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# Mind your language: Political discourse affects deforestation in the Brazilian Amazon

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# Abstract

Land users make decisions in an increasingly dynamic environment. Changes in expectations are driven by market and non-market factors, but research on market related drivers of land use change so far dominates in the literature. This paper examines how political discourses affect deforestation rates in the Brazilian Amazon region. Relying on novel data from Twitter, we present the first causal evidence of political discourse on deforestation. Our analysis relies on municipal level monthly panel data for 2019 with alternative remotely sensed measures of forest loss and vegetation fires as outcome variables. The effect of political discourse on these outcomes is identified using a shift-share regression approach. High exposure to laissez-faire political discourses increases forest loss by 2.3-3%, and fires by 2.2%. Our findings are robust across land tenure regimes, varying levels of policy enforcement, and alternative shift-share measures. Moreover, excluding dry season periods from the analysis does not change the main result. Land use in the Brazilian Amazon is highly sensitive to whether, how, and when authorities communicate their will to enforce environmental policy regulations. 'Walking the talk' remains imperative to protect the world's tropical forests, but this study suggests that policy makers must carefully choose their words while walking.



Keywords: political discourse, deforestation, Twitter, Amazon, Brazil

JEL Codes: Q15, Q56, Q58

# 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 (see for example Koch et al., 2019, Assunção et al., 2020, 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 the form of concrete laws, regulations, or decrees (Burgess et al., 2012). However, little is known about how political discourses, i.e. the public expression of political interests, affect the behavior of land users.

It is well known that information can cause behavioral change (Simon, 1955). Different channels through which information changes behavior, such as door-to-door information campaign (Madajewicz et al., 2007) and mass media and newspapers (Campa, 2018; Tu et al., 2020), have been studied. Madajewicz et al. (2007) shows that information alone can cause a rapid change of behavior, although sufficient conditions for this change lie in providing specific details on how and to what extent such information affects one's life. Campa (2018) finds a decrease in environmental impact in corporate decisions due to media coverage and consumer pressure for firms' accountability in the US. Tu et al. (2020) scrutinize how mass media can affect people's behavior by increasing their awareness of environmental pollution and level of risk perception in China. They suggest that, compared with traditional media such as newspapers and radio, social media is more effective in drawing public attention to environmental protection through emotional mobilization, agenda-setting, and information-transfer (Tu et al., 2020).

Besides awareness campaigns and mass media effects, we must expect political discourses to affect human behavior. For instance, politicians can act as role models and motivate their supporters to follow their example. They can also convey strategic information (either explicitly or implicitly) about planned government action (or non-action) encouraging opportunistic behavior by both supporters and opponents (Downs, 1957a, 1957b; Street, 2010; Barberá et al., 2019). In the context of land use, discourses transmitting changes in environmental law enforcement or public statements on road infrastructure investments can lead to more or less conversion of forests to agriculture. Such discourses contain information that affects 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 the timing of decisions to deforest.

The study of how political discourses affect land use change is a relatively new field that can still benefit from improvements in research designs toward internal validity. To date, there is only one correlational study that examines the relationship between political discourses and land use change. Caetano (2021) analyzes social media activity and keywords in Google Trends and finds positive correlations between presidential tweets and forest fires in the Brazilian Amazon region. We in turn focus on establishing causality between forest-related political discourses and deforestation rates in the same region. To the best of our knowledge, this is the first empirical investigation of the causal effects of political discourse on deforestation.

Under transaction costs and asymmetric information, land users have to make decisions in a dynamic and volatile environment with expectations being driven by market and non-market factors. Uncertainty about future economic, environmental, and institutional conditions makes information a valuable asset in land use decision-making. Moreover, the decision to deforest implies sunk costs, which motivates the theory of real options and adds a temporal dimension to land use decisions under uncertainty (Song et al., 2011; Ewald et al., 2017; Lundberg and Abman, 2022). The real options approach treats the problem of assessing the value of an asset vis-à-vis current and potential future returns as a choice between anticipating and delaying an investment decision given the access to information of the decision-maker (McDonald and Siegel, 1986; Dixit and Pindyck, 1994).

Few studies of land use change based on real options theory consider non-market factors (Regan et al., 2015), such as political discourse. If such discourse insinuates a shift towards a laissez-faire type of government attitude with regard to illegal deforestation, real option theory predicts a corresponding preference shift to invest in deforestation now rather than later. As deforestation rates can significantly differ by land tenure regimes (Pacheco and Meyer, 2022), we also expect political discourse to have different impacts across these regimes due to their diverse degree of either de facto or de jure property right protection, effective exclusion rights, and monitoring and enforcement mechanisms.

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 time fixed effects, we estimate how forest cover change responds to information conveyed by political discourses that transmit a laissez-faire attitude with respect to deforestation. Over the last decade, Brazilian politicians and public institutions increasingly relied on Twitter to disseminate information to an ever-growing number of Twitter users, which can be geographically identified. This enables us to study whether specific centrally provided information provokes land use change across municipalities in the Brazilian Amazon. For identification we rely on a shift-share measure that combines forest-related laissez-faire Tweets from governmental accounts (shift) to past forest-related Twitter activity at municipal scale (share). Robustness checks using alternative shift and share measures plausibly confirm 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 laissez-faire discourse across baseline models with alternative outcome variables. We find an increase of 2.2% in forest fires, and an increase of 2.3-3.0% in deforestation, depending on the source of data used to measure deforestation. Our findings also hold when we exclude dry season months, during which deforestation rates are naturally higher. Effect magnitudes differ across various land regimes, such as indigenous, settlement, legal reserve, and permanent preservation areas (PPA), suggesting sensitivity to the associated monitoring and sanctions mechanisms.

The remainder of this article is organized as follows. Sections 2 and 3 present the theoretical framework used to study the research question and describe our empirical setting. In section 4, the empirical framework is presented, first by detailing our data, and then by discussing the estimation and identification strategies. Sections 5 and 6 present and discuss the empirical results, followed by robustness checks and a discussion of the limitations of the results with suggestions for future research. In section 7, we conclude with policy recommendations.

## 2. Political economy of deforestation literature and real options theory

Tropical deforestation can be driven by interactions between political forces and market dynamics. Recent work identified elections as a key political driving force underlying forest loss (Pailler, 2018; Balcony 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 in particular 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 in the interest of raising funds for electoral campaigns from the agricultural sector. The interplay between agricultural production and political incentives will then drive forest harming activities in this context (Burgess et al., 2012).

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, such as "official salaries, private sector opportunities after leaving office, and also nonsalary earnings while in office, legal or otherwise" (Fisman et al., 2014, p. 807). 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 political discourses 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).

Real options theory posits that decision-makers anticipate or delay decisions based on information about current and potential future returns (McDonald and Siegel, 1986; Dixit and Pindyck, 1994). This idea has informed numerous models of land use change, for example, to investigate decisions to convert forests to farmland or to switching between alternative crops (Regan et al., 2015). Real-options models of land-use change usually assume that change will occur only when land users experience sufficiently large changes in relative returns (Schatzki, 2003). Most empirical applications consider output price volatility due to uncertainty from unexpected supply or demand shocks as one of the main driving forces in such decisions (Song et al., 2011; Ewald et al., 2017; Spiegel et al., 2020; Lundberg and Abman, 2022). In many tropical forest economies, however, politics can come to be an equally relevant source of uncertainty with political discourses being an important source of information for land users to build expectation on.

We adapt Schatzki (2003)'s model of land conversion under uncertainty with sunk costs focusing exclusively on agricultural uses as an alternative to forest. More specifically, we consider forest use in terms of non-timber forest products, such as acai berry, natural rubber and Brazilian nuts.[1]

Think about the following objective function. To maximize value, a risk-neutral land user with forestland chooses the maximum of one of the two land uses: convert forest to agriculture or keep the forest standing and obtain returns from non-timber products:

$$\max V_t = \max\left\{F_t + E[R_t^a] + e^{-rt}E[V_{t+1}^a] - C_t^f \;,\; E\left[R_t^f\right] + e^{-rt}E\left[V_{t+1}^f\right]\right\} \qquad (1)$$

where $F_t$ is the one-off value of timber removed prior to the conversion of forest to agriculture, $E[]$ represents the expected value, $R_t^a$ is the annual returns to agricultural production, $V_{t+1}^a$ is the value of land in agriculture, $C_t^f$ is the one-time costs of conversion from forest to agriculture, $R_t^f$ is the annual returns to non-timber extractive products, $V_{t+1}^f$ is the value of forestland, $r$ is the discount rate, and $t$ denotes the period.

The land user will convert forest to agriculture when:

$$F_t + E[R_t^a] + e^{-rt}E[V_{t+1}^a] - C_t^f > E\left[R_t^f\right] + e^{-rt}E\left[V_{t+1}^f\right] \qquad (2)$$

Following Schatzki (2003), the decision to convert from forests to agriculture is a simple decision rule, which implies that conversion is optimal when the relative returns of agriculture to forest, $R_t = \frac{R_t^a}{R_t^f}$, rises above a threshold that is independent of the current return from either use:

$$R_t > R^A\,(\sigma_{at}, \sigma_{ft}, \mu_{at}, \mu_{ft}, \rho_t, r, C_t) \qquad (3)$$

where $R^A$ is an optimal conversion threshold as a function of variance parameters reflecting uncertainty around agriculture and forest-based activities $(\sigma_{at}, \sigma_{ft})$, drift parameters reflecting deterministic trends of both land uses $(\mu_{at}, \mu_{ft})$, correlation between shocks to agriculture and non-timber forest returns $(\rho_t)$, discount rate $r$, and conversion costs $C_t$.

We assume that $C_t$ is composed of two parts: legal and illegal conversion costs. The legal component encompasses labor and capital costs. The illegal conversion costs refer to the expected punishment costs and probability of getting caught (Becker, 1968). Although there are enforcement rules constraining illegal deforestation, there is uncertainty around the actual implementation of such rules. Hence, in addition to market drivers, political factors could also affect this decision-making process (Assunção et al., 2015).

The imposition of land use restrictions or changes in enforcement practice can affect expected profits from illegal deforestation by increasing the risk of being sanctioned (Börner et al., 2015). In countries like Brazil, where agri-environmental policies still affect a large share of the population, such policy regime shifts are often signaled by political statements. We expect such information signals to affect profit expectations of land users and the costs of illegal forest conversion thus become subject to uncertainty, i.e. $E\left[C_t^f\right]$. The decision rule in equation (3) then expands to:

$$R_t > \; R^A\left(\sigma_{at}, \sigma_{ft}, \sigma_{ct}, \mu_{at}, \mu_{ft}, \mu_{ct}, \rho_t, r\right) \qquad (4)$$

where the optimal conversion threshold $R^A$ now includes variance parameters of uncertainty ($\sigma_{ct}$) and deterministic trends ($\mu_{ct}$) of conversion costs.

With equation (4) given, a sudden shift from *law and order* to *laissez-faire* type of political discourse linked to environmental policy enforcement reduces enforcement risk from the perspective of land users implying a lower variance of the illegal component of conversion costs. Put differently, the conversion threshold is increasing in the level of uncertainty around $C_t^f$ and $\frac{\partial R^A}{\partial \sigma_c} > 0$. While an increase in $\sigma_c$ would thus on average delay deforestation decisions, the opposite must be expected in response to *laissez-faire* discourse. Our empirical strategy outlined below is designed to test this hypothesis in the context of the Brazilian Amazon, where land users were exposed to a continuous regime shift in both political discourse and environmental policy enforcement between 2019 and 2022.

# 3. Environmental policy discourse and the Brazilian Amazon

Deforestation in the Brazilian Amazon has historically been closely tied to road network expansion. Public subsidies to land intensive economic activities, such as cattle ranching, have accelerated the conversion of large 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 its implementing institutions (Abessa et al., 2019). The existing environmental governance regime was systematically dismantled, for example, via budged 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).

Examples of the new government's discourse include "I won't allow Ibama to go around issuing fines left and right" (Jair Bolsonaro, WashingtonPost, 2019) and "Solution to save the Amazon is to monetize it" (Minister of Environment, OGlobo, 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 political discourses and land use decisions.

# 4. Empirical framework

## 4.1 Data

Our spatial units of analysis are Brazilian municipalities located in the Legal Amazon region. Legal Amazon is an administrative area currently defined by the Complementary Law 124/2007 that covers 61% of the Brazilian territory. The area fully includes the Brazilian states of Acre, Amapá, Amazonas, Pará, Rondônia e Roraima and parts of the states of Maranhão, Mato Grosso, and Tocantins (Figure 1). Our panel data covers the 12 months of the year 2019, in which Twitter was heavily used for political messages by the recently elected Bolsonaro government and deforestation rates were still unaffected by the Covid-19 pandemic (Brancalion et al., 2020). We also restrict our main analysis to municipalities which had at least 1% of initial forest cover in 2018.

### *4.1.1 Outcome variables*

Our main dependent variables of interest are the monthly total deforested area (hectares) and the number of fire alerts within each municipality. The newly deforested area is derived from MapBiomas (2022), which organizes information from different *deforestation alert systems*. We focus specifically on both GLAD (Global Land Analysis and Discovery – University of Maryland) and DETER (*Sistema de Detecção de Desmatamento em Tempo Real* - INPE). While each GLAD alert indicates a disturbance in the forest canopy in a 30x30 meter area, the DETER produces daily alerts on changes in forest cover for areas larger than or equal to 3 hectares. Fire alerts are derived from the database BDQueimadas organized by the National Institute for Space Research (INPE). INPE collects this data to monitor the spatial and temporal dynamics of fires in Brazil.

### *4.1.2 Exposure measure*

We measure exposure to the spread of information on *laissez-faire* type of forest conservation in political discourses through a shift-share measure, $DiscourseExposure_{it}$, that varies across municipalities *i* and months *t.* It is derived by interacting Twitter activity related to forest conservation in municipality *i* ($ForestTwitterExp_i$) with political discourses inducing land users to deforest by month *t* ($ForestPoliticalTweets_t$):

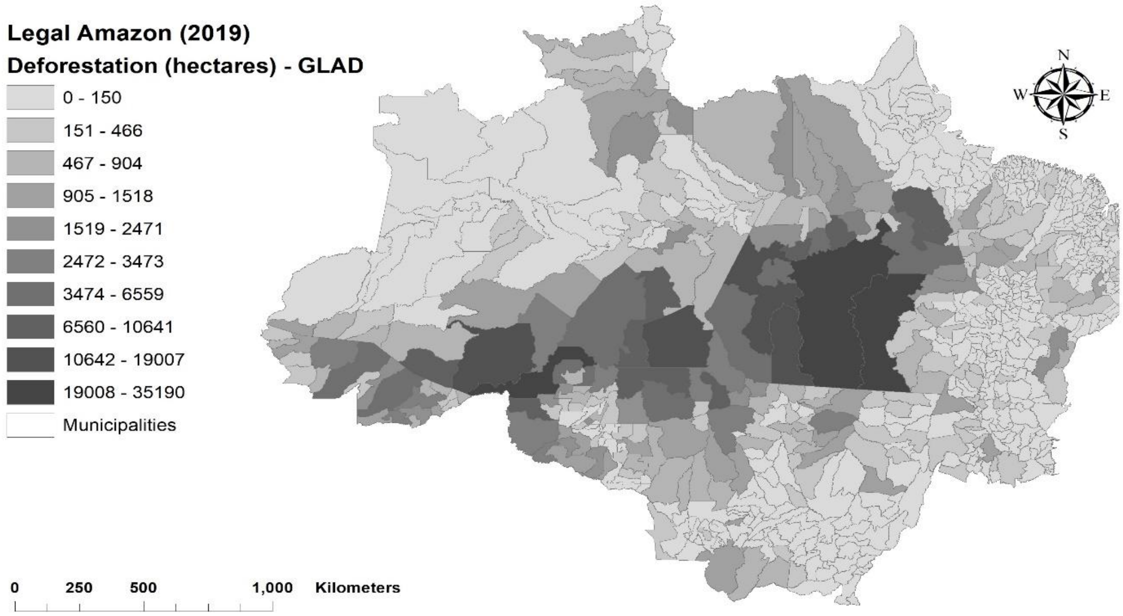
$$DiscourseExposure_{i(2015-2018)\,t(2019)} = ForestTwitterExp_{i\,(2015-2018)} \times ForestPoliticalTweets_{t\,(2019)} \qquad (5)$$

where $ForestTwitterExp_{i(2015-2018)}$ denotes the Twitter activity as measured by the sum of all tweets related to forest conservation in a given municipality *i* in a period prior to our main analyses (2015-2018). It is important to note that $ForestTwitterExp_{i(2015-2018)}$ is time-invariant in 2019. We also consider the placebo check proposed by Goldsmith-Pinkham et al. (2020), i.e., our exposure is constructed using a short and recent period as we expect that we should not observe impacts of exposure on outcomes in earlier periods due to the recent use of Twitter as a tool for disseminating political discourses in our empirical setting. $ForestPoliticalTweets_{t\,(2019)}$ is computed as the monthly municipality-invariant number of Tweets by governmental accounts including information on *laissez-faire* type of forest conservation in 2019.

More specifically, we collected tweets using academic access and the standard Automated Programming Interface (API) provided by Twitter through the python library *twarc* (Summers et al., 2022). For our share measure, we collected geotagged Tweets to all municipalities in the Legal Amazon region from 2015 to 2018. We used the latitude and longitude points of 'sede municipal' in order to measure the Twitter activity related to forest conservation in each municipality. A radius of 5km was also included. To measure the links to forest conservation, we only collected geotagged tweets including the following keywords: *fogo* OR *desmatamento* OR *amazonia* OR *amazônia* OR *floresta*[2], which resulted in 74329 tweets in total. Finally, we adopt a time-invariant count variable of all tweets by municipality *i* as our share measure.

For our shift measure, we collected data from the following governmental accounts in Twitter in 2019: President of Brazil, Ministry of Agriculture, Livestock and Food Supply (MAPA), Ministry of Environment (MMA), and Ministry of Foreign Affairs (MRE). We then read all tweets to classify them as being related to the spread of information on *laissez-faire* type of forest conservation. Only about 1% of all tweets from these accounts in 2019 were classified as such. Finally, we adopt a municipality-invariant count variable measured as the sum of all these '*laissez-faire*' tweets by month *t* as our shift measure.

Figure 1 shows the spatial distribution of total forest loss (GLAD) in 2019 and our Twitter exposure measure (2015 to 2018) per municipality in the Legal Amazon region.



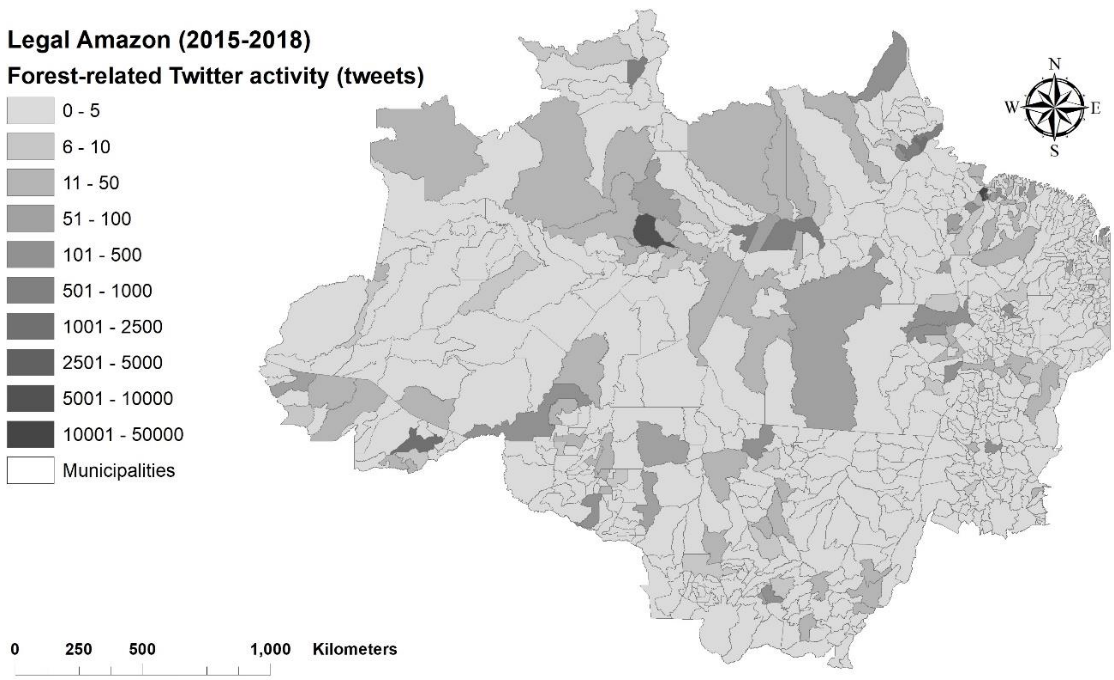




**Figure 1: GLAD deforestation in 2019 and spatial distribution of share measure (2015-2018) per municipality in Legal Amazon.**

**Table 1: Descriptive statistics**

| Variables | Description | Mean | Std. Dev. |
|---|---|---|---|
| $ForestTwitterExp_{i\,(2015-2018)}$ | Arcsinh transformed: sum of all tweets on forest conservation by municipality *i.* Source: Twitter API. | 1.12 | 1.71 |
| $ForestPoliticalTweets_{t\,(2019)}$ | Arcsinh transformed: sum of all government tweets representing political discourses of the *laissez-faire* type on forest conservation per month *t.* Source: Twitter API. | 1.43 | 1.25 |
| Deforest.Glad$_{it}$ | Arcsinh transformed: total size (hectares) of newly deforested area detected by GLAD per municipality *i* and month *t*. Source: Mapbiomas (2022). | .99 | 2.06 |
| Deforest.Deter$_{it}$ | Arcsinh transformed: total size (hectares) of newly deforested area detected by DETER per municipality *i* and month *t*. Source: Mapbiomas (2022). | 1.7 | 2.52 |
| Fire$_{it}$ | Arcsinh transformed: number of fire alerts per municipality *i* and month t. Source: BDQueimadas – Inpe. | 1.44 | 1.67 |
| Precipitation$_{it}$ | Average rainfall precipitation (mm) per municipality *i* and month t. Source: Inpe. | 4.02 | 4.11 |
| Temperature$_{it}$ | Average temperature (Cº) per municipality *i* and month t. Source: Inpe. | 25.82 | 1.43 |
| Embargoes$_{it}$ | Number of embargoes due to environmental harm per municipality *i* and month t. Source: Ibama. | .05 | .32 |
| Env.Fines$_{it}$ | Number of environmental fines per municipality *i* and month t. Source: Ibama. | .39 | 2.25 |
| RuralCredit_Production$_{it}$ | Number of rural contract loans for production purposes (e.g., working capital) in municipality *i* and month *t.* Source: Central Bank – Brazil. | 2.13 | 4.76 |
| RuralCredit_Investments$_{it}$ | Number of rural contract loans for expansion of production in municipality *i* and month *t.* Source: Central Bank – Brazil. | 4.16 | 9.93 |
| Transport*SoybeanBRL$_{it}$ | Interaction term between the number of transportation modes (road, air, and rail) in municipality *i* and an average price (Brazilian reais – BRL) of soybeans sold at the Port of Paranaguá, Brazil in month *t.* Source: Mapbiomas and CEPEA/USP. | 372.02 | 532.06 |

Notes: (a) Arcsinh transformed refers to the inverse hyperbolic sine transformation.

### *4.1.3 Covariates*

Our empirical analysis combines time-variant remotely-sensed data on forest cover, measures of the local exposure to variation in Twitter activity, climatic information (precipitation and temperature), environmental enforcement (fines and embargoes released by Ibama), rural credit contracts, a measure of access to roads and economic incentives (price of soybean). Descriptive statistics are displayed in Table 1 below.

## *4.2 Estimation strategy*

Our empirical strategy links the dynamics of municipality-level fire and deforestation to the local variation in exposure to political discourses conveying *laissez-faire* messages on forest conservation. We are especially interested in whether and to what extent this exposure makes land users deforest now rather than later. We do this by running regressions of the following type:

$$Y_{it} = \alpha_i + \gamma_t + \beta DiscourseExposure_{i(2015-2018)\,t(2019)} + X'_{it}\delta + \varepsilon_{it} \qquad (6)$$

Following common practice, our main dependent variables, $Y_{it}$, are expressed as the inverse hyperbolic sine of the newly deforested area or the number of fire alerts in municipality *i* and month *t*. The inverse hyperbolic sine function transformation has the advantage of being defined at zero and yielding near-zero positive values, but still allowing for interpreting coefficients in percent similarly to a log transformation (Bellemare and Wichman, 2020). Our variable of interest, $DiscourseExposure_{i(2015-2018)\,t(2019)}$, is derived as an interaction after both share and shift were also transformed using the inverse hyperbolic sine function. This is a shift-share measure that uses a lagged share component. We regress these outcomes on an indicator of the variation in exposure to political discourses and *laissez-faire* information on forest conservation, plus further controls. $\alpha_i$ depicts municipality fixed effects to control for all sources of time invariant heterogeneity at municipal level, and $\gamma_t$ are month fixed effects to control for unexplained fluctuations in deforestation and fire alerts, for example, due to seasonal shocks.

The changes of expectations and behavior are captured by our variable of exposure to spread of information on *laissez-faire* type of forest conservation in political discourses, $DiscourseExposure_{it}$. This discourse exposure varies across municipalities and across time due to differences in Twitter activity on forest conservation of the population of a given municipality and time variation in political discourses spreading information of the *laissez-faire* type on forest conservation. Positive values for $\beta$ would show that politicians spreading such messages contribute to deforestation at the municipality level. Further identification details are explained in the following section (Section 4.3).

All regressions also include a vector of municipality- and time-varying controls, $X'_{it}$, to control for weather, environmental enforcement, rural credit, and economic incentives for agricultural production. Controls variables are specified as 2-month lags. The term $\varepsilon_{it}$ is the error component, clustered at the municipality level to account for serial correlation within cross-sectional units over time, as idiosyncratic disturbances may be correlated within municipalities on a monthly basis.

### *4.3 Identification strategy and robustness checks*

Our identification strategy relies on the assumption that municipalities in which people are more active in tweeting on forest conservation are more prone to be affected by political discourses on Twitter in the same topic. We address the following potential threats to identification: (i) political discourses posted on Twitter can affect municipalities differently, depending on how intensively locals use social media and general interest in forest related issues; (ii) social network activity on forest conservation is likely correlated with deforestation rates, i.e., people tweeting more about forest related topics in municipalities experiencing higher deforestation rates; and (iii) *laissez-faire* type of information can also be spread in response to high levels of forest loss, for example, in the dry season when deforestation typically peaks.

With these issues linked to the exogeneity of the share dimension in mind, we first perform two balance checks proposed by Goldsmith-Pinkham et al. (2020). We use Twitter data from a period prior to the one used in our main analysis to construct our plausibly exogeneous share component. As our shift or "shock" measure (derived from political discourse) is constant across municipalities, variation in exposure to the shock must come from the municipal level "shares" reflecting relevant Twitter activity. Municipalities having high Twitter activity are more exposed to forest conservation tweets, i.e. larger "shares". Moreover, in order to correctly identify this exposure to these types of political discourses, we replace our preferred share measure by a general type of Twitter exposure (see Table 4). $\mathrm{GeneralTwitterExp}_i$ is derived from subtracting general Twitter activity (without any keywords) and forest-related Twitter exposure, i.e., this variable captures general Twitter activity except for forest-related by municipality *i*. We also used the same period (2015-2018) and coordinates (longitude and latitude) of each *'sede municipal*', as we did in our main share measure. As shown in Table 4, we find no effects when using general Twitter activity, strengthening the reliability of our identification strategy.

Second, we ‘check’ the validity of the assumption that the shares are as good as random and that our coefficients are unaffected by past events. We test the correlation between past Twitter activity on forest conservation (i.e., exposure) and deforestation rates. We split our Twitter exposure share measure by year and test correlation with annual deforestation using the Prodes alert system, both by municipality *i*. We find no significant correlations between the share measure (at time *t*) and deforestation rates (at time $t$ and *t-1*) (see Table 2). It suggests that people are not necessarily tweeting on forest conservation after facing deforestation in their municipality, and that our exposure measure is conditionally independent on deforestation.

Third, we also focus on the recent literature on the ‘shift’ component (Borusyak et al., 2022). We check whether our results hold after handling potential reverse causality related to politicians using periods of high deforestation to push their interests further. For this empirical exercise, we run additional analyses excluding dry season months to ensure our main findings are not driven by idiosyncrasies of the deforestation dynamics across the different seasons. Results are similar (see Tables 3 and 6).

Finally, we also include a diagnostic test on alternative shocks. Assuming that our shares are as good as random, one should not expect to observe substantially different sets of shocks acting as weights on the shares when estimating the exposure effect. Therefore, similar estimates should not be found in this case. Following this approach, we now replace the political discourses shift measure ($ForestPoliticalTweets_t$) by a measure capturing messages of increasing environmental enforcement against illegal deforestation. We used a similar procedure as in Section 5. $EnforcementTweets_t$ is computed as the number of Tweets by the Twitter account of the Federal Prosecutor’s Office on police/army operations and the results of judicial processes and environmental fines in the Amazon by month $t$ in 2019. We first collect all 2019 tweets of those accounts and then read all tweets to classify them as being related to these strict measures against illegal deforestation. Results displayed in Table 5 illustrate null effects, suggesting that it is easier to destroy than to build the reputation of the enforcement system.

To sum up, we believe our empirical strategy enables us to identify causal effects because: (a) we use historical archives from years prior to the period of our analysis to construct our share measure; (b) we restrict our measure to a specific flow of information on *laissez-faire* type of forest conservation; (c) we test another a general type of Twitter exposure and find no signification effects. Moreover, our empirical exercises corroborate our conceptual framework. Our results illustrate a change in expectations and behavior towards more deforestation when political discourses spread *laissez-faire* type of information on forest law enforcement.

**Table 2: Correlations between local Twitter activity related to forest conservation and annual deforestation from Prodes system**

| **Variables** | $Deforest.Prodes2014_i$ | $Deforest.Prodes2015_i$ | $Deforest.Prodes2016_i$ | $Deforest.Prodes2017_i$ | $Deforest.Prodes2018_i$ |
|---|---|---|---|---|---|
| $ForestTwitterExp2015_i$ | 0.004 | 0.004 | | | |
| | (0.914) | (0.916) | | | |
| $ForestTwitterExp2016_i$ | | 0.004 | 0.004 | | |
| | | (0.917) | (0.919) | | |
| $ForestTwitterExp2017_i$ | | | 0.006 | 0.006 | |
| | | | (0.871) | (0.874) | |
| $ForestTwitterExp2018_i$ | | | | 0.013 | 0.013 |
| | | | | (0.720) | (0.721) |

Notes: (a) Pearson correlation coefficients are shown with p-values in parentheses. *** p<0.01, ** p<0.05, * p<0.1. (b) Our preferred main analysis uses the entire time period (2015-2018) to create our share measure.

# 5. Results

Table 3 presents our baseline estimates based on Equation (6), including all controls, and municipality- and month- fixed effects. Column (1) shows results for newly deforested areas detected by GLAD system suggesting a significant increase in deforestation rates by 2.3% [+/- 2.2%] in response to a 1% increase in exposure to forest-related *laissez-faire* type political discourses. Column (2) indicates a somewhat more pronounced effect (3% [+/- 1.9%]) for forest cover change detected by the DETER system. Effects on forest fires (Column (3) are consistent with the results for our area-based outcome variables (2.2% [+/- 2.1%]).

**Table 3: Baseline models**

| VARIABLES | (1)<br>Deforest.Glad | (2)<br>Deforest.Deter | (3)<br>Fire |
|---|---|---|---|
| $DiscourseExposure_{i(2015-2018)\ t(2019)}$ | 0.023* | 0.030** | 0.022* |
| | (0.013) | (0.012) | (0.013) |
| Observations | 6,270 | 6,270 | 6,270 |
| R-squared | 0.266 | 0.171 | 0.417 |
| Municipality FE | YES | YES | YES |
| Month FE | YES | YES | YES |
| Control variables | YES | YES | YES |

Notes: (a) robust standard errors in parentheses and clustered at municipality-level. *** p<0.01, ** p<0.05, * p<0.1. (b) Deforest.Glad = inverse hyperbolic sine transformation of hectares of deforestation detected by GLAD system in municipality i and month t. (c) Deforest.Deter = inverse hyperbolic sine transformation of hectares of deforestation detected by DETER system in municipality i and month t. (d) Fire = inverse hyperbolic sine transformation of fire outbreaks in municipality i and month t. (e) $DiscourseExposure_{i(2015-2018)\ t(2019)}$ = a shift-share measure resulted from the interaction of the inverse hyperbolic sine transformation of political discourses inducing land users to deforest in Twitter and the Twitter activity related to forest conservation of inhabitants of a given municipality. (f) We use 2-month lagged control variables. (g) All models are restricted to municipalities that have shown at least 1% of forest cover in PRODES system in 2018.

In our setting, causal identification implies that our composite measures of exposure to political discourses must genuinely explain variation in forest cover. We now scrutinize the sources of variation in this shift-share variable and discuss potential concerns. Our tests follow the rationale of a placebo test as we investigate whether our results are driven by spurious correlation.

In Table 4, we replace our original share variable, which measures exposure to specific forest-related Twitter activity, with a general measure of Twitter exposure. This exercise aims to demonstrate that the content of social media activity matters for exposure to specific discourses and related expectation formation. Repeating our regression analyses with the unspecific share measure consistently produces null results across all outcome variables (Columns 1-3).

**Table 4: Changing share measure**

| VARIABLES | (1)<br>Deforest.Glad | (2)<br>Deforest.Deter | (3)<br>Fire |
|---|---|---|---|
| $GeneralTwitterExp_{i\,(2015-2018)}$ $\times\ ForestPoliticalTweets_{t\,(2019)}$ | -0.001 | -0.000 | 0.007 |
| | (0.010) | (0.009) | (0.009) |
| Observations | 6,270 | 6,270 | 6,270 |
| R-squared | 0.265 | 0.170 | 0.417 |
| Number of Municipalities | 627 | 627 | 627 |
| Municipality FE | YES | YES | YES |
| Month FE | YES | YES | YES |
| Control variables | YES | YES | YES |

Notes: (a) robust standard errors in parentheses and clustered at municipality-level. *** p<0.01, ** p<0.05, * p<0.1. (b) Deforest.Glad = inverse hyperbolic sine transformation of hectares of deforestation detected by GLAD system in municipality i and month t. (c) Deforest.Deter = inverse hyperbolic sine transformation of hectares of deforestation detected by DETER system in municipality i and month t. (d) Fire = inverse hyperbolic sine transformation of fire outbreaks in municipality i and month t. (e) $GeneralTwitterExp_{i\,(2015-2018)}$ is measured as a variable resulted from subtracting general Twitter activity (without keywords) and forest-related Twitter exposure, i.e., this variable captures general Twitter activity except for forest-related ones. We used the same collection period (2015-2018), per latitude and longitude of 'sede municipal'. (f) We use 2-month lagged control variables. (g) All models are restricted to municipalities that have shown at least 1% of forest cover in PRODES system in 2018.

Table 5 displays results after replacing the shift component in our exposure variable. The new shift measure captures tweets suggesting rigorous environmental enforcement against illegal deforestation. More specifically, we examine exposure to messages of the Federal Prosecutor's Office containing information about police and army operations as well as the results of judicial processes linked to environmental fines in the Amazon region.

All regressions summarized in Table 5 produced null effects, i.e. tweets with a different content do not reproduce our main findings. Interestingly, we also do not observe a reverse effect for tweets that convey information about effective law enforcement. Expectation formation in our context thus seems to be subject to hysteresis, where reputational damage to the law enforcement system, once done, is not simply reversible. Earlier work reporting evidence on heterogeneous effectiveness of law enforcement actions in the region supports this conjecture (Börner et al., 2015).

**Table 5: Changing shift measure**

| VARIABLES | (1)<br>Deforest.Glad | (2)<br>Deforest.Deter | (3)<br>Fire |
|---|---|---|---|
| $ForestTwitterExp_{i\,(2015-2018)}$ $\times\ EnforcementTweets_{t\,(2019)}$ | 0.032 | 0.032 | -0.022 |
| | (0.024) | (0.020) | (0.017) |
| Observations | 6,270 | 6,270 | 6,270 |
| R-squared | 0.265 | 0.171 | 0.417 |
| Number of Municipalities | 627 | 627 | 627 |
| Municipality FE | YES | YES | YES |
| Month FE | YES | YES | YES |
| Control variables | YES | YES | YES |

Notes: (a) robust standard errors in parentheses and clustered at municipality-level. *** p<0.01, ** p<0.05, * p<0.1. (b) Deforest.Glad = inverse hyperbolic sine transformation of hectares of deforestation detected by GLAD system in municipality i and month t. (c) Deforest.Deter = inverse hyperbolic sine transformation of hectares of deforestation detected by DETER system in municipality i and month t. (d) Fire = inverse hyperbolic sine transformation of fire outbreaks in municipality i and month t. (e) $EnforcementTweets_{t\,(2019)}$ is measured as the number of Tweets by the Twitter account of the Federal Prosecutor's Office on police/army operations and the results of judicial processes and environmental fines in the Amazon by month $t$ in 2019. (f) We use 2-month lagged control variables. (g) All models are restricted to municipalities that have shown at least 1% of forest cover in PRODES system in 2018.

Another potential threat to our identification strategy is reverse causality, i.e. high deforestation actually being the cause rather than the response to forest related Twitter activity. We address this by working with a lagged shift-share measure. As a further robustness check, we exclude the dry season period from our sample, because deforestation usually peaks in the dry months from June to August (Table 6).

**Table 6: Removing dry season effects – June, July and August**

| VARIABLES | (1)<br>Deforest.Glad | (2)<br>Deforest.Deter | (3)<br>Fire |
|---|---|---|---|
| $DiscourseExposure_{i(2015-2018)\ t(2019)}$ | 0.021* | 0.036*** | 0.031** |
| | (0.012) | (0.011) | (0.014) |
| Observations | 4,389 | 4,389 | 4,389 |
| R-squared | 0.242 | 0.113 | 0.507 |
| Number of Municipalities | 627 | 627 | 627 |
| Municipality FE | YES | YES | YES |
| Month FE | YES | YES | YES |
| Control variables | YES | YES | YES |

Notes: (a) robust standard errors in parentheses and clustered at municipality-level. *** p<0.01, ** p<0.05, * p<0.1. (b) Deforest.Glad = inverse hyperbolic sine transformation of hectares of deforestation detected by GLAD system in municipality i and month t. (c) Deforest.Deter = inverse hyperbolic sine transformation of hectares of deforestation detected by DETER system in municipality i and month t. (d) Fire = inverse hyperbolic sine transformation of fire outbreaks in municipality i and month t. (e) $DiscourseExposure_{i(2015-2018)\ t(2019)}$ = a shift-share measure resulted from the interaction of the inverse hyperbolic sine transformation of political discourses inducing land users to deforest in Twitter and the Twitter activity related to forest conservation of inhabitants of a given municipality. (f) We use 2-month lagged control variables. (g) All models are restricted to municipalities that have shown at least 1% of forest cover in PRODES system in 2018.

Our results hold even after excluding dry season months from the data set. This is reassuring, because our findings do not seem to be driven by seasonal fluctuations in deforestation rates.

Another concern relates to the idiosyncrasies of deforestation dynamics in particular municipalities in the Legal Amazon region. After 2004, when the PPCDAm was launched, environmental policy actions sometimes focused on specific municipalities, for example, as a result of the "Priority List" of municipalities (Cisneros et al., 2015; Assunção and Rocha, 2019). Beyond naming and shaming municipalities with high deforestation rates, the list also enabled additional cross-compliance measures, such as restrictions on access to public credit and licenses for legal deforestation.

Being subject to particular public scrutiny in the past could have affected the expectation formation of land users in these municipalities in response to public social network activity still in 2019. We thus test whether our main findings are robust to the exclusion of municipalities included in the Priority List and present results in Table 7.

**Table 7: Removing municipalities that have been included in Priority List**

| VARIABLES | (1)<br>Deforest.Glad | (2)<br>Deforest.Deter | (3)<br>Fire |
|---|---|---|---|
| $DiscourseExposure_{i(2015-2018)\ t(2019)}$ | 0.026* | 0.033*** | 0.019 |
| | (0.014) | (0.012) | (0.013) |
| Observations | 5,750 | 5,750 | 5,750 |
| R-squared | 0.241 | 0.153 | 0.407 |
| Number of Municipalities | 575 | 575 | 575 |
| Municipality FE | YES | YES | YES |
| Month FE | YES | YES | YES |
| Control variables | YES | YES | YES |

Notes: (a) robust standard errors in parentheses and clustered at municipality-level. *** p<0.01, ** p<0.05, * p<0.1. (b) Deforest.Glad = inverse hyperbolic sine transformation of hectares of deforestation detected by GLAD system in municipality i and month t. (c) Deforest.Deter = inverse hyperbolic sine transformation of hectares of deforestation detected by DETER system in municipality i and month t. (d) Fire = inverse hyperbolic sine transformation of fire outbreaks in municipality i and month t. (e) $DiscourseExposure_{i(2015-2018)\ t(2019)}$ = a shift-share measure resulted from the interaction of the inverse hyperbolic sine transformation of political discourses inducing land users to deforest in Twitter and the Twitter activity related to forest conservation of inhabitants of a given municipality. (f) We use 2-month lagged control variables. (g) All models are restricted to municipalities that have shown at least 1% of forest cover in PRODES system in 2018.

When excluding municipalities in the Priority List, parameter estimates are similar in magnitude to the results in the baseline models, though the effect in forest fires is statistically not significant.

Finally, our main result seems fairly robust, but we expected some variation across tenure regimes, such as indigenous, settlement, legal reserve, and permanent preservation areas (PPA). Cultural backgrounds of land users and historical exposure to forest law enforcement varies substantially across tenure regimes and so should expectation formation in response to our main treatment. We now focus exclusively on municipal-level deforestation detected within the respective tenure categories. We ran separate models for each tenure category, excluding municipalities from the analysis if they do not feature a specific category (see Table 8).

**Table 8: Effects across land tenure regimes**

| VARIABLES | (1)<br>Conservation Units areas | (2)<br>Indigenous areas | (3)<br>Settlement areas | (4)<br>Legal reserve areas | (5)<br>PPA |
|---|---|---|---|---|---|
| $DiscourseExposure_{i(2015-2018)\ t(2019)}$ | 0.020 | 0.027* | 0.032** | 0.027** | 0.011** |
| | (0.013) | (0.015) | (0.012) | (0.011) | (0.005) |
| Observations | 3,130 | 2,690 | 5,530 | 6,270 | 6,270 |
| R-squared | 0.093 | 0.097 | 0.112 | 0.096 | 0.084 |
| Number of Municipalities | 313 | 269 | 553 | 627 | 627 |
| Municipality FE | YES | YES | YES | YES | YES |
| Month FE | YES | YES | YES | YES | YES |
| Control variables | YES | YES | YES | YES | YES |

Notes: (a) robust standard errors in parentheses and clustered at municipality-level. *** p<0.01, ** p<0.05, * p<0.1. (b) Conservation Units areas = inverse hyperbolic sine transformation of the number of hectares of deforestation within conservation unit areas. (c) Indigenous areas = inverse hyperbolic sine transformation of the number of hectares of deforestation within indigenous areas. (d) Settlement areas = inverse hyperbolic sine transformation of the number of hectares of deforestation within settlements. (e) Legal reserve areas = inverse hyperbolic sine transformation of the number of hectares of deforestation within legal reserve areas. (f) PPA areas = inverse hyperbolic sine transformation of the number of hectares of deforestation within permanent preservation areas (PPA). (g) $DiscourseExposure_{i(2015-2018)\ t(2019)}$ = a shift-share measure resulted from the interaction of the inverse hyperbolic sine transformation of political discourses inducing land users to deforest in Twitter and the Twitter activity related to forest conservation of inhabitants of a given municipality. (h) We use 2-month lagged control variables. (i) All models are restricted to municipalities that have shown at least 1% of forest cover in PRODES system in 2018.

The results in Table 8 show the effect of political discourses on deforestation for each land tenure category. Results in column (1) suggest no effect in conservation units (i.e. protected areas). As expected, we find positive effects of exposure to *laissez-faire* political discourses on deforestation in all other land tenure regimes though, with impacts being most pronounced in settlement areas (3.2%), followed by indigenous and legal reserve areas with about 2.7% increase, and a small effect in PPAs (1.1%).

As noted by Pacheco and Meyer (2022), varying response of deforestation to policy-related shocks in indigenous and settlement areas likely owes to fundamental differences in the governance arrangements that regulate the distribution of use and exclusion rights within local communities in these tenure regimes. Although not tenure regimes, permanent preservation areas (PPA) and legal reserve areas are subject to conservation rules established by the legal framework (Brazilian Forest Code). Both restrictions present similar results in Table 8.

## 6. Discussion

This paper provides evidence that political discourse signaling a *laissez-faire* attitude of public authorities with regard to forest law enforcement can increase deforestation. This effect is likely driven by how such information changes land users' assessment of future returns to deforestation. Based on monthly forest loss detected by GLAD and DETER systems, we find that a Twitter mediated 1% increase in exposure to political discourse, increases deforestation by 2.3% [+/- 2.2%] and by 3% [+/- 1.9%,], respectively. Similarly, forest fires increase by 2.2% with 90% confidence intervals ranging from +/-2.1%. The magnitude of this effect varies across common tenure regimes in the Amazon region.

Our main finding is robust to excluding peak season months of deforestation and municipalities that received special attention due to historically high deforestation rates. We also show that our model specification consistently responds to the use of alternative shift and share measures in placebo tests (Adão et al., 2019; Goldsmith-Pinkham et al., 2020).

Our findings are in line with a real options theory framing (Song et al., 2011; Ewald et al., 2017; Lundberg and Abman, 2022), where political discourse conveys valuable information about uncertain impacts of future government action to combat illegal deforestation. If land users are receptive to such information they may change the timing of decisions to invest in land use change, here deforestation. Deforestation is an irreversible land use change and, especially if illegal, can involve substantial and uncertain sunk and transactions costs, which further motivates our theoretical framing. Our empirical approach confirms conjectures based on an earlier correlational analysis (Caetano, 2021).

We contribute to this literature by showing that observable manifestations of political will to enforce forest law (i.e., as in political discourses) can change the expectation formation and corresponding behavior of land users. Information conveyed in political discourses likely matters more when land users face high uncertainty about the future economic, environmental, and institutional conditions that affect their land use decisions (Spence, 1973). 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; Balcony et al., 2021; Cisneros et al., 2021; Ruggiero et al., 2021). The underlying mechanisms are linked to political incentives and eventually associated with rent seeking and corruption (Burgess et al., 2012). Our main contribution here lies in isolating the effect of political discourse in this complex relationship. Discourses can be used to create or maintain expectations and political support by conveying either rhetoric or a real commitment (Chilton, 2004). 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.

At least three additional caveats apply. First, our main results potentially underestimate the effects of exposure to political discourses as we only examine discourses disseminated via Twitter, a specific social media channel. Other communication tools such as television or radio are likely to also matter for expectation formation. Second, our analysis focused on short run effects, but our results warrant future work on the medium and long-run effects of political discourse on land use. Finally, more sources of effect heterogeneity may exist than those we have analyzed here. Future research could explore the role of state-level variation in environmental law enforcement capacity or the responsiveness of culturally diverse groups of land users to information signaled in political discourses.

## 7. Policy implications

We show that political discourses insinuating a *laissez-faire* type of government attitude towards illegal deforestation have changed expectations of land users in the Brazilian Amazon in favor of higher deforestation rates. Policy makers are usually aware that words must be followed by action if policy goals were to be achieved effectively. After 2004, Brazil's political leadership has impressively confirmed this principle when implementing its plan to combat deforestation (PPCDam). Our results suggest that a sudden change in discourse can partially revert past conservation achievements in ways that are not reversible merely by discursive means. Politicians should just literally mind their language when engaging in public discourse 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 law even when political preferences happen to temporarily suggest otherwise.

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[1] In 2019, the northern region of Brazil, which concentrates most of the Legal Amazon area, corresponded to 92%, 93% and 94% of the national production of acai berries (200,000 tonnes), Brazilian nuts (30,000 tonnes), and natural rubber (798 tonnes), respectively (IBGE, 2019).

[2] In English, these translate to: fire OR deforestation OR Amazon OR forest.