Economic Causes of Deforestation in the Brazilian Amazon: An Empirical Analysis of the 2000s[1]

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Resumo: Esse artigo discute as recentes causas econômicas e de políticas públicas do desmatamento na Amazônia Legal Brasileira. Ele se baseia em um modelo teórico em que agentes escolhem o quanto desmatar de acordo com suas expectativas sobre o lucro futuro esperado da pecuária e do plantio de soja. O trabalho empírico utiliza principalmente variáveis econômicas e de políticas públicas que afetam as expectativas de lucratividade dos agentes. Usando dados recentemente lançados e alguns nunca antes analisados em artigos econométricos o artigo traz uma análise empírica ao estimar um modelo de painel com 783 cidades da região de 2002 a 2007. O desmatamento no período se mostra sendo dirigido por flutuações no tempo dos preços de carne e de soja, assim como por diferenças no espaço nos preços pagos aos produtores em diferentes regiões. Disponibilidade de credito rural, presença de áreas protegidas e assentamentos de reforma agrária também influenciam as taxas de desmatamento. Além disso, o artigo mostra que por alterar a percepção de risco dos agentes, uma maior presença do Ibama (polícia ambiental) é efetiva em reduzir as taxas de desmatamento.

Palavras-chave: Desmatamento; Amazônia; Causas Econômicas; Brasil

Abstract: This study discusses the recent economic and policy drivers of deforestation in the Brazilian Amazon. It is based on a theoretical framework in which agents choose how much forest to clear based on their expectations about future profits from cattle ranching and soybean cropping. The empirical study is based on economic and policy variables that affect this expected profitability. Using newly launched and some never-before analyzed datasets, it provides empirical evidence by estimating a model using panel data for 783 municipalities of the region from 2002 to 2007. Deforestation in the period is found to be driven by fluctuations in meat and soybean prices over time, as well as differences in prices paid to producers over space. Availability of rural credit, presence of protected areas and rural reform settlements also influence deforestation rates. Moreover this study shows that by impacting the risk perception of agents, higher presence of the Brazilian Environmental Police (Ibama) was effective in reducing deforestation rates.

Key words: Deforestation; Amazon; Economic causes; Brazil;

Área ANPEC: Economia agrícola e do meio ambiente

JEL: Q56

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1. Introduction

Deforestation of tropical forests, especially in the case of the Brazilian Amazon, is one of the most debated topics in the environmental field today. The issues involving deforestation of tropical forests cover a wide range from environmental problems, such as the cause of carbon emissions in the context of the Global Warming Process or the loss of biodiversity, the provision of essential ecosystem services to economical and social concerns such as income generation for the traditional and poor population that live in the area (SEEHUSEN 2007).

The deforestation process has not taken place constantly either over space or time. Over space it is highly concentrated in the so called "deforestation arch". On a time perspective, after being state driven from the 1960s to the 1980s, from the 1990s on, it assumed a new dynamic more linked to market forces, with special presence of cattle ranching and soybean cropping, with its ups and downs closely related to the changes in the economic context (FEARNSIDE 2005).

The majority of the existing economic literature about deforestation of the Brazilian Amazon can be divided into two groups. The larger group focuses on explaining deforestation during this state driven period from the 1960s to the 1980s. The second, and more recent group, analyzes recent data and tries to access the new drivers of the deforestation, which are more related to an economic endogenous process. However, most of these new studies incorporate only cross-sectional aspects of it (e.g. ARIMA ET AL. 2007), leaving the recent time dynamics mostly unexplained. Another characteristic of the existing literature is that, for different reasons, it has focused more on what Kaimowitz and Angelsen (1998) call the "direct causes of deforestation".

This study deviates from the existing literature in these two aspects. Firstly, it focuses on the dynamics of the yearly deforestation of the Brazilian Amazon from 2002 to 2007. During this period deforestation rates have been above historical levels. More important than that however, is the fact that within this relatively short period, deforestation rates have fluctuated significantly (INPE 2009). Although there exists significant amount of media reports, some scientific papers and anecdotal evidence that most of these fluctuations were driven by the movements of meat and soybean prices, this hypothesis "has never been submitted to a rigorous econometrical analysis" (EWERS ET AL. 2008). Using panel data from all 783 municipalities of the Legal Amazon area, I assess the drivers that caused these yearly fluctuations in the deforestation rates of the region.

Secondly it focuses on economic and policy drivers that influence the expected profitability of different land use methods and therefore affect agents' decisions concerning land use choices.

Another main contribution of this study is to put together and analyze some data that has never been analyzed, or at least not with the necessary depth, such as the data on yearly fluctuations of national annual meat and soybean prices, official rural credit by municipality, and municipal environmental fines from the Brazilian Environmental Police (Ibama).

The main results show that deforestation rates, during this period, were strongly affected by the evolution of the main economic and policy variables studied. According to the theoretical framework used, by having an effect on the expected profitability of different land use methods, these variables directly affect agents' land use choices and therefore deforestation decisions. While controlling for several relevant factors, I find empirical evidence that increases in meat and soybean prices, and in the availability of official rural credit are associated with increases in the deforestation rates in the Brazilian Amazon. This supports the claims made by media and many non-econometrical studies (e.g. BARRETO ET AL. 2008, THE ECONOMIST 2008).

The biggest novelty brought by this study is the empirical evidence showing that the environmental fines at the municipality level had a statistically significant effect in decreasing the deforestation rates during the studied period.

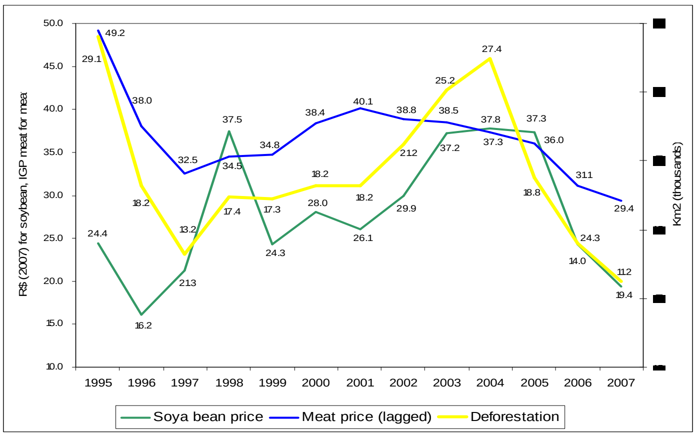
The remaining of this paper is organized as follows: the next section presents some stylized facts that were the motivation for my empirical work. Afterwards I briefly review the literature on econometrical studies about deforestation of the Brazilian Amazon. The following sections contain a theoretical framework, the description of the dataset used in the empirical part and its model specification. I then present the empirical results of the analyzed dataset. The last section concludes and highlights the policy implications as well as provides scope for future research.

2. Stylized facts

There is almost a consensus in the media and in the literature that cattle ranching and soybean cropping are among the most important recent causes of deforestation in the region (NEPSTAD ET AL. 2006a, THE ECONOMIST 2008). There are compelling arguments and descriptive data to support this fact. Soybean cropping and cattle ranching have expanded significantly in the region during the last 15 years. The region's cattle herd, for example, almost tripled from 26 million in 1995 to 73 million in 2006 (BARRETO ET AL. 2008). Several studies showed that the expansion of cattle ranching basically coincides with the *deforestation arch*, and that deforestation is highly correlated with it (e.g. ANDERSEN AND REIS 1997, PRATES 2008).

National and international press, as well as NGOs, politicians and the academic community have been claiming that the deforestation rates during the 2000s have been very influenced by fluctuations in international market prices of soybean and meat (e.g. NEPSTAD ET AL. 2006a, BARRETO ET AL. 2008, THE ECONOMIST 2008). During the 2000s deforestation rates became closely correlated with the prices of these two commodities, both in spatial (ARIMA ET AL. 2007), and in the time dimension (BARRETO ET AL. 2008). Graph 1 shows the fluctuations of soybean and meat prices in Brazilian currency (R$) and the deforestation rates from 1995 to 2007. However compelling the story, to my knowledge, and also according to Ewers at al. (2008), no econometric empirical study has been published analyzing this interaction in detail.

Graph 1: Meat prices, soybean prices and deforestation (1995 - 2007)



Source: Adapted from Barreto et al. (2008)

Fluctuations in the availability of rural credit in the region seem also to be closely connected to the deforestation rates in the region (BARRETO ET AL. 2008). Another claim made by the Brazilian Government is that environmental fines were important, essentially after 2005, for the decrease in deforestation rates. This has also never been submitted to any rigorous econometric analysis.

All the effects described above came into play simultaneously, but with different intensities in distinct parts of the region. In order to disentangle the influence that each one of them had on the recent fluctuation in the deforestation rates an appropriately specified econometric model with a finer scale than the region as a whole is necessary. The aim of this study is precisely to build such a model in order to disentangle all these influences.

3. Literature review

Given the short length of this paper and that this is an empirical work, literature review will be brief and will focus only on empirical works that analyze variables which are among the most important variables that I tested. For a thoroughly literature review please refer to Kaimowitz ad Angelsen (1998).

The major part of economic literature on the topic still uses panel data from old periods (1960-1995) (e.g. PFAFF 1999, ANDERSEN ET AL. 2002) or cross-section from the 2000s (e.g. ARIMA ET AL. 2007). The first group brings up typical explanatory variables such as population (ANDERSEN 1996, KIRBY ET AL. 2006), roads (e.g. ANDERSEN 1996, PFAFF 1999), cattle herd (REIS AND GUZMAN 1992, ANDERSEN AND REIS 1997, PRATES 2008), and rainfall (e.g. MARGULIS 2003, ARIMA ET AL. 2007, AGUIAR ET AL. 2008). These are the causes of deforestation that are not analyzed by this paper since they are not decision parameters of deforestation agents. Other recent papers argue that these drivers may not be the actual causes of deforestation. Pfaff (1999), for example, finds population to be endogenous. Other studies show that causality, from roads to deforestation could be more intense in the opposite direction and that their effects depend on where the roads are built (e.g. ANDERSEN ET AL. 2002, WEINHOLD AND REIS 2008).

The second group brings up variables which are more relevant for my analysis. The effects of differences in prices paid to producers is found to influence deforestation by Arima et al. (2007) cross-section wise and with a short panel by Prates (2008) using a short panel from 2000 to 2004. Prates (2008) also finds credit availability to fuel deforestation. For old periods, using less robust proxies, Andersen (1996) found it to explain deforestation from 1975 to 1985.

The presence of protected areas is believed by many authors, using different methodologies, to decrease fire incidence or deforestation (ARIMA ET AL. 2007, AGUIAR ET AL. 2008).

There are not any econometric studies which focus on the effectiveness of the Ibama fighting illegal deforestation. The first attempt is made by Barreto et al. (2009), who estimate how high would the deforestation rates be without the measures taken by Ibama in 2008. The author argues that the difference to the observed values corresponds to its effectiveness.

4. Theoretical framework

A significant part of the econometrical studies about deforestation of the Brazilian Amazon does not explicitly use a theoretical framework (e.g. ANDERSEN ET AL. 2002, KIRBY ET AL. 2006). These studies usually use reduced form models and some in combination with a general-to-simple approach. They start with a large number of demand and supply variables that may affect deforestation and reduce it step-by-step in order to find the most relevant variables[2]. I chose to explicitly use a theoretical framework because of some reasons. First, using a theoretical framework facilitates the description of the expected relations between variables and makes it more explicit. Second, it makes the assumptions of the model more explicit and facilitates the debate about them. Third, the aim of this study is not to exhaust all possible causes of deforestation but to discuss the relevance of some economic and policy influenced drivers of its recent fluctuations[3].

With some modifications, the theoretical framework used here is based on one of the models presented by Angelsen (1999). I will follow the framework that the author called the "small, open economy with open access and deforestation leading to private property". I chose this model because it is the one that has characteristics that are similar to the Brazilian Amazon region and also because it has some desired features, such as exogenously given prices, population being endogenously determined, production sold at markets, and badly defined property rights with clearing leading to the obtaining of land tittles (ANGELSEN 1999).

In my specific model, deforestation size (*D*) is a positive function of the expected difference between the expected profits (revenues - costs) of unsustainable land uses ($R^d - C^d$) (logging followed by deforestation and agriculture or cattle ranching) and sustainable land uses ($R^s - C^s$). The larger the differential, the larger deforestation is expected to be:

$$D = f\left[E\left(\left(R^d - C^d\right) - \left(R^s - C^s\right)\right)\right] \tag{1}$$

Even recognizing that what matters is the relative rent from sustainable versus unsustainable land use, due to the complexity and still incipient role that sustainable land uses plays in the region, it would be difficult to estimate its rents. I hence chose to assume it as constant and focus on the fluctuations of expected profits from cattle ranching and soybean cropping. Another reason to exclude them is that most of the services provided by forests have public goods' characteristics and therefore are mostly ignored in the individual decision making (ANGELSEN 1999, SEEHUSEN 2007).

Deforestation is basically driven by the expected future profits of cattle ranching and soybean cropping. The higher the expected profitability of these two main activities is, the higher the incentives for farmers to clear one forested area and the higher I expect the deforestation rate to be.

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[2] Some studies even introduce a "random reduction" methodology through which they manage to reduce the degree of arbitrariness on a researcher's hand once having chosen the most relevant variables (Andersen et al. 2002, Weinhold and Reis 2008).

[3] Due to the obvious and likely possibility of omitted variables, during the model specification I make explicit how I expect the variables used to be affected by possibly omitted variables and to be sometimes proxies for them. However this should not affect the validity of the conclusions.

Expected revenues of unsustainable land uses [E(R^d)] is determined by revenues of logging (R^l) and expected revenues from agriculture and cattle ranching (R^a) (equation 2), which is in turn determined by prices of meat (P^m), prices of soybean (P^s), agents market access and conditions, proxied by the meat price index (I^m), and some initial conditions that are specific for each municipality (IC) (equation 3).

$$E(R^d) = f(R^l, E(R^a)) \tag{1}$$

$$E(R^a) = f(P^m, P^s, I^m, IC) \tag{3}$$

Unsustainable land use costs are in turn determined by direct costs of clearing (C^c), expected agricultural and cattle ranching costs (C^a), credit availability (Cr) and the risk of being fined by the environmental police (RI):

$$E(C^d) = f(C^c, E(C^a), Cr, RI) \tag{4}$$

Agents maximize the expected profits from land use by choosing a level of clearing activity that will be implemented in the next period (D), taking into consideration prices of meat (P^m) and soybean (P^s) as follows:

$$Max(E(\pi(P^m, P^s))) \tag{5}$$

$$\text{w.r.t } D$$

$$\text{s.t. } I^m; IC; RI; Cr; R^l; C^c; C^a \tag{6}$$

Where: $\pi =$ profits from agricultural use of cleared area.

Agents are constrained by their initial market conditions and access (I^m) and specific municipality characteristics (IC), such as distance to Brasília, initial deforestation and population. On the policy side they face given credit availability (Cr) and risk of being caught illegally clearing by the environmental police (*RI*). They also face economic costs of clearing (C^c) and of agricultural and cattle ranching inputs and necessary investments (C^a) (equation 6).

One could divide the drivers of expected profits into three groups: market conditions, policy influence and natural or initial conditions. For the first, I conjecture that if prices of meat and soybean increase, there should be an upward pressure on deforestation. To assess the differences in the price paid to producers through a spatial perspective (which proxies market conditions and access), I use an index based on Arima et al. (2007). This index captures the differences in the farmgate prices paid to producers of cattle in one moment in time. Higher prices paid at a farmgate level lead to higher profitability expectation and should increase deforestation as well.

On the policy influence group I hypothesize that larger availability of official subsidized credit increases deforestation. The rational is that credit is not pushing deforestation; rather it only makes the clearing plans resulting from higher expected profits possible. Environmental fines applied by Ibama are modeled as a risk factor of clearing. Given any expected profitability, a positive chance that an agent could be fined for illegal clearing has a negative effect on his expected profitability. As a result higher fines intensity should lead to lower deforestation rates. Lastly, protected areas should work as a barrier to deforestation whereas the existence of agrarian rural reform settlements in one municipality is hypothesized to fuel clearing.

On the natural and initial conditions side, several variables are considered as controls. I expect deforestation to be higher where the distance to Brasilia, as a proxy for transport costs, and rainfall are lower[4]. Initial population and deforestation are proxies of how far the deforestation process is in each municipality. The hypothesis is that larger initial population and deforestation rates are associated with more advanced occupation and thus higher municipal clearing rates.

5. Data

This study deals with data of deforestation by municipality from 2002 to 2007. I chose the municipal scale because it is the finest scale of deforestation possible to which data for several economic and policy variables such as credit and fines can also be found. Basic summary statistics are presented in table 1[5].

The data on municipal deforestation comes from the Prodes project of the Brazilian Space Research Institute (INPE)[6]. All economic variables were deflated by IPCA – the official Brazilian consumer price index[7]. Meat prices were obtained at Anualpec (2009) that reports monthly average price received by cattle ranchers in Brazil[8]. The Meat Price Index is the same used in Arima et al. (2007)[9]. This index should essentially reflect the transport costs from each municipality to the main consumer markets and also local market conditions. For soybeans I used Fundação Getúlio Vargas (FGV) monthly average prices received by farmers for the 60kg bag[10].

Availability of official subsidized rural credit was obtained at the Rural Credit Annual Report of the Brazilian Central Bank. The figures reflect the annual flow of credit granted to rural properties in each municipality within the official rural credit system[11].

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[4] There are two possible theoretical links between rainfall and profitability. First, the higher rainfall rates, the more difficult it is to construct and conserve roads, which increases transport costs. More indirectly, higher precipitation (after a certain threshold) leads to lower productivity for both cattle ranching and soybean cropping (ARIMA ET AL. 2007).

[5] Tables and graphs in the appendix.

[6] Deforestation is reported from September of one year to August of the following year. It is important to notice that degradation in the forest caused by logging can not be assessed.

[7] Although this may not be the perfect deflator for the Amazon region and for agricultural prices, the non-existence of a special deflator for it was the most important reason for its choice. Meat prices are deflated by IGP as they are published by FGV and at the Anualpec (Annual cattle ranching survey). I ran some specifications with credit and soybean prices deflated by IGP (inflation index with higher weights for wholesale) and also with nominal data but results did not change significantly.

[8] For 15kg of Boi Gordo. I calculated annual averages from September of one year to August of following year and also deflated accordingly to match the period in which deforestation is measured by INPE.

[9] Adjusted to municipal base instead of pixel based. It was calculated based on field interviews that assessed prices paid at slaughterhouses all over the region. These prices were then discounted considering average transport costs and the availability of roads in each pixel of the region in order to estimate a farmgate (or pixel wise) meat price using GIS software. I normalized this information and transformed the prices into an index that indicates how municipal meat prices deviate from average prices at one point in time. Although this study was conducted in 2001 to my knowledge it is the best proxy available to assess the variability of prices paid among Amazonian municipalities.

[10] Also average from September of one year to August of the following year.

[11] This system operates with fixed rules and very low fixed interest rates determined by the government that do not depend on market interest rates. Therefore it is enough to use credit availability and not include interest rates fluctuation in our model since it is the main credit line to producers.

The percentage of the municipality area under official environmental protection such as National Parks or Indigenous Areas was obtained from Imazon (Amazon Institute of People and the Environment). I use as a proxy the available data for 2006 extrapolated to all other years, as if it would be constant over the entire period, even knowing it was not[12]. A similar proxy is made for the share of municipality area that is under an agrarian reform project. I use data obtained at Imazon of area of agrarian reform settlement projects by municipality for 2008.

Data on environmental fines were obtained at Ibama. Recognizing that fines are, to a certain extent, endogenous to deforestation, I use the amount of issued fines by municipality divided by deforestation observed in the period. This variable proxies the intensity of Ibama presence in each municipality and is now independent of the amount of deforestation in each municipality[13].

As for the control variables, distance to Brasilia, municipal area, and population at the beginning of the period analyzed were obtained at the Brazilian Statistic and Geography Institute (IBGE). Given the impossibility of receiving a complete dataset of annual municipal rainfall, I work with two proxies: one that accomplishes the spatial differences in rainfall severity among the different municipalities and another that takes into consideration the annual fluctuations from 2002 to 2007 that affected the region as a whole. The second proxy in particular, should be seen cautiously[14].

Table 1: Summary statistics

	Nr. obs.	*Mean*	*St. dev.*	*Min.*	*Max.*
Deforestation	4566	1.739	1.747	0.000	7.248
Meat price	4566	35.695	3.566	29.160	38.850
Index meat price	5292	0.689	0.091	0.077	0.788
Soy price	5327	22.614	5.476	16.855	31.217
Protected areas	4566	3.857	3.722	0.000	11.834
Credit	4294	13.928	1.796	6.732	18.888
Area	4566	7.829	1.357	4.174	11.981
Fines intensity	1882	0.701	0.910	0.004	6.646
Settlement areas	4566	3.104	2.764	0.000	9.291
Initial deforested area	5327	762.313	1,066.893	0.000	9,690.400
Initial population	5215	2.590	7.946	0.070	128.584
Distance to Brasilia	5215	1.326	0.539	0.307	2.868
Rainfall over space	4753	30.452	66.609	1.518	686.658
Rainfall over time	4566	0.973	0.183	0.740	1.220
Meat price x index	5292	3.558	0.260	1.163	3.861

Note: All variables but meat price, initial population, distance to Brasilia, initial deforestation, rain over space and time and soy price are presented with natural logs.

[12] I do not discriminate between the three types of protected areas present in the region (integral protection, sustainable use and indigenous areas).

[13] I used number of fines issued instead of value since only a small part of the fines are actually paid. So number is a proxy for how intensive is the presence of Ibama in a municipality. (BARRETO ET AL. 2008)

[14] The fluctuations across space were estimated based on year rainfall observed in each municipality from 2005 to 2007 gently provided by Imazon. I use the average rainfall per municipality for this period as a rainfall index. The yearly fluctuations are a rougher proxy. The only public available data is the data on some rainfall measurement stations for some cities in the region provided by INMET. So I constructed an index which is the average yearly rainfall of 10 of these stations, trying to pick stations well distributed allover the region.

6. Model specification

One important innovation of this study is its concentration on the analysis of deforestation only where there is forest. This seems fairly obvious. Nevertheless, the majority of the studies until now have focused on the Brazilian Legal Amazon, which encompasses large areas with little forest remaining (highly deforested) or Cerrado areas (Tropical Savanna). These Cerrado areas were therefore never forested by Amazon forest, therefore no deforestation is possible there since only deforestation of the Amazon forest is reported by INPE. In studies including areas with low levels of forest, low deforestation rates can occur due to two reasons: first there are factors that keep the forest standing. Second, there is no (or almost no) forest to be cleared. While researches are trying to access the causes for the first reason, since dataset is "dirty" with second reason cases, analyses are biased. To avoid this kind of problem I create a filter so that I analyze only areas with at least 20% of forest cover in 2002. With this filter I eliminate a large part of the municipalities that have little Amazon forest and therefore follow a different environmental, economic and social dynamic[15]. With this cleaner dataset we can actually assess the real drivers of deforestation where there is actually forest[16].

In order to get to our reduced form estimated equation a number of assumptions are necessary: first, expected profits from sustainable use are assumed to be zero (or at least constant). Second, since some variables are not directly observable or have no data available, such as logging revenues, clearing costs, agricultural and ranching costs, and risk of clearing, I assume all of them to be constant so that they do not influence fluctuations in profitability expectations.

We observe fluctuations in meat and soybean prices at a national level, as well as cleared area, meat price index, credit availability, fines, area under protection, rural settlements area, and initial conditions such as distance to Brasilia, initial population, and level of initial clearing and typical rainfall at a municipal level.

In the main estimated equation I use meat price lagged in one year to take in consideration the yearly fluctuations of national meat prices and the meat price index to account for the differences of prices paid to producers over space. I do not include soybean prices in the main specification but in some alternative specifications. These two prices are highly correlated due to the dynamics of international commodity markets and also exchange rate movements[17]. Therefore it is hard to disentangle the effect of each of them. Since cattle is widespread throughout the whole region, and soybean in concentrated in the South, most of the time I use only the meat price, but recognize that this might be partially capturing the effect of soybean price fluctuations. I also include rural credit availability, protected areas and settlement area by municipality. I also include fines intensity as a proxy for the risk of deforestation and area of each municipality.

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[15] With the 20% filter, for example, I eliminate a large part of the municipalities of the States of Mato Grosso (47%), Maranhao (58%), and Tocantins (97%). And only a small part of Acre and Amapá (0%), Amazonas (2%), Roraima (13%), Rondônia (23%), Pará (38%). For Maranhao specifically, I had to drop the whole state since data for environmental fines are not available for one year. However, I did the analysis with Maranhao and excluding the missing year and results do not change significantly.

[16] This corresponds to 400 municipalities out of the 783 cities of the Legal Amazon. The 20% threshold was chosen since it is the largest possible sample in which all explanatory variables behave close to their average behavior. Since I had to exclude all municipalities from MA, it reduces the sample to 318 municipalities. Moreover because of some data missing for one or other variable, the main specifications have 294 municipalities.

[17] Correlation is 0,76.

The main dependent variable is the amount of yearly new deforested cleared area by municipality. In most of the specifications I use level variables. For these, I control for municipality area given the wide range of municipality sizes and the main role that it plays in determining all level variables[18]. The main estimated equation is:

$$\begin{aligned} Ln(D_{it}) = \alpha \ + \beta_1 * \ln(P_{t-1}^{m}) + \beta_2 * \ln(I_i^{m}) + \beta_3 * \ln(Cr_{it}) + \\ \beta_4 * \ln(R_{it}^{d}) + \beta_5 * \ln(\Pr_i) + \beta_6 * \ln(St_i) + \beta_7 * \ln(A_i) + \beta_8 * S_i + \varepsilon_{it} \end{aligned} \quad (7)$$

Where: $\Pr =$ Protected areas; $St =$ Rural settlement area; $A =$ Municipality area; $S =$ Vector with controls; $\varepsilon =$ Robust-clustered error term.

I use least squares for panel data and present results both for fixed effects and random effects models[19]. Fixed effects (FE) should be used when we assume that there are municipality specific non-observable effects. This method considers that there are unit (municipality) specific characteristics which are constant over time and are captured by a α_i specific for each municipality (GREENE 1997). Random effects (RE) should be used if we consider that the resulting effect of several omitted variables, affecting units and years, is randomly distributed over time and municipalities and therefore uncorrelated with other explanatory variables (HSIAO 2003). If its more restrictive assumption, that omitted variables are uncorrelated with explanatory variables, holds, it is more efficient. However it can be inconsistent if the assumption does not hold (WOOLDRIDGE 2002).

In order to decide between using RE and FE models I performed the Hausman test. It suggested that RE and FE coefficients estimates are statistically different and therefore I should use FE method because it is more likely to consistent. In table 2 and 3 I present results from FE and RE estimates. Coefficients of both models have the same signs, comparable sizes and are highly significant. Given that their results are similar, in tables 4 and 5 I present estimation results from RE regressions. The reason for this is that this way time invariant variables, which are important determinants of the deforestation process, can also be included in the analysis. Variables for which only one observation was available include the meat price index (measuring relative remoteness and transport costs), and the size of protected and settlement areas. Only by using the RE method can I test the relationship of these important variables with deforestation.

To reduce the effects of not working with FE models, and as suggested by Weinhold and Reis (2008), in some specifications I include several controls to account for municipality specific (time-invariant) fixed effects. Among the controls used are state dummies, municipality area, municipal specific average rainfall, distance to Brasilia, initial deforestation and population. However there might be more effects that I do not capture such as the existence of roads for which I could not get reliable data on time.

In order to control for time-variant (year-specific) effects, in some specifications I also include year dummies and region wise yearly rainfall variation. The meat price index should also work as

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[18] In table 2 this is not necessary, since I use densities (each variable divided by municipality area). Meat price, meat index and soy prices are not divided by area; fines intensity are not either since it is already divided by deforestation. The dependent variable is deforestation of one year divided by forest at the beginning of that year.

19 Regressions were run with the *xtreg* function of STATA 10.0, with error terms clustered and corrected for heteroskedasticity and autocorrelation.

a proxy to control for the initial conditions. Following several other previous studies (e.g. ANDERSEN 1996, AGUIAR ET AL. 2007) I use logarithmic forms for all variables.

Typically panel data on deforestation suffers from both: spatial and time-series autocorrelation (FERRAZ 2001). To deal with spatial autocorrelation many authors explicitly modeled the effect of neighboring area deforestation rates in each municipality (e.g. ARIMA et al. 2007, AGUIAR ET AL. 2007). Due to lack of time and of GIS software knowledge, I did not do it. However, I follow Ferraz (2001) and Weinhold and Reis (2008) and also use robust and clustered standard errors to correct for heteroskedasticity and serial correlation.

It is important to acknowledge that for some variables, such as credit availability or fines intensity, one could expect causality to run in both directions, which could bias the coefficients. For example, if demand for subsidized credit increases with deforestation activities, this would bias the coefficients on credit availability upwards, and thus results on credit should be interpreted with caution. Similar rational could be applied for the strictness of the local police (in giving out fines) responding to current deforestation activities.

7. Results

7.1. Main results and interpretation

The overall results support most of the hypothesis made in the theoretical framework. Not only do all the most important coefficients have the expected signs, but also the main variables and controls interact in the expected way. The results are also robust across different specifications including modeling with levels and densities, and random and fixed effects.

As the main driver of the expected profitability, increases in meat price in one year are associated with increases in deforestation rates in the following year. The variable is highly significant and robust through all different specifications. In table 2 and 3 not only does its robustness become clear, but also its relationship with other variables. For example, in table 2, columns II and V, the meat price coefficient is smaller when I include soybean price fluctuations. For the majority of the specifications, I use meat prices fluctuations in space and time separately since I have two different datasets for each dimension.

Increases in soybean prices are associated with increases in deforestation rates in the same year and are robust across different specifications. Also as expected, its coefficients are typically half the size of the one of the meat price (table 2 and 3, columns II and V). The smaller size should reflect the fact that soybean plantations are restricted to a relatively small area of the region.

For credit, larger credit volumes are associated with higher deforestation rates in all tested specifications, and it is significant in most of the main equations. Even if partially endogenous (since it depends on credit demand), credit granting is also the result of an exogenous political decision since it is part of a governmental regional development strategy. My hypothesis is that credit is not pushing deforestation, but only making it possible.

Fines present the most robust results among all variables. Increases in the intensity of fines are associated with decreases in deforestation rates. Not only is it highly significant in all specifications, but also its coefficients show little change with the introduction of additional controls or when using FE models. Protected areas seem to represent a barrier to deforestation, while the existence of agrarian reform settlement areas is significantly linked to higher deforestation rates. Higher rainfall over space and time are associated with lower deforestation rates (table 5, columns III, IV and VI)[20].

When I mention control variables in the tables, I imply municipal distance to Brasilia, initial deforestation of 2002 and population in 2000. In several cases I also include state and year dummy variables to capture possible fixed local characteristics or special year events, but they do not significantly alter the results[21].

Table 2: Main results in levels

	Dependent variable: ln(deforestation)					
	I	II	III	IV	V	VI
	RE	RE	RE	FE	FE	FE
Meat price	0.075***	0.042***	0.047***	0.073***	0.034***	0.046***
	(14.49)	(6.24)	(7.24)	(13.93)	(5.13)	(6.88)
Index meat price	0.944**	1.023**	-0.055			
	(2.19)	(2.35)	(0.09)			
Soya prices		0.027***			0.032***	
		(7.26)			(8.62)	
Credit	0.132***	0.117***	0.035	0.057**	0.032	0.023
	(6.76)	(6.07)	(1.60)	(2.23)	(1.28)	(0.86)
Fines intensity	-0.784***	-0.776***	-0.765***	-0.763***	-0.753***	-0.764***
	(15.69)	(15.64)	(15.40)	(14.71)	(14.64)	(14.32)
Protected areas	-0.066***	-0.070***	-0.032**			
	(3.97)	(4.10)	(2.07)			
Settlement	0.165***	0.171***	0.098***			
	(8.35)	(8.47)	(5.02)			
Area	0.567***	0.578***	0.468***			
	(9.14)	(9.22)	(7.58)			
Constant	-6.858***	-6.288***	-3.639***	0.475	1.454***	1.832***
	(10.83)	(9.78)	(4.25)	(1.08)	(3.33)	(3.66)
Control variables	No	Yes	Yes	No	No	No
Year dummy	No	Yes	Yes	No	No	yes
State dummy	No	Yes	Yes	No	No	No
Observations	1370	1370	1336	1370	1370	1336
Number of Municipalities	294	294	285	294	294	285
R-squared	0.61	0.61	0.72	0.50	0.53	0.54

* significant at 10%; ** significant at 5%; *** significant at 1%

Notes: Robust t statistics in parentheses. R-squared is overall for RE and within for FE models.

Control varibles include distance to Brasilia, initial deforestation in 2002 and population in 2000.

[20] Controlling for rainfall makes the meat price index flip sign (table 4, columns III, IV and VI). This probably means that this index embodies to certain extent information about space rainfall variation. When in combination with year dummies the yearly rainfall fluctuation also flips sign (table 4, columns III and IV). This can be because they are all capturing mostly the same thing.

[21] Initial deforestation area and initial population have the expected positive sign. The first is consistently significant and the second is not in most of the cases. Distance to Brasilia has the expected negative sign and is significant only in some specifications and here it is a proxy for transport costs. All time invariant variables are dropped out in the FE regressions.

Table 3: Main results in densities

	Dependent variable: ln(deforestation / area)					
	I	II	III	IV	V	VI
	RE	RE	RE	FE	FE	FE
Meat price	0.002***	0.001***	0.001***	0.002***	0.001***	0.001***
	(11.53)	(4.00)	(5.83)	(11.28)	(3.92)	(5.86)
Index meat price	0.040***	0.040***	(0.01)			
	(4.32)	(4.26)	(1.15)			
Soya prices		0.001***			0.001***	
		(4.76)			(5.10)	
Credit density	2.455***	2.253***	1.132***	3.633***	2.983***	2.498***
	(3.89)	(3.79)	(3.34)	(4.86)	(4.75)	(4.15)
Fines intensity	-0.010***	-0.010***	-0.008***	-0.009***	-0.009***	-0.009***
	(8.14)	(8.02)	(6.39)	(5.93)	(5.85)	(5.98)
Protected areas density	-0.016***	-0.016***	(0.00)			
	(3.05)	(3.12)	(0.78)			
Settlement density	0.049***	0.049***	0.024**			
	(5.12)	(5.08)	(2.46)			
Constant	-0.064***	-0.050***	(0.03)	-0.039***	-0.024***	-0.018**
	(7.24)	(5.59)	(1.61)	(6.74)	(3.87)	(2.57)
Control variables	No	No	Yes	No	No	No
Year dummy	No	No	Yes	No	No	Yes
State dummy	No	No	Yes	No	No	No
Observations	1370	1370	1336	1370	1370	1336
Number of Municipalities	294	294	285	294	294	285
R-squared	0.33	0.34	0.45	0.18	0.20	0.22

* significant at 10%; ** significant at 5%; *** significant at 1%

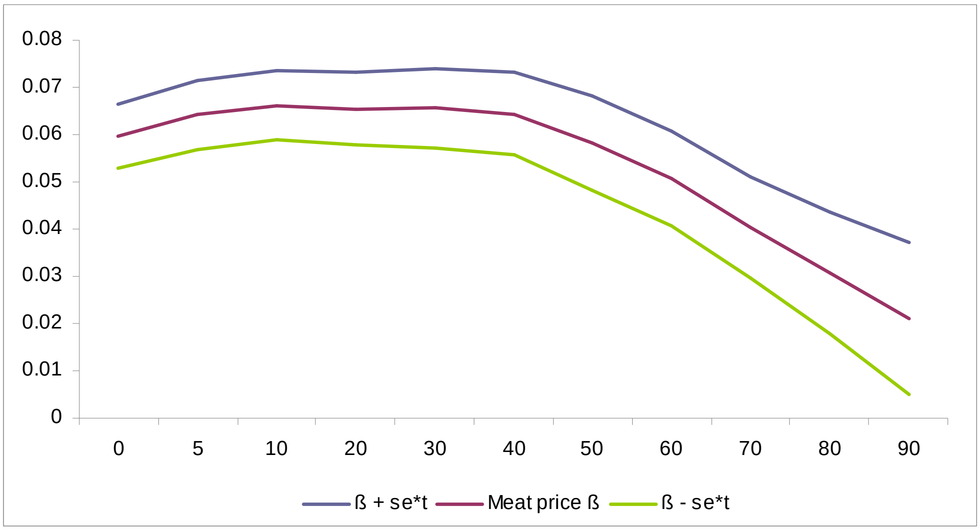
Notes: Robust t statistics in parentheses. R-squared is overall for RE and within for FE models.

Control varibles include distance to Brasilia, initial deforestation in 2002 and population in 2000.

7.2. Further results and robustness checks

One innovation of this study is that it assesses the robustness of each of the main explanatory variables to a variation of the number of municipalities analyzed. In order to diminish the discretionarity of the choice of the 20% filter, I assess how each of the main variables would behave with larger and smaller samples. The results are presented in graph 2. By eye balling we can see that with between 15% and 70% of minimum initial forest cover (or excluding the extremes) the coefficients do not depart so much from an average value. After 70%, there are less than 120 municipalities in the sample and variables present a different behavior with all of them converging towards zero. This convergence is expected since this small sample consists of regions almost fully forested (and probably of difficult access) where little deforestation takes place and market forces are expected to be lower. With between 0% and 15% of the minimum initial forest cover, variables also present a different path from their average. These parts of the region are totally integrated with markets and have little forest remaining. Thus studies about deforestation dynamics and its causes should exclude these extreme areas and focus on the areas where we indeed observe forest and with a similar path and threat of deforestation. In terms of confidence intervals, there is a clear increase in it when we decrease the number of observations (going to the right in the graph) and therefore the estimates become less reliable.

Graph 2: Meat price coefficient for different filters of initial deforestation



I also performed several robustness checks by creating different variable definitions and changing model specifications. In table 4 (columns I, II and III), I interact meat price index (which is specific for each municipality but constant over time) with yearly fluctuations of meat price in an attempt to estimate what would theoretically be the yearly meat price fluctuations for each municipality of the region. This is the first study that tries to estimate it. This estimation is done in two different ways (columns I and II versus III).

In table 4 (columns IV and V) a dummy variable indicating locations that had a significant soybean production (1 if there is production, 0 if not), and its interaction with the national soybean prices are tested together with the national price. In line with the theoretical framework, the interaction term is positive and significant, showing that the positive impact on deforestation from higher soybean prices gets amplified in municipalities that produce it[22]. The puzzling result here is that the dummy has a negative sign, indicating that, everything else remaining constant, municipalities with significant soybean production have, on average, lower deforestation rates than other municipalities. This may reflect that this production is done in municipalities already highly cleared, with little remaining forest to be cleared[23].

Data on both credit and fines are not reported for many municipalities. It is unclear whether these are missing values or if they would be zeros. In most of the specifications, I consider them as missing values, what reduces the sample. In table 5, columns I and II, I test what would happen if we consider them to be reported as zeros. Since there are less missing values, the number of

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[22] With this, I could estimate local annual prices for soybean for each municipality where soybean cropping took place. However, price in other localities is not observed. Even recognizing that it is a strong assumption, I then assumed that where no production took place prices were zero – so production was not economically viable.

[23] In the same table in column VI, I use a different soybean price measurement derived from the Municipal Agricultural Survey (PAM). This method also brings us significant results and a coefficient in line with the prior results using national prices.

observations slightly increases and significance of the new variables where zeros were inputted is similar to the original ones and coefficient of fine intensity is similar, but coefficients of credit are smaller if compared to specifications of table 2 (columns I and II).

In columns III, IV and VI, I also introduce new controls for rainfall over time and space. Rainfall over space is robust among all specifications. Rain over time, which is a rougher estimate, is not robust throughout different specifications. Additionally, in table 5 (columns V and VI) we see that using real fines in Reais (R$) instead of number of fines (as in all other specifications) would not change the sign and significance of this variable (compared to table 2 columns I and II).

Table 4: Further results changing meat and soybean price definitions

	Dependent variable: ln(deforestation)					
	I	II	III	IV	V	VI
	RE	RE	RE	RE	RE	RE
Meat price				0.042***	0.028***	0.072***
				(6.27)	(3.28)	(14.98)
Index meat price				1.021**	(0.03)	0.823*
				(2.33)	(0.04)	(1.88)
Meat price * index	0.067***	0.018*				
	(13.82)	(1.77)				
Meat price + index			0.060***			
			(12.66)			
Soya prices				0.021***	0.027***	
				(5.17)	(4.85)	
Dummy soya				-0.829***	-1.173***	
				(3.51)	(4.47)	
Soy prices * dummy				0.044***	0.049***	
				(4.33)	(4.78)	
Local soy price						0.025***
						(3.77)
Credit	0.101***	0.03	0.100***	0.103***	0.03	0.115***
	(5.23)	(1.46)	(5.20)	(5.21)	(1.14)	(5.88)
Fines intensity	-0.822***	-0.770***	-0.818***	-0.772***	-0.761***	-0.783***
	(16.63)	(15.43)	(16.50)	(15.90)	(15.69)	(15.73)
Protected areas	-0.045***	-0.027*	-0.046***	-0.066***	-0.032**	-0.058***
	(2.59)	(1.77)	(2.65)	(3.82)	(2.08)	(3.34)
Settlement	0.178***	0.106***	0.178***	0.176***	0.098***	0.173***
	(8.45)	(5.31)	(8.44)	(8.55)	(4.97)	(8.61)
Area	0.648***	0.499***	0.648***	0.566***	0.470***	0.534***
	(9.68)	(7.96)	(9.66)	(8.58)	(7.30)	(8.30)
Constant	-6.215***	-3.244***	-5.968***	-5.901***	-3.400***	-6.268***
	(10.05)	(4.30)	(9.58)	(8.81)	(3.93)	(9.62)
Control variables	No	Yes	No	No	Yes	No
Year dummy	No	Yes	No	No	Yes	No
State dummy	No	Yes	No	No	Yes	No
Observations	1370	1336	1370	1370	1336	1370
Number of Municipalities	294	285	294	294	285	294
R-squared	0.58	0.72	0.58	0.61	0.72	0.60

* significant at 10%; ** significant at 5%; *** significant at 1%

Notes: Robust t statistics in parentheses. R-squared is overall for RE models.

Control varibles include distance to Brasilia, initial deforestation in 2002 and population in 2000.

Table 5: Robustness checks and additional controls

	Dependent variable: ln(deforestation)					
	I	II	III	IV	V	VI
	RE	RE	RE	RE	RE	RE
Meat price	0.073***	0.048***	0.043***	0.112***	0.077***	0.119***
	(15.09)	(7.03)	(5.13)	(6.93)	(11.83)	(6.19)
Index meat price	2.011***	0.54	(0.56)	(0.09)	1.097**	(0.71)
	(4.46)	(0.95)	(1.18)	(0.15)	(2.15)	(1.04)
Credit			0.085***	0.03	0.173***	0.052**
			(4.17)	(1.53)	(7.31)	(2.02)
Credit with zeros	0.035***	0.014*				
	(4.30)	(1.68)				
Fines intensity in R$					-0.119***	-0.123***
					(10.48)	(10.24)
Fines intensity			-0.773***	-0.765***		
			(15.42)	(15.46)		
Fines with zeros	-0.569***	-0.551***				
	(15.82)	(15.90)				
Protected areas	-0.080***	(0.03)	-0.029*	-0.037**	-0.089***	-0.049***
	(3.77)	(1.54)	(1.79)	(2.39)	(4.58)	(2.82)
Settlement	0.246***	0.144***	0.116***	0.094***	0.205***	0.130***
	(12.21)	(7.20)	(6.58)	(4.83)	(8.89)	(5.83)
Area	0.633***	0.481***	0.460***	0.594***	0.681***	0.697***
	(9.54)	(7.23)	(5.85)	(7.37)	(9.46)	(7.56)
Rain over space			-0.002**	-0.002*		-0.002*
			(2.05)	(1.87)		(1.85)
Rain over time			-0.637***	1.517***		1.661***
			(3.98)	(3.48)		(3.22)
Initial deforested area		0.000***	0.000***	0.000***		0.000***
		(6.25)	(7.05)	(7.11)		(6.47)
Initial population		0.00	0.00	0.007***		(0.00)
		(1.42)	(1.05)	(2.66)		(0.59)
Distance Brasilia		(0.24)	-0.268**	(0.26)		-0.534**
		(0.93)	(2.44)	(1.11)		(2.03)
Constant	-7.266***	-3.945***	-2.407***	-7.700***	-8.085***	-7.802***
	(11.03)	(3.60)	(2.69)	(4.99)	(10.95)	(4.29)
Control variables	No	Yes	Yes	Yes	No	Yes
Year dummy	No	Yes	No	Yes	No	Yes
State dummy	No	Yes	No	Yes	No	Yes
Observations	1938	1884	1331	1331	1370	1331
Number of Municipalities	323	314	282	282	294	282
R-squared	0.52	0.67	0.68	0.72	0.47	0.64

* significant at 10%; ** significant at 5%; *** significant at 1%

Notes: Robust t statistics in parentheses. R-squared is overall for RE models.

Control varibles include distance to Brasilia, initial deforestation in 2002 and population in 2000.

8. Conclusion

This study analyzed the current determinants of deforestation of the Brazilian Amazon. It is based on a framework in which agents choose either to clear a forested area or not, based on their expectations about future profits to be derived from economic activities implemented in the cleared area, such as cattle ranching and soybean cropping. Using a panel data of 783 municipalities of the Brazilian Legal Amazon from 2002 to 2007 it tests how changes in several economic and policy variables affected the observed fluctuations in deforestation rates during the period.

This study advances beyond previous studies in several aspects for the discussion about today's determinants of deforestation. Firstly, in terms of data, it uses recently launched panel data of deforestation of the 2000s at municipal level. It also uses some data that has not been deeply or properly analyzed in econometric papers, such as municipal credit or commodity prices, and even some that has never been used, such as municipal environmental fines. Secondly, it focuses on the economic and policy decision parameters that affect agents' deforestation decisions rather than on direct causes of clearing. Therefore it studies how the incentive structure for deforestation works. A third aspect is that this study innovates by excluding from the analysis areas that were never forest or that are almost completely deforested in order to better assess the recent deforestation drivers. By not doing this, previous works included important biases in their analysis.

A major empirical finding was the significance of all of the most important economic variables (meat and soybean prices) and policy variables (rural credit and environmental fines) studied as drivers of the fluctuations of deforestation rates during the period analyzed. According to the presented theoretical model, changes in these variables are responsible for changes in the expected profitability of future land use and therefore in the incentives for deforestation. By showing empirically that the fluctuation of these variables drive the ups and downs of deforestation rates, we see that deforestation decisions are taken rationally by agents that are comparing expected profitability of different land use methods. More specifically, higher meat and soybean prices, as well as higher availability of official subsidized rural credit, are associated with higher deforestation rates. Meat price variations are found to drive deforestation rates, both from a time and space perspective. Higher issuing of environmental fines is associated with lower deforestation rates. The existence of rural reform settlement areas is related to larger deforestation, whereas the presence of protected areas represents a barrier to deforestation. Additionally, lower rainfall, larger initial population and smaller distance to Brasilia are also associated with higher deforestation rates.

There are a wide range of policy implications related to this study's findings. The most important of them is that policy makers should recognize explicitly that the deforestation of the region is now an endogenous economic process driven by rational economic decisions made by agents that live in the region. Therefore the focus of new policies should be to modify the economic incentive structure that agents face by changing the expected profits of different land use methods (sustainable versus unsustainable).

One more specific implication is that commodity prices, and also commodity future prices, should be taken seriously in consideration for policy design, for deforestation forecasts and also for evaluation of implemented policies. For example, the Brazilian government has openly claimed that the new plan to combat illegal deforestation has alone driven the decrease of deforestation rates from 2005 to 2007. This study shows that although the greater issuing of fines played an important role, the decrease in meat and soybean prices also contributed toward it.

The evidence about the effectiveness of the environmental fines is probably the most innovative result of this study. Being aware of it, policy makers should intensify the combat against illegal deforestation. More studies are, however, necessary in order to understand in detail where, when and under which conditions this combat is more effective and, therefore, how it should be focused.

Another major implication is that the credit granting rules and practices for farmers should be reviewed so that credit is only granted to those agents who respect the environmental legislation. Additionally the Brazilian government should re-think its strategy of establishing rural settlements in forested areas, and also consider the possibility of using already deforested areas[24].

The first natural extension of this study is to integrate its analysis with spatial econometric techniques such as explicit controls for spatial autocorrelation. This could refine the accuracy of coefficient sizes.

Another way to refine the sizes of coefficients is by doing variable specific studies. New studies are being conducted, for example, to assess the effectiveness of protected areas comparing selected pixels inside and outside parks with similar characteristics. This type of study could be done with other variables as well. They do not substitute the kind of model proposed in this study, which tries to capture general patterns, but rather complement it.

Other required extensions to this study, depend on data availability. For protected areas and rural settlements, using a complete dataset with all years should produce more accurate estimates. For rainfall, besides extra data for all years, more effort should be done in order to improve its specification and take in consideration the existence of threshold effects for example.

Possibly, the most important extensions of this study concern the refinement of the time dimension. It would be important to use monthly data, instead of yearly data, whenever possible, especially because deforestation is very concentrated in some months. Furthermore, because deforestation is measured from September to August, one should try to fit all the data into this time window, as I did with meat and soybean prices.

Combining econometrics and field research is also needed. It would be helpful to conduct interviews with deforestation agents to understand what kind of information they have access to and what part of this information is more important to them when they take their clearing decisions. It would also be important for understanding the timing between the decision of clearing, its execution and the beginning of an economic activity such as cattle ranching. One question, for example, is whether the deforestation agents look at current or future prices and, if future, what is the relevant time horizon considered. Once we know that, specifications can be improved and one can use future prices instead of ex-post observed lagged prices in models. It could be the case that not yearly average prices are relevant, but only future prices for 12 months, for example.

Ultimately the goal is to find out when the deforestation decision is made and which variables are most important in an agents' decision making process. After knowing that, new policies can be more efficiently designed to change the economic incentive structure to foster a more sustainable use of the Amazon region.

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[24] In line with it but not a direct implication of my results, there is an urgent need for the implementation of "Zonemento ecológilo econômico" (Economic Ecological Land Use Planning) to promote a more sustainable and rational use of the forest.

References

AGUIAR, A. P. D., CÂMARA, G., ESCADA, M. I. S. Spatial statistical analysis of land-use determinants in the Brazilian Amazonia: Exploring intra-regional heterogeneity. **ScienceDirect / Ecological Modelling 209**, pp.169 – 188, 2007.

ANDERSEN, L. E.. The Causes of Deforestation in the Brazilian Amazon**. The Journal of Environment & Development**; 5; 309, 1996.

ANDERSEN, L. E., GRANGER, C. W. J., REIS, E. J. and WEINHOLD, D. The Dynamics of deforestation and economic growth in the Brazilian Amazon. **Cambridge University Press**, 2002.

ANDERSEN, L. E. and REIS, E. J. Deforestation, development and government policy in the Brazilian Amazon: an econometric analysis. **Texto para discussão No. 513, IPEA-Instituto de Pesquisa Econômica Aplicada**, 1997.

ANGELSEN, A. Agricultural expansion and deforestation: modelling the impact of population, market forces and property rights. **Journal of Developments Economics**, Vol. 58, 185 – 218, 1999.

ANUALPEC. **Anuário da pecuária brasileira 2008**. São Paulo: IFNP, 2008

ARIMA, E. Y., SIMMONS, C. S., WALKER, R. T. and COCHRANE, M. A. Fire in the Brazilian Amazon: a spatially explicit model for policy impact analysis. **Journal of Regional Science**, vol. 47, No. 3, pp. 541 – 567, 2007.

BARRETO, P., PEREIRA, R. and ARIMA, E. A Pecuária e o Desmatamento na Amazônia na Era das Mudanças Climáticas. **IMAZON – Instituto do Homem e Meio Ambiente da Amazônia**. Belém, dez. 2008.

BARRETO, P., ARIMA, E. and SALOMÃO, R. Qual o efeito das novas políticas contra o desmatamento na Amazônia? **IMAZON – Instituto do Homem e Meio Ambiente da Amazônia**. Belém, março 2009.

EWERS, R. M., LAURANCE, W. F. and SOUZA JR., C. M. Temporal fluctuations in Amazonian deforestation rates. **Foundation for Environmental Conservation**, 2008.

FEARNSIDE, P. M. Deforestation in Brazilian Amazonia: History, Rates and Consequences. **Conservation Biology**, Vol. 19, No. 3, pp. 680 – 688, June 2005.

FERRAZ, C. Explaining agriculture expansion and deforestation: evidence from the Brazilian Amazon - 1980/1998. **Texto para discussão IPEA , 265.** 2001.

FGV. FGV dados. Available at: http://www.fgvdados.fgv.br/ (accessed January 22, 2009). 2009.

GREENE, W. H. **Econometric Analysis.** New Jersey: Prentice Hall. 1997.

HSIAO, C. **Analysis of panel data.** Cambridge: Cambridge University Press, 2nd edition. 2003.

IBGE. Sistema IBGE de Recuperacao automatica – **SIDRA**. Available at: http://www.sidra.ibge.gov.br/ (accessed January 22, 2009). 2009.

INMET. Instituto Nacional de Meteorologia. Available at: http://www.inmet.gov.br/ (accessed March 29, 2009). 2009.

INPE. Prodes: Monitoramento da Floresta Amazônica por Satélite. Available at: http://www.obt.inpe.br/prodes/index.html (accessed January 22, 2009). 2009.

KAIMOWITZ, D. and ANGELSEN, A. **Economic Models of Tropical Deforestation – A Review.** CIFOR – Center for International Forrest Research, Indonesia, 1998.

KIRBY, K. R., LAURANCE, W. F., ALBERNAZ, A. K., SCHROTH, G., FEARNSIDE, P. M., BERGEN, S., VENTICINQUE, E. M., COSTA, C.. The future of deforestation in the Brazilian Amazon. **Futures, 38:** 432–453. 2006.

LAURANCE, W. F., ALBERNAZ, A. K. M., SCHROTH, G., FEARNSIDE, P. M., BERGEN, S., VENTICINQUE, E. M. and COSTA, C. DA. Predictors of deforestation in the Brazilian Amazon. **Blackwell Science Ltd., Journal of Biogeography, 29**, pp. 737 – 748, 2002.

MARGULIS, S. Causes of deforestation of the Brazilian Amazon. **World Bank Working Paper Series, 22,** 2003.

NEPSTAD, D., SCHWARTZMAN, S., BAMBERGER, B., SANTILLI, M., RAY, D., SCHLESINGER, P., LEFEBVRE, P., ALENCAR, A., PRINZ, E., FISKE, G. and ROLLA, A. Inhibition of Amazon Deforestation and Fire by Parks and Indigenous Lands. **Society for Conservation Biology, Conservation Biology**, Vol. 20, No. 1, pp. 65 – 73, 2006.

NEPSTAD, D. C., STICKLER, C. M. and ALMEIDA, O. T. Globalization of the Amazon Soy and Beef Industries: Opportunities for Conservation. **Society for Conservation Biology, Conservation Biology**, Vol. 20, No. 6, pp. 1595 – 1603, 2006b.

PFAFF, A. S. P. What Drives Deforestation in the Brazilian Amazon? – Evidence from Satellite and Socioeconomic Data. **Journal of Environmental Economics and Management 37**, pp.26 – 43, 1999.

PRATES, R.C.. O desmatamento desigual na Amazônia brasileira: sua evolução, suas causas e consequências sobre o bem-estar. **Escola Superior de Agricultura “Luiz de Queiroz” – Universidade de São Paulo**, Piracicaba, 2008.

REIS, E. J. and GUZMÁN, R. M. An Econometric Model of Amazon Deforestation. **Texto para discussão No. 265, IPEA-Instituto de Pesquisa Econômica Aplicada**, 1992.

SEEHUSEN, S. E.. 2007. Master thesis. **Can payments for ecosystem services contribute to sustainable development in the Brazilian Amazon? With case study in the Rio Capim Pole of Proambiente.** Faculty of Forestry and Sustainable Land Use. University of Freiburg, Freiburg, Germany.

THE ECONOMIST**.** “Welcome to our shrinking jungle.” The Economist, 387 (8583): 49-50. 2008.

WEINHOLD, D. and REIS, E. Transportation costs and the spatial distribution of land use in the Brazilian Amazon. **Global Environmental Change 18**, pp. 54 – 68, 2008.

WOOLDRIDGE. **Econometric Analysis of Cross Section and Panel Data.** Cambridge: MIT Press. 2002.