Mind your language: Political signaling and deforestation in the Brazilian Amazon*

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Abstract

Halting illegal economic activities requires effective law enforcement, including credible prosecution. Signs of weakening political support for enforcement efforts can reduce the expected costs of illegal behavior. This paper investigates the impact of anti-conservation statements by political leaders on subsequent deforestation in the Brazilian Amazon. We use monthly municipality data from Twitter (currently known as X) in 2019 – during Bolsonaro's first presidential year – to track anti-conservation political information signals and build a forest-related social-media penetration index. Relying on a shift-share approach, we identify the effect of these anti-conservation signals on deforestation. High exposure to such signals increases forest loss by 2.2–6.6%. Effects are stronger in areas with high opportunity costs of conservation but insensitive to measures of political allegiance. Political cycles with fluctuating conservation commitments undermine otherwise effective enforcement mechanisms and threaten sustainable tropical forest protection.

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1 Introduction

Tropical deforestation is a major cause of climate change and biodiversity loss (DeFries et al., 2002; Lawrence and Vandecar, 2015). Policies to control tropical forest loss, such as protected areas, land use restrictions, and payments for environmental services, exhibit varying degrees of effectiveness across instrument categories and implementation contexts (Burgess et al., 2023; Börner et al., 2020). Among the contextual factors that mediate the effectiveness of conservation policies, the role of political factors has only recently received some attention (Pailler, 2018; Balboni et al., 2021; Cisneros et al., 2021; Ruggiero et al., 2021). Political interests can affect land use decisions even without manifesting themselves in concrete laws, regulations, or decrees (Burgess et al., 2012). However, little is known about how governmental information signals for laxer environmental enforcement affect the behavior of land users.

Recent evidence indicates that information dissemination through mass media can lead to increased public pressure on governments to promptly address environmental issues (Araujo et al., 2022). Similarly, one can expect that information conveyed in government messages also affects behavior. Politicians can convey strategic details (either explicitly or implicitly) about planned government action (or non-action), encouraging certain behavior (Street, 2010; Barberá et al., 2019). In the context of land use, government statements transmitting intended changes in environmental law enforcement or in road infrastructure investments can lead to more or less conversion of forests to agriculture, for instance. Such signals affect land users' expectations of relative returns to both legal and illegal (e.g., costs of punishment) land-use choices and may thus lead to changes in deforestation decisions.

Tropical deforestation is largely illegal (Silva Junior et al., 2021). Land users thus likely weigh the expected benefits of deforestation against the costs associated with the probability of facing legal consequences (Becker, 1968). In the presence of transaction costs (Coase, 1960), expectation formation with respect to legal consequences, i.e., the probability of being caught, is the result of both actual and perceptual deterrence. If information changes the perceived risk of being sanctioned, it can change the behavior of potential offenders (Apel, 2013). This motivates our use of Becker's economic model of crime to conceptualize land use decisions under risk and transaction costs.

Few economic studies of crime focus on perceptual deterrence (Chalfin and McCrary, 2017). Perceptions are, however, likely to play an important role in deterring illegal deforestation, which tends to occur in settings where enforcement costs exhibit high spatial variability (Börner et al., 2015). In these settings, information about enforcement intentions from official sources becomes particularly valuable for potential offenders (Apel, 2013). If such information indicates a shift towards lax enforcement, the economic model of crime sketched above predicts increased deforestation.

Our empirical analysis captures deforestation dynamics in a monthly panel of Brazilian municipalities in the Legal Amazon region between January and December 2019. Conditional on municipality and month-fixed effects, we estimate how forest cover change responds to government messages signaling a decline in enforcement efforts. Over the last decade, Brazilian politicians and public institutions increasingly relied on Twitter to disseminate messages to an ever-growing number of Twitter users.

Despite Twitter only ranking third in popularity among Brazilian farmers as a social media platform (Colussi et al., 2022), Tweets from public institutions and opinion leaders are further disseminated through other social media platforms, such as WhatsApp (Jungherr, 2016; Hale et al., 2024). To test if our Twitter data follows the general discussion trends, we cross-check if monthly forest-related tweets are related to monthly forest-related Google search trends. Figure A1 in the appendix shows that the Twitter dynamics are closely related to Brazilians' interest in forest conservation topics. For our empirical design, Twitter data facilitates the flow of information and, uniquely, provides observable links between original signals and primary recipients. These characteristics enable us to study whether specific centrally provided government information provokes land use change across municipalities in the Brazilian Amazon.

Our analysis relies on the premise that the transmission of information closely resembles contagion processes observed in epidemiological studies. Similar to the spread of infectious diseases, information can rapidly disseminate and catalyze behavioral changes depending on network proximity and the strength (influence) of the information spreader (Banerjee et al., 2019). Upon receiving a message, individuals may either accept it as true, dismiss it as false, or verify its accuracy, conditioned by the level of effort required (Merlino et al., 2023). Building on the premise that identical content permeates various online platforms such as Twitter and WhatsApp (Jungherr, 2016; Hale et al., 2024), we posit that our empirical analysis captures the indirect effects of the original signaling message. Once individuals are exposed to messages on Twitter, we assume that they locally disseminate such information — either showing support or criticism — through their social networks, ultimately reaching individuals who have a genuine interest in the content of the message and who will use this information to shape their expectations.

To identify the effects of anti-conservation signaling, we rely on a shift-share approach. Our shift-share combines the flow of governmental Tweets signaling a reduction in federal environmental enforcement efforts (shift) with a forest-related susceptibility index at the municipality level (share). We thereby assume that government Tweets that convey intentions to limit enforcement efforts translate into lower perceived probabilities of being sanctioned among potential offenders. The anti-conservation signals that were echoed by the Brazilian president Jair Bolsonaro throughout his administration could be seen as simple rhetoric (Escobar, 2019). Therefore, to highlight the clear distinction between rhetorical expressions and substantive policy changes affecting environmental enforcement mechanisms, we present a chronological overview of significant political events throughout the year 2019. This overview of events shows no evidence of regulatory changes that could have triggered (or be correlated with) the increase in anti-conservation tweets (see Appendix A.2 for a timeline of events). Additional diagnostic tests plausibly confirm the exogeneity of the 'share' dimension and thus the validity of our identification strategy (Adão et al., 2019; Goldsmith-Pinkham et al., 2020).

Our results suggest that deforestation increases in response to reduced expected risk of being caught, fined, and prosecuted. A one standard deviation increase in exposure to the anti-conservation signals increases deforestation by 2.2–6.6%. Our findings also hold when allowing for differential trends in selected conditions – population, initial forest area, levels of the share, and state-level characteristics. We also investigate how the response to government signals of reduced enforcement on deforestation varied across municipalities with different economic, agricultural and political characteristics.

The remainder of this article is organized as follows. Section 2 outlines the theoretical framework, while section 3 introduces the Brazilian context of forest conservation. Section 4 describes the data, and section 5 presents the empirical strategy. Results are presented in section 6 while section 7 investigates potential heterogeneity. Section 8 concludes.

2 Theoretical framework

Tropical deforestation can be driven by interactions between political forces and market dynamics (Abman and Lundberg, 2024; Salemi, 2021; Carreira et al., 2024; Abman and Lundberg, 2020). Recent work identified elections as a key political driving force underlying forest loss (Pailler, 2018; Balboni et al., 2021; Cisneros et al., 2021; Ruggiero et al., 2021). A common explanation is that candidates seek to increase their (re-)election chances by manipulating voters' expectations, particularly during election and pre-election periods. Given the economic importance of agricultural production in the tropics, politicians may also reinforce the link to deforestation during and before elections to raise funds for electoral campaigns from the agricultural sector. The interplay between agricultural production and political incentives then comes to drive forest-harming activities in this context (Burgess et al., 2012; Cisneros et al., 2021).

The relationship between political processes and deforestation, however, goes beyond election cycles. Once elected, politicians can often seek re-election or be motivated by the benefits of being in office (Fisman et al., 2014). If the agricultural sector provides such incentives, politicians can offer subsidies, road investments, or reduced environmental enforcement in return. As implicitly suggested by the environmental economics literature on elections, support of this kind could be signaled in government messages that provide justification or purport intentions to cater to agricultural interest groups (Pailler, 2018; Balboni et al., 2021; Cisneros et al., 2021; Ruggiero et al., 2021).

The economic theory of crime posits that individuals make decisions based on information about potential benefits and costs of criminal activity (Becker, 1968). This idea has informed numerous models of criminal behavior, for example, to investigate criminal behavioral change to collective clemency (Buonanno and Raphael, 2013), decrease of police enforcement (DeAngelo and Hansen, 2014), and labor-market conditions (Raphael and Winter-Ebmer, 2001). More specifically, much of the existing research in this field has emphasized the deterrent effects of sanctions and policing (see Nagin, 2013; Chalfin and McCrary, 2017). This line of research typically links actual and observable changes in law enforcement efforts to behavioral changes among offenders. This involves, for example, translating observed (past) patrolling efforts into future expected enforcement probabilities, i.e., a calculable risk. Politics, however, can introduce a relevant source of uncertainty into this simple arithmetic. Reading between the lines of government statements thus becomes an important source of information for potential offenders to build expectations on.

Following Becker (1968), we assume that land users eventually engage in illegal land conversion guided by economic logic and rational decision-making. If market incentives are such that forest conversion is more profitable than conservation, deforestation is always an optimal choice unless deforestation is punished with a non-zero probability.

Law enforcement in tropical forests is costly and, thus, usually imperfect and subject to political will and budget constraints (Börner et al., 2015). Potential offenders must, therefore, form expectations of future enforcement pressure under risk and uncertainty. Under stable political conditions, observed past enforcement efforts may represent a suitable basis to predict future enforcement risk. In unstable political environments or during regime shifts, increasing uncertainty may induce potential offenders to rely more heavily on perceptual judgments.

Most empirical research on forest law enforcement uses measures of actual enforcement, such as documented field inspections and infraction notices (see, for instance, Cisneros et al., 2015; Assunção et al., 2023). Following our argument above, these measures will become less powerful predictors of deforestation as uncertainty about future enforcement pressure increases.

As information about political intentions is costly to obtain, potential offenders likely have varying levels of access to information from official government sources. If these sources credibly convey information about political intentions, perceptions of future enforcement pressure and related costs of punishment among potential offenders will vary accordingly. Expectation formation with regard to the costs of illegal deforestation thus comes to be influenced by both actual enforcement actions and perceptions of the related political climate (Apel, 2013).

In countries where agri-environmental policies still affect a large share of the population, political statements by incoming political leaders may also often be interpreted as signals of policy regime shifts. We expect such information signals to affect deforestation via their influence on the expected land-use returns. Our empirical strategy outlined below is designed to test this hypothesis in the context of the Brazilian Amazon, where land users were exposed to an environmental policy regime shift towards laxer enforcement between 2019 and 2022.

3 Forest conservation politics in Brazil

In Brazil, public subsidies to land-intensive economic activities, such as cattle ranching, have accelerated the conversion of large forest areas to pasture (Fearnside, 2005). Starting in the 1990s, growing global demand for soy-based feed and fuels has fostered a new wave of, mostly illegal, deforestation at the forest frontier, which peaked in 2004 when 27,772 km^2 of forests were cleared (Silva Junior et al., 2021). Between 2005 and 2012, forest loss decreased markedly in response to effective policy action but then began to rebound, especially after the 2018 election (Silva Junior et al., 2021).

Several public and private initiatives have aimed to reduce illegal deforestation in the region. This includes, for example, the Action Plan for Prevention and Control of Deforestation (PPCDAm, acronym in Portuguese) in 2004, the creation of the list of priority municipalities (Cisneros et al., 2015; Assunção and Rocha, 2019), land tenure reforms (Lipscomb and Prabakaran, 2020; Probst et al., 2020), a rural credit restriction policy (Assunção et al., 2020), the Soy Moratorium (Gibbs et al., 2015), and the G4 Cattle Agreement (Moffette et al., 2021). In 2019, however, Brazilian land users experienced a political regime shift after the 2018 presidential election. The government of the newly-elected president, Jair Bolsonaro, openly advocated for a weakening of the environmental legislation and the related institutional infrastructure (Abessa et al., 2019). The existing environmental governance regime was systematically dismantled, for example, via budget cuts and dismissal of committed officials, weakening environment agencies such as the Brazilian Institute of the Environment and Renewable Natural Resources (IBAMA) and National Institute for Space Research (INPE) (Nytimes, 2019; Reuters, 2019; Science, 2019).

Recent studies have demonstrated that such behavior, coupled with significant fire-related incidents, has sparked temporary public attention, prompting the Brazilian government to address pressing environmental concerns (Araujo et al., 2022). But these effects and actions proved to be short-lived, primarily alleviating the pressure on both the government and the environment only temporarily. In fact, the anti-conservation rhetoric endured over time.

Examples of the government's statements include "I won't allow Ibama to go around issuing fines left and right" (Jair Bolsonaro Washington Post, 2019) and "Solution to save the Amazon is to monetize it" (Minister of Environment O Globo, 2019). According to anecdotal evidence, these messages encouraged a "Day of Fire" in 2019, when the press reported that a group of farmers allegedly set fire to the Amazon rainforest to show support for President Jair Bolsonaro and his actions in that period (e.g., firing Inpe's director) (Caetano, 2021). Public authorities exchanged official messages (ofícios) aimed at planning responses of law enforcement after media outlets released news articles suggesting coordinated actions by some farmers and loggers to set fire to clear land in the Amazon region (MPF, 2019). There are ongoing confidential investigations by the Brazilian Federal Police inspecting whether the "Day of Fire" was a result of actions from an organized communication between these farmers. These events outline Brazil as an ideal empirical setting to test the relationship between perceptual deterrence and land use decisions.

4 Data

Our spatial units of analysis are Brazilian municipalities located in the Legal Amazon region[1]. Our monthly panel data covers the year 2019, during which Twitter was increasingly used for political statements by the then-recently elected Bolsonaro government. We focus on the year 2019 (the first year of the Bolsonaro government) for two reasons. First, the beginning of a new government is a crucial period where constituents assess if verbal commitments are met by political actions. Second, politicians also want to signal that they are fulfilling their election promises.

Deforestation Our main dependent variable is the monthly total deforested area (km^2) per municipality. It is derived from MapBiomas (2022), which compiles information from multiple deforestation alert systems. Our main outcome is based on the DETER system (*Sistema de Detecção de Desmatamento em Tempo Real - INPE*). We further also use deforestation outcomes based on the GLAD (Global Land Analysis and Discovery – University of Maryland) and SAD (*Sistema de Alerta de Desmatamento* - Imazon) systems. Each system differs in its detection technology, using varying spatial and temporal resolutions, potentially generating independent measurement errors. For instance, GLAD alerts indicate a disturbance in the forest canopy at a 30-meter resolution every eight days, while DETER produces daily alerts based on forest cover changes of at least three hectares. Finally, we also use data on fire foci released by INPE. Our results do not change across these outcomes, reducing concerns about measurement bias.

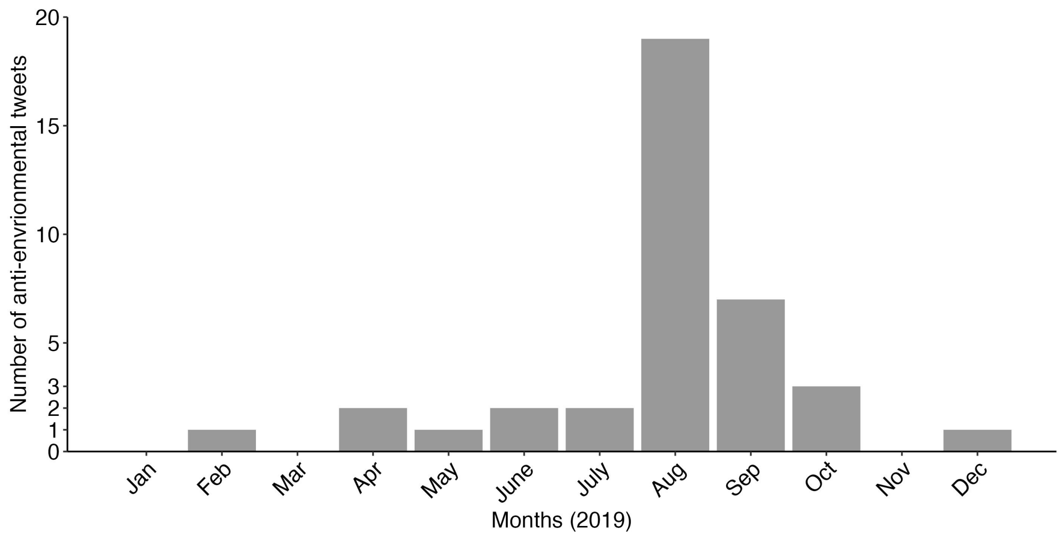
Anti-conservation political signals To capture the political anti-conservation signals of Bolsonaro's government during the first year of its legislature, we collect Twitter posts via an academic API – using the python library `Twarc` (Summers et al., 2022).[2] We scrape tweets from the four most important government institutions for impacting Brazil's environmental legislation and enforcement capacity: The president of Brazil (@jairbolsonaro), the Ministry of Agriculture, Livestock and Food Supply (@TerezaCrisMS), the Ministry of Environment (@rsallesmma), and the Ministry of Foreign Affairs (@ernestofaraujo). We then classify each tweet as anti-conservation when it spreads information on the potential of reduced enforcement and prosecution in forest conservation. Only about 1% of all tweets from these accounts are classified as such. Finally, we count the number of these anti-conservation signals per month, T_m.

Anti-conservation policy exposure We use a shift-share approach to model the information dissemination of the political anti-conservation signals across the Brazilian Amazon.

[1] The Legal Amazon is an administrative area currently defined by the Complementary Law 124/2007 covering 59% of the Brazilian territory (IBGE, 2024)

[2] The Twitter data was downloaded before April 2023. Unfortunately, it can not be updated since X / Twitter suspended all academic APIs in April 2023.

Figure 1: Monthly anti-conservation government signals



Note: The figure shows the monthly frequency of anti-conservation policy signals which Brazilian governmental institutions sent via Twitter in 2019. We account for tweets from President Jair Bosonaro (@jairbolsonaro), the Ministry of Agriculture, Livestock and Food Supply (@TerezaCrisMS), the Ministry of Environment (@rsallesmma), and the Ministry of Foreign Affairs (@ernestofaraujo).

We hereby assume that places where people frequently tweet about forest and deforestation-related topics are more likely to be exposed to these political signals and subsequently disseminate such information - either in support or criticism. To measure the potential susceptibility in space, we collect all geo-located tweets in the Brazilian Amazon that were posted between 2015 and 2018 and mention at least one of the following keywords: *fire*, *deforestation*, *forest*, or *Amazon*.[3] The provided geo-location of the tweets allows us to create municipality-specific susceptibility measures. We use as our susceptibility index the inverse hyperbolic sine of all tweets in a municipality, i, that are linked to forest-related topics, S_i.[4] The transformation allows us to give lower weight to areas with a high pre-existing level of tweets. Furthermore, results are robust to including susceptibility-specific FE as controls (see next section). Figure 2 maps the distribution of the susceptibility to anti-conservation political signals across the Amazon.

The monthly exposure to anti-conservation political signals per municipality (short: Anti-Cons. signals exposure) is then constructed as the interaction between both indices:

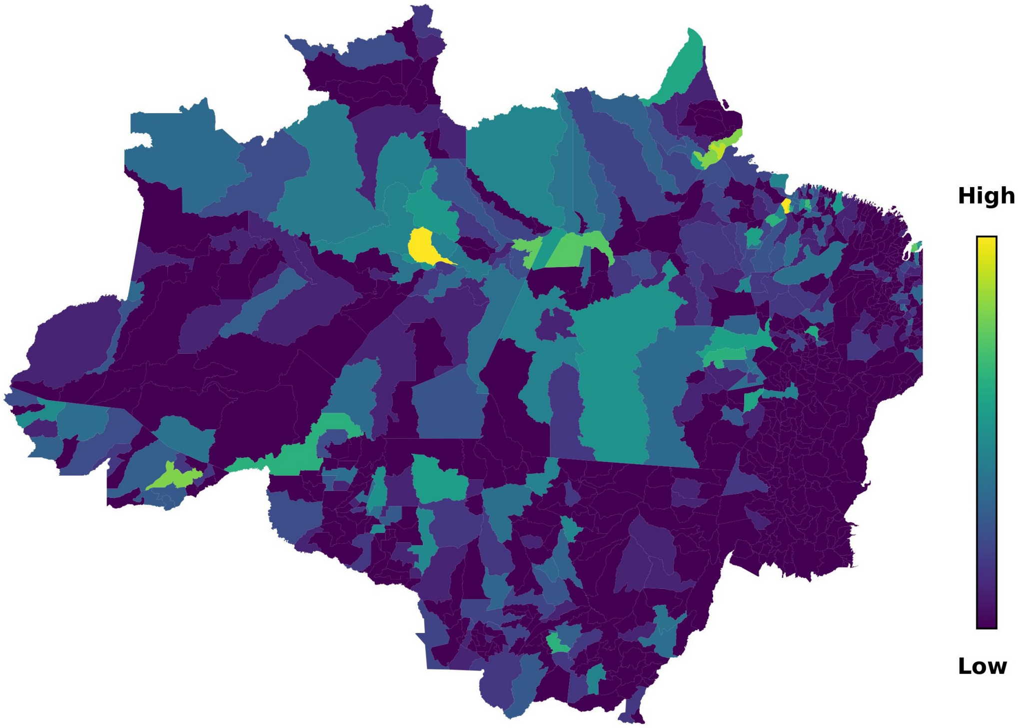
$$E_{im} = S_i \times T_m \tag{1}$$

Places with a high level of susceptibility will thereby receive a higher exposure to the anti-conservation political signals. Whereas in months with low numbers of anti-conservation

[3]In Portuguese: *fogo*, *desmatamento*, *floresta*, *amazonia*, or *amazônia*.

[4]Similar to a log transformation, the inverse hyperbolic sine transformation re-weights right-skewed distributions while being defined at zero.

Figure 2: Susceptibility to anti-conservation political signals



Note: The figure plots the susceptibility to anti-conservation signals via Twitter, based on the frequency of forest-related tweets from 2015 to 2018 (cf. eq. 1).

signals, exposure levels are low or zero across all municipalities. This 'one-dimensional' shift-share approach thereby strongly resembles a Difference-in-Differences (DiD) but with a varying treatment intensity. In Robustness checks, we therefore (a) test alternative share specifications and (b) test for parallel trends.

Additional variables Our empirical analysis further incorporates monthly deforestation-related environmental fines released by Ibama, annual remotely-sensed data on forest cover detected by PRODES (*Projeto de Monitoramento do Desmatamento na Amazônia Legal por Satélite - INPE*), and time-invariant remotely-sensed data on soybean plantations and pastureland organized by (MapBiomas, 2021). We also explore information on GDP growth per sector organized by the Brazilian Institute of Geography and Statistics (IBGE), election data from the Superior Electoral Court in Brazil (TSE), and information on protected areas as defined by the Ministry of the Environment (MMA), indigenous lands as defined by National Foundation of Indigenous Peoples (FUNAI), and the Priority List policy released by MMA in Brazil. Table A1 in the Appendix provides summary statistics on the main variables used.

5 Empirical strategy

We use a shift-share approach to estimate the impact of anti-conservation political statements on deforestation. We regress monthly remotely sensed forest losses across Amazonian municipalities on a shift-share instrument that captures the exposure to governmental Tweets, signaling shifts in the enforcement and prosecution of environmental offenses. Our estimation model is:

$$D_{im} = \alpha_i + \gamma_m + \beta\, E_{im-1} + S_i \times \gamma_m + \mathbf{Z}_{i0} \times m\, \delta + \varepsilon_{im} \tag{2}$$

where D_{im} is the inverse hyperbolic sine of newly deforested area (in km^2) in municipality i and month m. E_{im-1} is the lagged exposure index to anti-conservation political signals that varies across municipalities and months (see previous section). We use lagged values for two reasons. First, an immediate response seems unlikely as it may take some time to organize forest clearings. Second, a lagged structure can potentially avoid reverse causality, as politicians could respond to higher deforestation with more anti-conservation signals. Our estimation leverages a susceptibility index that does not sum up to one. Following Borusyak et al. (2021), this is a case of "incomplete shares" that could lead to bias when regions with high susceptibility are related to higher deforestation through other unobservable characteristics. In such cases, it is necessary to control for the interaction between shares and month FE, $S_i \times \gamma_m$. Z_{i0} captures additional differential time trends by initial conditions in 2018 that could determine both the level of exposure as well as deforestation trends. Here, we include forest area, population size, and state indicators. The use of municipality-specific time trends reduces the risk of potential biases. For example, initial forest area or the forest-related Twitter susceptibility could correlate with underlying socio-economic structures that influence deforestation trends (e.g., internet access, past enforcement) as well as the anti-conservation signals biasing the shift-share estimate. α_i and γ_m are municipality and month fixed effects, respectively. ε_{im} is the error term, clustered at the municipality level to account for serial correlation within cross-sectional units over time, as idiosyncratic disturbances may be correlated within municipalities. We also restrict our main analysis to municipalities with at least 1% forest cover in 2018. We expect β to be positive, reflecting a decrease in the expected punishment of illegal deforestation due to the higher levels of exposure to anti-conservation signals.

Our causal identification relies on the conditional exogeneity of our local information exposure measure about reduced environmental enforcement efforts. We provide several tests to corroborate the conditional exogeneity assumption. First, we allow for differential trends based on the share component of our exposure measure. This ensures that underlying trends do not drive our treatment effect due to other local factors, i.e., any spuriously correlated with forest-related susceptibility (S_i). Second, given that our shifter is not strictly exogenous, we investigate potential variations in deforestation rates across different levels of the share during the period between 2015 and 2018 before treatment and in 2019 during the period of treatment. This allows us to test if our shift-share assumption converges to a standard parallel trends assumption of DiD estimators. The analysis presented in Appendix section A.1 and Figure A2 confirms that deforestation rates are on a parallel trend before anti-conservation signaling started in 2019.

6 Results

6.1 Main results

The main results of estimating eq. (2) are presented in Table 1. The estimations show a positive and significant effect of an increase in the local exposure to anti-conservation political signals on monthly forest losses. A one standard deviation increase in the exposure level leads to a 2.2–6.6% increase in forest losses.[5] Results are robust to controlling for the interaction between shares and months fixed effects (column 2) and initial population- and forest-dependent trends (column 3). Our preferred specification in column 4 further narrows down the identifying variation by controlling for state-specific trends. The estimate remains stable and significant, indicating that the estimated effect is not driven by unobserved factors determining susceptibility and deforestation trends. Table A2 in the Appendix shows the results depending on the source of anti-conservation signals. While all institutions in the Bolsonaro administration had a significant impact on deforestation rates, the signals of the President Bolsonaro were most impactful, with a semi-elasticity of 17.4%.

Table 1: Effects of anti-conservation policy signals on deforestation

Dependent:	Forest losses (asinh)			
	(1)	(2)	(3)	(4)
Anti-Cons. signals exposure (st.dev.)	0.022***	0.063**	0.056*	0.066**
	(0.007)	(0.031)	(0.030)	(0.031)
Municip. and month FE	Yes	Yes	Yes	Yes
Susceptibility × month FE	No	Yes	Yes	Yes
Initial characteristics specific trends	No	No	Yes	Yes
State-specific trends	No	No	No	Yes
Observations	6358	6358	6358	6358
Municipalities	578	578	578	578
Adj. R^2	0.497	0.498	0.501	0.505

Notes: The dependent variable is the inverse hyperbolic sine function of monthly forest losses detected by the DETER satellite monitoring system. Exposure to anti-conservation policy signals is a shift-share combining a time-invariant susceptibility index with the monthly number of anti-conservation tweets of government intuitions (see eq. 1). The exposure index has been standardized to $N(0,1)$ for easier interpretation. Estimates include municipality and month fixed effects. Standard errors are clustered at the municipality level and reported in parentheses. */**/*** denote significance levels at 10/5/1 percent respectively.

[5] For large values of the dependent variable, coefficients can be directly interpreted as elasticities in asinh-linear regressions (Bellemare and Wichman, 2020).

6.2 Identification issues and robustness

Our main results show that local exposure to anti-conservation political signals drives forest losses in the Brazilian Amazon. We have argued that this signaling affects landholders' expectations of being fined and prosecuted in the near future. Alternatively, anti-conservation statements could also impact local environmental enforcement efforts through the same channel. Places with a higher susceptibility to anti-conservation statements might reduce their enforcement efforts as any environmental fines would likely not be prosecuted. Furthermore, even after controlling for local conditions, the local susceptibility index could be correlated with the probability of an agency receiving less funds to conduct enforcement missions. We test for this rival explanation by estimating the effect of anti-conservation exposure on the aggregate number and value (in *Brazilian reais*) of monthly fines per municipality. Table 2 displays the results for the impact of the governmental information signals hinting at laxer environmental enforcement on actual enforcement measures. We observe no change in either the number or the value of fines. This finding provides support for the hypothesized underlying mechanism whereby the observed increase in forest loss was driven by a shift in expected, rather than actual, enforcement.

Table 2: Actual enforcement measures

Dependent:	Number of Fines (asinh) (1)	Number of Fines (asinh) (2)	Value of Fines (asinh) (3)	Value of Fines (asinh) (4)
Anti-Cons. signals exposure (st.dev.)	−0.017	−0.023	−0.045	0.304
	(0.014)	(0.054)	(0.078)	(0.449)
Municip. and month FE	Yes	Yes	Yes	Yes
Susceptibility × month FE	No	Yes	No	Yes
Initial characteristics specific trends	No	Yes	No	Yes
State-specific trends	No	Yes	No	Yes
Observations	6358	6358	6358	6358
Municipalities	578	578	578	578
Adj. R^2	0.283	0.302	0.258	0.266

Notes: The dependent variable is the inverse hyperbolic sine function of the monthly number and monetary value (in *Brazilian reais*) of deforestation-related fines at the municipality level. Exposure to anti-conservation policy signals is our shift-share measure based on Eq. 1. The exposure index has been standardized to $N(0,1)$ for easier interpretation. Estimates account for municipality and month-fixed effects. Standard errors are clustered at the municipality level and reported in parentheses. */**/*** denote significance levels at 10/5/1 percent respectively.

Remote sensing is prone to detection errors which can correlate with past deforestation, economic activity, as well as our susceptibility index (Durieux, 2003; Wang et al., 2009). Our results have been robust even after including susceptibility-specific month FE. We further test for potential measurement errors by comparing our results when using two alternative sources of remotely sensed forest losses. Table 3 presents results when using alternative remotely sensed deforestation products (columns 1–4). Results remain stable and significant in the same range with a 2.8–5.8% increase in deforestation for a one standard deviation higher exposure level. Furthermore, the number of monthly fires also increases by more than 30%

when conditioning on initial trends and share-month FE (columns 5–6). These results confirm that our main effects are independent of measurement errors.

Table 3: Alternative remotely-sensed data

Dependent:	Forest losses (asinh)				Fire foci (asinh)	
Data source:	GLAD		SAD		INPE	
	(1)	(2)	(3)	(4)	(5)	(6)
Anti-Cons. signals exposure (st.dev.)	0.028***	0.027*	0.032***	0.058**	0.036	0.323**
	(0.009)	(0.016)	(0.009)	(0.031)	(0.026)	(0.129)
Municip. and month FE	Yes	Yes	Yes	Yes	Yes	Yes
Susceptibility $\times$ month FE	No	Yes	No	Yes	No	Yes
Initial characteristics specific trends	No	Yes	No	Yes	No	Yes
State-specific trends	No	Yes	No	Yes	No	Yes
Observations	6358	6358	6358	6358	6358	6358
Municipalities	578	578	578	578	578	578
Adj. R^2	0.455	0.459	0.575	0.583	0.537	0.593

Notes: The dependent variable is the inverse hyperbolic sine of yearly deforestation in km^2. The remotely sensed forest losses are detected using different technologies and sources – GLAD (columns 1–2), SAD (columns 3–4), and INPE-fire (columns 5–6). The exposure to anti-conservation policy signals is standardized to $N(0, 1)$ (cf. eq. 1). Standard errors are clustered at the municipality level and reported in parentheses. */**/*** denote significance levels at 10/5/1 percent respectively.

Shift-share approaches for causal identification traditionally rely on the shifter component or the share component to be conditionally exogenous (Cunningham, 2021). The shifter, the number of government anti-conservation statements, are concentrated during August and September 2019 (cf. Figure 1). Even if the timing of this shock is exogenous it might still be correlated with unobserved confounding factors determining deforestation dynamic. Therefore, we rely more strongly on the assumption that the share, i.e., the forest-related susceptibility index, is conditionally exogenous to deforestation. To test this assumption, we design several tests suggestions made by Goldsmith-Pinkham et al. (2020).

First, following the idea that shift-share approaches have assumptions similar to DiD estimates (Cunningham, 2021), we test if deforestation trends were independent of the shifter component before the anti-conservation signaling started in 2019. We hereby use annual forest loss data from 2015 to 2018 to test for non-parallel trends between municipalities with high or low levels of the susceptibility index (shifter). The analysis and results are presented in section A.1 indicate that deforestation was most likely on a parallel trend between highly susceptible and non-susceptible regions.

Second, our main specification uses 2015–2018 data to create the susceptibility index and exposure measure. We test if the results are robust to different time frames and specifications. Results are presented in Table A3 in the Appendix. We first use different pre-2019 time frames to create our share component. Results remain positive and significant (columns 1–2). In addition, we test if our main specification is prone to a systematic over-reject of the Null-hypothesis using two placebo tests: we randomly shuffle the existing shares among all municipalities and randomly draw shares from a normal distribution with the same mean and standard deviation as the original data. Both placebo tests show that only 7.7-11.1%

of 1000 random draws produce statistically significant results, confirming that the use of our susceptibility index is valid (see columns 3–4 of Table A3).

Third, the shares of our exposure measures may exhibit a high correlation among neighboring municipalities. Spatial correlation is connected to the over-rejection problem in shift share designs (Adão et al., 2019). We test for the sensitivity of our estimates clustering at higher spatial levels of administration or within quantile bins of the susceptibility share index. Table A4 in the Appendix presents the results. The estimates remain highly significant throughout.

7 Economic and political contexts

The evidence presented so far suggests that exposure to anti-conservation signaling increases deforestation. However, these impacts may have varied across time and regions with different economic, agricultural and political characteristics. We analyze the effects of economic and agricultural incentives by extending our baseline model with interactions between our exposure variable and indicators for economic production growth, and measures of the average municipal growth rate of soybean and pasture land from remotely sensed data between 2004 and 2018. We define high growth rates for municipalities with growth above the median.

Table 4 presents the results. The effects of anti-conservation policy exposure on deforestation are not different for municipalities with a high level of general economic growth or growth in the manufacturing or services sector (columns 1–3). In contrast, municipalities with high levels of agricultural GDP growth are associated with larger impacts of the anti-conservation policy signaling (column 4). Differentiating agricultural growth by its growth in land use, we find no different effect of municipalities with capital-intensive and export-oriented soybean cultivation (column 5). This is expected, as public awareness of the soy sector increased internationally during the 2000s and the Soy Moratorium in 2006 established a monitoring and enforcement mechanism among soy producers that prohibits soy expansion into forests (Heilmayr et al., 2020). This might have limited land users' frame of action even if political signals in 2019 reduce the expected punishment from federal enforcement agencies. In contrast, the effects of cattle production with its complex supply chain system remain difficult to monitor and enforce (Skidmore et al., 2021; Levy et al., 2023; Miranda and Oliveira, 2023). In consequence, column 6 shows larger exposure effects on deforestation for more cattle-oriented municipalities. While the baseline estimate is at 4.5% (insignificant), in regions where cattle production has become more prevalent, deforestation increases by an additional 4.7%. The imperfect environmental regulation surrounding cattle production may be driving the opportunistic behavior of ranchers.

In terms of political allegiance, we examine whether municipalities with a higher vote share for President Jair Bolsonaro in the 2018 presidential election or those governed by local politicians from his party exhibit stronger effects to the political messages from his administration. Table A5 in the Appendix displays the results from regressing deforestation on the interaction

Table 4: Heterogeneous impact based economic incentives

Dependent:	Forest losses (asinh)					
Moderator:	High GDP growth by sector				High soy plantation growth	High pasture growth
	All	Manuf.	Services	Agric.		
	(1)	(2)	(3)	(4)	(5)	(6)
Anti-Cons. signals exposure (st.dev.)	0.073**	0.068**	0.076**	0.051	0.072**	0.045
	(0.031)	(0.031)	(0.031)	(0.032)	(0.031)	(0.030)
Anti-Cons. signals exposure (st.dev.)	−0.017	−0.007	−0.018	0.025**	−0.019	0.047***
× Moderator	(0.012)	(0.012)	(0.012)	(0.012)	(0.013)	(0.011)
Municip. and month FE	Yes	Yes	Yes	Yes	Yes	Yes
Susceptibility × month FE	Yes	Yes	Yes	Yes	Yes	Yes
Initial characteristics specific trends	Yes	Yes	Yes	Yes	Yes	Yes
State-specific trends	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6358	6358	6358	6358	6358	6358
Municipalities	578	578	578	578	578	578
Adj. R^2	0.505	0.505	0.506	0.506	0.505	0.506

Notes: The dependent variable is the inverse hyperbolic sine function of monthly forest losses detected by the DETER satellite monitoring system. Exposure to anti-conservation policy signals is our shift-share measure based on Eq. 1. The exposure index has been standardized to $N(0,1)$ for easier interpretation. Estimates account for municipality and month fixed effects. Standard errors are clustered at the municipality level and reported in parentheses. */**/*** denote significance levels at 10/5/1 percent respectively.

of our exposure measure and indicators for political allegiance to Bolsonaro.[6] Results show no evidence of political allegiance effect, highlighting the primary role of agricultural incentives for immediate land use decisions.

In terms of past enforcement efforts, we examine whether municipalities with higher environmental enforcement intensity before 2019 show stronger effects from the anit-environmental political signals. In Table 5 we interact our exposure index with indicators of high environmental enforcement. Effects are stronger for Priority List municipalities (column 1). While our baseline estimates indicate a 5.7% increase in deforestation, the effect on municipalities on the Priority List is substantially higher (10.1%). This indicates that law enforcement plays a particularly important role as an incentive mechanism in these municipalities. We find similar results for municipalities that have protected areas or indigenous territories (columns 2–3). Lastly, municipalities within the Amazon biome are subject to more restrictive environmental laws, monitoring, and enforcement (West and Fearnside, 2021; Assunção et al., 2020). Comparing a restricted sample of municipalities close to the Amazon-Cerrado biome border, shows stronger effect for municipalities within the Amazon biome (column 4). These heterogeneous effects indicate that locations with historically higher enforcement levels exhibit greater sensitivity to changes in perceived risk of punishment.

[6] We use the voting statistics of the second round in the presidential elections of 2018. We use the different parties Bolsonaro was affiliated since 2016 to identify political allegiance.

Table 5: Heterogeneous impact by federal protection efforts

Dependent:	Forest losses (asinh)			
Moderator:	On the priority list	Has a protected area	Has an indigenous area	In the Amazon biome
	(1)	(2)	(3)	(4)†
Anti-Cons. signals exposure (st.dev.)	0.057*	0.045	0.046	0.036
	(0.030)	(0.032)	(0.030)	(0.090)
Anti-Cons. signals exposure (st.dev.) × Moderator	0.101***	0.026**	0.052***	0.057**
	(0.026)	(0.012)	(0.012)	(0.029)
Municip. and month FE	Yes	Yes	Yes	Yes
Susceptibility × month FE	Yes	Yes	Yes	Yes
Initial characteristics specific trends	Yes	Yes	Yes	Yes
State-specific trends	Yes	Yes	Yes	Yes
Observations	6358	6358	6358	1716
Municipalities	578	578	578	156
R^2	0.506	0.505	0.506	0.411

Notes: The dependent variable is the inverse hyperbolic sine function of monthly forest losses detected by the DETER satellite monitoring system. Exposure to anti-conservation policy signals is our shift-share measure based on Eq. 1. The exposure index has been standardized to $N(0, 1)$ for easier interpretation. Estimates account for municipality and month fixed effects. †Only municipalities within a 150km radius around the Amazon-biome border are included. The number of observations increases with larger bandwidths. We use the city hall locations to calculate the distance to the Amazon Biome border, while excluding municipalities crossed by the biome border. Standard errors are clustered at the municipality level and reported in parentheses. */**/*** denote significance levels at 10/5/1 percent respectively.

8 Conclusion

This paper provides evidence that information signals conveying intentions to reduce forest law enforcement efforts by public authorities are sufficient to increase deforestation. Based on remotely sensed monthly forest losses, we find that a one standard deviation increase in exposure to messages signaling lower punishment risks, increases deforestation by 2.2–6.6%. The magnitude of this effect varies across municipalities with differing leading economic activities and past enforcement levels in the Amazon region. Specifically, deforestation effects are stronger in areas with high opportunity costs of conservation due to agricultural incentives or past conservation policies but insensitive to measures of political allegiance.

We show several diagnostic tests that provide support for our identification strategy, suggesting that our share measure is as good as random (Adão et al., 2019; Goldsmith-Pinkham et al., 2020). Specifically, we test the parallel trends assumption across different groups based on their share levels during a pre-treatment period while also employing different clustering procedures in our baseline estimates.

Our results are in line with an economic model of crime (Becker, 1968; Chalfin and McCrary, 2017), where potential offenders have to balance expected returns to illegal deforestation against the potential costs of punishment. Information signals from government sources then represent valuable information about future enforcement pressure. We contribute to this literature by showing that observable manifestations of political will to enforce forest law (i.e., as in government statements) can change the expectation formation and corresponding behavior of land users. Information conveyed by governments likely matters more when land users face high uncertainty about the enforcement conditions that affect their land use decisions (Assunção et al., 2023). This is likely to have been the case after the 2018 presidential election in Brazil, which marks the beginning of our study period.

Our study also contributes to the literature on the political economy of deforestation. We provide additional evidence on the interactions between political forces and market dynamics driving tropical deforestation. Election cycles have proved to be a key determinant of forest loss in different contexts (Pailler, 2018; Balboni et al., 2021; Cisneros et al., 2021; Ruggiero et al., 2021). While these studies underline the political incentives that are eventually associated with rent-seeking and corruption driving deforestation (Burgess et al., 2012; Cisneros and Kis-Katos, 2021), our main contribution here lies in isolating the effect of information signals on reduced environmental enforcement efforts in this complex relationship. We acknowledge that this effect is likely mediated by observed past behavior of the political elite, but note that our study period marked the beginning of a comparatively unpredictable course of government action.

Drawing upon the criminal deterrence literature (see Apel, 2013; Chalfin and McCrary, 2017), we provide further evidence illustrating the critical role of perceived enforcement in combating deforestation. While prior empirical research has emphasized the importance of actual enforcement policies (Cisneros et al., 2015; Assunção et al., 2023), our study expands on this literature by showing that the risk perception regarding the probability of being fined in case of deforestation also drives land user behavior. Deforestation seems to be responsive to not only command-and-control instruments, but also to whether, how, and when authorities communicate their will to enforce environmental policy regulations.

At least three additional caveats apply. First, our main results potentially underestimate the effects of exposure to enforcement information as we only examine messages disseminated via Twitter, a specific social media channel. Other communication tools, such as television or radio, are likely to also matter for expectation formation. Note, however, that these alternative distribution channels also increasingly rely on Twitter as an information source. Second, our analysis focused on short run effects, but our results warrant future work on the medium and long-run effects of signaling to reduce environmental enforcement efforts on land use. Finally, more sources of effect heterogeneity may exist than those we have analyzed here. Future research could also explore the responsiveness of culturally diverse groups of land users to information signaled in government statements by applying a sentiment-based approach. Understanding the responses to the actual and perceived effectiveness of public policies in the Brazilian Amazon will continue to be an important research topic.

Our findings show that statements from political authorities conveying increased tolerance with respect to illegal deforestation have changed expectations of land users in the Brazilian Amazon in favor of higher deforestation rates. Policymakers are usually aware that words must be followed by action if policy goals are to be achieved effectively. After 2004, Brazil's political leadership demonstrated this principle when implementing its plan to combat deforestation

(PPCDam). Our results suggest that a sudden change in government attitude can partially revert past conservation achievements in ways that are not reversible merely by discursive means. Politicians should mind their language when engaging in public statements linked to tropical forest conservation.

Such advice may be futile when democratically elected political authorities are not committed to existing environmental legislation. This underlines the need to establish strong and independent institutions with the capacity to effectively enforce conservation laws even when political preferences happen to temporarily suggest otherwise.

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A Online Appendix

A.1 Testing for parallel trends

Our shift-share approach relies on a single share and shift component. This approach is closely related to Difference-in-differences applications (Cunningham, 2021). We can test for parallel trends (a) using pre-2019 annual data on deforestation and (b) using the monthly 2019 data set and see if parallel trends might hold before the increase of anti-conservation signals in July (cf. Figure 1). We use an annual panel of deforestation to test for non-parallel trends in the years 2015–2018 using the following model:

$$D_{it} = I(S_i > \kappa) \times \gamma_t + \mathbf{Z}_{i0} \times t\,\delta + \gamma_t + \varepsilon_{it} \tag{3}$$

where D_{it} represents the inverse hyperbolic sine of forest loss in municipality i and year t. We set a threshold, κ, to segment the susceptibility index, S_i into high and low levels using the median level of susceptibility in our sample. We interact our susceptibility index, S_i, with the year fixed effects to test if there are structural differences between low and high susceptibility areas in 2015, 2016, and 2017 (2018 is the omitted category). We control for the same set of initial conditions as in our main specification (cf. eq. 2), i.e., for differential trends in initial forest cover, initial population, and state-specific trends. Figure A2a presents the results showing no statistically significant differences in deforestation with higher susceptibility levels. We further estimate the same model on the 2019 monthly data, which provides a time profile of deforestation difference depending on the susceptibility level. Panel b of Figure A2b shows that deforestation levels remain relatively equal independent of the susceptibility level during the first half of the year. After the anti-conservation signals start increasing, also deforestation rates start to diverge for municipalities with higher susceptibility. These findings strongly corroborate our assumption of parallel trends underlying our main shift-share results.

A.2 Anti-conservation signaling precedes policy reforms in 2019

To better distinguish between anti-conservation signals and actual policy reforms affecting environmental enforcement actions, we present here a timeline of relevant political news during the year 2019. The result is a timeline of events that delineates the anti-conservation agenda enacted under the administration of former President Jair Bolsonaro. We hereby use the publicly accessible database of *Folha de São Paulo*, one of Brazil's most widely circulated news outlets (https://acervo.folha.com.br/). To filter news articles relevant to the anti-conservation policies and signals, we search for news published in 2019 including any of the following terms: *deforestation*, *INPE* or *IBAMA*. The following list of events shows no evidence of regulatory changes, laws, or policies (e.g., a defunding of the enforcement agency, IBAMA) that could have triggered (or be correlated with) the increase in anti-conservation tweets.

01/01/2019 Dissolution of the Secretariat of Climate Change and Forests of the MMA (Ministry of the Environment).

01/01/2019 Dissolution of the General Subsecretariat of the Environment, Energy, and Science and Technology of the Ministry of Foreign Affairs.

01/01/2019 Transfer of the Brazilian Forest Service (SFB) from the MMA to the Ministry of Agriculture.

02/28/2019 Twenty-one (21) out of twenty-seven (27) regional superintendents of the Brazilian Institute of Environment and Renewable Natural Resources (IBAMA) were sacked.

04/11/2019 Establishment of an Environmental Conciliation Committee for negotiating environmental infractions and administrative sanctions.

04/13/2019 Bolsonaro undermines ongoing IBAMA operation against illegal logging in the state of Rondônia:

"Yesterday, the Minister of the Environment, Ricardo Salles, came to speak with me about this information. He has already ordered the opening of an administrative process to investigate who is responsible for this. The directive is not to burn anything - machinery, tractors, whatever it may be. This is not the procedure, this is not our guidance."

04/15/2019 President of the Chico Mendes Institute for Biodiversity Conservation (ICMBio) resigned following pressure from the Minister of Environment regarding ICMBio's activities.

05/08/2019 Eight (08) former Ministers of the Environment have jointly issued an open letter condemning the "dismantling" of national policies aimed at environmental protection and sustainable development.

05/17/2019 Minister of the Environment, Ricardo Salles, openly declared during a collective media press event that he has identified irregularities in the Amazon Fund and intends to propose changes to the project selection process. These statements have taken donors by surprise, as they claim they were not informed about such issues.

07/04/2019 Minister of the Environment Ricardo Salles argues that relative zero deforestation is already a reality in Brazil.

07/19/2019 President Bolsonaro contested the deforestation data provided by INPE (National Institute for Space Research) and suggests that INPE president, Ricardo Galvão, might be serving the interests of some NGO (non-governmental organization).

07/22/2019 Minister of Science, Technology, and Innovation, Marcos Pontes, has echoed President Jair Bolsonaro's skepticism regarding the accuracy of deforestation statistics. President Bolsonaro contends that the presidential office should have the authority to review raw deforestation data collected by INPE before its public release.

07/26/2019 Minister of Science, Technology, and Innovation, Marcos Pontes, stated that the INPE deforestation alert system data should not be made fully accessible to the public immediately upon release. Minister Pontes advocated that restricting access to this information initially could aid IBAMA efforts to combat illegal deforestation activities.

07/31/2019 A meeting between Minister of the Environment Ricardo Salles and delegates from IBAMA and INPE is held. INPE President Ricardo Galvão was unexpectedly excluded from the invited participants. Minister Salles asserted that INPE's deforestation data were inaccurate, claiming the institute itself acknowledged such flaws. However, INPE firmly rejected and refuted the allegation.

08/02/2019 President of INPE Ricardo Galvão is sacked.

08/10/2019 Ricardo Salles (MMA) and Ricardo Galvão (former INPE) took part in a nationally televised roundtable discussion on GloboNews. Minister Salles alleged that Ricardo Galvão is influenced by an ideological agenda different from that of the current administration under President Jair Bolsonaro. In response, Dr. Galvão asserted that objective scientific evidence, rather than ideology, informed his actions.

08/10/2019 "Day of Fire" when the press reported that a group of farmers allegedly set fire to the Amazon rainforest as a display of support for President Jair Bolsonaro.

08/16/2019 Amazon Fund is shut down.

08/21/2019 President Bolsonaro claimed that NGOs may allegedly be behind the incredibly high number of fire outbreaks in order to damage the reputation of his administration.

08/22/2019 On Twitter, the President of France characterized the fires burning in the Amazon as an "international crisis" and urged leaders at the G7 Summit to address the issue. In response, President Bolsonaro stated that the French President's proposal to have the G7 nations debate matters related to the Amazon rainforest, without including countries from the region, harkened back to outdated colonialist attitudes.

08/24/2019 President Bolsonaro asserts that the Amazon rainforest is not experiencing the widespread fires as widely claimed. He argues that the average number of fire outbreaks is lower compared to previous years, suggesting that the situation is following usual patterns.

08/26/2019 G7 summit. President Bolsonaro criticizes the assistance offered by G7 countries, questioning their intentions regarding the Amazon Rainforest. He suggests that Brazil is being treated as a colony or no man's land, emphasizing a sentiment of sovereignty over the region.

09/09/2019 The regional superintendent of IBAMA in the state of Rondônia, Evandro Cunha dos Santos, stated that he received an order to cease the destruction of vehicles and equipment used to commit environmental crimes in the Amazon.

09/10/2019 A large police operation was conducted to reclaim land in the National Forest of Bom Futuro in the state of Rondônia. Intruders claimed they were encouraged by campaign promises made by Bolsonaro. In August 2018, still running for the Presidential Election, Bolsonaro criticized the excessive designation of protected areas, stating, "Here in Rondônia there are 53 conservation units and 25 indigenous land areas. It is absurd what is being done in Brazil under the guise of environmentalism".

09/10/2019 The regional superintendent of IBAMA in the state of Rondônia is fired.

09/12/2019 Minister of Foreign Affairs, Ernesto Araújo, claims that the INPE system is not capable of distinguishing between fire outbreaks and camping bonfires.

09/24/2019 Speech by the President of the Republic, Jair Bolsonaro, at the opening of the 74th United Nations General Assembly:

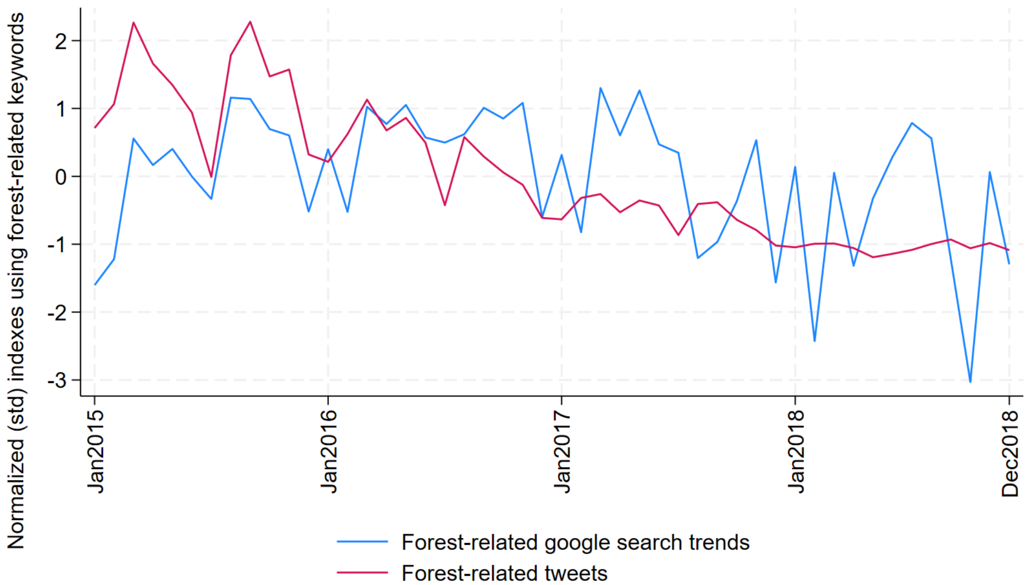
"First and foremost, my government is solemnly committed to preserving the environment and sustainable development for the benefit of Brazil and the world. Brazil is one of the richest countries in biodiversity and mineral wealth. Our Amazon is larger than all of Western Europe and remains virtually untouched, proof that we are one of the countries that most protect the environment. At this time of year, the dry climate and winds favor spontaneous and criminal fires. It is worth noting that there are also fires set by indigenous peoples and local populations as part of their respective culture and means of survival."

11/15/2019 Out of fear of reprisals, scientists declined to include their names as collaborators in a scientific study that revealed forest fires were unusually higher than in previous years, contradicting the argument put forth by the government.

11/20/2019 President Bolsonaro argues that it is not possible to stop neither deforestation nor fire outbreaks. "This is cultural", he says.

A.3 Figures

Figure A1: Forest-related tweets and forest-related google searches (2015-2018)

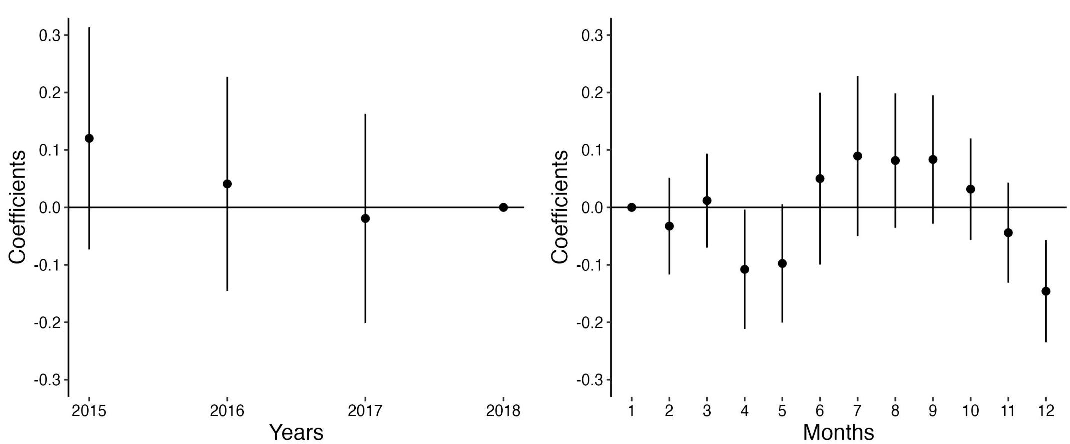


Note: The figure displays the forest-related Twitter discussions and forest-related google trend searches. Both trends are normalized for better comparability. Own visualization based on data from Twitter API and Google Trends. The keywords used to define forest-related tweets and google searchers are: *fire*, *deforestation*, *Amazon forest*. Both lines show similar trends and are closely related at a monthly basis, with a Pearson correlation index of 0.38.

Figure A2: Testing for parallel trends

(a) Parallel trends (2015–2018)

(b) Parallel trends before mid of 2019



Note: The figure presents two estimations testing for parallel trends in the data. Both sides regress the inverse hyperbolic sine of forest losses measured yearly (panel a) or monthly (panel b) on indicators of high susceptibility following eq. 3 (see Appendix section A.1). Dots depict point estimates, while bars show 10% confidence intervals.

A.4 Tables

Table A1: Descriptive statistics

Variables	Description	Mean	Std. Dev.	Min.	Max.
Forest losses (DETER)	Total size (km2) of newly deforested area detected by DETER per municipality i and month m in 2019. Source: Mapbiomas.	0.94	4.82	0	190.61
Forest losses (GLAD)	Total size (km2) of newly deforested area detected by GLAD per municipality i and month m in 2019. Source: Mapbiomas.	0.676	4.60	0	189.32
Forest losses (SAD)	Total size (km2) of newly deforested area detected by SAD per municipality i and month m in 2019. Source: Mapbiomas.	0.90	4.97	0	182.37
Fire foci (INPE)	Number of fire foci per municipality i and month m in 2019. Source: INPE.	15.50	77.94	0	2670
No. Fines (IBAMA)	Number of deforestation-related fines per municipality i and month m in 2019. Source: IBAMA.	0.46	2.42	0	45
Value of fines (IBAMA)	Value (in Brazilian reais) of deforestation-related fines per municipality i and month m in 2019. Source: IBAMA.	0.23 Mi	2.7 Mi	0	139 Mi
Forest losses (PRODES)	Total size (km2) of newly deforested area detected by PRODES per municipality i and year t in the period between 2015 and 2018. Source: PRODES/INPE.	1249.30	1612.43	0	18733.90
Anti-conservation susceptibility	Sum of all tweets on forest and deforestation by municipality i in the period between 2015 and 2018. Source: Twitter API.	29.18	241.63	0	3688
Anti-conservation signals	Sum of all government tweets signaling reduced enforcement efforts on forest conservation per month m in 2019. Source: Twitter API.	3.16	5.11	0	19

Table A2: Effects by member of Bolsonaro's government

Dependent:	Forest losses (asinh)			
Source of political signals:	(1) President (Bolsonaro)	(2) Ministry of Environment	(3) Ministry of Agriculture†	(4) Ministyr of Foreign Affairs
Anti-Cons. signals exposure (st.dev.)	0.174*** (0.044)	0.082*** (0.021)	0.013*** (0.005)	0.024** (0.010)
Municip. and month FE	Yes	Yes	Yes	Yes
Susceptibility × month FE	Yes	Yes	Yes	Yes
Initial characteristics specific trends	Yes	Yes	Yes	Yes
State-specific trends	Yes	Yes	Yes	Yes
Observations	6358	6358	6358	6358
Municipalities	578	578	578	578
Adj. R^2	0.505	0.505	0.505	0.505

Notes: The dependent variable is the inverse hyperbolic sine function of monthly forest losses detected by the DETER satellite monitoring system. Exposure to anti-conservation policy signals is a shift-share combining a time-invariant susceptibility index with the monthly number of anti-conservation tweets of government intuitions (see eq. 1). The exposure index has been standardized to $N(0,1)$ for easier interpretation. Estimates include municipality and month fixed effects. †Ministry of Agriculture, Livestock and Supply. Standard errors are clustered at the municipality level and reported in parentheses. */**/*** denote significance levels at 10/5/1 percent respectively.

Table A3: Alternative share definitions

Dependent:	Forest losses (asinh)			
Alternative shares:	Share based on 2018–2017 data (1)	Share based on 2018–2016 data (2)	Randomly reshuffled shares (3)†	Random shares (4)†
Anti-Cons. signals exposure (st.dev.)	0.021* (0.011)	0.055* (0.029)	−0.002 (0.045)	−0.010 (0.033)
Municip. and month FE	Yes	Yes	Yes	Yes
Susceptibility × month FE	Yes	Yes	Yes	Yes
Initial characteristics specific trends	Yes	Yes	Yes	Yes
State-specific trends	Yes	Yes	Yes	Yes
Observations	6358	6358	6358	6358
Municipalities	578	578	578	578
Adj. R^2	0.504	0.505	0.526	0.525
Share of significant results ($p<0.1$)			11.1%	7.7%

Notes: The dependent variable is transformed by the inverse hyperbolic sine function. †Statistics refer to median values of the placebo regressions across 1000 iterations with randomly drawn susceptibility indices. Column 3 randomly reshuffles the existing values of the share component among all municipalities. Column 4 draws from a random distribution based on the original mean and standard deviation values. */**/*** denote significance levels at 10/5/1 percent respectively.

Table A4: Correcting for errors clustering

Dependent:	Forest losses (asinh)			
Clustering errors by:	Geography		Quantile bins of the share	
	Micro Reg.	Meso Reg.	25 quantiles	100 quantiles
	(1)	(2)	(3)	(4)
Anti-Cons. signals exposure (st.dev.)	0.066*	0.066*	0.066*	0.066**
	(0.035)	(0.034)	(0.035)	(0.027)
Municip. and month FE	Yes	Yes	Yes	Yes
Susceptibility × month FE	Yes	Yes	Yes	Yes
Initial characteristics specific trends	Yes	Yes	Yes	Yes
State-specific trends	Yes	Yes	Yes	Yes
Observations	6358	6358	6358	6358
Municipalities	578	578	578	578
Adj. R^2	0.505	0.505	0.505	0.505

Notes: Columns 1 and 2 cluster errors using micro or meso regions, respectively. In our sample, we have 100 micro and 30 meso regions. Columns 3 and 4 cluster the errors in groups with similar shares by using either 25 or 100 quantiles. */**/*** denote significance levels at 10/5/1 percent respectively.

Table A5: Heterogeneous impact based on political characteristics

Dependent:	Forest losses (asinh)		
Moderator:	High Bolsonaro's voting share 2018	Mayor of of the same party	High share of city councilors of the same party
	(1)	(2)	(3)
Anti-Cons. signals exposure (st.dev.)	0.063**	0.066**	0.071**
	(0.031)	(0.031)	(0.031)
Anti-Cons. signals exposure (st.dev.) × Moderator	0.004	0.028	−0.012
	(0.012)	(0.051)	(0.011)
Municip. and month FE	Yes	Yes	Yes
Susceptibility × month FE	Yes	Yes	Yes
Initial characteristics specific trends	Yes	Yes	Yes
State-specific trends	Yes	Yes	Yes
Observations	6358	6358	6358
Municipalities	578	578	578
Adj. R^2	0.505	0.505	0.505

Notes: The dependent variable is the inverse hyperbolic sine function of monthly forest losses detected by the DETER satellite monitoring system. Exposure to anti-conservation policy signals is our shift-share measure based on Eq. 1. The exposure index has been standardized to $N(0, 1)$ for easier interpretation. Estimates account for municipality and month fixed effects. Standard errors are clustered at the municipality level and reported in parentheses. */**/*** denote significance levels at 10/5/1 percent respectively.