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Economic complexity and deforestation in the Brazilian Amazon

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ABSTRACT

As the Amazon rainforest faces ever-increasing deforestation, finding a balance between conservation and economic progress becomes imperative. This study investigates the relationship between regional economic complexity (ECI-R) and deforestation in municipalities within the Brazilian Amazon between 2006 and 2021. Employing different econometric techniques, we untangle the multifaceted factors determining land use choices while considering variables associated with agriculture, extraction, and livestock activities. Rigorous testing confirms the validity of our findings. The results suggest an “environmental Kuznets curve” at play in the Amazon. This means that a slight increase in regional economic complexity (0.1 unit) initially leads to a significant rise in deforestation (28 %) but is followed by a decrease (8.4 %) in the following year. Interestingly, environmental fines appear to be a powerful tool for controlling deforestation. Further analysis using Probit regressions reinforces the key roles of economic complexity and environmental enforcement. Municipalities with higher regional complexity were 20 % more likely to experience low deforestation and high employment growth between 2006 and 2011. However, this trend reversed in later periods. Ultimately, the results indicate a complex relationship between economic complexity and deforestation. These findings highlight governments’ critical role in promoting sustainable development in the Amazon. There are limits to such an approach but supporting “green” industries and curbing deforestation-related activities can steer the region towards a more prosperous and environmentally responsible future.

1. Introduction

A growing body of empirical research on economic complexity has yielded compelling evidence across various analytical dimensions. This research explores the intricate relationship between the Economic Complexity Index (ECI) and income growth (Hausmann et al., 2014). The ECI serves as a proxy measure of a region’s productive knowledge base. Regions with a more diversified production structure and a lower prevalence of commonly produced goods exhibit higher economic complexity. This is because diversified production of less ubiquitous goods necessitates a broader range of productive knowledge. The acquisition of new knowledge, manifested by diversification into less common goods, has been associated with several positive outcomes, including increased green patents (Mealy and Teytelboym, 2022), reduced greenhouse gas (GHG) emissions (Romero and Gramkow, 2021), and lower economic disparities (Hartmann et al., 2017). Similar studies conducted at the regional level further suggest that complexity also influences long-term growth in formal employment (Romero et al., 2022).

These findings highlight the potential of fostering productive complexity as a catalyst for sustainable development. This approach presents itself as a potential solution to a critical challenge faced by developing nations in the context of profound climate change that threatens humanity’s future (Stern, 2007). Since 2015, major international agreements like the Paris Agreement and the Sustainable Development Goals have strived to find solutions that achieve a balance between transitioning to a low-carbon future and mitigating the devastating effects of climate change, while simultaneously promoting inclusive development.

The Brazilian Amazon, encompassing roughly 60 % of the Amazon rainforest, presents a crucial case study for sustainable development. This vast region has suffered from deforestation since the mid-1960s, often under the guise of economic progress (Andersen et al., 2002). Paradoxically, it lags behind most of Brazil in key development metrics.

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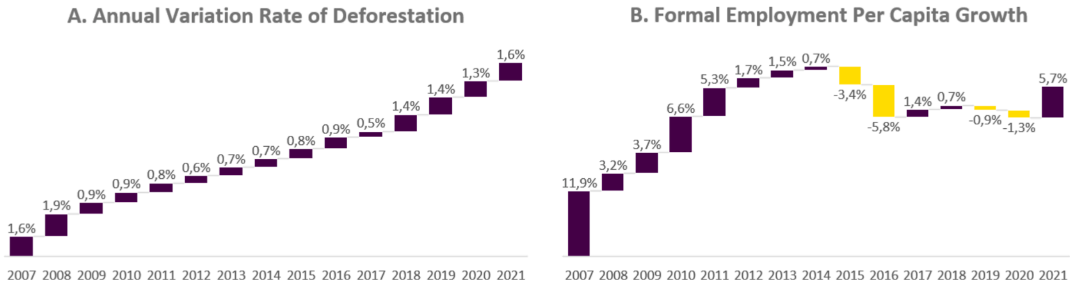

Fig. 1. Deforestation and Employment Trends in Legal Amazon. .
Source: own elaboration based on deforestation data from INPE and employment data from RAIS

Beyond its vital role as a carbon sink, the Amazon rainforest plays an even more critical role in the global water cycle. Teeming with biodiversity, much of it still unknown, the Amazon holds immense potential. However, a recent unsettling trend suggests parts of the Amazon are now emitting more CO2 than they absorb (Gatti et al., 2021). Left unchecked, this could disrupt regional and even global climate patterns. Finding sustainable economic alternatives for the Amazon is thus crucial not only for Brazil and the region itself but for the entire planet.

However, a simplistic approach of boosting Amazonian environmental preservation solely through economic complexity requires closer scrutiny. In theory, any new activity, even those directly or indirectly harming the rainforest, could raise a region's Economic Complexity Index (ECI), especially in areas with limited existing production. A logical hypothesis emerges: a minimum level of local capabilities is likely needed before economic complexity translates into activities less damaging to the environment. This hypothesis aligns with the environmental Kuznets curve (Tritsch & Arvor, 2016), which suggests an inverted U-shaped relationship between deforestation and income. Initial growth may lead to increased deforestation, but later growth leads to a decline. Similar findings were documented by Rodrigues et al. (2009), who observed a positive correlation between deforestation and development indicators in early stages, followed by a negative association in later stages.

Beyond the local stock of capabilities, the complex relationship between economic complexity and deforestation is influenced by other factors. Deforestation has various contributing forces, which can also shape the types of industries a region specializes in. Therefore, before considering increased economic complexity as a panacea for sustainable development, it's crucial to investigate under what conditions and by what other factors the relationship between deforestation and complexity is mediated.

This study utilizes econometric techniques to analyze the complex factors influencing land-use choices and deforestation within municipalities in the Brazilian Legal Amazon from 2006 to 2021. While the primary focus is on the role of economic complexity changes in deforestation, the model also incorporates other key drivers known to influence deforestation in the region. These factors include commodity prices (such as meat, soy, and timber), government policies related to settlements and protected areas, environmental agency actions (including enforcement actions by IBAMA), and variables tied to the political-economic cycle that might influence land-use decisions. Generalized Method of Moments (GMM) models are employed to ensure the robustness of the results and mitigate potential endogeneity issues associated with various policy outcomes in the base model. Finally, a probit model is used to assess the predictive power of the Economic Complexity Index (ECI) in relation to municipalities demonstrating exceptional performance, either positive or negative, in terms of deforestation control and formal job creation.

2. Deforestation, employment, and economic complexity in the Brazilian Amazon

The inception of Amazon deforestation traces back to the 1960s, spurred by the Brazilian government's extensive infrastructure initiatives, tax incentives, and rural settlement policies in the region. Consequently, an annual deforestation scale of around 1,000 square kilometers took root. Market forces started intertwining with deforestation dynamics in the 1980s, with livestock farming and soy cultivation emerging as pivotal drivers (Andersen et al., 2002), propelling the deforestation rate upwards. In 1988, the National Institute for Space Research (INPE) started the satellite monitoring of the Amazon, revealing an annual deforestation rate equivalent to Northern Ireland's area (roughly 13,800 square kilometers), with the states of Pará and Mato Grosso as the most significant contributors to this loss.

Despite the consistent expansion of the Amazon's overall deforested area, the pace of deforestation has demonstrated fluctuations in response to economic, political, and local cycles. Fig. 1A shows the annual change in deforestation in Legal Amazon[1] from 2006 to 2021. The high deforestation rate in the initial three years is noteworthy. Between 2009 and 2017, the growth in total deforested areas was considerably reduced. A renewed deforestation surge was witnessed from 2018 to 2021.

However, this deforestation progress hasn't yielded the anticipated economic gains for the region. As depicted in Fig. 1B, formal employment per capita growth in Legal Amazon municipalities aligns with the country's economic cycles. Between 2006 and 2014, the average increased by 39 %, reaching its peak at around 165 formal positions per 1,000 inhabitants in the region. Following a dip in 2015–2016, relative stability persisted until 2020. The year 2021 brings a relative upswing, with a 6 % increase compared to 2020. A comparison between Fig. 1A and B indicates that the economic activities linked with deforestation hold minimal ties with formal job creation in the region, presenting a doubly negative scenario: biome degradation alongside limited formal employment advancement.

Analyzing Amazonian municipalities based on deforestation and employment levels, Rodrigues et al. (2009) uncovered a positive correlation between deforestation and socioeconomic development indicators in the initial deforestation stages, transitioning to a negative association in the advanced stages. This trend echoes the environmental Kuznets curve, indicating a U-shaped relationship between income and deforestation in the region during 2010 (Tritsch and Arvor, 2016). This implies that higher income is associated with increased deforestation during early developmental phases, eventually leading to reductions as income grows higher.

Given the established empirical linkage between economic

[1] The Legal Amazon is an area that corresponds to 59% of the Brazilian territory and encompasses a total of eight states (Acre, Amapá, Amazonas, Mato Grosso, Pará, Rondônia, Roraima and Tocantins) and part of the State of Maranhão (west of the meridian 44ºW), totaling 5.0 million km^2.

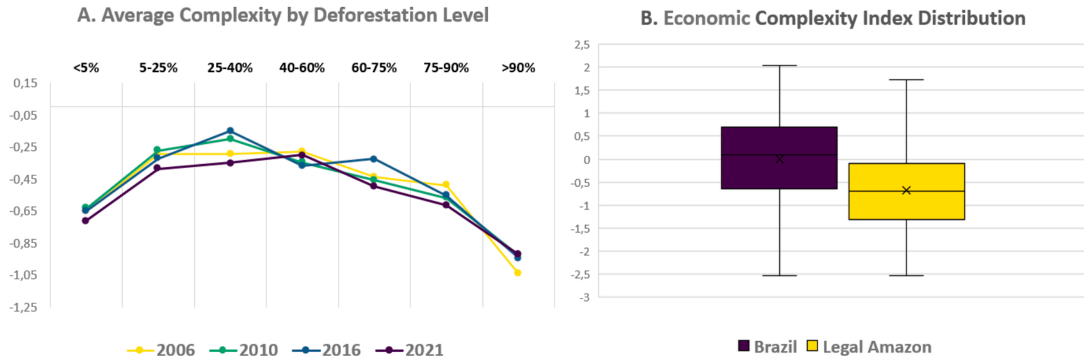

Fig. 2. Municipal Economic Complexity in the Amazon. .
Source: own elaboration based on deforestation data from INPE and employment data from RAIS

complexity and socio-economic and environmental development metrics, it is natural to anticipate a parallel phenomenon concerning the association between deforestation and complexity. In theory, according to Romero and Gramkow (2021), an increase in economic complexity indicates the accumulation of productive knowledge in the region, which would translate into (i) structural change towards sectors with lower emission intensity; and (ii) the adoption of technologically advanced and less pollutant production methods. Fig. 2 presents data from diverse Legal Amazon municipalities, considering different levels of deforestation and complexity. Notably, these curves appear to echo the mirrored pattern witnessed in the correlation between deforestation and socio-economic indicators. Municipalities undergoing intermediate deforestation stages tend to exhibit notably higher complexity levels compared to those in more advanced deforestation stages. The figure also highlights the recent decline in complexity indicators across Amazonian municipalities, particularly in areas with diminished vegetation cover preservation.

Intriguingly, this aggregated data implies that nurturing alternative economic avenues for income and employment growth in the region, characterized by productive diversification, might entail an initial acceleration of deforestation. This phenomenon could potentially be "counterbalanced" by boosting complexity, thereby facilitating future productive specialization less dependent on deforestation-related sectors. However, affirming this deduction's partial or complete validity requires a more comprehensive investigation. Moreover, delving into sectors that harmonize preservation and development and identifying the complexity threshold required for accessing such sectors becomes of paramount relevance. This concern is amplified in the Amazonian context due to the region's relatively underdeveloped municipal productive structures, which constrain diversification opportunities toward higher-complexity sectors.

3. Determinants of deforestation in the Legal Amazon

To understand the association between economic complexity and deforestation and better define controls for the econometric regressions, it is necessary to explore the known economic drivers of deforestation. In a simple approach, deforestation hinges on the disparity between anticipated profits from unsustainable land use and sustainable alternatives, where a larger gap means higher anticipated deforestation of preserved zones (Angelsen, 1999). As Hargrave and Kis-Katos (2013) argue, the expected gains from both unsustainable and sustainable land utilization in the Amazon are influenced by several objective factors such as commodity prices, credit, environmental policies, law enforcement, etc. In the next paragraphs, we explore some of those objective drivers pointed out by the literature.

First, agricultural product prices are important factors for increasing deforestation. It is widely accepted that agricultural expansion for commodities production is the main driver of deforestation in the world and the Amazon Rainforest, even if there is no consensus about the size of agricultural-driven deforestation (Carter et al., 2017; Curtis et al., 2018; De Sy et al., 2019; Pendrill et al., 2022). As prices of agricultural products from areas with deforestation (chiefly meat and soy) increase, the gap between those predatory activities and sustainable alternatives also increases, and deforestation pressures rise as well. The same is valid for the price of timber, which is directly extracted from the forest and sold locally or abroad[2] (Hargrave and Kis-Katos, 2013). Hence, higher prices of agricultural goods and deforestation-related products are factors that tend to increase agricultural-driven deforestation, as well as "agricultural-driven deforestation with no agricultural production expansion", which is deforestation associated with agriculture but not its direct result, such as land speculation and logging for later agricultural land use (Pendrill et al., 2022; Costa, 2023).

Besides the product prices, government fiscal and credit policies for agriculture historically fostered deforestation. The tax policies allowed cattle ranch owners to reinvest taxes from other activities in the cattle ranch production in Amazon, fostering cattle production and, consequently, deforestation. Also, subsidized credit allows cattle ranchers to access lower interest rates, easily fund production and increase the profitability of agriculture (Fearnside, 2005; Barreto et al, 2008). On the lens of Angelsen's conceptual framework presented before, these policies reduce the cost of investments, allowing for more risky actions by the agents or, in other words, enlarging the gap between net expected profits of sustainable activities and activities related to illegal deforestation. From 2008 on, however, this connection between credit and deforestation has been minimized since the Brazilian Central Bank published resolution 3545, which demands the credit concession to be subject to compliance with environmental regulations (Assunção et al., 2020).

Mining activities are another important driver of deforestation. According to Sonter et al. (2017), the mining sector and related activities were responsible for about 9 % of all deforestation in the Brazilian Amazon between 2005 and 2015. The direct removal of forest within the extraction area accounts for just part of the mining-induced deforestation, while the effects of mining-driven changes like urbanization, development of mining supply chains, land use displacement and waste discharge have impacts on deforestation that extend up to 70 km beyond the mining sites. Hence, regions that diversify towards the mining sector

[2] It is also possible that higher prices of forest product (predominantly timber) imply the reverse effect on deforestation, amplifying forest investment attractiveness, possibly fostering more sustainable forest or logging applications. However, the Brazilian Agricultural Census data as well the data from the Forest Activities and Vegetal Extraction Research (PEVS/IBGE) show that the weight of forestry activities products derived from deliberated investments in the North region economy is too low comparing to other regions and to vegetal extraction activities (Hargrave and Kis-Katos, 2013). As it is going to be clear ahead, the econometric analysis confirm that wood prices are positively associated to deforestation.

may increase deforestation, while regions that push their economy away from mining into more complex sectors may present reductions in deforestation rates.

Road construction is also related to deforestation in tropical forests, even though there is no consensus about the direction of this relation. Besides the forest clearance needed to build the road itself, its construction allows people to access and start economic activities in areas that were completely conserved before that, especially natural-resources exploitation activities. On the other hand, there's an argument that the effect of roads in the forestation depends on the initial land use conditions of the regions. Improving road infrastructure in already populated areas brings the possibility of developing new economic activities that will enhance the region's productive knowledge basis. The higher the productive knowledge within a locality, the higher the income and employment augmentation alternatives without deforestation. This last line of analysis, however, does not find solid empirical evidence ground (Andersen et al., 2002; Weinhold and Reis, 2008; Laurance et al., 2009; Barber et al., 2014; Silva et al., 2023).

While higher product prices, credit policies, mining and road construction tend to increase deforestation, important constraints also tend to reduce the expected gains of predatory activities and decrease deforestation. Studies suggest that law enforcement policies, such as the environmental fines imposed by the Brazilian overseeing agency, IBAMA, are field-based enforcement policies that effectively disincentive deforestation. The prospect of fines for illegal deforestation is considered in the cost-benefit analysis of agents when deciding about deforesting or not. Higher probabilities of being fined an effective amount per deforested area tend to reduce the expected gains of deforestation. In this sense, law enforcement tends to lower deforestation rates (Assunção et al., 2013; Börner et al., 2014).

Official environmental safeguards also constitute barriers to deforestation. Brazilian legislation assumes three protection classifications: integral, limited (sustainable), or indigenous. Integral protection shields uninhabited zones to preserve complete ecosystems. Sustainable use regulations allow forest utilization in traditional ways. Indigenous areas are exclusive to indigenous populations (Brasil, 2000; 2012). Several studies show that protected areas are effective in reducing deforestation. Moreover, there is evidence that a great part of deforestation in the last years occurred in public land, especially in undesignated public forests. The evidence points out that deforestation tends to be higher in undesignated public land compared to any other kind of legal designation, including private land. Hence, there is a strong argument in favor of designating public land as protection areas and environmental safeguards in general as a way of effectively reducing deforestation (Soares-Filho et al., 2010; Barber et al., 2014; Spracklen et al., 2015; Azevedo-Ramos and Moutinho, 2018; Stabile, 2020, Salomão et al., 2021, Soares-Filho, 2023; Moutinho and Azevedo-Ramos, 2023).

The reformation of Amazon municipalities' productive structure could also act as a catalyst for safeguarding regional vegetation. Contemporary studies of Amazonian transformation call attention to forest asset valuation, biological-cultural-social diversity preservation via territorial planning, indigenous/traditional community land assurances, and combatting destructive illegal actions. Additionally, a burgeoning focus on the bioeconomy highlights sustainable forest product utilization (primarily non-timber) within family-oriented arrangements, diverging from the extensive livestock and grain operations that burgeoned recently (Costa, 2012; Costa et al., 2022; Fernandes et al., 2022).

Moreover, as Costa (2023) argues, speculation in the land market, especially around illegally grabbed public land, is an essential driver of deforestation because the use-value of the land in the region is associated with deforestation-based activities. Lands that presently have forests are seen in the market as the raw material for producing land without forests. The upsurging of new sustainable possibilities is a possible path to dissociate the land in the Amazon from the deforestation-driven use-value and redirect the speculative land markets towards less harmful practices.

All these factors that boost or dampen deforestation are related to economic activities in one way or another. More broadly, it points to a connection between the productive structure of regions and deforestation. As we saw, the nature of some activities, such as agriculture and mining, are intrinsically related to deforestation, while redirecting the productive structure towards sectors related to bioeconomy could potentially preserve the forest. In this perspective, exploring the connection between indexes that measure (or are proxies for) the productive structure and deforestation becomes necessary. As the economic complexity indexes are the state-of-the-art indexes to assess productive structure through the productive knowledge embedded in regions, they are the natural choice to analyze this relationship.

4. Data and empirical strategy

In order to estimate the impact of economic complexity on deforestation in Amazon municipalities over the period 2006–2021, two distinct exercises were carried out. The first exercise consists of estimating econometric models to establish the complexity-deforestation nexus while controlling for other determinants and scrutinizing potential moderating variables and sources of endogeneity, as described in Section 3.2. The second exercise investigates whether augmented economic complexity translates into improved or worsened municipal performance in employment and forest cover preservation, as described in Section 3.3. This latter endeavor bears the benefit of assessing supplementary factors and their relative influence in singling out exceptional municipalities across these dimensions. This assessment is further replicated across distinct sub-periods to isolate cyclic effects.

4.1. Data

Local economic complexity indicators for municipalities are derived from employment data within the RAIS (Annual Report of Social Information) of the Ministry of Labor, following Freitas (2019) and Freitas et al. (2023), and available on the DataViva platform. Data on deforestation is sourced from PRODES, an annual monitoring system gauging deforestation in the Brazilian Legal Amazon. Developed by the National Institute for Space Research (INPE), PRODES is the main source of information for regional deforestation, employed by researchers and governmental bodies to devise and enact forest conservation policies. PRODES employs satellite imagery to observe forested zones and trace vegetation cover alterations over time.

Table 1 presents the variables used in the econometric investigation, their source, and disaggregation level. Due to the absence of municipal-level agricultural and livestock product pricing data, certain proxies were adopted. For instance, the value of a cattle "arroba" (a weight measure) was employed as a proxy for meat prices, sourced from the Brazilian Mercantile and Futures Exchange (BMFBovespa). It is important to acknowledge that this method entails limitations and might not mirror regional meat price fluctuations, as supplementary factors like transportation, logistics, and local demand also mould local prices. As an alternative, milk price was used in some regressions, estimated from production value-to-quantity ratios per municipality. An analogous approach was adopted to approximate local prices of timber, silviculture, and soy production. Additionally, the CEPEA-ESALQ/BM&FBOVESPA Soybean Indicator, gauging regional product prices, was assessed for soy production.

To account for the influence of road infrastructure on deforestation, we incorporated a variable capturing the total change in road length (kilometers) for each municipality, as a proportion of its area. The numerator of the variable was constructed by subtracting the total state and federal road network length in kilometers for 2010 from the same data for 2021. Unfortunately, limitations in available data necessitated this approach. Shapefiles and maps for the complete study period (2006–2021) are not available for either state or federal roads, nor are they published annually.

Box 1
Variables and data sources

Name	Source	Time availability	Disaggregation
Total Deforested Area (km2)	PRODES - INPE	2006–2021	Municipality
Forest Area (km2)		2006–2021	Municipality
Increase in Deforested Area (km2)		2006–2021	Municipality
Regional Economic Complexity Index (ECI-R)	DataViva	2006–2021	Municipality
Round wood production (m3)	Plant Extraction and Forestry Production - IBGE	2006–2021	Municipality
Value of roundwood production (R$)		2006–2021	Municipality
Silviculture production (tons)		2006–2021	Municipality
Silviculture production value (R$)		2006–2021	Municipality
Soy production (tons)	Municipal Agricultural Production - IBGE	2006–2021	Municipality
Soybean production value (R$)		2006–2021	Municipality
Soy price (BRL per 60kg bag)	Soy Indicator CEPEA-ESALQ/BM&FBOVESPA	2006–2021	National
Heads of herds (unit)	Municipal Livestock Survey - IBGE	2006–2021	Municipality
Milk production (thousand liters)		2006–2021	Municipality
Milk production value (BRL)		2006–2021	Municipality
Arroba of fat ox (R$)	BM&FBOVESPA	2006–2021	National
Financial Compensation for Exploitation of Mineral Resources (CFEM)	National Mining Agency (ANM)	2006–2021	Municipality
Indigenous areas in the Legal Amazon	TerraBrazilis/INPE	Shapefile – 2006	Municipality
Conservation Units in the Legal Amazon	TerraBrazilis/INPE	Shapefile - 2006	Municipality
Road structure change (kilometers)	National Department of Transport Infrastructure (DNIT)	2010 and 2021	Municipality
GDP per capita (BRL)	IBGE	2006–2021	Municipality
Gross Added Value (BRL)		2006–2021	Municipality
Infraction notices	IBAMA	2006–2021	Municipality
Issuance of fines		2006–2021	Municipality

Note: All monetary variables were deflated using the National Consumer Price Index (INPC), baseline 2006.
Source: own elaboration.

4.2. Model specification

Equation (1) forms the benchmark model for comprehending the drivers of municipal deforestation:

$$lnD_{it} = \beta_0 + \beta_1 ECIR_{it,t-1} + \beta_n lnX_{it} + \lambda_t + \alpha_i + \varepsilon_{it} \tag{1}$$

Where lnD_{it} represents the natural logarithm of annual deforestation levels at the end of year t in municipality i. Regional economic complexity is denoted by *ECIR*, and X_{it} stands for the vector of control variables. Municipality-specific fixed effects are denoted by α_i, accounting for local idiosyncrasies impacting deforestation variations. To capture overall trends within deforestation dynamics, time-fixed effects (λ_t) are also included. Additionally, dummies for three sub-periods (2006 to 2011, 2012 to 2016, and 2017 to 2021) are introduced to isolate macroeconomic shocks and policy changes' average effects on price levels. These divisions, aligning with distinct economic and political phases within the country, aid in capturing pertinent contextual shifts.

The vector X_{it} of control variables encompasses variables such as meat and soybean prices in regions, timber prices, the logarithm of fine intensity (quantity or value of environmental fines per area), excessive rainfall index, logarithm of mining tax revenue, along with indicators of general economic activity (logarithm of real per capita municipal GDP and 2006 per capita GDP). Notably, some variables might exhibit a greater impact in future periods than in the current period, such as rainfall and ECI-R. Acquired capabilities take some time to foster new activities. Rainfall, frequently intense between November and March, might impact activities influencing vegetation suppression in the subsequent year. Moreover, the nonlinearity of ECI-R's impact on deforestation is investigated through the interaction with other variables.

While theoretically sound, specification (1) might yield biased parameters if the potential endogeneity of some explanatory variables is not properly controlled. This becomes particularly salient if specific municipal discrepancies in deforestation dynamics affect some explanatory factors or are simultaneously driven by unobservable influences. Some economic and political variables included in the explanatory framework may also endogenously react to deforestation, influencing estimated coefficients.

Productive diversification within activities requiring less deforestation augments local complexity, concurrently fostering income stability and growth. However, this process might increase the pressure on the green surroundings of rapidly expanding regions, potentially triggering deforestation for local agricultural and livestock production. Theoretically, this second effect might outweigh the first, establishing a positive correlation between complexity and deforestation. This result is expected to be milder in municipalities with lower preserved areas. Conversely, higher deforestation could amplify income, theoretically fueling local demand growth and productive diversification. The incorporation of logarithms of per capita GDP, total preserved area, and their growth rates seeks to mitigate these potential endogeneity sources. Estimations using subsamples for distinct income and complexity levels further serve to untangle these error sources.

Elucidating the impact of complexity gains on regional deforestation is further complicated by the mediation of local productive structures. Diversification might amplify deforestation in municipalities in the initial stages of development, characterized by low complexity. This hypothesis, aligned with the concept of an environmental Kuznets curve (Can and Gozgor, 2017), suggests that entry into more intricate deforestation-detached activities would only begin at higher diversification levels. Notably, municipalities with more complex productive structures possess a larger canvas for eco-friendly growth relative to their less complex counterparts. Consequently, differentiation among municipalities based on complexity levels becomes imperative to prevent the underestimation of parameters stemming from the extensive prevalence of low-complexity municipalities in the region.

To mitigate potential endogeneity issues associated with various policy outcomes,[3],[4] equation (1) was also estimated using Arellano and Bond's (1991) difference GMM and Blundell and Bond's (1998) system GMM, incorporating Windmeijer's (2005) correction in one and two stages. These estimators are tailored for dynamic panels with "small T and large N", encompassing fixed effects and heteroskedastic and time-correlated idiosyncratic errors, which are uncorrelated across individuals. These models rely on an instrumental variable approach where lagged explanatory variables (or their differences) serve as instruments.

The difference model (GMM-Dif) removes municipality fixed effects (α_i) from equation (1), representing distinctive municipal deforestation variances attributed to time-constant, municipality-specific unobservables. This eliminates potential sources of bias, such as geoclimatic, agroecological, and political factors. This approach surpasses the first differencing in traditional estimation by accommodating predetermined, albeit non-strictly exogenous, variables. Using differences here might render them endogenous.

The GMM-Dif estimator poses a challenge when levels verge on a random walk, as levels constitute weak instruments for first differences. The system model (GMM-Sys) augments the GMM-Dif by introducing the original level equation, thereby introducing supplementary instruments enhancing efficiency. The estimator's robustness depends on the assumption that the instruments remain uncorrelated with unobserved idiosyncratic effects. The dynamic model for deforestation to be estimated using GMM is represented by:

$$lnD_{it} = \beta_0 + \beta_1 ECI\_R_{it} + \beta_2 lnD_{it-1} + \beta_n X_{it} + \lambda_t + \alpha_i + \varepsilon_{it} \tag{2}$$

Where past deforestation, ECI-R, environmental fine intensity, and, in some specifications, timber prices, real per capita GDP, and protected areas are treated as endogenous variables. D_{it-1} is the vector of exogenous variables/instruments. Soy and meat prices, and the period dummies, are always treated as exogenous and thus used as instruments.

4.3. Economic complexity's predictive power: municipal typology

To assess ECI-R's predictive power concerning municipalities demonstrating exceptional performance, either positively or negatively, in terms of deforestation control and formal job creation, a categorization of Amazon municipalities was devised using the dispersion of vegetation loss and formal job gains over specific periods (2006–2011, 2012–2016, and 2017–2021). These timeframes were selected due to the significance of (i) employment within local productive and social dynamics and (ii) the substantial impact of these three political-economic periods on both deforestation trends and employment. This represents the second econometric strategy employed in this paper.

Employment and deforestation were cross-referenced, yielding four municipality groups: Group (1) (preservation-employment) encompasses municipalities with minimal vegetation loss and significant job gains in the period. Group (2) (preservation-unemployment) consists of municipalities achieving notable preservation (top 50 %) but underperforming in job creation (bottom 50 %). Group (3) (deforestation-employment) covers municipalities excelling in job creation but struggling to uphold vegetation coverage. Lastly, Group 4 (deforestation-unemployment) includes municipalities facing both deforestation and insufficient job generation. Fig. 3 illustrates the spatial distribution of municipalities across these groups per period.

The probability of group affiliation was estimated using a Probit model. This model supposes that the probability of a positive outcome in a binary variable is governed by the cumulative normal distribution function (Cameron and Trivedi, 2022), demonstrated as follows:

$$Pr(Group1_i = 1) = \Omega(\beta_0 + \beta_1 ECI_{it} + \beta_n X_{it}) \tag{3}$$

where Ω represents the cumulative normal function. Since annual data rather than cross-sectional data were employed, the model was adapted to incorporate intragroup correlation. Alongside ECI-R, explanatory variables encompass total deforestation levels (%), soy, timber, meat, and extractive production, IBAMA fines, Gross Value-Added sectoral participation (agriculture, industry, public administration, and services), as well as an environmental preservation levels.

The Probit model facilitates the evaluation of each included variable's effect on the average marginal probability of belonging to a specific group. For ECI-R, the model unveils the probability of a municipality experiencing ECI-R growth during the designated period affiliating with one of the aforementioned groups.

5. Results and discussion

5.1. Assessing initial hypotheses

Table 1 presents the baseline model's estimations for the 807 municipalities within the Legal Amazon. Overall, the model exhibits a good fit, explaining approximately 25 % of the annual variation in deforestation.[5] Appendix 1 details the strategy followed and the results for all covariates. Overall, the results reveal a statistically significant negative correlation between changes in the Economic Complexity Index (ECI-R) and deforestation patterns, with a two-year lag. Ultimately, this implies that a 0.1 unit increase in ECI-R is associated with a 1.7 % reduction in deforestation over a two-year period.[6]

Beyond this key finding, the interaction terms in the model highlight an important interplay between changes in complexity (ECI-R) and the existing level of forest preservation (preserv). The level of preservation itself is associated with a cumulative trend, where areas with higher initial forest cover tend to experience less deforestation. Furthermore, the interaction between ECI-R and preservation levels (Preserv # ECI-R) suggests that increases in ECI-R are particularly effective in reducing deforestation in these well-preserved areas. Similarly, a negative association between ECI-R and deforestation is observed for municipalities with low and lower-middle levels of preservation. Interestingly, a positive association between complexity and deforestation is only evident in municipalities with lower-middle preservation levels.

This outcome warrants further exploration of the transmission channel between deforestation and economic complexity. The path-dependent nature of development, characterized by the "relatedness

[3] Additionally, fluctuating food prices (soy and meat) are expected to intensify deforestation pressures, while timber prices could curtail them due to more favorable net profits from unsustainable land use. Yet, extensive deforestation might also drive down local agricultural and forest product prices owing to increased supply, thereby accentuating endogeneity bias. While this bias is relatively constrained for meat and soy prices, as national prices are adopted in some estimations, concerns loom larger for local timber prices, potentially prompting negative parameter coefficients. Partially alleviating this concern, timber prices are measured not locally but as state-level averages in certain specifications, as proposed by Hargrave and Kis-Katos (2013).

[4] Likewise, increases in IBAMA activities in municipalities with higher deforestation rates could lead to a positive correlation between environmental fine intensity and deforestation, possibly skewing environmental fine coefficients for territory area (resulting in less negative values). Establishing protection zones or settlements might also respond to expected deforestation trends, contributing to a positive bias for anticipated negative coefficients.

[5] The results of the Hausman test, which tests the null hypothesis that the intercepts of the fixed-effects model are uncorrelated with the regressors, was rejected for each specification. This led to the decision to exclude the random-effects model.

[6] A more complete analysis of all the regressions in the fixed effect models can be found in the appendix.

Table 1
Municipal deforestation determinants: panel (2006–2021).

ln Deforestation (annual)	(1)	(2)	(3)	(4)	(5)
ECI-R	0.078	−0.0313	−0.063	–	–
	(0.082)	(0.082)	(0.092)		
L1 (ECI-R)	−0.008	−0.1166	−0.088	–	–
	(0.083)	(0.083)	(0.097)		
L2 (ECI-R)	–	–	−0.166*	−0.189**	−0.165**
			(0.094)	(0.094)	(0.083)
Soy price	−0.003	−0.009	−0.006	−0.006	−0.006
	(0.008)	(0.008)	(0.009)	(0.009)	(0.008)
Wood price	0.103**	0.115**	0.149***	0.145***	0.14***
	(0.047)	(0.046)	(0.049)	(0.049)	(0.047)
Meat price	−0.0000787	0.0000139	−0.0001296	−0.0000933	−9.05E-05
	(0.0002472)	(0.0002439)	(0.0002618)	(0.000262)	(0.0002467)
Extract price	−2.19e-06	−3.91e-06*	−4.59e-06*	−4.75e-06*	−4.52E-06**
	(2.13e-06)	(2.13e-06)	(2.28e-06)	(2.28e-06)	(2.18E-06)
L1 (Rainfall deviances)	−0.033***	−0.034***	−0.035***	−0.035***	−0.034***
	(0.006)	(0.005)	(0.006)	(0.006)	(0.006)
ln Fines intensity	−0.423***	−0.41***	−0.404***	−0.405***	−0.403***
	(0.007)	(0.007)	(0.008)	(0.008)	(0.007)
ln Protected areas	0.026**	3.298	3.351	3.434	3.367
	(0.013)	(3.697)	(3.853)	(3.858)	(3.753)
ln Credit (general)	0.004	−0.007	−0.004	−0.004*	−0.004
	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)
ln Credit (agriculture)			0.003	0.003	0.003
			(0.004)	(0.004)	(0.004)
ln GDPpc	−0.004*	−0.004*	−0.004	−0.004	−0.004
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
ln GDPpc0	0.334***	(ommited)	–	–	–
	(0.076)				
Interactions (see columns)			Preserv	Preserv # ECI-R	ECI-R # Complex
Low	–	–	(ommited)	−0.237*	−0.057
				(0.139)	(0.095)
Lower-middle	–	–	0.261**	0.227*	0.008
			(0.111)	(0.13)	(0.174)
Upper-middle	–	–	−0.0828	−0.027	−0.916**
			(0.158)	(0.134)	(0.373)
High	–	–	−0.564***	−0.266*	0.432
			(0.194)	(0.153)	(0.822)
Period dummies (base = 2006–2011)					
2012–2016	−0.397***	−0.398***	−0.398***	−0.397***	−0.38***
	(0.028)	(0.027)	(0.031)	(0.031)	(0.029)
2017–2021	−0.368***	−0.368***	−0.381***	−0.378***	−0.366***
	(0.034)	(0.034)	(0.038)	(0.038)	(0.036)
Constant	−1.13*	−13.062	−13.974	−14.487	−13.293
	(0.665)	(15.915)	(17.61)	(17.634)	(16.16)
N	1210	1210	1063	1063	11,285
Municipalities	807	807	760	760	807
Fixed effects	no	yes	yes	yes	yes
R2	0.381	0.269	0.262	0.261	0.263
F	4744.74	319.037	194.421	192.763	206.946
Corr	0 (assumed)	−0.991	−0.99	−0.99	−0.988

Notes: Significance level * 0.1 ** 0.05 *** 0.01. Robust standard deviations in parenthesis. L1 and L2 denote, respectively, first and second order lags. # denotes a multiplicative of two variables.
Source: own elaboration.

principle" (Hidalgo et al., 2018; Hidalgo, 2021), offers a potential explanation. Preserved regions, lacking a history of deforestation-related activities like agriculture or mining, possess a productive knowledge base fundamentally different from such activities. These regions are likely specialized in non-predatory economic pursuits. Following the relatedness principle, where economies tend to diversify into activities related to their existing knowledge base, these well-preserved regions are on a path towards sustainable development. In such cases, increasing economic complexity through diversification is more likely to involve transitioning into other non-predatory activities. Furthermore, applying Angelsen's (1999) framework, these regions might exhibit a smaller gap between the profitability of predatory and non-predatory activities, thereby disincentivizing deforestation during the complexification process. This scenario may be particularly relevant for municipalities located deeper within the Legal Amazon, geographically distant from the expanding agricultural frontiers.

Conversely, in areas with extremely low forest preservation, the expansion of deforestation-related activities like agriculture and mining might have reached its peak, necessitating diversification into complementary sectors. These regions might transition into services or manufacturing industries that could complement existing agriculture, potentially offering alternative economic opportunities. In such a scenario, the anticipated returns from non-predatory activities might outweigh the cost of acquiring land from established farmers,

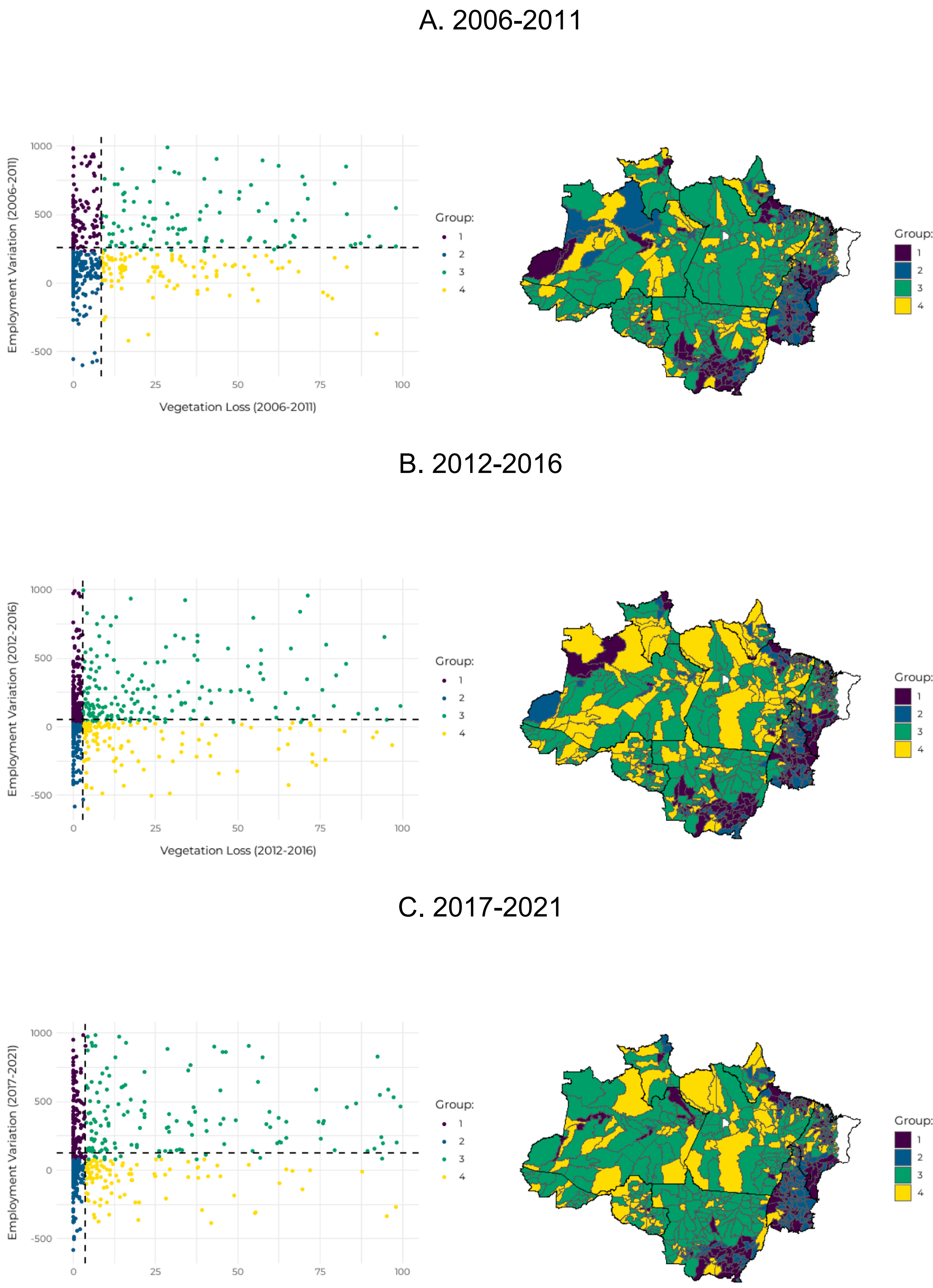

Fig. 3. Vegetation Loss and Employment Variation per Inhabitant in the Amazon. .
Source: own elaboration based on deforestation data from INPE and employment data from RAIS

incentivizing a shift towards a less-predatory economic model. This situation could be observed in older cities or areas that were previously on the agricultural frontier but are no longer.

A similar logic applies to the positive association between rising economic complexity and deforestation observed in lower-middle preservation regions. These areas have historically engaged in deforestation-related activities, which are now embedded within their productive knowledge base. If opportunities exist for further diversification within this existing framework, even deforestation-related activities may be included. Therefore, economic complexity in these regions may initially increase alongside continued deforestation. For instance, this might be the case for municipalities on the current agricultural frontier where mining activities are also prominent.

However, a closer examination of Figure 4 reveals a more nuanced relationship between economic complexity, deforestation, and development stage (as measured by GDP per capita). The figure suggests a U-shaped relationship between the marginal effects of ECI-R on deforestation, mediated by both preservation level and GDP per capita. This interaction becomes clearer when plotted along the development trajectory.

Figure 4 (left) depicts the average marginal effect of ECI-R on deforestation across various GDP per capita levels (on a log scale). This figure mirrors regression (4) by including GDP per capita as a multiplicative factor for ECI-R. The results confirm that municipalities with higher initial preservation and income levels experience the greatest reduction in deforestation associated with ECI-R increases. At lower GDP levels, the marginal effect tends to be near zero for municipalities with high preservation, while remaining positive for those with medium and low preservation. Interestingly, municipalities with the lowest level of forest cover appear largely unaffected by ECI-R changes, regardless of GDP level. This suggests that these regions might be locked into development trajectories incompatible with higher environmental protection, highlighting the potential dangers of promoting regional economic growth without fostering environmentally sustainable practices.

These findings align with the concept of an environmental Kuznets curve, where economic complexity may initially lead to increased deforestation during the mid-development stages. However, the results also support the hypothesis that a more sophisticated set of capabilities and productive sectors can ultimately reduce deforestation by offering individuals greater incentives to pursue non-deforestation-related activities, at least during specific development phases.

While the level of forest preservation captures information about a region's historical development path and helps explain a Kuznets-like curve between ECI-R and deforestation, GDP per capita also reveals a similar U-shaped relationship within specific preservation levels, as shown in Figure 4. Figure 4 (left) further clarifies this interaction by depicting the average marginal effect of ECI-R on deforestation across various GDP per capita levels.

The results support the notion that municipalities with higher initial preservation and income levels experience the greatest reduction in deforestation with increasing ECI-R. This aligns with the observed correlation between income and economic complexity. Places with higher incomes often possess a more diversified and sophisticated productive structure, potentially making them less reliant on deforestation-related activities, similar to the low-preservation case discussed earlier.

Conversely, low-income economies might not have yet engaged in deforestation-related activities like mining, which can initially boost complexity and income. These regions lack a pre-existing economic foundation based on deforestation. This explains why the marginal effect of increasing economic complexity on deforestation tends to be close to zero for municipalities with high preservation at lower GDP levels. This observation suggests that these regions might be trapped in development trajectories incompatible with higher environmental protection, highlighting the importance of promoting green transformations alongside regional economic growth.

Figure 4 (right) highlights the potential role of public policies in enhancing the impact of ECI-R on deforestation control. The average marginal effect of ECI-R on deforestation decreased between 2006 and 2011 and subsequent periods. This suggests that the diversification witnessed in Brazilian Amazon municipalities since 2012 has increasingly shifted away from non-deforestation sectors. The figure also reveals substantial case-level variability within each period, underscoring the potential to develop the region's productive structure while minimizing environmental impact. These observations emphasize the importance of well-designed green development policies.

Among the control variables, the intensity of environmental fines emerged as the most influential explanatory factor for deforestation reduction, as anticipated by existing literature (Assunção et al., 2013; Börner et al., 2014). Notably, the coefficient for this variable remained robust across all specifications, suggesting its independent effect on deforestation. Aligned with the framework proposed by Angelsen (1999) and the findings of Hargrave and Kis-Katos (2013), a positive correlation was observed between wood prices, growth in extractive activities, and annual deforestation rates. This suggests that higher returns from unsustainable activities incentivize deforestation. Furthermore, the inclusion of time-period dummies in all estimations consistently confirmed the presence of aggregate temporal trends in deforestation dynamics. These dummies account for macroeconomic shocks, average effects of product prices, and policy changes at both regional and national scales.

However, as discussed in the methodology section and elaborated upon in Appendix 1, the fixed effects model employed here may be susceptible to endogeneity issues. Certain variables, such as meat prices,

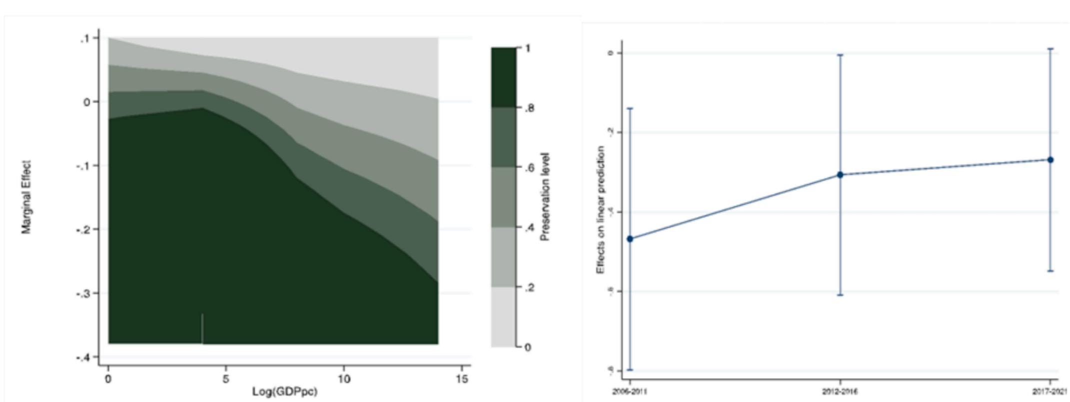

Fig. 4. Average marginal effects of ECI-R on annual deforestation by GDP and preservation levels (left) and by period (right). Note: Figures considered with a 95 % confidence interval. .
Source: own elaboration based on the results of the estimated models

could theoretically react endogenously to changes in deforestation. Increased deforestation could lead to higher meat production and lower prices. A similar effect could occur with environmental fines, which are partly driven by deforestation itself, and GDP per capita, which might increase as forest land is converted for economic activities. More importantly, economic activities like wood processing or logging equipment production could be established in the region as a consequence of deforestation. In such cases, deforestation could influence diversification processes, leading to further changes in economic complexity. Indicators of endogeneity in the model results are further discussed in Appendix 1.

5.2. Dealing with potential endogeneity

To address potential endogeneity concerns and further validate our findings, we employed a dynamic panel method to re-examine the effect of economic complexity on deforestation. Table 2 presents the results of the Generalized Method of Moments (GMM) estimations, estimated in both differences (regressions (1)–(3) and system form (regressions 4–6). The instruments' exogeneity within the estimation subgroups has been confirmed across all models. More detail on the estimates and covariates can be found in Appendix 2.

Overall, the results reveal a consistently positive association between current-period ECI-R and the logarithm of annual deforestation area across all six specifications. This consistency highlights the model's

Table 2
Determinants of municipal deforestation: dynamic panel (2006–2021).

ln Deforestation (annual)	(1)	(2)	(3)	(4)	(5)	(6)
L1 ln Deforestation	0.0527***	0.0594***	0.0318*	0.1056***	0.1029***	0.0658***
	(0.0149)	(0.0169)	(0.0191)	(0.0148)	(0.0163)	(0.0163)
ECI-R	0.7857*	0.5200	1.1915**	2.1865***	2.0715***	2.7797***
	(0.4024)	(0.3856)	(0.4966)	(0.4603)	(0.4077)	(0.5702)
L1 ECI-R	−0.4554**	−0.3864**	−0.7069***	−0.4863**	−0.3821**	−0.8390***
	(0.1843)	(0.1832)	(0.2478)	(0.2021)	(0.1945)	(0.2513)
L2 ECI-R	−0.2472**	−0.2168*	−0.3015*	0.0122	0.0099	−0.2071
	(0.1239)	(0.1211)	(0.1611)	(0.1432)	(0.1445)	(0.1861)
Soy price	0.0000	0.0000	−0.0145	0.0001	0.0000	0.0008*
	(0.0002)	(0.0002)	(0.0186)	(0.0003)	(0.0003)	(0.0004)
Wood price	0.0507	0.0528	−0.1295	0.0098	0.0681	0.1268
	(0.1598)	(0.1686)	(0.2167)	(0.1856)	(0.1128)	(0.0999)
L1 Meat price	−0.0003	−0.0004	−0.0418	−0.0009***	−0.0006**	−0.0007**
	(0.0002)	(0.0002)	(0.0284)	(0.0003)	(0.0003)	(0.0003)
Extract price	−2.80e-06	−3.29e-06	−3.28e-06	7.52e-06	9.01e-06*	0.0000134***
	(6.74e-06)	(6.00e-06)	(8.67e-06)	(5.60e-06)	(4.73e-06)	(4.47e-06)
L1 Rainfall deviances	−0.0459***	−0.0361***	−0.0597***	−0.0426***	−0.0385***	−0.0384***
	(0.0061)	(0.006)	(0.009)	(0.0057)	(0.006)	(0.0065)
ln Fines intensity	−0.4039***	−0.4007***	−0.3916***	−0.5377***	−0.5394***	−0.4888***
	(0.0121)	(0.014)	(0.0145)	(0.0118)	(0.0134)	(0.0167)
ln GDPpc	−0.0026	−0.0024	−0.0061*	0.0000	0.0012	0.0059
	(0.0027)	(0.0028)	(0.0036)	(0.003)	(0.0031)	(0.0041)
Period Dummies (base = 2017–2021)						
2006–2011	0.3001***	0.2383***	0.4339***	0.2689***	0.2604***	0.3237***
	(0.0344)	(0.0364)	(0.0508)	(0.0381)	(0.0431)	(0.0459)
2012–2016	−0.0490**	−0.0558***	−0.0310	−0.0531**	−0.0276	−0.0340
	(0.0213)	(0.0206)	(0.0268)	(0.0235)	(0.0266)	(0.0299)
ln Credit (rea)	0.0016	0.0008	−0.0117***	0.0544***	0.0063	0.0048
	(0.0074)	(0.0078)	(0.0042)	(0.0113)	(0.0051)	(0.0054)
ln Credit (agriculture)	—	—	−0.0038	—	0.0475***	0.0226**
			(0.0081)		(0.01)	(0.0101)
ln GDPpc0	—	—	(ommited)	—	—	0.5380***
						(0.2062)
Preserved forest rea (%)	—	—	—	—	—	0.0002***
						(0)
Constant	—	—	—	−0.1614	−0.2185	−5.3309***
				(0.1674)	(0.1446)	(1.6677)
N	10,477	10,477	7250	11,285	11,285	10,630
Municipalities	807	807	558	807	807	760
Model	GMM-DIFF	GMM-DIFF	GMM-DIFF	GMM-SYS	GMM-SYS	GMM-SYS
	1-stage	2-stage	2-stage	1-stage	2-stage	2-stage
F	115.5885	82.8364	83.1155	219.8638	16.9052	82.8391
Sargan	1.1e + 03	1.1e + 03	872.276	1.6e + 03	1.6e + 03	3.3e + 03
P-value (Sargan)	0.00	0.00	0.00	0.00	0.00	0.00
Hansen	602.7916	602.7916	46.2074	641.0358	662.1640	72.8181
P-value (Hansen)	0.00	0.00	0.004	0.00	0.00	0.01
AR1 (p-value)	0.00	0.00	0.00	0.00	0.00	0.00
AR2 (p-value)	0.6984	0.9509	0.3083	0.2604	0.4493	0.8628

Notes: Period dummies, meat and soybean prices are treated as exogenous in all models. Past deforestation, fines intensity and wood prices are treated as endogenous and instrumented within the model. Protected areas are treated as exogenous in columns (2) and (5) and as endogenous in columns (3) and (6). Robust standard errors were adopted in all specifications. Specification (3) used the local soy price and state wood price to instrument the original variables. The value 0 for parameters or deviations refer to nonzero estimatives beyond the fourth decimal case.
Caption: Significance level * 0.1 ** 0.05 *** 0.01. Robust standard deviations in parenthesis.
Source: own elaboration.

robustness, with minimal variation observed in the parameters of most explanatory variables except ECI-R.

The preferred specification, regression (6), demonstrates a particularly strong and robust association between current changes in complexity and deforestation. In this model, a 0.1 unit increase in ECI-R is associated with a 27.8 % increase in deforestation. This result aligns with the positive association observed up to the 40 % deforestation rate depicted in Figure 2A.

However, the estimated effect of ECI-R on deforestation becomes negative in subsequent years, supporting the validity of the environmental Kuznets curve hypothesis. This finding reinforces the notion that, on average, increasing economic complexity (essentially driven by diversification) presents future opportunities in non-deforestation sectors. For instance, consider an economy initially reliant solely on deforestation-related activities. Early increases in economic complexity might initially occur through the development of comparative advantages in sectors related to the existing knowledge base, potentially leading to a rise in deforestation.

However, the introduction of a new sector, even if related to existing ones, brings new knowledge into the economy. This new knowledge opens a window for agents to invest in novel activities, potentially transitioning from deforestation-related pursuits to non-deforestation alternatives. In the framework adopted in this study, this translates to a potential decrease in the gap between the anticipated returns from predatory and non-predatory activities in future periods, ultimately leading to reduced deforestation. It is important to reiterate, however, that the observed effects will vary depending on the existing productive structure of each region.

The lagged effect of ECI-R on deforestation remains statistically significant across all specifications and models. Interestingly, in the GMM-Differences regressions (1)–(3), the short-term positive effect of an ECI-R on deforestation, in which an increase in ECI-R increases deforestation, diminishes almost entirely in the long term. However, the negative lagged effect does not completely offset the positive short-term effect in the GMM-System regressions. In the preferred specification (regression 6), a 0.1 unit increase in complexity leads to an 8.4 % decrease in deforestation in the second year.

These results underscore the importance of economic complexity in deforestation dynamics, while also reaffirming the crucial role of environmental fines as a deterrent, as previously demonstrated by Assunção et al. (2013) and Börner et al. (2014). A 10 % increase in fines is estimated to result in a 4.9 % reduction in annual municipal deforestation.

5.3. Exploring complexity's role in deforestation and employment patterns in the Amazon

Table 3 details the probabilities associated with the Probit regression results. These probabilities illustrate the likelihood of municipalities belonging to groups with distinct employment and deforestation dynamics across different periods. The findings align with existing research, highlighting the importance of economic complexity in explaining group membership. However, intriguing shifts in the pattern of productive transformation emerge when comparing the earliest period (2006–2011) with more recent ones (2012–2016 and 2017–2021).

During the 2006–2011 period, high levels of ECI-R increase the probability of membership in Group (1) (characterized by environmental preservation and employment growth) by 20 %. Conversely, for the 2017–2021 period, a high level of ECI-R decreases the likelihood of municipalities falling into Group (1) by around 18 %. Furthermore, for the periods 2012–2016 and 2017–2021, a higher complexity level increases the likelihood of belonging to Group (3) (marked by employment growth and deforestation) by approximately 25 %. These contrasting results across periods suggest how different policy choices might influence growth trajectories.

For the first and second periods (2006–2011 and 2012–2016), municipalities experiencing gains in complexity demonstrate a slightly higher probability of belonging to Group (2), which combines preservation with minimal formal employment growth. Additionally, these municipalities displayed a reduced probability of being part of Groups 1 and 4 during the first and second periods, respectively. Finally, the variation in economic complexity in the final period (2017–2021) is marginal, leading to coefficients close to zero.

For categorical variables like municipal preservation level, the parameter estimates indicate discrete changes relative to the baseline group. For instance, being in the third and fourth quartiles of preservation (medium–high and high) increases the probability of belonging to Group (3) by 25 % and 27 %, respectively, compared to low-deforestation municipalities during 2006–2011. As expected, across all assessed periods, municipalities within the top 50 % of preserved area exhibit up to 28 % higher probabilities of belonging to higher annual deforestation groups (Groups 3 and 4) relative to those with the greatest proportion of total deforested area. Conversely, municipalities within the highest preservation quartiles experience a decreased probability of up to 24 % of belonging to lower deforestation groups (Groups (1) and (2) compared to those with the least proportion of preserved area. These observations suggest that while employment growth may vary, municipalities with medium–high preservation face consistently higher deforestation pressures.

Cattle ranching is a variable of particular emphasis, as it significantly enhances the probability of belonging to higher deforestation groups and diminishes the likelihood of being part of lower deforestation groups across all periods. The probability of Group (1) membership decreases by up to 5 % in all periods, while the likelihood of Group 3 and 4 membership sees heightened probabilities between 2006 and 2016 and between 2017 and 2021, respectively. Notably, the variable pertains to the number of cattle heads rather than the price of a cattle unit, as in prior tests.

Another noteworthy aspect is the logarithm of the number of fines from IBAMA (Brazilian Institute of Environment and Renewable Resources). This variable increases the likelihood of belonging to lower annual deforestation groups by up to 4 % in each period, and conversely, curtails the probability of joining higher deforestation groups by up to 5 %. A similar trend is observed with the agricultural credit variable, although its influence is only significant for Group (1) membership during the second period.

Lastly, the study investigates whether heightened dynamism in the agricultural, industrial, and service sectors (quantified by the logarithm of Gross Value-Added) increases the chances of group membership. The findings reveal that augmented agricultural sector dynamism increases the probability of municipalities falling into higher deforestation groups in all periods, while diminishing the odds of belonging to lower deforestation groups. The other sectors exhibit distinct effects in different periods, with the service sector notably reducing Group 4 membership probability. The remaining control variables are most often not significant. Moreover, when they show up significant, their effects are modest.

6. Discussion and limitations

The landmark Paris Agreement, adopted by 196 nations at the 2015 UN Climate Change Conference, established a global commitment to limit the rise in average global temperatures to well below 2 degrees Celsius, ideally 1.5 degrees, compared to pre-industrial levels (UNFCCC, 2024). This ambitious target is essential to mitigate the most severe consequences of climate change. To achieve this objective, signatory countries pledged to develop and implement Nationally Determined Contributions (NDCs), outlining their strategies to reduce greenhouse gas emissions and ultimately achieve net-zero emissions.

However, ensuring a sustainable future goes beyond merely addressing climate change; it necessitates fostering inclusive development. Municipalities within the Brazilian Amazon face distinct challenges compared to other regions of the country. Limited infrastructure and unreliable power supplies impede development and restrict access

Table 3
Probit Model: probability of membership.

Variables	2006–2011				2012–2016				2017–2021			
	Group (1)	Group (2)	Group (3)	Group 4	Group (1)	Group (2)	Group (3)	Group 4	Group (1)	Group (2)	Group (3)	Group 4
ECI	0.195*	−0.134	−0.069	0.208	−0.125	0.041	0.243*	0.063	−0.179*	0.035	0.248*	0.161
Δ ECI	−0.053***	0.021*	0.0158	−0.011	−0.002	0.009*	−0.008	−0.048**	0	0	0	0
Preservation group												
Mid-low	−0.104***	−0.133***	0.170***	0.017	−0.192***	−0.049	0.058	0.128***	−0.154***	−0.04	0.120***	0.047
Mid-high	−0.167***	−0.182***	0.253***	0.066	−0.245***	−0.158***	0.213***	0.143***	−0.239***	−0.111***	0.219***	0.101**
High	−0.109**	−0.203***	0.275***	0.092	−0.218***	−0.127***	0.082	0.278***	−0.191***	−0.120**	0.262***	0.081
ln Soy	0.004	0.001	−0.008	0.005	0.007	−0.007*	0.005	−0.007	−0.003	−0.0003	0.011**	−0.009**
ln Wood	−0.010	0.006	−0.003	0.009	−0.004	0.001	−0.0002	0.005	−0.0005	−0.008*	−0.004	0.013**
L1ln Meat	−0.054***	−0.010	0.0694***	0.013	−0.042***	−0.032***	0.042***	0.027**	−0.036***	−0.019**	0.018	0.035**
ln Extract	−0.002	0.001	−0.009	0.009	0.011	−0.004	−0.0004	−0.007	−0.001	0.014*	0.008	−0.022*
ln Mining	−0.003	−0.005	0.005	−0.001	−0.003	−0.004	0.0004	0.004	−0.001	0	0.004	−0.005
ln Credit (agriculture)	0.009	0.004	−0.007	−0.005	0.012**	0.004	−0.01	−0.004	0.006	0.004	−0.005	−0.004
L1 ln Fines intensity	0.029***	0.044***	−0.045***	−0.032***	0.005	0.034***	−0.015	−0.009	0.042***	0.028***	−0.05***	−0.002
ln GDPpc0	−0.060*	0.050	−0.061	−0.013	−0.004	0.043	−0.03	−0.004	−0.051	0.032	0.039	−0.041
Gross Value Added												
ln Agriculture	0.002	−0.063***	0.044**	0.065***	−0.088***	−0.031*	0.117***	0.034	−0.009	−0.065***	0.07***	0.038*
ln Manufacturing	0.034	−0.053**	0.041*	−0.016	−0.081***	0.023	−0.05**	0.092***	−0.018	−0.031	0.014	0.026
ln Services	−0.025	−0.039	0.086***	−0.114***	0.097***	−0.048**	0.016	−0.089***	0.037	−0.034	0.022	−0.073**

Notes: Group 1: Preservation-Employment; Group 2: Preservation-Unemployment; Group 3: Deforestation-Employment; Group 4: Deforestation-Unemployment. See Section 3.3. for a detailed description of each group.
Base group: low preservation.
Caption: Significance level * 0.1 ** 0.05 *** 0.01.
Source: own elaboration.

to essential services. Furthermore, economic dependence on resource extraction activities like logging and mining fuels environmental degradation and social conflict. Additionally, traditional communities struggle to preserve their land rights and way of life amidst these mounting pressures. These factors coalesce to create a situation of poverty, limited economic opportunity, and heightened environmental vulnerability, often more severe than in other parts of Brazil.

This study reveals a multifaceted relationship between economic complexity and deforestation in the Amazon rainforest. While some findings may appear contradictory at first glance, they contribute to a nuanced understanding with significant implications for the region's sustainable development.

Overall, the results suggest that economic complexity increases deforestation in the current period, followed by a reduction in subsequent periods. This implies that economic diversification might not lead to immediate reductions in deforestation. However, higher complexity could foster environmental preservation in the long run. These findings, however, appear contingent on other factors, particularly the existing productive structure and development trajectory of each region.

These observations support the hypothesis of an environmental Kuznets curve between economic complexity and deforestation in the Amazon. This signifies a trade-off between productive development and short-term deforestation. Furthermore, the study suggests that increases in ECI might actually accelerate deforestation in regions with lower-middle deforestation rates. This suggests a potential tipping point, where initial economic growth can lead to increased forest loss before a transition to more sustainable practices occurs. Additionally, municipalities with medium–low conservation status were identified as most vulnerable to deforestation pressures. This highlights the need for targeted conservation efforts in these areas.

Environmental policies also appear to play a crucial role in mediating this relationship. Stricter enforcement of environmental regulations appears to amplify the negative effect of economic complexity on deforestation. Encouragingly, the study also finds that economic complexity can significantly increase the probability of municipalities achieving high employment without deforestation, particularly during periods of strong environmental law enforcement. This suggests that a green economic pathway is indeed possible for the Amazon.

Limitations to the study include the lack of data for all deforestation-related variables during the analyzed period. These limitations include local commodity prices and road infrastructure changes (see section 3.1). Additionally, the research did not explicitly address deforestation within agrarian settlements of the Legal Amazon. However, as Alencar et al. (2016) concluded, the deforestation dynamics in these settlements mirror those of the region as a whole, typically beginning with road construction for logging followed by conversion of cleared land to pasture for livestock farming. The municipal deforestation records employed in this study inherently capture these dynamics. Furthermore, it is important to note that the registered area of settlements across the nine Legal Amazon states represents only 10 % of the total area (CAR, 2023).

Another limitation is the study's reliance on formal employment data to calculate economic complexity and assess economic activity levels within each sector. Brazil has a high share of informal employment, likely even more prevalent in the Amazon region due to its relative poverty and remoteness. Therefore, future research employing alternative data sources (if available) would be necessary to solidify the understanding of the relationship between economic complexity, structural change, and deforestation in the Amazon.

Future research should prioritize two key areas. First, a deeper exploration of the qualitative initial conditions of productive structures is necessary to understand when boosting economic complexity increases or reduces deforestation. The relatedness perspective proposed by Hidalgo et al. (2018) offers valuable insights in this regard. Second, future research should identify the specific types of economic activities that can contribute to a "green" economic pathway for the region, considering the diverse characteristics of Amazon municipalities, including deforestation rates, economic complexity levels, infrastructure, and other facto**rs.**

7. Conclusion

This study investigated the relationship between economic complexity and deforestation in the Brazilian Amazon. The results suggest that while economic complexity might initially increase deforestation, it can also reduce it in the long run. Specifically, a 0.1 unit increase in regional complexity leads to a 27.8 % increase in deforestation in the current period, followed by an 8.4 % decrease in the following year. This pattern suggests that economic diversification may not immediately reduce deforestation but can lead to long-term environmental benefits.

Environmental policies play a crucial role in this relationship. Stricter enforcement of environmental regulations, such as higher environmental fines, significantly reduces deforestation. Municipalities with higher regional complexity and strong environmental law enforcement are more likely to achieve high employment without increasing deforestation, showing that a green economic pathway is possible for the Amazon.

However, the study has limitations, including the lack of comprehensive data on all deforestation-related factors and the reliance on formal employment data, which may not fully capture economic activity due to the high prevalence of informal employment in the Amazon. Future research should address these gaps by exploring the initial conditions of productive structures and identifying specific economic activities that can support a sustainable development path for the region.

The evidence suggests, nonetheless, that increasing economic complexity can be a viable path towards sustainable development in the Amazon. Yet, the results highlight also that increasing economic complexity should not be seen as a standalone strategy. A multifaceted policy approach is necessary, combining the promotion of green sectors with strong environmental law enforcement and policies that reduce the profitability of deforestation-related activities.

CRediT authorship contribution statement

Fabricio Silveira: Writing – review & editing, Writing – original draft, Visualization, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **João P. Romero:** Conceptualization, Investigation, Writing – review & editing, Writing – original draft, Supervision. **Arthur Queiroz:** Writing – original draft, Visualization, Data curation. **Elton Freitas:** Data curation. **Alexandre Stein:** Writing – review & editing, Data curation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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Appendix 1

Appendix 1:. Notes on the fixed effects model

In Table 1, the results indicate that changes ECI-R are negatively (and significantly) correlated with shifts in deforestation patterns with a two-year lag. This finding is not unexpected, considering the relatively lower average complexity levels of municipalities in the analyzed region compared to the national average. The correspondence between rising ECI-R values in low-complexity municipalities and environmentally impactful activities resonates with the principles of the environmental Kuznets curve theory. On an aggregate level, the lack of significance for current-term explanatory variables might be attributed to a trade-off, where the potential positive correlation of these variables in higher-complexity municipalities results in a counteractive effect.

The regressions show also that the most influential explanatory variable for deforestation reduction is the intensity of environmental fines. Remarkably, this variable's coefficient remains robust across all specifications, suggesting its influence operates independently of other factors. Additionally, excessive rainfall in the preceding year and increases in per capita GDP (PIBpc) exhibit a moderate correlation with annual deforestation reductions. Conversely, the outcomes reveal a positive correlation between wood prices, growth in extractive activities, and annual deforestation rates. Throughout all estimations, the inclusion of time-period dummies consistently confirms the presence of aggregate temporal deforestation dynamics. This accommodates macroeconomic shocks, average effects of product prices, and policy changes at both regional and national scales. However, the coefficients for other variables generally lack statistical significance in most specifications.

The variable capturing the change in municipal road length, along with the measure of 2010 road infrastructure, were excluded from most models due to collinearity. This issue arises for two reasons. First, road infrastructure exhibits a high degree of correlation with other included variables, such as GDP per capita, deforestation level, and credit availability. Second, the study is limited by the lack of yearly data on road infrastructure changes.

Regressions (1) and (2) present the results for the baseline specification without and with fixed effects, respectively. In both cases, the ECI-R fails to exhibit significance at both the current level and the first lag. The primary distinction between these estimations lies in the inversion of the coefficient for the current-term variable – positive in the former and negative in the latter. Beyond ECI-R, the significance of protected areas is evident in regression (1). However, positive coefficients across all other specifications contradict initial expectations, suggesting potential endogeneity of the variable. Other control variables maintain similar levels of significance and impact in both models.

Selecting estimation with individual fixed effects eliminates time-invariant explanatory variables redundant such as the initial income level (PIBpc0) and state-specific dummies. Regression (1) also enables an examination of how these variables contribute to explaining the variance in annual municipal deforestation in the region. As anticipated, estimations assuming random effects indicate a strong and significant positive association between PIBpc0 and annual deforestation. These same estimations also highlight variations in annual deforestation levels among states: Acre exhibits higher average levels, while Tocantins, Maranhão, and Amapá experience lower levels.

Regression (3) introduces an additional lag into the basic model to explore the hysteresis effect of the ECI-R on deforestation. The significant lag effect is replicated across all other estimations, suggesting that a 0.1 increase in the ECI-R is associated with a 1.7 % reduction in deforestation over two years. This estimation also includes dummies for groups formed by quartiles of the municipality's percentage of non-deforested area (preserv). These results demonstrate that municipalities with lower deforestation rates are associated with lower levels of non-deforested area, while municipalities in the intermediate position (2nd quartile, higher deforestation) exhibit significantly higher annual deforestation rates.

Regressions (4) and (5) explore whether the preservation level and the complexity level of municipalities influence the relationship between ECI-R and annual deforestation. In both cases, ECI-R parameters remain stable and statistically significant. The results in regression (4) reveal a significant U-shaped association between the interaction of preservation (preserv) groups and ECI-R with annual deforestation. This interaction demonstrates a consistent negative impact across both the highest and lowest deforestation quartiles, with a positive impact in the intermediate group characterized by higher deforestation. This finding reinforces the results presented in Fig. 2A. Conversely, the findings in regression (5) partly support the hypothesis that the effect of ECI-R on deforestation should strengthen as municipal complexity level increases. The coefficient for the interaction between ECI-R and the dummy variables representing municipalities in lower complexity quartiles of the region approaches zero and lacks statistical significance. The parameter is substantial and highly significant for the medium–high complexity group, where ECI-R expansions correspond to a similar percentage reduction in current deforestation. The situation for municipalities in the region's highest complexity quartile is intriguing. The positive parameter might suggest that ECI expansions contribute to deforestation increases in these municipalities, hinting that despite better opportunities, the current productive specialization might constrain these municipalities to non-green structural change trajectories. However, the insignificance of the parameter indicates high case variability within the group, possibly arising from omitted relevant factors or endogeneity issues.

Certain results reported in Table 1 are inconsistent with recent findings in the literature, particularly the insignificance of meat and soybean prices. This incongruence prompts us to consider various possibilities, including the interaction of these elements with other factors, measurement errors in the adopted variables, shifting patterns of influence over time, and/or localized impact due to the existence of an agricultural belt in the region. Another possible explanation for those results is the importance of the land markets in the amazon region, as argued by Costa (2023). In those markets, deforestation is the technology to produce "land-without-forest" from "land-with-forest", and the land-without-forest is the product itself. Consequently, this market works "relatively autonomously in relation to the economy of agricultural products, producing land-without-forest in countercyclical movements to business" (p. 330). A deeper investigation on this hypothesis can constitute an interesting path for future studies.

Measurement errors could arise, for instance, from the fact that the data does not distinguish between events occurring in January and December of the same year. This might be the case not only for ECI-R and rainfall, but also for wood and soybean prices. For instance, a price surge at the end of one year could lead to increased forest clearance or planting/harvesting in the following year. Take soybeans, for example, with a planting window between September and October, and harvesting between January and May. Price fluctuations for a bag of soybeans might impact both the current and future periods, depending on timing. Consequently, the effect on deforestation might not be fully identified within the current period. However, introducing lags for these variables into the model did not change their significance.

The livestock sector operates on a longer cycle due to its nature, involving the fattening of calves over several years. These cycles, though historically diminishing due to reduced average cattle slaughter age, presently span about 5–6 years (Embrapa, 2023). When fat cattle supply increases, prices drop, affecting other categories (lean cattle, calves, and breeding cows) as well. Driven by financial difficulties, breeders sell more female cattle for slaughter. This influx of females into the market reduces meat prices even further. Conversely, during periods of low supply, when the number of breeding cows shrinks, calf production decreases. After several years, this shortage of cattle for slaughter and replacement heifers leads to increased prices, restarting the cycle. The period from 2006 to 2011 saw an upswing followed by a downturn between 2012 and 2014.

This cycle was disrupted by a sharp increase after the 2014 Brazilian water crisis, impacting until the end of 2016. The years 2017 to 2019 again brought a period of decline, causing a scarcity of breeding cows and initiating a new cycle of growth starting in 2020. Consequently, part of the insignificance of this variable in the estimations could theoretically be attributed to the inclusion of period dummies, as these coincide with the cycles of the Brazilian livestock industry.

Appendix 2:. Notes on the dynamic panel model

As previously emphasized, GMM facilitates the incorporation of lags of the explained variable among the regressors, allowing us to probe the dependence of the annual deforestation trajectory. This exploration is essential in our study due to the potential influence of preservation/deforestation levels on the impact of ECI-R on deforestation. Such interaction could introduce bias in estimating the ECI-R parameter.

As expected, the regressions indicate the existence of deforestation trajectory dependence, with the lagged variable exhibiting a highly significant positive parameter across all specifications. Regressions (1) and (4) show one-step coefficient estimates, while the rest employ two-step processes. Although the latter is asymptotically more efficient, we adopt robust estimates with Windmeijer's (2005) correction for finite samples to counteract potential downward bias in standard errors. The use of robust methods ensures consistent standard error estimates in the presence of heteroskedasticity and autocorrelation patterns within the panels (Roodman, 2006). Furthermore, all specifications include period dummies, as the autocorrelation test and robust coefficient standard error estimates assume no interindividual correlation in idiosyncratic errors. Additionally, we exercised caution in selecting the number of lagged instruments to avoid excessive adjustments that might eliminate components responsible for endogeneity without overcorrecting. The Hansen statistic validates the exogeneity of the instrument subgroups in all estimations.

Likewise, the regressions indicate a negative connection between the average value derived from extractive production and deforestation. However, the average wood value remains insignificant across all tested specifications. Both soybean and meat prices are significant in the GMM-Sys models. This outcome suggests that heightened soybean prices might indeed contribute to deforestation, although this impact is relatively modest compared to other factors. Conversely, a significant negative association emerges between meat price and deforestation. Yet, this seemingly contradictory phenomenon might be elucidated by the cycle of the Brazilian livestock industry, as discussed earlier. Meat prices tend to rise precisely when the cattle population decreases.

In regression (3), meat price is instrumented using milk price. Additionally, the specification incorporates state averages for wood prices and local soybean prices as instruments for the original variable. The instrumentalized variables' parameters remain not significant. Alternative instrumentalization options were also explored, incorporating lags of the variables, but these did not yield significant coefficients. Lastly, the specification encompasses agricultural activity credit allocation, initial GDP per capita, and complexity group dummies. Although the former lacks significance (general credit is significant and negatively parameterized), the latter were ultimately omitted from the model due to collinearity with other variables.

Regression (6) probes the model's sensitivity to the inclusion of potentially endogenous variables, such as initial GDP per capita and total deforestation levels. Both variables were significant and aligned with anticipated outcomes. The parameter values for other variables experienced minimal changes, except for soybean price. Similar to specifications (3) and (5), specific agricultural activity credit was introduced. The positive significance of this variable supports that credit could be linked to deforestation in the region. Lastly, it's noteworthy that the inclusion of the variable capturing formal mining activity failed to yield significant parameters across any model, leading to its exclusion from the baseline model.

Appendix 3:. Probit Model: Factors influencing membership

Variables	2006–2011				2012–2016				2017–2021			
	Group (1)	Group (2)	Group (3)	Group 4	Group (1)	Group (2)	Group (3)	Group 4	Group (1)	Group (2)	Group (3)	Group 4
ECI	1.0816*	−0.7234	−0.2354	0.8084	−0.5542	0.2204	0.7375	0.1978	−0.9021*	0.1828	0.8010*	0.5693
Δ ECI	−0.2967**	0.1186*	0.0541	−0.0443	−0.011	0.0533*	−0.0261	−0.1512**	0	0	0	0
Preservation group												
Mid-low	−0.478***	−0.614***	0.6225***	0.0762	−0.725***	−0.2069	0.1892	0.4648***	−0.6187***	−0.1785	0.4198***	0.1839
Mid-high	−0.911***	−0.901***	0.9020***	0.2641	−1.000***	−0.847***	0.6444***	0.5107***	−1.1404***	−0.551***	0.7376***	0.3679**
High	−0.5085*	−1.039***	0.9785***	0.3573	−0.851***	−0.6218**	0.2647	0.8962***	−0.8131***	−0.6086**	0.8738***	0.3023
ln Soy	0.024	0.0105	−0.0291	0.0194	0.0318	−0.0378*	0.018	−0.0231	−0.0198	−0.0019	0.0368**	−0.0351*
ln Wood	−0.0555*	0.0352	−0.0117	0.0377	−0.0202	0.0079	−0.0006	0.0183	−0.0026	−0.0424*	−0.0148	0.0482**
ln Meat	−0.302***	−0.058	0.2365***	0.052	−0.188***	−0.174***	0.1281***	0.0868**	−0.1854***	−0.1009*	0.0598	0.1236***
ln Extract	−0.0123	0.0101	−0.0313	0.0374	0.0491	−0.0237	−0.0014	−0.024	−0.009	0.0731*	0.0288	−0.0797*
ln Mining	−0.0202	−0.0287	0.0177	−0.0058	−0.0168	−0.0242	0.0013	0.0144	−0.0066	0	0.0161	−0.0209
ln Credit (agriculture)	0.0530**	0.0248	−0.0239	−0.0229	0.0572**	0.0217	−0.0317	−0.0156	0.0342	0.0252	−0.0187	−0.0146
ln Fines intensity	0.1643***	0.2416***	−0.153***	−0.124***	0.0224	0.1867***	−0.0472	−0.0313	0.2121***	0.1465***	−0.178***	−0.0095
ln GDPpc0	−0.3376*	0.2708	−0.2103	−0.0534	−0.0204	0.2312	−0.0916	−0.0145	−0.2602	0.1693	0.1271	−0.146
Gross Added Value												
ln Agriculture	0.0113	−0.341***	0.1530**	0.2548***	−0.392***	−0.1672*	0.3541***	0.1073	−0.0486	−0.340***	0.2272***	0.1369*
ln Manufacturing	0.1900*	−0.2872**	0.1407*	−0.063	−0.357***	0.1281	−0.1649*	0.2888***	−0.0921	−0.1613	0.0472	0.0938
ln Services	−0.1389	−0.2146	0.2939***	−0.441***	0.4303***	−0.2617**	0.0507	−0.280***	0.1886	−0.1781	0.0725	−0.2595**
Constant	4.1506***	5.8953***	−6.972***	0.9389	4.7491***	2.3509*	−4.293***	−2.7465**	3.2437*	5.6974***	−6.528***	−0.6146
N	2755	2755	2755	2755	2729	2729	2729	2729	1653	1653	1653	1653
Wald chi2	138.33	199.36	179.59	78.57	143.07	123.05	87.07	69.20	136.10	111.27	14.27	35.20
Pseudo R2	0.2137	0.3318	0.2669	0.1121	0.2199	0.152	0.1293	0.094	0.2177	0.2082	0.2338	0.0632

Notes: 1. Group (1): Highlight in the increase of formal jobs and lower level of deforestation; Group (2): Outstanding in preservation, but not in jobs; Group (3): Highlight in the increase of formal jobs, but with high loss of vegetation cover, comparatively; Group 4: High deforestation and low employment dynamics. Base group: low preservation.

Caption: Significance level * 0.1 ** 0.05 *** 0.01.

Source: own elaboration.

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