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Assessing the impact of economic development on the environment depends on a number of factors that have plagued the empirical literature for decades and led many economists to focus on more microeconometric and RCT studies on the underlying forces behind income and environmental quality. The micro-level literature has produced a number of insights on the growth-environment nexus, but its conclusions are viewed with caution in policy making due to the difficulty in accounting for general equilibrium effects that often evade these studies. We take advantage of the recent microeconometric literature on the determinants of environmental quality along the development path to revisit the aggregate relationship between income and deforestation with a focus on deforestation and ecosystem health of the Brazilian Amazon region. Our results indicate a significant, negative, and non-linear relationship that is mediated by factors such as urbanization, poverty, policies to combat extreme poverty, access to both local and national markets and more efficient production in the agricultural frontier. Heterogeneity tests shows that this relationship is significant only in middle- and high-income municipalities, aligning with the Environmental Kuznets Curve (EKC) hypothesis.

Keywords: Economic Development; Deforestation; Amazon.

JEL Codes: Q23, Q56, Q57.

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Pedro Henrique Batista de Barros* Ariaster Baumgratz Chimeli†

Abstract

Assessing the impact of economic development on the environment depends on a number of factors that have plagued the empirical literature for decades and led many economists to focus on more microeconometric and RCT studies on the underlying forces behind income and environmental quality. The micro-level literature has produced a number of insights on the growth-environment nexus, but its conclusions are viewed with caution in policy making due to the difficulty in accounting for general equilibrium effects that often evade these studies. We take advantage of the recent microeconometric literature on the determinants of environmental quality along the development path to revisit the aggregate relationship between income and deforestation with a focus on deforestation and ecosystem health of the Brazilian Amazon region. Our results indicate a significant, negative, and non-linear relationship that is mediated by factors such as urbanization, poverty, policies to combat extreme poverty, access to both local and national markets and more efficient production in the agricultural frontier. Heterogeneity tests shows that this relationship is significant only in middle- and high-income municipalities, aligning with the Environmental Kuznets Curve (EKC) hypothesis.

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1 Introduction

The question whether economic growth harms or contributes to protect the environment is as important today as it was in the beginning of the second half of the twentieth century, when pollution extremes and environmental movements in more developed nations eventually led to the creation of regulatory agencies and the iconic Brundtland Report. At one end of the spectrum, some argue that economic growth is the best path to environmental protection,[1] whereas at the other end, some argue that we should strive for degrowth and consumption reduction.[2] Among the top environmental problems closely associated with past, present and future economic development, tropical deforestation stands out not only due to its significant contribution to climate change, but also because of the resulting biodiversity loss and damages to environmental services that impact both production, wealth and human well-being.

This paper revisits the environment and development nexus with a focus on deforestation of the Brazilian Amazon region. The Amazon forest is the largest tropical forest in the world, one of the most biodiverse places on the planet with a genetic library that can boost future economies and is a key player in the regional, continental and global climate dynamics.[3] At the same time, poverty remains a regional problem and local economic pressures make the Amazon biome home to the most active agricultural frontier in terms of forest loss and CO_2 emissions globally.[4] The Brazilian Amazon region is therefore strategically important for our understanding of the relationship between economic growth and the environment, an issue that we explore by estimating the link between deforestation and income aggregated at the municipal level.

A number of other studies have investigated the relationship between economic development and deforestation in the Brazilian Amazon and obtained mixed results. For

[1] On January, 21, 2020, the then Economy Minister of Brazil, Paulo Guedes, claimed that "nature's worst enemy is poverty" as he advocated a "delicate balance" between growth and the environment. https://www1.folha.uol.com.br/internacional/en/business/2020/01/people-destroy-the-environment-because-they-need-to-eat-says-guedes-at-davos.shtml.

[2] The degrowth movement had its origins in the early 1970s with the philosopher André Gorz and gained traction more recently due to the threats posed by climate change.

[3] Flores et al. (2024)

[4] Assuncao, Gandour, and Rudi Rocha (2015)

example, while some suggest an inverted U-shaped relationship between income and deforestation - a pattern known in the environmental economics literature as the Environmental Kuznets Curve (EKC) - (Polome and Trotignon (2016), Tritsch and Arvor (2016), and Silveira et al. (2025)), others estimate a U-shaped pattern (Araujo et al. (2009) and Jusys (2016)), or even an N-shaped relationship (Oliveira et al. (2011)). Given that the region's economic prosperity and deforestation patterns are typically sensitive to a number of forces such as market conditions, institutional quality, population pressures, and spatial effects, these mixed empirical findings may stem from failure to account for these potential confounding factors. In fact, quasi-experiments involving income and the environment at the more aggregate level are rarely available, and estimating the relationship between economic growth and the environment is a difficult task that is plagued with endogeneity due to omitted variables and reverse causality.

In view of these endogeneity problems, the recent literature on environment and development has turned to quasi-experiments and randomized control trials (RCTs) at the microeconomic level. Jayachandran (2022) reviews a number of these studies that explore several drivers of the development-environment relationship at the micro level and groups them as household purchasing power, access to credit, secure property rights, technological progress, and stronger regulatory capacity. These studies shed light into how development affects the environment, but tend to focus on partial equilibrium effects and overlook aggregate general equilibrium impacts that may be important. In this paper, we take advantage of recent evidence at the microeconomic level and revisit the more aggregate relationship between growth and deforestation in the Brazilian Amazon.

To mitigate concerns with omitted variables, we estimate the relationship between GDP per capita and deforestation, as well as other indicators of ecosystem health, and account for a number of drivers of ecosystem degradation for a panel of 490 municipalities over 2002 to 2011 in the Brazilian Amazon. More specifically, we control for the role of population (Cropper and Griffiths (1994)), agricultural market conditions (Assuncao, Gandour, and Rudi Rocha (2015)), political party in power (R. Burgess et al. (2012)), access to credit (Wilebore et al. (2019), Assunção, Gandour, Romero Rocha, and

Rudi Rocha (2020), and Jayachandran (2013)), strength of institutions for environmental protection (Alston, Libecap, and Mueller (2000) and Araujo et al. (2009)), agricultural productivity (Barbier and J. C. Burgess (2001)), indirect land use changes (ILUC) (Andrade de Sá, Palmer, and di Falco (2013)), protected areas (Amin et al. (2019)), economic structure (Hanusch (2023)), access to markets (Faria and Almeida (2016)), and Bolsa Família, a cash transfer policy of the Brazilian Federal government (Alix-Garcia et al. (2013) and Ferraro and Simorangkir (2020)). We use lagged GDP per capita to address reverse causality concerns.

Our results suggest a significant negative and nonlinear relationship between economic activity and deforestation for the range of municipal incomes in the Brazilian Amazon, as well as an important role for some agricultural commodities, access to credit, the strength of forest protection institutions, agricultural productivity, structural transformation and urbanization. The results are robust to spatial and dynamic effects,[5] which do seem to matter, alternative measures of deforestation and an alternative measure of economic activity that is also closely related to urbanization (nightlights).[6] Urbanization is particularly important as some argue that urban settings have an economic structure that is less forest intensive and contributes to forest protection in the Brazilian Amazon (Hanusch (2023)), whereas others argue that higher incomes in urban areas contribute to increased deforestation through general equilibrium effects (Castelani (2013)). Finally, we follow Amin et al. (2019) and reject the hypothesis of remaining endogeneity in our specifications.

In addition to deforestation, we also consider the Normalized Difference Vegetation Index (NDVI) as an outcome variable. NDVI captures environmental degradation beyond clear-cut deforestation and full-growth reforestation, providing a more comprehensive view of ecosystem changes.[7] To construct the NDVI index, we leveraged remote sensing

[5]Oliveira et al. (2011), Andrade de Sá, Palmer, and di Falco (2013), Jusys (2016), Pfaff and Robalino (2017), Amin et al. (2019), and Assunção, Gandour, Romero Rocha, and Rudi Rocha (2020)

[6]Henderson, Storeygard, and Weil (2012) argue that nightlights are a better proxy for economic performance for remote areas with poor economic statistics, including the failure to precisely measure the informal sector, which is perceived to be large in Brazil. Increases in night light reflect income gains, as they capture the intensity of outdoor lights, a portion of indoor lighting in human settlements and urbanization.

[7]Foster and Rosenzweig (2003) and R. Burgess et al. (2012) are examples of studies that also use

data from Landsat 7 imagery. The results for NDVI and GDP per capita are similar to those for deforestation.

We investigate heterogeneity of the results in two dimensions: income and whether the municipality is in the agricultural frontier. We divide the municipalities in our sample into three equal groups of GDP per capita and the negative relationship between income and deforestation is significant only in middle- and high-income municipalities, consistent with the EKC hypothesis, which suggests that greater economic development reduce environmental impacts. Similarly, municipalities in the agricultural frontier exhibit a stronger negative relationship between income and deforestation. This could be due to variation in the presence of forests depending on whether or not the municipality is in the agricultural frontier. However, since we control for the stock of forests, a better candidate explanation for the observed heterogeneity appears to be increases in agricultural productivity along the agricultural frontier.

As we explore potential mechanisms for the relationship between municipal income and deforestation, urbanization, poverty, policies to combat extreme poverty, and access to both local and national markets stand out as important channels linking economic activity and the reduction of deforestation.

We contribute to the existing literature in two different ways. First, we take advantage of the recent microeconometric literature on the determinants of environmental quality along the development path to revisit the more aggregate relationship between income and deforestation. The microeconometric literature offers important guidance on which variables to control for in order to mitigate the problem of omitted variable bias that is so common in more aggregate non-experimental studies. As we revisit the link between GDP per capita and deforestation in the Brazilian Amazon, we contribute to incorporating general equilibrium effects that are important at the regional level. Our result of a non-linear and decreasing rate of deforestation as income grows for the range of GDP per capita in the Brazilian Amazon contrasts to a number of other studies that estimate variable shapes for the development and deforestation relationship in the region. In addition,

NDVI as a measure of ecosystem changes.

our results suggest some mechanisms that shed light on the local dynamics of deforestation. Second, we go beyond deforestation to estimate the impact of economic activity on a broader measure of ecosystem health, as recent evidence indicates that long-term forest degradation now exceeds deforestation in the Brazilian Amazon (Matricardi et al. (2020)). The bioeconomy in the Amazon, which relies on ecosystem services and biodiversity, has recently gained a prominent role in discussions about regional development both from academic, market, and policy perspectives.[8]

This paper is organized into six sections in addition to this introduction. Section 2 discusses the theoretical and institutional setting linking development and deforestation in the Brazilian Amazon. Sections 3 and 4 specifies our data and empirical strategy, respectively, whereas section 5 presents and discusses our main results. Section 6 conducts heterogeneity analysis and explores mechanisms behind our results and section 7 concludes.

2 Background

2.1 Economic Development and the Environment

The economics literature has investigated the connection between economic growth, natural resources and the environment for many decades, but renewed interest emerged when Gene M Grossman and Alan B Krueger (1991), Shafik and Bandyopadhyay (1992) and Gene M. Grossman and Alan B. Krueger (1995) first gathered empirical evidence of an inverted U-shaped relationship between economic growth and emissions for some pollutants. Investigation of an EKC for deforestation quickly followed the evidence for selected pollutants in an ever expanding avenue of research.[9] A theoretical literature then proposed several mechanisms to explain the EKC, including differences in marginal utility of consumption and marginal cost of pollution abatement, structural transforma-

[8] See, for example, Hanusch (2023) and the efforts of the Brazilian Federal Government - https://www.gov.br/mdic/pt-br/assuntos/noticias/2024/marco/bioeconomia-da-amazonia-legal-tem-potencial-mundial-aponta-estudo-contratado-pelo-mdic.

[9] See for example, Bhattarai and Hammig (2001), Van and Azomahou (2007), Culas (2007) and Culas (2012) and Crespo Cuaresma et al. (2017).

tions in the economy, scarcity of productive capital relative to environmental quality and institutions.[10]

A second generation of empirical work on pollution and growth with access to more data and econometric tools then questioned the robustness of the EKC result,[11] leading to both theoretical and empirical work on the heterogeneity of transition timing and microeconomic forces that shape the relationship between growth and the environment.[12] Also important in the relationship between the environment and development is the role of trade in national or international markets. Trade can affect the environment through economic growth (scale effect), the diffusion of innovations (technique effect) and the restructuring of economies based on their comparative advantages (composition effect).[13]

The evidence on how growth impacts deforestation is far from clear and difficult to generalize. Globally, although some empirical studies provide support for an EKC for deforestation (Cropper and Griffiths (1994), Barbier and J. C. Burgess (2001), Bhattarai and Hammig (2004), Crespo Cuaresma et al. (2017), Andrée et al. (2019), Ajanaku and Collins (2021), and Sohag, Gainetdinova, and Mariev (2023)), other studies fail to find support for the EKC hypothesis (Van and Azomahou (2007) and Assa (2021)), and some have identified an 'N'-shaped relationship for income and deforestation (Bhattarai and Hammig (2001)). These conflicting results suggest the importance of region-specific analyses and the control of an array of covariates to mitigate potential endogeneity and spatial considerations that might bias empirical estimates. In this paper, we use the

[10]See for example, Selden and Song (1995), Stokey (1998), Cropper and Griffiths (1994), Arrow et al. (1995), Pamayotou (1997), Andreoni and Levinson (2001), Dasgupta et al. (2002), Chimeli and Braden (2009), Kijima, Nishide, and Ohyama (2010) and Greenstone and Jack (2015).

[11]See for example, Stern and Common (2001), Harbaugh, Levinson, and Wilson (2002) and Millimet, List, and Stengos (2003).

[12]In the theoretical literature, Chimeli and Braden (2005) and Chimeli (2007) explore the role of differences in total factor productivity, efficiency of environmental protection and pollution intensity of production in determining the transition points for environmental quality in different economies. Failure to account for these types of heterogeneity can lead to income-environmental quality relationships that are not even functional forms that can be econometrically estimated. In the empirical literature, Dijkgraaf and Vollebergh (2005) and Van and Azomahou (2007) find evidence of heterogeneity in the relationship between environmental quality and income, Andrée et al. (2019) estimates different tipping points for pollution and deforestation resulting from differences between countries and Jayachandran (2022) summarizes microeconometric and RCT studies that explore the underlying causes of environmental quality and deforestation in different economic settings.

[13]See for example, Brian R. Copeland and M. Scott Taylor (2004) and Cherniwchan, Brian R Copeland, and M Scott Taylor (2017). Andrée et al. (2019) estimates that environmentally friendly technique effects alone are not sufficient to mitigate the negative environmental impacts of the scale effect.

recent insights from the literature on growth and the environment to investigate the determinants of the rate of deforestation in the Brazilian Amazon and some underlying mechanisms behind our findings.

2.2 Deforestation and Economic Development in the Brazilian Amazon

The Amazon biome houses the largest tropical forest in the world with high levels of biodiversity, water resources, and forest biomass. However, deforestation in the region has raised global concern due to the irreparable loss of its natural wealth and the emission of greenhouse gases. The Amazon is also the most active agricultural frontier globally in terms of forest loss and CO2 emissions.[14] At the same time, poverty remains a persistent issue in the region, highlighting the need for greater economic prosperity. However, promoting economic development may drive land use changes and structural transformations that exert additional pressure on natural resources.[15]

Large-scale deforestation in the Brazilian Amazon began in the 1960s, driven by infrastructure and colonization projects designed to develop and populate the region. Key initiatives included the construction of highways, subsidized credit, and colonization incentives. Since the 1980s, deforestation has been increasingly influenced by commodity markets, especially those for cattle and soybeans. Deforestation rates peaked in 2004, with around 28,000 km^2 of forest cleared, largely driven by rising agricultural prices and the inefficacy of conservation policies (Assuncao, Gandour, and Rudi Rocha (2015)).

Starting in 2004, the Brazilian government responded with significant institutional changes implemented mainly through the Plan for the Prevention and Control of Deforestation in the Legal Amazon (PPCDAm). PPCDAm was implemented in four phases. Phase I (2004-2008) created conservation units and increased delimitation of indigenous lands. It also improved monitoring with the introduction of the Real-Time Deforestation Detection System (DETER), which uses satellite images to detect deforestation every 15

[14] Assuncao, Gandour, and Rudi Rocha (2015).
[15] Bustos, Caprettini, and Ponticelli (2016).

days. Despite the success of Phase I in reducing deforestation, enforcement remained weak, since only a small fraction of the fines imposed on farmers who cleared their land was actually collected. Phase II (2009-2011) then improved enforcement by creating a list of priority municipalities targeted for their high rates of forest removal and restricting rural credit to farmers in those municipalities. Deforestation rates decreased by 40% during Phase II.[16] Next, Phase III (2012-2015) focused on monitoring more pulverized deforestation. Finally, Phase IV was characterized by a weakening of the institutions that monitored and enforced deforestation control, and the Amazon region experienced an increasing trend in forest loss.[17]

Despite tightening environmental regulations, this policy effort did not seem to have significantly impacted local economic development.[18] The success of the forest protection policies, especially during PPCDAm Phases I and II, deserves further investigation accounting for the lessons from the recent literature. The apparent decoupling of growth and deforestation in the Amazon was possibly due both to economic restructuring (composition effect) and more efficient agriculture (technique effect). These are two mechanisms we investigate below as we examine an urbanization indicator and the relationship between deforestation and the agricultural frontier in the Brazilian Amazon region.

3 Data

Deforestation

Official deforestation data are provided by the National Institute for Spatial Research (INPE) through the Program for Calculation of Amazon Deforestation (PRODES). The data are derived from Landsat-type satellite images, aggregated at the municipal level, and deforestation for year t reflects primary forest loss between August 1st of year $t-1$ and July 31st of year t. To investigate the driving forces behind the period of successful

[16] Assunção, Gandour, and Romero Rocha (2023) discuss the importance of DETER and Assunção, McMillan, et al. (2023) discuss the impact of Phase II on deforestation. See also Hansen et al. (2013).
[17] Mello and Artaxo (2017).
[18] Caviglia-Harris et al. (2016) and Tritsch and Arvor (2016).

deforestation reduction policies during PPCDAm I and II, we use PRODES data for 760 municipalities covering the period from 2002 to 2011. To account for variation in deforestation due to differences in municipality size, we follow Assunção, Gandour, Romero Rocha, and Rudi Rocha (2020) and normalize our deforestation variable as follows:

$$\text{Deforest}_{it} = \frac{(PFL_{it} - \overline{PFL_i})}{\text{sd}(PFL_i)}, \tag{3.1}$$

where Deforest_{it} is the normalized deforestation rate for municipality i in year t, PFL_{it} is the primary forest loss as reported by PRODES, and $\overline{\text{PFL}}_i$ and $\text{sd}(\text{PFL}_i)$ represent the deforestation mean and standard deviation for municipality i between 2002 and 2011, respectively.

Since deforestation data relies on satellite images, which can be obscured or blocked by cloud cover, there is a risk of measurement error that could bias our estimates. To mitigate these issues, we control for both the extent of cloud cover and unobservable pixels in each municipality for year t. These data are also sourced from the PRODES. Furthermore, some municipalities had already lost almost all of their forests during our sample period, and this could bias our results as deforestation in those areas would be virtually zero. We address this issue by restricting our sample to municipalities with at least 10% of their forest cover, which produces a final dataset with 490 municipalities.

As alternative proxies for deforestation, we also use forest loss data from Hansen et al. (2013), land use and land cover data from the MapBiomas project, and the NDVI (Normalized Difference Vegetation Index). The Hansen et al. (2013) dataset is globally recognized for assessing forest change and the MapBiomas dataset has gained widespread recognition for its detailed land use and land cover mapping capabilities specifically tailored to Brazilian biomes (Souza et al. (2020)). In our econometric specifications we use MapBiomas data to control for nonlinear time trends in deforestation for each municipality by interacting the proportion of their forest cover in year 2000 with a linear trend. The NDVI is widely used in remote sensing literature(Pettorelli et al. (2005)) to capture gradual forest recovery or degradation. We calculated the NDVI pixel by pixel using Landsat-7 satellite imagery as follows:

$$NDVI = \frac{(NIR - RED)}{(NIR + RED)}, \tag{3.2}$$

where NIR stands for near-infrared reflectance and RED is red reflectance. Considering that plants reflect light in the near-infrared spectrum and absorb it in the red during photosynthesis, the NDVI provides a simple yet powerful measure of vegetation presence and health by comparing the difference between these two reflectances. Values close to 1 indicate healthy, dense vegetation, whereas values near 0 suggest sparse or stressed vegetation. After calculating the NDVI pixel by pixel, we averaged the values at the municipality level. NDVI's robustness and reliability have also led to its adoption in the economic literature as a valuable proxy for deforestation (Foster and Rosenzweig (2003) and R. Burgess et al. (2012)).

Economic Activity and Urbanization

Data on Gross Domestic Product (GDP), industrial and services GDP, and population come from the Brazilian Institute of Geography and Statistics (IBGE). We used GDP per capita, adjusted to 2010 US dollars, as an indicator of economic development and well-being to estimate how economic prosperity at the municipality level is related to deforestation. To check the robustness of our results, we also used night light data as an alternative proxy for local economic activity. Night lights are typically associated with urban areas and variation in this indicator also allows us to investigate the role of urbanization on deforestation. Night light data come from the DMSP-OLS Nighttime Lights Time Series database, a cloud-free composite provided by the Defense Meteorological Satellite Program (DMSP), operated by the National Oceanic and Atmospheric Administration (NOAA). The DMSP satellites, equipped with the Operational Linescan System (OLS), orbit the Earth 14 times a day capturing night light intensity, and have been operational since the 1970s.[19] To match our spatial unit of analysis, we aggregated

[19] Originally designed to detect "moonlit clouds", these sensors also capture night lights from human settlements, collecting data globally between 8:30 and 10:00 pm local time.

the satellite's 1 km^2 pixel values at the municipal level for each corresponding year.

Commodities

We use data from IBGE to track crop productivity and area expansion for soybeans and corn to account for deforestation pressures driven by land use changes and technology adoption of these high-value crops, typically grown in a crop rotation system. We also include data on herd size from IBGE and cattle productivity from Cisneros, Zhou, and Börner (2015) to control for the effects of cattle ranching, an activity that has expanded rapidly in recent decades in the Brazilian Amazon (Freitas Junior and Barros (2021)). We control for indirect land use changes (ILUC) by interacting the expansion of soybean and sugarcane plantations outside of the Amazon region at time $t-2$ with the expansion of cattle herds in Amazon municipalities at time $t-1$. Descriptive statistics for all the variables are provided in the Appendix.

Considering that local commodity prices are endogenous to agricultural production and economic activity, we followed Assuncao, Gandour, and Rudi Rocha (2015) and used exogenous price variations for soybeans and cattle from Paraná, a non-Amazonian state. To capture the impact of these price changes, we constructed an indicator weighted by the proportion of municipal land dedicated to each activity. Algebraically,

$$PPA_{itc} = PP_{tc} \times A_{ic,2000-2001}, \tag{3.3}$$

where PPA_{itc} represents the real weighted price of activity c in municipality i and year t, and $A_{ic,2000-2001}$ is the proportion of land allocated to activity c in 2000-2001. Timber prices, another possible driver of deforestation, come from Cisneros, Zhou, and Börner (2015).

Institutions

To account for institutional variability, particularly those related to environmental conservation policies, we control for a number of variables from the Brazilian Institute for the Environment and Renewable Resources (IBAMA), National System for Rural Environmental Registry (SISCAR), the Brazilian Central Bank (BACEN) and the Electoral Supreme Court (TSE): i) environmental fines (IBAMA), and ii) the proportion of embargoed areas (IBAMA), both reflecting stronger enforcement of environmental laws; iii) protected areas (IBAMA), where land use is restricted to preserve ecosystems; iv) total rural credit (BACEN), which can either promote sustainable practices or drive agricultural expansion and deforestation; v) a dummy for municipalities listed as Priority Municipalities (IBAMA), which are subject to stricter deforestation control; vi) the proportion of municipal land registered under the Rural Environmental Registry (CAR), a mandatory system to monitor land use and enforce environmental regulations (SISCAR); and vii) political diversity (TSE), which can influence how municipalities approach land use and conservation efforts (Indicator set to 1 if the district mayor belongs to the same party as the federal president).

Descriptive statistics for all variables are provided in Appendix A.1.

4 Empirical Strategy

We adopted a linear two-way fixed-effects (TWFE) specification as it captures within-unit variation and controls for both time-invariant unit-specific factors and time-specific effects. This approach allows us to account for structural, historical, physical, and institutional characteristics that remain stable over time, while also adjusting for temporal trends such as technological changes and macroeconomic shocks. Furthermore, the model's ability to handle lagged explanatory variables is crucial for analyzing the delayed impacts of economic drivers of deforestation while also mitigating simultaneity bias. More specifically, we estimate the following equation:

$$
\begin{aligned}
\text{Deforest}_{i,t} = {} & \theta_t + \eta_i + \beta_1 GDP_{i,t-1} + \beta_2 GDP^2_{i,t-1} + \beta_3 GDP^3_{i,t-1} + \beta_4 \text{Population}_{i,t} \\
& + \beta_5 \text{Institutions}_{i,t} + \beta_6 \text{Commodi.Prices}_{i,t-1} + \beta_7 \text{Forest.Trend}_{i,t-1} \\
& + \beta_8 \text{Agriculture}_{i,t-1} + \beta_9 \text{Cattle}_{i,t-1} + \beta_{10} \text{Economic.Structure}_{i,t} \\
& + \beta_{11} \text{ILUC}_{i,t-1} + \beta_{12} \text{Clouds}_{i,t} + \beta_{13} \text{Unobserved}_{i,t} + v_{i,t},
\end{aligned}
\tag{4.1}
$$

where $\text{Deforest}_{i,t}$ is the normalized deforestation rate for municipality i in year t; $GDP_{i,t-1}$ is per capita GDP in US dollars in $t-1$; $\text{Population}_{i,t}$ stands for population growth rate; $\text{Institutions}_{i,t}$ is a vector including: i) environmental fines, ii) embargoed areas, iii) protected areas, iv) rural credit, v) priority municipalities, vi) CAR, and vii) political diversity; $\text{Commod.Prices}_{i,t-1}$ is a price vector for soybeans, livestock, and timber; $\text{Forest.Trend}_{i,t-1}$ captures the proportion of forests in 2000, interacted with a time effect; $\text{Agriculture}_{i,t-1}$ is a vector representing productivity of soybean and corn in t and area expansion in $t-1$, while $\text{Cattle}_{i,t-1}$ refers to cattle productivity in t and herd size in $t-1$; $\text{Economic.Structure}_{i,t}$ is the value added of the industrial and service sectors as a percentage of municipal GDP; $\text{ILUC}_{i,t-1}$ accounts for indirect land use changes related to soybean and sugarcane; $\text{Clouds}_{i,t}$ and $\text{Unobservable}_{i,t}$ are the extent of cloud cover and unobservable pixels in the municipality; θ_t represents time-fixed effects, and η_i represents municipality-fixed effects. We also include $GDP^2_{i,t}$ and $GDP^3_{i,t}$ in our specifications to account for a possible non-linear relationship between income and deforestation.

To test for potential dynamic and spatial effects of deforestation, we use a general dynamic spatial panel model, represented as follows:

$$
D_{i,t} = \alpha D_{i,t-1} + \rho W_1 D_{j,t} + \beta_1 GDP_{i,t-1} + \beta_2 GDP^2_{i,t-1} + \beta_3 GDP^3_{i,t-1} + \beta_4 X_{i,t} + \beta_5 W_1 X_{j,t} + v_{i,t} \tag{4.2}
$$

$$
v_{i,t} = u_i + \gamma_t + \epsilon_{i,t} \tag{4.3}
$$

$D_{i,t}$ represents the deforestation level in municipality i at time t. $D_{i,t-1}$ is lagged deforestation, capturing the dynamic component of the dependent variable. The spatial weighted matrix, W_1, reflects neighborhood relations between municipalities, and $W_1 D_{j,t}$ represents the spatially lagged deforestation, which can be interpreted as the mean value for neighboring units as defined by the spatial weight matrix, W_1.[20] $GDP_{i,t-1}$ is the gross domestic product per capita, $X_{i,t}$ is the matrix of explanatory variables described in equation (4.1), and $W_1 X_{j,t}$ is a vector with spatially lagged control variables. Finally, the error term, $v_{i,t}$, consists of u_i (individual fixed-effects), γ_t (time fixed-effects), and $\epsilon_{i,t}$ (error term).

This general model can be simplified into various spatial models by applying different parameter restrictions.[21] Our objective is to test whether deforestation in a given municipality is influenced not only by its past deforestation but also by deforestation and socioeconomic conditions in neighboring regions. An important motivation for a spatial approach is that is accounts for general equilibrium effects, where interactions among regions collectively shape resource allocation and externalities. In our context, it is also particularly useful for analyzing how deforestation patterns spread across both space and time, helping to identify whether actions or policies in one area could signal monitoring and enforcement strength, and influence deforestation in surrounding regions. The dynamic component of equation (4.2) sheds light on the persistence of deforestation and land-use changes.

5 Results

Table 1 presents the results for equations (4.1) and (4.2). In the non-spatial models (columns 1 to 3) based on equation (4.1), the results reveal a strong and statistically significant relationship between GDP per capita and deforestation. Columns (2) and (3) indicate that a cubic specification best describes the relationship between GDP per capita and deforestation with income negatively influencing deforestation for lower levels of income. Since an eventual increase in deforestation implied by the estimated coefficients

[20] Elhorst (2014).

[21] See Appendix A.2 for additional technical details. We used the Stata package *xsmle* for estimation of our spatial models.

would only occur for a level of GDP per capita that is significantly above the observed figures for the Amazon region, we interpret our results as indication of a non-linear negative relationship between income and deforestation.[22]

Among the dynamic-spatial models, the Spatial Autoregressive Regression (SAR) model (columns 4 to 6) emerges as the best-performing specification and we will use it as our the benchmark model for subsequent analyses and robustness checks.[23] Even after accounting for the influence of deforestation in neighboring areas, the results remain robust and following the same pattern across all specifications.[24]

In addition to the impact of income on deforestation, our results suggest that population growth, rural credit, protected areas and the expansion of soybeans in the Amazon contribute to increased deforestation, although the coefficients for population and soybeans are less precisely estimated. Whereas some studies present evidence that protected areas tend to reduce deforestation within their territories with negligible spillovers, other studies find evidence that they may also deflect deforestation to other locations.[25] Since our goal is to focus on income and deforestation, we don't pursue this issue further and recommend caution in the interpretation of the coefficient for protected areas.

[22] In the quadratic model (column 2), the turning point occurs at US$44,091, an income level that is significantly higher than the average GDP per capita in the Amazon region (US$3,180.87). In the cubic model (column 3), the turning points are US$32,690 and US$38,232.

[23] According to Elhorst (2014), selecting the best specification begins with a general model, the Dynamic Spatial Durbin Model (DSDM), which includes both spatially lagged dependent and independent variables. We then compared it with simpler models to find the most appropriate specification. First, we tested the Dynamic Spatial Autoregressive Model (DSAR) against the DSDM by assessing the significance of the spatially lagged explanatory variables. The test yielded a χ^2 statistic of 22.11 with a p-value of 0.3343, indicating that we cannot reject the DSAR in favor of the DSDM, as the spatially lagged variables are not jointly significant at the 5% level. Next, we performed a likelihood ratio (LR) test to evaluate the significance of the dynamic component, which resulted in a χ^2 statistic of -1.25 with a p-value of 0.9999, suggesting that it is statistically insignificant. We also tested whether the Spatial Error Model (SEM) might be a better fit by examining if the spatially lagged independent variables could be represented as $\rho\beta_i$. This test produced a χ^2 statistic of 32.45 (p-value < 0.0035), leading us to reject the SEM at the 1% significance level. Finally, based on the Akaike Information Criterion, we chose a 5-neighbor matrix (we explored options ranging from 3 to 100 neighbors) and used it for estimating the spatial models.

[24] Even though the turning point in column 5 is at US$18,200, this figure is still significantly larger than the income we observe in the region. For the cubic model (column 6), no real-valued turning points exist, reinforcing our interpretation of a non-linear negative relationship between GDP per capita and deforestation in the Amazon region. After accounting for indirect spatial effects, the turning point in our spatial model is revised to U$42,409 USD for the quadratic equation — slightly below the estimate from the non-spatial model — while the cubic specification remains without real-valued solutions. Detailed results for the spatial effects have been omitted for conciseness and are available upon request.

[25] See for example, Andam et al. (2008) and Herrera, Pfaff, and Robalino (2019).

Table 1: Results

Variable	(1)	(2)	(3)	SAR (4)	SAR (5)	SAR (6)
GDP	-0.00003550***	-0.00007680***	-0.00012010***	-0.00001820**	-0.00003790***	-0.00005450***
	(0.00000733)	(0.00001180)	(0.00002030)	(0.00000418)	(0.00000843)	(0.00001480)
GDP²	-	9.61e-10***	3.48e-09***	-	0.0000000005***	0.0000000014**
	-	(2.13e-10)	(8.51e-10)	-	(0.0000000001)	(0.0000000006)
GDP³	-	-	-3.19E-14**	-	-	-1.22E-14*
	-	-	(1.03E-14)	-	-	(6.86E-15)
Population	0.00320310**	0.00380220**	0.00401100**	0.00208290**	0.00237000*	0.00245110*
	(0.0016032)	(0.00160180)	(0.00159840)	(0.00143860)	(0.00143930)	(0.00143910)
Rural Credit	7.59E-09***	7.50E-09***	7.38E-09***	2.84E-09**	2.81E-09**	2.77E-09**
	(1.53E-09)	(1.59E-09)	(1.57E-09)	(1.32E-09)	(1.36E-09)	(1.35E-09)
Protected Area	0.73603080***	0.72067150***	0.71005200***	0.39473450***	0.38801380***	0.38419010***
	(0.2442371)	(0.24792220)	(0.24961830)	(0.19568020)	(0.19612330)	(0.19651240)
Priority List	-0.38726970***	-0.37646830***	-0.38002800***	-0.23993490***	-0.23504810***	-0.23651820***
	(0.0644504)	(0.06391640)	(0.06194570)	(0.04514490)	(0.04509280)	(0.04470970)
Fines Value	-4.08E-10	-4.28E-10	-4.11E-10	-4.54E-10	-4.63E-10	-4.57E-10
	(6.21E-10)	(6.31E-10)	(6.39E-10)	(5.56E-10)	(5.61E-10)	(5.65E-10)
Embargoe	-0.05762540**	-0.05661740**	-0.05015090**	-0.02847910	-0.02804970	-0.02657170
	(0.0226792)	(0.02248140)	(0.02251510)	(0.02242980)	(0.02223070)	(0.02237840)
CAR	-1.14920700***	-1.13445300***	-1.16932700***	-0.39914840***	-0.39342340***	-0.40734610***
	(0.1611102)	(0.15910330)	(0.15712830)	(0.12901590)	(0.12835380)	(0.12837240)
Party Affiliation	0.00382410	0.00361910	0.00156210	-0.01703130	-0.01704260	-0.01781580
	(0.06186160)	(0.06071010)	(0.06023820)	(0.05000030)	(0.04975260)	(0.04957390)
Corn Expansion	-0.0000041	-0.00000370	-0.00000334	-0.00000235	-0.00000216	-0.00000203
	(0.00000313)	(0.00000295)	(0.00000304)	(0.00000197)	(0.00000189)	(0.00000192)
Herd Expansion	0.00000183	0.00000151	0.00000131	-0.00000046	-0.00000061	-0.00000069
	(0.00000121)	(0.00000120)	(0.00000120)	(0.00000084)	(0.00000084)	(0.00000084)
Soybean Expansion	0.00000156	0.00000147	0.00000228**	0.00000173*	0.00000168*	0.00000199*
	(0.00000108)	(0.00000114)	(0.00000109)	(0.00000101)	(0.00000101)	(0.00000105)
Corn Price	-0.00000301	-0.00000346	-0.00000376	-0.00000542	-0.00000563	-0.00000574
	(0.0000107)	(0.00001080)	(0.00001090)	(0.00000744)	(0.00000749)	(0.00000753)
Timber Price	-0.00074340***	-0.00062120**	-0.00057400**	-0.00030390*	-0.00024650	-0.00022870
	(0.0002327)	(0.00022980)	(0.00022970)	(0.00017450)	(0.00017440)	(0.00017490)
Soybean Price	0.00000321	0.00000318	0.00000319	0.00000470	0.00000468	0.00000469
	(0.00000738)	(0.00000739)	(0.00000738)	(0.00000413)	(0.00000414)	(0.00000414)
Cattle Productivity	-0.00510330**	-0.00524660**	-0.00530670**	-0.00292310**	-0.00299510	-0.00301990
	(0.0022025)	(0.00218550)	(0.00216720)	(0.00195610)	(0.00194630)	(0.00193860)
Soybean Productivity	0.00004650*	0.00004740*	0.00004780*	0.00002850	0.00002890	0.00002910
	(0.0000264)	(0.00002630)	(0.00002620)	(0.00002290)	(0.00002290)	(0.00002290)
Corn Productivity	0.0000168	0.00001410	0.00001250	-0.00000312	-0.00000441	-0.00000500
	(0.0000337)	(0.00003370)	(0.00003360)	(0.00001990)	(0.00001990)	(0.00001990)
Forest_t	-6.98E-07**	-6.74E-07**	-6.60E-07**	-4.43E-07	-4.32E-07	-4.27E-07
	(2.80E-07)	(2.90E-07)	(2.89E-07)	(2.94E-07)	(2.96E-07)	2.97E-07
ILUC Soybean	-2.50E-12	-2.08E-12	-1.77E-12	1.24E-12	1.44E-12	1.55E-12
	(1.86E-12)	(1.85E-12)	(1.85E-12)	(1.34E-12)	(1.34E-12)	(1.35E-12)
ILUC Sugarcane	-3.01E-14	3.56E-14	5.77E-14	6.02E-13	6.32E-13	6.40E-13
	(4.43E-13)	(4.37E-13)	(4.34E-13)	(3.44E-13)	(3.44E-13)	(3.43E-13)
Industrial Sector	0.00638890**	0.00455180	0.00287670	0.00299670	0.00212800	0.00148760
	(0.0032077)	(0.00318470)	(0.00338930)	(0.00201310)	(0.00187870)	(0.00193090)
Service Sector	-0.02100140**	-0.01815650*	-0.01798860*	-0.00201600	-0.00069450	-0.00064310
	(0.0090183)	(0.00936490)	(0.00943840)	(0.00625560)	(0.00632700)	(0.00641260)
Spatial rho (ρ)	-	-	-	0.68291220***	0.68342120***	0.68460680***
	-	-	-	(0.01479310)	(0.01478710)	(0.01478880)
Observations	4,920	4,920	4,920	4,920	4,920	4,920
AIC	11664.22	11650.4	11643.55	9618.69	9611.01	9626.176
BIC	11878.76	11871.44	11864.59	9833.226	9825.545	9840.711

Note: *** Significant at 1%; ** Significant at 5%; * Significant at 10%. Standard errors were clustered at the municipality level.

Focusing on the estimates for the variables meant capture the strength of institutions for forest protection, municipalities on the priorities list experienced reduced deforestation, the reduction of rural credit contributed to a slow down in deforestation (positive and significant coefficient), increases in areas effectively covered by the Rural Environmental Registry also reduce deforestation.

Next, we proceed with some robustness exercises and explore potential mechanisms for the negative relationship between income and deforestation in the Brazilian Amazon.

5.1 Robustness Checks

To ensure the robustness of our findings, we first applied alternative measures for deforestation, as detailed in Table 3 in Appendix A.3. Specifically, we examined four different measures: columns 1-3 use the logarithm of deforestation as the dependent variable; columns 4-6 represent an alternative normalization based on deforestation as a fraction of the municipal area as opposed to deforestation levels in our main specification; columns 7-9 normalize deforestation by forest area in 2000; and columns 10-12 measure deforestation in hectares. Across these specifications, we consistently estimate a statistically significant and negative non-linear relationship between income and deforestation.

Next, we follow Amin et al. (2019) and conduct an endogeneity test for our benchmark specification. The approach involves re-estimating all models using residuals as the dependent variable, with the expectation that, in the absence of endogeneity, the explanatory variables would exhibit no statistical significance. Table 4 in Appendix A.3 reports the results. Our benchmark SAR models consistently exhibited coefficients that are not statistically significant, whereas models excluding spatial controls seem to still be plagued by endogeneity.

We then employed an alternative proxy for economic development: night light intensity. In remote areas like the Amazon, measuring nominal GDP is challenging due to the large informal sector, limited economic integration, and weak governmental infrastructure. In addition, tracking real GDP growth over time is complicated by the absence of reliable price indices, a common issue in underdeveloped regions. Building on prior research, we used aggregated municipal-level changes in night light as a proxy for economic activity, as increases in per capita income correlate with higher consumption of lighting per capita, both indoors and outdoors (Henderson, Storeygard, and Weil (2012)). The coefficients on Table 5 in Appendix A.3 reinforce the negative relationship between income and deforestation from our benchmark specification. Night lights are also associated with urbanization and the estimated results provide evidence of a mechanism for our results: urbanization is typically associated with the industrial and services sectors and structural changes in the local economy (composition effect) may have contributed to economic growth that is less dependent on deforestation during the time period covered by our sample.

Lastly, whereas many studies in the economics literature focus solely on deforestation, a relatively small number of these studies consider forest recovery or broader environmental health as an outcome of interest.[26] We further explore the robustness of our results by using the Hansen et al. (2013) database alongside data from the MapBiomas project and the NDVI calculated from Landsat 7 images.[27] The results in Table 6 in Appendix A.3 reinforce the negative relationship between income and forest degradation in the Brazilian Amazon. The statistically significant coefficients indicate that our findings are not dependent on the PRODES methodology. They also suggest that the impact of higher income levels extend beyond primary forest loss to include forest regrowth and broader forest ecosystem health.

6 Heterogeneity and Underlying Mechanisms

We further explore the income-deforestation nexus by splitting our sample into three equal groups of municipalities ranked by income per capita, and then by focusing on mu-

[26] See for example, Busch and Ferretti-Gallon (2017). Foster and Rosenzweig (2003) and R. Burgess et al. (2012) are two examples of studies in the economics literature that use the NDVI.

[27] Although Hansen et al. (2013) is widely recognized in global deforestation studies, MapBiomas data and the NDVI index may better align with the Amazon's unique characteristics. The MapBiomas project is tailored to the measurement of deforestation and land use changes in Brazil. Its data are well-regarded in both the Brazilian and international scientific communities, making this dataset particularly suited for research focusing on the Amazon (Souza et al. (2020)). The NDVI provides valuable insight into overall environmental health beyond just deforestation (Pettorelli et al. (2005)), whereas Hansen et al. (2013) captures binary tree cover loss, limiting its scope in studies pursuing more nuanced forest dynamics.

nicipalities on the agricultural frontier versus municipalities outside of the agricultural frontier. Agricultural frontier regions were defined as municipalities showing agricultural area expansion during the previous decade (1990–2000), based on data from the Map-Biomas project. Table 7 in Appendix A.3 reports statistically insignificant coefficients for low income municipalities and indicates that our benchmark results are driven mostly by middle and higher income municipalities. This result, combined with the fact that if deforestation decreased during our sample period it must have increased at earlier times, is consistent with the Environmental Kuznets Curve hypothesis for deforestation. That is as income grows, deforestation increases, peaks and eventually starts to decrease.

Table 8 in Appendix A.3 shows the parameter estimates for agricultural frontier and non-agricultural frontier municipalities. Both sets of coefficients replicate the qualitative results from our benchmark specification, but the absolute values are one order of magnitude larger along the agricultural frontier. This might be due to the fact that non-agricultural frontier municipalities include both more degraded areas where agriculture is consolidated and areas that have more forests, but that are also less accessible. However, since we control for forest trends at the municipal level starting with their baseline forest stock, we interpret the coefficients in table 8 as suggestive of less forest intensive agriculture along the agricultural frontier. This is a technique effect given by more productive agriculture that contribute to reduced deforestation.

We conclude our empirical investigation by turning to some mechanisms that might explain the reduction in deforestation associated with higher income levels. Columns (1), (2) and (3) in table 9 in Appendix A.3 revisit the role of urbanization by interacting GDP per capita with the variable for night lights. Our preferred specification (column 3) suggests that more urbanized municipalities tend to deforest less, a likely consequence of structural changes in the local economy where less forest intensive activities gain relative importance (composition effect). Columns (4) through (9) focus on the role that aggregate poverty and cash transfer programs (*Bolsa Familia*) play on the forest cover. The coefficients for aggregate poverty are positive, suggesting that poverty contributes to deforestation, although the coefficient is not precisely estimated in our preferred specification. Similarly, the poverty reduction cash transfer program targeted to the poorest families seems to be effective in reducing deforestation, although the estimated coefficients are only marginally significant. Our final set of results in columns (10) through (15) test whether access to local and national markets influence deforestation. Although the estimated coefficients are positive in our preferred specification, they are either not significant or only marginally significant. Overall, these results are consistent with the recent microeconometric literature (Alix-Garcia et al. (2013), Ferraro and Simorangkir (2020), and Jayachandran (2022)), providing evidence that these mechanisms operate at the aggregate level and are robust to general equilibrium effects.[28]

7 Conclusion

Achieving a sustainable balance between economic advancement and environmental preservation depends on a set of complex factors, including population dynamics, institutional quality, economic structure, land-use practices, and market accessibility. These confounding factors raise endogeneity concerns and have hindered credible empirical estimates of the relationship between economic growth and environmental quality. To address the endogeneity issues, recent research in environmental and development economics has shifted towards quasi-experimental methods and randomized controlled trials (RCTs) at the microeconomic level. Although these studies provide essential insight into how development affects environmental outcomes, they often focus on partial equilibrium effects, potentially missing broader aggregate general equilibrium impacts that may be important.

This paper builds on the recent micro-level evidence to revisit the aggregate relationship between economic development and deforestation in the Brazilian Amazon, with the goal of capturing these broader, often overlooked, dynamics. We estimate a non-linear negative relationship between income and deforestation in the region that seems to be driven by structural economic changes in more urbanized areas, poverty reduction policies, enforcement of forest protection policies and more efficient agriculture along the

[28]We tested for other mechanisms, including wood extraction, remaining forest cover, education and migration. However, these did not yield statistically significant results and are not reported here for conciseness.

agricultural frontier. These findings are consistent with recent reversals in deforestation trends as the country experienced a recession in 2015-2016, the economic slowdown during the pandemic and the weakening of environmental protection institutions.

In recent years, Brazil and other nations have improved their understanding of the importance of the Amazon rainforest to global climate, national agricultural productivity in other biomes with consequences to global food supply, and as a repository of a biodiversity that can help to shape a more sustainable economy. At the same time, the Brazilian Amazon is home to almost 30 million people and one of the poorest regions in the country with citizens that long for better living standards. The recent experience suggests that a path that reconciles economic development and forest protection in the region will likely have to rely on strong environmental protection institutions and economic activities that are not as dependent on deforestation, especially in a more urbanized setting. This creates new challenges for policy makers and businesses as urbanization is often associated with a different set of environmental problems and better paying urban jobs require substantial investments in human capital. Whether or not the Brazilian Amazon is heading towards a more sustainable bioeconomy with high value added, inclusive growth and that relies on a standing forest depends on strategic investments in areas such as education, health, the strengthening of institutions and poverty alleviation.

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A Appendix

A.1 Descriptive Statistics

Table 2: Descriptive Statistics.

	Units	Mean	Std. Dev.	Minimum	Maximum
GDP pc	2010 US$	3180.8710	4109.8770	231.9713	65594.9900
Population	%	2.0689	6.4724	-48.9391	101.0510
Protected Area	Proportion	0.2316	0.2951	0.0000	1.0000
Environmental Fine	2010 BRL	3,137,128	15,990,000	0.0000	460,000,000
Embargoed Area	%	0.0178	0.2042	0.0000	10.7908
Priority List	Binary	0.0335	0.1801	0.0000	1.0000
CAR	Proportion	0.0240	0.0768	0.0000	0.7349
Party Affiliation	Binary	0.1116	0.2967	0.0000	1.0000
Timber Price	Index	88.4818	85.5773	0.0000	959.9780
Soybean Price	Index	205.6926	2308.6470	0.0000	63908.7000
Cattle Price	Index	3890.0880	11617.4600	0.0000	344538.0000
Forest Trend	-	36134.0000	94479.0000	0.0000	1508861
Corn Expansion	Hectares	187.4520	3836.2680	-53240.0000	133100.0000
Soybean Expansion	Hectares	552.8476	5467.4930	-152094.0000	85000.0000
Corn Productivity	kg/ha	1695.0950	1077.0860	0.0000	8720.0000
Soybean Productivity	kg/ha	578.2669	1157.6810	0.0000	3750.0000
Herd Expansion	Head	4797.9290	24636.2800	-455639.0000	441738.0000
Cattle Productivity	Head/km2	8.2761	13.8884	0.0001	319.3750
Industrial Sector	% GDP	10.6961	3.6996	0.0661	28.7000
Service Sector	% GDP	34.5430	3.0705	0.5094	46.3374
ILUC Soybean	-	1.15e+09	1.31e+10	-3.10e+11	3.50e+11
ILUC Sugarcane	-	6.88e+09	3.17e+10	-2.90e+11	7.60e+11
Cloud Cover	Pixels	330.7857	1739.7320	0.0000	53742.7000
Unobserved	Pixels	41.2814	228.9359	-379.6000	4978.6000
Night Lights	Index	1212.9070	3028.4330	0.0000	51116.0000
NDVI	Index	0.7193	0.3128	0.0000	1.0000
Hansen	%	0.7059	0.7461	0.0027	8.7938

Source: Prepared by the authors.

A.2 Dynamic Spatial Panel Models

Various spatial models can be derived by applying restrictions to the parameters in Equation (2), with each model capturing different aspects of spatial and temporal interactions. The models resulting from these restrictions are:

1. **Dynamic Spatial Durbin Model (DSDM)**: The DSDM includes both temporal

and spatial lags, meaning $\alpha \neq 0$, $\rho \neq 0$, and $\beta_5 \neq 0$. It captures full interactions over time and space.

2. **Dynamic Spatial Autoregressive Model (DSAR)**: If spatial lags of explanatory variables are excluded ($\beta_5 = 0$), but temporal ($\alpha \neq 0$) and spatial lags ($\rho \neq 0$) remain. Deforestation depends on past values and neighboring deforestation.

3. **Spatial Autoregressive Model (SAR)**: By setting $\alpha = 0$, the DSAR reduces to SAR, where deforestation depends only on neighboring municipalities.

4. **Spatial Error Model (SEM)**: If the spatial lag affects only the error term ($v_{i,t} = \lambda W_1 u_{j,t} + \epsilon_{i,t}$).

5. **SLX (Spatial Lag of X)**: When spatial lags appear only in the explanatory variables ($\rho = 0$, $\beta_5 \neq 0$), the SLX model captures how neighboring characteristics influence deforestation.

6. **Spatial Durbin Model (SDM)**: If there's no temporal component ($\alpha = 0$), but spatial lags exist in both dependent and explanatory variables ($\rho \neq 0$, $\beta_5 \neq 0$).

The model's parameters are estimated using Quasi-Maximum Likelihood Estimation (QMLE), which is a flexible approach that accommodates errors that may not follow a normal distribution. Given the potential issue of an increasing number of parameters as the sample size grows, a concentrated likelihood function is used, which focuses on a reduced set of parameters. This method allows the fixed effects to be factored out, simplifying the asymptotic analysis. To correct for potential biases, especially when the time dimension is small relative to the cross-section size, a bias-corrected estimator is applied, ensuring more reliable parameter estimates in dynamic spatial panel data settings (Yu, de Jong, and Lee (2008)).

A.3 Results

Table 3: Robustness Check: Dependent Variable

	ln			*area*			*time norm.*			*hectares*		
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
GDP	-0.000032***	-0.000054***	-0.0000526***	-0.0000121***	-0.0000352***	-0.0000627***	-6.20e-06	-0.0000156	-0.000013	-0.0006247	-0.0025977***	-0.0041183***
	(5.48e-06)	(0.0000143)	(0.0000206)	(5.06e-06)	(0.0000117)	(0.0000217)	(7.35e-06)	(0.0000126)	(0.0000203)	(0.0004443)	(0.0008681)	(0.0014539)
GDP^2	-	5.09e-10*	4.23e-10	-	5.38e-10***	2.13e-09**	-	2.17e-10	8.19e-11	-	4.57e-08***	1.34e-07**
	-	(2.93e-10)	(1.07e-09)	-	(1.93e-10)	(8.40e-10)	-	(2.11e-10)	(7.58e-10)	-	(1.42e-08)	(5.62e-08)
GDP^3	-	-	1.08e-15	-	-	-2.02e-14***	-	-	1.71e-15	-	-	1.12e-12*
	-	-	(1.36e-14)	-	-	(8.95e-15)	-	-	(7.88e-15)	-	-	(5.98e-13)
Population	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Institutions	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Commodities Prices	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Forest Trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Agriculture	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cattle	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Economic Structure	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
ILUC	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clouds	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Unobserved	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Spatial rho (ρ)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,920	4,920	4,920	4,920	4,920	4,920	4,920	4,920	4,920	4,920	4,920	4,920
AIC	9264.117	9256.144	9256.13	10334.08	10327.01	10323.1	11833.7	11832.81	11832.79	49148.67	49129.97	49125.59
BIC	9478.652	9470.679	9470.665	10548.62	10541.55	10537.63	12048.23	12047.35	12047.33	49350.2	49331.5	49327.12

Note: *** Significant at 1%; ** Significant at 5%; * Significant at 10%. Standard errors were clustered at the municipality level.

Table 4: Endogeneity Test

Variable	Non-spatial models (1)	(2)	(3)	Spatial Models (SAR) (4)	(5)	(6)
GDP	-0.0000221***	-0.0000488***	-0.000094***	1.34e-06	4.13e-06	2.34e-06
	(5.38e-06)	(8.80e-06)	(0.0000125)	(5.32e-06)	(8.69e-06)	(0.0000123)
GDP^2	-	6.17e-10***	3.27e-09***	-	-8.80e-11	-2.20e-11
	-	(1.64e-10)	(6.48e-10)	-	(1.62e-10)	(6.39e-10)
GDP^3	-	-	-3.38e-14***	-	-	-4.78e-16
	-	-	(8.95e-15)	-	-	(8.84e-15)
Population	Yes	Yes	Yes	Yes	Yes	Yes
Institutions	Yes	Yes	Yes	Yes	Yes	Yes
Commodities Prices	Yes	Yes	Yes	Yes	Yes	Yes
Forest Trend	Yes	Yes	Yes	Yes	Yes	Yes
Agriculture	Yes	Yes	Yes	Yes	Yes	Yes
Cattle	Yes	Yes	Yes	Yes	Yes	Yes
Economic Structure	Yes	Yes	Yes	Yes	Yes	Yes
ILUC	Yes	Yes	Yes	Yes	Yes	Yes
Clouds	Yes	Yes	Yes	Yes	Yes	Yes
Unobserved	Yes	Yes	Yes	Yes	Yes	Yes
Spatial rho (ρ)	No	No	No	Yes	Yes	Yes

Note: *** Significant at 1%; ** Significant at 5%; * Significant at 10%. Standard errors were clustered at the municipality level.

Table 5: Robustness Check: Night Lights

Variable	Night Lights (1)	(2)	(3)
Night Lights	-0.0000276*	-0.0000716***	-0.0000929***
	(0.0000161)	(0.0000204)	(0.0000340)
Night $Lights^2$	-	1.00e-09**	2.51e-09
	-	(4.82e-10)	(1.64e-09)
Night $Lights^3$	-	-	-2.23e-14
	-	-	(2.25e-14)
Population	Yes	Yes	Yes
Institutions	Yes	Yes	Yes
Commodities Prices	Yes	Yes	Yes
Forest Trend	Yes	Yes	Yes
Agriculture	Yes	Yes	Yes
Cattle	Yes	Yes	Yes
Economic Structure	Yes	Yes	Yes
ILUC	Yes	Yes	Yes
Clouds	Yes	Yes	Yes
Unobserved	Yes	Yes	Yes
Spatial rho (ρ)	Yes	Yes	Yes
Observations	4,920	4,920	4,920
AIC	9623.638	9619.417	9618.884
BIC	9838.173	9833.952	9833.419

Note: *** Significant at 1%; ** Significant at 5%; * Significant at 10%. Standard errors were clustered at the municipality level.

Table 6: Robustness Check: Different Measures of Deforestation

Variable	*Hensen* (1)	*Hensen* (2)	*Hensen* (3)	*Mapbiomas* (4)	*Mapbiomas* (5)	*Mapbiomas* (6)	*NDVI* (7)	*NDVI* (8)	*NDVI* (9)
GDP	-0.0000126***	-0.0000225***	-0.0000319***	-0.1541869***	-0.2751054***	-0.301511***	-2.88e-07	-1.40e-06***	-2.02e-06***
	(3.06e-06)	(6.32e-06)	(8.45e-06)	(0.0492653)	(0.0707344)	(0.0808913)	(1.83e-07)	(2.90e-07)	(4.11e-07)
GDP²	-	2.48e-10**	8.79e-10***	-	3.00e-06***	4.77e-06	-	2.79e-11***	7.09e-11***
	-	1.07e-10	(2.98e-09)	-	(9.60e-07)	(4.05e-06)	-	(5.83e-12)	(2.02e-11)
GDP³	-	-	-8.50e-15**	-	-	-2.39e-11	-	-	-5.80e-16**
	-	-	(4.24e-15)	-	-	(4.94e-11)	-	-	(2.35e-16)
Population	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Institutions	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Commodities Prices	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Forest Trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Agriculture	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cattle	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Economic Structure	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
ILUC	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clouds	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Unobserved	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Spatial rho (ρ)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,640	1,640	1,640	1,640	1,640	1,640	1,640	1,640	1,640
AIC	2777.295	2768.203	2763.746	92924.11	92910.83	92910.48	-25627.73	-25660.58	-25666.51
BIC	2939.822	2930.73	2926.273	93008.62	92995.34	92994.99	-25465.2	-25498.05	-25503.98

Note: *** Significant at 1%; ** Significant at 5%; * Significant at 10%. Standard errors were clustered at the municipality level.

Table 7: Heterogeneity Test by Income Level

Variable	*Low Income* (1)	*Low Income* (2)	*Low Income* (3)	*Middle Income* (4)	*Middle Income* (5)	*Middle Income* (6)	*High Income* (7)	*High Income* (8)	*High Income* (9)
GDP	0.0001673	0.0002662	-0.0004976	-0.0000252***	-0.0000681***	-0.0000987***	-9.69e-06*	-0.0000119	-0.0000525*
	(0.0001508)	(0.0002008)	(0.0003851)	(7.22e-06)	(0.0000142)	(0.0000308)	(5.25e-06)	(0.0000158)	(0.0000278)
GDP²	-	-3.84e-08*	9.91e-08	-	7.58e-10***	2.33e-09*	-	4.80e-11	2.02e-09**
	-	1.80e-08	(8.87e-08)	-	(1.95e-10)	(1.29e-09)	-	(2.70e-10)	(9.95e-10)
GDP³	-	-	5.21e-12	-	-	-1.83e-14	-	-	-2.62e-14**
	-	-	(6.93e-12)	-	-	(1.40e-14)	-	-	(1.15e-14)
Population	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Institutions	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Commodities Prices	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Forest Trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Agriculture	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cattle	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Economic Structure	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
ILUC	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clouds	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Unobserved	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Spatial rho (ρ)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,640	1,640	1,640	1,640	1,640	1,640	1,640	1,640	1,640
AIC	3651.551	3648.171	3642.984	3678.344	3665.518	3661.751	3176.923	3171.816	3158.761
BIC	3792.015	3777.83	3772.643	3808.003	3795.177	3791.41	3306.581	3301.475	3288.419

Note: *** Significant at 1%; ** Significant at 5%; * Significant at 10%. Standard errors were clustered at the municipality level.

Table 8: Heterogeneity Test by Agricultural Frontier

	Agricultural Frontier			*Non-Agricultural Frontier*		
Variable	(1)	(2)	(3)	(4)	(5)	(6)
GDP	-0.0000101	-0.0000735**	-0.0001705**	-0.0000303***	-0.0000493***	-0.0000649***
	(0.0000109)	(0.0000329)	(0.0000673)	(4.53e-06)	(0.000011)	(0.0000189)
GDP^2	-	2.06e-09**	1.04e-08**	-	3.97e-10***	1.24e-09*
	-	(8.74e-10)	(4.29e-09)	-	(1.54e-10)	(7.51e-10)
GDP^3	-	-	-1.90e-13**	-	-	-1.03e-14
	-	-	(8.66e-14)	-	-	(8.63e-15)
Population	Yes	Yes	Yes	Yes	Yes	Yes
Institutions	Yes	Yes	Yes	Yes	Yes	Yes
Commodities Prices	Yes	Yes	Yes	Yes	Yes	Yes
Forest Trend	Yes	Yes	Yes	Yes	Yes	Yes
Agriculture	Yes	Yes	Yes	Yes	Yes	Yes
Cattle	Yes	Yes	Yes	Yes	Yes	Yes
Economic Structure	Yes	Yes	Yes	Yes	Yes	Yes
ILUC	Yes	Yes	Yes	Yes	Yes	Yes
Clouds	Yes	Yes	Yes	Yes	Yes	Yes
Unobserved	Yes	Yes	Yes	Yes	Yes	Yes
Spatial rho (ρ)	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,180	1,180	1,180	3,740	3,740	3,740
AIC	2424.799	2403.314	2394.095	7653.899	7648.053	7646.051
BIC	2546.557	2525.072	2515.853	7803.343	7797.498	7795.495

Note: *** Significant at 1%; ** Significant at 5%; * Significant at 10%. Standard errors were clustered at the municipality level.

Table 9: Mechanisms

	Night Light			Poverty			Bolsa Familia			Local Market			National Market		
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
GDP	-0.0000239***	-0.0000518***	-0.0000834***	-0.0000314***	-0.000054***	-0.0000845***	-0.0000231***	-0.0000513***	-0.0000766***	-0.0000268***	-0.000063***	-0.0000859***	-0.000023***	-0.0000688***	-0.0000917***
	(6.00e-06)	(7.14e-06)	(0.0000113)	(5.36e-06)	(7.12e-06)	(0.0000136)	(4.65e-06)	(7.15e-06)	(0.0000114)	(8.88e-06)	(8.83e-06)	(0.0000121)	(9.51e-06)	(0.0000113)	(0.0000142)
GDP^2	-	7.22e-10***	2.96e-09***	-	6.80e-10***	2.55e-09***	-	6.99e-10***	2.40e-09***	-	7.90e-10***	2.40e-09***	-	8.67e-10***	2.49e-09***
	-	(1.30e-10)	(6.01e-10)	-	(1.37e-10)	(6.89e-10)	-	(1.37e-10)	(5.57e-10)	-	(1.52e-10)	(5.45e-10)	-	(1.79e-10)	(5.48e-10)
GDP^3	-	-	-2.96e-14***	-	-	-2.56e-14**	-	-	-2.28e-14***	-	-	-2.17e-14***	-		-2.20e-14***
	-	-	(7.90e-15)	-	-	(1.00e-14)	-	-	(7.30e-15)	-	-	(7.19e-15)	-		(6.89e-15)
GDP*NightLight	3.34e-06	-0.0000178	-0.0000688***	-	-	-	-	-	-	-	-	-	-	-	-
	(0.0000363)	(0.0000232)	(0.0000219)	-	-	-	-	-	-	-	-	-	-	-	-
GDP*Poverty	-	-	-	0.0001489***	0.0000586	0.0001251	-	-	-	-	-	-	-	-	-
	-	-	-	(0.0000489)	(0.0000642)	(0.0001188)	-	-	-	-	-	-	-	-	-
GDP*BolsaFamilia	-	-	-	-	-	-	-1.80e-09**	-1.44e-09*	-1.42e-09*	-	-	-	-	-	-
	-	-	-	-	-	-	(9.09e-10)	(8.61e-10)	(8.02e-10)	-	-	-	-	-	-
GDP*LocalMarket	-	-	-	-	-	-	-	-	-	3.25e-06	8.10e-06*	7.18e-06	-	-	-
	-	-	-	-	-	-	-	-	-	(5.48e-06)	(4.43e-06)	(4.46e-06)	-	-	-
GDP* NationalMarket	-	-	-	-	-	-	-	-	-	-	-	-	-2.41e-07	3.44e-06*	3.15e-06*
	-	-	-	-	-	-	-	-	-	-	-	-	(2.13e-06)	(1.72e-06)	(1.64e-06)
Population	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Institutions	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Commodities Prices	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Forest Trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Agriculture	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cattle	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Economic Structure	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
ILUC	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clouds	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Unobserved	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Spatial rho (ρ)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,920	4,920	4,920	4,920	4,920	4,920	4,920	4,920	4,920	4,920	4,920	4,920	4,920	4,920	4,920
AIC	9678.925	9661.093	9650.487	9676.041	9660.934	9651.934	9675.333	9658.331	9650.738	9678.332	9657.843	9650.999	9678.913	9657.747	9650.732
BIC	9841.452	9823.62	9813.013	9838.568	9823.461	9814.46	9831.359	9814.356	9806.763	9840.858	9820.369	9813.525	9841.439	9820.274	9813.259

Note: *** Significant at 1%; ** Significant at 5%; * Significant at 10%. Standard errors were clustered at the municipality level.