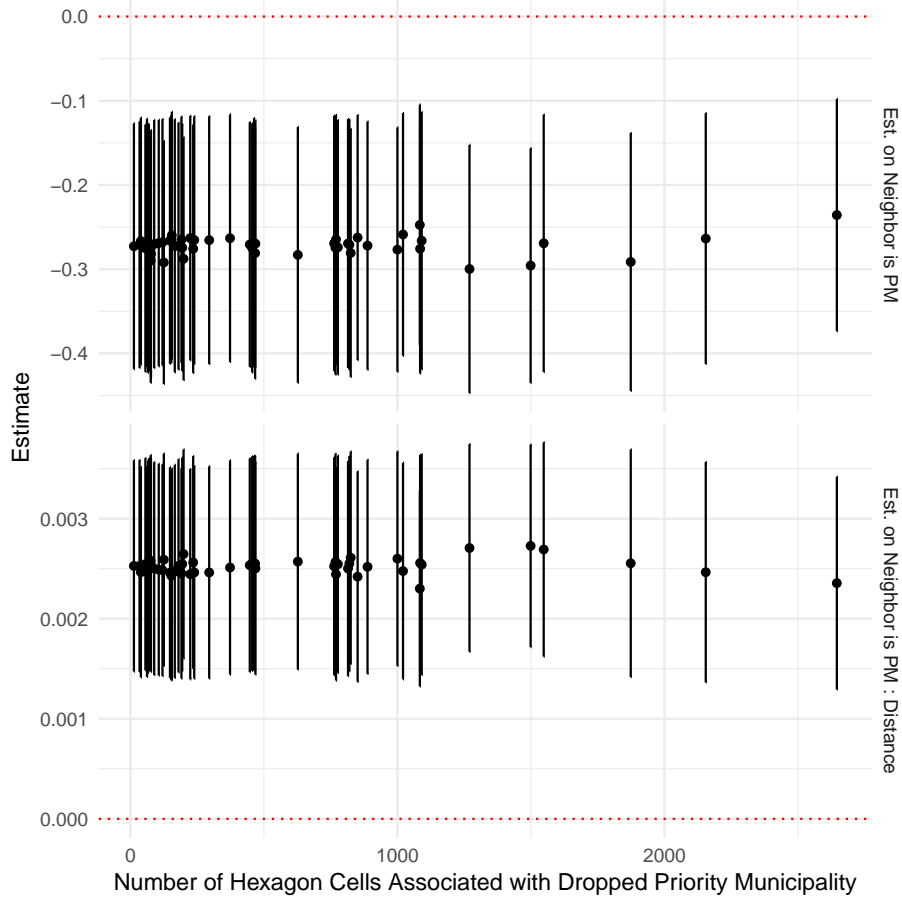


Figure A9: Conditional ATT estimates using the estimator from Table 4, Model 5, dropping each cluster sequentially. 95% confidence intervals about each point estimate are estimated using by standard errors clustered at the priority municipality level.

A7.3 Temporal Aggregation

In the main manuscript, our unit of analysis is the hexagon-month. Because the deforestation data (DETER) is compiled monthly, this is most disaggregate temporal unit available to us. In this section, we illustrate that the results presented in Table 2 of the main paper are not driven by this choice of the temporal unit, t . To do so, we aggregate to the quarter (January-March, April-June, July-September, and October-December) and year and estimate specifications that parallel those presented in Table 2.

Note that the treatment indicator is somewhat less precisely timed when we aggregate up. Here a unit is considered to be “in treatment” if a unit is treated at all within the quarter or year. In this sense, the treatment indicator includes additional noise relative to the baseline monthly specification.

Table A3 presents estimates of specifications analogous to those in Table 2 where the dependent variable is aggregated to the quarterly and yearly level. In Columns [1]-[5], the dependent variable is a binary indicator of whether or not a deforestation event occurred. Note that the estimates do not “aggregate up” as directly with this measure, as two events in a hexagon in a quarter would be coded as one event in the quarterly analysis but two in the monthly analysis. Nevertheless, the coefficient on “Neighbor is a PM” is negative and statistically significant and the interaction on “Distance : Neighbor is a PM” is positive and statistically significant. As expected, as the level of temporal aggregation increases, the magnitude of point estimates increases.

Columns [6]-[10] use logged deforested area as the dependent variable. Here, the estimates “aggregate up” much more directly. Again, the substantive findings and inferences support the patterns indicated in the monthly analysis. As above, the magnitude of coefficients increases in the level of temporal aggregation.

A7.4 Multiple Post-Treatment Periods and the ATT

Recent discussions of difference-in-difference designs with multiple periods of post-treatment periods have clarified the nature of the resultant ATT estimand (Callaway and Sant’Anna, 2018; Hull, 2018; Goodman-Bacon, 2018). In the presence of non-constant treatment effects, these estimates represent a weighted average of multiple difference-in-difference comparisons (Hull, 2018; Goodman-Bacon, 2018). While this decomposition is less important to our substantive conclusions, it is important to examine whether our inferences would change when examining shorter (and cleaner) comparisons that use fewer periods of post-treatment data. To examine these concerns, we examine how our estimates of the conditional ATT change as we add periods of post-treatment data progressively.

The cleanest comparisons occur during the first year of post-treatment data (through February 2009) during which the original set of PMs was designated (see Figure A3). This is the comparison for which we examine the parallel trends identifying assumption. In Figure A10, we replicate the specification in Table 2, Model [4] incrementally adding months of post-treatment data. The graph depicts estimated coefficients. It is clear that the direction of effects persists across all specifications. Prior to February 2009 (left of the vertical blue line), estimates of the effect of a neighbor’s designation as a PM are somewhat larger in magnitude, though estimated with less precision (less data).

We conduct a similar analysis on Table 2, Model [5] Panel A in Figure A11 which adds hexagon-month fixed effects. This analysis omits several of the initial periods of outcome data because missing pre-treatment data precludes the estimation of hexagon-month specific fixed effects. In general, however, the substantive conclusions maintain in this specification as well.

	Binary Event Indicator				Log(Area Deforested + 1)					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Neighboring Municipality is PM	-0.719 (0.344)	-0.816 (0.223)	-0.647 (0.244)	-1.654 (0.924)	-1.856 (0.607)	-1.006 (0.270)	-0.866 (0.185)	-0.772 (0.188)	-2.667 (0.776)	-2.329 (0.567)
Distance from PM	-0.005 (0.001)			-0.039 (0.005)		-0.004 (0.001)			-0.037 (0.005)	
Neighboring Municipality is PM: Distance	0.007 (0.002)	0.008 (0.002)	0.006 (0.002)	0.016 (0.006)	0.019 (0.005)	0.007 (0.002)	0.008 (0.001)	0.008 (0.002)	0.021 (0.005)	0.023 (0.004)
DV Scale	{0, 100} Quarter	{0, 100} Quarter	{0, 100} Quarter	{0, 100} Year	{0, 100} Year	[0, 422.59] Quarter	[0, 422.59] Quarter	[0, 422.59] Quarter	[0, 422.59] Year	[0, 422.59] Year
Temporal Unit										
Hexagon FE		✓	✓		✓		✓	✓	✓	✓
Quarter FE		✓								
Year FE					✓					✓
Hexagon-Quarter FE			✓			✓				
Observations	3,227,334	3,227,334	3,227,334	301,620	301,620	3,227,334	3,227,334	3,227,334	301,620	301,620

Table A3: Conditional ATT estimates of neighbor's status as a priority municipality on the probability of a deforestation event within a hexagon (Columns [1]-[5]) and on the the logged area deforested (Columns [6]-[10]). The ATT is the sum of the coefficient for neighbor's PM status and the coefficient for the interaction term multiplied by the distance. Standard errors are clustered at the level of the priority municipality.

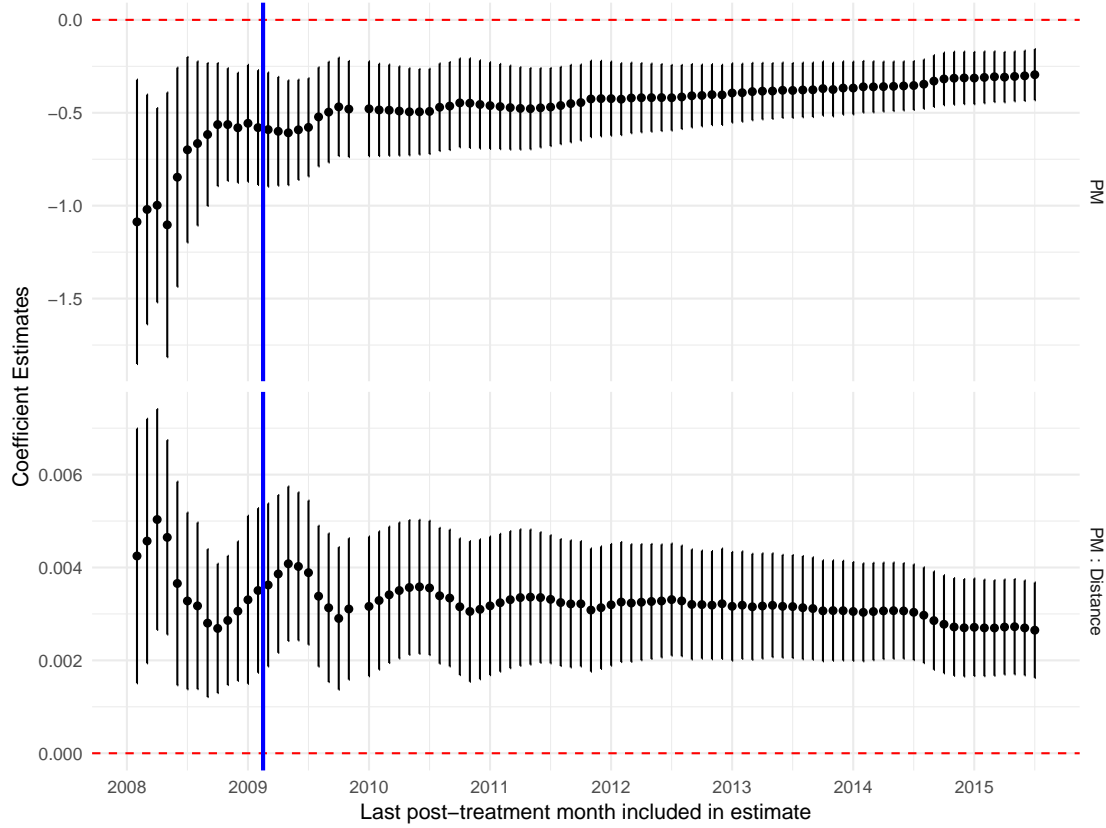


Figure A10: Re-estimating Table 2, Model [4], Panel A incrementally increasing the number of periods of post-treatment data. The top panel depicts estimates of the “main” effect of a neighbor’s designation as a PM (at distance 0). The bottom panel depicts estimates of the “interaction” effect between a neighbor’s designation as a PM and distance from the boundary with a PM. Lines to the left of the vertical blue line represent estimates during the first pattern of PM designation, enabling the cleanest comparisons. Bars represent 95% confidence intervals calculated on robust standard errors.

In general, this analysis suggests that the testable implications of the model obtain even when examining much shorter periods of the post-treatment period. This increases our confidence that the effects that we estimate are not driven by subtle reweighting of the post-treatment data in our generalized difference-in-difference estimator.

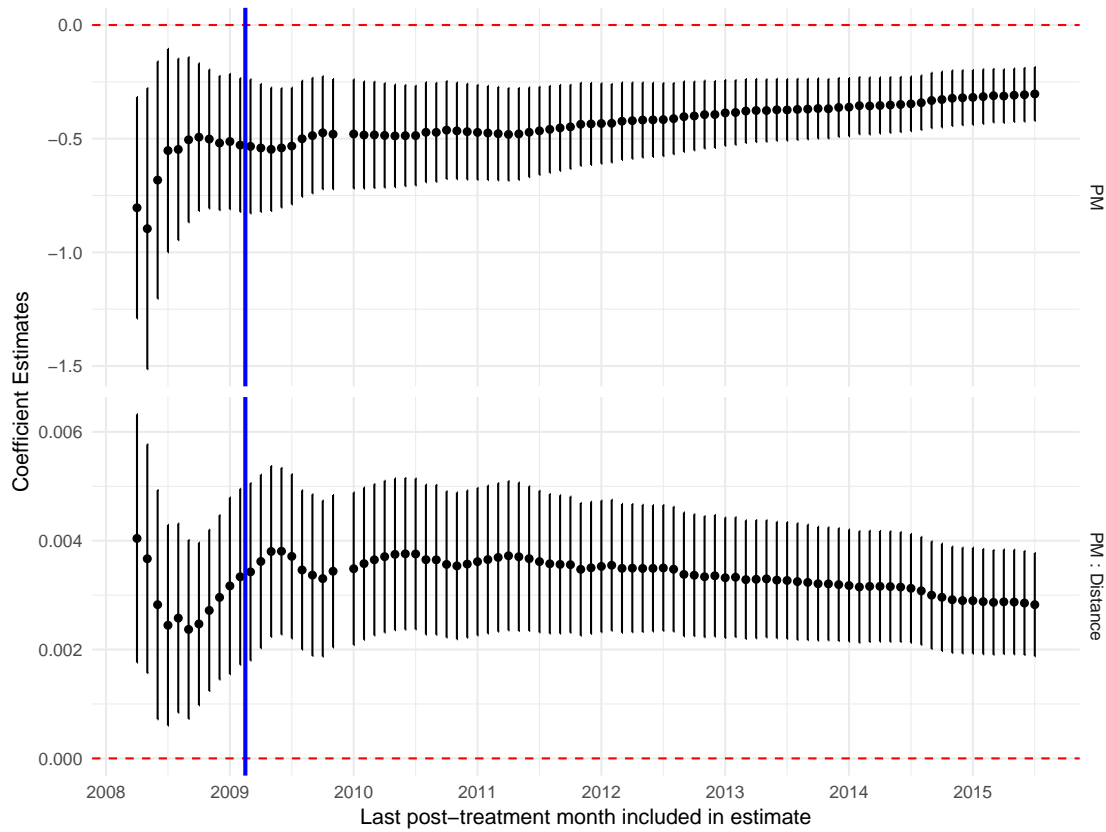


Figure A11: Re-estimating Table 2, Model [4], Panel A incrementally increasing the number of periods of post-treatment data. The top panel depicts estimates of the “main” effect of a neighbor’s designation as a PM (at distance 0). The bottom panel depicts estimates of the “interaction” effect between a neighbor’s designation as a PM and distance from the boundary with a PM. Lines to the left of the vertical blue line represent estimates during the first pattern of PM designation, enabling the cleanest comparisons. Missing periods of estimates occur due to missing pre-treatment data and the use of hexagon-month FE. Bars represent 95% confidence intervals calculated on robust standard errors.

A8 Effect Size Contextualization

This section proposes a back-of-the-envelope comparison of the estimated conditional ATTs of a neighbor’s designation as a priority municipality, by distance, relative to pre-treatment deforestation rates as a measure of the “substantive significance” of findings.

We show that the effect sizes provided in the main estimates represent substantive differences in the extent of deforestation. To do this, we compare the conditional ATTs that we estimate to baseline levels of deforestation in the pre-treatment period (2006 and 2007). We estimate the average levels of both dependent variables, by distance from the boundary with a priority municipality by Loess regression (span = 0.75) in the pre-PM program period. These estimates are depicted in Figure A12 by the solid (orange) lines.

The conditional ATT represents a *difference* in deforestation rates. To show the magnitude of this effect relative to baseline rates of deforestation, we add the estimated conditional ATT of a neighbor’s designation as a PM, to the baseline predicted outcome, by distance. This quantity is represented by the dotted (red) line in Figure A12.

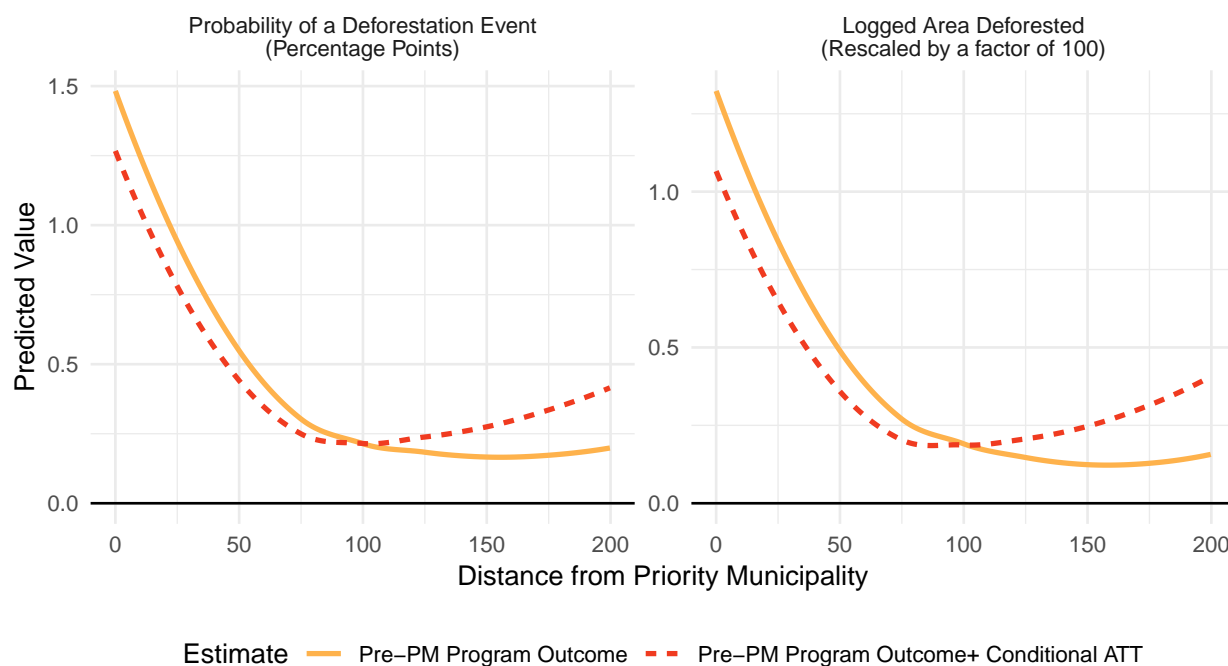


Figure A12: Estimates of the pre-PM program rates of deforestation by hexagon (solid line). The dotted line depicts this rate added to the estimated conditional ATT, by distance from Table 2, Column [5].

In general, the spillover effects that we estimate (both negative and positive) are substantively large relative to baseline rates of deforestation. At a distance of 0, the large reduction in defor-

estation events and deforested area attributable to a neighbor's designation as a PM represent an approximately 17-percent reduction in deforestation, relative to pretreatment levels. The magnitude of the increase in deforestation levels far from PMs is even larger substantively. This analysis suggests that the patterns we identify are both substantively and statistically significant.

A second, and rougher, calculation considers how these monthly effect estimates compound over time. Consider the binary measure of deforestation events. If events were independent, the probability that a hexagon does not observe a deforestation event within M months, is given by:

$$(1 - \Pr(\text{Event}))^M \quad (4)$$

Parameterize the ATT as τ and the probability of an event in “control” (neighboring municipality not designated) as ρ . Then the difference in the probability that a hexagon experiences a deforestation event is:

$$(1 - \rho - \tau)^M - (1 - \rho)^M \quad (5)$$

Note that one implication of this expression is that the impact of the spillover effects (τ) depend on baseline rates of deforestation (ρ). Using the data in Figure A12 to approximate ρ and Table 2, Panel A, Model [5] to approximate τ , Figure A13 examines how these effects compound over a 1-, 3-, and 10-year horizon ($M \in \{12, 36, 120\}$).

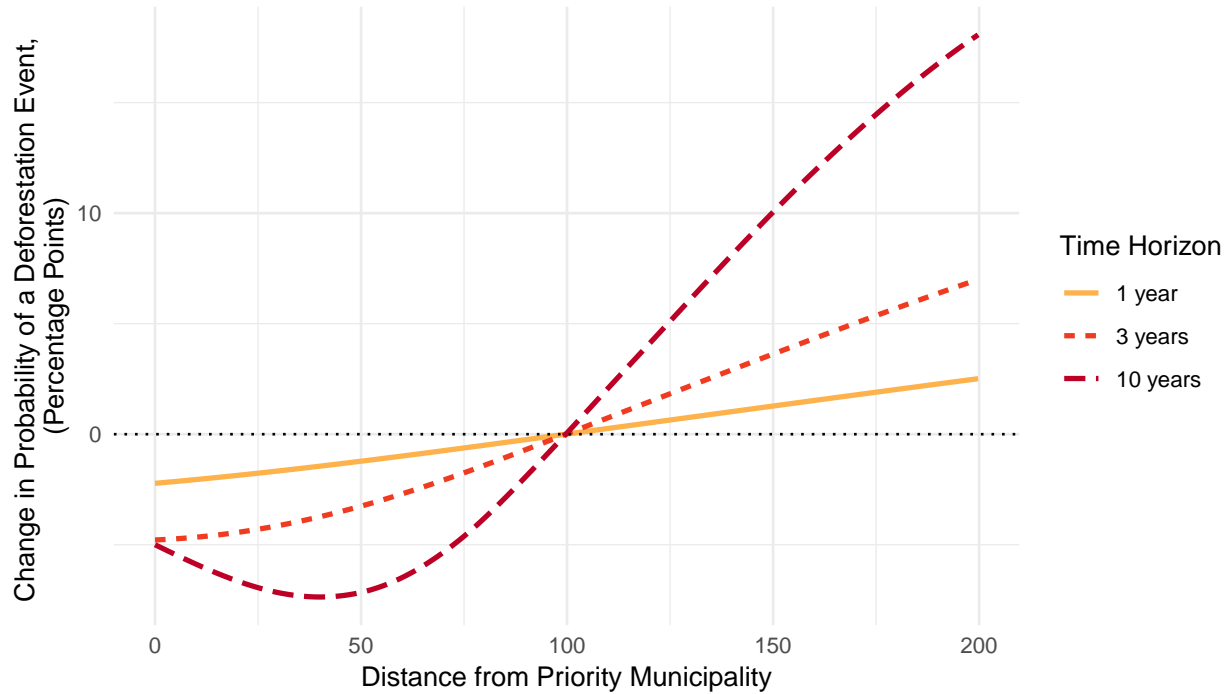


Figure A13: Estimates of differences in the probability of a deforestation event attributable to the spillover effects of the PM program, under the model specified in Equation 5.

A9 Heterogeneous Treatment Effect Analysis: Distance from Waterways

A9.1 Map of Waterway and Grid Cell Classification

- Access to roads (albeit typically not highways) provides a means to transport wood to markets. We analyze whether the conditional effect of distance from a priority municipality is also conditional on close access to pre-existing roads (highways in 1993). For clarity in interpretation of the triple interaction, we specify a binary variable denoting “easy access” to highways.
- This variable is defined on the basis of proximity to the nearest highway (Euclidean distance) and we utilize three distinct thresholds: 2.5, 5, 7.5, and 10-km to assess the robustness of findings.
- A map of these highways and grid cell classification appears in Figure A14.

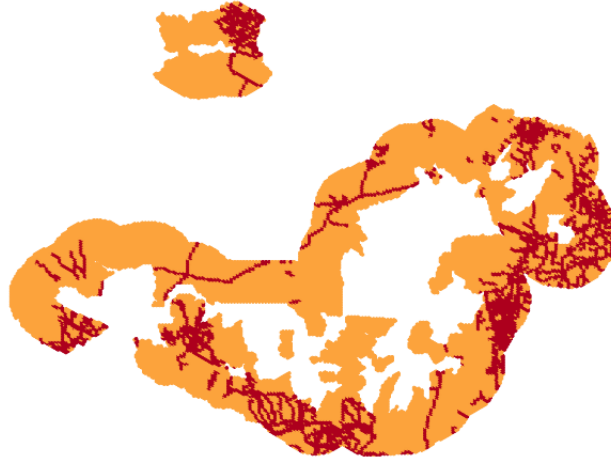


Figure A14: This map depicts the grid cells included in the specifications of grid cells that are proximate to highways from the analysis below. Note that only grid cells within national boundaries are included in the analysis.

A9.2 Heterogeneous Treatment Effects: Distance from Waterways

- Define the indicator of proximity to water as $P_i \in \{0, 1\}$. We estimate the following specification:

$$Y_{ijktm} = \beta_0 Z_{jt} + \alpha_0 Z_{jt} P_i + \beta_1 Z_{jt} \text{Distance}_{ij} + \alpha_1 Z_{jt} \text{Distance}_{ij} P_i + \phi_t + \gamma_i + \epsilon_{ijktm} \quad (6)$$

- We present the results graphically in Figure A15 to facilitate interpretation of the triple interaction.

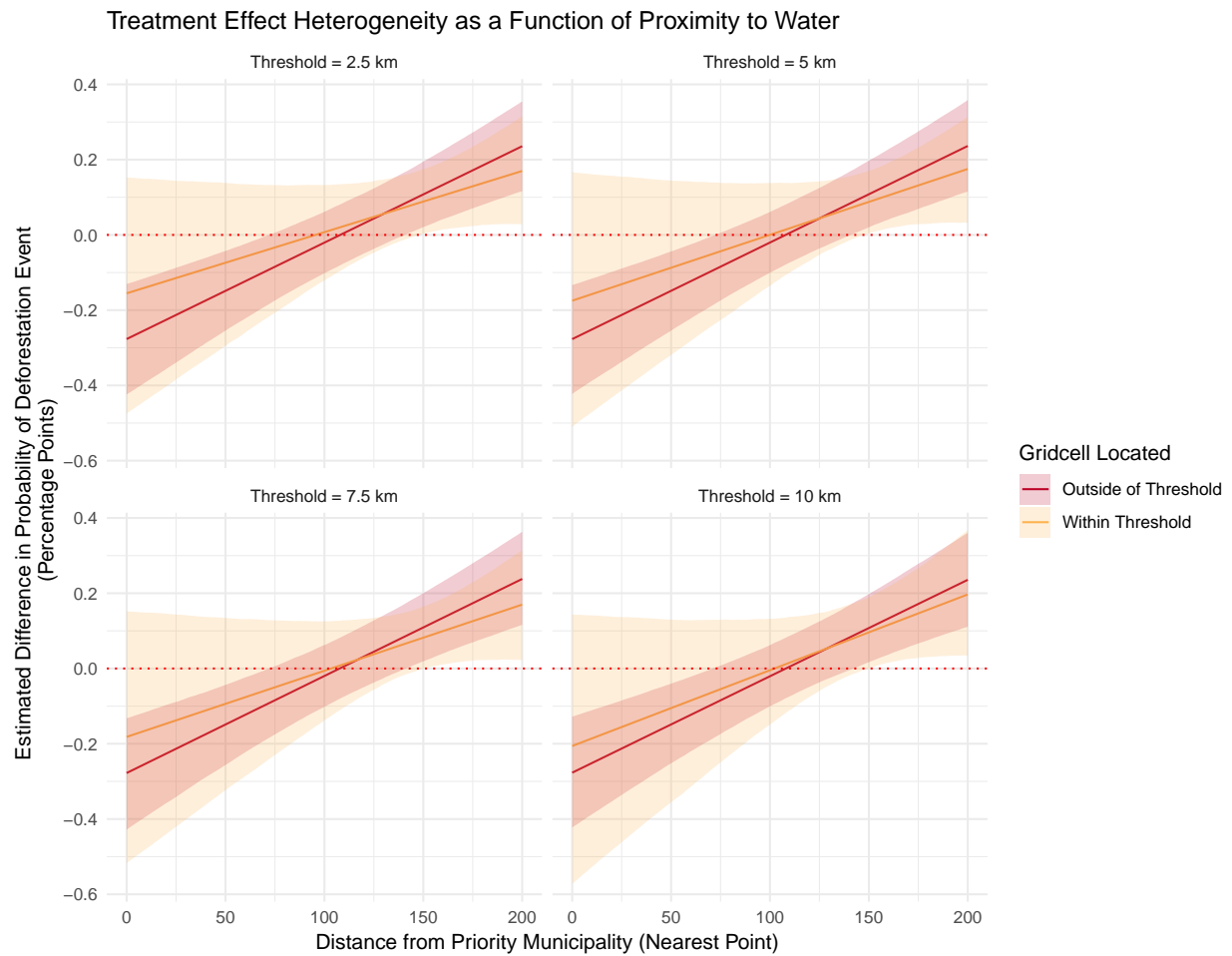


Figure A15: This graph depicts the estimated conditional ATT by distance and proximity to major waterways. The shaded region represents 95% confidence intervals. Standard errors are clustered at the priority municipality level.

A10 Heterogenous Treatment Effects: Distance from Highway

A10.1 Map of Highway and Grid Cell Classification

- Access to roads (albeit typically not highways) provides a means to transport wood to markets. We analyze whether the conditional effect of distance from a priority municipality is also conditional on close access to pre-existing roads (highways in 1993). For clarity in interpretation of the triple interaction, we specify a binary variable denoting “easy access” to highways.
- This variable is defined on the basis of proximity to the nearest highway (Euclidean distance) and we utilize three distinct thresholds: 2.5, 5, 7.5, and 10-km to assess the robustness of findings.
- A map of these highways and grid cell classification appears in Figure A16.

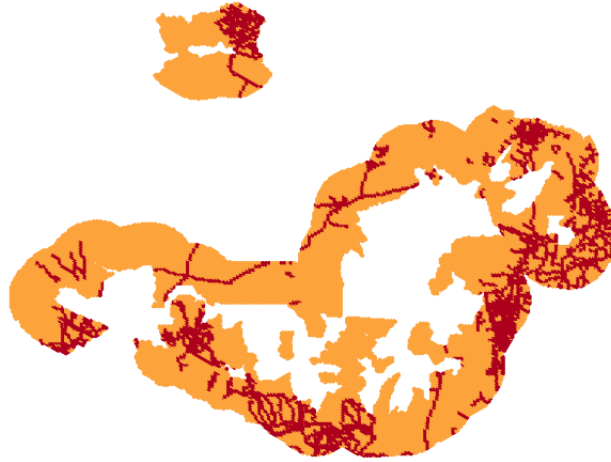


Figure A16: This map depicts the grid cells included in the specifications of grid cells that are proximate to highways from the analysis below. Note that only grid cells within national boundaries are included in the analysis.

A10.2 Heterogeneous Treatment Effect Analysis

- Define the indicator of proximity to a highway as $P_i \in \{0,1\}$. We estimate the following specification:

$$Y_{ijkmt} = \beta_0 Z_{jt} + \alpha_0 Z_{jt} P_i + \beta_1 Z_{jt} \text{Distance}_{ij} + \alpha_1 Z_{jt} \text{Distance}_{ij} P_i + \phi_t + \gamma_i + \epsilon_{ijkmt} \quad (7)$$

- We present the results graphically in Figure A17 to facilitate interpretation of the triple interaction.

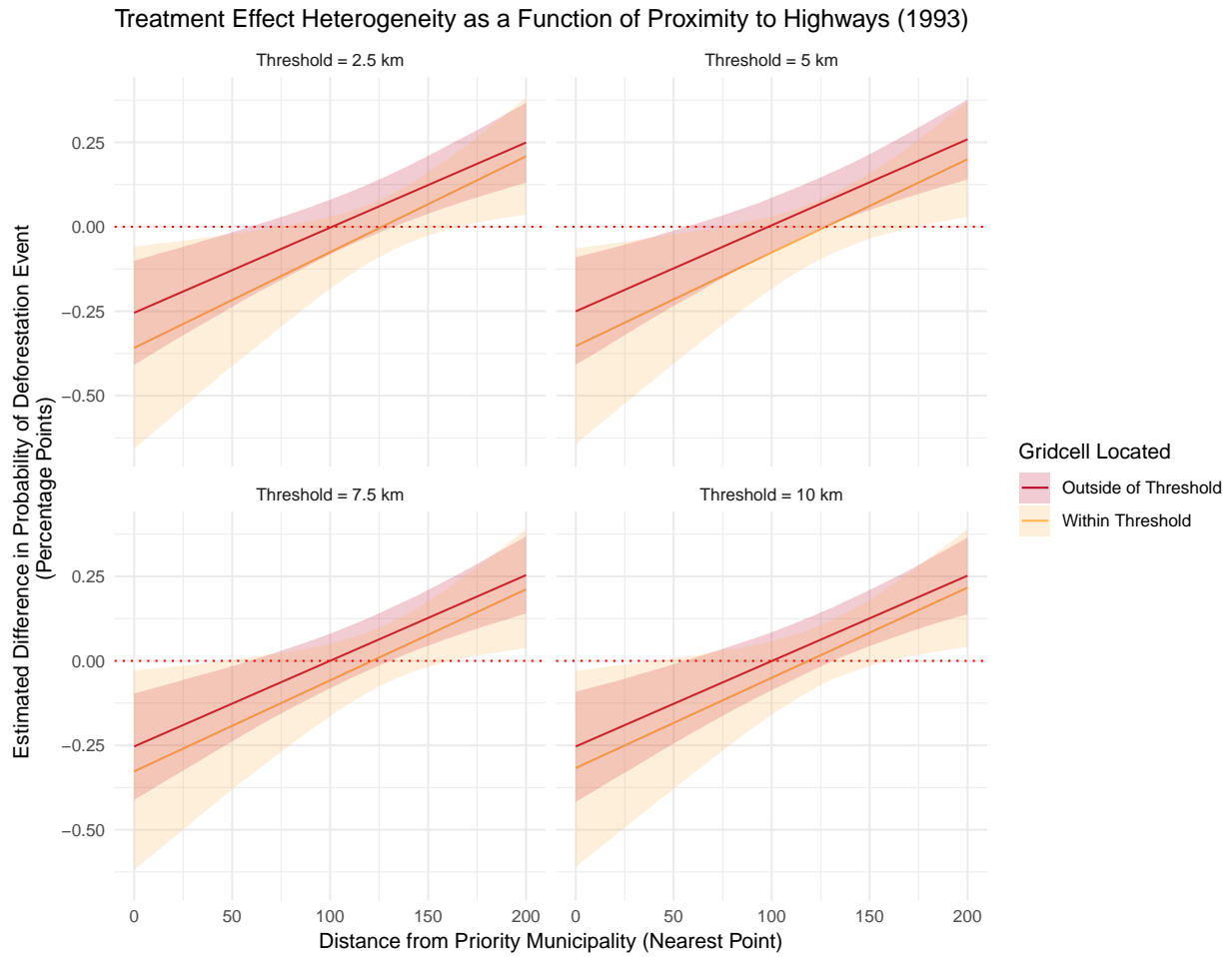


Figure A17: This graph depicts the estimated conditional ATT by distance and proximity to highways. The shaded region represents 95% confidence intervals. Standard errors are clustered at the priority municipality level.

A11 Persistence of Spillover Effects

As in Figure A3, several municipalities exited PM status during the course of our panel. In this section we disaggregate the “control” group such that post-priority municipality “monitored” status is operationalized as follows:

$$Z_{ij} = \begin{cases} 0 & \text{if not yet designated a priority municipality} \\ 1 & \text{if designated a priority municipality} \\ 2 & \text{if graduated from PM program and designated a “monitored” municipality} \end{cases}$$

We estimate the specification:

$$Y_{ijkmt} = \beta_1 I[Z_{jt} = 1] + \beta_2 I[Z_{jt} = 1] \text{Distance}_{ij} + \delta_1 I[Z_{jt} = 2] + \delta_2 I[Z_{jt} = 2] \text{Distance}_{ij} + \phi_t + \gamma_i + \nu_{im} + \epsilon_{ijkmt}$$

where $I[\cdot]$ represents an indicator function. The estimators conditional ATTs of interest are thus:

- $\beta_1 + \beta_2 \text{Distance}_{ij}$ for priority municipalities
- $\delta_1 + \delta_2 \text{Distance}_{ij}$ for “monitored” municipalities

We test the hypothesis that $\beta_1 + \beta_2 \text{Distance}_{ij} = \delta_1 + \delta_2 \text{Distance}_{ij}$. We are unable to reject that the conditional ATTs differ by municipal designation, as depicted in Figure A18.

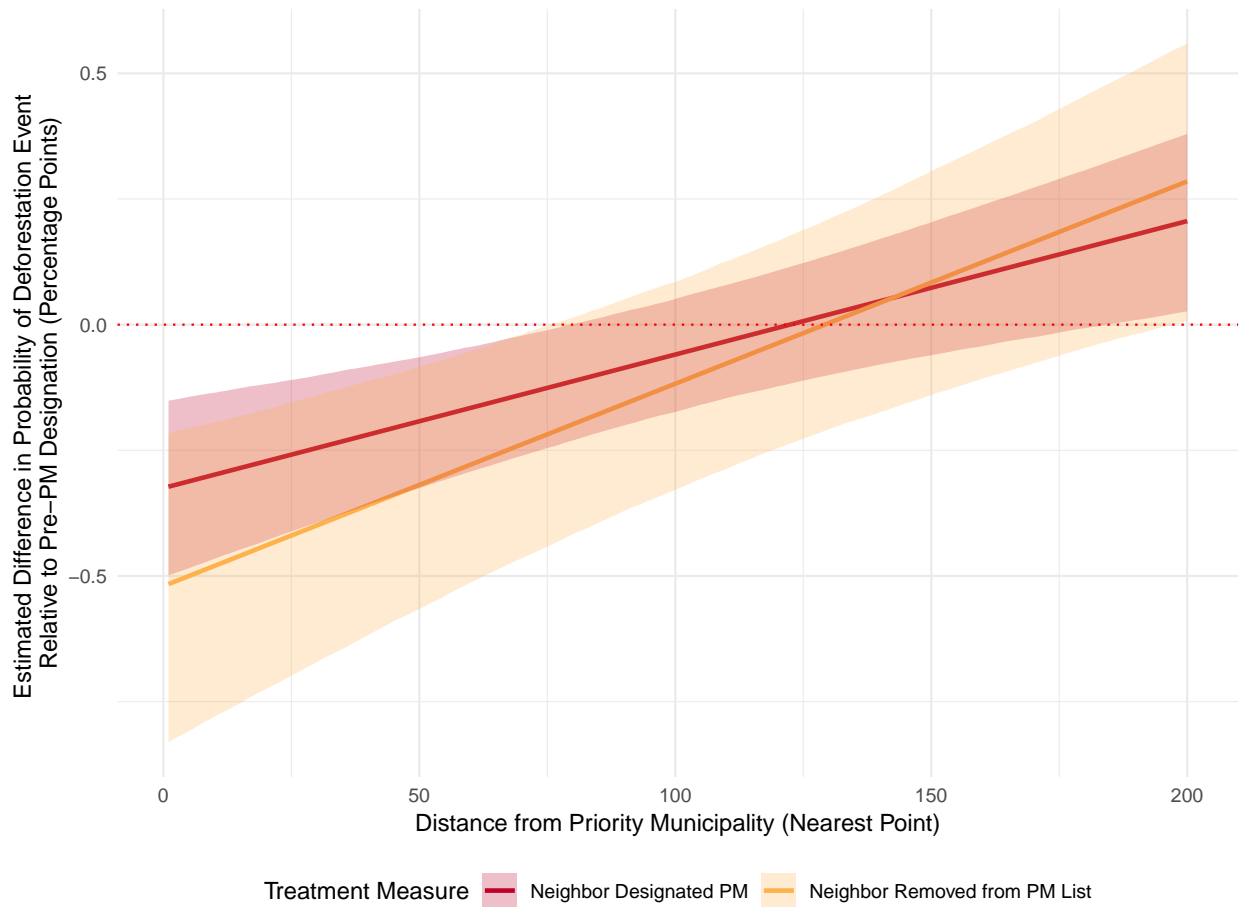


Figure A18: Graph of the conditional effects of a neighbor’s designation as a priority municipality versus a neighbor’s designation as a “monitored” municipality (subsequent to graduation from priority municipality status).

A12 Analysis of Embargos

A12.1 Territorial Classification

For the analysis of embargos, we consider a slightly different classification of distance. We consider embargos by municipality, not hexagon. To this extent, we look at municipalities in terms of proximity to the priority municipalities. Specifically, we define all municipalities as priority municipalities (PMs) or first-, second-, third-, or fourth-degree neighbors of a PM, as depicted in Figure A19.

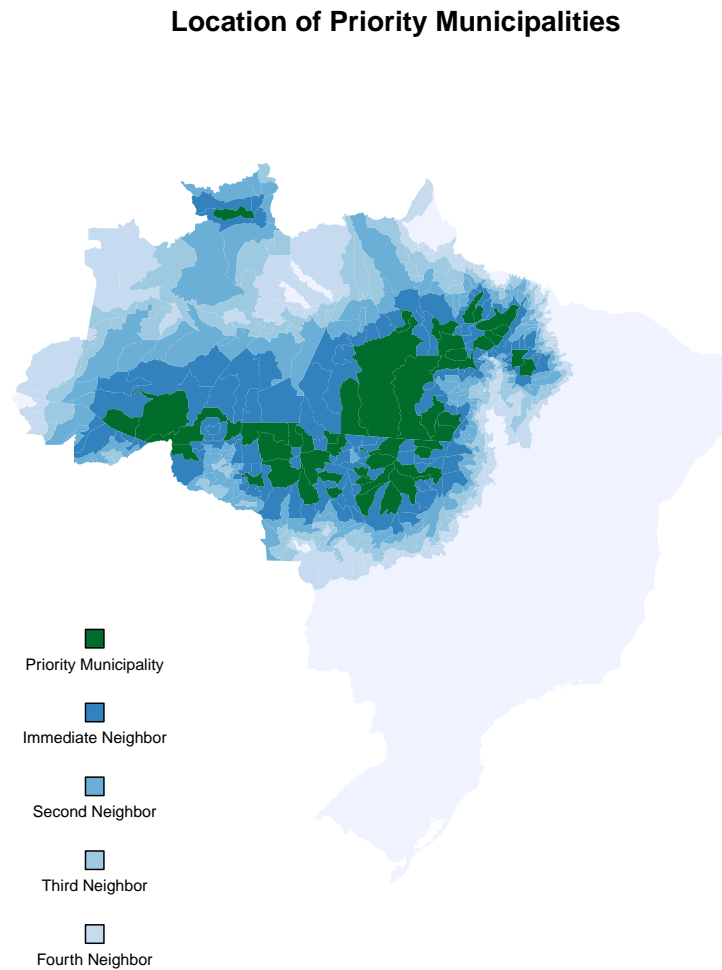


Figure A19: Priority municipalities in the Brazilian Amazon.

	Embargoes Levied			Any Embargo Levied		
	(1)	(2)	(3)	(4)	(5)	(6)
PM × Designated PM	1.305 (0.545)	1.375 (0.526)	0.533 (0.198)	0.135 (0.047)	0.184 (0.041)	0.085 (0.021)
First-Degree Neighbor × Designated PM	0.101 (0.143)	0.173 (0.134)	−0.032 (0.053)	0.015 (0.030)	0.033 (0.029)	−0.001 (0.014)
Second-Degree Neighbor × Designated PM	−0.100 (0.080)	−0.085 (0.088)	−0.070 (0.040)	−0.034 (0.024)	−0.023 (0.024)	−0.015 (0.010)
Third-Degree Neighbor × Designated PM	−0.101 (0.089)	−0.076 (0.094)	−0.048 (0.040)	−0.036 (0.023)	−0.022 (0.024)	−0.009 (0.010)
Fourth-Degree Neighbor × Designated PM	−0.184 (0.129)	−0.136 (0.096)	−0.035 (0.030)	−0.037 (0.025)	−0.019 (0.023)	−0.003 (0.008)
Fifth-Degree Neighbor × Designated PM	−0.104 (0.070)	−0.128 (0.082)	−0.048 (0.031)	−0.022 (0.017)	−0.033 (0.020)	−0.008 (0.013)
DV Scale	[0, 119]	[0, 119]	[0, 119]	{0,1}	{0,1}	{0,1}
Sample	2007-2008	First Assignment	All Assignments	2007-2008	First Assignment	All Assignments
Municipality FE	✓	✓	✓	✓	✓	✓
Month FE	✓	✓	✓	✓	✓	✓
Observations	14,496	22,348	72,480	14,496	22,348	72,480

Table A4: Estimates of the conditional ATT of designation of the nearest PM on rates (Columns 1-3) and probability (Columns 4-6) of embargoes levied. Standard errors are clustered at the nearest PM level.

A12.2 Robustness

The difference-in-difference estimator used in Table 6 and Table A4 is the following:

$$\text{Embargos}_{ijt} = \sum_{D=0}^5 Z_{jt} I[\text{Degree}_i = d] + \phi_t + \gamma_i + \epsilon_{ijt} \quad (8)$$

where i indexes a municipality, j indexes the nearest PM (at any time), and t indexes the month. Note that a degree of “0” indicates that a municipality is a priority municipality.

In Table A4 we show that the estimates presented in the main paper are not a product of sample selection or specification of the dependent variable. We show that there is evidence that PM designation substantially increases enforcement in PMs. The effects outside of PMs are consistently null, despite changing deforestation patterns.

Supplementary Appendix: References

- Callaway, Brantly, and Pedro H.C. Sant’Anna. 2018. “Difference-in-Differences with Multiple Time Periods and an Application on the Minimum Wage and Employment.” <https://arxiv.org/pdf/1803.09015.pdf>.
- Goodman-Bacon, Andrew. 2018. “Difference-in-Differences with Variation in Treatment Timing.” https://s3.amazonaws.com/vu-my/wp-content/uploads/sites/2318/2018/06/18160651/ddtiming_6_15_2018.pdf.
- Hull, Peter. 2018. “Estimating Treatment Effects in Mover Designs.” http://www.mit.edu/~hull/movers_042018.pdf.