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Is global deforestation under lockdown?*

Santiago Saavedra†

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Abstract

The COVID-19 pandemic and the associated responses by governments have halted economic activity abruptly across the world. The environment has benefited with reductions in pollution in urban areas, but what has happened in rural areas to deforestation has not been studied yet. A priori the effect is unclear: deforestation might decrease with the restrictions on economic activity. But it might have increased given the reductions in monitoring. I combine bi-weekly data from 70 countries covering the entire world's tropical forest with the dates each country started lockdown restrictions. Using difference-in-differences I find that, although deforestation is higher in 2020 compared to 2019, it is not driven by the lockdowns but rather by higher deforestation that precedes them. There is heterogeneity by the level of government effectiveness of the country: countries with effective governance experience a reduction in deforestation, probably because they can enforce the lockdown restrictions.

JEL codes: Q23, Q58

Keywords: COVID-19; Deforestation

1 Introduction

The COVID-19 pandemic and the associated responses by governments have halted social and economic activity abruptly across the world. Per capita income in 2020 is expected to fall in the largest fraction of countries globally since 1870 (World Bank, 2020). The slowdown has affected the environment in positive ways, from reductions on air pollution to wildlife returning in numerous urban areas (Cicala, Holland, Mansur, Muller,

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& Yates, 2020; López-Feldman et al., 2020). But what has happened in rural areas with deforestation has not been studied yet. To address this gap, in this paper I study what happened to deforestation after the start of COVID-19 lockdowns using micro-data.

The pandemic and lockdown restrictions can theoretically affect deforestation through multiple channels. On one hand, deforestation could decrease if loggers comply with the government lockdown orders; and, if the demand for land and wood decrease as a result of the worldwide economic recession. On the other hand, deforestation might increase for at least two reasons. First, some countries may lack the state capacity to enforce the lockdown in remote rural areas where forests are located. The lockdown may have even reduced the enforcement capacity as government agencies and NGOs are forced to retreat their field operations. Second, the reduction in alternative sources of income due to the recession may induce inhabitants to switch to forest clearing activities. Given all these theoretical possibilities, I turn to the data to study this issue empirically.

I combine weekly data from 70 countries covering the entire world's tropical with the dates each country started lockdown restrictions. I obtain weekly data for vegetation cover change alerts from (Hansen et al., 2016). This data records abrupt changes in vegetation and it has a resolution of 0.00025° degrees —approximately 28 meters at the equator. As the data does not differentiate between changes in vegetation in natural forest and forest plantations (Fergusson, Saavedra, & Vargas, 2020), I restrict the data to areas of primary forest. As a result, these vegetation alerts can be thought as deforestation alerts. The date on which lockdown orders started in each country comes from the Oxford COVID-19 policy tracker Hale, Webster, Petherick, Phillips, and Kira (2020) and the government effectiveness index from World Bank (2018).

I use difference-in-differences regressions to study the effect of the lockdowns on deforestation (Greenstone & Gayer, 2009). My empirical strategy compares deforestation across countries before and after the beginning of each country's lock-down. I use municipality fixed effects to control for time-invariant characteristics that make an area more or less vulnerable to deforestation . For example, this accounts for the presence of roads and rivers, the slope of the terrain, and whether the forest is under a protected natural area (Busch & Ferretti-Gallon, 2017; Deng, Huang, Uchida, Rozelle, & Gibson, 2011). I also use regionXbi-week fixed effects to account for common shocks to an area in a given bi-week (such as weather conditions). Ultimately, this allows me to compare neighboring regions in different countries that have different lock-down start dates, in the spirit of (Burgess, Costa, & Olken, 2018). The estimated effect on deforestation is a bundle of the lockdown, the COVID-19 health shock, and the economic slowdown.

I find that in 2020 there are around 150,000 more deforestation alerts each bi-week compared to 2019. However, this is not due to the lockdowns. Rather, this higher level predates the COVID-19 lockdowns. The results are robust to different lockdown definitions, and a diverse set of fixed effects. There is however heterogeneity by the government effectiveness of the country. Countries with effective governments experience a reduction in deforestation, probably because they can enforce the lockdown restrictions.

This is the first paper looking at the effect of the COVID-19 pandemic response on world's deforestation using microdata. López-Feldman et al. (2020) discussed the possible relation. Previous research has studied the opposite relation: the effect of environmental conditions on health. For example, UV radiation on COVID-19 transmission (Carleton, Cornetet, Huybers, Meng, & Proctor, 2020), forest loss on malaria and infectious diseases (Garg, 2019; Keesing et al., 2010). Numerous papers have used the yearly satellite data for regression analysis of deforestation before (Blackman, Goff, & Planter, 2018; Jung & Polasky, 2018; Berazneva & Byker, 2017; Alix-Garcia, Sims, &

Yañez-Pagans, 2015). However, to the best of my knowledge, this is the first taking advantage of the bi-weekly alerts.

2 Data and estimating equations

2.1 COVID-19

There have been diverse government responses to the pandemic. Some countries have tried to continue with minimum restrictions and others have imposed strict measures. Hale et al. (2020) tracks the policies of each country in different categories. In the main specification I use the date on which workplace closures orders started on each country.[1] See Table 1 for descriptive stats. On average the countries started restrictions on bi-week 6.7 of the year, which is around March 31st. Most of the countries have not ended the restrictions on July 12th, and that is why we only have 21 observations for the bi-week when lockdown ended. We try robustness using the date when stay at home was required or restrictions on internal movement started.

We use an index of government effectiveness provided by World Bank (2018). This index captures perceptions of the quality of the civil service and the quality of policy formulation and implementation, among others. This measure is standardized to have mean zero, and standard deviation one. The index goes from approximately -2.5 to 2.5, with higher values corresponding to better governance. Countries in our data have an average of -0.4 in this index, so there effectiveness is below average.

Around a third of the countries are in the Americas, 38% in Africa and 27% in Asia-Oceania. We obtain the map of the administrative divisions of each country from

[1] Specifically level 2 "require closing (or work from home) for some sectors or categories of workers" and level 3 "require closing (or work from home) for all-but-essential workplaces (eg grocery stores, doctors)" Hale et al. (2020)

(University of California Davis, 2018). For most countries we use the second administrative division which is the equivalent of counties and municipalities. For some small countries we use level one. See Table A.1 on the Online Appendix for details of each country.

Table 1: Summary statics countries

Variable	Mean	Std Dev	Min	Max	N
	(1)	(2)	(3)	(4)	(5)
N defo alerts/ bi-week (2019)	4642.6	13137.6	0.0	98866.3	70
N defo alerts/ bi-week (2020)	6798.5	14162.4	0.0	90642.7	70
Alerts as forest share/ bi-week (2020)	0.0	0.0	0.0	0.0	70
Alerts as forest share/ bi-week (2019)	0.0	0.0	0.0	0.0	70
Bi-Week start lockdown	6.7	1.2	5.0	13.0	64
Bi-Week end lockdown	11.2	1.4	8.0	13.0	21
% Americas	34.3	47.8	0.0	100.0	70
% Africa	38.6	49.0	0.0	100.0	70
% Asia/Oceania	27.1	44.8	0.0	100.0	70
Government Effectiveness Index	-0.4	0.7	-1.9	2.2	67

Notes: Data on the countries used in the regression analysis. Column 1 is the mean and Column 2 the standard deviation. Column 3 and 4 are the minimum and maximum value of the variable for a country. There are less observations for lockdown bi-week because some countries did not impose workplace closure restrictions.

2.2 Deforestation

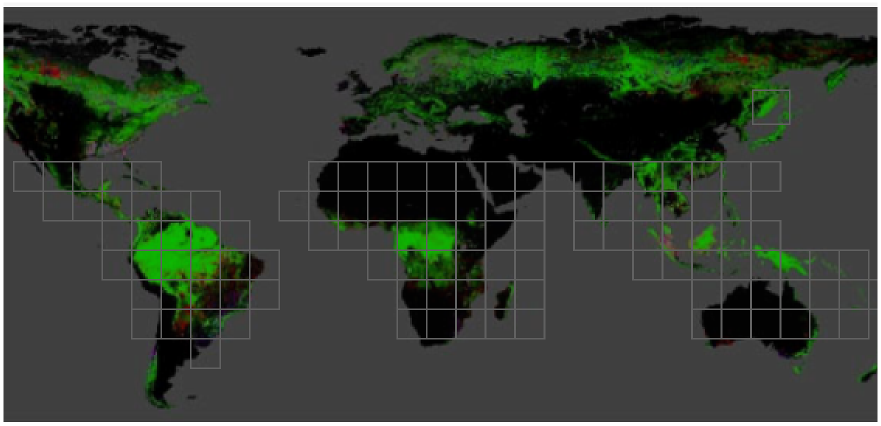
I obtain data for vegetation cover change alerts from (Hansen et al., 2016) for every bi-week between January 1st and July 12th for 2019 and 2020. This data records an alert in squared pixels of 0.00025°, which is approximately 28 meters at the equator. As the alert data does not differentiate between deforestation of natural forest and forest plantations activity (Fergusson et al., 2020), we restrict the alerts to areas of primary forest and call them deforestation alerts. The data is for humid tropical forests, so the forests of Canada, Russia and Europe are not included. See Figure 1A for the areas of the world included in the alerts. Note that the alerts data comes in pathrows (squares) of neighboring regions. I will use the pathrows in one of the estimation strategies to compare neighboring regions.

See Figure 1B for the map of the countries we have information and Table A.1 on the Appendix for the full list. The largest countries in the analysis are Brazil, Democratic Republic of the Congo and Indonesia. Although some countries are covered by the alerts pathrows, they are not in the regression because they do not have primary forests.

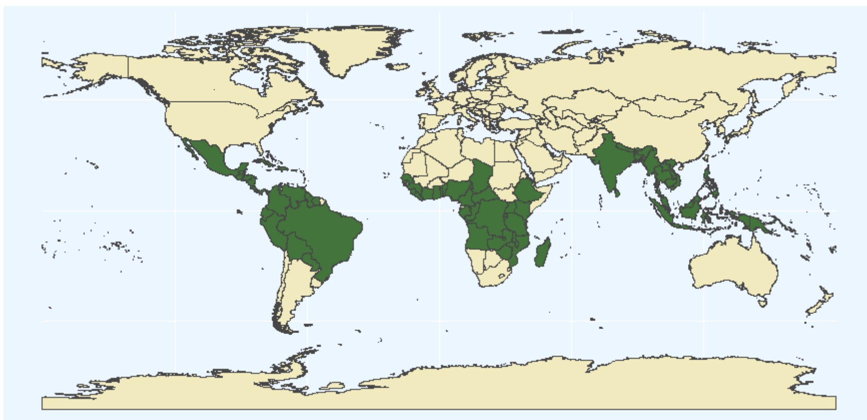
Figure 1C presents the total number of alerts in the world by week. We observe that globally there have been around 150,000 more deforestation alerts by bi-week of 2020 compared to 2019. But we do not observe any differential change around bi-week 7 (end of March) when most countries started lockdown orders. I collapse the data at the municipality-bi-week level and calculate the percentage of forest pixels that have deforestation alerts. Although the percentage of forest pixels that is deforested is my main dependent variable, I also use the number of alerts as robustness.

Figure 1: Deforestation alerts data

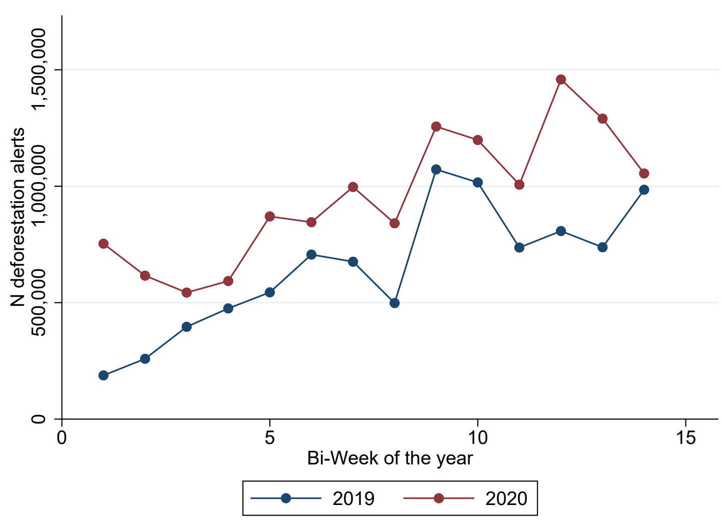
(A) Data pathrows



(B) Countries



(C) Number of alerts by bi-week



Notes: Panel A of this graph shows the pathrow division across the world. Panel B in dark green the countries in the regression. Panel C of this graph presents the number of deforestation alerts in 2019 and 2020. Map Source: http://glad-forest-alert.appspot.com/

2.3 Estimating equations

I estimate the effect of COVID-19 lockdowns on deforestation comparing deforestation alerts at the municipality level before and after lockdown requirements. I start with the simplest form of difference-in-differences (equation 1), comparing countries with different lockdown timing in 2020. Y_{wmc} is a measure of deforestation on bi-week w, for municipality m, country c. My prefred measure is the percentage of forest area with deforestation alerts. $Lockdown_{cw}$ is an indicator for whether country c was under lockdown on bi-week w. γ_c are country and γ_w bi-week fixed effects, respectively. Finally ε_{wmc} is an error term. I weigh the observations by the area of primary forest in the municipality. Consequently I am estimating the effect on the average forest pixel. I cluster the standard errors two ways, at the municipality and at the path-row week level. As mentioned above, the data is processed by pathrows so municipalities in the same pathrows are correlated because of errors in each satellite image.

$$Y_{wmc} = \beta Lockdown_{wc} + \gamma_c + \gamma_w + \varepsilon_{wmc} \tag{1}$$

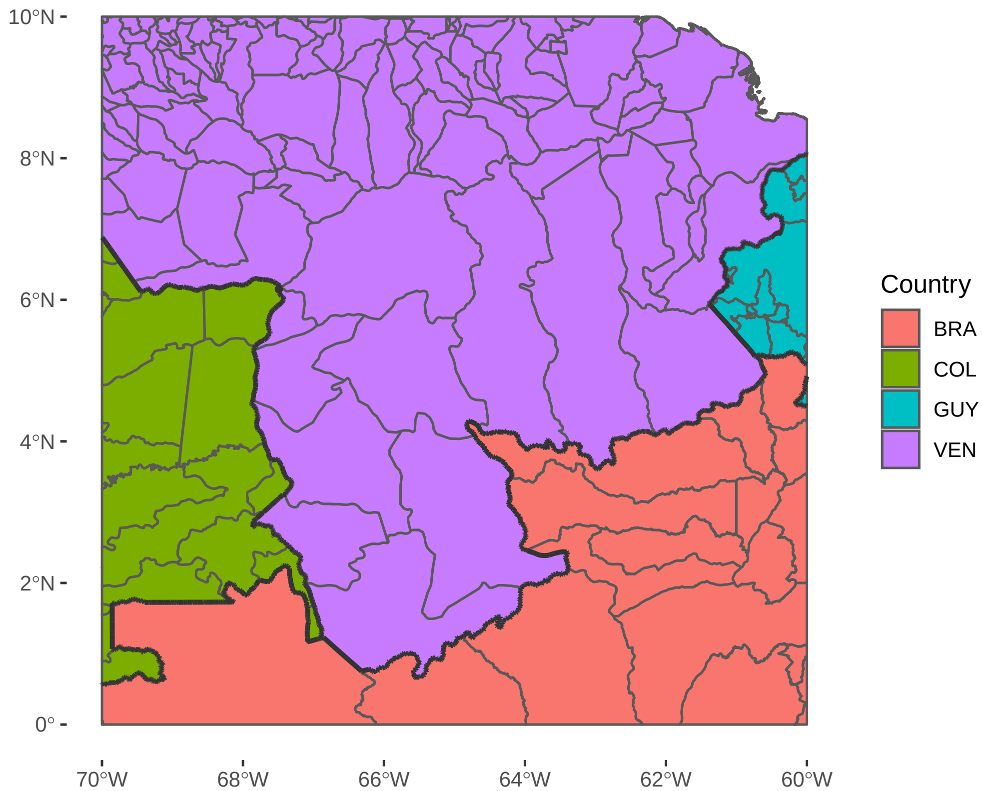
I prefer to use municipality fixed effects to control for time-invariant characteristics that make an area more or less vulnerable to deforestation . For example, this accounts for the presence of roads and rivers, the slope of the terrain, and whether the forest is under a protected natural area (Busch & Ferretti-Gallon, 2017; Deng et al., 2011). And also continent-bi-week fixed effects γ_{wn} to allow variation across continents each bi-week.

$$Y_{wmc} = \beta Lockdown_{wc} + \gamma_m + \gamma_{wn} + \varepsilon_{wmc} \tag{2}$$

The equation above assumes a common shock for all countries in the same continent bi-week. But there is considerable variation in the weather within the same continent.

So I prefer to include information about the satellite image pathrow p to which the municipality belongs. See Figure 2 for an example of a pathrow in the border of Brazil, Colombia, Guyane and Venezuela. The municipality fixed effects absorb the differences on the municipalities that are constant through time. While the pathrow-bi-week fixed effects (γ_{wp}) absorb any common shock to the area on a given bi-week, like a dry spell or rain. If a path-row is entirely in a single country, the pathrow-bi-week fixed effect will absorb the effect of the lockdown there. While if the pathrow covers many countries, it allows me to compare the different timing of lockdowns. For example, as Colombia started lockdown on bi-week 7 and Brazil on bi-week 9, the empirical strategy compares differential deforestation on those two bi-weeks in in the municipalities in the same pathrow.

Figure 2: Example of pathrow covering many countries



Notes: This figure presents one of the pathrows (squares) where deforestation alerts are reported. Using pathrow-bi-week fixed effects absorbs any common weather to the area and captures the effect of differential lockdown timing.

$$Y_{wmcp} = \beta Lockdown_{wc} + \gamma_m + \gamma_{wp} + \varepsilon_{wmcp} \quad (3)$$

Finally I can use the data on 2019, in a triple difference-in-differences specification.

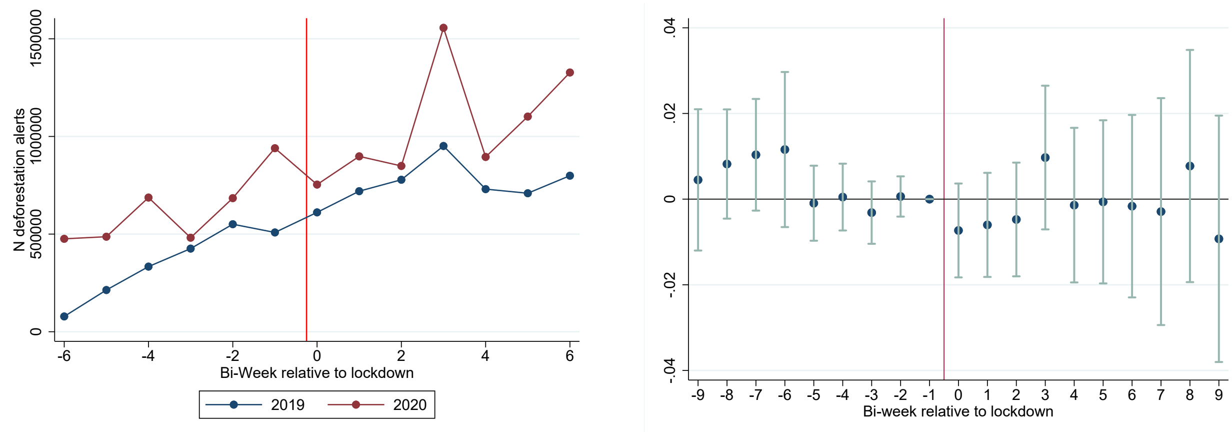
$$Y_{wymcp} = \beta Lockdown_{wyc} + \gamma_{yc} + \gamma_{wc} + \gamma_{wy} + \varepsilon_{wymcp} \quad (4)$$

Y_{wymcp} is a measure of deforestation on bi-week w, year y, for municipality m, country c and pathrow p. $Lockdown_{cyw}$ is an indicator for whether country c was under lockdown on bi-week w of year y, that is only for observations of 2020 ($y = 2020$). γ_{yc} are year-country fixed effects, γ_{wc} are bi-week of the year-country fixed effects and γ_{wy} bi-week-year- fixed effects. Finally ε_{wymcp} is an error term.

3 Results

I present graphically on Figure 3 the results of estimating the dynamic difference-in-differences version of equation (2). There are no statistically significant differences before the start of the lockdown providing support for the parallel trends assumption. And after the start of the lockdown there are also no statistically significant differences.

Figure 3: Dynamic specification



(A) Raw data relative to lockdown

(B) Coefficients

Notes: This figure reports the dynamic coefficients obtained from the estimation of Equation (**??**) together with 95% confidence intervals. The sample covers the window 9 bi-weeks before and 9 bi-weeks after the lockdown restriction.

Table 2 presents the main regression results. Columns 1-3 present the results of estimating equations (1)-(3), respectively. In the first two cases there is no statistically significant change as we saw on Figure 3. That is, deforestation did not change differentially after the start of the lockdowns. Column 3 shows an increase with a p-value of 10%. But it is similar to the coefficient of the placebo using 2019, and consequently is not significant when doing the triple difference at the border (Column 6).[2] Columns 5 present the results for the simple triple difference-in-differences. Again we do not observe statistically significant results.

I then perform a series of heterogeneity analysis and robustness checks of 2 on Table 3. First, I interact the lockdown defined by work place closure with the government effectiveness index. I find that countries with good governance experience a reduction in deforestation with the lockdown. Then I try different definitions of the start of lockdown in a country. Column 2 uses the date of the stay at home orders and Column 3 the date when restrictions on internal movement started. We still do not observe a statistically

[2]The border result is also not significant when varying the lockdow definition.

Table 2: Main results

	Dependent variable: Percentage of forest area with deforestation alert					
	Simple FE	Finer FE	Border FE	Placebo border FE	3D simple FE	3D border FE
	(1)	(2)	(3)	(4)	(5)	(6)
Lockdown	0.0023	-0.00098	0.0048*		-0.00088	0.0027
	(0.0040)	(0.0034)	(0.0027)		(0.0043)	(0.0036)
Lockdown placebo				0.0021		
				(0.0015)		
Mean dep. var.	0.01	0.01	0.01	0.01	0.01	0.01
SD dep. var.	0.05	0.05	0.05	0.04	0.05	0.01
Observations	122,818	122,818	122,748	123,742	246,718	246,592
Adjusted R^2	0.06	0.15	0.25	0.33	0.12	0.21
Geography fixed effects	c	m	m	m	–	m
Time fixed effects	w	nw	pw	pw	wy, cy, cw	wyp, cy, cw

Notes: The fixed effects notation represent bi-week w, year y, municipality m, country c and pathrow p and continent n. Columns 1-3 of this table reports the coefficient β obtained from the estimation of Equations (1)-(3). Column (4) reports coefficient for the placebo estimation of equation (3), asuming the lockdowns hapenned in 2019. Finally, columns 5 and 6 present coefficients from the estimation of Equation (4). *** p<0.01, ** p<0.05, * p<0.1.

significant change when lockdowns are imposed. Column 4 explores heterogeneity by the week of the lockdown. Maybe at the beginning people respected the lockdown order but stopped complying as they ran out of savings. However the coefficients are similar and not statistically different from zero. Column 5 explores the results using as dependent variable the number of alerts and not the percentage of forest area with alerts. The coefficient is also not significant.

Finally I explore heterogeneity of the effect of the lockdown on deforestation for the countries with the largest forest area. For most of the countries the effect is not statistically different from zero. But I observe there is a differential increase in Mexico, and Brazil . The Mexico result is in line with the media reports on increased deforestation due to monitoring reduction (Gómez, 2020). For Colombia we observe a statistically significant differential decrease, the opposite of the report by (FCDS, 2020). This is because deforestation was considerably higher in Colombia in the first two months of

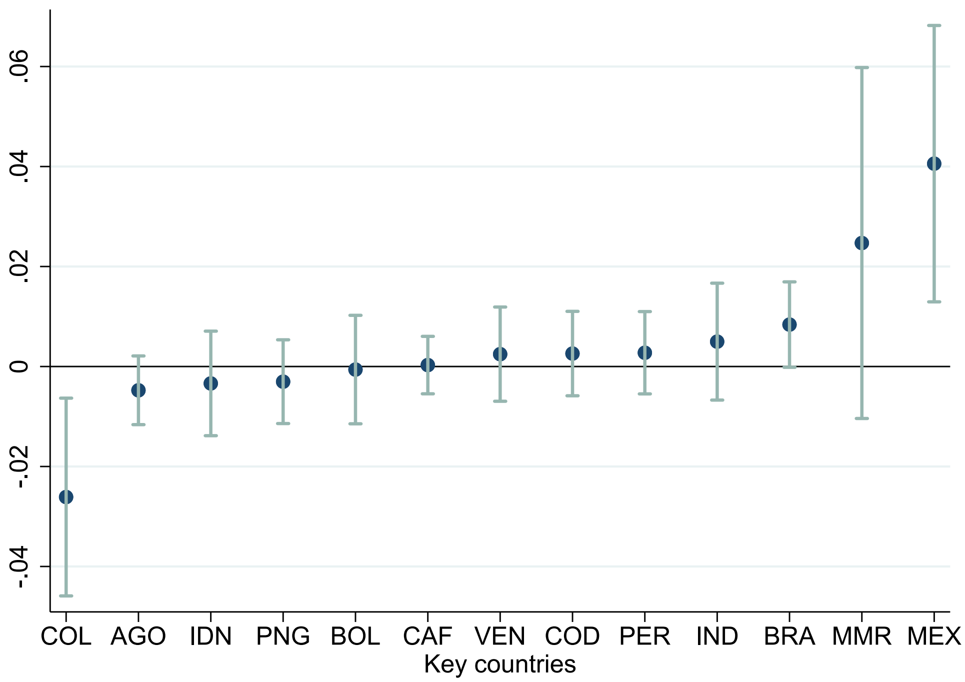
Table 3: Heterogeneity and robustness

Dependent variable:	Percentage of forest area with deforestation alert				N alerts deforestation
	(1)	(2)	(3)	(4)	(5)
Work closure	-0.0042				2.82
	(0.0040)				(25.9)
Lockdown X Governance	-0.0072**				
	(0.0034)				
Stay home		-0.0030			
		(0.0023)			
No internal transport			0.00018		
			(0.0041)		
Lockdown First 3 bi-weeks				-0.0010	
				(0.0040)	
Lockdown After 3 bi-weeks				-0.00089	
				(0.0036)	
Mean dep. var.	0.01	0.01	0.01	0.01	108.49
SD dep. var.	0.06	0.05	0.05	0.05	1047.86
Observations	121,614	122,818	122,818	122,818	122,818
Adjusted R^2	0.15	0.15	0.15	0.15	0.27

Notes: This table presents heterogeneity and robustness results for 2. Column 1 explores heterogeneity by government effectiveness. Column 2 uses stay at home orders as definition of lockdown. While column 3 uses the restrictions on internal transport. Column 4 explore heterogeneous effects by length of the lockdown. Finally, Column 5 uses as a dependent variable the number of deforestation alerts. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

2020 before the start of the lockdown.

Figure 4: Heterogeneity by country



Notes: This figure reports the dynamic coefficients obtained from the estimation of Equation (**??**) together with 95% confidence intervals. The key countries are in order: Colombia (COL), Angola (AGO), Papua New Guinea (PNG), Indonesia (IDN), Bolivia (BOL), Central African Republic (CAF), Venezuela (VEN), Peru (PER), India (IND), Democratic Republic of the Congo (COD), Brazil (BRA), Myanmar (MMR) and Mexico (MEX)

4 Conclusion

Using bi-weekly deforestation alerts I have shown that deforestation has not differentially changed with COVID-19 lockdowns. This is different from the observed reductions in pollution in cities. It is likely that the lockdown orders given in capital cities have not much bite in the forest areas of the country. We confirm this hypothesis when including the index of government effectiveness. Deforestation is reduced in countries with good governance. Other mechanisms behind the effect of lockdowns could be explored further with within country studies.

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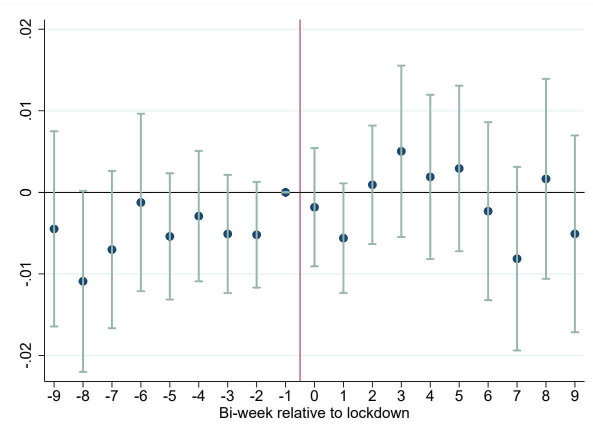
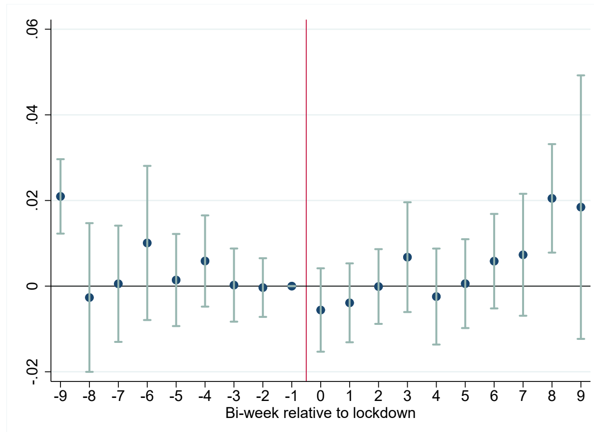
Appendix A Online Appendix

Figure A.1: Dynamic specification



(A) Stay at home order



(B) Internal movement restriction

Notes: This figure reports the dynamic coefficients obtained from the estimation of Equation (**??**) together with 95% confidence intervals. The sample covers the window 6 bi-weeks before and 6 bi-weeks after the lockdown restriction. Panel A reports coefficients for the stay at home closure order. Panel B reports coefficients for the internal movement restriction.

Table A.1: Country details

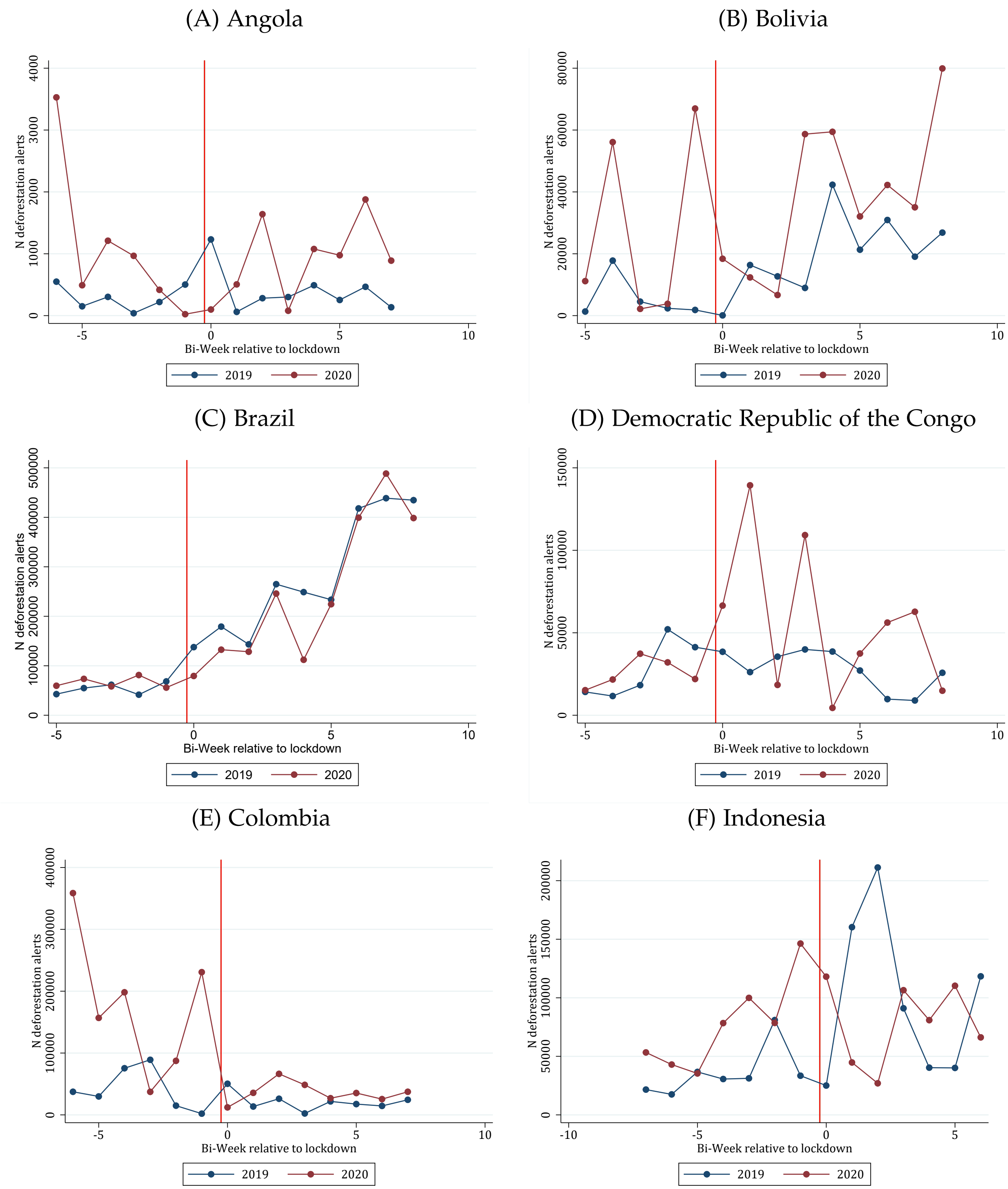
Country Name	Forest (Mkm2)	Admin Level	N unit	Start Lockdown	End Lockdown
Brazil	519.19	2	1,554	11	-
Democratic Republic of Congo	199.22	2	20	12	-
Indonesia	160.98	2	186	15	-
Colombia	81.78	2	654	13	-
Peru	78.07	2	122	11	-
Bolivia	64.52	2	56	12	-
Venezuela	56.53	2	272	11	-
Angola	55.32	2	80	13	-
Mexico	53.18	2	712	13	-
Central African Republic	47.07	2	41	13	24
Papua New Guinea	42.94	2	66	12	25
Myanmar	42.86	2	29	13	-
India	38.81	2	206	12	26
Cameroon	31.47	2	46	12	18
Malaysia	29.42	2	141	12	-
Mozambique	28.91	2	49	25	-
Tanzania	26.42	2	86	-	-
Congo	26.39	2	46	13	-
Gabon	24.70	2	37	12	-
Paraguay	24.30	2	113	11	-
Zambia	24.09	2	12	18	-
Thailand	19.96	2	443	11	23
Laos	19.12	2	134	13	22
Ecuador	19.06	2	57	11	-
Guyana	19.00	2	86	13	-
Philippines	18.60	2	847	11	-
Madagascar	17.14	2	9	12	-
Vietnam	16.58	2	370	13	-
Cote d'Ivoire	14.87	2	16	12	-
Suriname	13.95	2	49	23	-
Ethiopia	12.04	2	27	13	-
Nigeria	10.03	2	175	13	-
Liberia	9.38	2	63	12	-
Cambodia	8.81	2	102	12	26
Guinea	8.16	2	12	13	24
Nicaragua	7.78	2	70	-	-
Uganda	7.77	2	67	13	-
Honduras	7.74	2	160	11	-
Guatemala	7.69	2	160	11	-
Ghana	6.96	2	49	13	16
Panama	5.70	2	71	12	-

Table A.1 – continued from previous page

Country Name	Forest (Mkm2)	Admin Level	N unit	Start Lockdown	End Lockdown
Sierra Leone	5.62	2	13	13	18
Nepal	5.16	2	14	12	-
Cuba	4.01	2	88	16	27
Sri Lanka	3.94	2	180	11	19
Costa Rica	3.91	2	68	10	-
Kenya	3.32	2	134	12	-
Solomon Islands	2.74	2	148	14	-
Dominican Republic	2.58	2	70	12	-
Bhutan	2.58	2	204	13	-
Bangladesh	1.96	2	21	12	22
Belize	1.75	1	6	14	-
Fiji	1.58	2	12	12	-
Malawi	1.52	2	14	-	-
Zimbabwe	1.41	2	6	13	23
Vanuatu	1.18	2	50	13	-
El Salvador	0.99	2	58	11	-
Haiti	0.86	2	17	12	22
Jamaica	0.77	1	13	13	22
Togo	0.56	2	3	12	-
Burundi	0.54	2	11	-	-
Brunei	0.53	2	32	-	-
Puerto Rico	0.52	1	49	11	21
Rwanda	0.50	2	10	12	22
Trinidad and Tobago	0.39	1	15	11	-
Benin	0.17	2	10	13	22
Dominica	0.07	1	10	14	21
Senegal	0.04	2	5	-	-
Singapore	0.02	1	4	14	25
Gambia	0.00	2	20	13	23

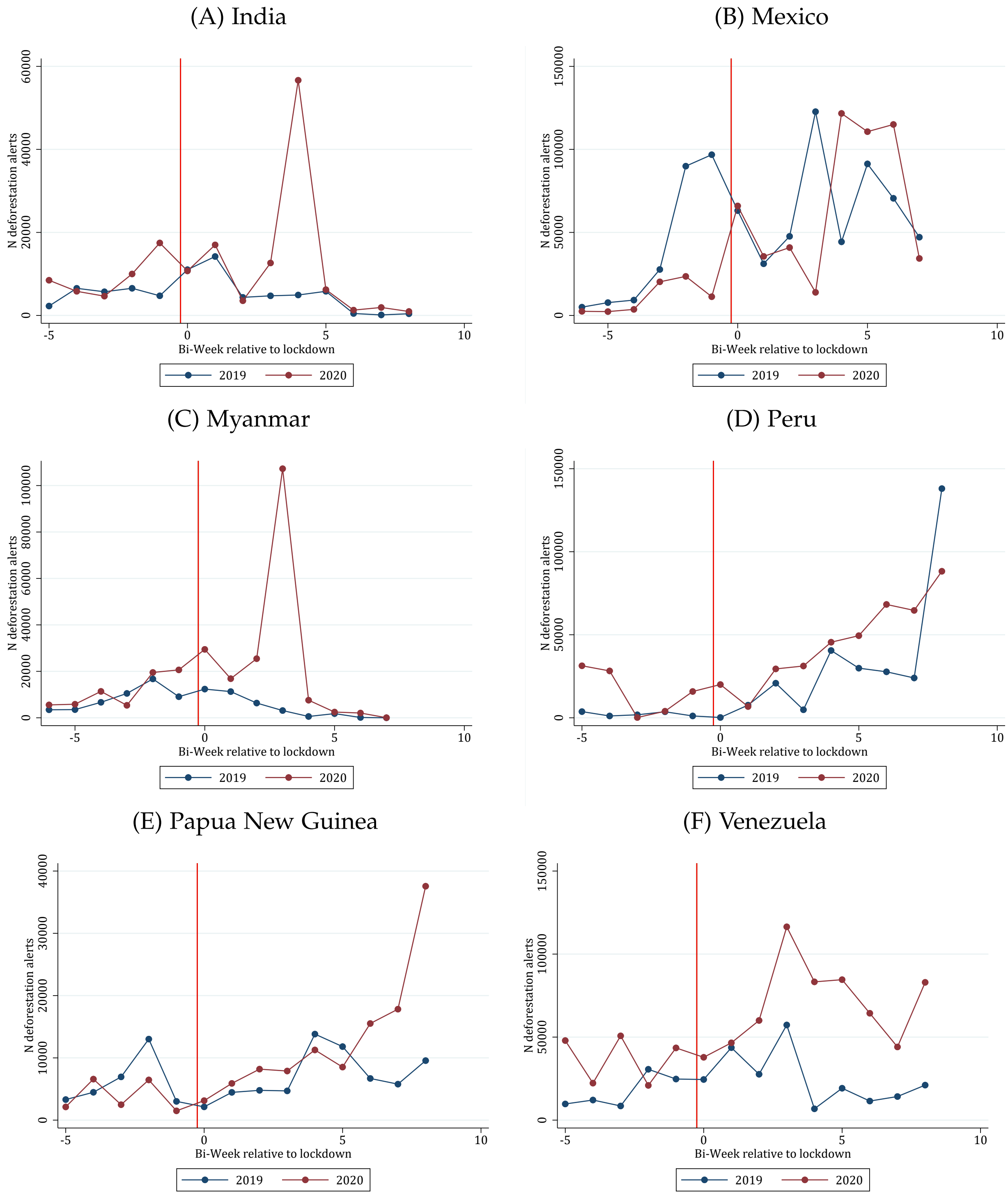
Notes: Details for each country used in the regression analysis

Figure A.2: Deforestation alerts by country



Notes: This figure shows deforestation alerts for 2019 and 2020, by key country. The sample covers the window 11 weeks before and 11 weeks after the lockdown restriction. Red line represents the beginning of lockdown and green line represents the end of the lockdown

Figure A.3: Deforestation alerts by country



Notes: This figure shows deforestation alerts for 2019 and 2020, for the countries with the largest forest area. The sample covers the window 6 bi-weeks before and 6 bi-weeks after the lockdown restrictions. The red line represents the beginning of lockdown and green line represents the end of the lockdown