Do local institutions impact the environment? Evidence from deforestation in Brazil

Abstract

The causal impacts of local institutions on tropical deforestation are still little explored in the literature because they involve endogenous mechanisms that act through socioeconomic and political channels that hinder identification. To fill such a gap, this paper explores exogenous geographical and historical variations in current local institutions to estimate their effects on forest cover in Brazil, an ecologically and economically important country. We assume that the initial conditions the country's settlers found led to institutional designs that conditioned its subsequent development, explaining current institutions' differences. Our main results show that the local institutional change has a positive heterogeneous causal effect on deforestation, even after several robustness checks. We also used a Causal Random Forest algorithm to estimate individual treatment effects, which further supported our main results. This empirical evidence demonstrates that public policies that aim to improve local institutional quality must adequately consider the potential side effects of deforestation.

Keywords: Institutions; Deforestation; Brazil; Causal Random Forest.

JEL Classification: Q5, O1.

1 Introduction

Institutions are widely perceived as a major determinant of economic growth and development[1]. More recently, the potential threats of global warming have placed environmental concerns at the center of the long-term economic development debate, and the need for new institutional arrangements has become increasingly important. For example, the success of the Paris Agreement relies on strong institutions to implement measures such as an international market for carbon credits and the intensification of forest protection efforts in the developing world.[2] Despite the perceived importance of strong institutions, the interplay between the quality of institutions, economic development, and environmental protection is still poorly understood.

This paper takes steps toward the estimation of the causal impact of institutional changes on environmental quality. More specifically, we estimate the impact of institutional changes on deforestation in different biomes and municipalities in Brazil, taking into account the possibility of hidden heterogeneous impacts of institutions on environmental outcomes. In addition to its strategic role in any global effort to curb deforestation, Brazil is a large country with significant variations in institutional quality and deforestation rates within its territory. Furthermore, as we concentrate on a single country, we avoid cross-country analyses that are subject to comparability concerns due to large cultural, historical, and economic differences.

In general, the literature supports that lower institutional quality increases deforestation rates (Barbier and Burgess 2001; Bhattarai and Hammig 2004; Culas 2007; Van and Azomahou 2007; Marchand 2016; Sohag, Gainetdinova, and Mariev 2023). However, theory suggests that institutional improvements may either positively or negatively impact environmental protection and that these effects are likely heterogeneous, making the connection between institutions and the environment an empirical question. For example, A. B. Chimeli and Braden (2005) and A. Chimeli (2007) state that if institutions

[1]See for example, Acemoglu, Johnson, and Robinson (2001), Engerman and Sokoloff (2002), Dell (2010), and Easterly and Levine (2016), etc.

[2]Article 6 of the Paris agreement sets the grounds for the international trade of carbon credits conditional on transparent governance of carbon markets. Many of these credits could originate from forest protection efforts that take center stage in Article 5 of the same agreement (Paris 2015).

influence Total factor productivity (TFP) and other efficiency parameters such as return on investment in environmental protection and capital pollution intensity, then the final effect on the environment is unclear, which should be investigated empirically. In fact, Koop and Tole (1999), List and Gallet (1999), and Van and Azomahou (2007) empirically confirm that the relationship between institutions and environmental quality has heterogeneous results according to geographical, historical, and environmental differences. For this reason, more reliable estimates of how institutions shift human behavior toward a forest are needed.

To address the likely endogeneity of institutional change, we use an IV approach by exploring exogenous variations in local institutional development to attempt to isolate its impact on forest cover in Brazil, an ecologically and economically important country. In practice, we propose to exploit geographical and historical variations to construct instruments for current institutions, hypothesizing that the initial conditions found by the country's settlers led to institutional designs that conditioned its subsequent development, explaining current institutions disparities (Acemoglu, Johnson, and Robinson 2001; Engerman and Sokoloff 2002; Dell 2010; Naritomi, Soares, and Assunção 2012; Marchand 2016; Easterly and Levine 2016). Based on this, we used distance to the Metropolis (Portugal), distance to the coast, and distance to former colonial villages to capture the true level of interference dictated by the metropolis; colonial economic booms - sugarcane and gold episodes; socioeconomic characteristics from the first Brazilian population census of 1872: proportion in the population of literate, slaves, white and foreigners. Menezes-Filho et al. (2006), Naritomi, Soares, and Assunção (2012), and Nakabashi, Pereira, and Sachsida (2013) show that these characteristics were important in shaping current institutions so that they are likely correlated with institutional development due to historical inertia. We also use our classical IV approach to search for potential heterogeneous impacts of institutional changes on different biomes in the country.

Finally, we also explore for potential hidden heterogeneous impacts of institutions on environmental protection by using an instrumental causal random forest model, a novel approach that allows us to estimate causal effect heterogeneity at the municipal level.

The instrumental Causal Random Forest avoids ad hoc hypotheses and specifications and estimates potential local heterogeneous effects, that could bias our results, allowing the estimation of individual treatment effects. The algorithm estimates a local Conditional Average Treatment Effect (CATE) that is robust in out-of-sample validation for each observational unit (Athey and Imbens 2016; Wager and Athey 2018; Athey, Tibshirani, and Wager 2019). Our main results show that the change in local institutional quality has statistically significant heterogeneous causal effects on deforestation in Brazil and that the classical IV approach is not sufficient to disentangle all hidden heterogeneity. Forest conservation is particularly sensitive to heterogeneous outcomes, so moving beyond the average effects is important to better understand its relationship with local institutions and how it varies spatially.

However, to further support that omitted factors do not drive our results and to eliminate potentially hidden bias, common in nonexperimental designs, we conducted a series of additional robustness checks in our IV approach to provide further evidence that the effects we estimate are indeed causal. First, we control for additional differences that potentially are correlated with institutional development and deforestation. In summary, our results are also robust when we control for geographical differences, demographic density, rural population, income inequality, openness to trade, Bolsa Família,[3] human capital and economic scale. Therefore, these geographic, social, economic, and macro-institutional variables do not confound the results, further validating our initial results.

Second, neighbors' interactions may influence local institutional quality, leading to an indirect spatial effect and spatial autocorrelation that could invalidate our estimates. In addition, deforestation decisions are affected by spatially correlated unobservables, which may invalidate our exclusion restriction that the instruments affect deforestation only through the institutional channel, also biasing the estimates. However, measuring such between-municipalities spatial interactions and correlations is difficult since neighbors simultaneously affect each other (J. A. Robalino and Pfaff 2012; Choumert, Combes-Motel, and Dakpo 2013; Baylis et al. 2016; Pfaff and J. Robalino 2017; Busch and

[3]Bolsa Família is a conditional cash transfer program that aims to alleviate poverty in Brazil.

Ferretti-Gallon 2017; Amin et al. 2019). To overcome this, we directly model these spatial effects by estimating a Spatial Autoregressive Model (SAR) as proposed by the spatial econometric literature[4]. The results confirmed the importance of significant spatial effects and autocorrelation and further supported the robustness of our main results.[5]

Third, we test whether the standardization used for the dependent variable, the forest change percentage, drives the results. First, we adopt alternative standardization procedures: (i) normalized forest change[6]; (ii) forest change (ha) divided by the municipality area in $\mathrm{km}^{\mathbf{2}}$ ($\mathrm{ha/km}^{\mathbf{2}}$); and (iii) forest change (ha) divided by forest stock (ha). The results for standardization (i) and (ii) further supported our empirical findings, but for (iii) the institutional variable is not statistically significant, indicating that our results may be driven by the remaining forest stock at the municipality level.

Fourth, we test two alternative proxies for institutional quality change: (i) land concentration, captured by a land Gini index, and (ii) property rights insecurity, represented by the proportion of squatters. The concentration of land aims to proxy *de facto* political and economic power, which could be concentrated in a small elite within the municipalities and, therefore, be correlated with extractive institutions (Naritomi, Soares, and Assunção 2012) and deforestation. On the other hand, the insecurity of property rights captures weak enforcement institutions that could lead to greater land use conflicts and expropriations, reducing incentives for forest conservation (Araujo et al. 2009). Our results indicated that higher land concentration and property rights insecurity are related to higher rates of forest clearings. However, the results also suggest that this relationship may hide potential heterogeneous outcomes because higher property rights insecurity is related to lower deforestation rates in the Cerrado biome.

Fifth, we also propose a test to further explore if our results are being driven by how the sample is composed. First, we constructed samples based on the county's re-

[4]See Elhorst (2014) for more details

[5]Following J. A. Robalino and Pfaff (2012), we also model spatial effects by instrumentalizing average deforestation in neighboring municipalities using neighbors' slopes and neighbors' slopes since they affect deforestation decisions but are not influenced by confounder variables. However, the slope instruments were not statistically significant, which rendered the estimates invalid for further analysis.

[6]We subtracted the municipality forest change from the country's mean and divided it by the standard deviation.

maining forest percentage. The results indicated that the forest threshold chosen made the institution coefficient unstable and was not statistically significant for samples with 20% remaining forest or more. This empirical evidence shows that our results are driven by the remaining forest stock in the initial period. In addition, the institutional quality interaction with the biomes indicators also changed, indicating that even the biomes heterogeneity is driven by the remaining forest stock at the municipality level.

Finally, we estimate the instrumental Causal Random Forest and then compare its results with our previous classical IV approach to check the potential contributions that the adoption of this novel method could bring to the debate. The estimations resulted in a mean Conditional Average Treatment Effect (CATE) and standard deviation that is qualitatively consistent with the classical IV approach. However, when considering the local estimates, 1398, 3975, and 594 were statistically significant and positive and only 77, 18, and 0 negative for the institutional quality change, land gini index, and property rights insecurity, respectively; which indicate that increases in those institutional proxies lead to higher deforestation rates in a significant sample of Brazilian municipalities. In addition, this empirical evidence contradicts our benchmark results from the classical IV, which supported that institutional quality changes in the Cerrado and Atlantic Forest were negative and statistically significant. In other words, the instrumental random forest was able to reveal important hidden heterogeneous causal effects for the institutional variables and demonstrate that it can bring up important hidden treatment effect heterogeneity that traditional methods may not.

These results stress the importance of paying attention to local heterogeneity and that average effects might be misleading. Therefore, this empirical evidence is important for a better understanding, design, and targeting of public policies that aim to control and curb deforestation. Our main results support that increases in institutional quality are leading to higher deforestation in many Brazilian municipalities. In addition, increases in the concentration of land (Gini Index) and in the proportion of squatters also lead to higher deforestation rates. Therefore, the results for these institutional proxies demonstrate that the causal effect of local institutions on deforestation can be mixed because institutional improvements can result in higher or lower deforestation rates depending on what dimension of the institutional arrangement is being considered. In other words, this paper demonstrated that better public administration in the municipality results in higher deforestation while less concentration of land and of squatters in the municipality reduce deforestation rates.

Therefore, our overall results support the hypothesis that local institutional change does have a significant and robust heterogeneous causal impact on deforestation in Brazil and that its direction is unclear and dependent on the institutional characteristic. Our work contributes to the literature in three directions. First, it is related to a growing literature that addresses the relationship between institutions and the environment (Ostrom 1990; Fredriksson, Matschke, and Minier 2010; Cabrales and Hauk 2010). Second, it is also associated with papers that specifically assess the impacts of local governments on forest conservation (Lemos and Agrawal 2006; Ribot, Agrawal, and Larson 2006; Sills et al. 2015; Marchand 2016; Larcom, van Gevelt, and Zabala 2016; Wehkamp et al. 2018; Fischer, Tamayo Cordero, et al. 2021). Finally, it relates to the tropical deforestation literature that aimed to further understand the causes of forest clearings in Brazil (Arima et al. 2014; Cisneros, Zhou, and Börner 2015).

The remainder of this project is organized as follows. Section 2 describes the theoretical framework between institutions and the environment, especially deforestation, in addition to its possible spatial interactions and heterogeneous patterns. Section 3 details the proposed methodologies and database, while the research results are outlined in Section 4. Finally, the robustness checks, heterogeneity tests, and conclusions are given in Sections 5, 6, and 7, respectively.

2 Theoretical Framework

2.1 Institutions and the environment

Despite its relevance, the relationship between institutions and deforestation remains an open debate (Choumert, Combes-Motel, and Dakpo 2013; Greenstone and Jack 2015;

Busch and Ferretti-Gallon 2017; Wehkamp et al. 2018; Polasky et al. 2019; Fischer, Giessen, and Günter 2020), in particular, because it involves endogenous mechanisms that act, to a large extent, through socioeconomic and political channels that hinder identification (Cropper and Griffiths 1994; Arrow et al. 1995; Pamayotou 1997; Bhattarai and Hammig 2001; Bhattarai and Hammig 2004; Dasgupta et al. 2002; A. B. Chimeli and Braden 2005; Van and Azomahou 2007; A. Chimeli 2007; Culas 2007; Culas 2012; Busch and Ferretti-Gallon 2017).

However, institutional improvements have been seen as an important way to reduce deforestation, especially in tropical forests (Fischer, Tamayo Cordero, et al. 2021). In general, weak institutions make it difficult for local governments to enforce laws and implement conservation policies effectively. In this context of the absence of the government and lower institutional quality, illegal activities and informational asymmetry are greater, which can lead to forest clearings Sohag, Gainetdinova, and Mariev 2023. In other words, local institutions shape the impact of conservation policies (Bonilla-Mejía and Higuera-Mendieta 2019). In this context, institutions are an underlying cause of deforestation, a fundamental force that underlies the proximate determinants by creating incentives for the behavior of agents (Larcom, van Gevelt, and Zabala 2016; Fischer, Tamayo Cordero, et al. 2021). However, the relationship between local institutions and deforestation is complex and context-specific (Wehkamp et al. 2018; Bonilla-Mejía and Higuera-Mendieta 2019). It often involves complex feedback mechanisms that act to a large extent through socioeconomic, historical, and political channels, making it difficult to infer causal effects.

Marchand (2016) supports that colonial heritage led to institutional persistence that shaped current institutions, creating different patterns and incentives for deforestation. In practice, institutional quality often plays a key role in smoothing out potential trade-offs of the structural transformation process, especially in the early stages of development when the impact of economic growth is greatest (Cropper and Griffiths 1994; Arrow et al. 1995; Pamayotou 1997; Bhattarai and Hammig 2001; Bhattarai and Hammig 2004; Dasgupta et al. 2002; A. B. Chimeli and Braden 2005; Van and Azomahou 2007; A. Chimeli

2007; Culas 2007). However, it is important to highlight that the impact of institutions on environmental quality is unclear. According to A. B. Chimeli and Braden (2005) and A. Chimeli (2007) show that environmental quality may increase or decrease with institutional improvements, especially in early stages of economic development, because it may affect Total factor productivity (TFP), the efficiency of spending on environmental protection or pollution intensity of capital

The evidence for deforestation is mixed and varies between regions and countries (Marchand 2016. Furthermore, forest conversion has many irreversible components, such as loss of biodiversity and species extinction, so institutional development may be insufficient to achieve environmental restoration. Therefore, the relationship between institutions and deforestation is difficult to generalize, which reinforces the need for specific investigations (Bhattarai and Hammig 2001; Bhattarai and Hammig 2004; Van and Azomahou 2007; Jusys 2016). In developing countries, in particular, forest clearings usually follow a boom and boost pattern if institutions do not create incentives for the preservation of the environment. Without the right incentives, the extraction of wood and forest products and land use conversion to agricultural and cattle production allows rapid economic growth, but, after a period, with the growing scarcity of forest areas and decreased soil fertility, the pace of economic development may slow down or even reverse (Hartwick 1977; Weinhold, Reis, and Vale 2015; Caviglia-Harris et al. 2016).

Spatial spillovers and heterogeneous patterns usually change the relationship between institutions, economic development, and environmental quality. For example, increased economic activity, especially in agricultural frontier regions where law enforcement is weak, generates agglomeration and externalities effects that attract labor and capital, which could boost environmental degradation (Choumert, Combes-Motel, and Dakpo 2013; Pfaff and J. Robalino 2017). Deforestation, in particular, is affected both directly and indirectly by the decision of neighbors and by spatially correlated unobservables, altering the balance between economic development and forest conservation (J. A. Robalino and Pfaff 2012). This process occurs mainly through three channels: i) Input Reallocation: economic agents, when faced with restrictions on land use, can reallocate capital and labor; ii) Market Prices: leakage effects arising directly from market conditions for agricultural and forestry products along with capital assets and labor. iii) Learning: Technology learning and adoption are affected by information networks (Pfaff and J. Robalino 2017).

In addition, the relationship between institutions and environmental quality can vary with historical, economic, and environmental differences, highlighting the need to consider heterogeneous responses and non-linearities (Koop and Tole 1999; List and Gallet 1999; Van and Azomahou 2007). In deforestation, this phenomenon potentially reflects differences in historic experiences, intrinsic environmental characteristics, and/or dynamics among the regions with forest clearings reflecting local conditions (Barbier and Burgess 2001).

2.2 Brazilian regions, biomes, and institutions

Brazil is one of the largest countries in the world with a territory of approximately 851 Mha and is also one of the richest countries in biodiversity in the world. It holds a significant portion of the planet's natural resources and plays an important role in regulating the global climate. The country has six biomes: Amazon 419 Mha (49,29%), Cerrado 203 Mha (23,92%), Atlantic Forest 111 Mha (13,04%), Caatinga 84 Mha (9,92%), Pampa 17 Mha (2,07%) e Pantanal 17 Mha (1,76%). These biomes have large stocks of carbon, biodiversity, and the largest reserve of fresh water in the world.

However, deforestation, forest fires, and environmental degradation, especially in the Amazon, have caused concern due to irreversible losses of its natural resources, biodiversity, emission of greenhouse gases, and the emergence of diseases (Ferrante and Fearnside 2019). For example, the forest area covered approximately 70.5% of the Brazilian territory in 1985 but was reduced to just over 60% in 2017, with the Amazon concentrating 41.8% of deforestation and the Cerrado 33.8%. The Atlantic Forest, in turn, is the biome that has undergone the most changes in land use and cover due to its older occupation (Souza et al. 2020).

The expansion of the agricultural frontier in Brazil is an important driver of deforestation, resulting from an increase in the demand for agricultural and forest products. However, it often promotes local economic growth and poverty alleviation in regions with lower development, such as the Amazon and Matopiba[7], highlighting potential trade-offs. The decision of land users to convert forest areas to farmlands is usually driven by cattle and high-value crops, such as soybeans and corn (Assuncao, Gandour, and Rocha 2015; Bustos, Caprettini, and Ponticelli 2016; Araújo et al. 2019). In this context, the implementation of protected areas is often adopted as a conservation policy to inhibit deforestation, although with mixed results, especially due to leakage, spatial spillovers, and location bias (P. J. Ferraro and Hanauer 2014; Amin et al. 2019). Command and control policies were also important to curb Brazilian deforestation by increasing enforcement of conservation laws (Hargrave and Kis-Katos 2013; Assuncao, Gandour, and Rocha 2015). Finally, it is important to mention that the literature, in general, supports heterogeneous patterns and spatial spillovers in Brazilian deforestation (Jusys 2016; Faria and Almeida 2016; Amin et al. 2019).

It is also important to note that a significant part of Brazil's land is public and faces land tenure insecurity, especially in the Amazon biome, which frequently drives higher rates of deforestation, illegal occupations, expropriations, and violence (Alston, Libecap, and Mueller 2000; Araujo et al. 2009; Hargrave and Kis-Katos 2013). To make matters worse, in this context, international trade plays an important and ambiguous role in determining deforestation patterns, because, on the one hand, it creates incentives for agricultural frontier expansion (Faria and Almeida 2016) while, on the other hand, can contribute to forest conservation by generating alternative economic opportunities (Lopez and Galinato 2005). In this context, national and local institutions play a key role in environmental sustainability, primarily for common property resources such as forests by creating incentives for conservation and law enforcement (Polasky et al. 2019).

Despite the existence of common macro-institutions, many components vary significantly across the country due to colonization heritages and geographical differences. There were no complex societies before colonization in Brazil, which made institutional

[7]Matopiba is the agricultural frontier in the Cerrado biome located in Maranhão, Tocantins, Piauí, and Bahia.

arrangements strongly associated with the colonization process along with climate and geographical conditions. The country was a Portugal colony from 1500 to 1822 and its colonization took place mainly through different extractive economic cycles, such as the sugarcane and gold cycles, which varied in their institutional characteristics. The sugarcane was the first major economic boom cycle in Brazil; occurred mainly on the Northeast coast side and was characterized by monoculture plantations based on slave labor. In this context, economic and political power was concentrated in a small elite with the Metropolis focusing on establishing rules to extract revenue from the colony, making institutions unequal and extractive (Menezes-Filho et al. 2006; Naritomi, Soares, and Assunção 2012; Nakabashi, Pereira, and Sachsida 2013).

Next, in the gold economic boom, Portugal also established a series of regulations to extract income from mining activity. However, despite their efforts, fraud was constant, which induced the Metropolis to adopt increasingly aggressive regulations and control mechanisms, resulting in a highly antagonistic environment between the public institutions and civil society. On the other hand, despite the widespread use of slaves, society was not as polarized as in the sugar cycle, because technologies and the scale of production allowed slaves to gain bargaining power due to the informational asymmetries present in the mining activity. Therefore, the disparities in institutional development between Brazilian municipalities can be traced back to these colonial origins and differences, which, in turn, are not related to the current deforestation Naritomi, Soares, and Assunção 2012.

3 Empirical Design

3.1 Data

To estimate the effect of local institutions on forest clearings, we used data at the municipality level covering the country's 5,570 municipalities. Our outcome variable is forest change in the 2005-2015 period from the annual maps of land cover and land use released by MapBiomas, which uses images from Landsat satellites with 30 meters pixel resolution to estimate land use changes. The initiative was formed in 2015 and covers all the Brazilian biomes.

However, municipalities in Brazil are very different in terms of their area, which could bias our results. Therefore, to overcome this, we divided our variable of interest by the municipality area, which resulted in the percentage of forest change in the period. In addition, we propose two robustness checks: (i) alternative normalization for our outcome variable; (ii) restrict our sample to municipalities with at least 10% and 20% of remaining forest. In addition, we explored potential heterogeneity in forest dynamics by considering forest gain and loss separately. In other words, this paper seeks to contribute to the conservation debate by including dynamics beyond primary forest loss, since the literature has few papers on forest regrowth (Busch and Ferretti-Gallon 2017; P. Ferraro and Simorangkir 2020).

To measure institutional quality change, we created an institutional quality indicator with Principal Component Analysis (PCA) based on Leão et al. (2020) for 2005 and 2015, which seeks to represent the quality of the public administration in the municipalities. The information used comes from the *Pesquisa de Informações Básicas Municipais (MUNIC)* from the Brazilian Institute of Geography and Statistics (IBGE). It is worth mentioning that the variables that make up the indicator are based on the municipalities' normative attributions granted by the Federal Constitution of 1988. However, many Brazilian municipalities have not yet been able to comply with these requirements, or have done so with poor quality, which creates cross-section variation that can be explored. The institutional quality indicator reflects the municipalities' administrative capacity, ranging from tax collection to administrative and planning instruments. Additional information is presented in Appendix A.

It is important to highlight that the indicator is restricted to the 0-100 range with the highest intitutional quality municipality with 100 and the lowest with 0. Therefore, the indicator reflects a relative position and, for example, it is possible that some particular municipality improved its institutional quality but has a negative absolute change in the 2005-2015 period its indicator if it increased less than others. To check how the institutional quality changed in the 2005-2015 period, we constructed a standard deviation map (Figure 1). We can note that there is a high concentration of municipalities in the North and Central-West regions (where the Amazon and Cerrado biomes predominate, respectively) that performed relatively worse than municipalities in other regions.

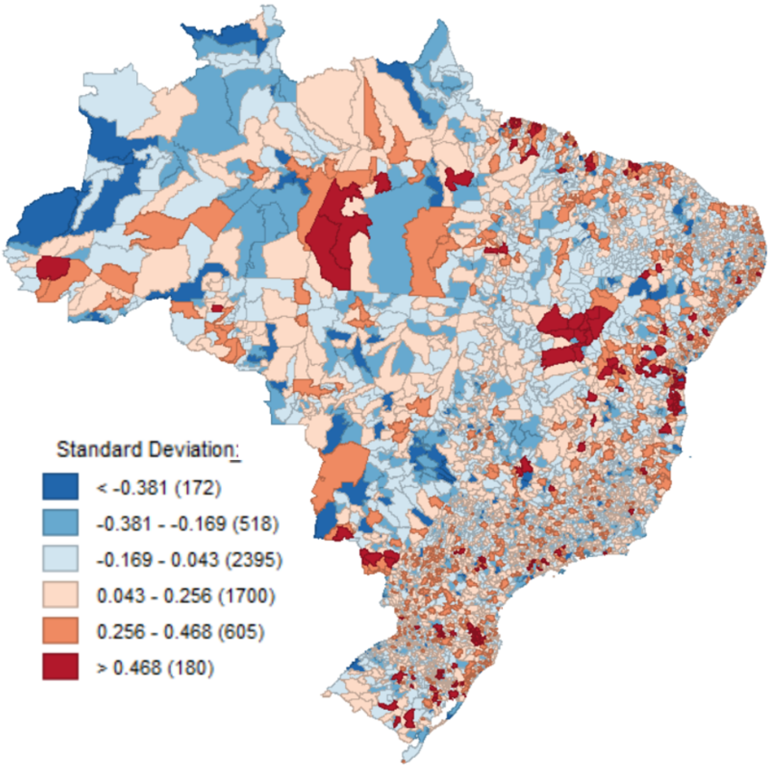

Figure 1: Institutional quality change (2005-2015).

To construct our distance instruments, we used spatial vector data to build specific variables to this empirical design. First, we used the municipalities centroids to measure the linear distance to (i) the metropolis, which we considered the Lisbon centroid, the capital of Portugal, and (i) to the coast. The shapefiles of the municipalities, the Lisbon and the Brazilian are available in the *Instituto de Geografia e Estatística (IBGE)*. Next, we constructed a variable that measure the linear distance from the municipalities centroid to the nearest colonial villages, which are the urban districts created in the colonial period (between 1500 and 1822). The data come from the Digital Atlas of America Lusa built by the University of Brasilia (UnB). The socioeconomic variables from the first Brazilian census of 1872 at the state level are also from IBGE. Finally, for the sugar and gold booms, we created two binary variables that assigned one for municipalities founded in regions affected by the economic cycles before its end; and zero otherwise.

The rainfall and temperature data are the average values from the 1961 to 1990 period, available in the Climate Research Unit from the University of East Anglia (CRU-UEA). For soil quality, we constructed a variable using the Map of Brazilian Agricultural Potential compiled by the Brazilian Institute of Geography and Statistics (IBGE) and made available by the Ministry of the Environment. The Brazilian territory was classified according to the agricultural potential of its soils, considering: fertility, physical and morphological characteristics, main limitations, and topography. The altitude and neighbors' slopes are constructed with the Land Elevation Data from NASA's Shuttle Radar Topography Mission (SRTM). The forest stock is the remaining forest percentage in 2005, previous to our considered period to avoid endogeneity and simultaneity problems. It is worth mentioning that we used raster and vector spatial models in R to construct the variables for each municipality in the country.

3.2 Identification strategy

We propose to estimate the causal effects of institutional quality change on deforestation. However, there are some challenges to achieving this goal. The simultaneity and endogeneity problems associated with institutions and deforestation make it difficult to assess a causal relationship, prompting the need for a source of exogenous variation to instrumentalize institutional quality change. In this context, since institutional inertia perpetuates initial differences in institution development (Acemoglu, Johnson, and Robinson 2001; Engerman and Sokoloff 2002; Dell 2010; Marchand 2016; Easterly and Levine 2016), we use different experiences of colonization as a source of exogenous variation in institutional quality to estimate its impact on deforestation.

We support the hypothesis that institutional differences between Brazilian municipalities are based on two basic assumptions: (i) colonization policies among Brazilian regions largely reflected different economic cycles and geographic characteristics that, in turn, resulted in institutional quality differences at the municipal level; (ii) institutional quality inertia so that initial differences in institutional quality perpetuate over time, impacting current changes. In addition, it is worth mentioning that municipalities are the smallest political and administrative units in Brazil and despite having a homogeneous formal role, there are still significant differences in institutional quality between them, both in terms of administrative quality and public goods provision. For example, municipalities have administrative autonomy, can collect some taxes, and decide on specific spending on education, health, and infrastructure.

Therefore, since land use changes, market conditions, and governance can impact both institutional development and clearings, this paper considers institutions as endogenous and, therefore, proposes a two-stage estimation, using different experiences of colonization as a source of exogenous variation to instrumentalize current institutions' quality growth differences. In this sense, we exploit differences at the municipality level related to colonial experience and geographical differences. As suggested by Menezes-Filho et al. (2006), Naritomi, Soares, and Assunção (2012), and Nakabashi, Pereira, and Sachsida (2013)), we use distance (in kilometers) to the coast, to the metropolis (Portugal), and to colonial villages to capture effective colonial interference. These variables reflect the higher administrative and trade costs that ultimately determined the degree of Metropolis intervention in the colony. Next, we constructed a binary variable that indicates if the county was founded during the sugar and gold booms to capture different institutional heritages that arise from these extractive economic cycles. We also used socioeconomic differences from the first Brazilian Census of 1872 at the state level: proportion in the population of literate, slaves, white, foreigners, and liberal professionals. We expect these baseline variables to be related to the evolution of institutions but not the current deforestation. Our first-stage equation is the following,

$$\Delta Institutions_i = \beta_0 + \beta_1 Z_i + \delta Controls_i + u_i \tag{3.1}$$

where Z_i is the instruments listed above; $\Delta Institutions_i$ is the change in the local institutional quality indicator between 2005 and 2015, and u_i is the error term. Our second stage equation is given by:

$$\Delta Deforestation_i = \beta_0 + \beta_1 \Delta Institutions_i + \delta Controls_i + \varepsilon_i \tag{3.2}$$

where $\Delta Deforestation_i$ is the forest cleared at municipality i between 2005 and 2015; ε is the error term. Therefore, we also eliminate the potential fixed effects that could compromise our exclusion restriction by estimating a first difference model between 2005 and 2015[8] at the municipality level. In other words, we propose to exploit differences in settlers' experiences to isolate the causal relationship between local institutional change and deforestation in Brazil.

To further support our exclusion assumption, we control for possible geographic confounders that may affect both deforestation and instruments. The geographic controls are composed of temperature, precipitation, soil quality, altitude, and forest stock, which capture remaining geographical differences that may affect local institutional development and clearing patterns. For example, these variables can affect road construction and maintenance, along with the potential for agricultural productivity, affecting both deforestation and colonization patterns (Chomitz and Thomas 2003), which would invalidate our exclusion hypothesis. The identifying assumption is that conditional on these local characteristics, instruments have no other effect on the deforestation patterns than through the institutional quality channel. However, it is important to highlight that the literature suggests that the causal effect of institutional quality on forest clearings is heterogeneous. For this reason, we propose, in the next section, to use an ad hoc method, the instrumental causal random forest, to search and estimate potential heterogeneity.

3.2.1 Causal Random Forest

The search for potential heterogeneous treatment effects and for by what mechanisms it occurs are important in the formulation and design of public policies. However, the

[8] We limited the empirical analysis for 2005 and 2015 due to data incompatibilities for other years to construct the local institutional quality indicator,

estimation of heterogeneous effects is an empirical challenge, as the most common methods usually require a pre-specification of how the effects occur either through variable interaction with a heterogeneity indicator, or through subgroups from the initial sample. Both approaches require ad hoc hypotheses, which can lead to biased inferences. In this context, advancements in the literature have been combining traditional causal inference methods with machine learning algorithms to disentangle heterogeneous outcomes. In this paper, we highlight Athey and Imbens (2016) and Wager and Athey (2018) who proposed a causal Random Forest that allows an estimation of the treatment effect for different subgroups and does not require ad hoc hypotheses, as it iteratively partitions the data based on the treatment effect. Therefore, the algorithm allows a parsimonious way to estimate sources of treatment effect heterogeneity that is robust in out-of-sample validation, while avoiding problems with multiple hypothesis tests. Athey, Tibshirani, and Wager (2019) generalized the method to estimate a local conditional treatment effect with binary and continuous instrumental variables and Biewen and Kugler (2021) further confirmed its applicability for multiple instrumental variables.

Athey, Tibshirani, and Wager (2019) considered the following structural equation that relates the outcome variable Y_i with the treatment W_i,

$$Y_i = \mu\left(X_i\right) + \tau\left(X_i\right) W_i + \varepsilon_i$$

(3.3)

where $\tau\left(X_i\right)$ is the causal effect of W_i on Y_i and ε_i is the error term that may be related with the treatment variable, which could invalidate potential causal claims for the estimations. In this context, we can use instrumental variables Z_i that are related to the treatment variable W_i but not with the error term ε_i. Then, the authors shows that is it possible to derive a forest that estimates a causal effect $\tau(x) = \operatorname{Cov}\left[Y_i, Z_i \mid X_i = x\right] / \operatorname{Cov}\left[W_i, Z_i \mid X_i = x\right]$ through a conditional two-stage least squares estimated via moment functions $E\left[Z_i\left(Y_i - W_i\tau(x) - \mu(x)\right) \mid X_i = x\right] = 0$ and $E\left[Y_i - W_i\tau(x) - \mu(x) \mid X_i = x\right] = 0$. For further estimation details, see Athey, Tibshirani, and Wager (2019).

The Causal Random Forest algorithm uses a modified version of regression trees, which are characterized by being flexible and non-parametric, for automated subgroup selection. The regression trees split the sample into subgroups in which treatment effects are estimated, however, in this causal context it is not possible to use the traditional mean squared error (MSE) metric to construct the tree leaves because the counterfactual value is not observed. The partition is chosen based on the minimization of the Expected Mean Squared Error (EMSE) between the estimated treatment effect and its true value. The authors propose an honest approach in which it separates the training sample into two; one to determine the tree splits and another to estimate the predicted value, avoiding model overfitting in which the predictions performed poorly out-of-sample. Then, it averages the predictive values over many causal trees to create a Causal Random Forest that is pointwise consistent for the true treatment effect and has an asymptotically Gaussian and centered sampling distribution.

4 Results

4.1 First Stage

To check our hypothesis that different colonial heritages resulted in distinct long-run institutional development along the Brazilian regions, we considered the first stage estimation, in Table A2 in the Appendix. To further support our results and exclude threats to our exclusion restriction, we control for geographical variables that may be related to both deforestation and local institutions: soil quality, altitude, annual precipitation, remaining forest area, and dummies for the main biomes in Brazil; Amazon, Cerrado, and Atlantic Forest. To check the robustness of our instruments, we added controls gradually, which resulted in six specifications.

All instruments are statistically significant in specifications (1) to (6), except the

Sugar Boom and its interaction with distance to Portugal. This result supports our main hypothesis that different historical heritages resulted in different local institutions in Brazil. In addition, the F statistic is statistically significant in all specifications, confirming the relevance of the instruments and reinforcing the validity of our empirical approach. In general, as the distance between Portugal and colonial villages increases, institutional quality became better, which supports our hypothesis that a higher control from the Metropolis and the colonial authorities resulted in forces that did not favor local institutions in the long run, leading to lower institutional quality growth today. In addition, the literate population proportion in 1872 also led to higher current local institutional quality development, indicating that education had an important long-run impact in Brazil.

On the other hand, higher distance to the coast is negatively correlated with institutional quality growth today. This evidence supports the hypothesis that institutions located in regions distant from the coast are relatively weaker, which may reflect differences in the colonial experiences, institutional heritages, and occupation of the territory. For example, the coast concentrated most of the Brazilian population until the construction of Brasília, the country's new federal capital in the 1950s. The proportion of slaves in the population in 1872 is also negatively correlated with the institutional development today. Considering that Brazil received the largest number of slaves from Africa and was the last in the West to ban slavery, our results support the long-standing negative impacts of enslavement on the institutions.

4.2 Second Stage

Considering the consistency of our results and the empirical support provided to our exclusion hypothesis in the first stage, we used a Two Stage Least Square (2SLS) approach to identify the causal impact of local institutional quality change on deforestation at the municipality level (Table 1). Similar to the first stage, we included geographical controls to further support our findings. In addition, since deforestation may be sensitive to heterogeneous outcomes, the average effect from the two-stage estimation may not be equal across different ecosystems, varying for different biomes. In this context, we exploit our empirical design to access these potential sources of heterogeneity and test whether local institutional quality growth has differential effects across different ecosystems.

We explicitly consider the three biggest biomes in Brazil; Amazon, Cerrado, and Atlantic Forest, respectively. The Amazon, for example, still has most of its territory occupied by native vegetation and is facing intensive agriculture-related land use occupation. On the other hand, the Atlantic Forest is the most degraded biome and densely populated in Brazil. Those factors may create underlying forces that could generate heterogeneous outcomes (Assuncao, Gandour, and Rocha 2015; Araújo et al. 2019). In practice, we include binary variables to control for those ecosystem differences and interact with our variable of interest to decompose potential heterogeneous outcomes of institutional change.

Table 1: Two-Stage Least-Squares Regression

	Dependent variable: ΔDeforestation				
	OLS	IV	IV	IV	IV
	(1)	(2)	(3)	(4)	(5)
ΔInstitutions	0.0001	0.0012	0.0015*	0.0006	0.0034**
	(0.0002)	(0.0008)	(0.0008)	(0.0010)	(0.0014)
Amazon	−0.0004			−0.0012	0.0101
	(0.0084)			(0.0087)	(0.0107)
Cerrado	−0.0062			−0.0068	0.0112
	(0.0067)			(0.0073)	(0.0071)
Atlantic Forest	0.0122			0.0097	0.0336**
	(0.0084)			(0.0111)	(0.0168)
ΔInstitutions*Amazon	−0.0001				−0.0020
	(0.0002)				(0.0015)
ΔInstitutions*Cerrado	−0.0003				−0.0049***
	(0.0002)				(0.0016)
ΔInstitutions*AtlanticForest	0.0001				−0.0039*
	(0.0003)				(0.0021)
Geographic	*Yes*	*No*	*Yes*	*Yes*	*Yes*
Observations	5,027	5,027	5,027	5,027	5,027
Note:	*** Significant at 1%; ** Significant at 5%; * Significant at 10%. Robust Standard Errors				

Our main findings confirmed a positive and statistically significant coefficient for institutions, meaning that local institutional quality growth has a causal impact on deforestation. The results from column 5 suggest a positive impact of institutions on deforestation on average, but a negative impact on the Cerrado and Atlantic Forest biomes. This reinforces the likely heterogeneous nature of the relationship between institutions and deforestation, which might have important implications for policy design.

Therefore, the Two-Stage Least Square (2SLS) estimation, which addressed the potential endogeneity problem arising from institutional development, led to different results when compared to the OLS estimation which does not account for possible confounders. However, to check the robustness of our results, search for additional insights, and overcome potential caveats with our empirical design, we realized several tests to further support our findings, which are presented in the next subsection.

To search for potential sources of bias that could be compromising our estimations, we test the robustness of the results by controlling for additional variables that may be correlated with institutions and deforestation at the municipal level. Table A3 (Appendix) presents the results. We included additional controls associated with socioeconomic features, international markets, macroenvironmental institutions, human capital, and economic development. In summary, our results are stable due to the inclusion of these controls. In other words, the causal effects of the institutional quality change are not confounded by these variables, confirming the robustness of the results and further supporting our empirical design. In this context, we considered the most complete estimation (Column 7) as our new Benchmark model for the next robustness checks.

For socioeconomic characteristics, we considered population density, the proportion of individuals living in rural areas, income inequality, and the Bolsa Familia program. These variables seek to capture population and agglomeration effects, size of the labor and consumer markets, social inequality, and poverty. Next, we created an openness to trade indicator (sum of exports and imports divided by gross domestic product) to control for possible effects arising from international market forces. To control for macro-environmental institutions, we used environmental fines per km2 issued by IBAMA as a proxy. This measure reflects the extent that which command and control policies from the federal government may affect deforestation at the municipality level. Then, we included a proxy for human capital, the average schooling as a proxy, to check if it is related to institutional development.

The data source for population density, rural population, inequality, and human capital comes from the 2000 demographic census carried out by *Instituto Brasileiro de Geografia e Estatística* (IBGE). It was conducted through direct interviews with the Brazilian population at the municipal level. The data from environmental fines comes from IBAMA (*Instituto Brasileiro do Meio Ambiente e dos Recursos Naturais Renováveis*). Finally, the data for Bolsa Familia and openness to trade comes from the Institute of Applied Economic Research (*Instituto de Pesquisa Econômica Aplicada*), IPEA.

Finally, we control for differences in the total visible night light emitted by the earth's surface, which is an important proxy for economic activity. This is supported by the fact that light is a normal good, that is, as income increases, the demand for lighting grows, reflecting a higher level of economic development (Henderson, Storeygard, and Weil 2012). The data is from the 2005 DMSP-OLS Nighttime Lights Time Series, which is a cloud-free composite from the Operational Linescan System (OLS) of the Defense Meteorological Satellite Program (DMSP) satellites operated by the National Oceanic and Atmospheric Administration (NOAA). The pixels from the image are 1 km wide, therefore, we calculated the mean value for each municipality considering all pixels that fall within its borders. In the next subsection, we considered potential spatial interactions and spillovers from deforestation.

4.3 Spatial Interactions and Spillovers

Spatially correlated unobservables and neighbors' interactions in deforestation decisions may affect both clearings and institutional performance and lead to leakage effects, invalidating our exclusion restriction and impact valuation (J. A. Robalino and Pfaff 2012; Baylis et al. 2016; Pfaff and J. Robalino 2017; Busch and Ferretti-Gallon 2017). In this context, it is important to include the average deforestation in neighboring municipalities to control for these potential spatial effects. However, to measure such between-municipalities spatial effects, we need to consider the endogenous nature of the problem. To overcome this caveat, we estimated a Spatial Autoregressive Model (SAR) from the spatial econometric literature[9], which use the average of the neighbors' characteristics

[9]For additional information about the spatial econometric literature, see (Elhorst 2014)

as instruments (WX). However, first, it is necessary to define a neighborhood criterion, which, in this paper, we used a k-nearest neighbor's spatial weight matrix W based on whether the municipalities share borders.[10]

In addition, we also instrumentalized neighborhood deforestation using neighbors' slopes and neighbors' neighbors' slopes, using the first stage in our identification strategy

$$WDeforest_i = \beta_0 + \beta_1 Neigh.Slopes_i + \beta_2 N.Neigh.Slopes_i + \delta Controls_i + u_i \quad (4.1)$$

$Neigh.\ Slopes_i$ and $N.Neigh.\ Slopes_i$ are the neighbors' slopes and neighbors' neighbors' slopes; $WDeforest_i$ is the weighted neighbors' deforestation defined from a neighborhood criterion. However, the empirical results do not support that the deforestation in the neighborhood is correlated with its terrain slopes, which invalidates these instruments. In this context, although we considered an exogenous source of variation, we were not able to isolate the effect of spatial interactions and spillovers from concurrent confounders and endogenous mechanisms. On the other hand, the instruments for the SAR model were statistically significant, which makes this model more suitable to further consider the potential effects of spatial spillovers on the relationship between deforestation and institutions. Therefore, we use the SAR model as our benchmark spatial model for further analysis. The results are outlined in Table A4 (Appendix).

The benchmark SAR results confirmed that spatial interactions and spillovers, which presented a positive and statistically significant coefficient, are important in explaining forest clearing decisions at the municipality. Although we can not directly decompose the channels that the interactions and spillovers operate, it captures potential impacts from input reallocation, leakages, market prices, technology learning, and social interactions, which could confound our results. Our outcomes of interest, the local institutional indicator, remained statistically significant, further supporting that it has a heterogeneous causal impact on deforestation.

In the next section, we exploit our empirical approach to search for potential biases

[10] In this paper, we choose the k-neighborhood based on the Akaike Information Criterion.

arising from alternative standardization procedures that could be misleading our results.

4.4 Alternative Standardisation

The standardization technique that we chose for our outcome variable, forest change (ha) divided by the municipality area (ha), which resulted in the percentage of forest change in the 2005-2015 period, could also be driving our empirical results. Therefore, in Table A5 (Appendix), we re-estimated our benchmark results by using alternative standardization techniques. We considered three additional standardization procedures: (i) the normalized deforestation constructed by subtracting the municipality forest change from the country's mean and diving it its standard deviation; (ii) the hectares of forest change divided by the municipality area in km^2 (ha/km^2); and forest change (ha) divided by the remaining forest stock (ha) in the initial period (2005).

The results for Columns (1) to (3) support the robustness of our identification strategy since the institution's coefficient remains statistically significant. In other words, our main results are not driven by the method of standardization adopted and the sample used. However, the institution's coefficient is not robust when our dependent variable is the percentage of forest change; only its interactions with Cerrado and Atlantic Forest are statistically significant. These empirical results indicate that institutional quality change in the Cerrado and Atlantic Forest biomes has a consistently negative causal effect on deforestation. Meanwhile, in the Amazon and the remaining biomes of Brazil, the impact is positive or not robust. Therefore, the results further support that institutional quality change has a causal effect on forest clearings after considering heterogeneity in biomes characteristics. However, it is worth mentioning that column (4) indicate that our results may still hide potential heterogeneous outcomes arising from the different remaining proportion of forest stock in the municipality. Therefore, in the next section, we realized a heterogeneity test to explore if different sample compositions related to remaining forest stock change our main results.

4.5 Alternative Institutional Indicators

Finally, we used two different proxies for institutional quality change to test the robustness of our results: (i) land distribution and (ii) property rights insecurity. The distribution of land aims to proxy *de facto* political and economic power, which could be concentrated in a small elite within the municipalities and, therefore, be correlated with extractive institutions (Naritomi, Soares, and Assunção 2012) and deforestation. On the other hand, the insecurity of property rights captures weak enforcement institutions that could lead to higher land use conflicts and expropriations, reducing incentives for forest conservation (Alston, Libecap, and Mueller 2000; Araujo et al. 2009). We constructed a land Gini coefficient to represent the land distribution and the proportion of land occupied by squatters to capture insecurity in property rights. To construct both variables, we used the 2006 and 2017 Brazilian Agricultural Census. It is worth mentioning that all regressions were instrumentalized in a two-stage estimation as in the benchmark regressions for the institutional quality change indicator. The results are in Table A6 (Appendix).

We can note that the proxies for institutional quality change, Land Gini (2) and Squatters (3) are positive and statistically significant, indicating that higher land concentration and propriety right insecurity lead to increasing rates of forest clearings. On the other hand, by considering biome heterogeneities on land concentration and property right insecurity, Land Gini (5) became statistically insignificant while Squatters (5) remained positive and statistically significant and its interaction with the Cerrado biome indicator was negative and statistically significant. Therefore, land concentration and property rights insecurity changes are in general associated with higher deforestation levels in Brazil, except property rights insecurity in Cerrado which is negatively associated with deforestation, suggesting potential heterogeneous outcomes for the causal effects of institutional quality changes on forest clearings in Brazil. In this context, we propose additional heterogeneity tests in the next section to further explore our results.

4.6 Alternative Sample Compositions

To show that the heterogeneous effects that we estimate for the percentage of forest change at the municipality level are indeed the causal impact of institutional quality change, we further estimate a series of regressions that considered the remaining forest stock to construct the samples used. The results are in Table A7 (Appendix). This test indicates that our results are driven by the remaining forest stock at the municipality in the initial period. In other words, the coefficients change according to the remaining forest stock threshold chosen to create the sample. In samples with municipalities with higher forest stock, the institutional quality coefficient turned to be unstable and not statistically significant, and even became negative for densely forested counties - more than 50% of forest area. Its interaction terms also changed with sample composition, indicating that the heterogeneous effects are also related to the forest stock.

5 Causal Random Forest

The instrumental Causal Random Forest estimates a local Conditional Average Treatment Effect (CATE) for each unit in the sample, which, in our empirical approach, resulted in a coefficient for each municipality in Brazil. In summary, the estimations indicated that the mean CATE is 0,000499 with 0,002375 of standard deviation. These results are qualitatively in line with our benchmark estimates that in general presented a positive estimate for institutional quality, but with a significant variance. Exploring this result shows that 1,833 municipalities presented a negative coefficient and 3,199 a positive one, which confirmed a significant heterogeneity for the institutional quality change causal effect on deforestation in Brazil, reinforcing our initial heterogeneity hypothesis and further corroborating with our benchmark results that the causal effect from institutional quality varies significantly within Brazil.

However, it is worth mentioning that only 1,475 (29,31%) of those results were statistically significant; 1398 with a positive coefficient and 77 with a negative one. This empirical evidence contradicts our benchmark results (as in Table A6) that support that institutional quality changes in the Cerrado and Atlantic Forest were negative and statistically significant. Anyway, it is important to remember that previous results pre-specified how the heterogeneous causal effect could occur by interacting the institutional variable with a biome indicator, but probably heterogeneity exists even within each biome, which may be reflected in the difference between our previous results and the local estimates from the causal random forest.

The fact that we have a Conditional Average Treatment Effect for each municipality in Brazil allows us to plot the results on a map to further explore its spatial distribution in the country. The results are presented in Figure 2. The coefficients that were not statistically significant are represented by zero while the remaining ones are statistically significant with 95% confidence. In summary, we can note that positive changes in the three institutional indicators are generally associated with increases in deforestation rates; only 77 municipalities presented a negative coefficient for the institution quality, 18 for the Gini indicator, and zero for Squatters.

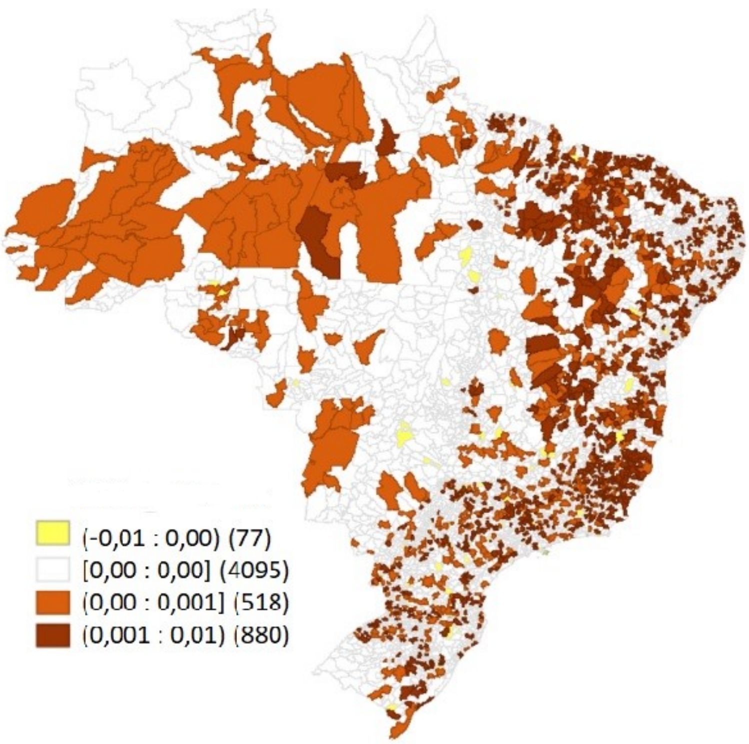

Figure 2: Local Conditional Average Treatment Effect (CATE).

Therefore, the instrumental random forest was able to disentangle a heterogeneous causal effect for the institutional variables and demonstrate that it can reveal important hidden treatment effect heterogeneity that traditional methods may not. The method, by interactively modeling hidden heterogeneity and by not requiring pre-specification of how the heterogeneous effects occur, allows us to get local treatment effects that otherwise would not be possible by using ad doc approaches. In summary, we can note in Figure 1 some degree of spatial concentration for the three institutional variables, especially for institutional quality and Gini coefficient, which is in line with our results from Table A4, where the spatial models confirm significant spatial autocorrelation in our sample. For the institutional quality change variable, the higher positive coefficients seem to be concentrated in the South, Southeast, and Northeast, where the Atlantic Forest and Semiarid biomes are located; while the insignificant coefficients are spatially concentrated in the Midwest, where the Cerrado is the main biome.

To confirm if the local institutional quality change from the Causal Random Forest is spatially concentrated, we estimated the Moran's I and the Local Moran's I[11] for the coefficients. The estimates resulted in a global Moran's I coefficient of 0,0242 that was statistically significant at 1%, confirming the presence of significant spatial autocorrelation in the local coefficients. Next, Figure 3 shows the Local Moran's I Lisa map, which highlights the statistically significant spatial clusters in the data. It is possible to see that Moran's I also confirms local spatial autocorrelation and captures significant heterogeneity with the Low-High spatial cluster being the most representative with 831 municipalities, i.e., counties with low causal effect are surrounded by municipalities with high causal impact.

To further explore our empirical design and check if the patterns found for the institutional quality change indicator also extend to the alternative institutional proxies,

[11]Moran's I is a statistical measure used in spatial statistics to assess the spatial autocorrelation and dependency in geographical data. While Moran's I is a global measure of spatial autocorrelation, local Moran's I seeks local spatial patterns, i.e., whether values at a specific region are locally clustered or dispersed in relation to their neighboring locations, identifying hotspots or coldspots.

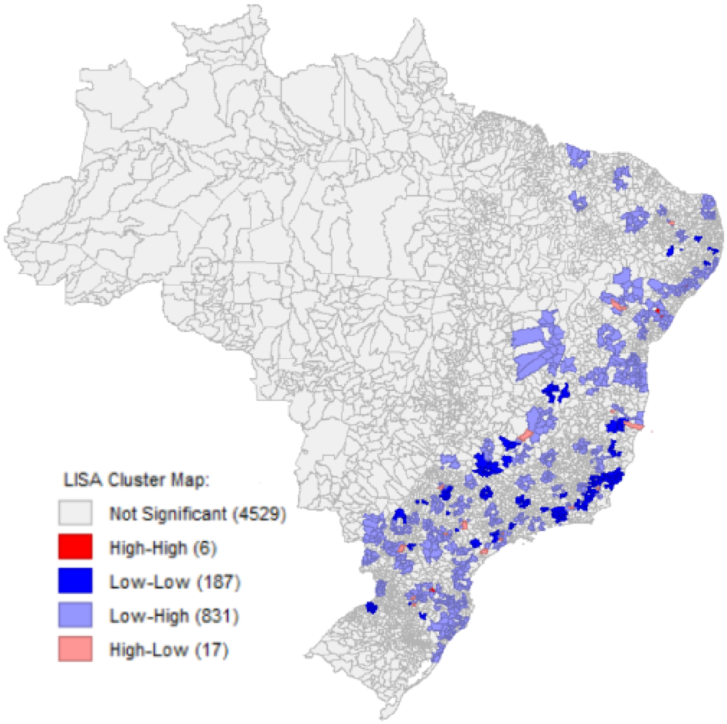

Figure 3: Local Moran's I for the local institutional quality change causal effect.

we also estimated the Causal Random Forest for the Gini and Squatters variables and then plotted the local CATE coefficients and estimated both Moran's statistics. The Gini index presented a mean CATE of 0,03126 and 0,09230 of standard deviation with 3975 being statistically positive and 18 negative. On the other hand, the squatters presented a mean CATE of 0,000682 and 2,924 of standard deviation with 594 positive statistically significant and 0 negative[12] These empirical findings are similar to those presented by the institutional quality variable. In other words, the mean CATE and its standard deviation follow the same pattern as our benchmark results, but when considering the statistically significant local estimates, the majority of the coefficients were positive, contradicting our benchmark results from Table A6 that supported a statistically significant and negative coefficient in the Atlantic Forest for Land Gini and in the Cerrado for Squatters. This fact further reinforces the need for methods that do not adopt ad hoc hypotheses.

Next, Figure 4 in the Appendix shows the local CATE coefficients. In summary, we can also note visually some degree of spatial concentration for these institutional

[12]When considering all coefficients (and not only the statistically significant ones), 4540 are positive and 492 negative for the Land Gini indicator; while 4825 are positive and 207 negative for the Squatters indicator.

variables, especially for Gini coefficient, which is in line with our results from the spatial models that confirmed significant spatial autocorrelation in our sample. Higher positive Gini coefficients are concentrated especially in the Atlantic Forest biome in the South, Southeast, and Northeast. On the other hand, the Squatter variable did not present many statistically significant coefficients in the Amazon biome and also did not show an apparently clear spatial pattern for the other regions. To confirm the presence of spatial autocorrelation, we also estimated the global and local Moran's I. The global Moran's I for the Gini and Squatter presented a statistically significant coefficient of 0.103 and 0.061, respectively. Considering the local Monran's I, the most numerous spatial cluster for Gini was the Low-Low, with 1056 statistically significant spatial clusters, which are concentrated especially in the Midwest, North, and extreme South. The Squatter, on the other hand, presented less variation between the spatial clusters, ranging from 60 municipalities in a Low-Low cluster to 345 in a High-Low. The majority of the High-Low and the High-High cluster are spatially concentrated in the Southeast and South, respectively. Therefore, both local coefficients are also spatially concentrated, supporting our initial hypothesis.

6 Final Considerations

Tropical deforestation is a worldwide concern and Brazil is a significant player in this environmental scenario since it has the biggest active agriculture frontier and the highest tropical deforestation area in the world. The Brazilian Amazon and the Cerrado biomes, for example, are important biological ecosystems with high levels of forest stock and biodiversity, but they have been presenting significant forest clearings in the last decades. In this context, the literature points out that intuitions can play a key role in curbing or increasing deforestation because they create the incentives and rules that economic, social, and political agents operate. However, although it is expected that institutional changes have a significant causal effect on forest clearings, the subject is still an open debate and needs further empirical investigation, especially because the relationship embodies important endogenous and confounding factors that hinder identification.

In this context, this paper aimed to estimate the causal effect of local institutional change on deforestation in Brazil. For that, we specifically constructed an indicator using Principal Component Analysis (PCA) to proxy local institutional quality change and used geographical and historical features as exogenous variations to instrumentalize the relationship and, therefore, estimate a credible causal impact. In other words, we followed the economic development literature that hypothesized that current institutions reflect, to a great extent, geographical and historical events faced by the country's settlers which conditioned initial institutional arrangements and, due to institutional inertia, perpetuated it to the current period. In addition, we searched for potential heterogeneous effects since deforestation is particularly sensitive to local heterogeneity and used alternative institutional proxies, such as land concentration and property rights insecurity.

Our main results confirm that local institutional change has a heterogeneous statistically significant causal effect on Brazilian forest clearings. We also confirm the robustness of this empirical evidence after several tests that aimed to find potential confounding factors that could be biasing the results. We also confirm the causal effect for the alternative proxies tested, which indicate that forest clearings in Brazil are related to institutions in a broader sense. To further explore our identification strategy, we used a Causal Random Forest, an algorithm that estimates a local Conditional Average Treatment Effect (CATE) that is robust in out-of-sample validation. This novel empirical approach indicates that, although there are significant heterogeneous effects between local institutions and deforestation, the majority has a positive causal impact. In other words, increases in local institutional quality, land concentration, and property rights insecurity lead to higher deforestation rates for a significant part of municipalities.

It is worth mentioning that, despite the robustness of our results, our empirical estimates must be considered with caution and future empirical design should consider these potential flaws. First, we used just a few potential institutional features as proxies to estimate the causal effects; local institutions Institutions can take many forms, designs, and arrangements with some characteristics being harder to capture, especially the in-formal ones. Second, the results may reflect only a snapshot of the relationship since our database is limited temporally and regionally. In other words, by further considering different temporal and/or regional settings in future papers, the estimates could change due to changes in structural or local characteristics. Finally, our empirical design considered just a handful of empirical methods and approaches; future research could try additional or newer methods to corroborate or not the results. However, it is important to state the results found in this paper can contribute to the debate by supporting the hypothesis that institutions have a causal impact on deforestation, although with heterogeneous effects. This fact, in turn, is important to show that public policies and institution design must move beyond the average effects and adequately consider potential deforestation side effects and heterogeneous outcomes,

Competing interests:

The author(s) declare(s) none.

References

Acemoglu, Daron, Simon Johnson, and James A. Robinson (2001). “The Colonial Origins of Comparative Development: An Empirical Investigation”. In: *American Economic Review* 91.5, pp. 1369–1401. DOI: 10.1257/aer.91.5.1369.

Alston, Lee J., Gary D. Libecap, and Bernardo Mueller (2000). “Land Reform Policies, the Sources of Violent Conflict, and Implications for Deforestation in the Brazilian Amazon”. In: *Journal of Environmental Economics and Management* 39.2, pp. 162–188. DOI: 10.1006/jeem.1999.1103.

Amin, A. et al. (2019). “Neighborhood effects in the Brazilian Amazônia: Protected areas and deforestation”. In: *Journal of Environmental Economics and Management* 93, pp. 272–288. DOI: 10.1016/j.jeem.2018.11.006.

Araujo, Claudio et al. (2009). “Property rights and deforestation in the Brazilian Amazon”. In: *Ecological Economics* 68.8, pp. 2461–2468. DOI: 10.1016/j.ecolecon.2008.12.015.

Araújo, Mayara Lucyanne Santos de et al. (2019). “Spatiotemporal dynamics of soybean crop in the Matopiba region, Brazil (1990–2015)”. In: *Land Use Policy* 80, pp. 57–67. DOI: 10.1016/j.landusepol.2018.09.040.

Arima, Eugenio et al. (2014). “Public policies can reduce tropical deforestation: Lessons and challenges from Brazil”. In: *Land Use Policy* 41, pp. 465–473. DOI: https://doi.org/10.1016/j.landusepol.2014.06.026.

Arrow, Kenneth et al. (1995). “Economic growth, carrying capacity, and the environment”. In: *Ecological Economics* 15.2, pp. 91–95. DOI: 10.1016/0921-8009(95)00059-3.

Assuncao, Juliano, Clarissa Gandour, and Rudi Rocha (2015). “Deforestation slowdown in the Brazilian Amazon: prices or policies?” In: *Environment and Development Economics* 20.6, pp. 697–722. DOI: 10.1017/S1355770X15000078.

Athey, Susan and Guido Imbens (2016). “Recursive partitioning for heterogeneous causal effects”. In: *Proceedings of the National Academy of Sciences* 113.27, pp. 7353–7360. DOI: 10.1073/pnas.1510489113.

Athey, Susan, Julie Tibshirani, and Stefan Wager (Apr. 2019). "Generalized random forests". In: *Annals of Statistics* 47, pp. 1179–1203. DOI: 10.1214/18-AOS1709.

Barbier, E. B. and J. C. Burgess (2001). "The Economics of Tropical Deforestation". In: *Journal of Economic Surveys* 15.3, pp. 413–433. DOI: 10.1111/1467-6419.00144.

Baylis, Kathy et al. (2016). "Mainstreaming Impact Evaluation in Nature Conservation". In: *Conservation Letters* 9.1, pp. 58–64. DOI: 10.1111/conl.12180.

Bhattarai, Madhusudan and Michael Hammig (2001). "Institutions and the Environmental Kuznets Curve for Deforestation: A Crosscountry Analysis for Latin America, Africa and Asia". In: *World Development* 29.6, pp. 995–1010. DOI: 10.1016/S0305-750X(01)00019-5.

— (2004). "Governance, economic policy, and the environmental Kuznets curve for natural tropical forests". In: *Environment and Development Economics* 9.3, pp. 367–382. DOI: 10.1017/S1355770X03001293.

Biewen, Martin and Philipp Kugler (2021). "Two-stage least squares random forests with an application to Angrist and Evans (1998)". In: *Economics Letters* 204, p. 109893. DOI: 10.1016/j.econlet.2021.109893.

Bonilla-Mejía, Leonardo and Iván Higuera-Mendieta (2019). "Protected Areas under Weak Institutions: Evidence from Colombia". In: *World Development* 122, pp. 585–596. DOI: 10.1016/j.worlddev.2019.06.019.

Busch, Jonah and Kalifi Ferretti-Gallon (2017). "What Drives Deforestation and What Stops It? A Meta-Analysis". In: *Review of Environmental Economics and Policy* 11. DOI: 10.1093/reep/rew013.

Bustos, Paula, Bruno Caprettini, and Jacopo Ponticelli (2016). "Agricultural Productivity and Structural Transformation: Evidence from Brazil". In: *American Economic Review* 106.6, pp. 1320–65. DOI: 10.1257/aer.20131061.

Cabrales, Antonio and Esther Hauk (Nov. 2010). "The Quality of Political Institutions and the Curse of Natural Resources". In: *The Economic Journal* 121.551, pp. 58–88. DOI: 10.1111/j.1468-0297.2010.02390.x.

Caviglia-Harris, Jill et al. (2016). "Busting the Boom–Bust Pattern of Development in the Brazilian Amazon". In: *World Development* 79, pp. 82–96. DOI: 10.1016/j.worlddev.2015.10.040.

Chimeli, Ariaster (July 2007). "Growth and the environment: Are we looking at the right data?" In: *Economics Letters* 96, pp. 89–96. DOI: 10.1016/j.econlet.2006.12.016.

Chimeli, Ariaster B. and John B. Braden (Mar. 2005). "Total factor productivity and the environmental Kuznets curve". In: *Journal of Environmental Economics and Management* 49.2, pp. 366–380. DOI: 10.1016/j.jeem.2004.06.003.

Chomitz, Kenneth and Timothy Thomas (2003). "Determinants of Land Use in Amazônia: A Fine-Scale Spatial Analysis". In: *American Journal of Agricultural Economics* 85, pp. 1016–1028.

Choumert, Johanna, Pascale Combes-Motel, and Hervé K. Dakpo (2013). "Is the Environmental Kuznets Curve for deforestation a threatened theory? A meta-analysis of the literature". In: *Ecological Economics* 90, pp. 19–28. DOI: 10.1016/j.ecolecon.2013.02.016.

Cisneros, Elías, Sophie Lian Zhou, and Jan Börner (2015). "Naming and Shaming for Conservation: Evidence from the Brazilian Amazon". In: *PLOS ONE* 10.9, pp. 1–24. DOI: 10.1371/journal.pone.0136402.

Cropper, Maureen and Charles Griffiths (1994). "The Interaction of Population Growth and Environmental Quality". In: *The American Economic Review* 84.2, pp. 250–254.

Culas, Richard J. (2007). "Deforestation and the environmental Kuznets curve: An institutional perspective". In: *Ecological Economics* 61.2, pp. 429–437. DOI: 10.1016/j.ecolecon.2006.03.014.

— (2012). "REDD and forest transition: Tunneling through the environmental Kuznets curve". In: *Ecological Economics* 79, pp. 44–51. DOI: 10.1016/j.ecolecon.2012.04.015.

Dasgupta, Susmita et al. (2002). "Confronting the Environmental Kuznets Curve". In: *Journal of Economic Perspectives* 16.1, pp. 147–168. DOI: 10.1257/0895330027157.

Dell, Melissa (2010). "THE PERSISTENT EFFECTS OF PERU'S MINING "MITA"". In: *Econometrica* 78, pp. 1863–1903.

Easterly, William and Ross Levine (2016). "The European origins of economic development". In: *Journal of Economic Growth* 21, pp. 225–257.

Elhorst, J. (Jan. 2014). *Spatial econometrics. From cross-sectional data to spatial panels.*

Engerman, Stanley L and Kenneth L Sokoloff (2002). *Factor Endowments, Inequality, and Paths of Development Among New World Economics.* Working Paper 9259. National Bureau of Economic Research.

Faria, Weslem Rodrigues and Alexandre Nunes Almeida (2016). "Relationship between openness to trade and deforestation: Empirical evidence from the Brazilian Amazon". In: *Ecological Economics* 121, pp. 85–97. DOI: 10.1016/j.ecolecon.2015.11.014.

Ferrante, Lucas and Philip M Fearnside (2019). "Brazil's new president and 'ruralists' threaten Amazonia's environment, traditional peoples and the global climate". In: *Environmental Conservation* 46.4, pp. 261–263. DOI: 10.1017/S0376892919000213.

Ferraro, Paul and Rhita Simorangkir (June 2020). "Conditional cash transfers to alleviate poverty also reduced deforestation in Indonesia". In: 6, eaaz1298. DOI: 10.1126/sciadv.aaz1298.

Ferraro, Paul J. and Merlin M. Hanauer (2014). "Quantifying causal mechanisms to determine how protected areas affect poverty through changes in ecosystem services and infrastructure". In: *Proceedings of the National Academy of Sciences* 111.11, pp. 4332–4337. DOI: 10.1073/pnas.1307712111.

Fischer, Richard, Lukas Giessen, and Sven Günter (2020). "Governance effects on deforestation in the tropics: A review of the evidence". In: *Environmental Science Policy* 105, pp. 84–101. DOI: 10.1016/j.envsci.2019.12.007.

Fischer, Richard, Fabian Tamayo Cordero, et al. (2021). "Interplay of governance elements and their effects on deforestation in tropical landscapes: Quantitative insights from Ecuador". In: *World Development* 148, p. 105665. DOI: 10.1016/j.worlddev.2021.105665.

Fredriksson, Per, Xenia Matschke, and Jenny Minier (Mar. 2010). “Environmental Policy in Majoritarian Systems”. In: *Journal of Environmental Economics and Management* 59, pp. 177–191. DOI: 10.1016/j.jeem.2009.10.001.

Greenstone, Michael and B. Kelsey Jack (2015). “Envirodevonomics: A Research Agenda for an Emerging Field”. In: *Journal of Economic Literature* 53.1, pp. 5–42. DOI: 10.1257/jel.53.1.5.

Hargrave, Jorge and Krisztina Kis-Katos (2013). “Economic Causes of Deforestation in the Brazilian Amazon: A Panel Data Analysis for the 2000s”. In: *Environmental & Resource Economics* 54.4, pp. 471–494. DOI: 10.1007/s10640-012-9610-2.

Hartwick, John M. (1977). “Intergenerational Equity and the Investing of Rents from Exhaustible Resources”. In: *The American Economic Review* 67.5, pp. 972–974.

Henderson, J. Vernon, Adam Storeygard, and David N. Weil (2012). “Measuring Economic Growth from Outer Space”. In: *American Economic Review* 102.2, pp. 994–1028. DOI: 10.1257/aer.102.2.994.

Jusys, Tomas (2016). “Fundamental causes and spatial heterogeneity of deforestation in Legal Amazon”. In: *Applied Geography* 75, pp. 188–199. DOI: 10.1016/j.apgeog.2016.08.015.

Koop, Gary and Lise Tole (1999). “Is there an environmental Kuznets curve for deforestation?” In: *Journal of Development Economics* 58.1, pp. 231–244. DOI: 10.1016/S0304-3878(98)00110-2.

Larcom, S., T. van Gevelt, and A. Zabala (2016). “Precolonial institutions and deforestation in Africa”. In: *Land Use Policy* 51, pp. 150–161. DOI: 10.1016/j.landusepol.2015.10.030.

Leão, Lucas et al. (2020). “Indicador de desenvolvimento institucional municipal: impactos sobre a economia dos municípios brasileiros.” In: *Estudos Econômicos* 50.4, pp. 733–766.

Lemos, Maria Carmen and Arun Agrawal (2006). “Environmental Governance”. In: *Annual Review of Environment and Resources* 31.1, pp. 297–325. DOI: 10.1146/annurev.energy.31.042605.135621.

List, John A. and Craig A. Gallet (1999). "The environmental Kuznets curve: does one size fit all?" In: *Ecological Economics* 31.3, pp. 409–423. DOI: 10.1016/S0921-8009(99)00064-6.

Lopez, Ramón and Gregmar I. Galinato (2005). "Trade Policies, Economic Growth, and the Direct Causes of Deforestation". In: *Land Economics* 81.2, pp. 145–169.

Marchand, Sébastien (2016). "The colonial origins of deforestation: an institutional analysis". In: *Environment and Development Economics* 21.3, pp. 318–349. DOI: 10.1017/S1355770X1500025X.

Menezes-Filho, N. et al. (2006). "Instituições e Diferenças de renda entre os Estados Brasileiros: uma Análise Histórica". In: XXXIV Encontro Nacional de Economia.

Nakabashi, Luciano, Ana Pereira, and Adolfo Sachsida (2013). "Institutions and growth: A developing country case study". In: *Journal of Economic Studies* 40, pp. 614–634. DOI: 10.1108/JES-09-2011-0111.

Naritomi, Joana, Rodrigo R. Soares, and Juliano J. Assunção (2012). "Institutional Development and Colonial Heritage within Brazil". In: *The Journal of Economic History* 72.2, pp. 393–422. DOI: 10.1017/S0022050712000071.

Ostrom, Elinor (1990). *Governing the Commons: The Evolution of Institutions for Collective Action*. Political Economy of Institutions and Decisions. Cambridge University Press. DOI: 10.1017/CBO9780511807763.

Pamayotou, Theodore (1997). "Demystifying the environmental Kuznets curve: turning a black box into a policy tool". In: *Environment and Development Economics* 2.4, pp. 465–484. DOI: 10.1017/S1355770X97000259.

Paris, Agreement (2015). *United Nations Environment Programme*. URL: https://wedocs.unep.org/20.500.11822/20830.

Pfaff, Alexander and Juan Robalino (2017). "Spillovers from Conservation Programs". In: *Annual Review of Resource Economics* 9.1, pp. 299–315. DOI: 10.1146/annurev-resource-100516-053543.

Polasky, Stephen et al. (2019). “Role of economics in analyzing the environment and sustainable development”. In: *Proceedings of the National Academy of Sciences* 116.12, pp. 5233–5238. DOI: 10.1073/pnas.1901616116.

Ribot, Jesse C., Arun Agrawal, and Anne M. Larson (2006). “Recentralizing While Decentralizing: How National Governments Reappropriate Forest Resources”. In: *World Development* 34.11, pp. 1864–1886. DOI: 10.1016/j.worlddev.2005.11.020.

Robalino, Juan A. and Alexander Pfaff (2012). “Contagious development: Neighbor interactions in deforestation”. In: *Journal of Development Economics* 97.2, pp. 427–436. DOI: 10.1016/j.jdeveco.2011.06.003.

Sills, Erin O. et al. (2015). “Estimating the Impacts of Local Policy Innovation: The Synthetic Control Method Applied to Tropical Deforestation”. In: *PLOS ONE* 10.7, pp. 1–15. DOI: 10.1371/journal.pone.0132590. URL: https://doi.org/10.1371/journal.pone.0132590.

Sohag, Kazi, Anna Gainetdinova, and Oleg Mariev (2023). “Economic growth, institutional quality and deforestation: Evidence from Russia”. In: *Forest Policy and Economics* 150, p. 102949. DOI: https://doi.org/10.1016/j.forpol.2023.102949.

Souza, Carlos M. et al. (2020). “Reconstructing Three Decades of Land Use and Land Cover Changes in Brazilian Biomes with Landsat Archive and Earth Engine”. In: *Remote Sensing* 12.17. DOI: 10.3390/rs12172735.

Van, Phu Nguyen and Théophile Azomahou (2007). “Nonlinearities and heterogeneity in environmental quality: An empirical analysis of deforestation”. In: *Journal of Development Economics* 84.1, pp. 291–309. DOI: 10.1016/j.jdeveco.2005.10.004.

Wager, Stefan and Susan Athey (2018). “Estimation and Inference of Heterogeneous Treatment Effects using Random Forests”. In: *Journal of the American Statistical Association* 113.523, pp. 1228–1242. DOI: 10.1080/01621459.2017.1319839.

Wehkamp, Johanna et al. (2018). “Governance and deforestation — a meta-analysis in economics”. In: *Ecological Economics* 144, pp. 214–227. DOI: 10.1016/j.ecolecon.2017.07.030.

Weinhold, Diana, Eustáquio J. Reis, and Petterson Molina Vale (2015). "Boom-bust patterns in the Brazilian Amazon". In: *Global Environmental Change* 35, pp. 391–399. DOI: 10.1016/j.gloenvcha.2015.09.013.

A Appendix

A.1 Institutional quality indicator

To construct the local institutional quality indicator, we used the Principal Component Analysis (PCA) in twenty variables that capture many dimensions of institutional quality for 2005 and 2015. We have chosen the variables based on the literature, especially Leão et al. (2020). The variables' descriptions are in Table A1.

Table A1: Variables used in the local institutional quality indicator.

Variables
Master Plan - existence
Legislation on land readjustment or granting of the right to build - existence
Legislation on special social interest area or zone - existence
Legislation on special interest zone or area - existence
Legislation on land subdivision - existence
Legislation on zoning or land use and occupation - existence
Legislation on joint urban operation - existence
Legislation on neighborhood impact studies - existence
Legislation on land regularization
Building code - existence
Does the municipality charge property tax (IPTU)?
Education consortia
Consortia for Social Assistance and Development - existence
Tourism consortia - existence
Cultural consortia - existence
Housing consortia - existence
Environmental consortia - existence
Transportation consortia - existence
Urban Development consortia - existence
Sanitation and/or Solid Waste Management consortia - existence

Source: Prepared by the authors.

The PCA enabled the extraction of six factors with characteristic roots greater than one ($\lambda_i \geq 1$). The explained variance was approximately 60%. The Kaiser-Meyer-Olkin (KMO) test resulted in a 0.9384 value, corroborating that the variables used are sufficiently correlated to use the PCA approach.

To construct the indicator, we used the following equation: $Institutions_m = \sum_{j=1}^{k} \frac{\lambda_j}{\mathrm{tr}(P_{nxn})} F_{jm}$, where $Institutions_m$ is the local institutional quality indicator for municipality m; λ_j is the j-th characteristic root of the correlation matrix; k is the number of factors with characteristic root greater than one; F_{jm} is the factorial load of municipality m from factor j; $\operatorname{tr}(P_{nxn})$ is the trace of the correlation matrix. Then, we transformed it so that the values are restricted to the 0-100 range.

A.2 Results

Table A2: First Stage

	Dependent variable: Δ Institutions					
	(1)	(2)	(3)	(4)	(5)	(6)
Distance Portugal	0.0012***	0.0013***	0.0014***	0.0015***	0.0017***	0.0017***
	(0.0004)	(0.0004)	(0.0004)	(0.0005)	(0.0005)	(0.0006)
Distance Coast	−0.0099***	−0.0098***	−0.0098***	−0.0097***	−0.0104***	−0.0108***
	(0.0011)	(0.0011)	(0.0011)	(0.0011)	(0.0011)	(0.0014)
Distance Villages	0.0113***	0.0118***	0.0115***	0.0117***	0.0130***	0.0089**
	(0.0040)	(0.0041)	(0.0041)	(0.0041)	(0.0041)	(0.0043)
Literate	0.2649***	0.2725***	0.2555***	0.2610***	0.2487***	0.2509***
	(0.0808)	(0.0808)	(0.0841)	(0.0838)	(0.0837)	(0.0868)
Slaves	−0.2537***	−0.2508***	−0.2515***	−0.2483***	−0.2344***	−0.3294***
	(0.0565)	(0.0567)	(0.0567)	(0.0573)	(0.0575)	(0.0623)
Gold Boom	225.4281***	226.9660***	228.0565***	224.9500***	211.1647***	224.1026***
	(69.8180)	(69.3591)	(69.6307)	(69.4652)	(67.9565)	(68.8793)
Sugar Boom	10.4868	10.3572	11.9811	12.3860	17.0026	20.3352
	(36.2810)	(36.3886)	(36.4314)	(36.4084)	(36.4381)	(36.4924)
D.Portugal.Gold	−0.0312***	−0.0314***	−0.0315***	−0.0311***	−0.0293***	−0.0311***
	(0.0097)	(0.0096)	(0.0096)	(0.0096)	(0.0094)	(0.0096)
D.Portugal.Sugar	−0.0020	−0.0020	−0.0023	−0.0023	−0.0030	−0.0036
	(0.0058)	(0.0058)	(0.0058)	(0.0058)	(0.0058)	(0.0059)
Soil		−1.7275	−1.6327	−1.7023	−1.0625	−0.9226
		(1.3524)	(1.3552)	(1.3605)	(1.3759)	(1.3830)
Altitude			−0.0009	−0.0010	−0.0006	−0.0007
			(0.0011)	(0.0011)	(0.0011)	(0.0012)
Precipitation				−0.0015	−0.0019	−0.0095***
				(0.0027)	(0.0027)	(0.0032)
Forest					4.5895***	6.0276***
					(1.5008)	(1.5707)
Amazon						5.4294***
						(1.5922)
Cerrado						3.2288***
						(0.9663)
Atlantic Forest						4.1989***
						(1.0854)
Constant	−3.1222	−3.1443	−3.3163	−3.2030	−6.8504***	−5.0547*
	(2.1365)	(2.1370)	(2.1533)	(2.1692)	(2.5355)	(2.8236)
Observations	5,027	5,027	5,027	5,027	5,027	5,027
F Statistic	21.469***	21.238***	21.265***	21.047***	22.411***	17.048***

Note: *** Significant at 1%; ** Significant at 5%; * Significant at 10%. Robust Standard Errors

Table A3: Robustness Check - Additional Controls

	Dependent variable: ΔDeforestation						
	OLS	Benchmark I	Social	Trade	Fines	HumanCap.	Development
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
ΔInstitutions	0.0001	0.0034**	0.0027**	0.0027**	0.0030**	0.0030**	0.0033**
	(0.0002)	(0.0014)	(0.0013)	(0.0013)	(0.0013)	(0.0013)	(0.0013)
Amazon	−0.0004	0.0101	0.0207	0.0207	0.0220	0.0220	0.0197
	(0.0084)	(0.0107)	(0.0155)	(0.0155)	(0.0166)	(0.0166)	(0.0157)
Cerrado	−0.0062	0.0112	0.0124	0.0125	0.0137	0.0137	0.0111
	(0.0067)	(0.0071)	(0.0098)	(0.0096)	(0.0088)	(0.0088)	(0.0096)
Atlantic Forest	0.0122	0.0336**	0.0274**	0.0272**	0.0285**	0.0285**	0.0294**
	(0.0084)	(0.0168)	(0.0108)	(0.0111)	(0.0117)	(0.0117)	(0.0120)
ΔInstitutions*Amazon	−0.0001	−0.0020	−0.0015	−0.0015	−0.0018	−0.0018	−0.0020
	(0.0002)	(0.0015)	(0.0014)	(0.0014)	(0.0014)	(0.0014)	(0.0014)
ΔInstitutions*Cerrado	−0.0003	−0.0049***	−0.0044***	−0.0044***	−0.0047***	−0.0047***	−0.0047***
	(0.0002)	(0.0016)	(0.0015)	(0.0015)	(0.0014)	(0.0014)	(0.0014)
ΔInstitutions*AtlanticForest	0.0001	−0.0039*	−0.0035**	−0.0035**	−0.0038**	−0.0038**	−0.0040**
	(0.0003)	(0.0021)	(0.0015)	(0.0015)	(0.0016)	(0.0016)	(0.0017)
Geographic	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Socioeconomic	*No*	*No*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
International Trade	*No*	*No*	*No*	*Yes*	*Yes*	*Yes*	*Yes*
Environmental Fines	*No*	*No*	*No*	*No*	*Yes*	*Yes*	*Yes*
Human Capital	*No*	*No*	*No*	*No*	*No*	*Yes*	*Yes*
Nightlight	*No*	*No*	*No*	*No*	*No*	*No*	*Yes*
Observations	5,027	5,027	4,971	4,971	4,971	4,971	4,971

Note: *** Significant at 1%; ** Significant at 5%; * Significant at 10%. Robust Standard Errors

Table A4: Robustness Check - Spatial Models

	Dependent variable: Δ*Deforestation*				
	OLS	Benchmark I	Benchmark II	Spatial IV	SAR/IV
	(1)	(2)	(3)	(4)	(5)
ΔInstitutions	0.0001	0.0034^{**}	0.0033^{**}	0.0012	0.0026^{*}
	(0.0002)	(0.0014)	(0.0013)	(0.0013)	(0.0015)
Amazon	-0.0004	0.0101	0.0197	0.0067	0.0146
	(0.0084)	(0.0107)	(0.0157)	(0.0095)	(0.0101)
Cerrado	-0.0062	0.0112	0.0111	0.0069	0.0100
	(0.0067)	(0.0071)	(0.0096)	(0.0073)	(0.0092)
Atlantic Forest	0.0122	0.0336^{**}	0.0294^{**}	0.0109	0.0164
	(0.0084)	(0.0168)	(0.0120)	(0.0143)	(0.0115)
ΔInstitutions*Amazon	-0.0001	-0.0020	-0.0020	-0.0006	-0.0011
	(0.0002)	(0.0015)	(0.0014)	(0.0013)	(0.0017)
ΔInstitutions*Cerrado	-0.0003	-0.0049^{***}	-0.0047^{***}	-0.0019	-0.0035^{**}
	(0.0002)	(0.0016)	(0.0014)	(0.0014)	(0.0016)
ΔInstitutions*AtlanticForest	0.0001	-0.0039^{*}	-0.0040^{**}	-0.0007	-0.0024
	(0.0003)	(0.0021)	(0.0017)	(0.0019)	(0.0016)
WΔDeforestation				0.5947^{**}	0.4967^{**}
				(0.2540)	(0.2042)
Geographic	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Socioeconomic	*No*	*No*	*Yes*	*Yes*	*Yes*
International Trade	*No*	*No*	*Yes*	*Yes*	*Yes*
Environmental Fines	*No*	*No*	*Yes*	*Yes*	*Yes*
Human Capital	*No*	*No*	*Yes*	*Yes*	*Yes*
Nightlight	*No*	*No*	*Yes*	*Yes*	*Yes*
Observations	5,027	5,027	4,971	5,027	4,750
Note:	*** Significant at 1%; ** Significant at 5%; * Significant at 10%. Robust Standard Errors				

Table A5: Robustness Check - Alternative Dependent Variables

	Dependent variable: Δ*Deforestation*			
	Percent (%)	Normalized	ha//km2	Forest Percent (%)
	(1)	(2)	(3)	(4)
ΔInstitutions	0.0033^{**}	0.0119^{**}	0.0014^{***}	0.0010
	(0.0013)	(0.0046)	(0.0005)	(0.0012)
Amazon	0.0197	0.0701	0.0028	0.0231^{**}
	(0.0157)	(0.0557)	(0.0034)	(0.0099)
Cerrado	0.0111	0.0395	0.0096^{***}	0.0059
	(0.0096)	(0.0340)	(0.0027)	(0.0084)
Atlantic Forest	0.0294^{**}	0.1043^{**}	-0.0044	-0.0110
	(0.0120)	(0.0425)	(0.0029)	(0.0106)
ΔInstitutions*Amazon	-0.0020	-0.0073	-0.0002	0.0024^{*}
	(0.0014)	(0.0049)	(0.0006)	(0.0014)
ΔInstitutions*Cerrado	-0.0047^{***}	-0.0169^{***}	-0.0014^{***}	-0.0035^{***}
	(0.0014)	(0.0051)	(0.0005)	(0.0014)
ΔInstitutions*AtlanticForest	-0.0040^{**}	-0.0142^{**}	-0.0013^{***}	-0.0035^{**}
	(0.0017)	(0.0061)	(0.0005)	(0.0015)
Geographic	*Yes*	*Yes*	*Yes*	*Yes*
Socioeconomic	*Yes*	*Yes*	*Yes*	*Yes*
International Trade	*Yes*	*Yes*	*Yes*	*Yes*
Environmental Fines	*Yes*	*Yes*	*Yes*	*Yes*
Human Capital	*Yes*	*Yes*	*Yes*	*Yes*
Nightlight	*Yes*	*Yes*	*Yes*	*Yes*
Observations	4,971	4,971	4,971	4,971
Note:	*** Significant at 1%; ** Significant at 5%; * Significant at 10%. Robust Standard Errors			

Table A6: Robustness Checks - Alternative Institutional Indicators

	Dependent variable: Δ Deforestation					
	Institutions	Land Gini	Squatters	Institutions	Land Gini	Squatters
	(1)	(2)	(3)	(4)	(5)	(6)
ΔInstitutions	0.0029			0.0030^{**}		
	(0.0026)			(0.0013)		
ΔLand Gini		0.5184^{***}			0.1221	
		(0.1767)			(0.0761)	
ΔSquatters			0.0106^{***}			0.0027^{**}
			(0.0035)			(0.0014)
Amazon	-0.0715^{**}	-0.0351	-0.0857^{**}	0.0181	0.0181	0.0118
	(0.0361)	(0.0322)	(0.0362)	(0.0142)	(0.0152)	(0.0209)
Cerrado	0.0717	0.0155	-0.0666^{**}	0.0114	0.0044	-0.0281^{**}
	(0.0572)	(0.0194)	(0.0292)	(0.0093)	(0.0071)	(0.0139)
Atlantic Forest	-0.0139	-0.0219	-0.0852^{***}	0.0302^{**}	0.0144^{*}	-0.0075
	(0.0140)	(0.0147)	(0.0249)	(0.0126)	(0.0087)	(0.0149)
ΔInstitutions*Amazon				-0.0018		
				(0.0014)		
ΔInstitutions*Cerrado				-0.0047^{***}		
				(0.0014)		
ΔInstitutions*AtlanticForest				-0.0038^{**}		
				(0.0016)		
ΔLandGini*Amazon					0.0157	
					(0.1059)	
ΔLandGini*Cerrado					-0.4191	
					(0.2880)	
ΔLandGini*AtlanticForest					-0.3682^{**}	
					(0.1671)	
ΔSquatters*Amazon						0.0030
						(0.0026)
ΔSquatters*Cerrado						-0.0039^{**}
						(0.0018)
ΔSquatters*AtlanticForest						-0.0015
						(0.0037)
Geographic	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Socioeconomic	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
International Trade	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Environmental Fines	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Human Capital	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Nightlight	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Observations	4,971	4,971	4,971	4,971	4,971	4,971

Note: *** Significant at 1%; ** Significant at 5%; * Significant at 10%. Robust Standard Errors.

Table A7: Heterogeneity Test - Sample

	Dependent variable: ΔDeforestation				
	10%	20%	30%	40%	50%
	(1)	(2)	(3)	(4)	(5)
ΔInstitutions	0.0033^{**}	0.0023^{*}	0.0003	0.0003	-0.0004
	(0.0013)	(0.0014)	(0.0013)	(0.0013)	(0.0008)
Amazon	0.0197	0.0311	0.0051	0.0051	0.0027
	(0.0157)	(0.0242)	(0.0100)	(0.0100)	(0.0084)
Cerrado	0.0111	-0.0053	0.0085	0.0085	0.0190^{**}
	(0.0096)	(0.0147)	(0.0082)	(0.0082)	(0.0074)
Atlantic Forest	0.0294^{**}	0.0230^{*}	0.0195^{*}	0.0195^{*}	0.0199
	(0.0120)	(0.0125)	(0.0113)	(0.0113)	(0.0215)
ΔInstitutions*Amazon	-0.0020	-0.0019	0.0003	0.0003	0.0018^{**}
	(0.0014)	(0.0014)	(0.0011)	(0.0011)	(0.0008)
ΔInstitutions*Cerrado	-0.0047^{***}	-0.0015	-0.0024^{***}	-0.0024^{***}	-0.0021^{**}
	(0.0014)	(0.0018)	(0.0009)	(0.0009)	(0.0009)
ΔInstitutions*AtlanticForest	-0.0040^{**}	-0.0030	-0.0007	-0.0007	-0.00003
	(0.0017)	(0.0018)	(0.0015)	(0.0015)	(0.0014)
Geographic	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Socioeconomic	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
International Trade	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Environmental Fines	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Human Capital	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Nightlight	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Observations	4,971	3,927	3,021	3,021	1,777

Note: *** Significant at 1%; ** Significant at 5%; * Significant at 10%. Robust Standard Errors

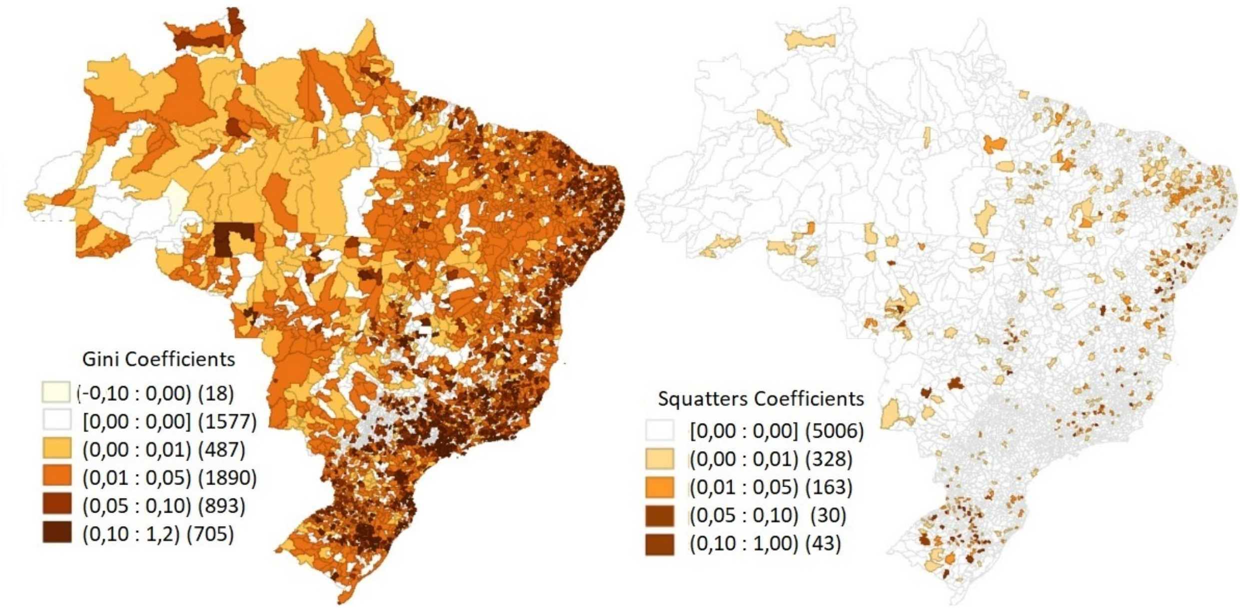

Figure 4: Local Conditional Average Treatment Effect (CATE) for Gini and Squatters.

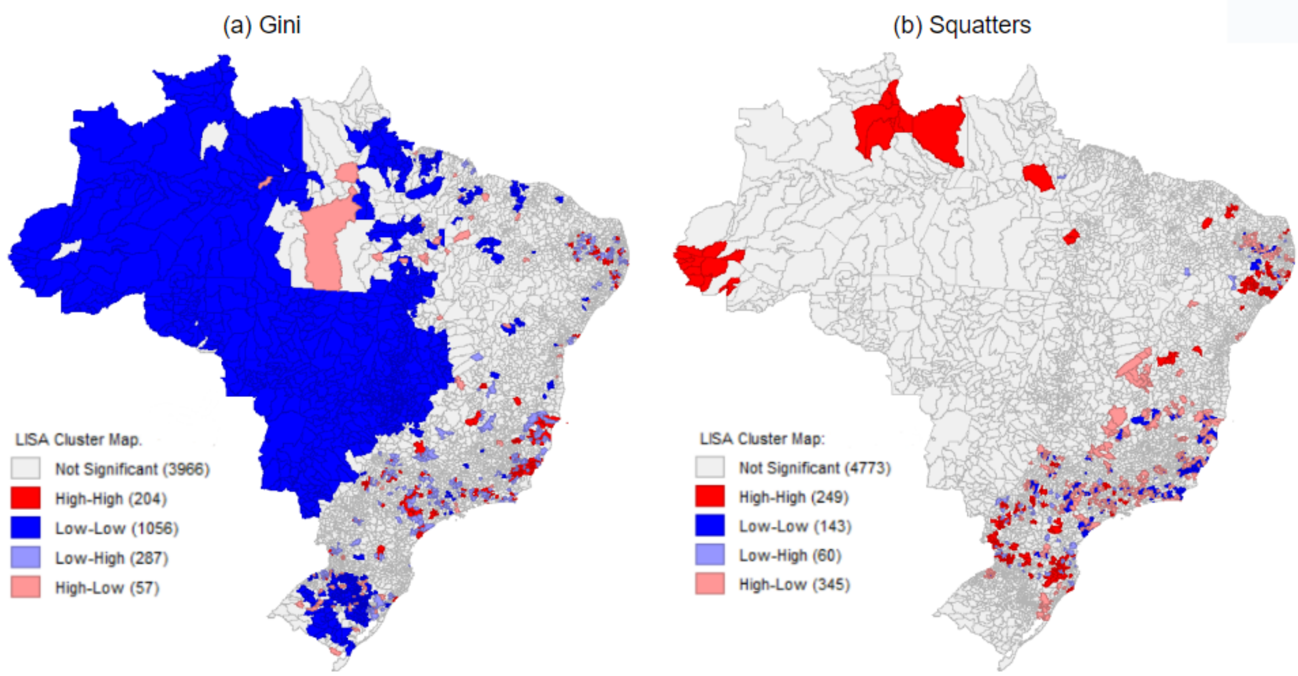

Figure 5: Local Moran's I for the local Gini and Squatters causal effect.