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

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Contents

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 $lim_{d \to 0} p = 0$ and $p' \to \infty$ as $d \to 0$. 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. The figure shows how deforestation at different distances from the priority municipality responds to monitoring. When monitoring yields a high equilibrium price (lower-right corner), 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.

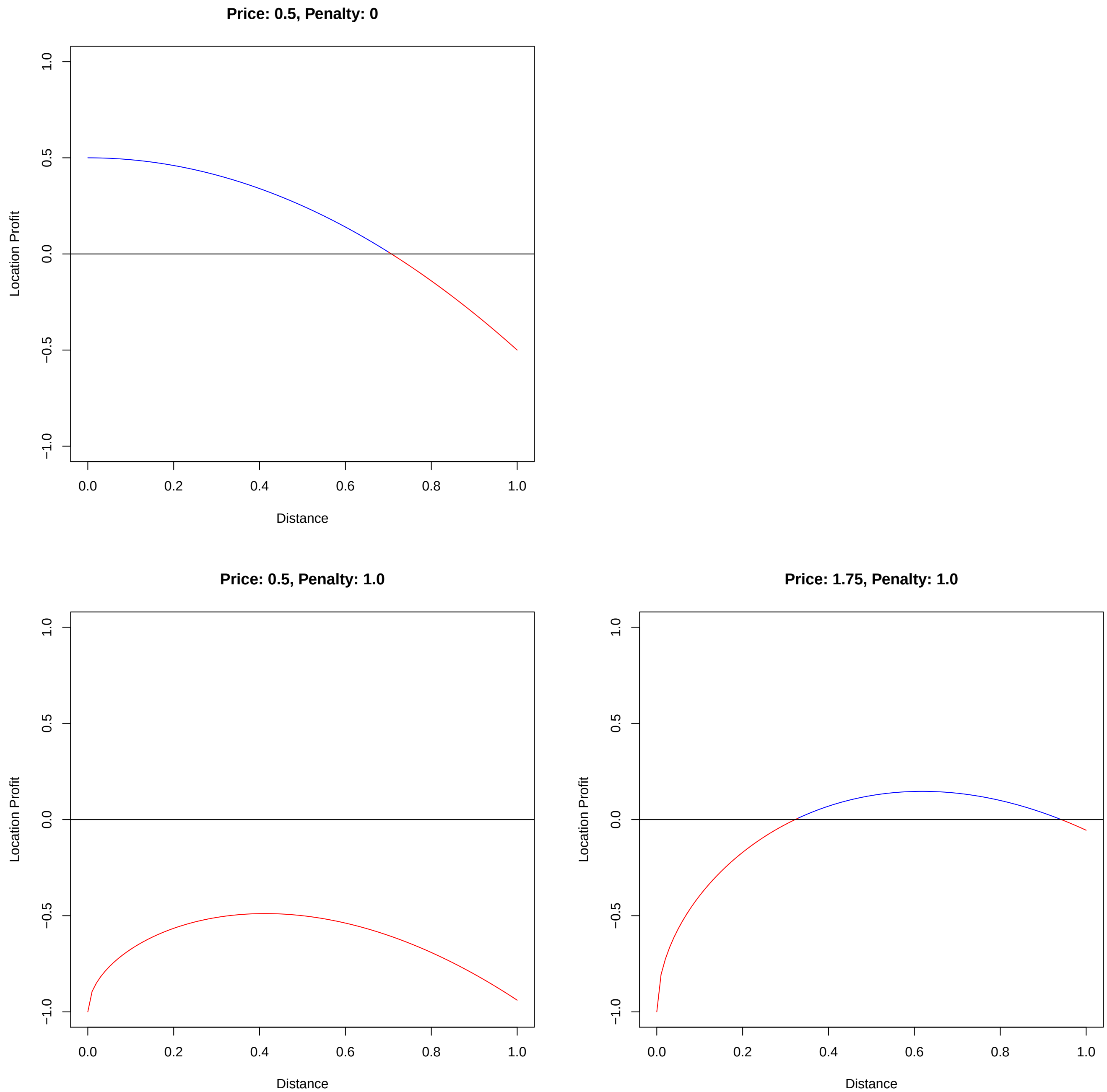

Figure A1: Graphical illustration of a formal model of forest clearing with and without monitoring. The blue color of the profit function indicates the area that will be deforested because the profit from doing so is positive at market-clearing price. As the upper-left corner shows, the cleared area 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 lower-left corner, 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 lower-left right corner.

A2 Municipality Summary Statistics

- Table A1 shows the summary of all municipalities targeted by the PM program.
- Table A2 describes the (hexagon) grid cell sample used in the main analyses.

	Priority Municipality	State	Year of Entry	Month of Entry	Share Deforested Area	Year of Exit	Month of Exit
January 2008 Entries							
1	Lábrea	AM	2008	1	0.047		
2	Alta Floresta	MT	2008	1	0.565	2012	6
3	Aripuana	MT	2008	1	0.153		
4	Brasnorte	MT	2008	1	0.35	2013	10
5	Colniza	MT	2008	1	0.124		
6	Confresa	MT	2008	1	0.697		
7	Cotriguaçu	MT	2008	1	0.194		
8	Gáucha do Norte	MT	2008	1	0.284		
9	Juína	MT	2008	1	0.181		
10	Marcelândia	MT	2008	1	0.283	2013	10
11	Nova Bandeirantes	MT	2008	1	0.317		
12	Nova Ubiratã	MT	2008	1	0.421		
13	Paranaíta	MT	2008	1	0.467		
14	Peixoto de Azevedo	MT	2008	1	0.249		
15	Porto dos Gaúchos	MT	2008	1	0.42		
16	Querência	MT	2008	1	0.324	2011	4
17	São Félix do Araguaia	MT	2008	1	0.413		
18	Vila Rica	MT	2008	1	0.635		
19	Altamira	PA	2008	1	0.041		
20	Brasil Novo	PA	2008	1	0.43	2013	10
21	Cumaru do Norte	PA	2008	1	0.444		
22	Dom Eliseu	PA	2008	1	0.626	2012	7
23	Novo Progresso	PA	2008	1	0.143		
24	Novo Repartimento	PA	2008	1	0.438		
25	Paragominas	PA	2008	1	0.481	2010	3
26	Rondon do Pará	PA	2008	1	0.643		
27	Santa Maria das Barreiras	PA	2008	1	0.735		
28	Santana do Araguaia	PA	2008	1	0.652	2012	6
29	São Félix do Xingu	PA	2008	1	0.204		
30	Ulianópolis	PA	2008	1	0.656	2012	7
31	Machadinho D'oeste	RO	2008	1	0.339		
32	Pimenta Bueno	RO	2008	1	0.451		
33	Porto Velho	RO	2008	1	0.233		
34	Nova Mamoré	RO	2008	1	0.311		
March 2009 Entries							
35	Amarante do Maranhão	MA	2009	3	0.377		
36	Feliz Natal	MT	2009	3	0.184	2013	10
37	Juara	MT	2009	3	0.384		
38	Itupiranga	PA	2009	3	0.58		
39	Marabá	PA	2009	3	0.547		
40	Pacajá	PA	2009	3	0.552		
41	Tailândia	PA	2009	3	0.476	2013	10
42	Mucajaí	RR	2009	3	0.165		
May 2011 Entries							
43	Boca do Acre	AM	2011	5	0.089		
44	Grajaú	MA	2011	5	0.482		
45	Alto Boa Vista	MT	2011	5	0.73		
46	Cláudia	MT	2011	5	0.411		
47	Santa Carmem	MT	2011	5	0.378		
48	Tapurah	MT	2011	5	0.568		
49	Moju	PA	2011	5	0.483		

Table A1: This table shows the summary of PM entry month, PM entry year, and percent deforested forest area for all municipalities blacklisted under the Priority Municipality (PM) program.

	Geographic Characteristics			Priority Municipality Information			
State	Municipality	n Grid Cells	Pretreatment Deforestation (2005)	Entrance	Exit	Months in "Control"	Months in "Treat- ment"
PA	Paragominas	1376	0.65	1-2008	2-2010	82	25
MT	Querência	665	0.78	1-2008	3-2011	69	38
PA	Santana do Araguaia	399	0.85	1-2008	5-2012	55.00	52
MT	Alta Floresta	175	0.60	1-2008	5-2012	55	52
PA	Dom Eliseu	80	0.82	1-2008	6-2012	54	53
PA	Ulianópolis	87	0.43	1-2008	6-2012	54	53
PA	Brasil Novo	1179	0.36	1-2008	9-2013	39	68
MT	Brasnorte	1051	0.79	1-2008	9-2013	39	68
MT	Marcelândia	68	0.44	1-2008	9-2013	39	68
RO	Machadinho D'Oeste	477	0.53	1-2008	Ongoing	17	90
RO	Pimenta Bueno	1151	0.59	1-2008	Ongoing	17	90
RO	Porto Velho	1101	0.19	1-2008	Ongoing	17	90
RO	Nova Mamoré	882	0.34	1-2008	Ongoing	17	90
AM	Lábrea	2374	0.04	1-2008	Ongoing	17	90
PA	Altamira	1801	0.17	1-2008	Ongoing	17	90
PA	Cumaru do Norte	317	0.60	1-2008	Ongoing	17	90
PA	Novo Progresso	1064	0.13	1-2008	Ongoing	17	90
PA	Novo Repartimento	117	0.46	1-2008	Ongoing	17	90
PA	Rondon do Pará	204	0.79	1-2008	Ongoing	17	90
PA	Santa Maria das Barreiras	948	0.93	1-2008	Ongoing	17	90
PA	São Félix do Xingu	255	0.36	1-2008	Ongoing	17	90
MT	Aripuanã	111	0.16	1-2008	Ongoing	17	90
MT	Colniza	909	0.09	1-2008	Ongoing	17	90
MT	Confresa	125	0.73	1-2008	Ongoing	17	90
MT	Cotriguaçu	500	0.07	1-2008	Ongoing	17	90
MT	Gaúcha do Norte	845	0.92	1-2008	Ongoing	17	90
MT	Juína	485	0.53	1-2008	Ongoing	17	90
MT	Nova Bandeirantes	154	0.23	1-2008	Ongoing	17	90
MT	Nova Ubiratã	877	0.88	1-2008	Ongoing	17	90
MT	Paranaíta	238	0.19	1-2008	Ongoing	17	90
MT	Peixoto de Azevedo	255	0.59	1-2008	Ongoing	17	90
MT	Porto dos Gaúchos	170	0.52	1-2008	Ongoing	17	90
MT	São Félix do Araguaia	1147	0.63	1-2008	Ongoing	17	90
MT	Vila Rica	199	0.75	1-2008	Ongoing	17	90
PA	Tailândia	59	0.52	10-2009	9-2013	53	54
MT	Feliz Natal	43	0.42	10-2009	9-2013	53	54
RR	Mucajaí	2871	0.30	10-2009	Ongoing	31	76
PA	Itupiranga	12	0.71	10-2009	Ongoing	31	76
PA	Marabá	824	0.75	10-2009	Ongoing	31	76
PA	Pacajá	590	0.14	10-2009	Ongoing	31	76
MA	Amarante do Maranhão	835	0.87	10-2009	Ongoing	31	76
MT	Juara	117	0.48	10-2009	Ongoing	31	76
AM	Boca do Acre	2056	0.10	10-2011	Ongoing	56	51
PA	Moju	1193	0.38	10-2011	Ongoing	56	51
MA	Grajaú	1666	0.44	10-2011	Ongoing	56	51
MT	Alto Boa Vista	37	0.69	10-2011	Ongoing	56	51
MT	Cláudia	134	0.53	10-2011	Ongoing	56	51
MT	Santa Carmem	68	0.60	10-2011	Ongoing	56	51
MT	Tapurah	325	0.63	10-2011	Ongoing	56	51

Table A2: This table describes the (hexagon) grid cell sample used in the main analyses. It indicates the number of grid cells with closest proximity to each of the Priority Municipalities. Additionally, it provides the dates of entrance and exit (where applicable) from Priority Municipality status. These dates, in turn, define the number of periods that each hexagon is considered to be in "treatment" and "control."

A3 Identifying Assumptions

- Figure A2 provides a non-parametric test of the parallel trends assumption.

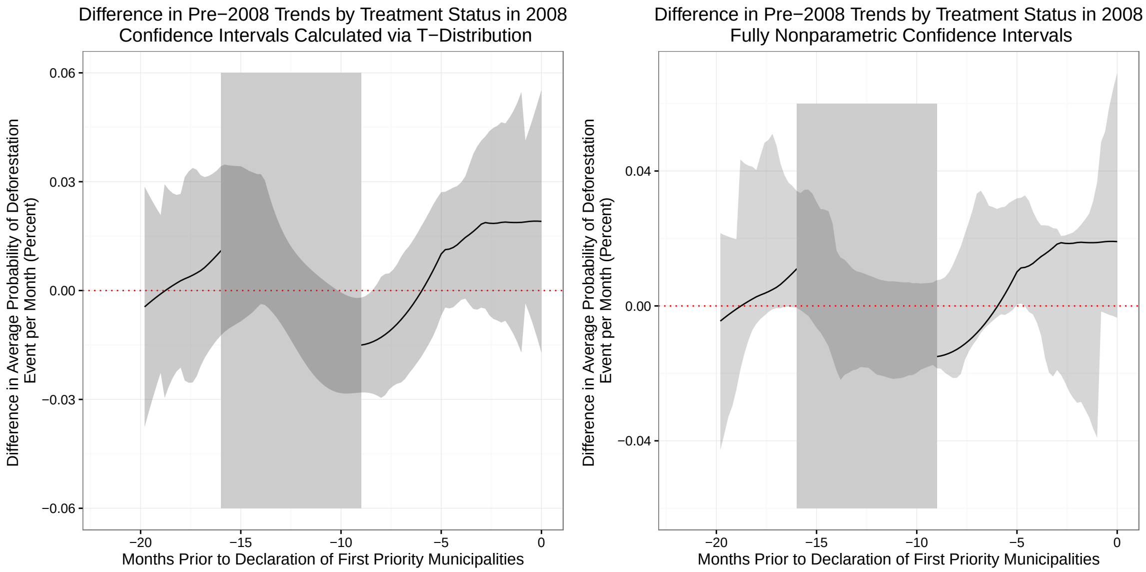

Figure A2: This figure provides a non-parametric test of the parallel trends assumption. The graphs show the difference in slope from a Loess regression between hexagons assigned to become Priority Municipalities in 2008 and those that became Priority Municipalities in subsequent years over the course of 2006-2007. The gray box indicates the months for which outcome data is missing. Standard errors are calculated via bootstrapping.

A4 Clustering of Grid Cells

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 ($n = 49$). This defines both the treatment indicator and serves as the cluster for the purposes of variance estimation. The colors here are arbitrary and are intended solely to show how the clusters are defined.

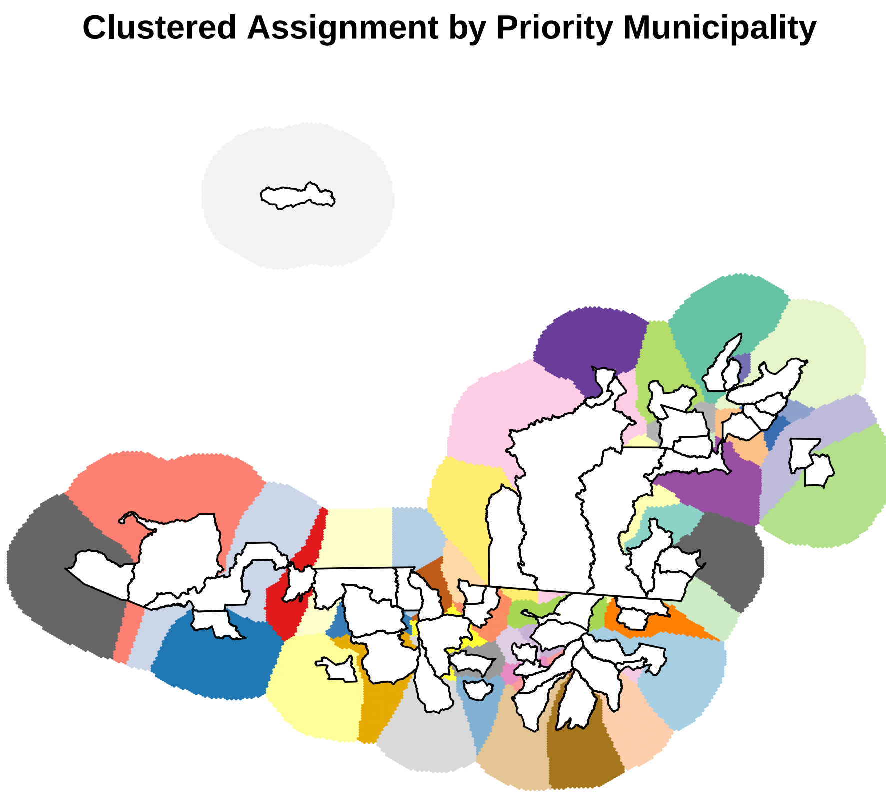

Figure A3: Definition of geographic clusters for the purpose of treatment assignment.

A5 Robustness: Conditional ATTs Using Polynomial 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 utilized here are as follows:

$$Y_{ijktm} = \beta_0 Z_{jt} + \beta_1 Z_{jt}\text{Distance}_{ij} + \beta_2 Z_{jt}\text{Distance}_{ij}^2 + \beta_1 Z_{jt}\text{Distance}_{ij}^3 + \phi_t + \gamma_i + \nu_{im} + \epsilon_{ijkt} \quad (1)$$

The ATTs, conditional on distance are plotted in the graph below, with the linear model from Table 2 and depicted in 6 superimposed. The differences in conditional ATTs (difference in the estimates at specific distance) across the three models are generally not statistically significant.

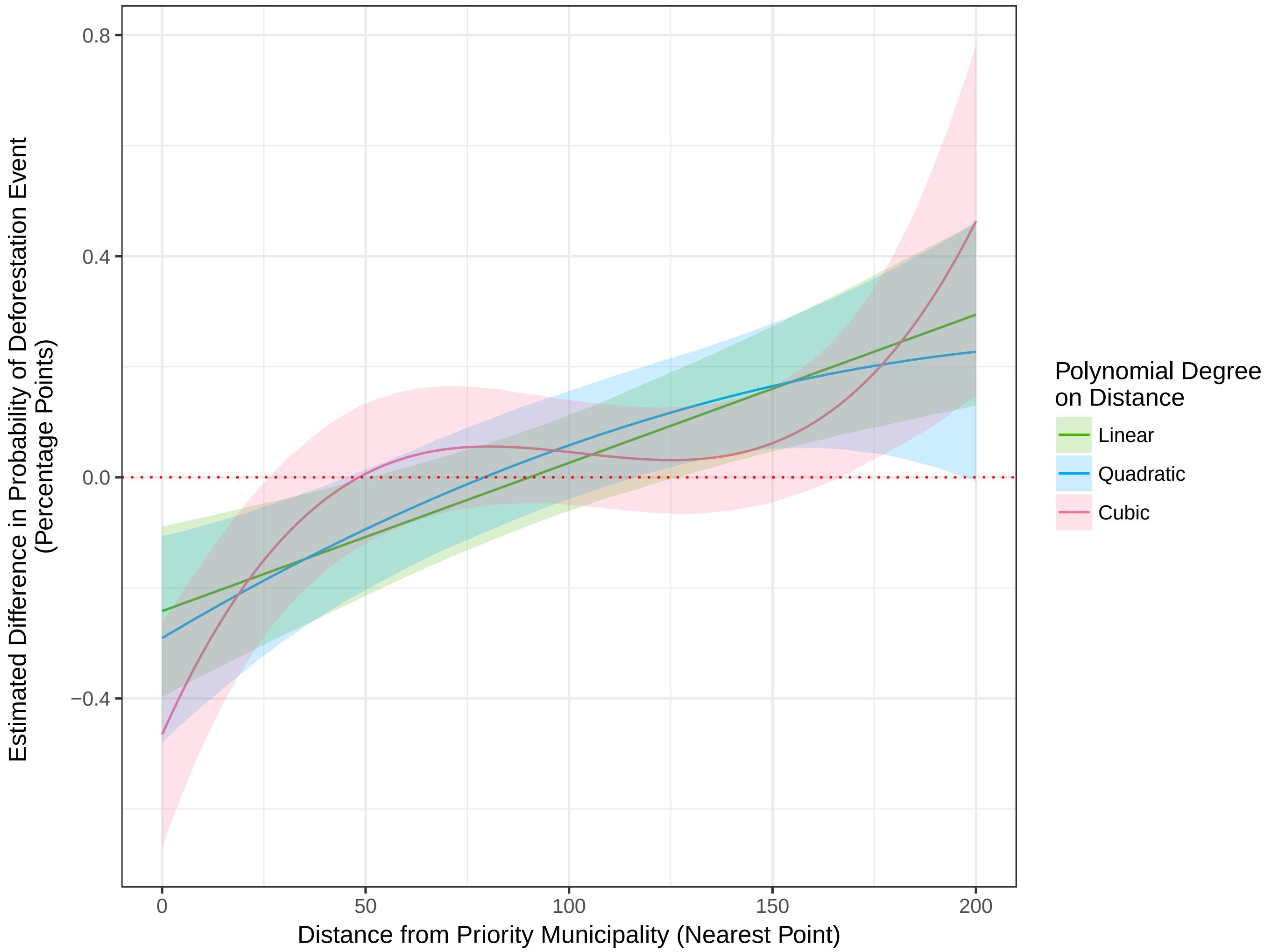

Figure A4: Conditional ATT estimates using linear, quadratic, and cubic polynomials on the Distance variable. 95% confidence intervals about each point estimate are estimated using by standard errors clustered at the priority municipality level.

A6 Robustness: Jackknife-Style Test

In this test, we reestimate the main specification from Table 2, Column 5 dropping priority muncipalities 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.

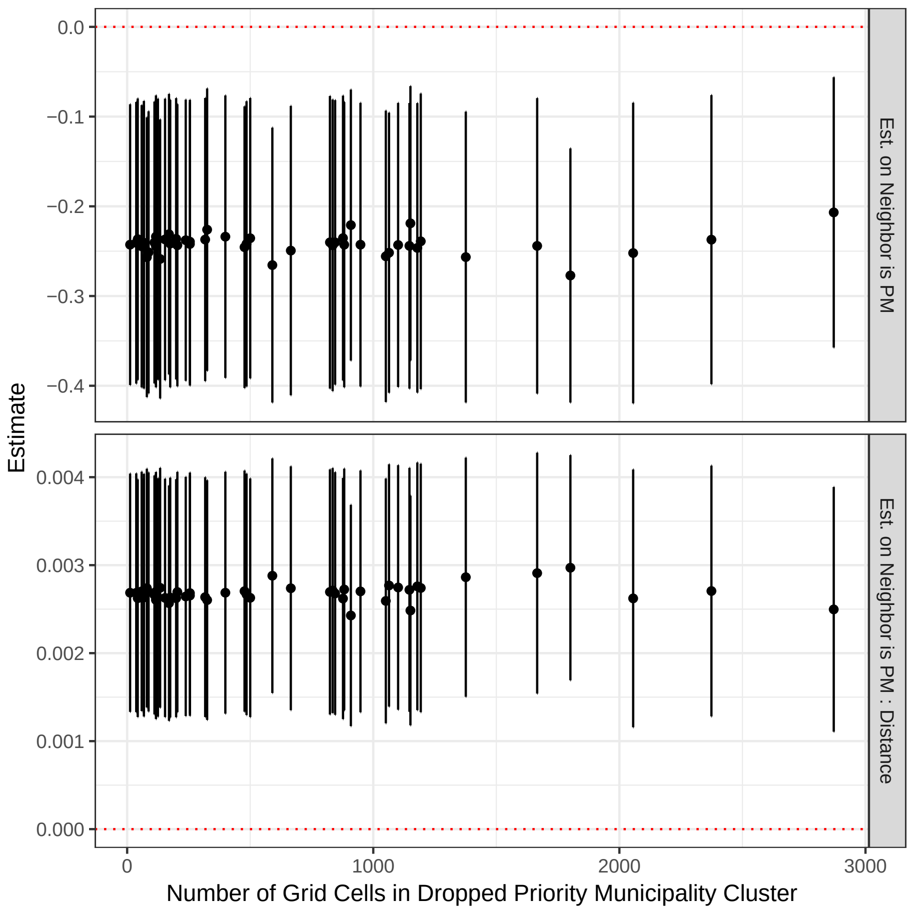

Figure A5: Conditional ATT estimates using the estimator from Table 4, Model 5, dropping each cluster sequentially. 95% confidence intervals about each point estimate are estimated using by standard errors clustered at the priority municipality level.

A7 Placebo Test: Additional Graph

This graph depicts the estimates from the lower panel of 4, Column 2.

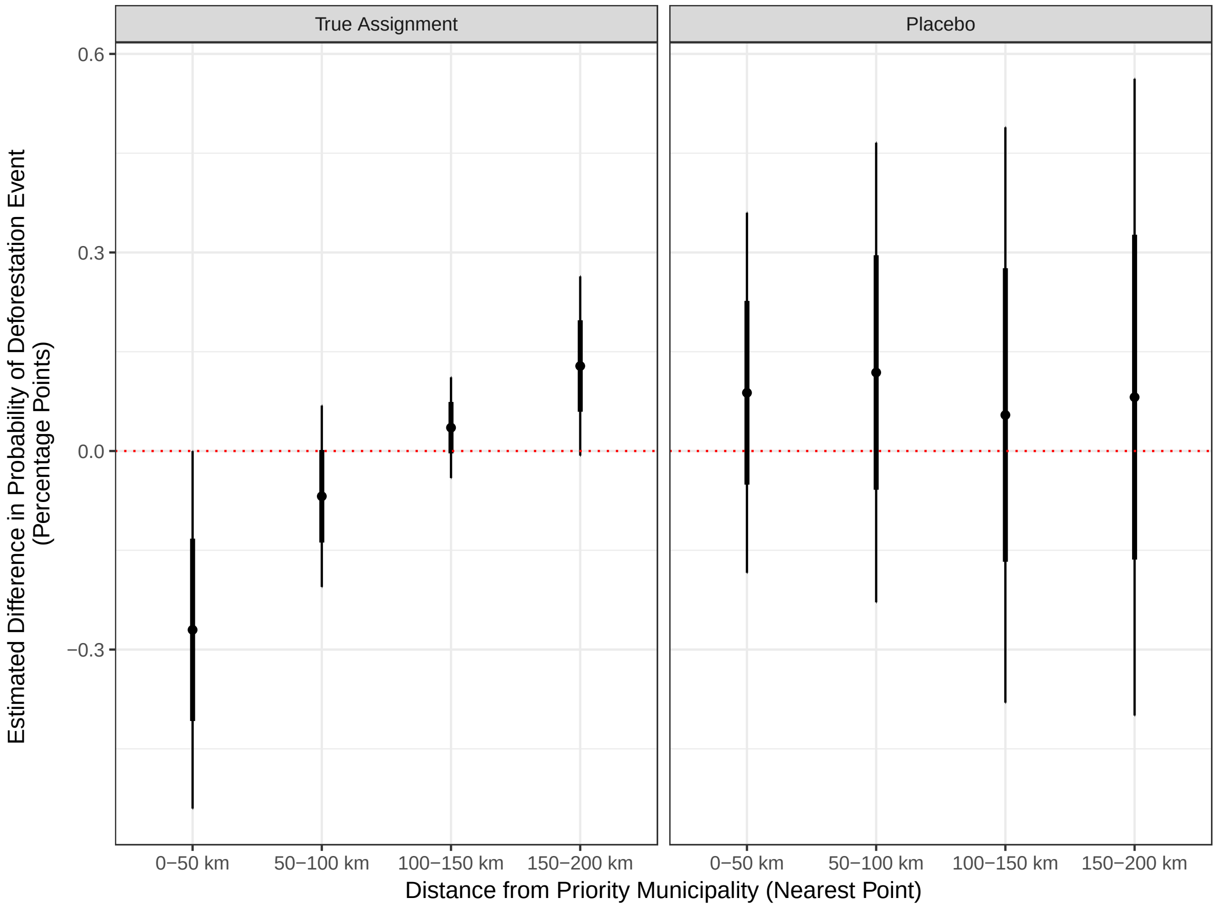

Figure A6: Conditional ATT estimates from Table 4, Panel 2, Model 2. 95% confidence intervals about each point estimate are estimated using by standard errors clustered at the priority municipality level.

A8 Heterogeneous Treatment Effect Analysis: Distance from Waterways

A8.1 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 A7.

A8.2 Heterogeneous Treatment Effects: Distance from Waterways

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

$$Y_{ijktm} = \beta_0 Z_{jt} + \alpha_0 Z_{jt} P_i + \beta_1 Z_{jt} \text{Distance}_{ij} + \alpha_1 Z_{jt} \text{Distance}_{ij} P_i + \phi_t + \gamma_i + \epsilon_{ijktm} \tag{2}$$

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

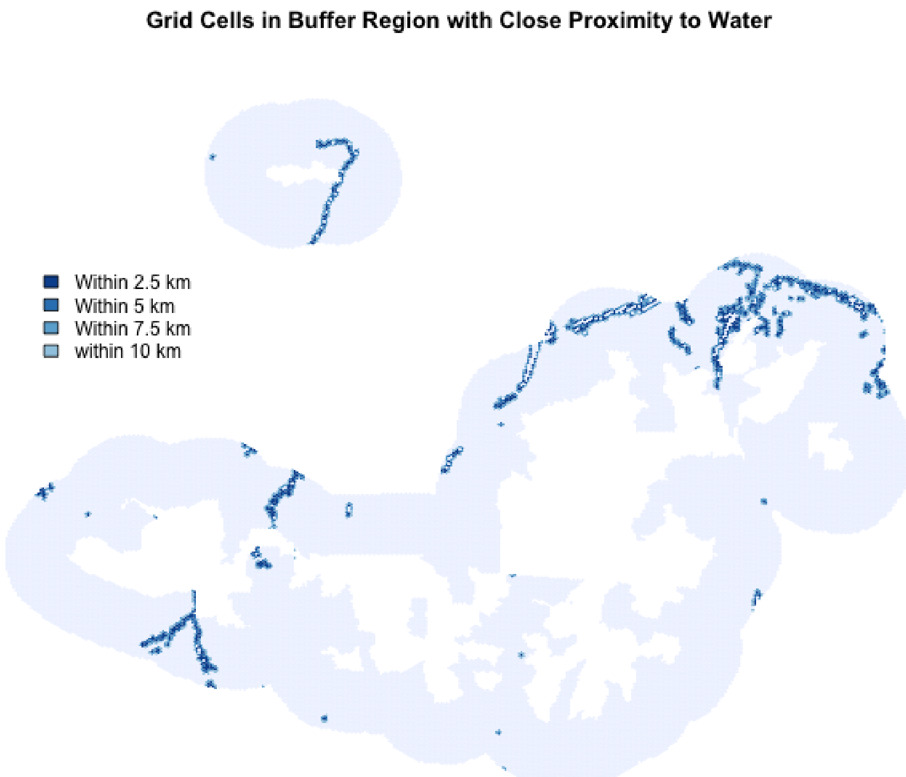

Figure A7: This map depicts the grid cells included in the specifications of grid cells that are proximate to highways from the analysis in Section X. Note that only grid cells within national boundaries are included in the analysis.

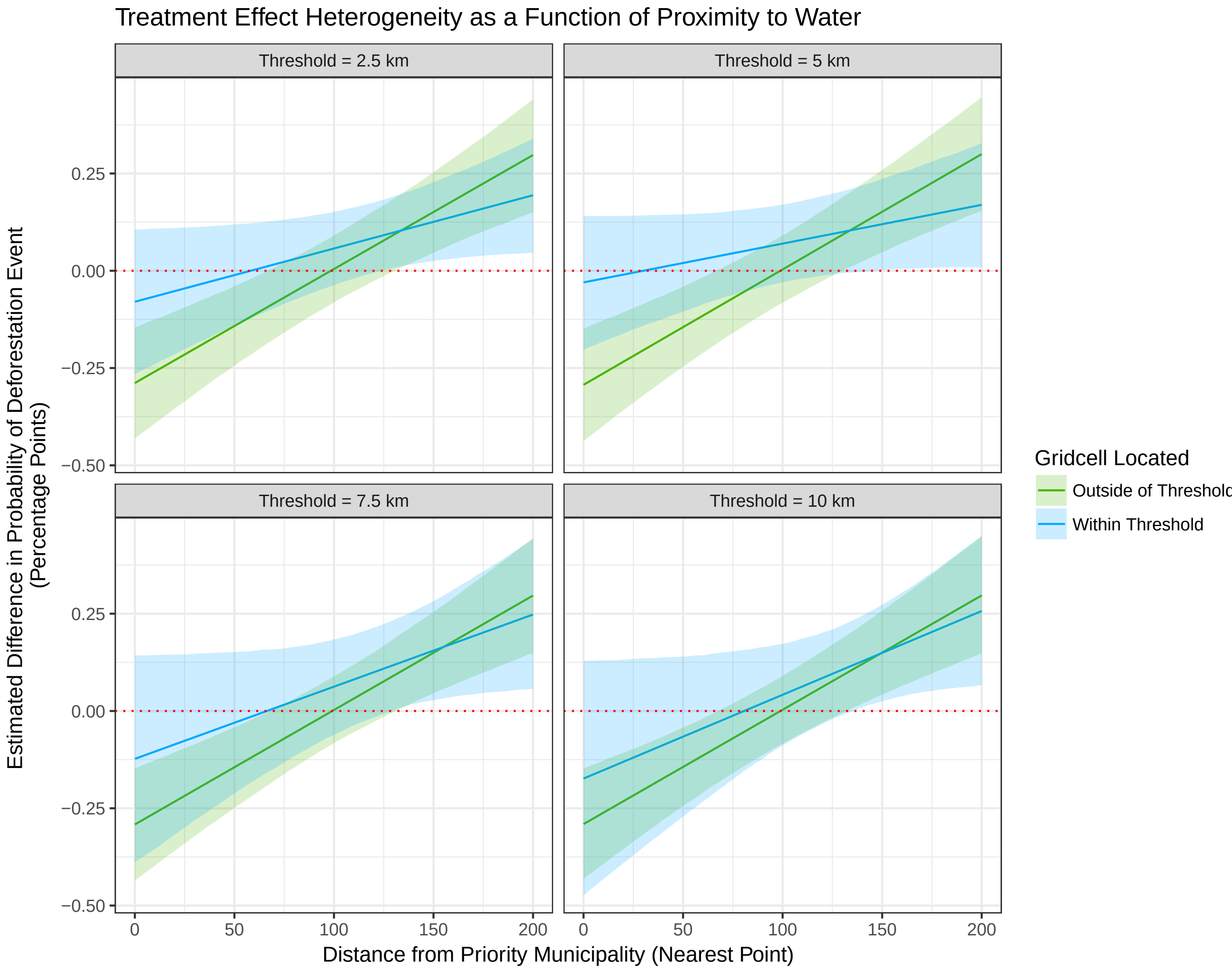

Figure A8: This graph depicts the estimated conditional ATT by distance and proximity to major waterways. The shaded region represents 95% confidence intervals. Standard errors are clustered at the priority municipality level.

A9 Heterogenous Treatment Effects: Distance from Highway

A9.1 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 A9.

A9.2 Heterogeneous Treatment Effect Analysis

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

$$Y_{ijktm} = \beta_0 Z_{jt} + \alpha_0 Z_{jt} P_i + \beta_1 Z_{jt} \text{Distance}_{ij} + \alpha_1 Z_{jt} \text{Distance}_{ij} P_i + \phi_t + \gamma_i + \epsilon_{ijktm} \quad (3)$$

- We present the results graphically in Figure A10 to facilitate interpretation of the triple interaction.

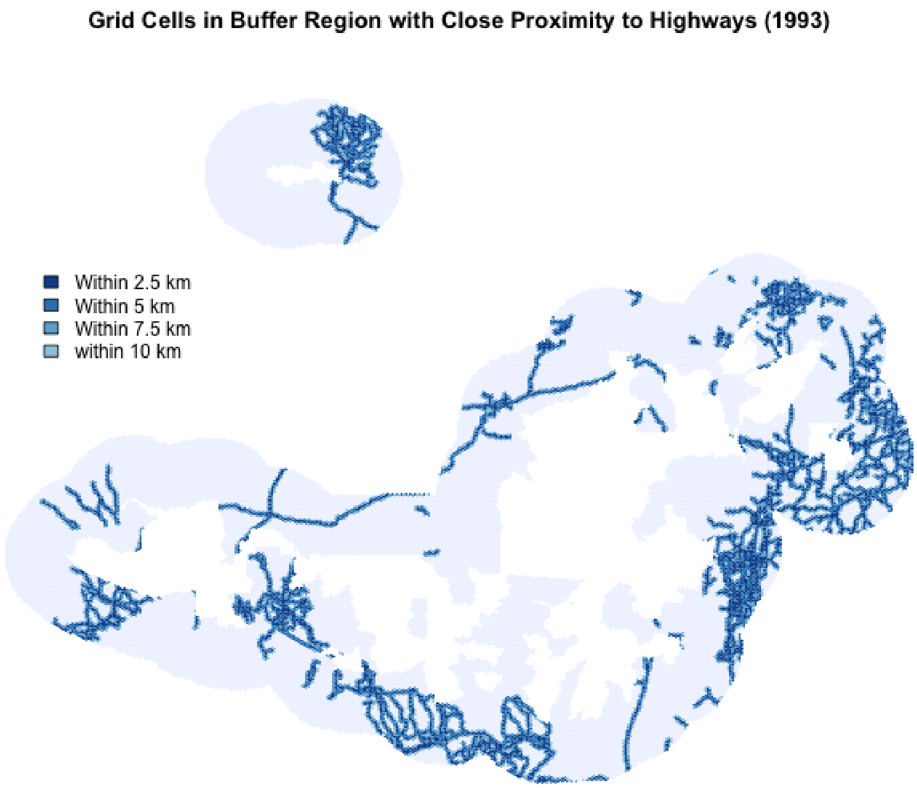

Figure A9: This map depicts the grid cells included in the specifications of grid cells that are proximate to highways from the analysis in Section X. Note that only grid cells within national boundaries are included in the analysis.

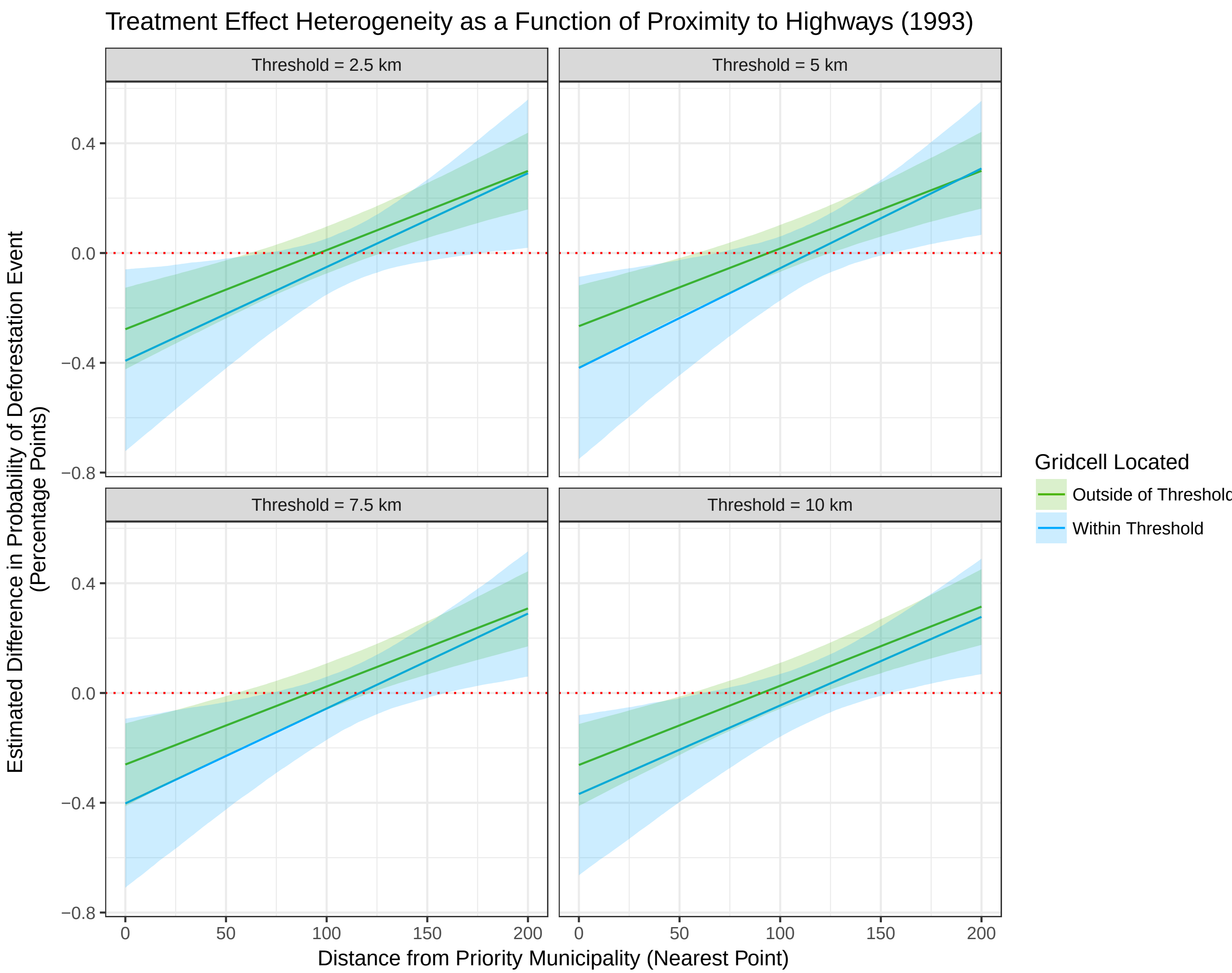

Figure A10: This graph depicts the estimated conditional ATT by distance and proximity to highways. The shaded region represents 95% confidence intervals. Standard errors are clustered at the priority municipality level.