Enforcement Risk, Credit Supply and Deforestation: Evidence from the Amazon*

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Abstract

Regulatory enforceability shapes credit risk even when statutes are unchanged. To study that our paper analyzes the case of anti-deforestation enforcement in the Brazilian Amazon, where satellite detection is mechanically constrained by cloud cover. Beginning in 2013, enforcement responsibilities shifted away from the federal agency, weakening enforcement follow-through. Exploiting seasonal cloudiness, we show that deforestation-related fines fall after decentralization precisely in low-cloud municipality–months, when monitoring was most effective. In the same localities (and months), agricultural credit provision expands and loan-loss provisions decline. Using heterogeneity in banks' ex-ante exposure to deforestation-enforcement risk in other municipalities, we provide evidence that the lending response reflects agricultural credit supply. Furthermore, we show that deforestation rises after enforcement decentralization and these results are amplified by three times in municipalities with greater agricultural lender presence. Our results highlight that enforcement stringency affects credit supply, magnifying the real effects of regulatory regime changes.

Keywords: regulation, enforcement, credit supply, deforestation.
JEL: G21, G28, K32, Q23, Q28.

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1 Introduction

Regulation affects financial intermediaries behavior through the content of rules and through the credibility of enforcement. Even when statutes are unchanged, changes in enforcement intensity alter the expected payoff to regulated activity and therefore the risk set faced by lenders. Enforcement matters for banks when sanctions impair borrower cash flows, restrict collateral, or trigger legal, compliance, and reputational costs that depend on the probability of regulatory action. Yet identifying the causal effect of enforcement risk on credit supply is difficult because regulators endogenously target inspections to high violation areas and banks may sort across locations in anticipation of enforcement.

A large literature in economics and finance argues that effective legal enforcement protects outside investors from opportunistic behavior and, in turn, supports external finance and financial development (e.g. La Porta et al. (1997); Porta et al. (1998); Ponticelli and Alencar (2016)). By contrast, we know much less about how changes in enforcement risk affect the behavior of financial intermediaries through borrowers' repayment capacity. Empirical work studies differences in enforcement stringency effects on firm-level outcomes (e.g. Besley and Burgess (2004); Amirapu and Gechter (2020); Heitz et al. (2023)), but evidence on how credit supply adjusts, an essential margin for understanding how enforcement changes transmit to the real economy, is limited. If financial intermediaries treat enforcement as a state variable that shifts expected default and recovery, then a weakening of enforcement can relax credit supply precisely for activities most exposed to regulation. Whether this mechanism operates, and how large it is, remains an open question. We address it by studying a centralized weakening of enforcement in Brazilian anti-deforestation policy in the Amazon, where compliance is costly, enforcement actions are salient and financially meaningful, and enforcement risk varies spatially due to institutional and technological reasons.

Our setting is particularly informative because the regulated activity is credit reliant, sanctions can be economically meaningful, and enforcement risk varies with transparent institutional and technological constraints. In 772 municipalities in the Amazon, monitoring relies on DETER, a high frequency satellite system that produces georeferenced deforestation alerts used to target enforcement actions (Assunção et al., 2023a; Araujo et al., 2025).[1] A mechanical constraint is that cloud cover blocks optical satellite visibility. As a result, detection capacity varies predictably across municipality-months, creating seasonal variation in the probability that illegal clearing generates alerts and enforcement follow-through. We combine this monitoring constraint with an institutional regime shift. As documented by Nunes et al.

[1]The 772 municipalities included in our sample are the ones located in the Amazon Biome and the Legal Amazon region, for which enforcement uses the DETER system.

(2024), Amazon faced a record low deforestation in 2012 (see Figure 1), the following policy phase emphasized decentralization and coincided with a weakening of command and control enforcement relative to the preceding period with a concurrent decrease in fines and increase in deforestation. Importantly, Burgess et al. (2026) also highlight changes regulatory leniency and tighter operational constraints that reduced follow-through conditional on detection starting in the second half of 2012. We treat this change in regime as a shock to effective enforcement and use predetermined seasonal cloudiness to construct differential changes in enforcement risk across municipality-months.

Our empirical strategy combines difference-in-differences and triple-differences designs. We classify municipality–months by low versus high seasonal cloud coverage using long-run averages and compare outcomes before and after 2013 controlling for municipality-by-month and month-by-year fixed effects. We first establish a first stage: before the shock, enforcement (deforestation related fines) increases during low-cloud municipality–months when monitoring is mechanically more effective, but this relationship weakens sharply after the change in regime, indicating reduced enforcement follow-through in high-detection environments. We then study bank outcomes using branch-level. First, we show a decline in credit default in the same municipality–months where enforcement weakens combined with increased agricultural lending. Second, to isolate credit supply, we exploit heterogeneity in banks' pre-2013 exposure to deforestation enforcement through their operations elsewhere in the Amazon and include municipality-by-time fixed effects, so identification comes from differential lending changes across banks operating in the same municipality at the same time. The results show that credit supply expands in the same localities, but only in land-intensive lending: agricultural credit provision increases while non-agricultural lending remains stable. Finally, deforestation rises after 2013, and the increase is about three times larger in municipalities with greater baseline agricultural lender presence, consistent with credit amplifying the real effects of weaker enforcement.

These findings contribute to three streams of the literature. First, they build on evidence that regulatory institutions shape credit and real outcomes. A large body of work links stronger legal enforcement and investor protection to deeper credit markets and faster firm growth (Demirgüç-Kunt and Maksimovic, 1998; Djankov et al., 2007, 2003), while within-country reforms to court enforcement and insolvency institutions show that strengthening enforcement increases credit availability and raises firm investment (Laeven and Woodruff, 2007; Bae and Goyal, 2009; Brown et al., 2017; Ponticelli and Alencar, 2016; Pezone, 2023). Our paper complements this tradition by shifting attention from creditor protection regulation and enforcement to other regulatory enforcement which affects firms cash flow affecting potentially default. We also relate to research showing that supervisory enforcement directed

at banks affects bank balance sheets, risk-taking, and lending (Delis et al., 2017; Bonfim et al., 2023; Heitz et al., 2026). Unlike previous literature which studies enforcement applied to financial institutions, we study regulatory enforcement applied to borrowers and show that changes in enforcement capacity affect credit supply. In this sense, we provide direct evidence that enforcement capacity is not only a background determinant of contracting outcomes, but a state variable that banks incorporate into lending decisions.

Second, our results connect to research on how financial providers respond to policy-induced risks arising from environmental and climate regulation, and to the related literature on policy uncertainty and expectations. In contrast to settings where transition risk is introduced through explicit market-based policies or mandated disclosure, our setting features an enforcement-based regulatory risk that changes the expected costs of noncompliance and therefore affects lending through borrower cash flows and collateral values. This complements evidence that banks adjust lending in response to climate and environmental regulation (Miguel et al., 2024; Assunção et al., 2020; Ivanov et al., 2024) and to transition-policy exposure (Ivashina and Scharfstein, 2010), and it relates to work that reviews how climate-related risks map into bank balance sheets (De Marco and Limodio, 2023; Albert et al., 2021; Martini et al., 2025). Our results are also consistent with the view that sustainability-related lending responds to institutional and contractual frictions, including the extent to which ESG considerations are embedded in credit terms (Chava, 2014; Kim et al., 2025). At the same time, the contribution speaks directly to an expectations-based view of regulatory risk: highlighting credit reallocation in response to environmental regulatory exposure (Ivanov et al., 2024; Mueller and Sfrappini, 2025), and broader climate-finance evidence emphasizing expectations through transition news (Engle et al., 2020) and carbon risk premia (Bolton and Kacperczyk, 2021; Sautner et al., 2023). We add to this literature by studying an enforcement regime change that directly shifts the probability that illegal environmental degradation is detected and sanctioned, affecting expected payoffs at the time credit is originated. Finally, our results complement evidence that regulatory uncertainty affects firms' financial conditions (Gissler et al., 2016; Ilhan et al., 2021), by isolating the effects of a realized change in enforcement capacity rather than changes in beliefs about future regulatory standards.

Finally, we contribute to the growing literature in economics that studies how regulation is implemented when monitoring is imperfect, discretion is valuable, and enforcement can be distorted by corruption or capacity constraints (Oliva, 2015; Duflo et al., 2018). Related work emphasizes that the organization of enforcement and the political economy of local bureaucracies shape environmental outcomes, including deforestation (Burgess et al., 2012). Recent research also analyzes optimal policy design when scarce enforcement resources must be targeted toward high-impact locations (Assunção et al., 2023b). We contribute to this literature

by incorporating financial intermediaries into the enforcement environment. Our setting is one in which enforcement capacity changes discretely and observably, allowing us to identify how banks change credit supply when the expected probability of punishment for environmental illegality falls. This mechanism is distinct from previous work on environmental policy where the key margin operates through trade policy or other instruments that primarily shift incentives rather than enforcement capacity itself (Scheinkman, 2024; Colmer et al., 2025; Hsiao, 2026; Araujo et al., 2026; Assunção et al., 2026). By showing that banks expand agricultural credit precisely where enforcement becomes less effective, we document a novel channel that can amplify real responses to enforcement policy, complementing previous literature on why enforcement reforms can have effects that extend beyond their direct effects on individual behavior (Johnson, 2020; Berlinski and Gagete-Miranda, 2025).

Section 2.2 describes the institutional setting and the decentralization regime shift. Section 2.2 describes the context and institutional design. Section 3 presents the data and empirical design. Section 4 reports the results on enforcement, lending, and deforestation, including evidence on credit supply and amplification. Section 5 discusses identification and robustness checks. Section 6 concludes.

2 Analytical Framework and Institutional Setting

2.1 Analytical Framework and Testable Implications

This section presents a parsimonious model to guide the empirical analysis and derive testable implications. The model connects enforceability to landowners' illegality choices, equilibrium credit quantities, and the implications for deforestation.

Borrower (landowner). A landowner finances cultivated land $K \geq 0$ with a one-period loan at gross rate r. Production yields a per-unit operating payoff A (common productivity). Legal land use requires paying a per-unit legal cost $c > 0$, while illegal land use avoids this cost. The landowner chooses the illegal share $x \in [0, 1]$. Illegal operation entails a private convex cost (cost of bribes, concealment or other legal risk management) and cultivation entails a standard convex scale cost. Detection occurs with probability $p \in [0, 1)$ and triggers a private penalty proportional to illegal activity, FxK, interpreted broadly as fines, embargoes, confiscation, or output losses borne by the landowner. We assume limited liability and zero recovery upon default, and we focus on the region where the borrower defaults whenever detected.

Under these assumptions, the landowner chooses (K, x) to maximize the ex-ante expected payoff:

$$\max_{K\geq 0,\, x\in[0,1]} \left\{ \left(A - r - (1-x)c - pFx - \frac{\psi}{2}x^2 \right) K - \frac{\phi}{2}K^2 \right\}, \tag{1}$$

where $\psi > 0$ governs the private cost of illegality and $\phi > 0$ governs the convex cost in scale.

Borrower optimal choices (interior). For an interior solution with $K > 0$ and $x \in (0,1)$, the first-order conditions yield

$$x^*(p) = \frac{c - pF}{\psi}, \tag{2}$$

$$K^*(r,p) = \frac{1}{\phi}\left(A - c - r + \frac{(c-pF)^2}{2\psi} \right). \tag{3}$$

with $0 < c - pF < \psi$ and $A - c - r + \frac{(c-pF)^2}{2\psi} > 0$.

Lender pricing under default-if-detected. Consider a competitive lender with per-loan gross funding cost r_d and zero recovery upon default. If detection occurs with probability p and the borrower defaults whenever detected, repayment occurs with probability $1 - p$. The zero expected profit condition implies

$$(1-p)r = r_d \qquad \Rightarrow \qquad r^*(p) = \frac{r_d}{1-p}. \tag{4}$$

Equilibrium objects. Combining (2), (3), and (4) yields

$$x^*(p) = \frac{c - pF}{\psi}, \tag{5}$$

$$r^*(p) = \frac{r_d}{1-p}, \tag{6}$$

$$K^*(p) = K^*(r^*(p), p) = \frac{1}{\phi}\left(A - c - \frac{r_d}{1-p} + \frac{(c-pF)^2}{2\psi} \right). \tag{7}$$

Testable implications. The enforcement shock in the empirics is a decline in effective enforceability, modeled here as a decline in p. The model takes the change in p as exogenous; enforcement outcomes are used diagnostically to validate that the institutional shift corresponds to $p \downarrow$ in high-detection environments.

Proposition 1 (Credit quantities). *Assume the interior region holds. Then:*

$$\frac{dr^*(p)}{dp} = \frac{r_d}{(1-p)^2} > 0, \qquad p \downarrow \Rightarrow r^*(p) \downarrow .$$

Moreover, equilibrium lending $K^*(p)$ changes with p through two components:

$$\frac{dK^*(p)}{dp} = \underbrace{-\frac{dr^*(p)}{dp}}_{\text{credit supply channel}} + \underbrace{\frac{(c-pF)}{\phi}\frac{dx^*(p)}{dp}}_{\text{credit demand channel}} < 0$$

where: $\frac{dx^*(p)}{dp} = \frac{-F}{\psi} < 0$. Therefore, weaker enforceability ($p \downarrow$) increases $K^*(p)$. This effect can be decomposed in two channels: a pure credit demand channel and an increase credit supply due to a decrease in default risk.

Proposition 2 (Deforestation). *Defining deforestation as the illegal planted area ($D(p) = x^*(p)K^*(p)$), enforceability affects deforestation through two margins:*

$$\frac{dD(p)}{dp} = \underbrace{K^*(p)\frac{dx^*(p)}{dp}}_{\text{illegal-share margin}} + \underbrace{x^*(p)\frac{dK^*(p)}{dp}}_{\text{credit margin}} < 0$$

Since $dx^*(p)/dp < 0$, weaker enforceability ($p \downarrow$) increases deforestation mechanically through the illegal-share margin. In addition, in the interior solution, $dK^*(p)/dp < 0$ therefore $p \downarrow$ increases deforestation also through the credit margin.

2.2 Institutional Setting

This section describes the institutional setting and dynamics of deforestation in Amazon during the period which we analyze.

Anti deforestation enforcement and deforestation dynamics The Brazilian Amazon has long combined ambitious environmental legislation with uneven enforcement capacity. Annual deforestation measurement began in 1988 and experienced pronounced swings that tracked macroeconomic and political conditions, see Nunes et al. (2024) for a review. Forest loss peaked in the mid 1990s and again in the early 2000s, culminating in the 2004 peak. In response, the federal government launched the Plan for the Prevention and Control of Deforestation in the Amazon, PPCDAm, in 2004 and organized policy around sequential phases with different priorities. In the early phase, PPCDAm emphasized

command and control and territorial governance. A major component was the designation of large tracts of public land as protected areas and indigenous lands, which the historical record links to lower deforestation under external pressure. Conservation unit coverage expanded sharply during the first phase, and the combined protected area footprint conserved a large share of remaining forest. Over the same period, deforestation declined markedly from its 2004 peak to much lower levels by 2007.

From 2008 to 2012, the policy regime entered what Nunes et al. (2024) describe as an effective command and control phase, during which deforestation fell further despite continued growth in agricultural production. The historical narrative attributes the decline primarily to enforcement and to complementary instruments that raised the cost of illegal clearing. These instruments included the publication of deforestation hot spots and the targeting of high deforestation municipalities through a priority list. Priority municipalities faced administrative sanctions and economic disincentives that included restrictions on access to public credit schemes. In parallel, the federal government increased the use of embargoes and other sanctions that restricted productive activity on illegally cleared land and aimed to increase financial constraints of the offenders, including asset confiscations and destruction of equipment. The scale of enforcement actions over this period is large. Between 2004 and 2018, tens of thousands of embargoes and fines were issued in the Legal Amazon, with penalties totaling billions of dollars. The central takeaway is that the anti deforestation regime was primarily driven by monitoring and sanction enforcement shifts.

Monitoring based enforcement technology A pivotal innovation of the anti-deforestation regime was the introduction of high-frequency remote monitoring to support enforcement. Prior to the mid-2000s, federal enforcement by the Brazilian Institute of Environment and Renewable Natural Resources (IBAMA) relied heavily on intelligence and reports and was constrained by the cost and risk of covering vast remote territories. PPCDAm made high-frequency monitoring a core operational priority and INPE developed Detection of Deforestation in Real-Time (DETER), a satellite-based system that produces georeferenced alerts of recent forest loss to guide inspections and sanctioning. DETER detects changes in land cover by comparing images over time and generates hotspot alerts for locations requiring rapid field verification. In its original implementation, DETER used optical imagery from the MODIS sensor on the Terra satellite, providing frequent coverage suitable for monitoring the Brazilian Amazon. DETER was designed to operate over the Legal Amazon and to support operational enforcement in the Amazon biome, representing 772 municipalities, and where deforestation activity is concentrated and where DETER coverage is most relevant for pol-

icy. Our empirical implementation reflects this institutional coverage and uses DETER-based cloud information only where the monitoring system produces valid monthly coverage.

Cloud cover is central to how DETER generates quasi-experimental variation in monitoring capacity. Because DETER relies on optical imagery, clouds mechanically block visibility and areas covered by clouds generate fewer actionable alerts. DETER's monthly products include cloud-mask information that identifies the fraction of a location that is cloud-obstructed, and months with inadequate visibility can yield missing monitoring information for affected areas. Assunção et al. (2023a) show empirically that higher cloud coverage reduces observed deforestation fines and argue that this is due to lower allocation of enforcement personnel to those locations. They use cloud-driven variation in DETER detection as an instrument for enforcement intensity and and analyze how monitoring and enforcement materially affected deforestation. The key implication for our design is that seasonal cloudiness shifts the effective probability that illegal clearing is detected and acted upon, providing predetermined within-location variation in enforcement risk that is tied directly to monitoring feasibility.

Decentralization and reduced enforcement Following the implementation of DETER in 2006, deforestation fell sharply and reached a historic low in 2012, but the subsequent period was marked by institutional changes that weakened the anti-deforestation regime and coincided with a renewed increase in forest loss. The earlier decline under PPCDAm is widely associated with a command-and-control strategy centered on enforcement and complementary deterrence instruments, including priority-municipality targeting, embargoes, credit restrictions, and protected areas (West and Fearnside, 2021; Nunes et al., 2024; Burgess et al., 2026). The post-2012 period is therefore best understood not as a disappearance of monitoring capacity, but as a change in the institutional environment governing how monitoring information was translated into realized sanctions.

In the policy phase that followed, PPCDAm III adopted a more decentralized approach, sharing responsibilities with states and municipalities and placing greater emphasis on land-tenure regularization and the Rural Environmental Registry (Cadastro Ambiental Rural, CAR). Registration incentives were strong because CAR became a requirement for rural credit and for formal land transactions, but the historical record provides limited evidence that registration by itself generated deterrence comparable to the earlier enforcement-centered regime (Nunes et al., 2024; West and Fearnside, 2021). At the same time, the broader enforcement environment became more permissive. The 2012 Forest Code granted amnesty to many properties with pre-2008 illegal deforestation and appears to have weakened expectations of future punishment, while repeated efforts to simplify land titling and envi-

ronmental licensing further softened the overall regulatory stance (Nunes et al., 2024; Burgess et al., 2026). Consistent with this interpretation, Burgess et al. (2026) show that the sharp reduction in deforestation at Brazil's Amazon border during 2006–2013 began to reverse from 2014 onward, indicating that the earlier gains in enforcement were not sustained.

Resource constraints interacted with these institutional changes. Nunes et al. (2024) document reductions in operational resources for field inspections and note that fiscal and political pressures, including the 2015 crisis, placed additional strain on IBAMA's enforcement budget and on the financing of field operations. Complementing this account, Burgess et al. (2026) report that IBAMA's budget was cut by 34.2% between 2013 and 2014, that the number of enforcement officers fell by 24% relative to 2010, and that by 2016 the agency's budget had fallen to 57% of its 2013 level. These reductions are also consistent with our argument that the post-2012 weakening of the regime operated primarily through enforcement follow-through rather than through a collapse in monitoring capacity: even if satellite systems continued to generate information on illegal clearing, lower operational capacity would reduce the state's ability to transform those signals into realized inspections, embargoes, fines, and seizures (Burgess et al., 2026).

For our purposes, the key implication is not that enforcement had to decline uniformly across all places and dates, but that the regime shift weakened the *conversion of monitoring signals into realized sanctions*. Because the monitoring technology is described in the previous subsection, the relevant implication here is straightforward: in municipality-months where monitoring conditions are ex ante more favorable, the pre-2013 regime should have translated detected clearing into stronger enforcement responses. If decentralization, regulatory leniency, and tighter operational constraints reduced follow-through conditional on detection, then the decline in realized sanctions should be strongest precisely in those municipality-months where monitoring remained most informative.

3 Data and Empirical Design

3.1 Data

Our analysis combines enforcement, deforestation, and bank lending data merged at the municipality level and at the bank–municipality level. In this section we describe the sources of data and the variables we use throughout the paper.[2]

[2]For more details on the data definitions, see Section A1

Anti-Deforestation Enforcement (IBAMA). Our enforcement outcomes are based on deforestation-related administrative sanctions issued by the Brazilian environmental authority (IBAMA). We construct two complementary enforcement measures. The extensive-margin measure indicates whether a municipality experiences any deforestation-related fine in a given month. The intensive-margin measure captures the magnitude of fines conditional on enforcement occurring, measured using the value of sanctions issued in that municipality-month.

Deforestation Monitoring (DETER). We complement fines with satellite monitoring information that motivates and helps interpret the monitoring channel. We use cloud cover measures that proxy for the effectiveness of satellite detection. The key institutional feature is that cloud cover mechanically reduces the ability of remote sensing systems to detect newly cleared areas, weakening the information available to regulators. Assunção et al. (2023a) show that when cloud cover is high, satellite detection is impaired, which translates into fewer actionable signals and, consequently, fewer enforcement actions. We use this insight to construct seasonal cloudiness classifications at the municipality–month level. Specifically, we classify municipality–month cells based on long-run seasonal cloudiness patterns and define an indicator for low seasonal cloud coverage, which identifies municipality-months in which satellite detection is predictably more effective. The central conceptual link is that DETER generates actionable information that can be used to target inspections and sanctions, so that any factor reducing the precision or availability of these alerts can lower realized enforcement.

Deforestation outcomes (PRODES). Deforestation outcomes are constructed from PRODES, INPE's annual deforestation monitoring system for the Brazilian Amazon. PRODES maps clear-cut deforestation using optical satellite imagery and releases annual deforestation increments as both georeferenced data and municipality-level aggregates. A key measurement feature is that PRODES years do not correspond to calendar years: because PRODES prioritizes dry-season imagery to minimize cloud obstruction, deforestation for PRODES year t is measured over the window from August of year $t-1$ through July of year t. We therefore align enforcement and lending panels to PRODES timing so that changes in annual municipal deforestation can be traced to changes in enforcement capacity and to differential local credit supply responses in the relevant enforcement window. Unless otherwise stated, when we refer to "year" in deforestation outcomes we refer to PRODES years.

Bank outcomes (ESTBAN). Bank outcomes are based on ESTBAN, a branch-level balance sheet dataset from the Central Bank of Brazil. The data originate from Document No. 13, a mandatory monthly branch-level report submitted by banks to the Central Bank, and contain branch balance sheet information that is suitable for building local credit measures. A key feature of ESTBAN is that loans are assigned to the branch that originates the contract and remain recorded on that branch's books, while deposits are analogously assigned to the branch where the account is opened.[3] This mapping implies that aggregating across branches within a municipality yields a natural measure of locally originated credit, which is central for our bank–municipality design.

We aggregate ESTBAN from the branch level to the bank–municipality–month level and construct total lending, agricultural lending, and non-agricultural lending. The panel structure supports fixed effects that absorb stable bank–location relationships and bank-specific shocks. It also supports specifications that compare banks within municipality–time cells, which is central for identifying credit supply responses while holding local credit demand constant. Finally, we construct bank exposure measures capturing banks' baseline footprint in municipalities where deforestation enforcement is empirically relevant, and use these exposure measures to separate credit supply adjustments from changes in local enforcement and local demand.

Agricultural production (PAM/IBGE). We also use information from local agricultural production to provider further evidence on the mechanism of deforestation, we complement the main panel with data from IBGE's *Produção Agrícola Municipal* (PAM). PAM is an annual municipality-level survey covering temporary and permanent crops and reports, for each crop and municipality-year, we use the total cultivated area (area planted or destined for harvest), harvested area, and productivity (ratio between havested and cultivate area).

3.2 Empirical Design

The empirical strategy exploits two features of the setting to estimate how a plausibly exogenous weakening of enforcement affects (i) realized sanctions, (ii) deforestation, and (iii) local credit outcomes. First, monitoring feasibility varies predictably with predetermined seasonal cloudiness: optical satellite detection is mechanically more effective in municipality–month cells with typically low cloud coverage (Assunção et al., 2023a; Araujo et al., 2025). Figure 2 illustrates this spatial and seasonal variation in monitoring feasibility using DETER-based cloud coverage, showing both the annual distribution

[3]For more information, see Mariani and Ricca (2026).

and the spatial dispersion of high levels of cloud coverage on the months of June and December, highligting the spatial and seasonal dimension we exploit. Second, beginning in 2013, we observe weakened enforcement follow-through, reducing the translation of monitoring capacity into realized sanctions as documented in Nunes et al. (2024). The design therefore compares enforcement, deforestation, and credit outcomes before and after the decentralization across municipality–months with typically high versus low satellite imagery monitoring capacity. The central identifying premise is that the change in enforcement follow-through—and thus enforcement risk faced by land users and lenders—in a way that is mechanically correlated with long-run seasonal cloudiness rather than with local economic fundamentals. Using long-run averages rather than contemporaneous cloud realizations mitigates concerns that cloud cover is itself affected by deforestation behavior or local economic conditions allowing us to disentangle enforcement risk.

Enforcement first stage: validating a decline in effective enforceability. We begin by estimating whether the decentralization period corresponds to a reduction in effective enforceability in high-detection environments. Specifically, we estimate how IBAMA fines change after 2013 in municipality–months with typically low seasonal cloud coverage (when monitoring is mechanically most feasible). Let $\text{LowSeasonalCloud}_{cm}$ be an indicator equal to one if municipality c has below-median long-run cloud coverage in calendar month m, computed from monthly averages over 2004–2016. Let Post_y indicate years 2013 and after. We estimate

$$\text{Fines}_{cmy} = \beta_1 \text{LowSeasonalCloud}_{cm} + \beta_2 \left(\text{LowSeasonalCloud}_{cm} \times \text{Post}_y\right) + \alpha_m + \alpha_{my} + \varepsilon_{cmy}, \tag{8}$$

where α_m are municipality fixed effects and α_{my} are month-by-year fixed effects. The municipality fixed effects absorb persistent differences across locations. Moreover, in a more stringent specification we also include municipality-by-month fixed effects which absorb any time-invariant correlation between geography and cloud patterns. The month-by-year fixed effects absorb aggregate shocks and national policy changes common to all municipalities in a given month-year. Coefficient β_1 estimates the increased monitoring capacity generated by lower cloud coverage months compared to other months in the same municipality but with lower enforcement capacity due to lower satellite visibility. The coefficient of interest is β_2, which measures the differential change in realized sanctions after 2013 in municipality–months where monitoring is typically most effective; we interpret a negative β_2 as evidence of a decline in enforceability. Standard errors are clustered at the municipality level.

Real Effects: the effect of weaker enforceability on deforestation. Next, we estimate the impact of the enforcement weakening on deforestation. The parameter of interest captures whether deforestation rises after 2013 in municipalities where monitoring is typically more feasible (and therefore where the enforcement decline implied by the first stage should be most salient). We use municipality–year deforestation data and focus on annual outcomes because deforestation accumulates over the year and the main outcome series is reported at annual frequency. We estimate

$$\text{Deforestation}_{cy} = \delta \left(\text{LowAvgCloud}_c \times \text{Post}_y\right) + \mu_c + \lambda_y + \Gamma_y \times Z_c + u_{cy}, \tag{9}$$

where LowAvgCloud_c is an indicator for below-median average cloud coverage and μ_c and λ_y are municipality and year fixed effects. The coefficient of interest is δ, which measures the differential post-2013 change in deforestation in low-average-cloud municipalities. The term $\Gamma_y \times Z_c$ captures time-varying controls interacted with baseline coverage measures, including baseline bins of PRODES forest coverage, cloud coverage, and non-observed coverage interacted with time.[4] This structure absorbs differential evolution across municipalities with different baseline land characteristics and mitigates concerns that the estimated effects reflect differential measurement error or differential exposure to baseline land conditions. Standard errors are clustered at the municipality level.

Credit response: the effect of weaker enforceability on local lending and provisions. We then estimate how enforcement risk affects bank behavior by studying lending outcomes at the bank–municipality–month level. The estimand of interest is the differential change in credit outcomes after 2013 in the municipality–months where monitoring is typically most feasible (low seasonal cloud months). Using branch-level ESTBAN data aggregated to the bank–municipality–month level, we estimate

$$\text{Credit}_{cbmy} = \theta_1 \text{LowSeasonalCloud}_{cm} + \theta_2 \left(\text{LowSeasonalCloud}_{cm} \times \text{Post}_y\right) + \alpha_{cb} + \alpha_{b,my} + \epsilon_{cbmy}, \tag{10}$$

where α_{cb} are bank–municipality fixed effects that absorb time-invariant bank–location sorting of banks into municipalities, and $\alpha_{b,my}$ are bank-by-month–year fixed effects that absorb

[4] PRODES and DETER can display different cloud-coverage patterns because they are designed for different purposes and operate at different temporal scales. DETER is a high-frequency alert system used to support environmental enforcement, so its cloud measure reflects short-run cloud obstruction in the imagery used to generate alerts. PRODES, by contrast, is INPE's official annual mapping system for clear-cut deforestation, based on higher-resolution annual comparisons, so cloud-related limitations appear in annual cloud or non-observed areas in the final map. We therefore use DETER to characterize monitoring conditions relevant for enforcement and PRODES to measure annual deforestation and baseline land-cover conditions.

bank-specific shocks, including changes in funding conditions, risk appetite, or balance-sheet constraints common to all locations in a given month-year. In an alternative specification, we replace α_{cb} with α_{cbm} bank–municipality–month fixed effects, which additionally absorb stable bank–location seasonality. The coefficient of interest is θ_2, which captures within-bank reallocation of credit across municipalities after enforcement weakens. Standard errors are clustered at the bank–municipality level.

Credit supply: isolating bank-level supply responses to enforcement risk. A remaining concern is that changes in observed lending reflect shifts in local credit demand if agricultural producers borrow more when enforcement weakens. To isolate credit supply, we estimate whether banks with higher ex ante exposure to deforestation-enforcement risk expand credit differentially *within the same municipality–time cell* following the enforcement weakening. We first construct a predetermined bank exposure index based on pre-decentralization enforcement intensity in the set of municipalities in which the bank operates, weighted by the bank's pre-period lending footprint. Let $\text{Loans}_{bc,2012}$ denote bank b's lending in municipality c in 2012 and let $\text{Fines}_{c,2012}$ denote the average intensity of deforestation-related fines in municipality c in 2012. Define

$$\text{ExposureIndex}_b = \sum_{c \in \mathcal{M}_b} \omega_{bc} \, \text{Fines}_{c,2012}, \qquad \omega_{bc} = \frac{\text{Loans}_{bc,2012}}{\sum_{c' \in \mathcal{M}_b} \text{Loans}_{bc',2012}}, \tag{11}$$

where $\mathcal{M}_b$ denotes the set of municipalities in which bank b has lending activity in 2012. We then define a high-exposure indicator,

$$\text{HighBankExposure}_b = \mathbb{1}\left\{\text{ExposureIndex}_b > \text{Median}\left(\text{ExposureIndex}\right)\right\}, \tag{12}$$

which captures banks' ex ante orientation toward locations where deforestation enforcement is empirically salient.

We estimate

$$\text{Credit}_{cbmy} = \beta_s \left(\text{LowSeasonalCloud}_{cm} \times \text{Post}_y \times \text{HighBankExposure}_b\right) + \alpha_{cbm} + \alpha_{b,my} + \alpha_{c,my} + \epsilon_{cbmy}, \tag{13}$$

where $\alpha_{c,my}$ are municipality-by-month–year fixed effects that absorb local credit demand and any municipality-specific changes in local economic conditions at each date. The coefficient of interest is β_s, which measures whether banks with higher ex ante exposure expand lending differentially when enforcement weakens, holding fixed all municipality–time conditions that affect demand. Standard errors are clustered at the bank–municipality level.

Amplification: whether local agricultural credit capacity magnifies deforestation responses. Finally, we test whether pre-2013 agricultural lender presence amplifies the deforestation response to weaker enforcement. The estimand of interest is whether the post-2013 deforestation increase in low-average-cloud municipalities is larger where pre-period agricultural credit capacity is higher. Let AgriIntensity_c denote agricultural lending in municipality c in 2012 scaled by municipal area. We estimate

$$\begin{aligned}\text{Deforestation}_{cy} &= \pi_1 \left(\text{LowAvgCloud}_c \times \text{Post}_y\right) + \pi_2 \left(\text{LowAvgCloud}_c \times \text{Post}_y \times \text{AgriIntensity}_c\right) \\ &\quad + \mu_c + \lambda_y + \Gamma_y \times X_c + \epsilon_{cy}, \end{aligned} \tag{14}$$

where π_2 is the coefficient of interest and captures whether the enforcement-driven deforestation response is larger in municipalities with greater pre-period agricultural credit capacity. Standard errors are clustered at the municipality level.

Identification and interpretation. We assess the validity of the identification strategy in several ways. First, we examine dynamic specifications to evaluate the plausibility of the parallel-trends assumption prior to the 2013 institutional break. Second, we implement placebo exercises using outcomes that should not respond to changes in deforestation enforcement through the proposed mechanism, namely non-agricultural lending and local deposits. These tests help rule out the possibility that the estimated effects reflect broad shifts in local credit demand, funding conditions, or general municipal shocks rather than enforcement-related changes in agricultural credit supply. Third, we verify that the results are not driven by functional-form choices or by the particular treatment definition by re-estimating the main specifications under alternative transformations of the outcome variables and alternative definitions of cloud exposure

4 Results

4.1 Enforcement Regime Shift and Deforestation

In this section links to the first stage of our design and also highlights the role of monitoring technology prior to the institutional break. Table 1 shows that, in the period prior to 2013, low seasonal cloud municipality–months are those in which optical satellite visibility is mechanically higher, so DETER is more likely to generate actionable deforestation alerts that can be used to target inspections and sanctioning. Consistent with this monitoring channel, the pre-period relationship between cloud conditions and enforcement

is positive in our event-study: relative to high-cloud municipality–months, low-cloud municipality–months exhibit higher fine incidence and higher fine intensity before 2013. This pattern matches the mechanism emphasized by Assunção et al. (2023a), who describe DETER as a near real-time system designed to support enforcement by producing geo-referenced alerts and show that cloud coverage blocks visibility and reduces the capacity to detect and target deforestation, lowering fine issuance.

After 2013, the mapping from monitoring feasibility to realized sanctions shifts sharply. The interaction between low seasonal cloud coverage and the post-2013 indicator in Table 1 is negative and statistically significant across specifications. Because low-cloud municipality–months are precisely those in which monitoring should be most effective, this reversal implies a weakening in the conversion of detection capacity into enforcement actions. Put differently, the associated reduction in effective enforcement capacity attenuated the deterrent value of DETER-based monitoring exactly where and when DETER would otherwise have generated the strongest enforcement response.

[INSERT TABLE 1 ABOUT HERE]

A natural concern is that this decline in fines could reflect a change in underlying deforestation activity or in the generation of monitoring signals rather than weaker enforcement follow-through. We address this directly in Table 2. Using municipality–month data on high-frequency DETER alerts, we separate changes in monitoring capacity from changes in realized sanctions. To avoid conflating the institutional break with the 2015 methodological update to DETER, we restrict this exercise to the 2007–2015 period.[5] As expected, low seasonal cloud coverage is strongly associated with more DETER alerts, reflecting better detection conditions. Crucially, however, the post-2013 effect on alerts in these low-cloud municipality–months is positive but small and statistically indistinguishable from zero, while deforestation-related fines decline sharply in the same sample and precisely in the same high-visibility environments. Thus, the enforcement break is not mirrored in the high-frequency monitoring data that proxy for detected deforestation activity. Monitoring signals remain broadly stable where detection is easiest, but realized sanctions fall. This divergence is important for interpretation. If the post-2013 pattern were driven primarily by weaker monitoring technology or by a decline in detected clearing, we would expect the number of DETER alerts to fall alongside fines. Instead, alerts do not decline in the municipality–months where DETER should be most informative, yet enforcement does. The evidence therefore points to a reduction in enforcement capacity and follow-through conditional on detection, rather than to a deterioration in monitoring or a mechanical reduction in observed deforestation activity.

[5] See INPE documentation for more details on DETER update and methodology changes: `http://www.obt.inpe.br/OBT/assuntos/programas/amazonia/deter/deter`.

[INSERT TABLE 2 ABOUT HERE]

Finally, Table 3 connects this enforcement break to real activity. Deforestation increases after 2013 in low average cloud municipalities, and the magnitude is stable as we add progressively richer time-varying controls interacted with baseline forest cover and other baseline characteristics. Taken together with the enforcement evidence, the results support a unified deterrence interpretation. When DETER-based monitoring is effective and enforcement capacity is intact, higher detection feasibility translates into more sanctions and stronger deterrence. Once enforcement capacity is weakened, the same high-detection environments no longer deliver commensurate sanctions, reducing expected punishment and increasing illegal clearing.

[INSERT TABLE 3 ABOUT HERE]

Figure 3 complements the main estimates by tracing the timing of the effects in dynamic specifications corresponding to Column (4) of Table 2 and Column (3) of Table 3. In the pre-period, coefficients are close to zero and statistically indistinguishable from zero, supporting the parallel-trends assumption. Following 2013, enforcement declines immediately in low-cloud municipality–months, consistent with a discrete regime shift in the conversion of monitoring signals into sanctions. The deforestation response is more gradual. Deforestation rises after 2013 in low average cloud municipalities and the increase persists in subsequent years, consistent with a dynamic adjustment process in which land-use decisions respond with lags to a sustained reduction in expected punishment. This pattern aligns with a deterrence mechanism: once enforcement credibility falls, clearing becomes relatively more profitable, and the cumulative nature of forest loss implies that the divergence in deforestation rates compounds over time.

[INSERT FIGURE 3 ABOUT HERE]

Overall, our evidence supports a coherent interpretation of the a change in policy regime in which enforcement became observably weaker. The combination of stable monitoring signals in high-detection environments, a sharp and immediate decline in fines, and a persistent, accumulating increase in forest loss is most consistent with a sustained reduction in deterrence driven by weaker enforcement follow-through rather than by any change in the frequency of detected deforestation alerts. Having established that the post-2013 regime weakened enforcement follow-through and led to higher deforestation, we next turn to the response of financial intermediaries. In particular, we examine whether banks expanded agricultural credit as enforcement risk declined.

4.2 Enforcement risk and local credit

Table 4 reports estimates of Equation (10). Agricultural lending increases after 2013 in low seasonal cloud municipality–months, while non-agricultural lending does not exhibit a comparable response. The sectoral pattern is consistent with the enforcement shock operating through activities that are directly tied to land-use change and deforestation risk. Low-cloud municipality–months are precisely those in which monitoring is mechanically more effective; after the regime shift, these same environments experience a sharper drop in realized enforcement. The results in Table 4 indicate that banks expand agricultural credit in the locations and periods where the effective probability of punishment falls the most. Figure 4 shows that this response reflects both an intensive-margin increase in the volume of agricultural lending within existing bank–municipality relationships and an extensive-margin increase in the likelihood that a bank supplies agricultural credit in a given municipality–month.

[INSERT TABLE 4 ABOUT HERE]

A potential alternative explanation is that changes in observed lending reflect shifts in loan performance or charge-offs rather than new credit supply. If lower enforcement increased expected penalties or operational disruptions for agricultural producers, one might expect higher credit risk and a contraction in credit. To assess this mechanism, we study measures of credit provision that proxy for local portfolio performance and repayment conditions. Table 5 shows that credit provision improves sharply after 2013 in low seasonal cloud municipality–months, consistent with a reduction in realized default risk or improved repayment conditions for agricultural borrowers when enforcement weakens. This pattern aligns with the idea that weaker enforcement relaxes a binding constraint on land-use activity and thereby raises cash flows in the short run, improving credit performance and increasing banks' willingness to lend.

[INSERT TABLE 5 ABOUT HERE]

The dynamics in Figure 4 further support this interpretation. Credit provision improves immediately around 2013 in the high-detection environments that experience the largest enforcement decline, while lending volumes increase with a lag. This timing is consistent with banks updating their assessment of local agricultural credit risk as enforcement changes become observable and only subsequently expanding lending. The lagged increase in credit also matches an adjustment process in which new loans are originated after banks revise internal risk assessments and after borrowers respond to the new enforcement environment by expanding activity.

[INSERT FIGURE 4 ABOUT HERE]

4.3 Disentangling Credit Supply

The patterns above could still reflect changes in local credit demand if agricultural producers expand borrowing in response to weaker enforcement. We therefore implement the triple-differences design in Equation (13), which compares banks with different ex ante exposure to deforestation-enforcement-sensitive lending within the same municipality–time cells. Table 6 shows that the coefficient on the triple interaction is large and statistically significant for agricultural lending. The magnitude is economically similar when municipality-by-time fixed effects are included, implying that the differential response across banks is not driven by local demand shocks common to all banks operating in the municipality at a given time. Instead, the evidence supports a credit-supply mechanism in which banks with higher exposure expand agricultural lending more when enforcement weakens. Consistent with this interpretation, the decomposition suggests that the supply response is primarily driven by the extensive margin, indicating that banks expand the set of bank–municipality relationships in which agricultural lending is active.

[INSERT TABLE 6 ABOUT HERE]

Table 7 reports the corresponding triple-differences estimates for non-agricultural lending. The coefficients are small and statistically indistinguishable from zero, providing a placebo test consistent with the enforcement shock operating through the land-use and agriculture channel rather than through a broad shift in local credit conditions.

[INSERT TABLE 7 ABOUT HERE]

Taken together, the results show that changes in enforcement capacity propagate to financial markets through banks' local credit supply. We then show that banks respond to this enforcement regime change by expanding agricultural credit precisely in those high-detection environments, with responses that are strongest for banks with greater ex ante exposure to enforcement-sensitive portfolios and that operate primarily through the extensive margin. These findings contribute to the law-and-finance literature on enforcement and contracting by moving beyond firm outcomes to document an intermediary channel through which enforcement affects credit supply (Demirgüç-Kunt and Maksimovic, 1998; Djankov et al., 2003; Ponticelli and Alencar, 2016; Pezone, 2023). They complement evidence that supervisory enforcement directed at banks affects bank risk-taking and lending (Delis et al., 2017; Bonfim et al., 2023) by studying enforcement applied to borrowers and showing that variation in regulatory enforceability re-allocates bank credit locally. They also speak to the

growing literature on climate-related risks, regulation, and financial intermediation by identifying an enforcement-based regulatory channel that operates through the realized probability of punishment rather than solely through expectations about future regulation (Engle et al., 2020; Giglio et al., 2026; Bolton and Kacperczyk, 2021; Mueller and Sfrappini, 2025). In the next section we document the effects of agricultural credit providers on deforestation when anti-deforestation enforcement reduces.

4.4 Bank presence and amplification of deforestation

Table 8 tests whether local bank presence amplifies the deforestation response to weaker enforcement. The baseline post-2013 effect is positive, consistent with the earlier evidence of reduced enforcement in high-detection environments and increased deforestation. Table 8 then interacts the enforcement-shock exposure with pre-2013 lending intensity. The interaction with total lending intensity is small and imprecise, indicating that general credit depth is not, by itself, a strong amplifier of the post-2013 deforestation response. By contrast, the interaction with agricultural lending intensity is positive and statistically significant. Economically, this pattern implies that the increase in deforestation after 2013 is larger in municipalities that entered the decentralization period with a stronger local footprint of agricultural lenders.

This amplification result links the enforcement and credit findings into a single mechanism. The first-stage evidence showed that the post-2013 regime weakened the translation of monitoring feasibility into sanctions, reducing deterrence most in low-cloud environments. We then documented that banks expand agricultural lending precisely in those locations and periods, with responses consistent with a credit-supply mechanism and concentrated among banks that are more exposed to enforcement-sensitive portfolios. Table 8 provides the corresponding real-outcome implication of this credit response: where agricultural lending capacity is locally larger, the enforcement-driven expansion in agricultural finance is stronger, and deforestation increases by more. The absence of a comparable interaction with total lending intensity reinforces that what matters for the real response is not credit per se, but credit targeted to the sector directly linked to land-use change.

[INSERT TABLE 8 ABOUT HERE]

Overall, these results imply that enforcement reforms have equilibrium effects that depend on the structure of local financial intermediation. When enforcement capacity weakens, banks relax financing constraints for enforcement-sensitive activities, and local bank specialization shapes how strongly real activity responds. Finally, our evidence contributes to the emerging work on environmental regulation and optimal enforcement under limited capacity

by showing that the equilibrium effects of enforcement reforms depend on the structure of financial intermediation and local bank presence (Duflo et al., 2018; Assunção et al., 2023b; Johnson, 2020; Berlinski and Gagete-Miranda, 2025).

5 Identification and Robustness Checks

5.1 Identification: Dynamic Effects

The goal of this section is to clarify why the empirical design identifies changes enforcement risk, rather than shifts in underlying economic fundamentals, and how the dynamic responses across enforcement, credit, and deforestation support the paper's mechanism. The central idea is that the 2013 decentralization period altered enforcement follow-through: conditional on detection capacity, fewer monitoring signals translated into realized sanctions. We therefore need a source of variation that isolates monitoring feasibility (and hence expected enforcement) but is not itself driven by contemporaneous deforestation behavior, local economic shocks, or bank lending conditions.

To implement this idea, treatment is defined using *seasonal cloudiness* rather than contemporaneous cloud realizations. Seasonal cloudiness captures persistent, predictable differences in optical satellite visibility within municipality–calendar-month cells, which is the relevant margin for the DETER-based detection channel (Assunção et al., 2023a). By construction, it is orthogonal to short-run local shocks and avoids contaminating the enforcement-risk proxy with high-frequency weather noise. In contrast, realized cloud cover can be correlated with contemporaneous economic activity and land-use choices (e.g., through smoke and aerosols from fires and clearing) and may therefore move with outcomes, making it a noisier and potentially endogenous measure of enforcement risk. Using long-run averages isolates the component of monitoring capacity that is known ex ante and stable, which is precisely the component that should govern how decentralization changes the translation of detection feasibility into realized sanctions.

Furthermore, the dynamic treatment effects provide complementary support for these identification assumptions and connect this section to the rest of the paper. In Figure 3, our findings are consistent with parallel trends across low- and high-seasonal-cloud municipality–months. After 2013, enforcement declines sharply and immediately in low-seasonal-cloud municipality–months, indicating a discrete break in enforcement follow-through exactly where monitoring is mechanically most effective. Deforestation responds more gradually and persistently, which matches a deterrence mechanism with adjustment lags and accumulation: once expected punishment falls, clearing becomes relatively more

profitable and forest loss compounds over time. The same timing logic helps interpret the financial results: loan-loss provisions improve around the decentralization break while agricultural credit expands with a lag (see Figure 4), consistent with banks updating perceived borrower risk as the new enforcement regime becomes observable and only then expanding agricultural lending relationships. Together, these dynamics align with the paper's mechanism—decentralization weakens enforceability in high-detection environments, banks reallocate credit toward land-intensive activity, and real outcomes adjust over time.

5.2 Identification: Ruling out the Local Funding Channel

A potential alternative mechanism is that the post decentralization lending patterns might reflect changes in local funding conditions, for instance, an inflow of deposits into the same municipality–months that experience weaker enforcement could relax branch-level funding constraints and mechanically expand credit, even absent a change in enforcement-related credit risk. To assess this possibility, Table A1 replicates our baseline lending specifications using total deposits as the dependent variable.

The deposit results provide no support for a funding-driven explanation. First, the interaction $\text{LowSeasonalCloud}_{cm} \times \text{Post}_y$ is small and not distinguishable from zero across specifications, indicating no systematic difference in deposits in the municipality-months where our enforcement was higher and which also experienced the largest decline in realized sanctions. Second, when we implement the exposure-based design, the triple interaction $\text{LowSeasonalCloud}_{cm} \times \text{Post}_y \times \text{HighBankExposure}_b$ is also close to zero, suggesting that banks more exposed to enforcement risk do not experience differential deposit inflows in the same locations and months. Third, the most demanding specification includes municipality-by-month–year fixed effects, which compares banks operating in the same municipality at the same time while absorbing any municipality-level funding shocks or local demand shifts. Even in this within-municipality–time comparison, deposits do not move differentially for high-exposure banks in low-cloud months after the enforcement reduction.

Taken together, Table A1 rules out a simple local-liquidity channel: the enforcement-driven patterns in agricultural credit and provisions are not mirrored by corresponding changes in local deposit funding. This evidence supports the interpretation that the estimated lending responses reflect changes in enforcement-related credit risk (and the associated willingness to extend agricultural credit), rather than a reallocation of local funding capacity or deposit-driven balance-sheet constraints.

5.3 Identification: Anti-Deforestation Enforcement, Green Banks and Credit Provision

This section examines whether the agricultural credit response to weaker enforcement differs across banks with stronger environmental commitments. We proxy for such commitments using membership in the United Nations Environment Programme Finance Initiative (UNEP FI). UNEP FI is a UN-backed platform that promotes the integration of environmental and social considerations into financial decision-making through voluntary commitments, frameworks, and disclosure-oriented principles. A growing literature argues that participation in international sustainability initiatives is associated with differences in banks' internal policies and risk-management practices related to environmental externalities. In our setting, this motivates testing whether UNEP FI participant banks respond differently to a decline in enforcement risk in the land-use sector.

We implement this heterogeneity test by interacting the enforcement shock with an indicator for UNEP FI membership and, separately, with an indicator for having joined UNEP FI before or after to the enforcement shock. The idea is to distinguish banks that were already committed to the initiative before the decentralization period from banks that joined later. The estimating equation follows the bank–municipality–month framework in Equation (10), augmenting the baseline $\text{LowSeasonalCloud}_{cm} \times \text{Post}_y$ interaction with bank-type interactions. The unit of observation is bank b by municipality c by calendar month m by year y, and the dependent variables are agricultural credit outcomes at the bank–municipality–month level.

Table A2 reports the results. The interaction $\text{Post}_y \times \text{LowSeasonalCloud}_{cm} \times \text{UNEPFI}_b$ is positive and statistically significant for both the intensive and extensive margins of agricultural lending. Thus, banks that eventually join the UNEP FI, agricultural credit expands more in the municipality–months where monitoring presents a sharper decline in realized enforcement. Morever, once we estimate the effects for banks that joined UNEP FI before 2013 and banks that joined later we find contrasting results While banks that joined UNEP FI before 2013 present negative and statistically insignificant across margins, implying that the differential response is not driven by pre-2013 UNEP FI members, banks that joined the initiative later experience a large and significant result on both margins.

Two implications follow. First, the lending response to weaker enforcement is heterogeneous across bank types in a way consistent with differences in bank practices rather than with purely local demand shifts: within the same municipality–time cell and the same levels of bank exposure to the enforcement shock, banks with UNEP FI membership exhibit a stronger agricultural credit expansion. Second, the fact that the effect is not concentrated among banks that were already UNEP FI members prior to 2013 weakens the interpreta-

tion that the result is mechanically driven by time-invariant differences between "green" and "non-green" banks that predate the decentralization period. Instead, it is consistent with the view that the post-2013 period features differential credit provision behavior across banks with observably different sustainability commitments.

This pattern relates to recent evidence on banks' climate commitments and lending behavior in emerging markets: Bernad et al. (2026) show that voluntary climate commitments are informative about banks' lending policies and can be associated with systematic differences in credit allocation across sectors. In our setting, UNEP FI membership similarly predicts differential agricultural credit supply when enforcement risk falls, suggesting that sustainability-commitments may shape how enforcement-based regulatory shocks transmit to local credit supply.

5.4 Identification: Enforcement, Bank Presence, Land Use and Agricultural Productivity

Table A3 examines whether the enforcement-driven reallocation of credit is associated with changes in agricultural land use and whether any land expansion translates into higher agricultural productivity. The specification follows Equation (14). Three patterns emerge. First, planted area increases sharply with a concurrent rise in the harvested area after enforcement decentralization in low-average-cloud municipalities. Second, both margins are amplified in municipalities with higher baseline agricultural credit intensity, indicating that locations with greater local credit capacity experience larger increases in cultivated and harvested land after enforcement reduces.

This evidence aligns with the deforestation results: when enforceability weakens in the high-detection environments identified by low average cloud coverage, land use expands, and the expansion is stronger where local agricultural lending capacity was already higher before decentralization. At the same time, the productivity results provide an important qualification. Using the harvested-to-planted area ratio as a proxy for agricultural productivity, we find no economically meaningful response: the coefficients on $\text{Post}_y \times \text{LowAvgCloud}_c$ are near zero and statistically insignificant, and the amplification term with agricultural credit intensity is also small and not statistically distinguishable from zero.

Taken together, these results indicate that the negative enforcement shock is associated with an extensive-margin expansion of land use, in line with the deforestation results in Section 4.4. Both planted and harvested area increase and these results are amplified by local credit capacity. However. the expansion in land use does not translate into improvements in productivity, even in municipalities where credit supply conditions would most plausi-

bly support efficiency-enhancing investment. This complements evidence that credit supply shocks can induce green investment (Accetturo et al., 2022), by showing that when regulatory risk falls, credit supply might instead support brown technologies usage.

5.5 Robustness: Controlling for Climate Controls

A concern is that seasonal cloud coverage may capture broader climatic conditions, rather than monitoring feasibility alone. To address this possibility, we re-estimate the main enforcement and lending specifications including contemporaneous controls for average monthly temperature and precipitation.

Table A4 shows that the enforcement first stage is robust to these controls. The interaction between low seasonal cloud coverage and the post-2013 period remains negative and highly significant across both the extensive and intensive margins of fines, with magnitudes very close to the baseline estimates. Table A5 shows that the lending results are similarly robust: agricultural credit continues to increase after 2013 in low-cloud municipality–months, and the triple interaction with high bank exposure remains large and precisely estimated.

Overall, these results indicate that the main enforcement and lending patterns are not driven by short-run temperature or precipitation shocks correlated with cloud coverage.

5.6 Robustness: Excluding Regional Banks

A potential concern is that the baseline lending results are driven by small "regional" banks whose lending is geographically concentrated and may respond differently to local shocks. To address this concern, Table A6 re-estimates the main agricultural credit specifications after excluding banks that operate in fewer than 100 municipalities in the Amazon. This restriction removes banks with limited spatial footprint and therefore reduces the scope for the results to be driven by idiosyncratic behavior of highly localized institutions.

The estimates remain consistent with the baseline findings. Taken together, Table A6 shows that the agricultural credit response to the enforcement shock is not an artifact of localized banking structures. Instead, the expansion in agricultural lending and the exposure-based supply heterogeneity are present among banks with wide geographic scope, reinforcing the interpretation that the results reflect a general credit-supply response to a persistent reduction in enforcement risk rather than a compositional shift toward small banks or a regional-bank-specific demand shock.

5.7 Robustness: Alternative Transformation of Enforcement Variables

This section assesses whether the main results are sensitive to alternative outcome transformations. Our baseline enforcement and lending specifications use the inverse hyperbolic sine transformation for extensive-margin outcomes so that zeros are retained while preserving an approximately log-scale interpretation. We now show that the core enforcement and deforestation findings are robust when we instead use log transformations that add one to accommodate zeros. The qualitative pattern is unchanged: following 2013, enforcement declines disproportionately in municipality–months with typically high monitoring feasibility (low seasonal cloudiness), and deforestation increases in municipalities with typically low average cloud coverage.

Table A7 re-estimates the enforcement first stage using $\log(1 + \cdot)$ transformations of fine outcomes. The decentralization-period interaction remains negative, consistent with a weakening in the conversion of monitoring signals into realized sanctions. Table A8 reports the deforestation estimates using alternative transformations of annual municipal deforestation. Across transformations, the differential increase in deforestation for low-average-cloud municipalities remains, reinforcing the deterrence interpretation that links the enforcement break to land-use outcomes.

5.8 Robustness: Alternative Thresholds for Cloud Coverage

This subsection evaluates whether the main results depend on the baseline definition of high monitoring feasibility (the below-median split in long-run seasonal cloud coverage). We re-estimate the enforcement, deforestation, and credit specifications using a stricter treatment definition that classifies municipality–months (and municipalities) in the *first quartile* of long-run cloud coverage as high-detection environments. If the findings are driven by a particular cutoff choice rather than by enforcement risk, the estimated effects should be unstable when moving from the median split to a more extreme threshold.

Table A9 reports difference-in-differences estimates of Equation (8) using *First Quartile Cloud Coverage* in place of the baseline low-cloud indicator. The post-2013 interaction remains negative and statistically significant across enforcement outcomes, indicating that fines fall after decentralization precisely in the municipality–months where monitoring is most feasible under this stricter definition. This confirms that the enforcement first stage is not sensitive to the baseline cutoff and supports the interpretation that decentralization reduced the conversion of monitoring capacity into sanctions in high-detection environments.

Table A10 re-estimates Equation (9) using the first-quartile cloud classification at the municipality level and an inverse-hyperbolic-sine transformation of annual deforestation. The

post-2013 interaction remains positive and statistically significant, implying that deforestation rises after decentralization in municipalities where monitoring is mechanically most effective under the stricter cloud threshold. The stability of the deforestation response under an alternative treatment definition strengthens the case that the real effects are tied to enforcement risk rather than to an arbitrary partition of the cloud distribution.

Finally, Table A11 shows that the agricultural credit results are also robust to the first-quartile treatment definition. Using this alternative threshold, the interaction between the post-2013 period and high-detection municipality–months continues to predict an expansion in agricultural lending. Moreover, the triple-interaction specification indicates that the increase is stronger for *HighBankExposure* banks, consistent with a credit-supply response rather than a purely local-demand shift. Taken together with the enforcement and deforestation robustness results, these estimates confirm that the main findings are not driven by the baseline median split used to define monitoring feasibility.

6 Conclusion

This paper shows that enforcement capacity is a first-order determinant of bank credit allocation. We study Brazilian anti-deforestation policy in the Amazon, where enforcement is operationally tied to satellite monitoring and therefore constrained by cloud cover (Assunção et al., 2023a). We exploit the decentralization phase that begins in 2013 and coincides with a weakening of enforcement follow-through relative to the preceding command-and-control period (Nunes et al., 2024), and we use predetermined seasonal cloudiness to isolate when monitoring should be most effective.

The results document a tight chain from enforceability to credit reallocation and real activity. First, enforcement declines precisely in municipality–months in which monitoring capacity is mechanically high. After 2013, low seasonal cloud municipality–months experience a sharp fall in the extensive and intensive margins of IBAMA fines, consistent with a deterioration in the conversion of monitoring signals into sanctions. Second, agricultural lending expands in the same high-detection environments, with no comparable change in non-agricultural lending. The lending response operates through both margins: banks increase agricultural lending within existing bank–municipality relationships and expand the set of local lending relationships that supply agricultural credit. Third, the credit response reflects supply rather than only local demand. In triple-differences specifications that compare banks within the same municipality–time cell, banks with higher ex ante exposure to deforestation-enforcement risk expand agricultural lending significantly more when enforcement weakens. Finally, deforestation rises after 2013 and the increase is economically larger

in municipalities with greater pre-2013 agricultural lending intensity, indicating that local financial intermediation amplifies the real effects of weaker enforcement.

These findings contribute to several strands of the literature while emphasizing a distinct margin: realized enforceability. First, they complement the law-and-finance tradition linking enforcement institutions to credit market depth and real outcomes (Demirgüç-Kunt and Maksimovic, 1998; Djankov et al., 2007, 2003; Laeven and Woodruff, 2007; Bae and Goyal, 2009; Brown et al., 2017; Ponticelli and Alencar, 2016; Pezone, 2023) by showing that enforcement is not only a slow-moving contracting environment but also a time-varying state variable that banks incorporate into credit supply decisions. Second, they connect to evidence on supervisory enforcement directed at banks (Delis et al., 2017; Bonfim et al., 2023). Rather than studying enforcement applied to financial institutions, we show that enforcement applied to borrowers can reallocate bank portfolios locally and that the effects are strongest for banks ex ante more exposed to enforcement-sensitive activity. Third, they add to the growing evidence on climate- and regulation-related risks in banking (Engle et al., 2020; Giglio et al., 2026; Bolton and Kacperczyk, 2021; Mueller and Sfrappini, 2025) by identifying a channel that operates through changes in the realized probability of sanctioning, rather than primarily through expectations about future regulation or repricing of transition news. Relatedly, our results complement evidence that regulatory uncertainty affects financing conditions (Gissler et al., 2016) by isolating an enforcement-regime change that directly shifts enforcement risk. Finally, our evidence contributes to work on environmental regulation and optimal enforcement under limited capacity (Duflo et al., 2018; Burgess et al., 2012; Assunção et al., 2023b) by showing that the equilibrium effects of enforcement reforms depend on the structure of financial financial sector and local bank presence.

From a policy perspective, the results underscore that regulation cannot be assessed solely by statutory design. When monitoring and sanctioning are capacity constrained, enforcement reforms change private incentives and can trigger portfolio reallocations that magnify real impacts. Designing effective enforcement therefore requires accounting for banks' incentives and local credit capacity, since financial intermediaries can propagate, and potentially amplify, the consequences of changes in regulatory enforceability.

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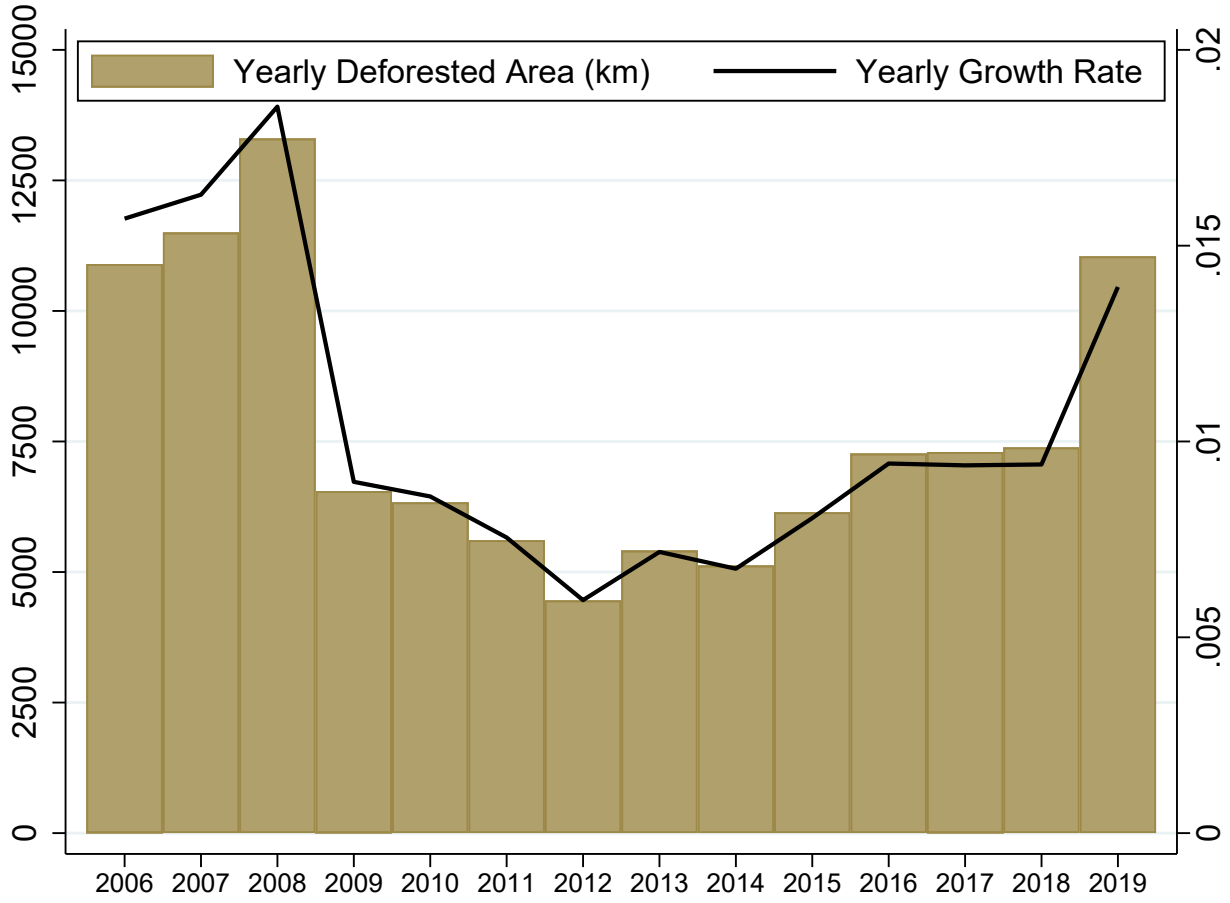
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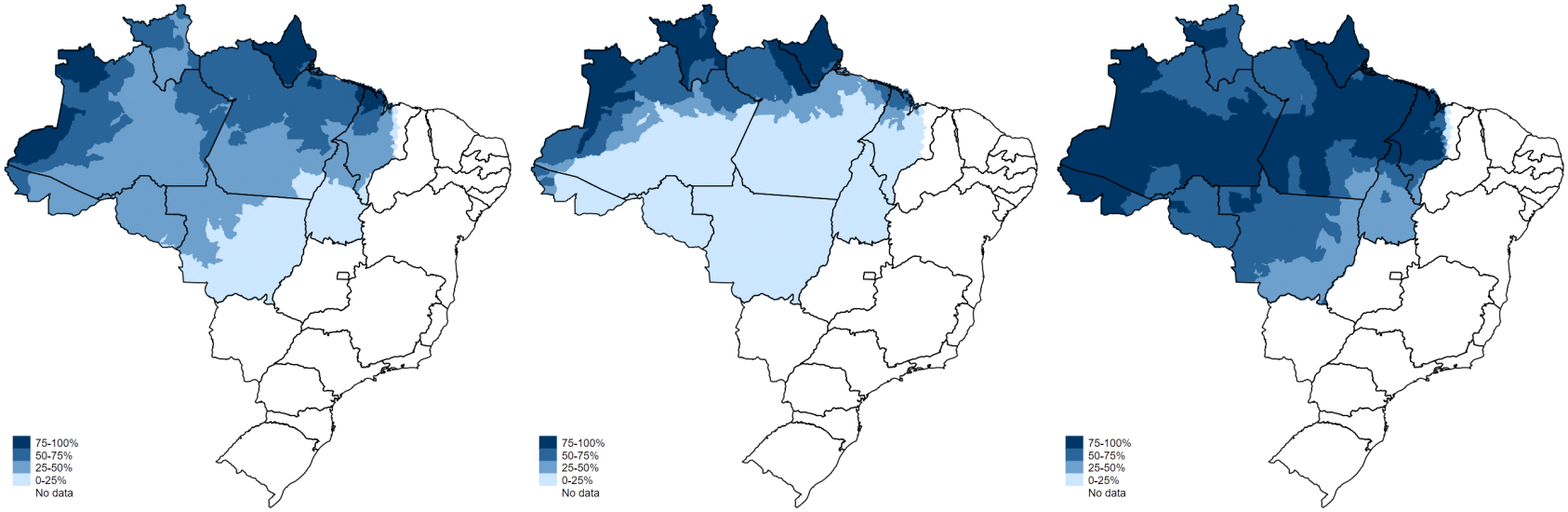
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Tables and Figures

Figure 1. Deforestation Levels and Growth in the Legal Amazon



Notes: Bars correspond to the share of area deforested (left axis). The solid line corresponds to the annual growth rate (right axis). The sample period is 2006–2019. All data refer exclusively to the Brazilian Legal Amazon region. Data are from INPE/PRODES (Projeto de Monitoramento do Desmatamento na Amazônia Legal por Satélite).



Avg. Annual DETER's Cloud Coverage | Seasonal June DETER's Cloud Coverage | Seasonal December DETER's Cloud Coverage

Figure 2. Cloud Coverage Seasonality

Notes: The figure maps municipality-level cloud coverage derived from the DETER monitoring system. Cloud coverage is computed from DETER's cloud-mask information and measures the fraction of a municipality's area that is classified as cloud-obstructed in DETER imagery. The left panel reports the municipality average cloud coverage over the full sample period, averaging across all months. The middle and right panels report municipality averages for June and December, respectively, illustrating seasonal variation in satellite visibility. Shading indicates cloud-coverage bins; lighter colors correspond to lower cloud coverage (higher monitoring feasibility). Municipalities with without DETER coverage are coded as no data.

Table 1. Enforcement Regime Shift

	Extensive Margin - Fines			Intensive Margin - Fines		
	(1)	(2)	(3)	(4)	(5)	(6)
Low Seasonal Cloud Coverage	0.016***	0.034***		0.032***	0.058***	
	(0.003)	(0.004)		(0.005)	(0.006)	
Low Seasonal Cloud Coverage × Post		-0.037***	-0.037***		-0.051***	-0.051***
		(0.005)	(0.005)		(0.009)	(0.009)
Observations	116088	116088	116088	116088	116088	116088
R Squared	0.2007	0.2012	0.2630	0.2523	0.2527	0.3189
Municipality FE	✓	✓	✓	✓	✓	✓
Municipality X Month	✓	✓	✓	✓	✓	✓
Year FE		✓	✓			✓

Notes: The table reports difference-in-differences estimates of Equation (8). The unit of observation is municipality c by calendar month m by year y. The dependent variables capture enforcement outcomes based on deforestation-related administrative fines issued by IBAMA. Extensive-margin outcomes are constructed using the inverse hyperbolic sine transformation of the relevant fine outcome with zeros included. Intensive-margin outcomes measure fine values conditional on enforcement occurring, as defined in the table. LowSeasonalCloud$_{cm}$ equals one if municipality c has below-median long-run cloud coverage in calendar month m, computed from monthly averages over 2004–2016. Post$_y$ equals one for years 2013 and later. All specifications include municipality-by-month fixed effects and month-by-year fixed effects. Standard errors are clustered at the municipality level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 2. Enforcement Regime Shift: Deforestation Alerts and Fines

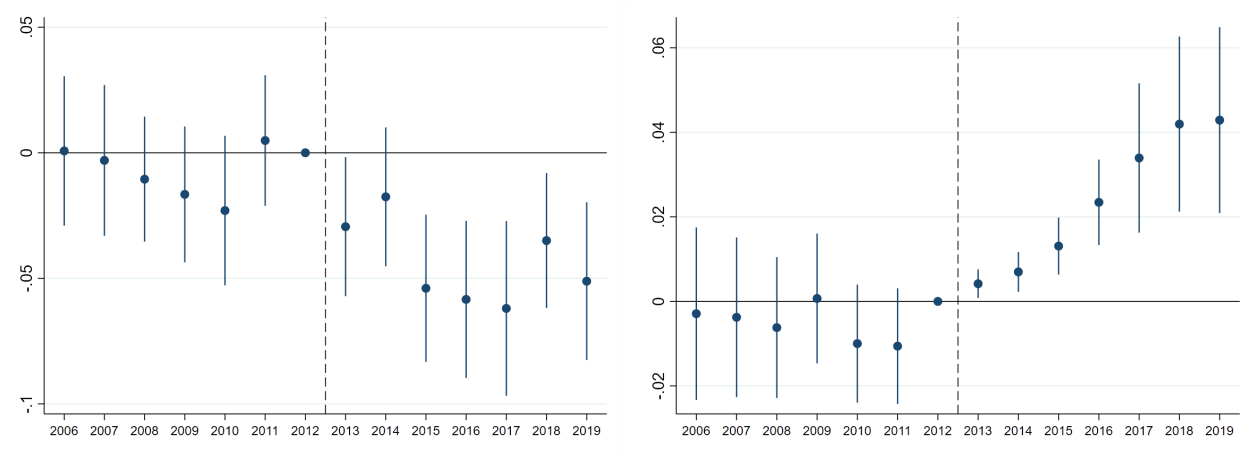
	DETER Alerts		Fines	
	(1)	(2)	(3)	(4)
Low Seasonal Cloud Coverage	0.143***		0.041***	
	(0.008)		(0.006)	
Low Seasonal Cloud Coverage × Post	0.004	0.004	-0.030***	-0.030***
	(0.008)	(0.008)	(0.010)	(0.010)
Observations	74628	74628	82920	82920
R Squared	0.3483	0.5205	0.2367	0.3257
Municipality X Month	✓	✓	✓	✓
Year FE	✓	✓	✓	✓

Notes: The table reports difference-in-differences estimates of Equation (8). The unit of observation is municipality c by calendar month m by year y. The dependent variables are the inverse hyperbolic sine transformation of DETER Alerts and deforestation-related administrative fines issued by IBAMA. LowSeasonalCloud$_{cm}$ equals one if municipality c has below-median long-run cloud coverage in calendar month m, computed from monthly averages over 2004–2016. Post$_y$ equals one for years 2013 and later. All specifications include municipality-by-month fixed effects and month-by-year fixed effects. Standard errors are clustered at the municipality level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 3. Enforcement Shock and Deforestation

	Deforestation		
	(1)	(2)	(3)
Post × Low Avg. Cloud Coverage	0.018*	0.031***	0.028***
	(0.009)	(0.010)	(0.010)
Observations	10626	10626	10626
R Squared	0.9998	0.9998	0.9998
Municipality FE	✓	✓	✓
Time X PRODES Forest Coverage FE	✓	✓	✓
Time X PRODES Cloud Coverage FE		✓	✓
Time X PRODES Non-observed Coverage FE			✓

Notes: The table reports reduced-form estimates of Equation (9). The unit of observation is municipality c by year y. The dependent variable is annual municipal deforestation. LowAvgCloud_c equals one if municipality c has below-median average cloud coverage (constructed from the baseline cloud measure described in the text). Post_y equals one for years 2013 and later. All specifications include municipality fixed effects and year fixed effects. The term $\Gamma_y \times Z_c$ denotes time-varying controls interacted with baseline bins of land characteristics (including baseline forest cover and coverage/non-observed coverage measures), as indicated in the column headers. Standard errors are clustered at the municipality level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.



Number of Deforestation Fines

Deforestation

Figure 3. Policy Decentralization, Law Enforcement, and Deforestation.

Notes: The figure plots event-study estimates corresponding to the enforcement and deforestation designs. The left panel reports coefficients from an event-study version of Equation (8), comparing low versus high seasonal cloud municipality–months for enforcement outcomes based on IBAMA fines. The right panel reports coefficients from an event-study version of Equation (9), comparing low versus high average cloud municipalities for annual deforestation. Specifications include the same fixed effects and controls as in Table 1 and Table 3. The vertical line marks 2013, the start of the decentralization period. Coefficients are normalized relative to the omitted pre-period year (or period) used in the underlying regression.

Table 4. Enforcement Risk and Local Credit

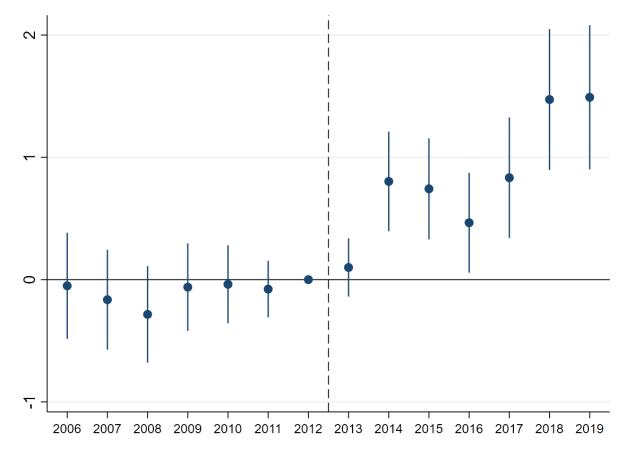
	Total Lending			Agricultural Lending			Non-Agricultural Lending		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Low Cloud Coverage	0.112	-0.067		-0.440***	-0.470***		0.150	-0.018	
	(0.124)	(0.113)		(0.098)	(0.098)		(0.124)	(0.112)	
Post × Low Cloud Coverage	-0.204	0.144	0.145	0.855***	0.926***	0.929***	-0.275	0.051	0.051
	(0.249)	(0.227)	(0.227)	(0.196)	(0.197)	(0.197)	(0.249)	(0.225)	(0.225)
Observations	186432	185592	185592	186432	185592	185592	186432	185592	185592
R Squared	0.668	0.747	0.749	0.807	0.831	0.833	0.658	0.747	0.748
Bank X Municipality FE	✓	✓		✓	✓		✓	✓	
Time X Bank-Municipality Employees FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Time X Bank FE		✓	✓		✓	✓		✓	✓
Bank X Municipality X Month			✓			✓			✓

Notes: The table reports estimates of Equation (10). The unit of observation is bank b by municipality c by calendar month m by year y, constructed by aggregating branch-level ESTBAN data to the bank–municipality–month level. Dependent variables measure total lending, agricultural lending, and non-agricultural lending, as indicated. Extensive-margin outcomes are constructed using the inverse hyperbolic sine transformation of the relevant lending outcome with zeros included. Intensive-margin outcomes measure lending amounts conditional on lending being positive, as defined in the table. $\text{LowSeasonalCloud}_{cm}$ and Post_y are defined as in Table 1. Specifications include bank-by-month–year fixed effects and bank-by-municipality (or bank-by-municipality-by-month) fixed effects as indicated in the column headers, absorbing bank-wide shocks and time-invariant bank–location differences (and, when applicable, stable bank–location seasonality). Standard errors are clustered at the bank–municipality level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

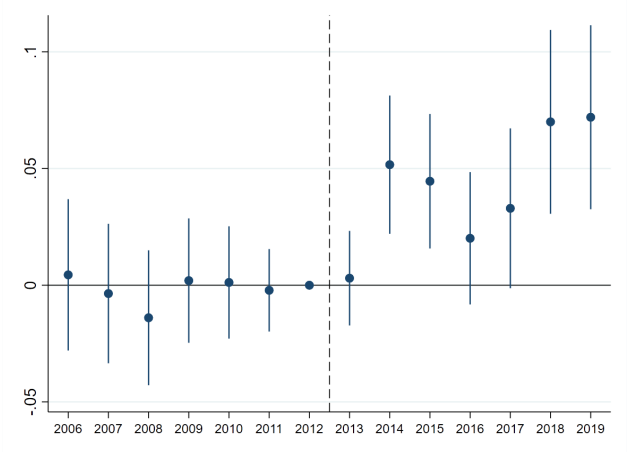
Table 5. Enforcement Risk and Local Credit Provision

	Credit Default Provision	
	(1)	(2)
Low Cloud Coverage	0.171***	
	(0.052)	
Post × Low Cloud Coverage	-0.342***	-0.343***
	(0.105)	(0.105)
Observations	185592	185592
R Squared	0.946	0.946
Bank X Municipality FE	✓	
Time X Bank FE	✓	✓
Time X Bank-Municipality Employees FE	✓	✓
Bank X Municipality X Month		✓

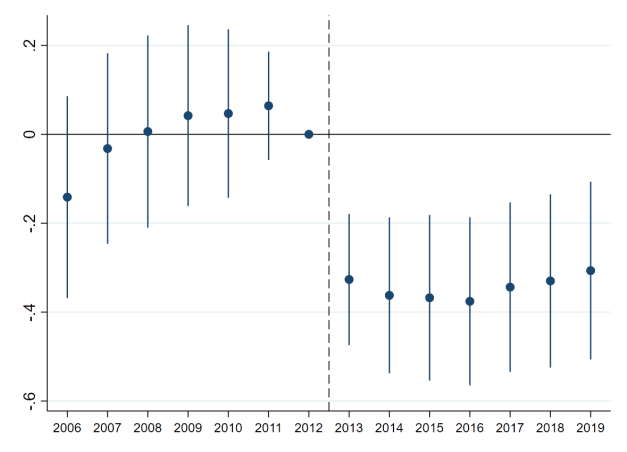
Notes: The table reports estimates of Equation (10) using loan-loss provision outcomes. The unit of observation is bank b by municipality c by calendar month m by year y, constructed by aggregating ESTBAN branch data to the bank–municipality–month level. Dependent variables capture credit provision measures, as indicated. Extensive-margin outcomes are constructed using the inverse hyperbolic sine transformation of the relevant provision outcome with zeros included. Intensive-margin outcomes measure provision amounts conditional on being positive, as defined in the table. $\text{LowSeasonalCloud}_{cm}$ and Post_y are defined as in Table 1. Specifications include bank-by-month–year fixed effects and bank-by-municipality (or bank-by-municipality-by-month) fixed effects as indicated. Standard errors are clustered at the bank–municipality level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.



Agricultural Credit: Intensive margin



Agricultural Credit: Extensive margin



Loan-Loss Provisions

Figure 4. Anti-Deforestation Enforcement, Agricultural Credit, and Credit Default Provision.

Notes: The figure presents event-study estimates corresponding to the lending and provision specifications. The agricultural credit panels plot dynamic coefficients from an event-study version of Equation (10) estimated at the bank–municipality–month level. The intensive-margin panel uses agricultural lending conditional on being positive. The extensive-margin panel uses the inverse hyperbolic sine transformation of agricultural lending with zeros included. The provisions panel plots coefficients from an analogous event-study specification with loan-loss provisions as the outcome. All regressions include the same fixed effects as the corresponding baseline specifications in Table 4 and Table 5. The vertical line marks 2013. Coefficients are normalized relative to the omitted pre-period year (or period) used in the underlying regression.

Table 6. Enforcement Risk and Local Agricultural Lending Supply

	Intensive Margin		Extensive Margin	
	(1)	(2)	(3)	(4)
Post × Low Cloud Coverage	0.295		-0.003	
	(0.249)		(0.017)	
Post × Low Cloud Coverage × High Bank Exposure	1.837***	1.636***	0.134***	0.126***
	(0.398)	(0.436)	(0.027)	(0.028)
Observations	185592	159348	185592	159348
R Squared	0.833	0.892	0.804	0.867
Bank X Municipality X Month	✓	✓	✓	✓
Time X Bank FE	✓	✓	✓	✓
Time X Bank-Municipality Employees FE	✓	✓	✓	✓
Time X Municipality FE		✓		✓

Notes: The table reports triple-differences estimates of Equation (13) for agricultural lending outcomes at the bank–municipality–month level. The main regressor is $\text{LowSeasonalCloud}_{cm} \times \text{Post}_y \times \text{HighBankExposure}_b$. $\text{HighBankExposure}_b$ is an indicator equal to one if bank b has above-median pre-2013 exposure to deforestation-enforcement risk, constructed from a lending-weighted average of fine intensity across the bank's 2012 municipal footprint (see Equations (11)–(12)). Extensive-margin outcomes are constructed using the inverse hyperbolic sine transformation of the relevant lending outcome with zeros included. Intensive-margin outcomes measure lending amounts conditional on being positive, as defined in the table. Specifications include bank-by-month–year fixed effects and bank-by-municipality-by-month fixed effects; columns that include municipality-by-month–year fixed effects absorb local credit demand and municipality-specific shocks at each date, so identification comes from comparing banks within the same municipality–time cell. Standard errors are clustered at the bank–municipality level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 7. Enforcement Risk and Local Non-Agricultural Lending Supply

	Total Lending		Non-Agricultural Lending	
	(1)	(2)	(3)	(4)
Post × Low Cloud Coverage	0.126		-0.000	
	(0.296)		(0.293)	
Post × Low Cloud Coverage × High Bank Exposure	0.053	0.052	0.147	0.140
	(0.459)	(0.457)	(0.454)	(0.457)
Observations	185592	159348	185592	159348
R Squared	0.749	0.847	0.748	0.844
Bank X Municipality X Month	✓	✓	✓	✓
Time X Bank FE	✓	✓	✓	✓
Time X Bank-Municipality Employees FE	✓	✓	✓	✓
Time X Municipality FE		✓		✓

Notes: The table reports placebo triple-differences estimates of Equation (13) for non-agricultural lending outcomes at the bank–municipality–month level. The main regressor is $\text{LowSeasonalCloud}_{cm} \times \text{Post}_y \times \text{HighBankExposure}_b$, where $\text{HighBankExposure}_b$ is defined as in Table 6. Extensive-margin outcomes are constructed using the inverse hyperbolic sine transformation of the relevant lending outcome with zeros included. Intensive-margin outcomes measure lending amounts conditional on being positive, as defined in the table. Specifications include the same fixed effects and clustering as in Table 6. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 8. Law Enforcement, Credit Provision, and Deforestation

	Deforestation		
	(1)	(2)	(3)
Post × Low Avg. Cloud Coverage	0.025**	0.015	0.019*
	(0.011)	(0.010)	(0.011)
Post × Low Avg. Cloud Coverage × High Loans per km^2	0.009		-0.021
	(0.020)		(0.022)
Post × Low Avg. Cloud Coverage × High of Agr. Loans per km^2		0.033*	0.046**
		(0.019)	(0.022)
Observations	10626	10626	10626
R Squared	0.9998	0.9998	0.9998
Municipality FE	✓	✓	✓
Time X PRODES Forest Coverage FE	✓	✓	✓
Time X PRODES Cloud Coverage FE	✓	✓	✓
Time X PRODES Non-observed Coverage FE	✓	✓	✓
Time X High Total Loans per km^2 FE	✓		✓
Time X High of Agr. Loans per km^2 FE		✓	✓

Notes: The table reports estimates of the amplification specification in Equation (14). The unit of observation is municipality c by year y. The key interactions combine the enforcement-shock term $\text{LowAvgCloud}_c \times \text{Post}_y$ with pre-2013 measures of local credit intensity. Pre-2013 lending intensity is constructed using 2012 lending and is scaled by municipal area; columns distinguish total lending intensity and agricultural lending intensity, as indicated. Specifications include municipality fixed effects and year fixed effects and the same set of time-varying controls interacted with baseline land characteristics used in Table 3. Standard errors are clustered at the municipality level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Online Appendix

A1 Data and Variables Description

This appendix provides detailed definitions for the variables reported in the main and appendix tables, with emphasis on (i) municipality–month enforcement and monitoring variables, (ii) municipality–year deforestation outcomes, and (iii) bank–municipality–month credit outcomes constructed from ESTBAN (Document No. 13) and aggregated to the bank–municipality level.

A1 Enforcement outcomes (IBAMA fines)

Fine incidence (Extensive margin). $\mathbb{1}\{Fines_{cmy} > 0\}$ equals one if IBAMA issues at least one deforestation-related fine in municipality c during calendar month m of year y.

Fine value (Intensive margin). $Fines_{cmy}$ is the total value (in R$) of deforestation-related fines issued in municipality c during calendar month m of year y, defined conditional on enforcement occurring (i.e., restricting to municipality–months with positive fine incidence).

A2 Monitoring variables (Cloud cover and DETER alerts)

LowSeasonalCloud$_{cm}$. Indicator equal to one if municipality c exhibits below-median long-run cloud coverage in calendar month m (computed from municipality-by-calendar-month cloud averages over a pre-period), and zero otherwise. This variable is predetermined and captures predictable seasonality in satellite monitoring feasibility.

Post$_y$. Indicator equal to one for years 2013 and later.

DETER alerts. DETER is a near real-time system that generates frequent deforestation warnings intended to support the targeting of inspections and sanctions. We use DETER alert information to motivate the monitoring mechanism.

A3 Deforestation outcomes (PRODES)

Deforestation$_{cy}$. Annual municipality-level clear-cut deforestation constructed from PRODES (INPE). PRODES years do not coincide with calendar years: PRODES year t spans August of year $t-1$ through July of year t.[6]

[6] Accordingly, when the dependent variable is annual deforestation, we align enforcement and credit measures to the relevant PRODES-year window.

A4 Bank outcomes (ESTBAN / Document No. 13) and aggregation to bank–municipality–month

Raw source and unit of observation. Bank outcomes are based on ESTBAN (*Estatística Bancária Mensal*), which originates from *Document No. 13*, a mandatory monthly branch-level report. We aggregate branch-level entries to the bank–municipality–calendar-month panel (b, c, m, y) used in the tables.

Mapping from Document No. 13 verbetes to constructed variables. Let k index branches of bank b located in municipality c. For each month-year (m, y) we sum branch balances across $k \in (b, c)$ to obtain bank–municipality aggregates.

- **Total lending** ($Loans_{bcmy}$): stock of credit operations (*"Operações de Crédito"*), aggregated across branches within (b, c, m, y).
- **Agricultural lending** ($AgLoans_{bcmy}$): sum of rural and agroindustrial financing balances (*"Financiamentos Rurais"* plus *"Financiamentos Agroindustriais"*)
- **Non-agricultural lending** ($NonAgLoans_{bcmy}$): residual lending in credit operations not classified as rural or agroindustrial financing,
- **Loan-loss provisions / Credit default provisions** ($Prov_{bcmy}$): provisions for credit operations ("*Provisão para Operações de Crédito*"), aggregated across branches within (b, c, m, y).
- **Total deposits** ($Deposits_{bcmy}$): branch-level deposits assigned to the branch where the account is opened. We construct total deposits as the sum of (i) demand deposits from public sector entities (*"Depósitos á vista - Governo"*), (ii) demand deposits from individuals and firms (*"Depósitos á vista - Setor Privado"*), (iii) savings deposits (*"Depósitos de Poupança"*), and (iv) term deposits (*"Depósitos á prazo"*).

Extensive vs. intensive margins and transformations (tables). For lending, deposits, and provisions, some specifications use the inverse hyperbolic sine transformation to accommodate zeros, $\text{asinh}(X_{bcmy})$, while others study intensive-margin outcomes in levels conditional on being positive, $X_{bcmy} \mid X_{bcmy} > 0$, as indicated by the relevant table column headers and notes.

A5 Pre-period credit intensity and exposure variables

High Total Loans per km^2 and **High Agricultural Loans per km^2** are indicators for municipalities with above-median pre-2013 lending intensity, constructed using baseline (pre-2013) lending scaled by municipality area.

High Bank Exposure$_b$ is an indicator for banks with above-median pre-2013 exposure to enforcement-relevant municipalities, constructed using banks' pre-period footprint and used in interactions in the appendix tables.

A6 Agricultural production and land use (PAM/IBGE)

We merge annual municipality-level agricultural production data from IBGE's *Produção Agrícola Municipal* (PAM). PAM reports, by crop and municipality-year, cultivated area (area planted or destined for harvest) and harvested area, among other production measures. We use PAM to construct municipality-year measures of planted (cultivated) area and harvested area, which serve as controls and complementary outcomes in the annual municipality-level analysis.

A2 Proofs

This appendix derives the closed-form solutions in Section 2.1 and proves Propositions 1–**??**. The maintained assumptions are: (i) $\phi > 0$ and $\psi > 0$ (strict convexity), (ii) an interior illegal share $x^*(p) \in (0,1)$ (implemented by $0 < c - pF < \psi$), (iii) positive scale $K^*(r,p) > 0$ (implemented by $A - c - r + \frac{(c-pF)^2}{2\psi} > 0$), (iv) limited liability and zero recovery upon default, and (v) the economy is in the "default-if-detected" region so repayment occurs only when no detection occurs.

A.1 Borrower solution. The borrower chooses (K, x) to maximize (1):

$$\Big(A - r - (1-x)c - pFx - \frac{\psi}{2}x^2\Big)K - \frac{\phi}{2}K^2.$$

For an interior optimum with $K > 0$ and $x \in (0,1)$, the first-order conditions are:

$$\frac{\partial}{\partial K}: \qquad A - r - (1-x)c - pFx - \frac{\psi}{2}x^2 - \phi K = 0, \tag{15}$$

$$\frac{\partial}{\partial x}: \qquad \Big(c - pF - \psi x\Big)K = 0. \tag{16}$$

Since $K > 0$, (16) implies

$$x^*(p) = \frac{c - pF}{\psi},$$

which is (2). Substituting $x^*(p)$ into (15) yields

$$K^*(r,p) = \frac{1}{\phi}\left(A - c - r + \frac{(c-pF)^2}{2\psi}\right),$$

which is (3). Differentiating gives

$$\frac{dx^*(p)}{dp} = -\frac{F}{\psi} < 0.$$

Default-if-detected region (consistency). Let the detected-state payoff under repayment (i.e., setting the detected indicator $s = 1$ in (1)) be

$$\Pi^D_{\text{repay}}(K, x; r) \equiv \Big(A - r - (1-x)c - Fx - \frac{\psi}{2}x^2\Big)K - \frac{\phi}{2}K^2. \tag{17}$$

Under limited liability, the detected-state default payoff is normalized to zero. Hence the borrower defaults upon detection if and only if

$$\Pi^{D}_{\text{repay}}\big(K^*(r,p), x^*(p); r\big) < 0. \tag{18}$$

Using

$$x^*(p) = \frac{c - pF}{\psi}, \qquad K^*(r,p) = \frac{1}{\phi}\left(A - c - r + \frac{(c-pF)^2}{2\psi}\right),$$

condition (18) can be written as

$$\left(A - c - r + (c - F)x^*(p) - \frac{\psi}{2}\big(x^*(p)\big)^2\right) K^*(r,p) \;<\; \frac{\phi}{2}\big(K^*(r,p)\big)^2. \tag{19}$$

For an interior solution with $K^*(r,p) > 0$, dividing both sides by $K^*(r,p)$ and substituting for $x^*(p)$ and $K^*(r,p)$ yields

$$r > \bar{r}_D(p) \equiv A - c + \frac{(c-pF)(4F - c - 3pF)}{2\psi}. \tag{20}$$

Thus, detection induces default at the optimal choices whenever

$$r > \bar{r}_D(p), \qquad \text{provided } K^*(r,p) > 0 \iff r < A - c + \frac{(c-pF)^2}{2\psi}. \tag{21}$$

Therefore, the default-if-detected region is the set of interest rates satisfying

$$A - c + \frac{(c-pF)(4F - c - 3pF)}{2\psi} < r < A - c + \frac{(c-pF)^2}{2\psi}. \tag{22}$$

A.3 Lender pricing. With default-if-detected, zero recovery, and detection probability p, the lender receives rK with probability $1 - p$ and 0 otherwise. Zero expected profit implies

$$(1-p)rK = r_d K \quad \Rightarrow \quad (1-p)r = r_d \quad \Rightarrow \quad r^*(p) = \frac{r_d}{1-p},$$

which is (4).

A.4 Proof of Proposition 1. From (4),

$$\frac{dr^*(p)}{dp} = \frac{r_d}{(1-p)^2} > 0,$$

so $p \downarrow$ implies $r^*(p) \downarrow$. Substituting $r^*(p)$ into (3) yields (7). Differentiating (7) gives

$$\frac{dK^*(p)}{dp} = \frac{1}{\phi}\left(-\frac{r_d}{(1-p)^2} - \frac{F(c-pF)}{\psi}\right) < 0 \quad \text{for } c - pF > 0.$$

Therefore, in the interior region, $p \downarrow$ implies $K^*(p) \uparrow$.

A.5 Proof of Proposition 2. With $D(p) = x^*(p)K^*(p)$, we have

$$\frac{dD(p)}{dp} = K^*(p)\frac{dx^*(p)}{dp} + x^*(p)\frac{dK^*(p)}{dp}.$$

Since $\frac{dx^*(p)}{dp} = -\frac{F}{\psi} < 0$ and (in the interior) $\frac{dK^*(p)}{dp} < 0$, both components are negative. Hence $dD(p)/dp < 0$, so $p \downarrow$ implies $D(p) \uparrow$.

A3 Alternative Channels

Table A1. Enforcement Risk and Local Funding

	Total Deposits			
	(1)	(2)	(3)	(4)
Low Cloud Coverage	-0.038			
	(0.115)			
Post × Low Cloud Coverage	0.088	0.089	0.049	
	(0.231)	(0.232)	(0.306)	
Post × Low Cloud Coverage × High Bank Exposure			0.115	0.097
			(0.457)	(0.462)
Observations	185592	185592	185592	159348
R Squared	0.740	0.742	0.742	0.846
Bank X Municipality	✓	✓	✓	✓
Time X Bank FE	✓	✓	✓	✓
Time X Bank-Municipality Employees FE	✓	✓	✓	✓
Bank X Municipality X Month		✓	✓	✓
Time X Municipality FE				✓

Notes: The table reports estimates of Equation (10). The unit of observation is bank b by municipality c by calendar month m by year y, constructed by aggregating branch-level ESTBAN data to the bank–municipality–month level. Dependent variable measure total deposits, as indicated. Extensive-margin outcomes are constructed using the inverse hyperbolic sine transformation of the relevant lending outcome with zeros included. Intensive-margin outcomes measure lending amounts conditional on lending being positive, as defined in the table. $\text{LowSeasonalCloud}_{cm}$ and Post_y are defined as in Table 1. Specifications include bank-by-month–year fixed effects and bank-by-municipality (or bank-by-municipality-by-month) fixed effects as indicated in the column headers, absorbing bank-wide shocks and time-invariant bank–location differences (and, when applicable, stable bank–location seasonality). Standard errors are clustered at the bank–municipality level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table A2. Enforcement Risk, Green Banks and Agricultural Credit

	Intensive Margin		Extensive Margin	
	(1)	(2)	(3)	(4)
Post × Low Cloud Coverage × UN Finacial Initiave Bank	1.493***		0.105***	
	(0.441)		(0.031)	
Post × Low Cloud Coverage × UN Finacial Initiave Bank before 2013		-0.572		-0.040
		(0.892)		(0.059)
Post × Low Cloud Coverage × UN Finacial Initiave Bank after 2013		1.854***		0.131***
		(0.465)		(0.032)
Observations	159348	159348	159348	159348
R Squared	0.923	0.923	0.905	0.905
Bank X Municipality X Month	✓	✓	✓	✓
Time X Bank FE	✓	✓	✓	✓
Time X Bank-Municipality Employees FE	✓	✓	✓	✓
High Exposure X Time X Municipality FE	✓	✓	✓	✓

Notes: The table reports estimates of Equation (10). The unit of observation is bank b by municipality c by calendar month m by year y, constructed by aggregating branch-level ESTBAN data to the bank–municipality–month level. The dependent variable is agricultural credit; intensive-margin outcomes measure amounts conditional on being positive, while extensive-margin outcomes use the inverse hyperbolic sine transformation of the corresponding outcome with zeros included. The key regressors interact the enforcement shock with banks' environmental-finance orientation, measured using membership in the United Nations Environment Programme Finance Initiative (UNEP FI). $\mathbb{1}\{\text{UNEP FI Bank}_b\}$ equals one for banks eventually become members of UNEP FI, based on the official UNEP FI membership roster and the date the bank joined the initiative. $\mathbb{1}\{\text{UNEP FI Bank before 2013}_b\}$ equals one for banks that joined UNEP FI before 2013, and zero otherwise. $\mathbb{1}\{\text{UNEP FI Bank after 2013}_b\}$ equals one for banks that joined UNEP FI after 2013, and zero otherwise. $\text{LowSeasonalCloud}_{cm}$ equals one if municipality c has below-median long-run cloud coverage in calendar month m, computed from monthly averages over 2004–2016, and Post_y equals one for years 2013 and later. Specifications include bank-by-month–year fixed effects and bank-by-municipality (or bank-by-municipality-by-month) fixed effects as indicated in the column headers, absorbing bank-wide shocks and time-invariant bank–location differences (and, when applicable, stable bank–location seasonality). Standard errors are clustered at the bank–municipality level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table A3. Law Enforcement, Credit Provision, Land Use and Agricultural Productivity

	Planted Area		Harvested Area		Productivity	
	(1)	(2)	(3)	(4)	(5)	(6)
Post × Low Avg. Cloud Coverage	1.021***	0.629***	1.019***	0.631***	-0.001	0.002
	(0.138)	(0.175)	(0.138)	(0.175)	(0.003)	(0.005)
Post × Low Avg. Cloud Coverage × High of Agr. Loans per km^2		0.956***		0.951***		-0.005
		(0.258)		(0.258)		(0.006)
Observations	10586	10586	10586	10586	10586	10586
R Squared	0.8963	0.8974	0.8962	0.8973	0.2616	0.2640
Municipality FE	✓	✓	✓	✓	✓	✓
Time X PRODES Forest Coverage FE	✓	✓	✓	✓	✓	✓
Time X PRODES Cloud Coverage FE	✓	✓	✓	✓	✓	✓
Time X PRODES Non-observed Coverage FE	✓	✓	✓	✓	✓	✓
Time X High of Agr. Loans per km^2 FE		✓		✓		✓

Notes: The table reports estimates of the amplification specification in Equation (14). The unit of observation is municipality c by year y. The key interactions combine the enforcement-shock term $\text{LowAvgCloud}_c \times \text{Post}_y$ with pre-2013 measures of local credit intensity. Pre-2013 lending intensity is constructed using 2012 lending and is scaled by municipal area. The dependent variables are the inverse hyperbolic sine transformation of the planted area and agricultural productivity measured by the ratio between the harvested area and the planted area, as indicated. Specifications include municipality fixed effects and year fixed effects and the same set of time-varying controls interacted with baseline land characteristics used in Table 3. Standard errors are clustered at the municipality level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

A4 Robustness Checks

Table A4. Enforcement Regime Shift - Climate Controls

	Extensive Margin - Fines			Intensive Margin - Fines		
	(1)	(2)	(3)	(4)	(5)	(6)
Low Seasonal Cloud Coverage	0.011***	0.030***		0.019***	0.044***	
	(0.004)	(0.005)		(0.007)	(0.009)	
Low Seasonal Cloud Coverage × Post		-0.037***	-0.037***		-0.050***	-0.051***
		(0.006)	(0.006)		(0.012)	(0.011)
Observations	116088	116088	116088	116088	116088	116088
R Squared	0.2023	0.2028	0.2630	0.2564	0.2567	0.3189
Municipality FE	✓	✓	✓	✓	✓	✓
Municipality X Month	✓	✓	✓	✓	✓	✓
Year FE		✓	✓			✓
Temperature and Precipitation Controls	✓	✓	✓	✓	✓	✓

Notes: The table reports difference-in-differences estimates of Equation (8). The unit of observation is municipality c by calendar month m by year y. The dependent variables capture enforcement outcomes based on deforestation-related administrative fines issued by IBAMA. Extensive-margin outcomes are constructed using the inverse hyperbolic sine transformation of the relevant fine outcome with zeros included. Intensive-margin outcomes measure fine values conditional on enforcement occurring, as defined in the table. Temperature and precipitation controls include average monthly temperature and average monthly precipitation. $\text{LowSeasonalCloud}_{cm}$ equals one if municipality c has below-median long-run cloud coverage in calendar month m, computed from monthly averages over 2004–2016. Post_y equals one for years 2013 and later. All specifications include municipality-by-month fixed effects and month-by-year fixed effects. Standard errors are clustered at the municipality level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table A5. Enforcement Risk and Local Credit - Climate Controls

	Agricultural Credit		
	(1)	(2)	(3)
Low Cloud Coverage	-0.463***		
	(0.098)		
Post × Low Cloud Coverage	0.924***	0.927***	0.293
	(0.196)	(0.197)	(0.249)
Post × Low Cloud Coverage × High Bank Exposure			1.836***
			(0.397)
Observations	185592	185592	185592
R Squared	0.831	0.833	0.833
Bank X Municipality	✓	✓	✓
Bank X Municipality X Month		✓	✓
Time X Bank FE	✓	✓	✓
Time X Bank-Municipality Employees FE	✓	✓	✓
Time X Municipality FE			✓
Temperature and Precipitation Controls	✓	✓	✓

Notes: The table reports estimates of Equation (10). The unit of observation is bank b by municipality c by calendar month m by year y, constructed by aggregating branch-level ESTBAN data to the bank–municipality–month level. Dependent variables measure agricultural lending, as indicated. Extensive-margin outcomes are constructed using the inverse hyperbolic sine transformation of the relevant lending outcome with zeros included. Intensive-margin outcomes measure lending amounts conditional on lending being positive, as defined in the table. Temperature and precipitation controls include average monthly temperature and average monthly precipitation. $\text{LowSeasonalCloud}_{cm}$ and Post_y are defined as in Table 1. Specifications include bank-by-month–year fixed effects and bank-by-municipality (or bank-by-municipality-by-month) fixed effects as indicated in the column headers, absorbing bank-wide shocks and time-invariant bank–location differences (and, when applicable, stable bank–location seasonality). Standard errors are clustered at the bank–municipality level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table A6. Enforcement Risk and Agricultural Credit - Excluding Regional Banks (Banks operating in less than 100 municipalities in the Amazon)

	Agricultural Credit			
	(1)	(2)	(3)	(4)
Low Cloud Coverage	-0.518***			
	(0.110)			
Post × Low Cloud Coverage	1.025***	1.025***	0.295	
	(0.217)	(0.217)	(0.253)	
Post × Low Cloud Coverage × High Bank Exposure			2.733***	2.290***
			(0.456)	(0.510)
Observations	160608	160608	160608	134232
R Squared	0.832	0.833	0.834	0.902
Bank X Municipality	✓	✓	✓	✓
Time X Bank FE	✓	✓	✓	✓
Time X Bank-Municipality Employees FE	✓	✓	✓	✓
Bank X Municipality X Month		✓	✓	✓
Time X Municipality FE				✓

Notes: The table reports estimates of Equation (10). The unit of observation is bank b by municipality c by calendar month m by year y, constructed by aggregating branch-level ESTBAN data to the bank–municipality–month level. Dependent variable measure agricultural lending, as indicated. Extensive-margin outcomes are constructed using the inverse hyperbolic sine transformation of the relevant lending outcome with zeros included. Intensive-margin outcomes measure lending amounts conditional on lending being positive, as defined in the table. $\text{LowSeasonalCloud}_{cm}$ and Post_y are defined as in Table 1. Specifications include bank-by-month–year fixed effects and bank-by-municipality (or bank-by-municipality-by-month) fixed effects as indicated in the column headers, absorbing bank-wide shocks and time-invariant bank–location differences (and, when applicable, stable bank–location seasonality). Standard errors are clustered at the bank–municipality level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table A7. Enforcement Regime Shift and Environmental Law Enforcement - Alternative Transformation

	log(1+# of Fines)	
	(1)	(2)
Low Seasonal Cloud Coverage	0.046***	
	(0.005)	
Low Seasonal Cloud Coverage × Post	-0.040***	-0.040***
	(0.007)	(0.007)
Observations	116088	116088
R Squared	0.2534	0.3199
Municipality	✓	✓
Year FE	✓	✓
Municipality X Month		✓

Notes: The table reports difference-in-differences estimates of Equation (8). The unit of observation is municipality c by calendar month m by year y. The dependent variables is the logarithmic transformation enforcement outcomes based on deforestation-related administrative fines issued by IBAMA plus one. $\text{LowSeasonalCloud}_{cm}$ equals one if municipality c has below-median long-run cloud coverage in calendar month m, computed from monthly averages over 2004–2016. Post_y equals one for years 2013 and later. All specifications include municipality-by-month fixed effects and month-by-year fixed effects. Standard errors are clustered at the municipality level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table A8. Enforcement Shock and Deforestation - Alternative Transformations

	IHS(Deforestation)		log(Deforestation)		log(1+Deforestation)	
	(1)	(2)	(3)	(4)	(5)	(6)
Post × Low Avg. Cloud Coverage	0.028***	0.019*	0.044***	0.025**	0.027***	0.019*
	(0.010)	(0.011)	(0.012)	(0.012)	(0.009)	(0.011)
Post × Low Avg. Cloud Coverage × High of Agr. Loans per km^2		0.046**		0.068**		0.043**
		(0.022)		(0.027)		(0.021)
Post × Low Avg. Cloud Coverage × High Loans per km^2		-0.021		-0.015		-0.022
		(0.022)		(0.027)		(0.021)
Observations	10626	10626	9254	9254	10626	10626
R Squared	0.9998	0.9998	0.9993	0.9993	0.9998	0.9998
Municipality FE	✓	✓	✓	✓	✓	✓
Time X PRODES Forest Coverage FE	✓	✓	✓	✓	✓	✓
Time X PRODES Cloud Coverage FE	✓	✓	✓	✓	✓	✓
Time X PRODES Non-observed Coverage FE	✓	✓	✓	✓	✓	✓
Time X High of Agr. Loans per km^2 FE		✓		✓		✓
Time X Low Total Loans per km^2 FE		✓		✓		✓

Notes: The table reports reduced-form estimates of Equation (9). The unit of observation is municipality c by year y. The dependent variable are alternative transformations of the annual municipal deforestation. LowAvgCloud_c equals one if municipality c has below-median average cloud coverage (constructed from the baseline cloud measure described in the text). Post_y equals one for years 2013 and later. All specifications include municipality fixed effects and year fixed effects. The term $\Gamma_y \times Z_c$ denotes time-varying controls interacted with baseline bins of land characteristics (including baseline forest cover and coverage/non-observed coverage measures), as indicated in the column headers. Standard errors are clustered at the municipality level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table A9. Enforcement Regime Shift and Environmental Law Enforcement - Alternative Thresholds for Cloud Coverage

	# Fines		
	(1)	(2)	(3)
First Quartile Cloud Coverage	0.021**	0.068***	
	(0.010)	(0.012)	
First Quartile Cloud Coverage × Post		-0.093***	-0.093***
		(0.016)	(0.015)
Observations	116088	116088	116088
R Squared	0.2522	0.2530	0.3195
Municipality FE	✓	✓	✓
Municipality X Month	✓	✓	✓
Year FE			✓

Notes: The table reports difference-in-differences estimates of Equation (8). The unit of observation is municipality c by calendar month m by year y. The dependent variables is the inverse hyperbolic sine transformation enforcement outcomes based on deforestation-related administrative fines issued by IBAMA plus one. First Quartile Cloud Coverage equals one if municipality c is in the first quartile of the long-run cloud coverage in calendar month m, computed from monthly averages over 2004–2016. Post_y equals one for years 2013 and later. All specifications include municipality-by-month fixed effects and month-by-year fixed effects. Standard errors are clustered at the municipality level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table A10. Enforcement Shock and Deforestation - Alternative Thresholds for Cloud Coverage

	Deforestation	
	(1)	(2)
Post × First Quartile Cloud Coverage	0.011**	0.002
	(0.005)	(0.008)
Post × First Quartile Cloud Coverage × High of Agr. Loans per km^2		0.020**
		(0.009)
Post × First Quartile Cloud Coverage × High Loans per km^2		-0.008
		(0.010)
Observations	10626	10626
R Squared	0.9998	0.9998
Municipality FE	✓	✓
Time X PRODES Forest Coverage FE	✓	✓
Time X PRODES Cloud Coverage FE	✓	✓
Time X PRODES Non-observed Coverage FE	✓	✓
Time X High of Agr. Loans per km^2 FE		✓
Time X Low Total Loans per km^2 FE		✓

Notes: The table reports reduced-form estimates of Equation (9). The unit of observation is municipality c by year y. The dependent variable is the inverse hyperbolic sine transformation of the annual municipal deforestation. First Quartile Cloud Coverage equals one if municipality c is in the first quartile of the average cloud coverage (constructed from the baseline cloud measure described in the text). Post_y equals one for years 2013 and later. All specifications include municipality fixed effects and year fixed effects. The term $\Gamma_y \times Z_c$ denotes time-varying controls interacted with baseline bins of land characteristics (including baseline forest cover and coverage/non-observed coverage measures), as indicated in the column headers. Standard errors are clustered at the municipality level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table A11. Enforcement Risk and Credit - Alternative Thresholds for Cloud Coverage

	Agricultural Credit			
	(1)	(2)	(3)	(4)
First Quartile Cloud Coverage	-0.603***			
	(0.105)			
Post × First Quartile Cloud Coverage	1.197***	1.201***	0.609**	
	(0.212)	(0.213)	(0.251)	
Post × First Quartile Cloud Coverage × High Bank Exposure			1.625***	1.683***
			(0.442)	(0.478)
Observations	185592	185592	185592	159348
R Squared	0.831	0.833	0.833	0.892
Bank X Municipality	✓	✓	✓	✓
Time X Bank FE	✓	✓	✓	✓
Time X Bank-Municipality Employees FE	✓	✓	✓	✓
Bank X Municipality X Month		✓	✓	✓
Time X Municipality FE				✓

Notes: The table reports estimates of Equation (10). The unit of observation is bank b by municipality c by calendar month m by year y, constructed by aggregating branch-level ESTBAN data to the bank–municipality–month level. Dependent variable measure total deposits, as indicated. Extensive-margin outcomes are constructed using the inverse hyperbolic sine transformation of the relevant lending outcome with zeros included. Intensive-margin outcomes measure lending amounts conditional on lending being positive, as defined in the table. $\text{LowSeasonalCloud}_{cm}$ and Post_y are defined as in Table 1. Specifications include bank-by-month–year fixed effects and bank-by-municipality (or bank-by-municipality-by-month) fixed effects as indicated in the column headers, absorbing bank-wide shocks and time-invariant bank–location differences (and, when applicable, stable bank–location seasonality). Standard errors are clustered at the bank–municipality level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.