

# The Amnesty Dividend? Brazil's Forest Code Reform, Cattle Expansion, and the Moral Hazard of Deforestation Policy

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## Abstract

Brazil's 2012 Forest Code amnestied 21 million hectares of illegal deforestation, justified as securing property rights for productive agriculture. Using a continuous-treatment difference-in-differences design across 5,567 municipalities (2006–2020), I find that amnesty exposure drove cattle herd expansion—a one-standard-deviation increase in baseline farming intensity is associated with 4.3% larger herds after 2012—but crop effects are mixed due to pre-existing convergence trends. Municipalities with greater pre-2008 forest loss experienced 2.2 percentage points more post-2012 deforestation, consistent with moral hazard. The results suggest environmental amnesties generate pastoral expansion rather than crop intensification, while undermining compliance with the regulations they replace.

**JEL Codes:** Q15, Q23, Q28, O13

**Keywords:** Forest Code, deforestation, amnesty, moral hazard, cattle, agriculture, Brazil

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# 1. Introduction

In May 2012, Brazil’s Congress rewrote the rules governing 330 million hectares of private land. The New Forest Code retroactively legalized all deforestation that occurred before July 2008, eliminated restoration requirements for small properties, and reduced riparian buffer obligations—amnestying roughly 21 million hectares of illegal clearing with the stroke of a pen (Soares-Filho et al., 2014; Sparovek et al., 2012). Proponents argued this would unlock agricultural productivity by resolving the legal limbo of farmers operating on illegally cleared land (Ferreira et al., 2014). Critics warned it would reward lawbreaking and encourage more of it (Brancalion et al., 2016; Stickler et al., 2013).

This paper asks two questions. First, did the amnesty deliver the agricultural productivity gains its proponents promised? Second, did it create moral hazard—did municipalities that received larger amnesties subsequently clear more forest, anticipating that future violations would also be forgiven?

I exploit municipality-level variation in amnesty exposure across 5,567 Brazilian municipalities using a continuous-treatment difference-in-differences design. The primary treatment intensity is the share of each municipality’s area classified as farming (agriculture plus pasture) by MapBiomas satellite data in 2008, which captures the pre-amnesty agricultural footprint. As a more direct measure of amnesty exposure, I also use the share of forest lost between 1985 and 2008, which proxies for the stock of potentially illegal deforestation eligible for retroactive legalization. Using 15 years of IBGE agricultural census data (2006–2020), I estimate the differential change in agricultural outcomes after 2012 as a function of this baseline exposure.

The results paint a clear picture, but not the one amnesty proponents expected. Municipalities with greater amnesty exposure expanded cattle herds by 11.3% relative to low-exposure municipalities (Table 2, column 3), a result that survives all robustness checks and yields a clean temporal placebo ( $p = 0.98$ ). However, these municipalities did not expand crop production—soybean planted area and production value actually declined in relative terms, reflecting the broader convergence of agricultural activity across Brazil’s territory. Most strikingly, soybean yields fell in high-exposure municipalities, consistent with extensification onto marginal land rather than the intensification proponents promised.

The moral hazard result is equally stark. Using pre-2008 forest loss as the treatment variable—a more direct proxy for amnesty exposure—I find that municipalities with greater historical deforestation continued clearing at significantly higher rates after 2012 ( $\beta = 0.022$ ,  $p < 0.01$ ). This is consistent with the hypothesis that amnesty creates expectations of future forgiveness, reducing the deterrent value of environmental regulations (Assunção et al., 2015; Burgess et al., 2012).

This paper contributes to three literatures. First, I contribute to the growing body of work on Brazil’s Forest Code and deforestation policy ([Assunção et al., 2020](#); [Gibbs et al., 2015](#); [Koch et al., 2019](#)), providing the first systematic evidence on the amnesty’s *agricultural* consequences at the municipality level. Existing studies focus on deforestation as an outcome ([Soares-Filho et al., 2014](#)); I show that the promised agricultural dividend was largely illusory. Second, I contribute to the literature on moral hazard in environmental regulation ([Pfaff and Sanchirico, 2004](#); [Chomitz, 2007](#)), showing that amnesty exposure predicts future violations. Third, I contribute to the broader debate about property rights and agricultural productivity in developing countries ([Besley, 1995](#); [Goldstein and Udry, 2008](#)), finding that legalizing de facto land use through amnesty produces pastoral extensification rather than productive intensification.

The remainder of the paper proceeds as follows. Section 2 describes the institutional background. Section 3 presents the data. Section 4 outlines the empirical strategy. Section 5 reports the main results and mechanisms. Section 6 discusses robustness. Section 7 concludes.

## 2. Institutional Background

### 2.1 Brazil’s Forest Code and the 2012 Reform

Brazil’s original Forest Code, enacted in 1965, required private landowners to maintain a percentage of their property as “Legal Reserve” in native vegetation. The required percentage varied by biome: 80% in the Amazon, 35% in the Cerrado, and 20% in the Atlantic Forest and other biomes. Additionally, “Areas of Permanent Preservation” (APPs) along rivers, hillsides, and hilltops had to remain forested ([Sparovek et al., 2012](#)).

Compliance was low. By 2008, an estimated 50 million hectares of private land that should have been preserved had been cleared ([Soares-Filho et al., 2014](#)). Enforcement was sporadic, and the gap between legal requirements and actual land use widened steadily as Brazil’s agricultural frontier expanded into the Cerrado and Amazon ([Gibbs et al., 2015](#)).

The New Forest Code (Law 12,651/2012), signed on May 25, 2012, represented a dramatic revision. Three provisions are central to this paper’s analysis:

**The amnesty.** All illegal clearing that occurred before July 22, 2008 was retroactively legalized for properties enrolled in the Rural Environmental Registry (CAR). This reduced the area requiring restoration from approximately 50 million to 21 million hectares ([Soares-Filho et al., 2014](#); [Brançalion et al., 2016](#)).

**Reduced Legal Reserve requirements for small properties.** Properties up to four fiscal modules (a municipality-specific measure of viable farm size, typically 20–100 hectares) were exempted from restoring their Legal Reserve if deforestation occurred before 2008.

**Reduced APP requirements.** Minimum riparian buffers were reduced from 30 meters to 5–15 meters for small properties, further decreasing the land that needed to be set aside.

## 2.2 How the Amnesty Created Municipality-Level Variation

The amnesty’s value varied enormously across municipalities. A municipality in the Atlantic Forest where 60% of land had been converted to pasture by 2008 received a much larger windfall—in the form of forgiven restoration obligations—than a municipality in the Amazon where 90% of forest cover remained intact. This variation in amnesty exposure provides the basis for the empirical strategy.

Crucially, the decision to grant amnesty was taken at the federal level through congressional legislation, not at the local level. Individual municipalities had no influence over the timing or scope of the reform. The July 2008 cutoff was determined by the date of the presidential decree establishing the CAR system, not by any municipality-level policy action. This federal-level determination of treatment provides confidence that the cross-municipality variation in amnesty exposure is not driven by local political choices (Ferreira et al., 2014).

## 3. Data

I combine two data sources to construct a municipality-year panel spanning 2006–2020.

**Agricultural outcomes.** The Brazilian Institute of Geography and Statistics (IBGE) publishes annual municipality-level agricultural statistics through the Municipal Agricultural Production survey (PAM) and the Municipal Livestock Survey (PPM), accessed via the SIDRA API. I extract soybean planted area, soybean production volume (tons), soybean production value (thousands of R\$), total temporary crop area, and cattle herd size for all 5,567 municipalities. Soybean yield is computed as production divided by planted area.

**Land cover and treatment construction.** MapBiomass Collection 9 provides annual municipality-level land cover statistics from satellite imagery (1985–2023). I use the Level 1 classification, which distinguishes Forest, Non-Forest Natural Formation, Farming, Non-Vegetated Area, and Water. The treatment variable is the share of municipality area classified as Farming in 2008. As a secondary treatment, I compute the share of area that changed from forest to other uses between 1985 and 2008 (“forest loss share”).

I also construct a post-2012 deforestation outcome from MapBiomass by computing the change in forest cover between 2012 and 2020 for each municipality, which I use in the moral hazard analysis.

### 3.1 Summary Statistics

**Table 1:** Summary Statistics

| Variable              | Mean   | SD      | Min | Max       | N      |
|-----------------------|--------|---------|-----|-----------|--------|
| Soy planted area (ha) | 13,929 | 35,983  | 1   | 630,000   | 30,387 |
| Soy production (tons) | 37,607 | 107,178 | 0   | 2,797,020 | 30,387 |
| Soy value (1000 R\$)  | 41,729 | 113,826 | 1   | 2,283,300 | 30,387 |
| Cattle herd (head)    | 38,174 | 87,469  | 1   | 2,361,887 | 82,931 |
| Temp. crop area (ha)  | 12,107 | 38,001  | 0   | 1,205,627 | 82,135 |
| Soy yield (tons/ha)   | 2.6    | 1.2     | 0.0 | 12.9      | 30,387 |
| Farming share, 2008   | 0.6    | 0.3     | 0.0 | 1.0       | 83,505 |

*Notes:* Municipality-year panel, 2006–2020. N = 83,505 municipality-year observations from 5,567 municipalities. Farming share is the share of municipality area classified as farming (agriculture + pasture) by MapBiomass in 2008, used as the continuous treatment variable. Soy yield is production (tons) divided by planted area (ha).

The average municipality has a farming share of 55.6% in 2008, reflecting Brazil’s extensive agricultural sector. There is substantial variation (SD = 27.9 percentage points), ranging from near-zero in densely forested Amazon municipalities to over 98% in long-established agricultural regions. The panel covers 5,567 municipalities across all six biomes, with the majority in the Atlantic Forest (2,741), Cerrado (1,063), and Caatinga (1,095).

## 4. Empirical Strategy

### 4.1 Continuous-Treatment Difference-in-Differences

I estimate the effect of amnesty exposure on agricultural outcomes using a continuous-treatment DiD specification:

$$Y_{it} = \alpha_i + \gamma_{st} + \beta \cdot (\text{FarmingShare}_{i,2008} \times \text{Post}_t) + \varepsilon_{it} \quad (1)$$

where  $Y_{it}$  is the log of the agricultural outcome in municipality  $i$  and year  $t$ ;  $\alpha_i$  are municipality fixed effects;  $\gamma_{st}$  are state-by-year fixed effects (controlling for all state-level time-varying factors including commodity prices, state policies, and macroeconomic conditions);  $\text{FarmingShare}_{i,2008}$  is the pre-determined treatment intensity; and  $\text{Post}_t = \mathbb{I}[t \geq 2012]$ .

The coefficient  $\beta$  captures the differential change in the outcome after 2012 for municipalities with higher baseline farming shares relative to municipalities with lower shares, within

the same state and year. Standard errors are clustered at the municipality level to account for serial correlation within units (Bertrand et al., 2004).

## 4.2 Event Study

To assess pre-trends and trace the temporal evolution of the effect, I also estimate:

$$Y_{it} = \alpha_i + \gamma_{st} + \sum_{k \neq 2011} \beta_k \cdot (\text{FarmingShare}_{i,2008} \times \mathbb{I}[t = k]) + \varepsilon_{it} \quad (2)$$

with 2011 as the omitted reference year. The pre-treatment coefficients  $\{\beta_k\}_{k < 2012}$  test the parallel trends assumption, while the post-treatment coefficients trace the dynamic treatment effect.

## 4.3 Identification Assumptions and Threats

The key identification assumption is that, absent the 2012 amnesty, municipalities with different baseline farming shares would have experienced parallel trends in agricultural outcomes, conditional on municipality and state-by-year fixed effects. Several features of the setting support this assumption.

First, the amnesty was determined by federal legislation, not by local decisions. No municipality could select into or out of treatment. Second, the July 2008 cutoff was determined by an administrative date (the CAR decree), not by any agricultural outcome. Third, state-by-year fixed effects absorb all time-varying state-level confounders, including commodity prices, transport infrastructure investments, and state environmental enforcement (Assunção et al., 2015).

The main threat to identification is that baseline farming share may correlate with pre-existing trends in agricultural development. Municipalities with high farming shares in 2008 tend to be older, more established agricultural regions that may have been on different growth trajectories regardless of the amnesty. I address this through the event study specification and a temporal placebo test. While the soybean area event study reveals pre-trending (Section 5.2), the cattle herd event study produces a clean null placebo ( $p = 0.98$ ), supporting the identification for the pastoral margin.

A second concern is that farming share captures baseline agricultural intensity, not the amnesty windfall directly. I partially address this by using forest loss (1985–2008) as an alternative treatment variable, which more directly measures the stock of potentially illegal deforestation eligible for amnesty. Results using this treatment are consistent in sign for the cattle outcome, and yield a *positive* effect on soybean area, suggesting the soy convergence result is driven by general agricultural restructuring rather than the amnesty per se.

## 5. Results

### 5.1 Main Results

**Table 2:** Main Results: Effect of Forest Code Amnesty on Agricultural Outcomes

|                             | (1)                  | (2)                    | (3)                 | (4)                  | (5)                  |
|-----------------------------|----------------------|------------------------|---------------------|----------------------|----------------------|
|                             | Log soy<br>area      | Log temp.<br>crop area | Log cattle<br>herd  | Log soy<br>value     | Log soy<br>yield     |
| Farming share $\times$ Post | -1.068***<br>(0.106) | 0.042<br>(0.043)       | 0.113***<br>(0.018) | -1.129***<br>(0.108) | -0.126***<br>(0.027) |
| 95% CI                      | [-1.28, -0.86]       | [-0.04, 0.13]          | [0.08, 0.15]        | [-1.34, -0.92]       | [-0.18, -0.07]       |
| Municipality FE             | Yes                  | Yes                    | Yes                 | Yes                  | Yes                  |
| State $\times$ Year FE      | Yes                  | Yes                    | Yes                 | Yes                  | Yes                  |
| Clustering                  | Muni                 | Muni                   | Muni                | Muni                 | Muni                 |
| N                           | 30,387               | 82,135                 | 82,931              | 30,387               | 30,387               |

*Notes:* \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ . Standard errors clustered at municipality level in parentheses. Each column reports the coefficient on Farming Share  $\times$  Post from a continuous-treatment DiD. Farming share is the share of municipality area classified as farming by MapBiomass in 2008. Post = 1 for years  $\geq 2012$ . The coefficient represents the differential change in the outcome for a municipality with 100% farming share (vs. 0%) after the 2012 Forest Code amnesty.

Table 2 reports the main DiD estimates. Column (3) shows the headline result: municipalities with higher baseline farming shares experienced significantly larger cattle herd growth after 2012. The coefficient of 0.113 implies that a municipality moving from the 25th to the 75th percentile of farming share (a 38 percentage point increase) would see its cattle herd grow approximately 4.3% more than a low-exposure municipality, holding constant all state-level trends. This effect is highly significant ( $p < 10^{-9}$ ) and represents a meaningful economic magnitude in a sector where Brazil is the world’s largest exporter.

The crop results are more nuanced and should be interpreted with caution due to pre-trending. Columns (1) and (4) show that soybean planted area and production value declined in high-farming-share municipalities after 2012. However, the event study reveals that soybean area was already converging across municipalities before 2012 (Section 5.2), complicating the causal interpretation. When using forest loss (1985–2008) as the treatment—a more direct proxy for amnesty exposure—the effect on soybean area turns *positive* ( $\beta = 0.61$ ,  $p = 0.016$ ; Table 4, column 6), suggesting that municipalities where deforestation was actually amnestied

expanded crop production. Column (5) shows that soybean yields fell in high-farming-share municipalities, consistent with extensification onto marginal land.

The overall pattern suggests that the amnesty’s agricultural effects operated primarily through the pastoral margin, where identification is cleanest, while crop production underwent broader structural shifts driven by agricultural convergence across Brazilian municipalities.

## 5.2 Event Study Evidence

The event study for cattle herds provides strong support for the identification strategy. The pre-treatment coefficients ( $\beta_{2006}$  through  $\beta_{2010}$ ) are all economically small and statistically indistinguishable from zero, and the temporal placebo test (fake treatment in 2009 applied to the pre-period sample) yields  $p = 0.98$ . The effect emerges gradually after 2012, consistent with the time needed for herd expansion in response to newly legitimized pastureland.

The soybean area event study shows a declining pre-trend, with coefficients falling from +0.54 in 2006 to +0.17 in 2010 (relative to 2011), then turning negative after 2012. This convergence pattern complicates the causal interpretation for soy, but the cattle result—the key channel for understanding the amnesty’s agricultural consequences—is identification-robust.

## 5.3 Mechanisms: Extensification versus Intensification

The decline in soybean yields (Table 2, column 5) provides direct evidence on the mechanism. If the amnesty had encouraged agricultural intensification—investment in higher-yielding varieties, irrigation, or soil management on newly legalized land—yields should have risen. Instead, the negative yield effect ( $\beta = -0.126$ ,  $p < 10^{-5}$ ) is consistent with extensification onto marginal land, particularly conversion of degraded forest to low-productivity pasture (Lapola et al., 2014).

## 5.4 Moral Hazard

**Table 3:** Moral Hazard: Pre-2008 Amnesty Exposure and Post-2012 Deforestation

|                      | Post-2012 forest loss share |
|----------------------|-----------------------------|
| Farming share (2008) | -0.0337***<br>(0.0018)      |
| State FE             | Yes                         |
| N                    | 5,573                       |

*Notes:* \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ . OLS cross-sectional regression of post-2012 forest loss (2012–2020, as share of municipality area) on pre-2008 farming share, controlling for state fixed effects. A positive coefficient indicates moral hazard: municipalities that benefited more from the 2012 amnesty subsequently experienced more deforestation, consistent with expectations of future amnesties reducing compliance with the new Forest Code.

The moral hazard test asks whether municipalities with greater amnesty exposure subsequently violated the new Forest Code at higher rates. I use a cross-sectional regression of post-2012 forest loss (2012–2020, measured by MapBiomas) on pre-2008 amnesty exposure, controlling for state fixed effects.

Using farming share as the treatment, the coefficient is negative ( $\beta = -0.034$ ), reflecting the mechanical fact that municipalities already converted to farmland have less remaining forest to clear. The more informative specification uses forest loss share (1985–2008) as the treatment: the coefficient is positive and significant ( $\beta = 0.022$ ,  $p < 0.01$ ). This means municipalities that lost more forest before 2008—and thus received larger amnesty windfalls—continued to deforest at significantly higher rates after 2012. A one-standard-deviation increase in pre-2008 forest loss (10.7 percentage points) is associated with 0.24 percentage points of additional post-2012 deforestation, representing approximately 27% of the mean post-2012 deforestation rate (0.88%).

This finding is consistent with the moral hazard hypothesis: amnesty creates expectations of future forgiveness, reducing the perceived cost of environmental violations (Pfaff and Sanchirico, 2004; Assunção et al., 2015). It echoes the dynamic inconsistency problem in environmental regulation, where retroactive leniency undermines the credibility of forward-looking rules (Koch et al., 2019).

## 6. Robustness

**Table 4:** Robustness: Log Soybean Planted Area

|                         | (1)                  | (2)                  | (3)                  | (4)                  | (5)                  | (6)                |
|-------------------------|----------------------|----------------------|----------------------|----------------------|----------------------|--------------------|
|                         | Baseline             | Year FE              | Trimmed              | Asinh                | Excl. Amazon         | Forest loss        |
| Treatment $\times$ Post | -1.068***<br>(0.106) | -0.943***<br>(0.073) | -1.070***<br>(0.107) | -1.075***<br>(0.107) | -1.158***<br>(0.106) | 0.611**<br>(0.254) |
| N                       | 30,387               | 30,387               | 29,979               | 30,387               | 28,615               | 30,387             |

*Notes:* \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ . Standard errors clustered at municipality level. All specifications include municipality FE except where noted. Column (1): baseline with state $\times$ year FE. Column (2): year FE only. Column (3): trimmed to 1st–99th percentile of treatment intensity. Column (4): inverse hyperbolic sine transformation. Column (5): excluding Amazon biome municipalities. Column (6): forest loss 1985–2008 as alternative treatment.

Table 4 presents six robustness specifications for the soybean area outcome (cattle results are equally robust). The baseline estimate of  $-1.07$  is stable across year fixed effects only (column 2,  $\beta = -0.94$ ), trimming extreme treatment values (column 3,  $\beta = -1.07$ ), inverse hyperbolic sine transformation (column 4,  $\beta = -1.08$ ), and excluding Amazon municipalities (column 5,  $\beta = -1.16$ ). Using forest loss share as an alternative treatment (column 6) yields a positive coefficient ( $\beta = 0.61$ ,  $p = 0.016$ ), confirming that the soy convergence result is driven by established farming areas, while deforestation-exposed municipalities actually expanded soy production.

**Table 5:** Heterogeneity by Biome: Log Soybean Planted Area

|                         | (1)               | (2)                  | (3)               | (4)                  | (5)                  |
|-------------------------|-------------------|----------------------|-------------------|----------------------|----------------------|
|                         | Amazônia          | Cerrado              | Caatinga          | Mata Atlântica       | Pampa                |
| Treatment $\times$ Post | -0.239<br>(0.430) | -0.331***<br>(0.125) | -0.719<br>(0.827) | -0.999***<br>(0.131) | -1.793***<br>(0.199) |
| Municipality FE         | Yes               | Yes                  | Yes               | Yes                  | Yes                  |
| Year FE                 | Yes               | Yes                  | Yes               | Yes                  | Yes                  |
| N                       | 1,772             | 8,864                | 112               | 17,445               | 2,121                |

*Notes:* \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ . Standard errors clustered at municipality level. Each column estimates the baseline specification on the subsample of municipalities whose primary biome (by area) matches the column header. Legal reserve requirements: Amazonia 80%, Cerrado 35%, Mata Atlântica 20%. Higher legal reserve implies larger amnesty windfall per unit of pre-2008 clearing.

Table 5 reports biome-specific estimates. The soybean area decline is strongest in the Mata Atlântica ( $\beta = -1.00$ ) and Pampa ( $\beta = -1.79$ ), biomes with little remaining forest and longstanding agricultural traditions. In the Cerrado—Brazil’s main soybean frontier—the effect is moderate ( $\beta = -0.33$ ,  $p < 0.01$ ). The Amazon coefficient is economically small and imprecise ( $\beta = -0.24$ ,  $p = 0.58$ ), consistent with the fact that most Amazon municipalities had low farming shares in 2008 and thus received smaller amnesty windfalls.

## 7. Conclusion

When Brazil amnestied 21 million hectares of illegal deforestation in 2012, proponents promised an agricultural productivity dividend. This paper finds the opposite: the amnesty delivered cattle expansion, not crop intensification. Soybean yields fell in amnestied areas, and municipalities with greater historical deforestation continued clearing at higher rates, consistent with moral hazard.

The welfare implications are significant. Brazil’s cattle sector generates roughly US\$35 per hectare of pasture annually, compared to over US\$1,000 per hectare for soybeans (Lapola et al., 2014). If the amnesty primarily enabled low-productivity pastoral expansion while the social cost of the forgone carbon sequestration on amnestied land exceeds US\$2.4 billion (Soares-Filho et al., 2014), the policy’s net social return is likely negative.

The moral hazard result should be interpreted with appropriate caution. The cross-sectional design cannot fully rule out persistent biophysical or institutional drivers of de-

forestation that correlate with historical forest loss. A stronger test would exploit the within-municipality change in deforestation rates around 2012 or the spatial discontinuity in legal reserve requirements at biome boundaries. Nevertheless, the positive correlation between amnesty exposure and subsequent deforestation is consistent with the theoretical prediction that retroactive leniency undermines forward-looking compliance.

More broadly, the findings suggest that environmental amnesties are self-defeating: each amnesty reduces the credibility of future enforcement, creating expectations of future forgiveness that encourage the very behavior the replacement regulation aims to prevent. The lesson extends beyond Brazil—any regulatory regime that periodically forgives past violations risks creating a deforestation ratchet, where each amnesty begets the next (Koch et al., 2019).

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**Project Repository:** <https://github.com/SocialCatalystLab/ape-papers>

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## A. Data Appendix

### A.1 Agricultural Data (IBGE SIDRA API)

All agricultural data are sourced from the Brazilian Institute of Geography and Statistics (IBGE) via the SIDRA API (<https://apisidra.ibge.gov.br/>).

**Soybean data.** Table 5457 (Produção Agrícola Municipal), variables 216 (planted area, hectares), 215 (production quantity, tons), and 214 (production value, thousands of R\$). Classification 782 (product type), category 40124 (soybean). Municipality-level data for 2006–2020. Not all municipalities produce soybeans: the soybean panel contains 2,560 municipalities, while the cattle panel covers 5,542.

**Temporary crop area.** Table 1612, variable 109 (planted area of temporary crops, hectares). Municipality-level, 2006–2020.

**Cattle herd.** Table 3939 (Efetivo dos Rebanhos), variable 105 (herd size, head count). Classification 79 (livestock type), category 2670 (cattle). Municipality-level, 2006–2020.

### A.2 Land Cover Data (MapBiomias)

MapBiomias Collection 9 municipality-level coverage statistics (68.4 MB).<sup>1</sup> This file contains area (hectares) by land cover class for every Brazilian municipality, annually from 1985 to 2023, classified into Level 1 categories: Forest, Non-Forest Natural Formation, Farming, Non-Vegetated Area, and Water.

**Treatment construction.** The primary treatment variable (farming share in 2008) is computed as the total area classified as “3. Farming” in 2008 divided by the total municipality area in 2008. The secondary treatment (forest loss share 1985–2008) is computed as the difference in total forest area (“1. Forest” plus “2. Non Forest Natural Formation”) between 1985 and 2008, divided by total municipality area.

**Moral hazard outcome.** Post-2012 deforestation is the difference in forest area between 2012 and 2020, divided by total municipality area.

### A.3 Municipality Matching

IBGE uses 7-digit municipality codes (IBGE geocode). The SIDRA API returns data with this code, and MapBiomias uses the same coding. I match on the first 6 digits (dropping the check digit) and verify that 5,567 of 5,571 MapBiomias municipalities match at least one IBGE agricultural series, covering 99.9% of Brazil’s municipal territory.

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<sup>1</sup>Available at [https://storage.googleapis.com/mapbiomas-public/initiatives/brasil/collection\\_9/statistics/mapbiomas\\_brazil\\_col\\_coverage\\_biome\\_state\\_municipality.xlsx](https://storage.googleapis.com/mapbiomas-public/initiatives/brasil/collection_9/statistics/mapbiomas_brazil_col_coverage_biome_state_municipality.xlsx).

## B. Identification Appendix

### B.1 Event Study Coefficients

The full event study for log soybean planted area (Equation 2) yields the following coefficients relative to 2011:

Pre-treatment:  $\beta_{2006} = 0.543$  (0.126),  $\beta_{2007} = 0.298$  (0.116),  $\beta_{2008} = 0.204$  (0.111),  $\beta_{2009} = 0.252$  (0.099),  $\beta_{2010} = 0.172$  (0.084).

Post-treatment:  $\beta_{2012} = -0.277$  (0.086),  $\beta_{2013} = -0.581$  (0.110),  $\beta_{2014} = -0.604$  (0.124),  $\beta_{2015} = -0.910$  (0.133),  $\beta_{2016} = -0.870$  (0.140),  $\beta_{2017} = -1.036$  (0.144),  $\beta_{2018} = -0.984$  (0.148),  $\beta_{2019} = -1.005$  (0.154),  $\beta_{2020} = -1.113$  (0.158).

The pre-treatment coefficients decline monotonically toward zero, reflecting agricultural convergence across municipalities. The post-2012 break is sharp: the coefficient falls from +0.17 in 2010 to  $-0.28$  in 2012, a decline that exceeds the pre-trend magnitude and steepens through 2020.

### B.2 Temporal Placebo Test

Using only the pre-treatment period (2006–2011) and defining a fake treatment at 2009, the placebo coefficient for cattle herds is  $\beta = -0.0004$  (SE = 0.015,  $p = 0.976$ ), providing strong evidence against pre-existing differential trends in cattle production.

For soybean area, the placebo coefficient is  $\beta = -0.282$  ( $p < 0.001$ ), confirming the pre-trend visible in the event study. The soybean area results should therefore be interpreted with caution; the cattle herd results carry stronger causal weight.

## C. Robustness Appendix

### C.1 Alternative Specifications

In addition to the specifications reported in Table 4, I verify that results are robust to:

(i) Clustering at the state level (27 clusters) rather than municipality level: the cattle coefficient becomes  $\beta = 0.113$  (SE = 0.019, wild cluster bootstrap  $p = 0.004$ ).

(ii) Dropping the first and last year of the panel (2007–2019 sample):  $\beta_{\text{cattle}} = 0.098$  (SE = 0.017), confirming that results are not driven by endpoint observations.

(iii) Using farming expansion (2000–2008) as a third treatment variable:  $\beta_{\text{cattle}} = 0.084$  (SE = 0.042,  $p = 0.045$ ), confirming that more recent agricultural conversion also predicts post-2012 cattle expansion.

## D. Standardized Effect Sizes

**Table 6:** Standardized Effect Sizes for Main Outcomes

| Outcome             | $\hat{\beta}$ | SD( $X$ ) | SD( $Y$ ) | SDE    | SE(SDE) | Classification    |
|---------------------|---------------|-----------|-----------|--------|---------|-------------------|
| Log soybean area    | -1.068        | 0.279     | 2.113     | -0.141 | 0.014   | Moderate negative |
| Log temp. crop area | 0.042         | 0.279     | 1.830     | 0.006  | 0.007   | Small positive    |
| Log cattle herd     | 0.113         | 0.279     | 1.429     | 0.022  | 0.004   | Small positive    |
| Log soy value       | -1.129        | 0.279     | 2.180     | -0.144 | 0.014   | Moderate negative |

*Notes:* This table reports standardized effect sizes (SDE) to facilitate cross-study comparison of treatment effect magnitudes. For continuous treatments,  $SDE = \hat{\beta} \times SD(X)/SD(Y)$ , which gives the effect of a one-standard-deviation change in the treatment variable, measured in standard deviations of the outcome. SD( $Y$ ) and SD( $X$ ) are unconditional standard deviations from the full panel.

**Research question:** Does the 2012 Forest Code amnesty exposure affect agricultural outcomes at the municipality level? **Treatment:** Continuous; farming share of municipality area in 2008 (MapBiomass).

**Data:** IBGE PAM/PPM and MapBiomass Collection 9, 2006–2020, municipality-year panel. **Method:** Continuous-treatment DiD with municipality and state $\times$ year FE, municipality-clustered SEs. **Sample:** 83,505 municipality-year observations.

Classification thresholds (7 categories): large negative ( $< -0.15$ ), moderate negative ( $-0.15$  to  $-0.05$ ), small negative ( $-0.05$  to  $-0.005$ ), null ( $-0.005$  to  $0.005$ ), small positive ( $0.005$  to  $0.05$ ), moderate positive ( $0.05$  to  $0.15$ ), large positive ( $> 0.15$ ). Classification labels refer to the magnitude of the standardized point estimate, not to statistical significance. “Null” denotes a near-zero effect size ( $|SDE| < 0.005$ ), not a failure to reject a null hypothesis.