When nobody is watching:
COVID-19 impacts on the Amazon rainforest

Jerico Fiestas-Flores, Minoru Higa, and Javier Montoya-Zumaeta*

May 11, 2023

Abstract

How has COVID-19 affected the Amazon rainforest? Using an event study design and a difference-in-differences approach, we find that COVID-19 increased deforestation by 35% across the Peruvian Amazon during the first year of the pandemic. This increased CO2 emissions by more than 17 million tons, representing a social cost equivalent to 3 times the national budget for forest management. The main mechanism behind these outcomes is the reduction in monitoring efforts, combined with an increase in illegal activities related to coca production and mining.

Keywords: Deforestation, Pandemic, Social Cost, Forest governance.

JEL Classification: Q23, Q24, Q28, Q54.

---

* *Contact Information:* Jerico Fiestas-Flores, Deparment of Resource Economics and Environmental Sociology, University of Alberta, Edmonton, AB, T6G 2H1, Canada (e-mail: fiestasf@ualberta.ca); Minoru Higa, Department of Economics, Simon Fraser University, Burnaby, BC, V5A 1S6, Canada (e-mail: minoru_higa@sfu.ca); Javier Montoya-Zumaeta, Center for International Forestry Research (CIFOR) - World Agroforestry (ICRAF), Lima, Peru (e-mail: J.G.Montoya@cifor-icraf.org). We are grateful for insightful comments from Fernando Aragon and Vic Adamowicz. We thank the Ministry of Environment in Peru for sharing information about illegal mining.

1 Introduction

Reducing deforestation has the potential to mitigate around one-third of global human-caused carbon emissions (cite ipcc report). Deforestation is most prevalent in developing countries' tropical forests (cite qje y are pp), however, its effects will be felt globally through climate change and biodiversity loss. Therefore, understanding the factors facilitating deforestation is crucial to curb its effects.

This paper examines the effect of the COVID-19 pandemic on Amazon deforestation, using data from Peru. The main contribution of the paper is to provide insights into how a developing country's capacity for environmental monitoring and enforcement was constrained by the pandemic, and how these constraints damaged environmental outcomes such as forest conservation. We provide new evidence of the impact of COVID-19 on deforestation and shed light on the underlying mechanisms driving the estimated causal impact.

Peru is an ideal context for such a study....

To do so, we build a district-level panel dataset with information about annual deforestation covering the period 2015-2020. Our outcome variable is derived from high-resolution Landsat satellite images, corrected to remove potential forest-cover confusions (e.g. plantations) and false positives as a consequence of prediction errors. We first exploit the time variation in deforestation before and after the pandemic in an event study design as our baseline specification. Next, we complement this approach with a difference-in-difference design that exploits the inter-district variation in COVID-19 cases and deaths.

The empirical analysis yields several significant findings. First, we observe a substantial increase in deforestation during the COVID-19 pandemic. Compared to pre-pandemic levels, deforestation in Peru rose by approximately 35%, resulting in a national forest loss of 54 thousand hectares. This finding holds true across various identification strategies, providing robust evidence of the impact.

Second, this surge in deforestation carries significant costs. In 2020 alone, COVID-19-induced deforestation led to emissions exceeding 17 million $tCO_2 - eq$ at the national level. This amounts to an additional social cost of US$131.38 million, three times the budget allocated for forest management in Peru in 2019.

Third, we document a potential mechanism that explains the pandemic's impact on deforestation, namely a decrease in forest monitoring efforts coupled with an increase in illegal deforestation activities. Investments in forest monitoring declined in 2020 at both national and regional levels. Moreover, we observe a spike in illegal activities related to coca leaf production and mining during the same period. Our analysis of heterogeneous effects reveals that districts engaged in coca production or characterized by informal or illegal mining experienced exacerbated levels of deforestation. Intriguingly, while illegal deforestation increased, legal logging activities actually decreased in 2020.

This study contributes to the literature on COVID-19 and environmental outcomes. Previous studies have analyzed the pandemic's impacts on air quality (Brodeur et al., 2021, Dang and Trinh, 2021, Silver et al., 2020), wildlife (Madhok and Gulati, 2022), and environmental regulation (Vale et al., 2021). Regarding the impacts of COVID-19 on deforestation, most studies trace potential impacts based on theoretical models (Wunder et al., 2021) or descriptive analysis (Brancalion et al., 2020, Lopez-Feldman et al., n.d.). The closest in spirit to our study is Saavedra (2020). It uses a difference-in-difference approach to study the effect of national-level lockdowns on deforestation using 70 countries, and it finds no statistically significant effects overall. However, the outcome variable in this study ("vegetation cover change alerts" instead of deforestation) is prone to measurement error that may be attenuating the statistical significance. Moreover, the outcome was measured between January 1, 2019 and July 12, 2020. This disregards a great part of the dry season in the Amazon region (usually between June and November) when slash-and-burn practices are intensified, given the higher prevalence of environmental conditions favoring the flammability of fallen forests

(Aragao et al., 2008).

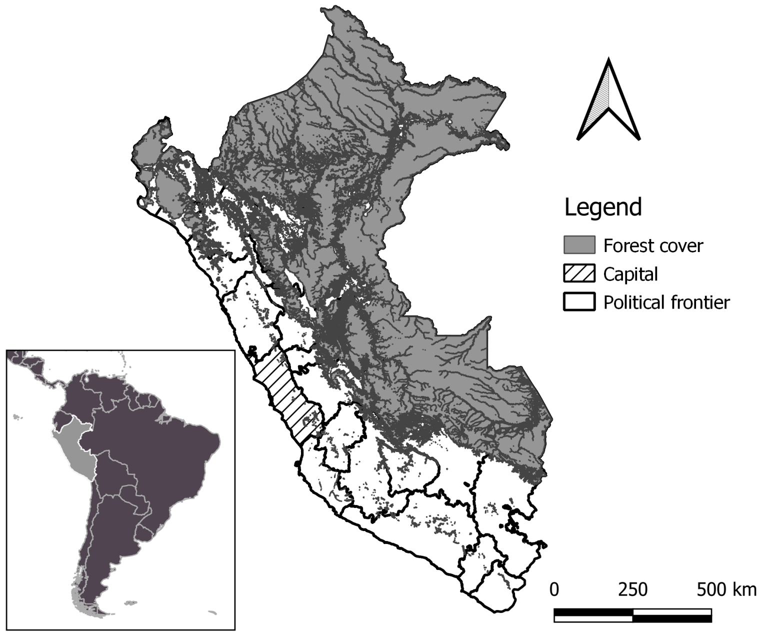
The rest of the paper is organized as follows. Section 2 describes the background. Section 3 describes the data and the empirical approach. Section 4 presents the main results, robustness checks, and heterogeneous effects. Section 5 presents a discussion about the mechanisms and the social cost of deforestation. Section 6 concludes.

2 Background

We use the context of Peru, one of the countries hardest hit by COVID-19 (Higa et al., 2022) and one with the largest extension of tropical forests (Keenan et al., 2015). Peru holds one of the highest COVID-19 mortality rates worldwide, even above countries such as Brazil and India. As of July 2021, there were 2 million COVID-19 cases and more than 600 COVID-19-related deaths per 100,000 inhabitants. Peru implemented stay-at-home orders and social distancing at the start of the pandemic in March 2020. Similar to other countries, the scope of the social restrictions has fluctuated in response to demands to open the economy and based on the number of COVID-19 cases. On the other hand, more than half of Peru's territory (53%) is covered by rainforests. However, on average, more than 128 thousand hectares were annually deforested nationwide between 2001 and 2019, which is equivalent to losing more than 20 soccer fields every hour. Forests in Peru are threatened by activities related to commercial agriculture, gold mining, coca production, and cattle ranching, among others (Finer and Novoa, 2017, Piotrowski, 2019). Figure 1 displays the location of rainforests in the territory.

In Peru, the Law of Forestry and Wildlife (FWL) constitutes the main policy oriented to guarantee the sustainable provision of the benefits generated by the forests. In the last two decades, two FWLs have been introduced in the country. The first one was enacted in 2000 and started to be enforced in 2001. Nevertheless, its numerous reforms were found to be

Figure 1: Forest cover in Peru, 2020



Source: MINAM, 2022

insufficient to effectively halt deforestation across the country (Sears and Pinedo-Vasquez, 2011). As a consequence, a second FWL was introduced in 2011 and enforced since 2015, after a long process of consultation with several groups, including indigenous communities and other stakeholders involved in the forestry sector (e.g., mestizo farmers and small- and medium-sized companies). One of the main reforms introduced by the new law was the creation of SERFOR (Forestry and Wildlife National Service) as the national ruling agency of the forestry sector, which operates jointly with regional forestry authorities. This has boosted the country's capacity to regulate forestry activities across the territory and track forest-related faults. Given the institutional landmark that the SERFOR creation represents in terms of the country's capacity for monitoring deforestation, we focus our analysis on the period after the new FWL, that is from 2015 onwards.

3 Data and Methods

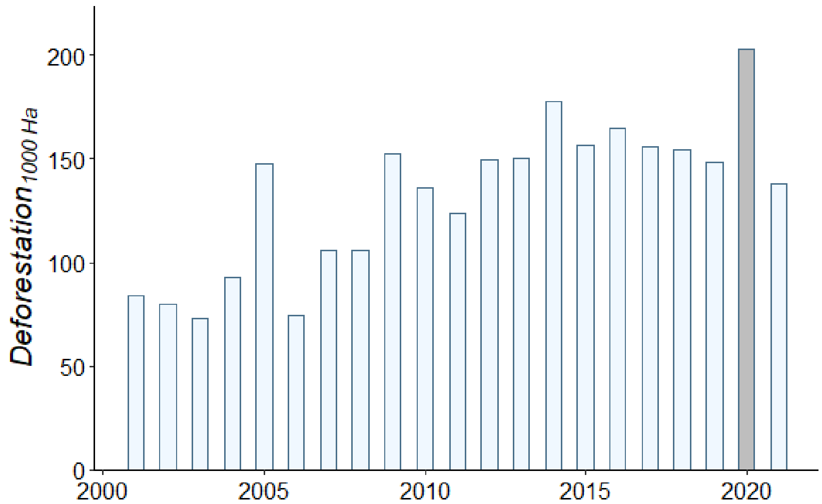
This paper explores the effects of COVID-19 on deforestation. We rely on the official annual forest cover loss data collected by the Ministry of Environment in Peru, which has been available since 2001 (MINAM, 2022). This data is derived from interpreting high-resolution (30m) Landsat satellite images that are corrected to remove potential forest-cover confusions (e.g., plantations) and false positives as a consequence of prediction errors. The information is available only for the 400 districts with tropical forest coverage, about 20% of the 1896 districts in the country. Figure 2, Panel (a), displays the number of deforested hectares by year and highlights that 2020 was the year with the largest deforestation on record. On the other hand, we use COVID-19 data collected by the Ministry of Health in Peru (MINSA, 2022). This data contains information about the number of COVID-19 cases and deaths caused by COVID-19 in each district in the country. A description of the main variables used in the analysis and summary statistics are provided in Tables B.1 and B.2, respectively, in the Appendix.

Baseline approach Figure 2, Panel (b), shows a positive correlation between the number of COVID-19 cases and the deforestation in each district, indicating a possible effect of the pandemic on deforestation. To study this potential effect, we use an event study and estimate the following model:

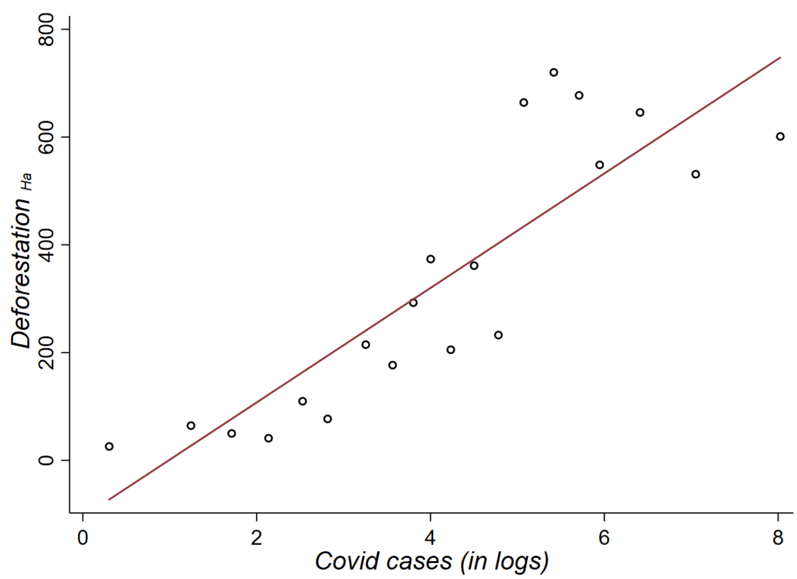
$$y_{it} = \sum_{Q=0}^{1} \beta_Q D_Q + \gamma_i + \epsilon_{it} \tag{1}$$

where the unit of observation is district i in year t. y_{it} represents the deforestation outcome variable. D_Q is an indicator variable that equals one when the year is 2020 and zero otherwise. The omitted category is the pre-pandemic year 2019. γ_i includes district fixed effects. Standard errors are clustered at the district level. Our identification strategy exploits time variation across years: we compare changes in deforestation before (2019) and

Figure 2: Deforestation and COVID-19



(a) Annual country-level deforestation, 2001-2021



(b) Correlation between COVID-19 and deforestation

Notes: Panel (a) depicts the annual deforestation ('000 ha) from 2001-2021. Panel (b) depicts a binscatter with deforestation (ha) on the vertical axis and COVID-19 infections (in logs) on the horizontal axis. Information comes from MINAM (2022), MINSA (2022).

after (2020) the pandemic. We also conduct robustness checks by extending the pre-pandemic period to 2015-2019.

Difference-in-Difference design We complement our baseline regression using a difference-in-difference approach. Specifically, we estimate the following model using our panel of districts:

$$y_{it} = after_t + \text{COVID-19}_i + \beta(\text{COVID-19}_i * after_t) + \epsilon_{it} \tag{2}$$

where the unit of observation is district i in year t. y_{it} is the deforestation outcome variable. $after_t$ is a dummy variable that equals one if the period corresponds to 2020 or zero if the period encompasses the years 2015-2019. COVID-19_i is our treatment indicator variable that equals one if the district had COVID-19 cases above the national median in 2020 (i.e., 28 cases). Hence, we exploit the district-level variation in exposure to COVID-19 to identify the effects of the pandemic on deforestation.

4 Results

Table 1 shows our main results. Column 1 presents estimates from our event study in Equation 1. Columns 2 and 3 present difference-in-difference (DiD) estimates from Equation 2.

Our main results suggest that deforestation in Peru increased significantly due to the pandemic. The average deforestation per district increased by approximately 35% in 2020 compared to pre-pandemic levels. This corresponds to an additional reduction in forest cover of 54 thousand hectares at the national level, which is equivalent to the surface of more than 77 thousand soccer fields. We can identify the combined effect of shocks associated with COVID-19 on deforestation, but we cannot single out a particular policy. Reverse causality is less worrisome in our context given the evidence that forest loss does not affect the incidence of respiratory diseases (Berazneva and Byker, 2017).

Table 1: Main results

	Dependent variable: Deforestation (ha)		
	(1)	(2)	(3)
Year 2020	137.12***		
	(17.589)		
DiD		153.54***	140.11***
		(35.68)	(31.62)
Design	Event study	DiD	DiD
District-specific time trends	No	No	Yes
Pre-pandemic period	2019	2015-2019	2015-2019
Mean outcome (pre-pandemic)	371.1	390.1	390.1
N	800	2,394	2,394
R-squared	0.966	0.04	0.04

Notes: Estimated standard errors, reported in parentheses, are clustered at the district level. Significance at the one, five, and ten percent levels is indicated by ***, **, and *, respectively. See Table B.3 in the Appendix for similar results using our event study design but expanding the pre-pandemic period to 2015-2019, and using our difference-in-difference approach but restricting the pre-pandemic period to 2019.

Identification concerns Results in Column (1) may be biased under the presence of unobserved time-varying confounders. For example, we cannot disentangle annual trends or other non-COVID-19 related shocks in Equation 1. To attenuate this concern, in Column (3), we complement our baseline approach with a difference-in-difference design that controls for district-specific time trends. The stability of our outcome variable before the pandemic also helps mitigate the concern (see Panel (b) in Fig 3).

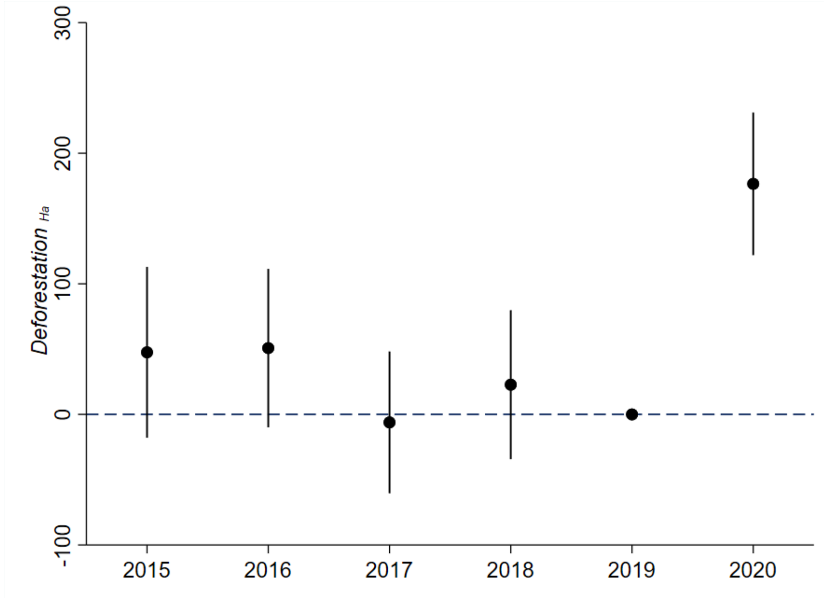
There may be some identification concerns regarding our DiD complementary approach. First, it relies on the assumption that the treatment and control groups have a common trend over time in deforestation. Figure 3 presents evidence that both groups may have been experiencing similar trends in the outcome variable prior to treatment. Panel (a) depicts the estimates from an event study that assesses whether there are differences in deforestation between treated and control districts every year. A district is treated if the number of

COVID-19 cases (in 2020) in their jurisdiction was above the national median. Circles represent point estimates from regressing deforestation on dummy variables corresponding to the interaction between the year and treatment dummies, controlling for year and district-fixed effects. The omitted category is the year 2019. Vertical lines show 95 percent confidence intervals, calculated using standard errors clustered at the district level. Except for 2020, the differences in deforestation between the treatment and control groups are not statistically significant at a five percent level of significance. Likewise, Panel (b) provides more graphical evidence of parallel trends over time. We also use recent developments to test violations of parallel trends, following Rambachan and Roth (2023). We find that our result is robust to allowing for violations of post-treatment parallel trends up to 1.5x as big as the maximum violation in the pre-treatment period (see Figure A.3 in the Appendix).

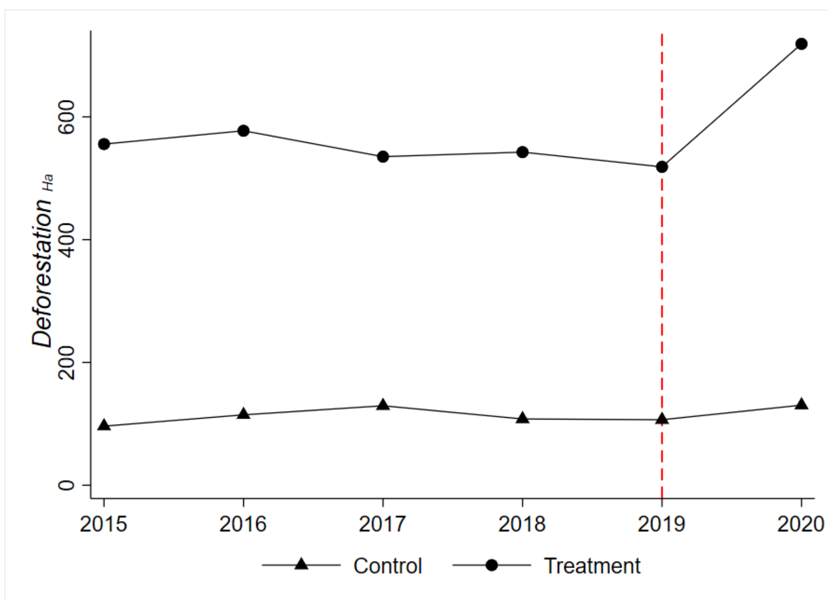
Second, our treatment may be correlated with unobserved events that differently affected the treatment and control groups. To address this concern, we include district-specific time trends to allow the treatment and control districts to follow different trends (see Column (3) in Table 1). Finally, the composition of the treatment and control groups may have changed between the pre-treatment and post-treatment periods. Given that our unit of observation is a district, it is unlikely that its composition and characteristics changed dramatically before vs. after the pandemic. However, in order to mitigate this potential concern, we combine our difference-in-difference design with propensity score matching (PSM).

Additional robustness checks Table 2 shows that our main results are robust across different specifications. Column (1) displays estimated coefficients from Equation 2 after restricting the sample to districts with forests that covered 20% or more of their territories in 2015. We use this threshold to avoid potential biases by including districts with substantially different environmental features in the sample. Results suggest that the higher the coverage percentage in the district, the higher the magnitude of the effect. To address concerns

Figure 3: Evidence of parallel trends



(a) Event study



(b) Average deforestation 2015-2020

Notes: Panel (a) depicts the estimates from an event study that assesses whether there are differences in deforestation between treated and control districts every year. Panel (b) depicts the average deforestation for treated and control districts during 2015-2020. A district is treated if the number of COVID-19 cases (in 2020) in their jurisdiction was above the median in the country.

regarding measurement error in our treatment variable, in Column (2), we use COVID-19 deaths instead of COVID-19 infection cases as an alternative measurement of our treatment. Here, a district is treated if it registered deaths due to COVID-19. Columns (4) and (5) display the results from applying the difference-in-difference approach to samples matched by their corresponding propensity score. Columns (4) and (5) use COVID-19 infection cases and deaths as the measures of treatment, respectively. We construct control groups based on the conditional probability of districts to be assigned to the treated group, given proxies for biophysical, geographical, and socioeconomic drivers that could exert some influences on deforestation (Busch and Ferretti-Gallon, 2017). We find larger coefficients than those in Table 1 as potential confounders are controlled. We use information from 2019 or earlier on district-level total surface area (IGN, 2022); river area, road number, and distance to the capital city (MTC, 2022); altitude (ECLAC, 2022); slopes (Farr et al., 2007); forest cover (MINAM, 2022); population density (ECLAC, 2022); and human development index scores (ECLAC, 2022). Post-matching covariate balance shows that the procedure achieves important bias reductions in the resulting samples (see Figure A.1 in the appendix).

Heterogeneous effects We also explore the heterogeneous effects of COVID-19 on deforestation based on the incidence of coca production, illegal or informal mining, and protected areas in the districts. We focus our analysis on coca production and mining due to their notorious potential to trigger short-term land use changes across the Peruvian Amazon (Swenson et al., 2011, Young, 1996). We also analyze the role of protected areas because this is the most frequent policy applied to deter deforestation processes in the country. Instead of being a single command-and-control instrument, it encompasses a wide range of governance regimes with different levels of national agencies participation. One-quarter of the Peruvian Amazon region is under some protected area regime (SERNANP, 2022). Aside from these

Table 2: Robustness Checks

	Dependent variable: Deforestation (ha)			
	(1)	(2)	(3)	(4)
DiD	193.93***	149.50***		
	(46.64)	(27.77)		
DiD-PSM			171.44*	220.43***
			(91.60)	(44.84)
Measure of COVID-19	Cases	Death	Cases	Death
N	1,728	2,394	1,710	1,705
R-squared	0.05	0.04	0.04	0.06

Notes: All regressions control for district fixed-effects and consider the years 2015-2019 as the pre-pandemic period. Estimated standard errors, reported in parentheses, are clustered at the district level. Significance at the one, five, and ten percent levels is indicated by ***, **, and *, respectively.

two drivers, commercial agriculture and cattle ranching have also been identified as relevant deforestation drivers across the Peruvian Amazon. However, both these activities follow complex dynamics that delay by several years the transition from forests to temporary land uses (Armas et al., 2009). Therefore, they are less likely to play a role in the impact of the pandemic on deforestation.

Table 3 displays our results. We find that deforestation is exacerbated in districts with coca production, or with informal or illegal mining. On the other hand, the presence of protected areas mitigated the effects of deforestation in the district, with increasing efficacy as the areas under protection get larger. This result is in line with previous findings that highlight the role of decentralized management models of protected areas in successfully mitigating deforestation (Schleicher et al., 2017). Our outcome variable is the annual rate of forest change between 2020 and 2019. Given that deforestation was higher in 2020 compared to 2019, the annual rate of forest change is a negative number. To ease the interpretation of

Table 3: Heterogeneous effects

	Dependent variable: Annual rate of forest change, 2019-2020	
	(1)	(2)
Year 2020	2.19***	2.17***
	(0.21)	(0.21)
Mining	0.17*	0.18*
	(0.09)	(0.09)
Coca	0.21**	0.19*
	(0.10)	(0.10)
Protected areas	-0.34***	-0.44***
	(0.08)	(0.08)
N	394	394
R-squared	0.53	0.54

Notes: Estimated standard errors, reported in parentheses, are clustered at the district level. Significance at the one, five, and ten percent levels is indicated by ***, **, and *, respectively. Regressions include other district characteristics such as population density, river area, altitude, number of roads, distance to the capital city, and slope (see Table B.4 in the Appendix).

results, we multiply the estimated rate by -1. We then regress our modified outcome variable on dummy variables that capture whether the year is 2020, whether coca production was recorded in the district in 2017 (using data from UNODC (2017)), and on whether there was illegal or informal mining activity in the district (using data provided by MINAM (2016)). All the regressions control for the average district slope, the total district area, and the extension of rivers and national roads. Columns (1) and (2) present the estimates from the regression. The only difference between the columns is the treatment of the variable protected areas. It equals one if there are protected areas in the district in Column (1), while in Column (2) it equals one if protected areas represent 10% or more of the territory in the district. We made this differentiation to assess the extensive margin and the intensity of the protected areas policy in mitigating the COVID-19 deforestation effects.

In summary, we identify the weakened institutional capacity of the country to conduct monitoring and enforcement activities as a mechanism through which COVID-19 emergence enabled an increase in deforestation. This institutional weakening led to an exacerbation of illegal and informal activities driving forest loss.

5 Discussion

5.1 CO2 emissions and social cost

We estimate the impact of the deforestation caused by the pandemic in terms of carbon (CO) emissions and the corresponding social costs. We use the following equation to calculate the released tonnes of equivalent CO:

$$tCO_2\text{-}eq = (Def_{2020} \times n \times E) * 3.67 \tag{3}$$

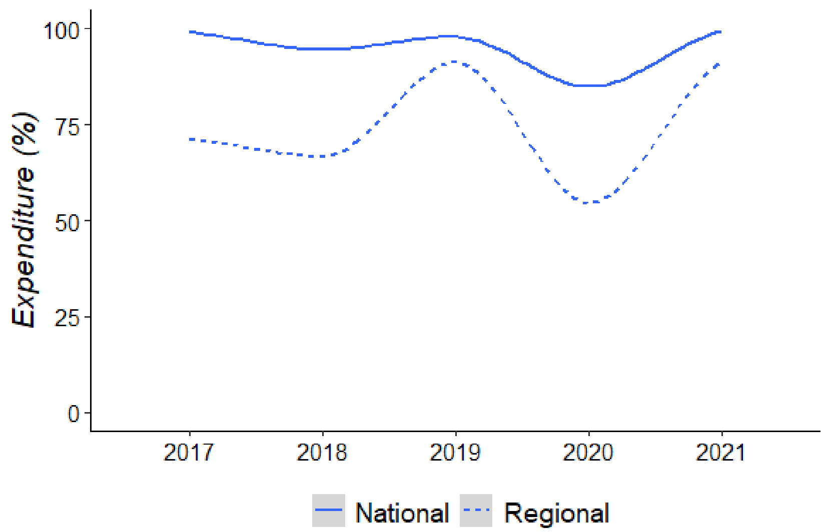
Where tonnes of $tCO_2\text{-}eq$ are estimated using the increase in deforestation observed in 2020 (Def_{2020}) and captured by our estimates from Equation 1 (Column 1 of Table 1). We multiplied this by the number of districts in our data ($n = 400$), and by a parameter representing a fixed amount of tonnes of CO released per deforested hectare ($E = 84.54\ tCO/ha$) that was previously estimated by the Ministry of the Environment in Peru, considering the different types of forest in the country (Malaga et al., 2014). This is then transformed to $tCO_2\text{-}eq$ by multiplying by 3.67 (i.e., the factor to transform carbon to carbon dioxide).

Our result shows that COVID-19 could have contributed to the release of 12.7 to 21.3 million $tCO_2\text{-}eq$ in 2020. Using the social cost of carbon of 7.72 USD/$tCO_2\text{-}eq$ estimated for Peru (MEF, 2021), we calculate the associated economic losses to be around USD 98.2 million and 164.5 million (see Table B.5 in the Appendix). This cost represents almost three times the national annual budget allocated to forest protection in the country.

5.2 Mechanisms

A potential mechanism explaining the impact of the pandemic on deforestation is a decrease in forest monitoring efforts, paired with an increase in illegal deforestation activities. Figure 4 shows that the investment in activities related to forest monitoring between 2019 and 2020, at the national and regional levels, experienced a reduction of 13 and 37 percentage points, respectively. We interpret this as evidence that monitoring activities may have decreased, making it more difficult to detect illegal activities in forested areas in the Amazon.

Figure 4: Budget expenditures (%) in forest monitoring, 2017-2021



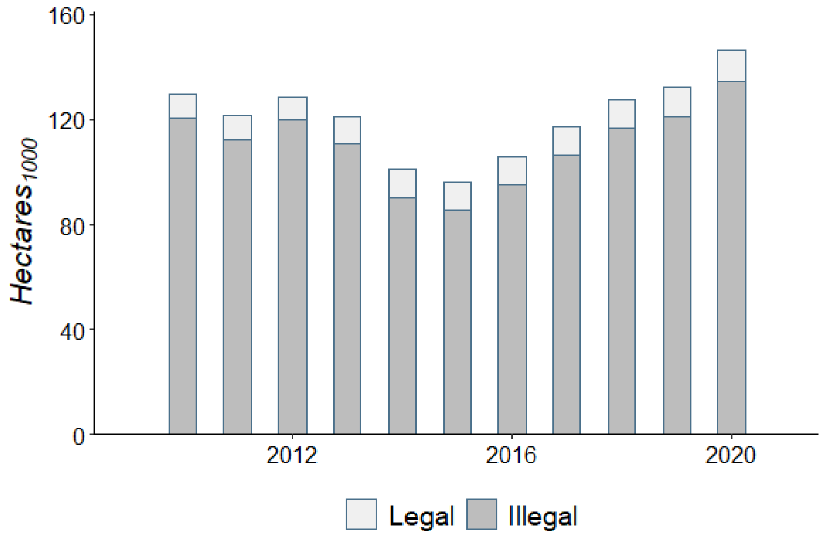
Notes: Figure depicts the budget expenditures (%) at the national and regional level for activities related to forest monitoring by the end of each year, from 2017 to 2021.
Source: MEF (2022)

Illegal coca production and illegal mining are also related to higher deforestation during the pandemic. Results from the heterogeneity section show that deforestation was exacerbated in districts with coca production or with informal or illegal mining. In addition, Panel (a) in Figure 5 shows that illegal coca production reached a peak in 2020, possibly caused by the reduction of eradication efforts during the pandemic, as shown in Panel (b). Likewise, journalistic reports (e.g., Vera (2020)) attest to the intensification of artisanal mining in highly forested areas in 2020.

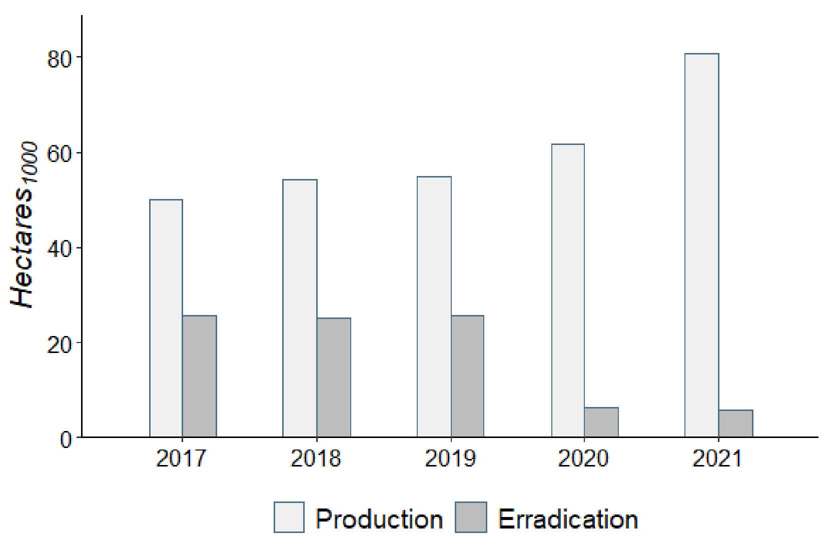
The variation in our deforestation outcome seems to be driven by illegal deforestation. Our outcome accounts for both legal (concession logging, agriculture, etc.) and illegal deforestation (mining, coca). However, legal logging activities decreased in 2020, as shown in Figure 6, which displays information regarding round wood production in the last decade. This suggests that our findings are mostly linked to deforestation related to the illegal activities described earlier.

The economic crisis generated by the pandemic offers two additional mechanisms: (i) the trade-off between livelihoods and the forests, and (ii) migration. The economic crisis and the lack of employment could have led to people clearing more forests. Individuals participating in forest-clearing activities could have intensified their efforts (intensive margin) or individuals could have switched from other activities to clearing forests (extensive margin). However, there is evidence that tropical forests have a key role in rural contexts in providing wild food (fish, bushmeat, fruits, etc.) to the community (Van Vliet et al., 2017). Moreover, we observe that deforestation and a food vulnerability index are negatively correlated (see Figure A.2 in the Appendix). Overall, although this could have explained some of the deforestation, it would be unlikely to explain the huge increase we observe. In terms of migration, the economic downturn pushed migrants located in cities to move back to their home rural areas. This increase in population could have put pressure on forests through residents' participation in economic activities driving deforestation. Fort et al. (2021) explore this hypothesis and find a weak correlation (0.086) between deforestation in 2019-2020 and the number of people returning to their cities of origin due to the pandemic. While this figure considers only returning migrants and not all migrants, due to a lack of data we cannot explore further this channel.

Figure 5: Coca production and eradication



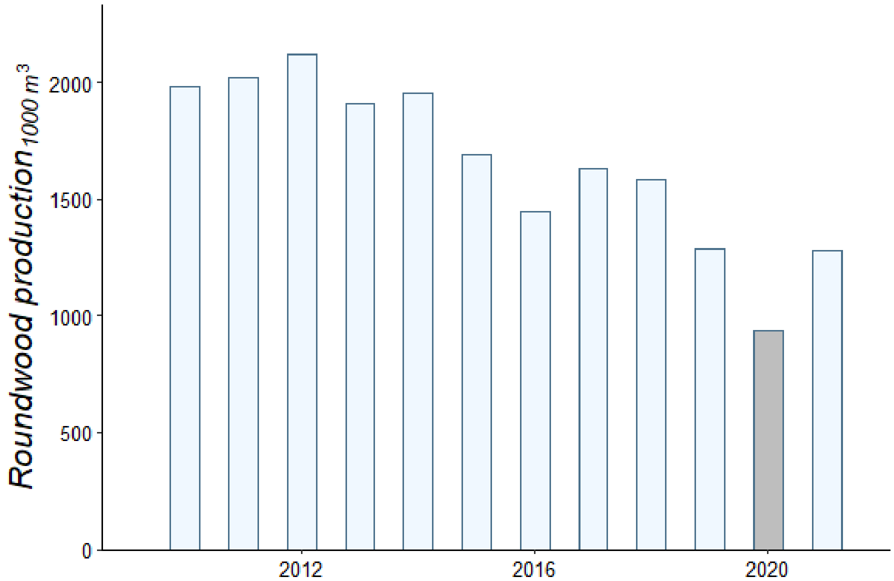
(a) Legal and illegal coca production, 2010-2020



(b) Hectares of Coca produced and eradicated, 2017-2021

Notes: Panel (a) depicts the production of coca leaves in metric tonnes for legal and illegal markets. Panel (b) depicts the hectares of coca leaves produced and eradicated. Data is from DEVIDA (2022).

Figure 6: Roundwood production, 2010-2020



Notes: This figure depicts the roundwood production for 2010-2021 recorded by the national government.
Source: SINIA, 2022

6 Concluding remarks

Forests provide multiple ecosystem services at both individual and societal levels. They promote soil health, good water quality, and biological diversity, all while providing a vital carbon sink. Forest conservation and sustainable forest management are crucial to engage global threats such as climate change and biodiversity loss.

However, this paper provides evidence that COVID-19 increased deforestation in the Amazon. This surge in deforestation might have had a considerable negative net impact on Peru's climate commitments. Our findings also unveil the role that illegal and informal activities, such as coca leaf production and mining, have had on tropical forest loss during the COVID-19 pandemic in the country, and highlight the importance of protected areas in significantly mitigating the deforestation triggered by the pandemic across the Peruvian Amazon.

Further research should be done to better understand the role of governance regimes in preventing forest loss during the COVID-19 pandemic, and to evaluate the consequences of the pandemic on biodiversity loss due to the increase in deforestation.

References

Aragao, Luiz Eduardo O.C, Yadvinder Malhi, Nicolas Barbier, Andre Lima, Yosio Shimabukuro, Liana Anderson, and Sassan Saatchi, "Interactions between rainfall, deforestation and fires during recent years in the Brazilian Amazonia," *Philosophical Transactions of the Royal Society B: Biological Sciences*, 2008, *363* (1498), 1779–1785.

Armas, Angel, Jan Borner, Marco Rugnitz Tito, Licely Diaz Cubas, Sandra Tapia Coral, Sven Wunder, Louis Reymond, and Nathalia Nascimento, "Inventario Nacional de Gases de Efecto Invernadero del Año 2016," Technical Report, SERNANP 2009.

Berazneva, Julia and Tanya S Byker, "Does forest loss increase human disease? Evidence from Nigeria," *American Economic Review*, 2017, *107* (5), 516–21.

Brancalion, Pedro HS, Eben N Broadbent, Sergio De-Miguel, Adrián Cardil, Marcos R Rosa, Catherine T Almeida, Danilo RA Almeida, Shourish Chakravarty, Mo Zhou, Javier GP Gamarra et al., "Emerging threats linking tropical deforestation and the COVID-19 pandemic," *Perspectives in ecology and conservation*, 2020, *18* (4), 243–246.

Brodeur, Abel, Nikolai Cook, and Taylor Wright, "On the effects of COVID-19 safer-at-home policies on social distancing, car crashes and pollution," *Journal of environmental economics and management*, 2021, *106*, 102427.

Busch, Jonah and Kalifi Ferretti-Gallon, "What Drives Deforestation and What Stops It? A Meta-Analysis," *Review of Environmental Economics and Policy*, 2017, *11* (1), 3–23.

Dang, Hai-Anh H and Trong-Anh Trinh, "Does the COVID-19 lockdown improve global air quality? New cross-national evidence on its unintended consequences," *Journal of Environmental Economics and Management*, 2021, *105*, 102401.

ECLAC, "Informacion para el planeamiento a nivel departamental, provincial y distrital," 2022. Website: https://www.ceplan.gob.pe/informacion-sobre-zonas-y-departamentos-del-peru/, accessed on September 22nd, 2022.

Farr, Tom G, Paul A Rosen, Edward Caro, Robert Crippen, Riley Duren, Scott Hensley, Michael Kobrick, Mimi Paller, Ernesto Rodriguez, Ladislav Roth et al., "The shuttle radar topography mission," *Reviews of geophysics*, 2007, *45* (2).

Finer, Matt and Sydney Novoa, "Patrones y drivers de deforestacion en la Amazonia Peruana," 2017. MAAP: Sintesis 2. Accessed July 15, 2022. https://www.maaproject.org/2017/maap-sintesis2/.

Fort, Ricardo, Mauricio Espinoza, and Alvaro Espinoza, "COVID-19 y las migraciones de la ciudad al campo en el Peru: Identificacion de amenazas y oportunidades para el uso sostenible del capital natural (Resumen)," 2021.

Higa, Minoru, Carlos Ospino, and Fernando Aragon, "The persistent effects of COVID-19 on labour outcomes: evidence from Peru," *Applied Economics Letters*, 2022, *0* (0), 1–12.

IGN, "GeoPortal - IGN Peru," 2022. Website: https://www.idep.gob.pe/geovisor/descarga/visor.html, accessed September 22nd, 2022.

Keenan, Rodney J., Gregory A. Reams, Frederic Achard, Joberto V. de Freitas, Alan Grainger, and Erik Lindquist, "Dynamics of global forest area: Results from the FAO Global Forest Resources Assessment 2015," *Forest Ecology and Management*, 2015, *352*, 9–20. Changes in Global Forest Resources from 1990 to 2015.

Lopez-Feldman, Alejandro, Carlos Chavez, and Ve, "Environmental impacts and policy responses to Covid-19: a view from Latin America."

Madhok, Raahil and Sumeet Gulati, "Ruling the roost: Avian species reclaim urban habitat during India's COVID-19 lockdown," *Biological Conservation*, 2022, p. 109597.

Malaga, Natalia, Renzo Giudice Granados, Christian Vargas Gonzales, and Eduardo Rojas Bae, "Estimacion de los contenidos de carbono de la biomasa aerea en los bosques de Peru," Technical Report, MINAM 2014.

MEF, "Nota tecnica para el uso del precio social del carbono en la evaluacion social de proyectos de inversion," Technical Report 2021.

MEF, "Transparencia Economica Peru - Consulta de Ejecucion del Gasto Mensual," 2022. Website: https://apps5.mineco.gob.pe/transparencia/mensual/, accessed September 22nd, 2022.

MINAM, "Zonas con Mineria Ilegal e Informal," Technical Report 2016.

MINAM, "GeoBosques. Plataforma de monitoreo de cambios sobre la cobertura de bosques," 2022. Website: http://geobosques.minam.gob.pe/, accessed September 22nd, 2022.

MINSA, "Datos Abiertos Minsa y Gestion del Conocimiento en COVID-19," 2022. Website: https://www.minsa.gob.pe/datosabiertos/, accessed September 22nd, 2022.

MTC, "Descarga de datos espaciales," 2022. Website: https://portal.mtc.gob.pe/estadisticas/descarga.html, accessed September 22nd, 2022.

Piotrowski, Matt, "Nearing the Tipping Point. Drivers of Deforestation in the Amazon Region," Technical Report, Andes Amazon Fund 2019.

Rambachan, Ashesh and Jonathan Roth, "A more credible approach to parallel trends," *Review of Economic Studies*, 2023, p. rdad018.

Saavedra, Santiago, "Do COVID-19 Lockdowns Affect Deforestation?," *Working paper*, 2020.

Schleicher, Judith, Carlos A Peres, Tatsuya Amano, William Llactayo, and Nigel Leader-Williams, "Conservation performance of different conservation governance regimes in the Peruvian Amazon," *Scientific reports*, 2017, *7* (1), 1–10.

Sears, Robin R. and Miguel Pinedo-Vasquez, "Forest Policy Reform and the Organization of Logging in Peruvian Amazonia," *Development and Change*, 2011, *42* (2), 609–631.

SERNANP, "GEO ANP - Visor de las Areas Naturales Protegidas," 2022. Website: https://geo.sernanp.gob.pe/visorsernanp/,accessed September 22nd, 2022.

Silver, Ben, Xinyue He, Steve R Arnold, and Dominick V Spracklen, "The impact of COVID-19 control measures on air quality in China," *Environmental Research Letters*, 2020, *15* (8), 084021.

Swenson, Jennifer J., Catherine E. Carter, Jean-Christophe Domec, and Cesar I. Delgado, "Gold Mining in the Peruvian Amazon: Global Prices, Deforestation, and Mercury Imports," *PLOS ONE*, 04 2011, *6* (4), 1–7.

UNODC, "Peru - Monitoreo de Cultivos de Coca 2017," Technical Report 2017.

Vale, Mariana M, Erika Berenguer, Marcio Argollo de Menezes, Ernesto B Viveiros de Castro, Ludmila Pugliese de Siqueira, and Q Portela Rita de Cássia, "The COVID-19 pandemic as an opportunity to weaken environmental protection in Brazil," *Biological Conservation*, 2021, *255*, 108994.

Vera, Enrique, "Madre de Dios: nuevo foco de mineria ilegal amenaza a indigenas del Pariamanu," 2020.

Vliet, Nathalie Van, Jessica Lizeth Moreno Calderón, Juanita Gomez, Wen Zhou, John Emmanuel Fa, Christopher Golden, Romulo Romeu Nobrega Alves, and Robert Nasi, "Bushmeat and human health: assessing the evidence in tropical and sub-tropical forests," 2017.

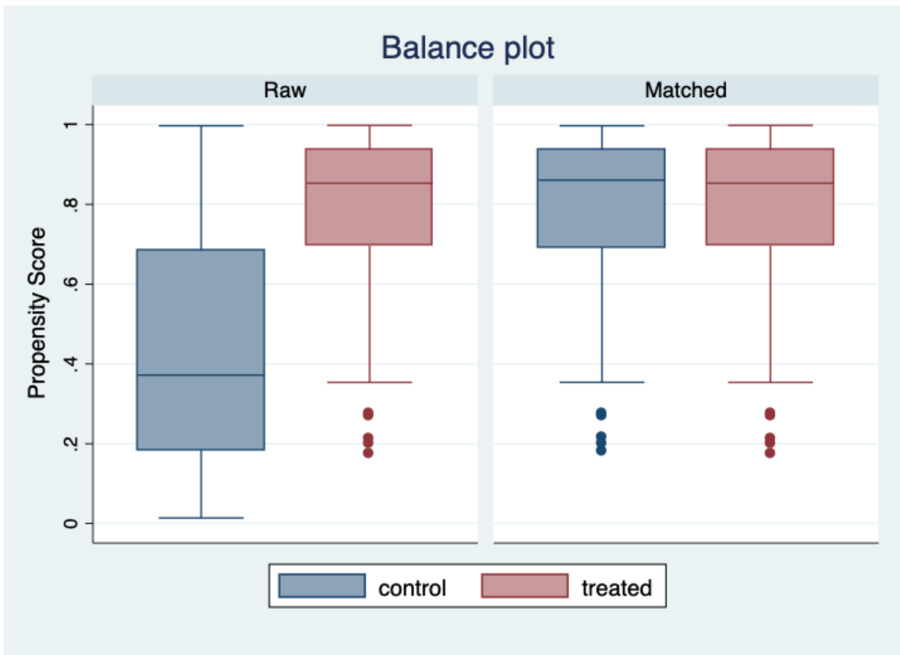
Wunder, Sven, David Kaimowitz, Stig Jensen, and Sarah Feder, "Coronavirus, macroeconomy, and forests: What likely impacts?," *Forest Policy and Economics*, 2021, *131*, 102536.

Young, Kenneth R., "Threats to biological diversity caused by coca/cocaine deforestation in Peru," *Environmental Conservation*, 1996, *23* (1), 7â15.

APPENDIX

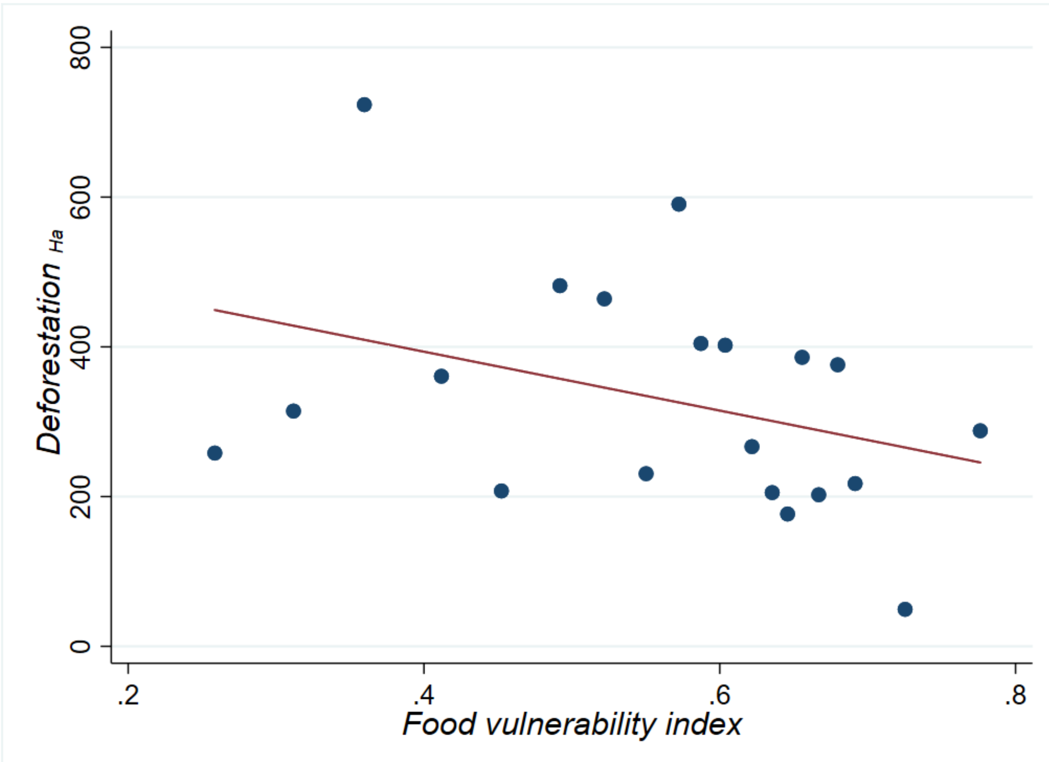
A Additional figures

Figure A.1: Balance plot - COVID-19 Cases



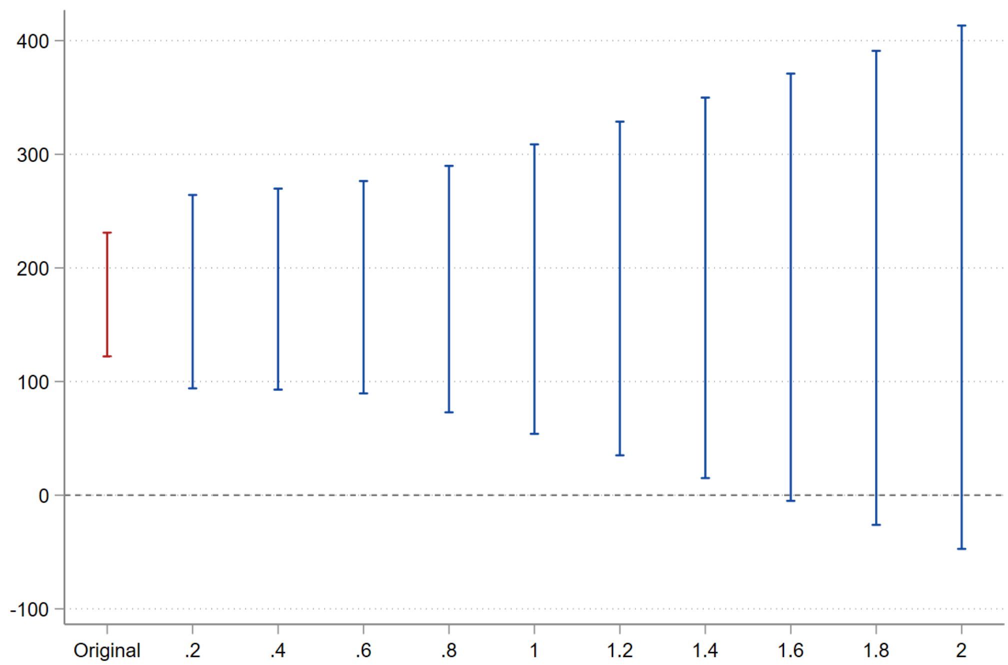
Notes: Sample balance before (left panel) and after (right panel) applying the propensity score matching procedure, using COVID-19 cases number per district as treatment variable (1 = above the country median).

Figure A.2: Deforestation and Food Vulnerabiltiy Index



Notes: Figure depicts a binscatter with deforestation (ha) in the vertical axis and food vulnerability index in the horizontal axis. Both are for the year 2018.
Source: CEPLAN, 2022, MINAM, 2022

Figure A.3: Sensitivity analysis of violations of parallel trends



Notes: Figure depicts a sensitivity analysis of post-treatment violations of parallel trends. It displays in red the confidence interval for the estimated coefficient associated with the year 2020 in the original event study in Figure 3. It displays in blue robust confidence intervals that allow for post-treatment violation of parallel trends to be no more than some constant (e.g. 0.2, 0.4, etc.) larger than the maximum violation of parallel trends in the pre-treatment period.

B Additional tables

Table B.1: Variables description and data sources

Variable	Description	Availability	Data Source
Panel A. Forest			
Deforestation	Forest cover reduction (hectares) in districts	2015-2020	MINAM, 2022
Panel B. Covid			
Cases	Number of people that tested positive to COVID-19 per district	2020	MINSA, 2022
Deaths	Number of people that died due to COVID-19 per district	2020	MINSA, 2022
Panel C. District characteristics			
Coca	Hectares of coca leaf production per district	2017	COVIDA, 2017
Mining	Districts with presence of illegal or informal mining	2016	MINAM, 2016
ANP	Districts with presence of a Natural Protected Area	2017	SERNAP, 2017
Roads	Number of national roads in the district	2017	MTC, 2022
Rivers	River's area in the district (km2)	2017	MTC, 2022
Population	Population in the district	2017 & 2020	CEPLAN, 2020
Area	District's area (km2)	2019	CEPLAN, 2020
HDI	Human development index	2015 & 2019	CEPLAN, 2020
Slope	Average slope of district	2007	Farr et al, 2007
Altitud	Average altitude of district (masl)	2020	CEPLAN, 2022

Notes: Table displays the description, availability, and source for the main variables. All variables are at the annual level.

Table B.2: Summary statistics by treated and control districts

	Treated districts	**Control districts**
	(1)	(2)
Panel A. Forest		
Deforestation	555.61	96.26
	(875.58)	(333.92)
Panel B. Covid		
Cases	503.26	8.88
	(1045.34)	(7.38)
Deaths	32.99	2.6
	(99.03)	(14.62)
Panel C. District characteristics		
Coca	540.58	323.64
	(842.53)	(647.61)
Mining	0.15	0.04
	(0.36)	(0.20)
ANP	0.17	0.06
	(4.69)	(0.24)
Roads	1.38	1.06
	(0.38)	(2.44)
Rivers	32.21	5.6
	(63.54)	(17.82)
Population (2020)	18796.32	3970.17
	(25626.16)	(6892.91)
Area	2732.18	956.52
	(4259.16)	(2330.02)
HDI (2019)	0.39	0.34
	(0.10)	(0.08)
Indigenous populations	2370.08	939.14
	(3923.48)	(2033.48)
Observations	257	142

Notes: Table displays summary statistics of the main variables. Column (1) shows the mean values for districts with COVID-19 cases above the median. Column (2) shows the mean values for districts with COVID-19 cases below the median. In Panel A, deforestation corresponds to 2015.

Table B.3: Main results with different periods

	Dependent variable: Deforestation (ha)	
	(1)	(2)
Year 2020	118.1***	
	(22.284)	
DiD		176.54***
		(27.76)
Design	Event study	Difference-in-Difference
Pre-pandemic period	2015-2019	2019
N	800	798
R-squared	0.940	0.18

Notes: Estimated standard errors, reported in parentheses, are clustered at the district level. Significance at the one, five and ten percent levels is indicated by ***, ** and *, respectively. Column (1) and Column(2) present the results of estimating Equation 1 and Equation 2, respectively.

Table B.4: Heterogeneous effects with all regressors

	Dependent variable: Annual rate of forest change, 2019-2020	
	(1)	(2)
Year 2020	2.19***	2.17***
	(0.21)	(0.21)
Mining	0.17*	0.18*
	(0.09)	(0.09)
Coca	0.21**	0.19*
	(0.10)	(0.10)
Protected areas	-0.34***	-0.44***
	(0.08)	(0.08)
Population density	-0.00	-0.00
	(0.00)	(0.00)
River area (m2)	-0.00***	-0.00***
	(0.00)	(0.00)
Altitud (m)	-0.00***	-0.00***
	(0.00)	(0.00)
Number of vias	-0.01	-0.01
	(0.01)	(0.01)
Distance to Lima	-0.00***	-0.00***
	(0.00)	(0.00)
Slope	-0.02***	-0.03***
	(0.01)	(0.01)
N	394	394
R-squared	0.53	0.54

Notes: Estimated standard errors, reported in parentheses, are clustered at the district level. Significance at the one, five, and ten percent levels is indicated by ***, **, and *, respectively.

Table B.5: CO2 emission and economic loss

	$tCO_2(millions)$	Economic loss (millions USD)
Lower bound	12.7	98.25
Average	17	131.38
Upper bound	21.3	164.53

Notes: Table displays the estimates of $tCO_2\text{-}eq$ and economic losses (million USD) caused by the deforestation originated by COVID-19. We use the estimate from column 1 of Table 1, as well as the confidence interval to obtain the lower and upper bound.