Online Appendix

DETERring Deforestation in the Amazon: Environmental Monitoring and Law Enforcement

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This Online Appendix provides additional material regarding data construction and descriptive statistics (Section A), results for counterfactual simulations (Section B), and results for robustness exercises (Section C).

A. Data

A.1. Controls: Weather Variables

We build our weather control variables from monthly gridded data on total precipitation and average air temperature interpolated to a 0.5° by 0.5° grid resolution (Matsuura and Willmott, 2018a,b). Using this grid, we construct monthly measures for precipitation and temperature in each municipality as follows: (i) for a municipality that intersects with at least one grid node, we calculate total precipitation and average temperature across nodes; (ii) for a municipality that does not intersect with any grid nodes, we identify nodes that intersect with its 30km buffer and calculate average precipitation and average temperature across nodes; and (iii) for a municipality that neither intersects nor has its 30 km buffer intersect with any grid nodes, we identify nodes that intersect with its 60 km buffer and calculate average precipitation and average temperature across nodes.[1] Monthly values are then added (precipitation) or averaged (temperature) to construct municipality-level annual measures.

A.2. Controls: Agricultural Commodity Prices

Assunção et al. (2015) show that commodity prices recorded by the Agriculture and Supply Secretariat of the State of Paraná (SEAB-PR) closely correlates with average local agricultural prices for Amazon municipalities.[2] Select commodity prices cover beef cattle, as well as soybean, cassava, rice, corn, and sugarcane to

[1]Buffer distance is based on the grid size, with 30 km being approximately equivalent to half the distance between grid nodes.

[2]Paraná is a non-Amazon state located in the far south of Brazil.

capture incentives for both cattle ranching and crop farming activities.[3] For each of the six commodities, we build an index of real prices for the first and second semester of each calendar year.[4] We start by deflating monthly nominal prices to year 2000 Brazilian currency, and averaging the deflated monthly prices across semesters (FGV/Conj. Econ. - IGP, 2019; SEAB-PR, 2019). To introduce cross-sectional variation in the commodity price series, we weight the prices using a measure of that commodity's relevance in each municipality in years immediately preceding the sample period. The weighted real price for each commodity is therefore given by:

$$PW_{c,i,st} = P_{c,st} * W_{i,c} \tag{1}$$

where $PW_{c,i,st}$ is the weighted real price of commodity c in municipality i and semester/year st; $PP_{c,st}$ is the real price of commodity c in semester/year t; and $W_{i,c}$ is the municipality/commodity-specific weight. For crops, the weight is given by the 2004 through 2005 average ratio of farmland to municipal area for crop c in municipality i, using annual data from Brazil's Municipal Crop Production Survey (PAM/IBGE) (IBGE, 2003–2017). For beef cattle, the weight is given by the 2004 through 2005 average ratio of heads of cattle to municipal area in municipality i, using data from Brazil's Municipal Livestock Survey (PPM/IBGE) (IBGE, 2014–2018).

A.3. Descriptive Statistics

Table A.1 provides descriptive statistics for the analysis' main variables. It shows that deforestation, law enforcement, and DETER cloud coverage exhibit substantial variation both across and within sample years. The downward trend in mean deforestation over time is consistent with a context in which forest clearing was slowing down in the Brazilian Amazon as a whole. Figure A.1 portrays the deforestation slowdown alongside the trajectory for total annual fine count, offering some insight into the endogeneity that exists among the two. While the sharp increase in the number of fines issued through 2008 could be expected to have contributed to the observed reduction in deforestation, lower forest clearing rates imply a lower incidence of illegal clearings and, thus, lower fine counts over time. The proposed IV strategy aims at disentangling these effects to isolate the impact of law enforcement on Amazon deforestation.

[3]Soybean, cassava, rice, and corn systematically account for more than 84% of the planted area in sample municipalities during the sample period (IBGE, 2001–2019; IBGE, 2003–2017). Although not present in the Amazon, sugarcane is also included to address concerns regarding the expansion of sugarcane-based ethanol biofuel production in Brazil over the past decades.

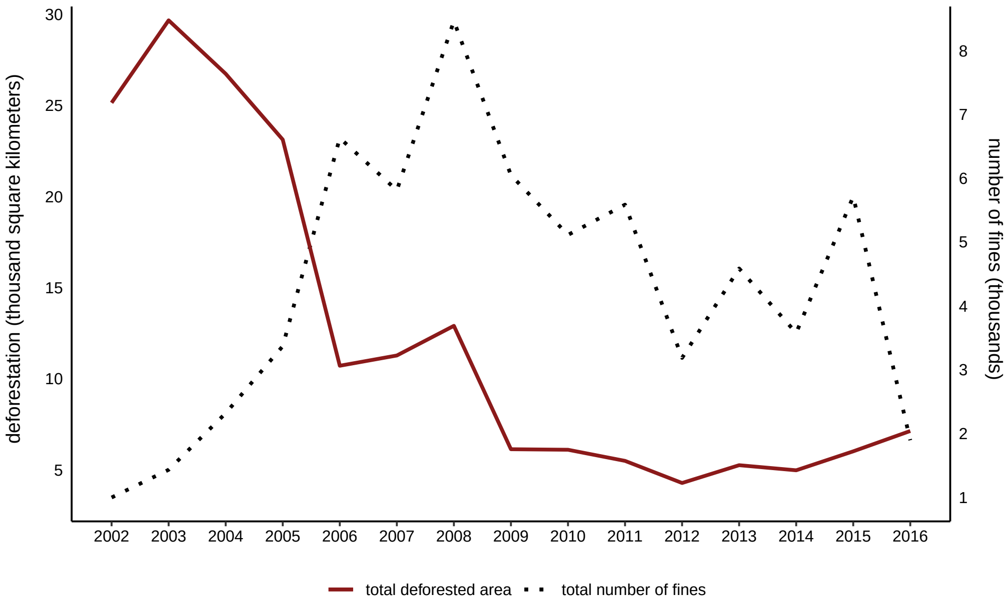
[4]We use January through July of year t as the first semester of year t to more closely match the breaks in PRODES years, which end in July. August through December of year t make up the second semester of year t.

Table A.1: Descriptive Statistics

	fullSample	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**
deforestation												
mean	14.00	20.55	21.63	24.76	11.76	11.71	10.54	8.21	10.08	9.54	11.54	13.68
sd	39.64	54.58	59.37	57.94	35.64	28.20	26.60	20.68	28.60	24.13	31.61	39.28
enforcement												
mean	9.87	12.72	11.15	16.25	11.61	9.81	10.72	6.11	8.80	6.86	10.96	3.63
sd	28.25	26.85	23.85	37.27	32.74	23.25	26.73	16.19	30.91	24.36	41.01	13.15
DETER cloud coverage												
mean	0.46	0.37	0.65	0.49	0.58	0.49	0.50	0.35	0.37	0.45	0.48	0.39
sd	0.23	0.06	0.16	0.23	0.23	0.25	0.20	0.20	0.21	0.27	0.24	0.27
NASA cloud coverage												
mean	0.71	0.73	0.70	0.73	0.74	0.69	0.71	0.71	0.72	0.74	0.71	0.65
sd	0.08	0.07	0.07	0.09	0.07	0.07	0.08	0.07	0.07	0.07	0.07	0.09
PRODES cloud coverage												
mean	664.3	376.33	568.60	441.75	434.12	827.65	557.99	585.36	1,237.18	783.31	487.27	1,007.75
sd	2,810.21	1,447.32	2,403.74	1,804.06	1,393.36	3,311.98	2,879.49	2,125.07	4,737.32	3,023.03	1,886.78	3,782.06
PRODES non-observable												
mean	15.20	46.64	47.45	21.71	9.27	7.66	7.62	7.13	7.26	6.97	0.00	5.48
sd	135.50	261.91	262.33	231.46	37.93	36.02	35.82	34.19	33.90	34.03	0.00	33.05
precipitation												
mean	6,962	7,493	7,057	7,414	7,393	6,524	7,084	6,911	7,034	7,164	6,678	5,825
sd	12,514	13,490	12,330	13,203	13,541	11,698	12,458	12,469	12,666	12,487	12,447	10,617
temperature												
mean	26.20	26.03	26.23	25.81	26.00	26.52	26.21	26.12	26.20	25.96	26.21	26.91
sd	1.29	1.22	1.13	1.28	1.21	1.32	1.21	1.28	1.30	1.38	1.26	1.24

Notes: The table reports municipality-level means and standard deviations. Variable labels, units, and sources are as follows. Deforestation: km^2, Project for Monitoring Deforestation in the Legal Amazon (PRODES) from the Brazilian Institute for Space Research (INPE) (INPE, 2017a); enforcement: number of fines, Brazilian Institute for the Environment and Renewable Natural Resources (Ibama) (Ibama, 2016); DETER cloud coverage: ratio of cloud to municipal area, Real-Time System for Detection of Deforestation (DETER) from the Brazilian Institute for Space Research (INPE) (INPE, 2017c) and Brazilian Institute for Geography and Statistics (IBGE) (IBGE, 2007); NASA cloud coverage: ratio of cloud to municipal area, Cloud Fraction (TERRA/MODIS) - MODIS Atmosphere L3 Monthly Product (V 6.01) (Platnick, King, and Hubanks, 2017) and IBGE (IBGE, 2007); PRODES cloud coverage: km^2, PRODES/INPE (INPE, 2017a); PRODES non-observable: km^2, PRODES/INPE (INPE, 2017a); precipitation: mm, Matsuura and Willmott (2018b); temperature: °C, Matsuura and Willmott (2018a).

Figure A.1: Descriptive Statistics: Amazon Deforestation and Fine Count



Notes: The graph displays total annual deforested area and total annual deforestation-related fine count for all sample municipalities. Sources: (INPE, 2017a; Ibama, 2016).

B. Results: Counterfactual

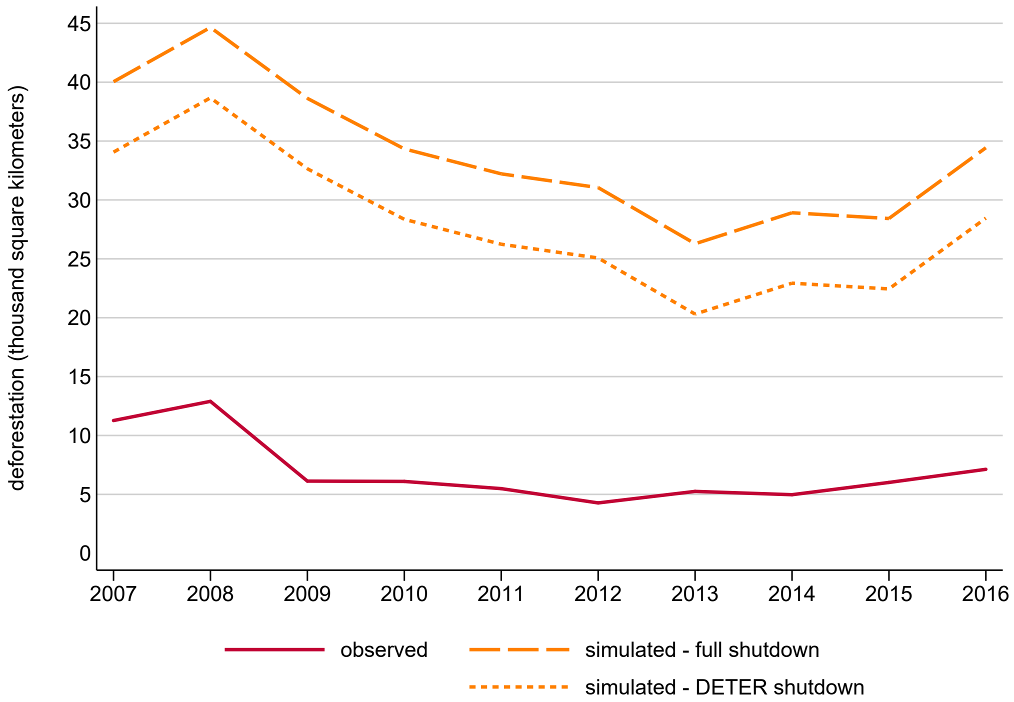
Using the specification from Table 2 column 3 (municipal area normalization for deforestation), we simulate what would have happened in two hypothetical scenarios: (i) one in which Amazon monitoring and law enforcement have been entirely shut down, and (ii) another one in which the novel satellite-based monitoring system was never adopted. We build these scenarios empirically by setting the total number of fines in each municipality to zero or pre-DETER (2002 through 2004 average fine count) levels, respectively, and simulating municipal deforestation outcomes under these conditions. Table B.2 and Figure B.2 report total sample observed and simulated deforested areas, showing that both scenarios yield systematically larger deforestation. Reported simulation outcomes are based on the municipal area normalization, but results are analogous for the mean-based normalization.

Table B.2: Counterfactual Exercise: Observed and Simulated Deforested Area

	deforestation (km^2)				
		full shutdown		**DETER shutdown**	
year	**observed**	**estimated**	**difference**	**estimated**	**difference**
2007	11,271	40,041	28,770	34,063	22,792
2008	12,899	44,650	31,751	38,673	25,774
2009	6,128	38,626	32,498	32,649	26,521
2010	6,100	34,338	28,238	28,360	22,261
2011	5,490	32,217	26,727	26,239	20,750
2012	4,276	31,050	26,774	25,072	20,797
2013	5,252	26,283	21,031	20,305	15,053
2014	4,973	28,912	23,939	22,934	17,961
2015	6,013	28,424	22,411	22,446	16,433
2016	7,129	34,434	27,305	28,456	21,327
total	**69,530**	**338,974**	**269,444**	**279,199**	**209,669**

Notes: The table reports observed and simulated annual values for total sample deforestation. The simulations refer to two hypothetical scenarios: (i) Amazon monitoring and law enforcement were entirely shut down, and (ii) DETER was never adopted. The simulations use estimated coefficients from the specification in Table 2 column 3 and set the total number of fines as: (i) zero in all municipalities and years; or (ii) the 2002 through 2004 (pre-DETER) average fine count for each municipality and year. Source: observed deforestation from (INPE, 2017a).

Figure B.2: Counterfactual Exercise: Observed and Simulated Deforested Area



Notes: The graph displays observed and simulated annual values for total sample deforestation. The simulated trajectories refer to two hypothetical scenarios: (i) Amazon monitoring and law enforcement were entirely shut down, and (ii) DETER was never adopted. The simulations use estimated coefficients from the specification in Table 2 column 3 and set the total number of fines as: (i) zero in all municipalities and years; or (ii) the 2002 through 2004 (pre-DETER) average fine count for each municipality and year. Source: observed deforestation from (INPE, 2017a).

C. Robustness Checks

C.1. Control Variables

We test whether results hold when using different combinations of benchmark and alternative datasets for precipitation and temperature variables. One of these tests is reported in the paper (Table 4, column 6); Table C.3 presents 2SLS estimated coefficients for all tested combinations. The benchmark controls are constructed using monthly average air temperature and total precipitation interpolated to a 0.5° by 0.5° grid resolution (Matsuura and Willmott, 2018b,a). The alternative datasets are both provided by the National Oceanic and Atmospheric Administration (NOAA) from the U.S. Department of Commerce. The Climate Prediction Center (CPC) dataset contains daily information on precipitation and maximum/minimum temperature registered by ground stations and interpolated to a 0.5° by 0.5° grid resolution (NOAA-CPC, 2018a; NOAA-CPC, 2018b; NOAA-CPC, 2018c). The National Centers for Environmental Prediction (NCEP) dataset contains monthly information on average precipitation derived from reanalysis and recorded at a 2.5° by 2.5° grid resolution (NOAA-NCEP, 2019). Alternative weather controls are constructed in the likeness of benchmark controls. The table shows that the paper's main results were not driven by our choice our benchmark weather datasets, with estimated coefficients remaining robust in terms of both magnitude and statistical significance.

Table C.3: Robustness Checks, IV Regressions: Alternative Weather Controls

	(1)	(2)	(3)
Panel A: 2SLS, second-stage results			
	depvar: IHS(deforest)		
enforcement, t-1	-0.0519	-0.0480	-0.0492
	(0.0245)	(0.0237)	(0.0232)
FE: muni & year	yes	yes	yes
controls: full	yes	yes	yes
precipitation dataset	MW	CPC	NCEP
temperature dataset	CPC	MW	MW
observations	5,198	5,210	5,210
municipalities	521	521	521
Panel B: 2SLS, first-stage results			
	depvar: enforcement		
DETER cloud coverage	-9.3122	-9.3844	-9.7835
	(2.9845)	(2.9971)	(3.0660)
first-stage F-statistic	9.736	9.804	10.18
FE: muni & year	yes	yes	yes
controls: full	yes	yes	yes
precipitation dataset	MW	CPC	NCEP
temperature dataset	CPC	MW	MW
observations	5,198	5,210	5,210
municipalities	521	521	521

Notes: 2SLS coefficients are estimated based on an adaptation of the benchmark specification (Table 2 column 1), in which weather variables from alternative datasets are included as controls. Panel A presents second-stage results; Panel B presents first-stage results. In Panel A, the normalization procedures for the dependent variables is inverse hyperbolic sine transformation (columns 1 through 3). The total number of fines issued in each municipality and year serves as a proxy for law enforcement. The set of control variables contains: precipitation and temperature (weather); PRODES cloud coverage and other non-observable areas (satellite visibility); and agricultural commodity prices. The table references the weather datasets as follows: MW for benchmark; CPC for NOAA's Climate Prediction Center; and NCEP for NOAA's National Centers for Environmental Prediction. The dataset is a municipality-by-year panel covering the 2006 through 2016 period. The sample includes all Amazon biome municipalities that exhibited variation in forest cover during the sample period and for which deforestation data were available. Robust standard errors in parentheses, clustered by municipality and microregion-year.

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