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RELATIONSHIP BETWEEN OPENNESS TO TRADE AND DEFORESTATION: EMPIRICAL EVIDENCE FROM THE BRAZILIAN AMAZON

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Relationship between Openness to Trade and Deforestation:

Empirical Evidence from the Brazilian Amazon

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Abstract. The main objective of this paper is to investigate how international trade has affected the dynamics of deforestation in the Brazilian Amazon at the level of the municipality. This analysis focuses on the expansion of crop and cattle activities, and other determinants of deforestation such as GDP, demographic density, and roads. We combine standard econometrics with spatial econometrics to capture the socio-economic interactions among the agents in their interrelated economic system. The data used in this study correspond to a balanced panel of 732 municipalities from 2000 to 2007. The main findings suggest that as openness to trade in the Amazon increases, deforestation also increases. We also find that it is the production of soybeans, sugarcane, cotton, and beef cattle that drives deforestation in the region. As expected, firewood and timber extraction also has a significant impact in deforestation. Moreover, as the GDP goes up, deforestation increases. On the other hand, as the square of GDP goes up, deforestation decreases a finding that supports the environmental Kuznets Curve hypothesis. The production of non-wood products has a negative impact on deforestation. Unexpected results included the findings that population density had a negative impact on deforestation, and that distance from state capitols had no impact.

1. Introduction

Since the 1980s, the importance of tropical forests has been internationally recognized. Tropical forests are home to much of the world's biodiversity and are also very important to global climate regulation (Barbier, 2001). It is also well known tropical forests are mostly located in very poor regions in developing nations along the equatorial line, and economic development in these regions is putting enormous pressure on the forests and their ecosystems. In recent years, substantial amounts of forest cover have been cut down. The understanding of this process has become one of the top priorities of any environmental development agenda, and deserves further investigation.

The Brazilian Amazon, the focus of this paper, is a large area (61% of the country) divided into nine states.[1] It is home to 12% of the population of Brazil, who live mostly in urban areas. The overexploitation of the forest resources is driven, for the most part,

[1] These states are Acre, Amapá, Amazonas, Mato Grosso, Rondônia, Roraima, Tocantins, Pará and parts of Maranhão.

by the economic activities of interests from outside the area. In the 1970s, abundant government subsidies and incentives for mining, crop and beef production, and gigantic road projects provided infrastructure for new settlers coming from other parts of the country (Mahar, 1989). Federal and state governments failed to regulate this settlement, with the result that there is considerable confusion about the ownership of key environmental resources. For the last few decades, frontier regions of the Amazon have been a major scene of land conflicts between cattle ranchers, squatters, miners, indigenous groups, and public authorities. In addition, since the enactment of free trade agreements in the 1990s, international markets for timber and agricultural commodities have been driving further deforestation in the region (Brandão et al., 2006).

The significant loss of Amazon virgin forest due to cattle ranching and agricultural activities, poorly defined property rights, road construction, and population growth have been extensively studied (Reis and Guzman, 1992; Pfaff, 1999; Walker et al., 2000; Weinhold and Reis, 2001; Andersen et al., 2002; Mertens et al., 2002; Margulis, 2003; Chomitz and Thomas, 2003; Pfaff et al., 2007; Diniz et al., 2009; Araujo et al., 2009; Rivero et al., 2009; Barona et al., 2010). However, to the best of our knowledge, there are very few studies that investigate the relationship between deforestation and openness to trade in developing countries.

The objective of this paper is to examine how international trade and the expansion of agriculture and the cattle industry have affected the dynamics of deforestation in the Brazilian Amazon. The analysis includes determinants such as gross domestic product, demographic density, and road distance. We combine standard econometrics with spatial econometrics in order to capture the socioeconomic interactions among the local, regional, and international agents in the Amazon region.

This paper has four sections in addition to this introduction. The second section presents a review of the literature and compares the theoretical models adopted in this work with models applied in other studies. The third section discusses the methodology, data, and specifications of the estimating models used to test the relationship between openness to trade and deforestation. The fourth section presents the results of unconditional tests and econometrics. The main results indicate a positive relationship between openness to trade and deforestation. The fifth section presents our conclusions.

2. Literature Review and Theoretical Background

Angelsen and Kaimowitz (1999) discuss more than 146 published studies that assess the causes of deforestation, classified according to two criteria: scale, which concerns the unit of analysis—microeconomic (households, firms or farmers), regional, or macroeconomic (national); and methodology, which classifies the studies according to whether they are analytical, empirical, or simulation models. In addition, they rank the variables used by the models of deforestation as: (1) the magnitude and location of deforestation; (2) the agents of deforestation; (3) the variables selected; (4) agents' decision parameters; and (5) the macroeconomic variables and policy instruments.

Both classifications, in terms of criteria and type of variables, may be important for assessing the strengths and weaknesses of the works in different contexts of analysis. Many studies have used microeconomic models or micro-data to consider the specific behavior of landowners (or families) (e.g., Bluffstone 1995; Angelsen, 1999; Chomitz and Thomas, 2003) in relation to deforestation. These models focus on the existence of credit and subsidies for agricultural production, years of schooling of the landowners, and land use intensity. However, these models ignore of broader causes of deforestation, such as the indirect effects of foreign trade and paved roads in the area of forest cover.

On the other hand, the empirical macroeconomic models use aggregate data. Such models have the advantage of using information that can be found easily, even for developing countries, such as Brazil, Ecuador, Indonesia, Malaysia, and Thailand (Allen and Barnes, 1985; Cropper and Griffiths, 1994; Deacon, 1994; Lópes and Galinato, 2005). One of the main data sources is the Food and Agricultural Organization (FAO), which provides information such as soil types, forest coverage, and population density. However, data aggregated from a number of regions are represented as average figures, which might distort the accuracy of the estimates for any given area. In Brazil, the adoption of a state-level analysis of deforestation from aggregate data is discouraged, since the dynamics of deforestation are quite different in different states.

Regional models are an appropriate solution in these cases, because they are based on local data and can be used to analyze an issue, such as deforestation, in a broader context than at the micro level. In addition, the regional-level model, with its disaggregation of data, allows a higher-quality analysis about the region under study than the macro-level analysis. In other words, regional data on deforestation is desirable, to avoid erroneous inferences being made from highly aggregated data, and at the same time, to ensure that local features are incorporated into the analysis.

In the literature, a handful of studies have looked directly at the relationship between the degradation of renewable natural resources and international trade (Chichilnisky, 1994; Brander and Taylor, 1996; and Ferreira, 2004). Generally speaking, the conclusion of these studies is that if property rights to the environmental resource in question are ill-defined, then trade between two countries does not make both better off in terms of resource allocations and income, as is usually claimed by the proponents of international trade. Chichilnisky, for example, assumes a trade agreement between two countries— a "north country" and a "south country"—where the property rights to a natural resource in the south country, which exports goods based on that natural resource, are ill-defined. She shows that although trade is able to equalize output and factor prices between north and south, it does not improve resource allocation in the south country. Since the south is poor and owns a subsistence sector (labor), tax policies on the use of the resource that would decrease the price of the resource is a reason to lead to even more extraction (overproduction) of the common property. In the Brazilian Amazon, since the 1970s, the roads, public land, and unused private land have been occupied at minimum (no) cost at all. Further evidence suggests that most landholders do not have legal titles or have fake titles of their land (Araujo et al., 2009).

Ferreira (2004) supports the idea that the lack of property rights in an exporting country leads to overexploitation of commonly owned resources. She built a model that exploits the difference between the marginal and average product of labor in a north and a south country, assuming that both countries share similar technological levels, stocks of natural resources, and labor. The main reason for trade is not the difference in the resource abundance in the two countries, but the difference in property rights over natural resources. Thus, increases in prices brought by trade shift up the value of the marginal product and the value of the average product curves, inducing labor migration from the manufacturing sector to the harvest sector. She concludes that even as the south becomes a net exporter, it experiences losses from trade. In addition, the elimination of trade distortions enlarges the effects of property rights distortions, which also damage the south country.

Brander and Taylor (1995) analyze an open small-country economy. Natural resources are abundant, and property rights are not enforced. In accord with Ricardian economics, the authors show that under free trade, the small country, even with a comparative advantage in natural resources, may still suffer losses in economic terms and the use of natural resources.

Some of these conclusions have been confirmed empirically. Ferreira (2004) analyzed data from 92 countries for 1961–1994 and found that the usual openness indicator (export + import/GDP) is a significant predictor of deforestation, but only when institutional factors such as expropriation, corruption, and bureaucracy are operating. Using household surveys for Brazil, Indonesia, Malaysia, and the Philippines, López and Galinato (2005) found that the net impact of trade openness between 1980 and 1999 was small for the four countries. For example, if openness to trade increases forest cover in Brazil and the Philippines, it decreases forest cover in Indonesia and Malaysia.

Using data of 1989 for Ghana, López (1997) found that the reduction of tariff protection and export taxes resulted losses of biomass (natural fertilizer used by farmers) of 2.5–4%, and the overexploitation of biomass through a more than optimal level of land cultivated due to tariff reductions had a small impact on national income. More recently, Arcand et al. (2008) show theoretically that depreciation of the real exchange rate and weaker institutions result in more deforestation in developing countries. In an empirical application, they did not reject any of the hypotheses above on annual data for 101 countries from 1961 to 1988.

3. Methodology

3.1. Data

This study used information for a balanced panel of 732 municipalities for the years 2000 to 2007, totaling 6,256 observations. These municipalities are part of a PRODES (*Programa de Monitoramento da Floresta Amazônica Brasileira por Satelite*) project funded by the Brazilian Government to monitor the level of deforestation in the Brazilian Amazon. These municipalities form the so-called Legal Amazon. Table 1 shows the description of each variable used, as well as its mean and standard deviation. [2]

Deforestation data are provided by The National Institute of Spatial Research (INPE), which collects and annually publishes rates of deforestation for all 732 municipalities that constitute the Legal Amazon, based on geo-referenced satellite images.[3]

The *openness to trade* indicator is the total volume of foreign trade, corresponding to the sum of exports and imports, as a proportion of GDP. The export and import data were obtained from the Ministry of Development, Industry, and Foreign Trade (MDIC), and the GDP data from the Brazilian Institute of Geography and Statistics (IBGE). The data relating to the yields of *soybeans, sugar cane*, *corn,* and *cotton* were obtained from the IBGE database called SIDRA, which provides information about the agricultural production of the municipalities. Data on *firewood, timber,* and *non-wood* extractives were obtained from this same database. The variable *non-wood* variable refers to aromatics, medicinals, dyes, rubber, waxes, fibers, non-elastic gums, charcoal, and tanning oil derived from vegetable products. The data on heads of *cattle* and beef were also extracted from the SIDRA database. The population data, referred to as *density*, were obtained at the IBGE demography channel. Data on roads, referencing the *distance* in kilometers between the city and the state capitol, were collected at the Institute of Applied Economic Research (IPEA).[4]

The variables related agricultural crops and livestock are important factors in the investigation of how trade liberalization affects deforestation, since the export of such products has increased dramatically in recent years. There are three reasons for this: (1) international increases in the price of agricultural commodities caused, in part, by the

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[2] Some variables had missing observations for some municipalities in a few years of the study's period. In order to overcome this problem, geographically weighted estimates were made for generating those observations. The procedure involves the estimation by the OLS procedure with the following specification: $m = \alpha + \beta_1 x + \beta_2 y + \beta_3 x^2 + \beta_4 y^2 + \beta_5 x^3 + \beta_6 y^3 + \varepsilon$, where x and y represent latitude and longitude of the centroid of each spatial unit; m refers to the vector of variables used in the econometric model to determine the dynamics of the deforestation that had missing observations; β^i is the vector of coefficients to be estimated for each i, where i indicates the relevant variable with missing observations and; ε the error term.

[3] Further information about the methodology of estimating the rates of deforestation can be found at http://www.obt.inpe.br/prodes.

[4] http://www.ipeadata.gov.br.

economic expansion of China; (2) the devaluation of the national currency (the Brazilian real) against the U.S. dollar since 1999 and; (3) the availability of land to increase crop yields. These facts combined have stimulated the agricultural sector to produce more commodities, mainly for export.

The last reason mentioned, the availability of land, refers primarily to climatic conditions and soil quality in the country, as well as the possibility of conversion of forest to grow crops or livestock areas. In some cases, as occurs in the production of sugar cane, the available technology for the production of ethanol is also an important factor. The combination of these elements makes Brazil's agriculture highly competitive, facilitating foreign sales. Therefore, the focus of this work is to investigate how the possibility of conversion of forest to other uses may be associated with foreign trade.

Figure 1 provides some background on the relationship between foreign trade, yield, and production area in Brazil. Graphics (a), (b) and (c) show the yields of soybeans, corn, and sugar cane in Brazil, as well as the area (hectares) in production. Noticed that for both soybeans and sugar cane, increases in production are directly related to increases in area used; however, corn production has increased without a corresponding increase in land use. The land devoted to livestock has also increased over the years (graphic (d)). Graphic (e) shows that both the export volume of soybeans and the total export volume of goods from Brazil have increased significantly, mainly since the early 1990s. Finally, graphic (f) shows that the *ad valorem* tariff in Brazil have decreased from 30% in the 1980s to an average of less than 10% in the 2000s.

These graphs show that there has been an increase in both land use and agricultural production in Brazil in recent decades, as well as an increase in exports and lower barriers to trade on the entry of foreign products. There appears to be a positive relationship between the expansion of agricultural activity, growth of land use, and growth of foreign trade. Thus, this study sought to determine whether the increase in land use for agricultural purposes, which in Brazil is often associated with the conversion of forest to crop or livestock, is actually associated with the intensification of foreign trade. The study focuses on the Amazon region of Brazil, whose forest covers almost 60% of the national territory.[5]

3.2. Empirical Implementation

The objective of this study is to investigate how trade liberalization affects deforestation. This sort of relationship can be described by the following model:

$$Y_i = f(X_i, \beta) \tag{1}$$

where Y_i is the dependent variable, deforestation; X_i is a vector of explanatory variables, including openess to trade; and β is the parameter vector.

Equation 1 schematizes the relationship that we want verify. Estimation by OLS could provide a solution. However, since we have data available over time for each unit of cross- section, the data are in panel format. It is well known that one of the main advantages of using panel data is to control for observed and also for unobserved characteristics (Baltagi, 1995). In such cases, fixed effects and random effects specifications are the most commonly used models in applied work.

First, consider the standard panel data model:

$$Y_{it} = X_{it}\beta + v_{it}, i = 1, \dots, N, t = 1, \dots, T \tag{2}$$

And

$$v_{it} = \mu_i + u_{it} \tag{3}$$

where Y_{it} is the dependent variable, X_{it} is a vector of explanatory variables; μ_i is the time-invariant individual component, and u_{it} is the error term. The vector β is the parameter(s) to be estimated.

[5] Brazilian Agricultural Census of 2006 (http://www.ibge.gov.br).

The consistent estimation of Equation (2) by a pooled OLS approach requires that the explanatory variables—both the error term and the unobserved effect—are uncorrelated. The fixed-effects model assumes that the intercept changes between the units of cross-section, but does not change over time. The fixed-effect specification allows that different intercepts may be used to capture all the differences between the units of cross-sections. The random-effects model assumes that the behavior of both the units of cross-section and the time is unknown. Therefore, the behavior of these units of cross-section and the time can be represented in the form of a random variable, and the resulting heterogeneity is treated as part of the error term. Moreover, the random-effects model present the futher assumption that the unobserved term is uncorrelated with the explanatory variables (Johnston and Dinardo, 1997).

However, in the presence of spatial autocorrelation, the adoption of these procedures is not enough, and some extensions specific to panel data have been developed (Elhorst, 2003). It is worth mentioning that these extended models (equations (4)–(6)) take into consideration the same properties as the traditional panel data ones; the major difference consists in adding more explanatory variables, to take into account the spatial effect. Nevertheless, no special treatment is given to residual values of these regressions.

Spatial dependence, according to Anselin (1988) and Anselin and Bera (1998), can make the OLS estimators inconsistent and/or inefficient. However, according to Anselin (1995), spatial dependence can be incorporated into linear regression models in two ways: (1) through the construction of new variables, both for the dependent variable and for the explanatory variables and error terms of the model. These new variables incorporate spatial dependence as a weighted average of the values of the neighbors; and (2) by using spatial autoregressive error terms. This study followed the first suggestion, adding variables to the model to mitigate the consequences of spatial dependence.

Now, consider the following models that take into account the spatial effect (Anselin and Bera, 1998; Anselin, 2001; Anselin, 2003, Carvalho, 2008):

1) Spatial Lag Model

$$Y_{it} = \rho W Y_{it} + X_{it}\beta + v_{it} \tag{4}$$

where the dependent variable Y_{it} is lagged spatially. It is added as explanatory variable in the model.

2) Crossed Regressive Model

$$Y_{it} = X_{it}\beta + W X_{it}\varphi + v_{it} \tag{5}$$

where the vector of explanatory variables X_{it} are now lagged, and are added as explanatory variables in the model.

3) Spatial Durbin Model

$$Y_{it} = \rho W Y_{it} + X_{it}\beta + W X_{it}\varphi + v_{it} \tag{6}$$

where both dependent Y_{it} and explanatory X_{it} variables area spatially lagged and added in the right-hand side of the model.

Equations (4) and (6) are very unusual, because they posit the dependent variable as an explanatory variable. If the value of this variable for a municipality is determined in part by its neighbors, then equilibrium will occur as a function of some existing spatial or social interaction process between both locations (Anselin et al., 2008). This might be justified in either theoretical or in practical terms, because deforestation may be a phenomenon that occurs as an interactive factor—the space being determined according to the availability and accessibility of the resource to the economic agents involved. Such models are gaining enormous popularity in the literature for the evaluation of similar situations in which social or spatial interactions exist (see Brueckner, 2003 and Glaeser et al., 2002).

We used spatial data at the level of the municipality. These data contain important information about the interactions that occur between the spatial units. If these interactions are significant in such a way that the result in one spatial unit affects the outcome in neighboring spatial units, then the data are considered to be spatially autocorrelated. The presence of spatial autocorrelation violates the assumption of linear regression models, that observations are independent. In this study, we use the Moran's *I* test to detect spatial autocorrelation, and thereby to verify the presence of spatial dependence. Such a test was performed on the residuals of estimated models, because the residuals are an indicator of unpredicted effects, which may contain the spatial effects.

3.3. Tests of Spatial Autocorrelation

We used two ways to test for spatial autocorrelation. The first was through an unconditional test on the variable of interest, deforestation. Although this test does not report the presence of spatial autocorrelation on the estimations of the models, it can indicate whether deforestation presents global and local spatial autocorrelation. The second test was the global autocorrelation test on the residuals of models. As the residuals are the non-modeled terms, if spatial effects exist, they will be contained in them. The global autocorrelation test used was the Moran's Index (Moran's *I*), and the local autocorrelation test was the LISA indicator.

The Moran's *I* is formally presented as:

$$I_t = \left(\frac{n}{S_0}\right)\left(\frac{Z_t' W Z_t}{Z_t' Z_t}\right), t = 1, \ldots, n \qquad (7)$$

where Z_t is a vector of n observations for the year t deviated from the mean for the variable of interest, i.e., the area of deforestation. W is the spatial weight matrix, such that: (1) the diagonal elements W_{ii} are equal to zero; and (2) the non-diagonal elements W_{ij} indicate the way that a region i is spatially connected with the region j. S is a scalar term that is equal to the sum of all W elements.

The Moran's *I* provides a very good approximation of any linear association between the vectors observed at time t and the weighted average of neighboring values, or spatial lags (Cliff and Ord, 1981). If the I value is greater than its expected value, it may suggest the presence of positive spatial autocorrelation; otherwise, there is negative spatial autocorrelation (Anselin, 1992).

The value of Moran's I was computed by the usual procedure, in which the variable analyzed is assumed to follow a normal distribution of non-correlated data. The alternative procedures, permutation and randomization, assume randomness of observations in the regions. The hypothesis of normal distribution of the variable transmits the asymptotic properties inherent to this distribution as standardization (mean equal to 0 and variance equal to 1) and sample size (i.e., assuming that the sample can become infinitely large) (Anselin, 1992).

LISA—also known as Moran Local—was used to identify spatial clusters related to our variable of interest among municipalities of the Legal Amazon. Formally, the Moran Local is used to test the null hypothesis of no local spatial autocorrelation. It is formally given by:

$$I_i = \frac{z_i \sum_j W_{ij} z_j}{\sum_i z_i^2} \tag{8}$$

where Z, W and the subscripts i and j are as defined in (7).

Both to implement the exploratory analysis of spatial data and to perform spatial econometric analysis, it is necessary to define a spatial weight matrix (W), which satisfies the criterion of contiguity between spatial units. Any spatial weight matrix must meet the conditions of regularity imposed by the need to rely on the asymptotic properties of estimators and tests. According to Anselin (1988), this means that the weights should be non-negative and finite and correspond to a particular metric.

This study used the spatial weight matrix based on the criterion of contiguity (k) to nearest neighbors. This weight matrix can be expressed as follows (Le Gallo and Ertur, 2003):

$$\begin{cases} W_{ij}(k)\ se\ i = j \\ W_{ij}(k) = 1\ se\ d_{ij} \leq D_i(k)\ e\ W'_{ij}(k) = W_{ij}(k)/\sum_j W_{ij}(k) \quad para\ k = 1,2,\dots,n \\ W_{ij}(k) = 0\ se\ d_{ij} > D_i(k) \end{cases} \tag{9}$$

where d_{ij} is the distance measured by the great circle between the centers of regions i and j. $D_i(k)$ denotes the cutoff value of acceptable values to neighboring regions i. Regions farther apart than this value are not considered to be neighbors. The weight matrix of type k nearest neighbors is a recommended solution when the weights in the distance and the units of area are very irregular. The matrix of k nearest neighbors was also used by Pace and Barry (1997), Pinks and Slade (1998), and Baller et al. (2001) for different applications.

The procedure for choosing the k value was based on information about the presence of higher global spatial autocorrelation, indicated by the Moran's I value. As will be seen in the results, the spatial weight matrix of 10 nearest neighbors is the best for evaluating the global spatial autocorrelation for deforestation, so this matrix was used in the following steps related to the estimations.

Finally, models (4)–(6) can produce consistent and non-biased estimates since such models represent alternatives whose purpose is to take in account the spatial effect of data. The procedures to be executed can be summarized as follow:

Step 1. Define a spatial weight matrix and test the presence of spatial autocorrelation at the global and local level.
Step 2. Run fixed and random effects models and get the residuals.
Step 3. Use the residuals to check for spatial autocorrelation.
Step 4. Run panel data models that take into account the spatial autocorrelation, and get the residuals.
Step 5. Perform the spatial autocorrelation tests again on the residuals generated in step 4.

4. Results

Before progressing to the backbone of the analysis, we needed to test for the presence of spatial autocorrelation in the data. As described above, values for Moran's I, both global and local, were calculated for the deforested area (km^2) for the 732 municipalities of Legal Amazon from 2000 to 2007. The results are shown in Table 2. For all the years analyzed, the coefficients were positive at the 1% level, indicating global spatial autocorrelation. We therefore rejected the hypothesis there is no global spatial autocorrelation, and accepted that spatial components must be considered in the regression model.[6] Otherwise, biased and inefficient estimates would be observed. The spatial weight matrix of 10 nearest neighbors presented spatial autocorrelation coefficients more significant than others in all the years analyzed. Therefore, the following steps were taken based on this matrix (Table 2).

Figure 2 illustrates the LISA statistics (Local Moran) of deforestation for 2000 and 2007. The maps show significant clusters that have significant spatial autocorrelation at local level. We can highlight two predominant local clusters in both years: (1) High-High: a cluster that covers a large part of Pará and northern Mato Grosso. This suggests that municipalities with high rates of deforestation are surrounded by municipalities that also present high rates of deforestation; (2) Low-Low: a cluster that represents parts of Amazonas and parts of Pará, and almost all regions of Amapá and Tocantins. From 2000 to 2007, the High-High cluster becomes more important with increasing extent of coverage, mainly in the states of Pará and Rondônia. Another cluster that appears is the Low-High, especially in the states of Pará and Mato Grosso. This cluster involves spatial units that have low rates of deforestation, but which are surrounded by spatial units that have high rates of deforestation.

Both statistics, Moran's *I* and LISA, clearly led to the conclusion that there is some spatiality in the data for deforested areas of Legal Amazon. However, it was not clear that spatiality would be also observed in the econometric results.

The second step, thus, was to verify if there is spatial autocorrelation among the determinants that are omitted in the econometric estimation. To do this, we performed spatial correlation tests on the residuals of the regressions. First, we ran our analysis with a fixed/random effect model without correcting for any spatial autocorrelation whatsoever. The results of pooled, fixed, and random effects are displayed in Table 1A (Appendix). The Hausman test indicates that the fixed effects model is more suitable to our data than the random effects model. Also, the Moran's *I* test performed for the vector of residuals from the fixed effects model does reject the hypothesis of no spatial

[6] A randomized procedure of Moran Indexes was used to run this test (details about the procedure can be found in Anselin, 2005).

autocorrelation at the 1% level of significance.[7] The coefficients of some of our variables of interest—openness to trade and areas of agricultural commodities—were positive and statistically significant. However, as mentioned previously, not taking into account any spatial effects leads to inappropriate analysis of the dynamic of deforestation at Amazon.

The next step was to estimate specific models that capture spatial effects. We generated estimates using the three models proposed (equations (4), (5) e (6)), plus a fourth model, the Spatial Error Model (Spatial Autoregressive Model – SAR). Anselin (2008) shows that when the SAR model is utilized, either for panel data or for cross-section, it produces efficient, unbiased, and consistent estimators. This model is estimated in two stages and is given by:

$$Y_{it} = X_{it}\beta + \epsilon_{it} \tag{10}$$

and

$$\epsilon_{it} = \lambda W_N \epsilon_{it} + u_t \tag{11}$$

where the predicted ϵ_{it} term from (11) is spatially lagged and used as an explanatory variable in the original model (10). The results of this model produce similar estimates as the ones observed in the ordinary fixed-effects model, although is possible to show that the statistical inference of SAR models might still be compromised. In such a case, a specific software (or procedure) to deal with spatial effects at the panel data level would be more appropriate.[8] To allow correct estimates regarding to standard deviation of SAR, alternative models can be found in Baltagi and Li (2006), Baltagi et al. (2006) and Baltagi et al. (2007).

The results presented in Table 3 are good, but still not sufficient to infer that the spatial effect was controlled. It is still necessary to verify if there is any spatial effect on the

[7] Table 2A (Appendix) presents the test of spatial autocorrelation for the residuals from the model that was chosen, the fixed effects model.
[8] Currently there is no software to perform spatial econometric analysis in the context of panel data. Routines were developed by independent researchers (e.g., James P. LeSage) that can be implemented in MATLAB or R.

residuals generated by these regressions.[9] The Moran's *I* test performed on the residual vectors showed that the spatial effect still persisted and had to be to take into account in some different way.[10] Anselin (1992) suggests two procedures: (1) create spatial regimes that consider distinct situations related to the variable of interest. Thus, the estimation will be executed following distinct groups of observations; (2) create dummies to control any effects stemming from spatial outliers. For convenience, we chose the second option to mitigate the persisting spatial effects.

Table 8 shows the results of three models (lagged, cross-regressive, and Durbin) with dummies for spatial outliers. Based on previous results (Table 3), the fixed effects specification was kept for the lagged and cross-regressive models, and a random effects model was estimated for the Durbin model. It is worth mentioning that the adoption of these different models for the analysis of conventional panel data is not a strict spatial econometric procedure; more information regarding to neighboring effect is be required for a complete analysis (Anselin, 2008). Our inclusion of spatial lagged explanatory variables, as well as dummies, is an attempt to reduce possible shortcomings due to the persistent spatial effects. The variable *DUMMY_S* represents spatial units with values ≥ 2.5 standard deviations and the variable *DUMMY_I* represents spatial units with values ≤ -2.5 standard deviations.

Spatial autocorrelation tests were performed on the residual for the three models estimated (Tables 9–11). The tests indicated that the Durbin model was more suitable to explain the dynamic of deforestation at Amazon. The hypothesis that there is no spatial autocorrelation was not rejected at the minimum statistical level of 7% (Table 11). Moreover, a Wald test in the Durbin model was calculated only on the variables that were spatially lagged, and the result (1,209.12) was significant at 1%. The results of the Durbin specification show that the coefficients were not only significant at the 1% level, but showed expected signs as well. An important result is the indication that the spatial effect is present; this implies that the rate of deforestation in each spatial unit is influenced by both the average rate of deforestation and the average values of the explanatory variables of the neighbors. This result suggests the interrelation of spatial

[9] Table 3 displays the results for the four models proposed. A Hausman test (H_o: FE versus RE) was performed for each.
[10] The results of these tests are presented in Tables 4–7.

interaction and deforestation: the spillover effects from both deforestation activities and other activities in neighboring spatial units are important in explaining deforestation in each spatial unit.

We were also able to corroborate many theoretical findings suggested by the literature. We found that in the period 2002–2007, greater openness to trade did result in increased deforestation in Legal Amazon. Second, the positive and statistically significant coefficient for GDP^2 suggests that as GDP increases, deforestation decreases, in keeping with the assumptions of the Environmental Kuznets Curve (Dinda, 2004). Barbier and Burgess (1997) analyzed FAO data for the period 1980–1985 on forest cover in 53 tropical countries and found that for most of them, including Brazil, when national income per capita goes up, the demand for continued deforestation diminishes. One explanation for this trend, according to them, is that as countries develop economically, the productivity of their agricultural land increases, reducing the pressure on forested land.[11]

We also observed that the production of cattle, soybeans, cotton, and sugarcane have indeed contributed to deforestation in Legal Amazon. Some authors argue that the reason the production of agricultural commodities on a large scale has increased so sharply in the Amazon region since the 1990s is the high international prices for soybeans (Brandão et al., 2006; Diniz et al., 2009). A more appropriated measure to infer about this causal interpretation would be through domestic and international prices of commodities, however because of higher transaction costs, especially transportation, that the region faces; we opted by not using them in this study. The sign of the coefficient for corn was significant and negative, which is not surprising, as corn prices have not been as high as those for soybeans in recent years. Corn is a very important staple food in the Amazon, but it is still raised on a small scale by local communities and indigenous groups.

Other determinants were significant and had the expected signs. For example, the extraction of timber drives deforestation, but the production of non-wood products does

[11] In fact, the issue is more complicated in the Amazon region. Some studies have shown that a farmer would rather spend until $500 dollars to expand your agricultural area into the forest virgin (slash-and-burn) than $1,200 to recuperate his degraded agricultural land (Marcovitch, 2011).

not. The coefficient for firewood is negative and has a negative sign. This may reflect the fact that its extraction is mostly done by local communities that use the forest as their livelihood.[12] Some unexpected results were the findings that population density had a negative impact on deforestation, and that the distance between municipalities and the state capitols had no impact.

Many spatially lagged variables were statistically significant, which clearly provides evidence that the neighbor effect is important in deforestation. In these cases, there are significant spillover effects of some other spatial units. For example, the coefficient of the variable *W_deforestation* indicates that the effect of deforestation on a spatial unit tends to be positively related to the deforestation of each of its neighbors. This is expected, since the deforestation activity expands in space from one spatial unit to its neighbor, in a form of contagion.

The variables *openness* and *cattle*, when spatially lagged, exhibit negative coefficients, indicating that situations of greater openness to trade and expansion of livestock in neighboring spatial units negatively affect deforestation in the spatial reference unit. This means that even if the increase in openness to trade and livestock activities in a spatial unit contributes to an increase in its deforestation, if it occurs in neighboring spatial units, the effect is to reduce its deforestation. One explanation for such a result is that these activities might compete in a local area. Thus, if activities focused on international trade are located in one municipality, and thereby increase deforestation in that location, such activities have may ceased in other municipalities, with a resulting decrease in deforestation in these other locations.

5. Concluding Remarks

The objective of this paper was to investigate how international trade has affected the dynamics of deforestation in the Brazilian Amazon. The analysis focuses on the expansion of crop and cattle activities, and other determinants such as gross domestic product, demographic density, and roads. The combination of standard econometrics

[12] There is an intensive ongoing debate among scholars and the general public as to the real role of local communities in the Amazon forest—whether they are helping to preserve the forest or are promoting more predatory overexploitation of natural resources. This subject is left to future analysis.

and spatial econometrics was designed to capture the socio-economic interactions among the agents throughout the Legal Amazon region.

The main findings allowed us to corroborate some of theoretical findings from the literature, particularly in the international trade field, that are not well documented. For example, as long as municipalities are more open to trade, the result is more deforestation. In fact, is not surprising that public authorities are failing to contend with the overexploitation of natural resources, especially timber, to attend domestic and mainly international markets. Poverty, land conflicts, illegal logging, and corruption are very old and chronic problems in the region (Araujo et al., 2009) and have to be tackled with more than efforts of political will by governments, NGOs, and local communities.

Other determinants, such as the expansion of beef cattle and the production of soybeans, sugarcane, and cotton are important determinants that are driving deforestation in the region. Some argue that increases in productivity for these economic activities through technological change could substantially alleviate the pressure on natural resources (Brandão et al., 2006). Also, we found important evidence that when the square of GDP goes up, the result is less deforestation, which supports, to some extent, the environmental Kuznets Curve hypothesis.

Finally, the results provide more support for the idea that strategies to be undertaken in region in order to alleviate poverty, while also benefiting the environment, should be designed to increase income through other economic activities, and increases in agricultural productivity, to supplant the ones that promote the overexploitation of natural resources.

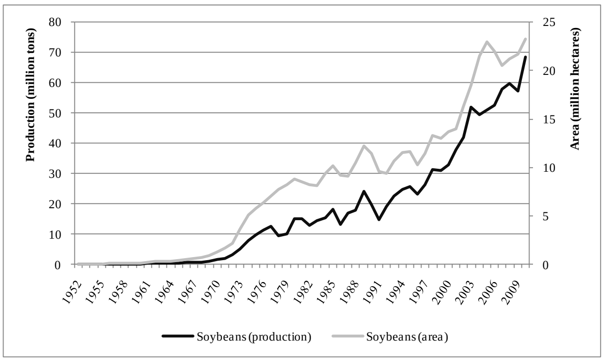
Table 1. Variable Definitions, Means and Standard Deviations

Variable	Description	Mean	SD
Deforestation	Deforested Area (Km^2)	825.21	1,163.08
Openness	(X+M/GDP) where X and M are, respectively, the import and export values, and GDP is the Gross Domestic Product	0.068	0.1482
Cattle	Number of heads	81,274.19	122,191.4
Soybeans	Soybean production (tons)	18,237.26	100,049.6
Density	Population/area	21.42	114.40
GDP	Gross Domestic Product	123,380	708,844.9
GDP^2	Square of Gross Domestic Product	5.18e+11	1.03e+13
GDP*Openness	Interactive term (GDP times Openess)	6,917.90	180,154.1
Sugar Cane	Sugar cane (ton)	19,480.25	159,992.1
Corn	Corn Production (tons)	5,736.61	29,281.39
Cotton	Cotton production (tons)	1,916.80	14,135.33
Firewood	Firewood production (tons)	16,322.97	37,121.8
Timber	Timber production (tons)	19,861.39	81,958.08
Nonwood[1]	Non-wood products (tons)	1,786.21	12,587.71
Distance	Distance (km) between the city and the state capitol	313.787	236.17

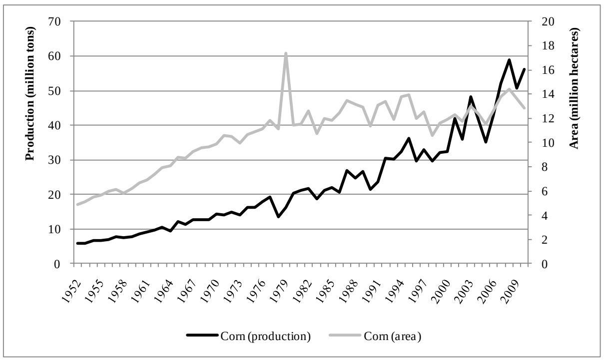
[1]Fruits, oils, medicinal plants, latex, etc.

Figure 1. Agricultural Production and Foreign Trade of Brazil

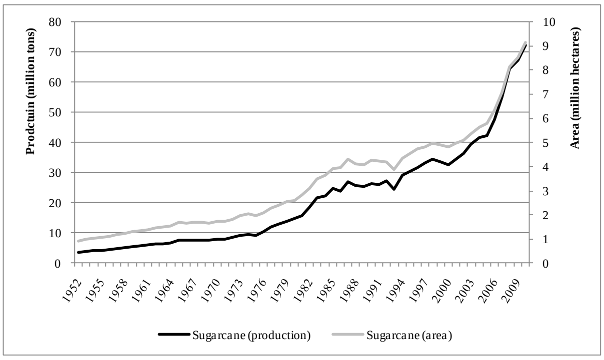
(a)



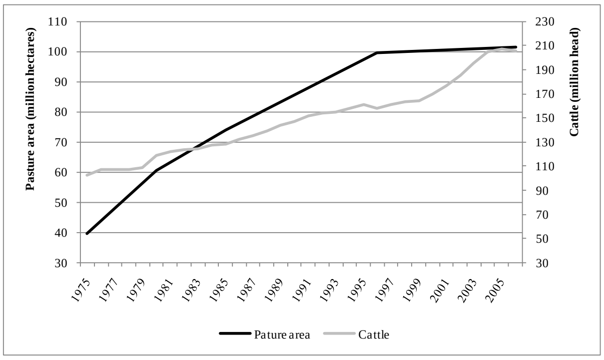
(b)



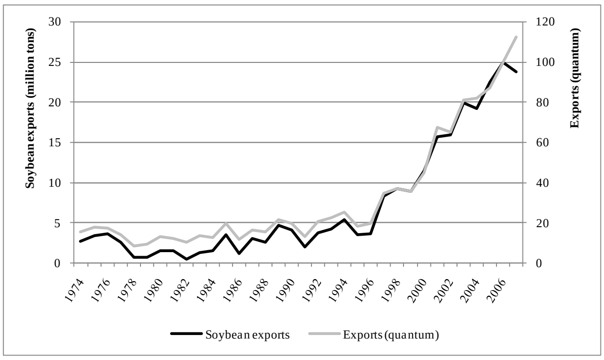
(c)



(d)



(e)



(f)

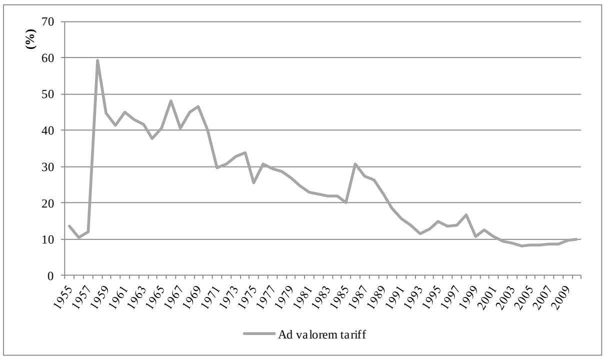
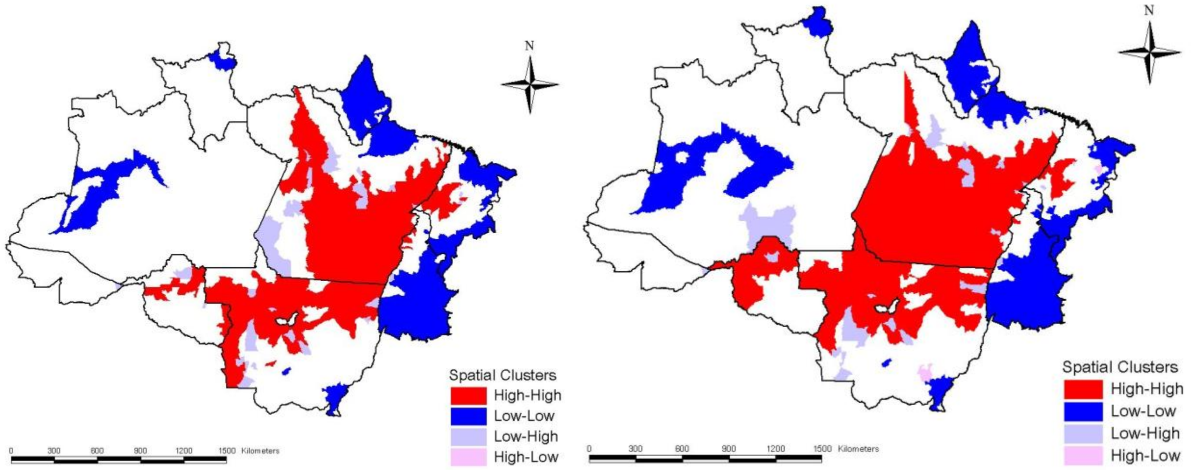


Table 2. Moran Index (*I*) for the Deforested Areas of Municipalities of Legal Amazon

Year	Spatial Weight Matrix	Moran's I	Mean	SD	p-value
	10 nearest neighbors	0.429	0.000	0.015	0.001
2000	15 nearest neighbors	0.403	-0.001	0.012	0.001
	20 nearest neighbors	0.381	-0.001	0.010	0.001
	10 nearest neighbors	0.415	-0.001	0.015	0.001
2001	15 nearest neighbors	0.388	-0.002	0.012	0.001
	20 nearest neighbors	0.367	-0.002	0.011	0.001
	10 nearest neighbors	0.415	-0.001	0.015	0.001
2002	15 nearest neighbors	0.389	-0.001	0.012	0.001
	20 nearest neighbors	0.367	-0.001	0.010	0.001
	10 nearest neighbors	0.417	-0.002	0.015	0.001
2003	15 nearest neighbors	0.393	-0.002	0.012	0.001
	20 nearest neighbors	0.372	-0.001	0.011	0.001
	10 nearest neighbors	0.418	-0.001	0.015	0.001
2004	15 nearest neighbors	0.395	-0.001	0.012	0.001
	20 nearest neighbors	0.374	-0.002	0.010	0.001
	10 nearest neighbors	0.417	-0.002	0.015	0.001
2005	15 nearest neighbors	0.394	-0.001	0.013	0.001
	20 nearest neighbors	0.373	-0.001	0.010	0.001
	10 nearest neighbors	0.412	0.000	0.015	0.001
2006	15 nearest neighbors	0.391	-0.001	0.012	0.001
	20 nearest neighbors	0.370	-0.001	0.012	0.001
	10 nearest neighbors	0.410	-0.002	0.015	0.001
2007	15 nearest neighbors	0.388	-0.001	0.012	0.001
	20 nearest neighbors	0.366	-0.001	0.011	0.001

Source: Authors' elaboration based on SpaceStat version 1.80, GeoDa and ArcView GIS 3.2.

Figure 2. Cluster Map of *LISA* Statistics of Deforestation in 2000 (left) and 2007 (right)



Source: Authors' elaboration based on SpaceStat version 1.80, GeoDa and ArcView GIS 3.2.

Table 3. Deforested Area Estimations with Correction for the Spatial Effect

Independent variables	*Error*	*Lagged*	*Cross Regresssive*	*Durbin*
Constant	451.798***	-59.956***	404.06***	-63.475*
	(6.96)	(12.18)	(16.82)	(37.53)
Openness	501.570***	-280.886***	406.60	943.872***
	(55.34)	(56.98)	(326.63)	(231.00)
Cattle	4E-03***	2.46E-03***	3.27E-03***	3.57E-03***
	(0.00)	(0.00)	(0.00)	(0.00)
Soybeans	9.66-04***	6.49E-04***	5.95E-04***	4.76E-04***
	(0.00)	(0.00)	(0.00)	(0.00)
Density	-3.73E-02	-4.23E-02	-3.79E-02	-3.60E-02
	(0.08)	(0.08)	(0.10)	(0.07)
GDP	12.12E-04***	1.12E-04**	1.75E-04***	1.34E-04***
	(0.00)	(0.00)	(0.00)	(0.00)
GDP^2	-3.74E-12***	-3.67E-12**	-5.73E-12***	-5.00E-12***
	(0.00)	(0.00)	(0.00)	(0.00)
GDP*Openness	-1.34E-04*	-6.94E-05	-1.42E-04	-8.56E-05
	(0.00)	(0.00)	(0.00)	(0.00)
Sugacane	5.78E-05	1.72E-05	3.38E-06	6.91E-05
	(0.00)	(0.00)	(0.00)	(0.00)
Corn	-7.72E-04***	-8.62E-04***	-1.15E-03***	-1.12E-03***
	(0.00)	(0.00)	(0.00)	(0.00)
Cotton	-1.52E-04	3.25E-04	1.48E-04	-5.79E-05
	(0.00)	(0.00)	(0.00)	(0.00)
Firewood	-2.58E-04**	-9.29E-05	-1.12E-04	-1.02E-04
	(0.00)	(0.00)	(0.00)	(0.00)
Timber	2.66E-05	7.58E-05	-1.62E-05	2.24E-04***
	(0.00)	(0.00)	(0.00)	(0.00)
Nonwood	-4.94E-04**	-6.54E-04***	-7.61E-04***	-2.51E-04***
	(0.00)	(0.00)	(0.00)	(0.00)
Distance				1.91E-03
				(0.20)
W_Residual	1.19E+00***			
	(0.02)			
W_Deforestation		9.07E-01***		1.13***
		(0.02)		(0.02)
W_Openness			-584.41*	-1026.365***
			(335.57)	(240.20)
W_Cattle			1.30E-03***	-3.46E-03***
			(0.00)	(0.00)
W_Soybeans			1.90E-03***	-2.93E-04
			(0.00)	(0.00)
W_Density			2.08E-01	6.77E-02
			(0.31)	(0.23)
W_GDP			2.28E-04***	1.73E-05
			(0.00)	(0.00)
W_GDP^2			7.24E-08	-1.41E-07
			(0.00)	(0.00)

Table 3. Deforested Area Estimations with Correction for the Spatial Effect (cont'd)

*W_ GDP*Openness*			4.10E-04**	1.95E-04
			(0.00)	(0.00)
W_Sugarcane			-4.00E-04***	-2.04E-04*
			(0.00)	(0.00)
W_Corn			3.37E-03***	1.81E-03***
			(0.00)	(0.00)
W_Cotton			-2.87E-03**	-1.16E-03
			(0.00)	(0.00)
W_Firewood			4.03E-04	-5.08E-05
			(0.00)	(0.00)
W_Timber			-1.56E-03***	-2.68E-04
			(0.00)	(0.00)
W_Nonwood			-3.22E-03***	-1.17E-03
			(0.00)	(0.00)
W_Distance				-1.96E-02
				(0.24)
N	6256	6256	6256	6256
R^2 *within*	0.638	0.625	0.479	0.657
Teste F / Wald $\chi^{2\ a}$	687.970***	650.140***	193.21***	12258.98***
Akaike	77560.98	77784.49	77666.6	-
Schwartz	77655.36	77878.86	77767.72	-
Hausman	28.29***	18.05***	424.04***	5.55

Source: Authors' Elaboration based on software SpaceStat version 1.80, GeoDa, ArcView GIS 3.2 and Stata/SE version 10.0.
Note: F test (fixed effects) and Wald test (random effects).
* p<0.10; ** p<0.05; *** p<0.01.
Standard deviations are in parentheses under the coefficients.

Table 4. Test of Spatial Autocorrelation of Error Model of Fixed Effects

Year	Moran's *I*	Mean	SD	p-value
2000	-0.035	-0.001	0.015	0.004
2001	-0.022	-0.001	0.015	0.070
2002	-0.056	-0.001	0.015	0.001
2003	-0.086	-0.001	0.015	0.001
2004	-0.039	-0.001	0.015	0.002
2005	-0.036	-0.001	0.015	0.006
2006	-0.047	-0.001	0.014	0.001
2007	-0.048	-0.001	0.014	0.001

Source: Authors' elaboration from SpaceStat version 1.80, GeoDa, ArcView GIS 3.2.

Table 5. Test of Spatial of Residuals of Spatial Lagged Model of Fixed Effects

Year	Moran's *I*	Mean	SD	p-value
2000	0.008	-0.001	0.014	0.247
2001	0.043	-0.001	0.014	0.004
2002	-0.003	-0.001	0.014	0.475
2003	0.061	-0.002	0.014	0.001
2004	0.234	-0.001	0.015	0.001
2005	0.055	-0.001	0.015	0.001
2006	0.004	-0.001	0.014	0.346
2007	0.028	0.000	0.014	0.031

Source: Authors' elaboration from SpaceStat version 1.80, GeoDa, ArcView GIS 3.2.

Table 6. Test of Spatial Autocorrelation of Residuals of Crossed Regressive Model of Fixed Effects

Year	Moran's *I*	Mean	SD	p-value
2000	0.332	-0.002	0.015	0.001
2001	0.256	-0.001	0.014	0.001
2002	0.211	-0.001	0.014	0.001
2003	0.304	-0.001	0.015	0.001
2004	0.432	-0.002	0.015	0.001
2005	0.258	-0.001	0.015	0.001
2006	0.173	-0.001	0.014	0.001
2007	0.245	-0.001	0.014	0.001

Source: Authors' elaboration from SpaceStat version 1.80, GeoDa, ArcView GIS 3.2.

Table 7. Test of Spatial Autocorrelation of Residuals of Spatial Durbin Model of Random Effects

Year	Moran's *I*	Mean	SD	p-value
2000	-0.044	-0.001	0.015	0.002
2001	-0.040	-0.001	0.014	0.004
2002	-0.055	-0.002	0.015	0.001
2003	-0.044	-0.001	0.015	0.004
2004	-0.067	-0.002	0.014	0.001
2005	-0.032	-0.001	0.015	0.014
2006	-0.051	-0.001	0.014	0.001
2007	-0.043	-0.001	0.015	0.001

Source: Authors' elaboration from SpaceStat version 1.80, GeoDa, ArcView GIS 3.2.

Table 8. Econometric Results for the Deforested Areas with Correction for Spatial Effect and Dummies for Outliers

Independent Variables	*Lagged*	*Cross-Regressive*	*Durbin*
Constant	27.236*** (43.05)	436.08*** (11.97)	-35.854 (35.80)
Openness	-249.812*** (56.98)	466.47** (232.50)	874.932*** (182.81)
Cattle	2.63E-03*** (0.00)	3.58E-03*** (0.00)	3.58E-03*** (0.00)
Soybeans	5.64E-04*** (0.00)	6.61E-04*** (0.00)	3.45E-04*** (0.00)
Density	-3.32E-02 (0.06)	-4.02E-02 (0.07)	-3.48E-02 (0.06)
GDP	5.01E-05 (0.00)	1.12E-04*** (0.00)	9.96E-05*** (0.00)
GDP^2	-1.21E-12 (0.00)	-3.32E-12** (0.00)	-3.57E-12*** (0.00)
GDP*Openness	2.52E-05 (0.00)	-4.68E-05 (0.00)	-5.45E-05 (0.00)
Sugarcane	2.42E-05 (0.00)	3.45E-05 (0.00)	7.45E-05** (0.00)
Corn	-7.16E-04*** (0.00)	-1.03E-03*** (0.00)	-1.28E-03*** (0.00)
Cotton	2.28E-04 (0.00)	2.16E-04 (0.00)	6.73E-04** (0.00)
Firewood	-2.47E-05 (0.00)	1.86E-05 (0.00)	-2.57E-04*** (0.00)
Timber	-5.97E-05 (0.00)	-1.12E-04* (0.00)	3.18E-04*** (0.00)
Nonwood	-1.01E-03*** (0.00)	-1.04E-03*** (0.00)	-5.65E-04*** (0.00)
distance			7.59E-03 (0.19)
W_Desforestation	7.86E-01*** (0.02)		1.07E+00*** (0.00)
W_Openness		-637.70*** (238.82)	-957.86*** (189.21)
W_Cattle		8.40E-04*** (0.00)	-3.38E-03*** (0.00)
W_Soybeans		1.48E-03*** (0.00)	-1.60E-04 (0.00)
W_Density		1.02E-01 (0.22)	8.13E-03 (0.17)
W_GDP		2.09E-04*** (0.00)	1.29E-05 (0.00)
W_GDP^2		-3.90E-08 (0.00)	-1.46E-07** (0.00)
*W_GDP*Openness*		3.78E-04*** (0.00)	1.68E-04 (0.00)
W_Sugarcane		-2.76E-04*** (0.00)	-1.33E-04 (0.00)

Table 8. Econometric Results for the Deforested Areas with Correction for Spatial Effect and Dummies for Outliers (cont'd)

W_Corn		3.35E-03***	1.79E-03***
		(0.00)	(0.00)
W_Cotton		-5.79E-03***	-1.26E-03
		(0.00)	(0.00)
W_Firewood		5.25E-04	-1.25E-04
		(0.00)	(0.00)
W_Timber		-1.38E-03***	-6.72E-04***
		(0.00)	(0.00)
W_Nonwood		-4.14E-03***	-1.61E-03***
		(0.00)	(0.00)
W_Distance			6.80E-02
			(0.23)
DUMMY_S	429.841***	545.70***	470.057***
	(14.48)	(15.60)	(13.52)
DUMMY_I	-566.257***	-671.57***	-513.523***
	(13.60)	(13.66)	(12.57)
N	6256	6256	6256
R^2 *within*	0.787	0.737	0.813
F / Wald $\chi^{2\ a}$	1256.28***	544.46***	24610.31***
Akaike	74266.81	75602.66	-
Schwartz	74374.67	75791.42	-

Source: Authors' elaboration based on software SpaceStat version 1.80, GeoDa, ArcView GIS 3.2 and Stata/SE version 10.0.

Note: (a) F test (fixed effects) and Wal test (random effects); (b) Hausman test was done with respect to two models: Error, Lagged and Durbin regarding to the first step of estimation when we chose the more suitable model to predict the residuals to be used in the second step of estimation.

* p<0.10; ** p<0.05; *** p<0.01.

Standard errors are in parentheses under the coefficients.

Table 9. Test of Spatial Autocorrelation of Residuals of Spatial Lagged Model of Fixed Effects and Dummies for Outliers

Year	Moran's *I*	Mean	SD	p-value
2000	0.071	-0.002	0.014	0.001
2001	0.129	-0.001	0.014	0.001
2002	0.049	-0.001	0.014	0.003
2003	0.024	-0.001	0.015	0.061
2004	0.098	-0.001	0.014	0.001
2005	0.131	-0.002	0.014	0.001
2006	0.097	-0.001	0.014	0.001
2007	0.020	-0.001	0.014	0.070

Source: Authors' elaboration from SpaceStat version 1.80, GeoDa, ArcView GIS 3.2.

Table 10. Test of Spatial Autocorrelation of Residuals of Crossed Regressive Model of Fixed Effects and Dummies for Outliers

Year	Moran's *I*	Mean	SD	p-value
2000	0.364	-0.002	0.014	0.001
2001	0.252	-0.001	0.014	0.001
2002	0.102	-0.002	0.015	0.001
2003	0.112	-0.001	0.015	0.001
2004	0.233	-0.001	0.015	0.001
2005	0.157	-0.002	0.015	0.001
2006	0.150	-0.001	0.014	0.001
2007	0.211	-0.001	0.014	0.001

Source: Authors' elaboration from SpaceStat version 1.80, GeoDa, ArcView GIS 3.2.

Table 11. Test of Spatial Autocorrelation of Residuals of Spatial Durbin Model of Random Effects and Dummies for Outliers

Year	Moran's *I*	Mean	SD	p-value
2000	-0.015	-0.001	0.015	0.182
2001	-0.020	-0.002	0.014	0.104
2002	-0.017	-0.001	0.015	0.162
2003	-0.016	-0.001	0.015	0.084
2004	0.000	-0.002	0.014	0.515
2005	-0.014	-0.002	0.015	0.234
2006	-0.024	-0.002	0.015	0.070
2007	-0.021	-0.001	0.015	0.083

Source: Authors' elaboration from SpaceStat version 1.80, GeoDa, ArcView GIS 3.2.

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Appendix

Table 1A. Deforested Area Estimations without Correction for the Spatial Effect

Independent Variables	*POOLS*	*Fixed Effect*	*Random Effect*
Constant	7.668 (16.42)	456.276*** (8.67)	150.488*** (42.02)
Openness	491.714*** (67.41)	233.954*** (68.67)	344.923*** (66.05)
Cattle	6.20E-03*** (0.00)	3.84E-03*** (0.00)	4.07E-03*** (0.00)
Soybeans	9.43E-04*** (0.00)	1.40E-03*** (0.00)	1.28E-03*** (0.00)
Density	-1.63E-01** (0.08)	-3.92E-02 (0.10)	-9.40E-02 (0.10)
GDP	2.48E-04*** (0.00)	2.52E-04*** (0.00)	1.93E-04*** (0.00)
GDP^2	-1.76E-11*** (0.00)	-8.32E-12*** (0.00)	-6.63E-12*** (0.00)
GDP*Openness	-4.55E-04*** (0.00)	-1.64E-04* (0.00)	-1.21E-04*** (0.00)
Sugarcane	2.29E-04*** (0.00)	2.00E-05 (0.00)	4.99E-05* (0.00)
Corn	4.04E-03*** (0.00)	-3.17E-04* (0.00)	-1.11E-04 (0.00)
Cotton	-1.37E-02*** (0.00)	-1.24E-04 (0.00)	-8.42E-04* (0.00)
Firewood	4.48E-04*** (0.00)	-1.69E-04 (0.00)	1.19E-05 (0.00)
Timber	2.31E-03*** (0.00)	-1.79E-04** (0.00)	1.58E-04* (0.00)
Nonwood	1.07E-02*** (0.00)	-9.54E-04*** (0.00)	-6.36E-04*** (0.00)
Distance	5.56E-01*** (0.04)		8.86E-01*** (0.11)
N	6256	6256	6256
R^2	0.631	0.438	0.436
F / Wald χ^2	763.220***	327.950***	5058.71***
Akaike	99859.18	80309.66	-
Schwartz	99953.55	80397.29	-
Hausman		35.87***	

Source: Authors' elaboration from Stata/SE version 10.0.
Note: a) R^2 adjusted (Pooled) and R^2 *within* (fixed effects and random effects models).
b) F test (Pooled and fixed effects) and Wald test (Random effects).
* p<0.10; ** p<0.05; *** p<0.01.
Standard errors are in parentheses under the coefficients.

Table 2A. Test of Spatial Autocorrelation of Residuals for the Fixed Effects Model

Year	Moran's *I*	Mean	SD	p-value
2000	0.349	-0.001	0.015	0.001
2001	0.264	-0.001	0.015	0.001
2002	0.242	-0.001	0.015	0.001
2003	0.204	-0.001	0.015	0.001
2004	0.317	-0.001	0.015	0.001
2005	0.225	-0.001	0.015	0.001
2006	0.200	-0.001	0.015	0.001
2007	0.266	-0.001	0.015	0.001

Source: Authors' elaboration from SpaceStat version 1.80, GeoDa, ArcView GIS 3.2.