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A Panel Data Analysis for the 2000s

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Economic Causes of Deforestation in the Brazilian Amazon: A Panel Data Analysis for the 2000s

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Abstract: We use under-explored municipality level datasets to assess the recent economic and policy determinants of deforestation in the Brazilian Amazon. We estimate yearly panel data models (from 2002 to 2009) for 457 municipalities in the region. The results show that recent deforestation is related to economic incentives, and especially to fluctuations in product (meat and soybean) prices. Moreover, we document that the increasing monitoring efforts of the Brazilian environmental police (IBAMA) were effective in reducing deforestation rates.

Key words: Causes of deforestation; Amazon; Brazil

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1. Introduction

The Brazilian Amazon is the largest tropical forest on Earth, and its deforestation raises a wide range of environmental issues. Tropical forests play a crucial role in biodiversity conservation and provide essential ecosystem services to the indigenous and traditional populations as well as for the entire society at various scales; moreover, as important carbon sinks, they have been receiving an ever-growing attention in the fight against global warming. The conservation of the vast Brazilian Amazon forest is a major priority of the national environmental policy, but it is also a major concern from a global perspective. Improvements in the monitoring technology, and especially the availability of yearly satellite-based information on deforestation at a municipality scale, allow us to study the dynamics of recent deforestation, which contributes to the understanding of how economic incentives and policy forces shape deforestation.

Deforestation of the Brazilian Amazon started in the mid 1960es as a state-driven process, fueled by large scale infrastructure and settlement projects as well as various fiscal incentives which induced yearly deforestation at a scale of around 10,000 square kilometers per year (see e.g., Andersen et al. 2002). The rural settlements policy (executed by INCRA, the National Agency for Land Reform), the building of national highways leading through the forest, or the provision of subsidized agricultural credits are all still a part of the governments' development policy for the region; at the same time all these policies have been argued to raise deforestation. Pacheco (2009) and Ludewigs et al (2009) show that INCRA's land redistribution activities had heterogeneous effects on deforestation; Andersen (1996), Barreto et al. (2008) and Prates (2008) document the strong correlation in the availability of agricultural credit and deforestation rates. The effects of road building projects have been more controversial: While Andersen et al. (2002) and Weinhold and Reis (2008) find that road building might even have reduced deforestation in some regions by increasing the profitability of alternative activities, studies based on a considerably finer geographic scale refute such effects (see e.g. Pfaff et al. 2007). By contrast, some of the more recent government policies are explicitly aimed at forest conservation, like the designation of protected areas[1] and the enhancement of activities of the environmental police (IBAMA, the Brazilian Institute of Environment and Renewable Natural Resources) fighting illegal deforestation.[2]

Starting with the 1980es, deforestation dynamics became also more closely linked to market forces, with cattle ranching and soybean cropping being among its central determinants (see e.g., Andersen 1996). During the last decade deforestation rates became closely correlated with the prices of these two commodities, both in spatial (Arima et al. 2007), and in time dimension (Ewers et al. 2008, Barreto et al. 2008). This relationship has received major attention by the national and international press, NGOs, as well as the academic community (see e.g., The Economist 2008, Kaimowitz et al. 2004, Nepstad et al. 2006b).[3] Several studies documented 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, Margulis 2003).

A large part of the earlier economic literature on deforestation of the Brazilian Amazon explains deforestation during its first, predominantly state driven period; it uses mainly state- or municipality-level data derived from agricultural censuses (e.g. Pfaff 1999, Andersen 1996, Andersen et al. 2002). These studies emphasize, among others, the role of population pressure, roads (see e.g., Andersen 1996, Pfaff 1999), and cattle herd (Reis and Guzman 1992, Andersen and Reis 1997).[4] Newer literature addresses the determinants of Brazilian deforestation often at a much finer scale (involving census-tract or satellite pixel data), but incorporates mostly only cross-sectional aspects of it (e.g. Arima et al. 2007 and Pfaff et al. 2007), leaving the recent time patterns of deforestation unexplored.[5]

Our study deviates from most of the existing literature by investigating municipal level determinants of yearly fluctuations in deforestation (total removal of the forest cover) in the Brazilian Amazon from 2002 to 2009. We also innovate by focusing on the economic and policy drivers that influence the expected profitability of different land use methods and therefore affect agents' decisions concerning land use choices. In particular, we explore the effects of product price variations (meat and soybean prices), and of government policies concerning designated settlement and protection areas, the flow of subsidized rural credit as well as the local presence of the environmental police (IBAMA).

During this period deforestation rates have been above historical levels (cf. Figure 1). More importantly, within this relatively short period, deforestation rates have fluctuated significantly. Deforestation peaked in 2004 with a forest loss of 27,423 square kilometers, and decreased sharply after that. This time-pattern closely resembles the fluctuations in meat and soybean prices (cf. Figure 1), which have been made responsible for the changing deforestation rates. However, econometric evidence on this hypothesis is scarce.[6] A second, not yet empirically tested, claim is that the dramatic increase in the monitoring and fining activity of the environmental police (IBAMA) has effectively contributed to the decrease in deforestation over the period.[7] The econometric analysis of these issues constitutes the main contribution of our study.

We analyze the determinants of this most recent period of deforestation by estimating panel data models that difference out the time invariant factors determining deforestation levels. We thus use the large within-municipality variation of economic and policy variables to identify their effects on deforestation, while controlling for all time invariant differences between municipalities (like climate, remoteness, economic structure, etc.). Furthermore, we include time effects that capture the effects of overall macroeconomic and climatic fluctuations on deforestation, differentiated at the national or state level. We also present evidence on further controls for economic activity, measured by the availability of subsidized rural credit and real agricultural GDP p.c. As economic activity is potentially endogenous to decisions on deforestation, we complement our results by regressions estimated by the general method of moments (GMM) that allows for the endogeneity of multiple regressors.

The main results show that deforestation rates were significantly affected by the evolution of few important economic and policy variables during this period. Especially increases in soybean prices, but also increases in the availability of official agricultural credit were associated with increases in the deforestation rates in the Brazilian Amazon. This supports the claims made by the media and many non-econometric studies (see above). Moreover, we find that the environmental police succeeded in reducing deforestation significantly by increasing its fining activities in the region. The effects of environmental fines increase once the possible endogeneity of this variable is accounted for. We also find evidence on spatial spillover effects of fines on the deforestation of neighboring municipalities. The results document thus not only the potentially harmful effects of increasing agricultural activities but also the countervailing effects of the monitoring activities by the environmental police.

The remainder of this paper is organized as follows. The next section outlines some theoretical concepts underlying our empirical study and our main hypotheses. Section 3 describes the data and the empirical models. Section 4 presents and discusses the results, while the last section concludes with policy implications and scope for future research.

2. Main hypotheses

Because of incomplete property rights regulation, large parts of the Brazilian Amazon forest can be still considered as open access. Since the establishment of the land statute of 1964 (which served as a basis for land reform) settlers are allowed to use undeveloped land which can become private property after ten (later five) years of continuous use (cf. Araujo 2009)[8]. For a small open economy with open access, the theoretical model of Angelsen (1999) predicts that deforestation depends positively on the expected profits from unsustainable land use (e.g. logging followed by deforestation and agriculture or cattle ranching). Since sustainable land use (e.g., sustainable forest management) is also prevalent in the Amazonas basin, land use decisions will be actually based on the expected differential in profits from sustainable and unsustainable land uses. The larger the differential, the larger deforestation is expected to be. In our analysis we make the reasonable assumption that rents from sustainable land use are time invariant and therefore can be captured within the time-constant municipality-fixed effects. Instead, we focus on the determinants of profitability of unsustainable land use.[9]

Expected revenues of unsustainable land use are directly determined by market prices of agricultural goods, agents' market access and other municipality specific conditions. Its costs are determined by the direct costs of clearing, the expected agricultural and cattle ranching costs, credit availability and the risk of being fined by the environmental police. Agents maximize the expected profits from land use by choosing a level of clearing activity that will be implemented, taking into consideration prices and other constraints. The drivers of expected profits can thus be divided into three groups: market conditions, policy influence and natural or initial conditions.

Market conditions in the Amazon should be well captured by local meat and soybean prices. If agricultural product prices increase, there should be an upward pressure on deforestation. Better market access and thus lower transport costs result in higher prices paid at a farm-gate level which lead to higher expected profitability and should increase deforestation as well.

Economic policies also directly affect the expected benefits from deforestation. Environmental fines, administered by the environmental enforcement agency IBAMA, constitute a risk factor for clearing. The Brazilian Forestry Code prescribes that properties in the Amazon retain 80% of their area in original forests and that all instances of deforestation must be communicated to the environmental agency and authorized by it. Violation of these rules might result in environmental fines and prohibition of any agricultural production in the deforested area. A positive chance that an agent could be fined for illegal clearing has a negative effect on the expected profitability of clearing. As a result higher fines intensity should lead to lower deforestation rates.[10] Protected areas should also work as a barrier to deforestation, but they might also turn out to be innocuous if they are established only in areas where deforestation pressure is low. Conversely, we might fail to capture their effect to a full extent if new protected areas are established as a response to recent large deforestation pressures leading to a positive correlation between protection and deforestation. Furthermore, the existence of agrarian rural reform settlements in one municipality can be expected to fuel clearing since peasants make their living of agriculture. The availability of official subsidized credit can also fuel deforestation by making the clearing plans resulting from a rise in expected profits possible.

Deforestation should also be influenced by geoclimatic factors, especially rainfall (see e.g., Kirby et al 2006, Arima et al. 2007, Aguiar et al. 2007). There are two possible theoretical links between rainfall and profitability. First, the higher the 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 of both cattle ranching and soybean cropping (Arima et al. 2007).

3. Data and empirical approach

3.1. Data and controls

Our dataset consists of yearly observations for 457 municipalities in the Brazilian Amazon for eight years from 2002 to 2009. The data on municipal deforestation comes from satellite based information of the Prodes project of the Brazilian Space Research Institute (INPE); it measures forest cover as well as newly deforested areas in square kilometers over a given year. Deforestation is reported from August of the previous year to July of the current year; hence we adjust all our controls within the same time window.[11] Our main dependent variable is the natural logarithm of deforestation per municipality and year, and we express most explanatory variables in logarithms.[12] Summary statistics are presented in Table 1.

Local meat prices are constructed by interacting the real values of the annual national average of beef prices received by cattle ranchers in Brazil (for 15 kg of Boi Gordo, from Anualpec 2009) with a meat price index based on Arima et al. (2007), which captures spatial variability of meat prices in 2001.[13,14] This variable thus should both reflect yearly fluctuations in beef prices and the average difference in transport costs from each municipality to the main consumer markets as well as local market conditions. However, this measure assumes constancy of relative differences in transport costs and market conditions, and thus might be less suitable to capture the differences in the time variation of meat prices. Soybean prices are reported at the municipality level by the Brazilian Statistical office (IBGE) for soybean producing regions: these regions (in the South and East of Brazilian Amazon) have a climate which is more favorable to soybean production. We impute zero prices for all municipalities without production of soybean and thus measure the direct effect of soybean prices on deforestation of soybean producing regions only.

Data on environmental fines come from the IBAMA. We calculate the intensity of the activity of the environmental police by dividing the real value of fines issued within a municipality by deforestation in any given year. Further policy variables include controls for the size of protected, indigenous and settlement areas within the municipality. Information on environmentally protected and indigenous areas was obtained from DAP/MMA (Protected Areas Directory of the Brazilian Environmental Ministry). Official protection encompasses different types of legal protection, notably integral protection and sustainable use. We include a separate measure for the size of indigenous areas, which have been argued to significantly inhibit deforestation (see e.g. Nepstad et al 2006a). The size of settlement areas reflects settlement activities within the agrarian reform project of INCRA, the Brazilian Agency of Agrarian Reform (source: INCRA).

As deforestation is a spatially strongly correlated process, we try to capture this spatial dimension by including neighborhood controls. Specifically, we control for the deforestation rate across neighboring regions which is measured as the share of overall forest cover deforested within any given year in all neighboring municipalities. Due to their geographic/climatic proximity and the relative similarity in their economic structure, neighborhood deforestation rates are also likely to capture some of the time-variant unobservable effects driving local deforestation. Additionally, we include measures of neighborhood presence of the environmental police (defined the same way as the municipality variables). This variable can partly capture the effects of environmental fines within the own municipality if these variables are measured with error and spatially correlated, but it can also capture genuine spillover effects. If higher presence of the environmental police in the neighborhood is perceived as increasing the risk of getting fined in the given municipality, we should find deforestation to be decreasing not only with fining activity within the own municipality but also with that within the neighborhood.

In order to control for the overall scale of economic activity, we include real GDP p.c. from agricultural production at the municipality level (from IBGE).[15] Another related control is the size of the official subsidized agricultural credit, which was obtained from the Rural Credit Annual Report of the Brazilian Central Bank. The figures reflect the annual flow of agricultural credit granted to rural properties in each municipality within the official agricultural credit system. We measure relative credit density by the natural logarithm of real credit per square kilometer of municipality area that was not covered by forest in 2001, and hence we normalize credit by the original size of potentially agricultural area. These credits are highly subsidized and target agricultural activities (Fearnside 2005), which might also include (directly or indirectly) conversion of forest into pasture or cropland. Thus, credit density results from the interactions of credit supply and demand and hence not only causes deforestation but also naturally follows from it. In a similar vein, agricultural production might not only raise deforestation but it could also be increasing as a result of current deforestation. In order to address these endogeneity concerns, we also report difference GMM results where we treat these variables as endogenous and jointly determined with deforestation.

We also control for variation in local rainfall (Source: NASA).[16] In all regressions we include an indicator variable measuring whether the average rainfall in a given year in a given municipality was in the upper two quintiles of the overall rainfall distribution in our sample. We prefer including this measure to the simple yearly average rainfall intensity included linearly in the regression as it outperforms the other measure in all specifications. This difference is most likely due to discontinuous effects of rainfall on deforestation:

rainfall seems indeed to inhibit deforestation only after reaching a certain threshold (see also Arima et al. 2007).

3.2. Empirical strategy

Our analysis of deforestation concentrates on the Brazilian Amazon rainforest and thus, unlike many other studies on the Brazilian Legal Amazon, it excludes some areas with little forest cover remaining as well as areas with tropical savanna (Cerrado).[17] In studies including areas with extremely low levels of forest, low deforestation can also simply occur because there is no (or almost no) forest to be cleared. To reduce this latter problem we analyze only areas with at least 10% of forest cover in 2002. Thus, we explain deforestation dynamics where forest size is still substantial,[18] eliminating a large part of not forested municipalities that follow a different environmental, economic and social dynamic.[19]

Identification of the effects of economic and policy variables on deforestation comes from the municipality panel structure of the data, and in particular from the large variation of the explanatory variables over time and space. The main specification of the municipal panel takes the following form:

$$\ln D_{it} = X_{it}'\beta + \lambda_{st} + \alpha_i + \varepsilon_{it} \tag{1}$$

where the dependent variable, $\ln D_{it}$, denotes the natural logarithm of the yearly level of deforestation at the end of year t in municipality i.[20] The inclusion of time fixed effects (λ_t) controls for aggregate time trends in deforestation dynamics and thus captures macroeconomic shocks as well as average product price effects. In some specifications we also allow the time effects to be state specific (λ_{st}) and thus control for average differences in unmeasured state policies affecting deforestation differently across the nine states (Acre, Amapa, Amazonas, Maranhao, Mato Grosso, Para, Rondonia, Roraima, and Tocantins). The vector of controls X_{it} includes meat prices, regional soybean prices for producing regions, the log of credit value per originally non-forested area (in 1000 sq kms), the log of fines intensity (real value of environmental fines per deforested area), the log of the size of protected, indigenous, and settlement areas (sq kms), neighborhood variables (deforestation rates and fines), overall agricultural activity (the log of the real agricultural GDP per capita), and an indicator variable for high rainfall. Standard errors are clustered at the municipality level and are robust to autocorrelation and heteroskedasticity.

We estimate equation (1) in first difference form by explaining the growth rate of deforestation $\ln D_{it} - \ln D_{it-1}$ by changes in the vector of control variables:

$$\Delta \ln D_{it} = \Delta X'_{it}\beta + \Delta\lambda_{st} + \Delta\varepsilon_{it}. \tag{2}$$

This purges the above equation of municipality fixed effects (α_i) that stand for the regional differences in the extent of deforestation by capturing time-constant municipality specific unobservables. Thus we identify the effects of explanatory variables based on within-municipality variation. Reasons for concern remain if municipality specific differences in deforestation dynamics also affect some of the explanatory factors or are jointly driven with them by unobservables.

We are especially concerned about the fact that several policy variables can be expected to endogenously respond to deforestation, which could bias our estimated coefficients. The activities of IBAMA are concentrated in municipalities where deforestation is the highest, which could lead to a positive correlation between environmental fining intensity and deforestation, weakening the findings of an eventual negative effect of fines. The establishment of protection or settlement areas could also respond to expected deforestation dynamics, just as neighboring deforestation rates are interdependent with deforestation in any given municipality. The value of subsidized agricultural credit granted to producers in a municipality does not only reflect the volume of official credit supply, arising from the regional development policy; it results from the interplay of the supply of and the demand for subsidized credit. If demand for subsidized credit increases with prospective deforestation activities, this would bias the coefficients on credit availability upwards and would lead us to overestimate the increase in deforestation that is due to credit availability. The extent of agricultural production, which is also included in some regressions as a control, can not only fuel deforestation but it can also rise as a result of current deforestation activities.

We investigate the scope of these concerns in several ways. First, we include credit and agricultural GDP only in some specifications as here we suspect the largest scope for endogeneity. Second, we instrument the intensity of the environmental fining activity in a municipality by the average size of IBAMA fines per deforested area in any given year within the state (excluding the given municipality). This instrument reflects relatively well the overall change in the intensity of the activities of the environmental police, which are organized primarily at state level. Moreover, this instrument is not directly affected by deforestation within the municipality. The identifying assumption behind this strategy is that the state-level fining intensity should affect deforestation in a municipality only through increasing the perceived likelihood of getting fined but not otherwise. As we are also controlling for potential spillover effects of neighboring fining intensity, state-level activities appear to us as a valid instrument in this context. As a further robustness check, we also present results for the real monetary value of fines within the municipality instead of the fining intensity, and instrument it with the average real fine size within the state.

In order to deal with concerns of multiple endogeneity, we also estimate equation (2) by the Arellano-Bond (1991) difference GMM estimator, with a two-step Windmeijer (2005) correction. This allows us to treat the intensity of environmental fining activities, local agricultural credit, real agricultural GDP p.c., and neighboring deforestation as endogenous variables, and instrument their first differences with past levels of all other variables in a GMM style.[21] Additionally, we can model deforestation as path dependent and include instrumented lagged values of deforestation as additional controls. In this framework we always treat the state-year effects, soy and meat prices and rainfall as exogenous; these variables are thus used as instruments for all endogenous variables. Finally, we include the size of protected, indigenous and settlement areas as exogenous regressors, but we also report results where we allow for the endogeneity of these three policy variables. In some further specifications, we also add credit intensity and agricultural GDP p.c. as endogenous controls.

4. Results

Results from our baseline specifications are presented in Table 2. The reported specifications differ with respect to the inclusion of year and state-year effects (excluding them in column 1, including year effects in column 2, and state-year effects in columns 3 and 4). The specification in column 4 is extended to also include spatial controls. The overall results confirm most of our expectations. Deforestation increases when product prices and thus the returns to unsustainable land use increase. Based on column 3 of Table 2, a one standard deviation increase in soybean prices leads to an around 6.7% increase in deforestation rates in the same year. While coefficients on meat price are of comparable relative magnitudes, the meat price effect can only be measured as long as no state-year effects are included. By contrast, the effects of soybean prices decrease with the inclusion of state-year effects but remain significant. This does not imply that meat prices (and cattle ranching) did not play a role in the recent deforestation dynamics; our results most likely reflect poor data quality, since because of the non-availability of regionally varied time data, we cannot distinguish the regional differences in meat price effects over time once common state-wise time differentials are controlled for.

We also find deforestation to be influenced by policy variables affecting the direct costs of deforestation activities. Increases in fining intensity are associated with decreases in deforestation rates with an elasticity of about 0.02-0.03%. However, as argued before, this result might be substantially biased downwards because of the concentration of fining activities in high-deforestation areas. As expected, changes in the size of both protected and indigenous areas are negatively related to changes in deforestation, although only indigenous areas stay significant in our preferred specification (column 4) that includes state-year and neighborhood effects. Deforestation increases with increases in the size of rural settlement areas, but this effect also loses significance once state-year effects are included. These results highlight nevertheless the conflict between policies of agricultural settlement and environmental protection.

The coefficients on neighborhood effects in column (4) confirm the presence of spatial effects in deforestation. An increase of neighboring deforestation rates by 1% is associated with an increase in own deforestation rates by around 0.16%. Including these neighborhood effects reduces most of other coefficient estimates since neighboring municipalities most likely underlie to similar economic and political dynamics. Deforestation also considerably decreases with neighboring fines intensity, which documents spatial spillover effects of deterrence intensity on the perceived risk of getting fined. Finally, deforestation is also significantly smaller when and where rainfall is high (which corresponds to the upper 40% of the total rainfall distribution). This rain indicator variable also considerably outperforms average yearly rainfall entered linearly in the regression, which suggests that the protection effects of rainfall are only effective after a certain threshold has been reached.

Table 3 further explores the role that environmental fines played in containing deforestation. Results in columns (1) and (4) are based on the baseline specification from column (4) of Table 2 (with year and state-year fixed effects respectively), and instrument fining intensity in the municipality with the overall fining intensity within the same state (excluding the municipality). This helps to reduce the endogeneity bias and leads to a considerable increase in the effect of environmental fines on deforestation, which results in an elasticity of minus 0.14–0.19%. The remaining specifications use real fines instead of fining intensity as an explanatory variable. When not instrumented, deforestation is increasing with real fines (as deforestation is a prerequisite for environmental fines being issued), and this correlation even becomes significant when state-year effects are added (column 5). However, when using the average changes in real fines per fining activity within the state as an instrument, real fines become once again significantly negatively related to deforestation (column 3). As this instrument varies only by state, the model performs poorly when state-year interactions are also included (in column 6). Neighboring fines stay significant throughout, which shows that there are also spatial spillover effects from police presence on the perceived likelihood of getting fined. Overall, these results support the importance of the activities of the environmental police in combating deforestation of the Brazilian Amazon.

In order to deal with concerns of multiple endogeneity, table 4 presents models estimated by the method of general moments (GMM). These models additionally include past deforestation as a control which is positively but not significantly related to current deforestation. Columns (1) and (4) present relatively lean specifications, while the other four columns additionally control for the size of protected, indigenous and settlement areas. When instrumented within the model, the effects of environmental fining intensity once again increase considerably as compared to the simple OLS estimates. Soybean prices also consistently raise deforestation, increases in rainfall mitigate it, while the other control variables mostly have the expected signs but turn out insignificant. In addition, columns (2) and (5) treat protected, indigenous and settlement areas as exogenous, whereas columns (3) and (6) allow them to endogenously respond to deforestation. However none of these two procedures yield significant results for these three variables.

Table 5 explores the role of the rural credit policy and the overall economic environment by introducing credit density and real agricultural GDP p.c. as two additional controls. As expected, both credit density and agricultural activities are significantly positively related to deforestation, with elasticities around 0.13-0.17%. When included together in column (3) these two variables are still jointly significant, even though credit turns insignificant in itself. However, as argued before, credit volume not only reflects the supply of cheap credit but also the demand for it, which might also arise as a consequence of deforestation activities. Agricultural activities might also be increasing due to deforestation in a similar way. We cannot thus give these two variables a strictly causal interpretation in these regressions, although they clearly document the interrelationship of deforestation with cheap credit and agricultural activities.

In order to address the causal effects of credit and agricultural production, table 6 presents estimates of the same models in a GMM framework, where credit, agricultural GDP but also lagged deforestation, fining intensity and neighboring deforestation are treated as endogenous. While both credit intensity and agricultural GDP show positive correlations with deforestation in most specifications, they become only significant when included jointly. Moreover, specification 6 does not pass the Hansen test of overidentifying restrictions, and thus its results should be interpreted with caution. Overall, although we see the positive correlation of agricultural activities and credit availability with deforestation, our results do not enable us to trace significant causal effects of these two variables.[22]

6. Conclusion

Based on panel data of 457 municipalities from 2002 to 2009, this study analyzed the current determinants of deforestation of the Brazilian Amazon. It investigated how changes in major economic and policy variables affected the observed fluctuations in deforestation rates during this period. This study made several contributions to the literature on the determinants of deforestation of the Brazilian Amazon. In terms of data, we used underexplored data of deforestation at the municipal level with yearly frequency. Some of the control variables included in this study—such as municipal credit or commodity prices—have not yet been thoroughly analyzed in the empirical literature, others—the data on municipal environmental fines—have never been used before. We excluded areas from the analysis that were never forest or that are almost completely deforested in order to better assess the recent deforestation drivers. We also focused more strongly on the economic and policy decision parameters that affect agents' deforestation decisions and our results emphasized the effects of the incentive structure on deforestation.

Our major empirical findings underline the significance of economic variables (especially soybean prices) and policy variables (especially the role of environmental fines) in driving the fluctuations of deforestation rates during the period of analysis. 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 who are comparing expected profitability of different land use methods. Higher product prices (or the availability of official subsidized agricultural credit) increase the expected net returns to deforestation and lead to higher deforestation rates. By contrast, the activities of the environmental police were successful in decreasing the expected net returns to deforestation and lowered deforestation rates.

These findings lead to a wide range of policy implications. Most importantly, deforestation can be seen as 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 2009. This study shows that although the greater issuing of fines played an important role, the decrease in meat and soybean prices also contributed towards it. The evidence about the effectiveness of the environmental fines in fighting deforestation of the Brazilian Amazon 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.[23]

It would also be important to combine our panel data analysis with case studies and field research. Interviews with deforestation agents could contribute to the understanding of what kind of information do agents have access to and what part of this information is more important to them for their clearing decisions. This could also improve the understanding of the timing of the decision of clearing, its execution, and the beginning of an economic activity. Ultimately, a better understanding of the agents' decision making process can lead to improved new policies that are able to change the economic incentive structure and thus foster a more sustainable use of the Amazon region.

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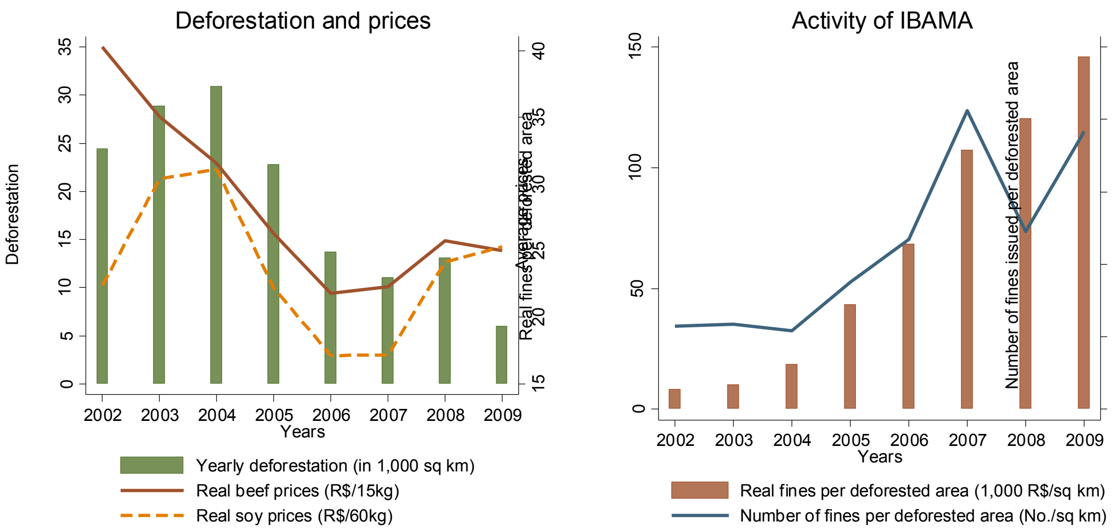
Appendix A. Figures

Figure 1. Deforestation of the Brazilian Amazon, average price movements and the activities of the environmental police (IBAMA) (2002—2009)



Source: Own calculations based on data from INPE, Anualpec, FGV and IBAMA.

Appendix B. Tables

Table 1: Summary statistics

	Mean	St. dev	Min.	Max.
ln Deforestation	2.418	1.580	0	7.248
Soy price	4.273	8.634	0	58.62
Meat price	25.65	6.639	1.743	41.00
ln Fines intensity	5.957	5.258	-5.487	17.08
ln Protected areas	3.356	3.704	0	11.14
ln Indigenous areas	2.860	3.561	0	11.41
ln Settlement areas	4.498	2.904	0	10.21
High rainfall	0.481	0.500	0	1
Deforestation rates (neighb.)	1.378	2.355	0	26.08
ln Fines intensity (neighb.)	9.191	2.196	0	18.57
ln Credit density	0.824	0.657	0	4.453
ln Real agricultural GDP p.c.	6.729	1.031	2.197	10.40
ln Fines intensity (state)	10.68	1.273	6.194	13.29
ln Real fines	8.366	5.955	0	19.24
ln Av. real fines (state)	13.51	1.503	9.645	15.59

Note: Statistics refer to N=3199 observations for 457 municipalities (2737 observations on agricultural GDP).

Table 2: Determinants of deforestation: Baseline estimates

	Dependent: Δ *ln* Deforestation			
	(1)	(2)	(3)	(4)
	OLS	OLS	OLS	OLS
Δ Soy price	0.0173**	0.0100**	0.0077*	0.0066*
	(0.0031)	(0.0029)	(0.0033)	(0.0030)
Δ Meat price	0.0131**	0.0320*	0.0011	0.0016
	(0.0038)	(0.0155)	(0.0186)	(0.0177)
Δ *ln* Fines intensity	-0.0353**	-0.0336**	-0.0264**	-0.0210**
	(0.0043)	(0.0042)	(0.0042)	(0.0036)
Δ *ln* Protected areas	-0.0287	-0.0355†	-0.0134	-0.0226
	(0.0200)	(0.0202)	(0.0223)	(0.0203)
Δ *ln* Indigenous areas	-0.0636†	-0.0419	-0.0374†	-0.0356†
	(0.0358)	(0.0311)	(0.0222)	(0.0214)
Δ *ln* Settlement areas	0.0657**	0.0331†	0.0225	0.0136
	(0.0123)	(0.0171)	(0.0171)	(0.0151)
Δ High rainfall	-0.1077**	-0.1837**	-0.1198**	-0.0983**
	(0.0366)	(0.0364)	(0.0387)	(0.0363)
Δ Deforestation rates (neighb.)				0.1609**
				(0.0125)
Δ *ln* Fines intensity (neighb.)				-0.0384**
				(0.0077)
Year fixed effects	No	Yes	No	No
State-year fixed effects	No	No	Yes	Yes
No. observations (municip.)	3199 (457)	3199 (457)	3199 (457)	3199 (457)
R-squared	0.056	0.137	0.240	0.379

Note: All models are estimated with OLS in first difference form. Robust standard errors, clustered at municipality level, are reported in parentheses. †,*,** denote significance at 10%, 5%, and 1% level.

Table 3: The role of environmental fines: IV results

	Dependent: *ln* Deforestation					
	IV	OLS	IV	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)
ln Fines intensity	-0.1855**			-0.1420**		
	(0.0361)			(0.0274)		
ln Real fines		0.0035	-0.0992*		0.0058†	-0.0019
		(0.0034)	(0.0458)		(0.0034)	(0.0246)
ln Fines intensity (neighb.)	-0.0206†	-0.0574**	-0.0431**	-0.0293**	-0.0401**	-0.0399**
	(0.0122)	(0.0085)	(0.0115)	(0.0093)	(0.0080)	(0.0079)
Year fixed effects	*Yes*	*Yes*	*Yes*	*No*	*No*	*No*
State-year fixed effects	*No*	*No*	*No*	*Yes*	*Yes*	*Yes*
Further controls	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
No. obs. (municip.)	3199 (457)	3199 (457)	3199 (457)	3199 (457)	3199 (457)	3199 (457)
R-squared	.	0.293	0.041	0.370	0.033	0.368

Note: All models are estimated in first difference form by OLS or IV and include additionally the full set of controls from Table 2. The state level fines intensity and fines levels variables are used as instruments in columns (1 and 4) and (3 and 6) respectively. Robust standard errors, clustered at municipality level, are reported in parentheses. †,*,** denote significance at 10%, 5%, and 1% level.

Table 4: Difference GMM estimates for the baseline

	Dependent: Δ *ln* Deforestation					
	(1) GMM	(2) GMM	(3) GMM	(4) GMM	(5) GMM	(6) GMM
Δ *ln* Deforestation (t-1)	0.8522	0.8622	0.4000	0.8486	0.8148	0.6341
	(0.7019)	(0.6400)	(0.4811)	(0.8326)	(0.7969)	(0.6746)
Δ Meat price	-0.0636	-0.0556	-0.0422	-0.0386	-0.0341	-0.0588
	(0.1034)	(0.1022)	(0.1312)	(0.0684)	(0.0680)	(0.1077)
Δ Soy price	0.0288*	0.0276*	0.0255†	0.0148†	0.0143†	0.0202*
	(0.0127)	(0.0126)	(0.0143)	(0.0082)	(0.0080)	(0.0102)
Δ *ln* Fines intensity	-0.4404*	-0.4139*	-0.4220†	-0.3199**	-0.3059**	-0.2996*
	(0.1977)	(0.1971)	(0.2193)	(0.1038)	(0.1049)	(0.1507)
Δ High rainfall	-0.2013†	-0.2057*	-0.1505	-0.2190†	-0.2193*	-0.2455†
	(0.1095)	(0.1035)	(0.1216)	(0.1132)	(0.1099)	(0.1360)
Δ Def. rates (neighb.)	0.1039	0.0907	0.1665	0.1574	0.1368	0.0892
	(0.0909)	(0.0902)	(0.1514)	(0.1276)	(0.1265)	(0.1316)
Δ *ln* Protected areas		0.0175	-0.5120		0.0242	0.0563
		(0.0772)	(0.7860)		(0.0555)	(0.4977)
Δ *ln* Indigenous areas		-0.0485	-0.3959		-0.0524	-0.1123
		(0.0708)	(0.5939)		(0.0563)	(0.2656)
Δ *ln* Settlement areas		0.0519	-0.1504		0.0584	0.0177
		(0.0510)	(0.2441)		(0.0391)	(0.1779)
Year fixed effects	Yes	Yes	Yes	No	No	No
State-year fixed effects	No	No	No	Yes	Yes	Yes
Arellano-Bond test for AR(2) in first diff.	0.861	0.744	0.910	0.471	0.423	0.583
Hansen test of overid. restr. (p-value)	0.910	0.916	0.955	0.964	0.977	0.980

Note: All models are estimated by difference GMM. (State-)Year indicators, prices and rainfall are treated as exogenous in all models. Past deforestation, fines intensity and neighboring deforestation rates are treated as endogenous and instrumented within the model. Protected, indigenous and settlement areas are treated as exogenous in columns (2) and (5), and as endogenous in columns (3) and (6). The number of observations is 2742, number of municipalities is 457. Robust standard errors are reported in parentheses. †,*,** denote significance at 10%, 5%, and 1% level.

Table 5: Further economic controls

	Dependent: Δ *ln* Deforestation		
	(1)	(2)	(3)
	OLS	OLS	OLS
Δ Soy price	0.0065*	0.0053†	0.0053†
	(0.0031)	(0.0032)	(0.0032)
Δ Meat price	0.0022	0.0054	0.0072
	(0.0180)	(0.0177)	(0.0178)
Δ *ln* Fines intensity	-0.0217**	-0.0245**	-0.0245**
	(0.0037)	(0.0041)	(0.0041)
Δ *ln* Protected areas	-0.0211	-0.0196	-0.0198
	(0.0201)	(0.0201)	(0.0201)
Δ *ln* Indigenous areas	-0.0404†	-0.0234	-0.0234
	(0.0213)	(0.0218)	(0.0219)
Δ *ln* Settlement areas	0.0156	0.0140	0.0140
	(0.0150)	(0.0157)	(0.0155)
Δ High rainfall	-0.1010**	-0.1063**	-0.1057**
	(0.0366)	(0.0390)	(0.0390)
Δ *ln* Credit density	0.1507*		0.1271
	(0.0685)		(0.0792)
Δ *ln* Real agricultural GDP p.c.		0.1737*	0.1586*
		(0.0746)	(0.0736)
State-year fixed effects	Yes	Yes	Yes
No. observations (municip.)	3199 (457)	2736 (456)	2736 (456)
R-squared	0.373	0.368	0.369

Note: All models are estimated in first difference form by OLS Robust standard errors, clustered at municipality level, are reported in parentheses. †,*,** denote significance at 10%, 5%, and 1% level.

Table 6: Difference GMM estimates for further economic controls

	Dependent: Δ *ln* Deforestation					
	(1) GMM	(2) GMM	(3) GMM	(4) GMM	(5) GMM	(6) GMM
Δ *ln* Deforestation (t-1)	0.0760 (0.6011)	0.7921 (0.5213)	0.2564 (0.2780)	0.1981 (0.7754)	0.3772 (0.4638)	-0.3059 (0.3349)
Δ Meat price	-0.1098 (0.1135)	0.0009 (0.0600)	-0.0095 (0.0548)	-0.0559 (0.0657)	0.0127 (0.0322)	-0.0050 (0.0286)
Δ Soy price	0.0291* (0.0140)	0.0176* (0.086)	0.0140* (0.0085)	0.0141† (0.0075)	0.0059 (0.0055)	0.0046 (0.0050)
Δ *ln* Fines intensity	-0.5006* (0.2334)	-0.2476† (0.1356)	-0.2811* (0.1137)	-0.3055** (0.1033)	-0.1332† (0.0749)	-0.1086† (0.0659)
Δ High rainfall	-0.1558 (0.1165)	-0.1761 (0.1252)	-0.0670 (0.0874)	-0.1750 (0.1090)	-0.1580* (0.0703)	-0.0804 (0.0511)
Δ Def. rates (neighb.)	0.0958 (0.0860)	0.1285 (0.0808)	0.1975** (0.0691)	0.1564 (0.1060)	0.0874 (0.0752)	0.1764** (0.0540)
Δ *ln* Protected areas	0.0310 (0.0872)	-0.0195 (0.0610)	-0.0009 (0.0533)	0.0268 (0.0526)	-0.0024 (0.0337)	-0.0115 (0.0358)
Δ *ln* Indigenous areas	-0.0172 (0.0744)	-0.0171 (0.0641)	-0.0006 (0.0571)	-0.0400 (0.0531)	-0.0211 (0.0380)	-0.0151 (0.0296)
Δ *ln* Settlement areas	0.0443 (0.0590)	0.0517 (0.0436)	0.0267 (0.0397)	0.0538 (0.0372)	0.0408 (0.0262)	0.0310 (0.0227)
Δ *ln* Credit density	0.5380 (0.7261)		0.6795 (0.5163)	-0.1423 (0.6988)		0.7036† (0.4005)
Δ *ln* Real agricultural GDP p.c.		0.5396 (1.3792)	1.5682* (0.7569)		0.6477 (0.3979)	0.7447† (0.4020)
Year fixed effects	Yes	Yes	Yes	No	No	No
State-year fixed effects	No	No	No	Yes	Yes	Yes
Arellano-Bond test for AR(2) in first diff.	0.516	0.662	0.420	0.981	0.402	0.457
Hansen test of overid. restr. (p-value)	0.670	0.794	0.668	0.546	0.325	0.020
No. observations (municipalities)	2742 (457)	2280 (456)	2280 (456)	2742 (457)	2280 (456)	2280 (456)

Note: All models are estimated by difference GMM. (State-)Year indicators, prices, protected, indigenous and settlement areas, and rainfall are treated as exogenous in all models. Past deforestation, fines intensity, credit, GDP and neighboring deforestation rates are treated as endogenous and instrumented within the model. Robust standard errors are reported in parentheses. †,*,** denote significance at 10%, 5%, and 1% level.

[1] See on the success of protected areas in forest conservation Fearnside (2003) and Nepstad et al. (2006).

[2] These policies are part of a new strategy of the Brazilian government in the region, which started with the symbolic launch of PPCDAm (Action Plan for Preventing and Controlling Deforestation in the Legal Amazon) in 2005 and has been further promoted by the Decree No. 6321 from 2008.

[3] 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).

[4] Kaimowitz and Angelsen (1998) provide a thorough review of earlier deforestation studies and their methodologies.

[5] Among the few exceptions are Prates (2008) on correlations between product prices, credit availability and deforestation for 2000-2004, Diniz et al. (2009) on the Granger causality between deforestation and cattle herd and soybean area (1997-2006), Riveiro et al. (2009) on correlations between deforestation, soybean area and cattle herd (2000-2006).

[6] State-level analyses of deforestation dynamics for earlier periods do not find an effect of agricultural prices on deforestation (see Araujo et al. 2009 for cattle prices over 1988-2000, and Ferraz 2001, for agricultural product prices over 1980-1998).

[7] Barreto et al. (2009) make a first attempt to assess the role of the environmental police by estimating how high deforestation rates could have been in 2008 without the measures taken by IBAMA.

[8] The Land Statute of 1964 originally stipulated a moratorium of 10 years, which has been decreased to 5 years with the Law 6969 of 1969 and was then incorporated in the Constitution in 1988. The limits on area size have also varied over time.

[9] Another reason to exclude sustainable use is that most of the services provided by forests have public goods' characteristics and therefore are mostly ignored by individuals deciding on land clearing (Angelsen 1999).

[10] The effect of expected environmental fines might be partly mitigated if forest conservation and hence "nonproductive use" also increases the likelihood of expropriation (which is the case according to INCRA's policies, see Alston, Libecap and Mueller 2000).

[11] We use monthly data on prices, fines and rainfall to compute yearly values for the August-July time window. We transform the remaining variables for which we have only yearly data to the August-July base by taking proportional shares of the corresponding yearly values.

[12] For all variables X that can also take zero values (like deforestation but also credit density or fines intensity, etc.), the logarithmic transformation is defined by $\ln(1+X)$.

[13]The original measure of Arima et al. (2007) was calculated based on field interviews that assessed prices paid at slaughterhouses all over the region. These prices were then recalculated net of the pixel-wise estimated average transport costs which resulted meat prices at the farm-gate. We readjusted their pixel based measure to municipal base, and used it to proxy the variability of prices paid across Amazonian municipalities.

[14]Prices as well as all other economic variables are deflated by IPCA – the official Brazilian consumer price index. The non-existence of regional price deflators for the Amazon region forced us to use the national CPI. Results are robust to changing the price deflator to the wholesale price index.

[15] We also experimented with including population density (per originally non-forest area) as an explanatory variable. Overall, its effects were not distinguishable from those of agricultural GDP because of high correlation between the two series, and thus are not reported.

[16] The rainfall data were acquired as part of the activities of NASA's Science Mission Directorate, and are archived and distributed by the Goddard Earth Sciences (GES) Data and Information Services Center (DISC).

[17] Cerrado areas were never forested by Amazon forest, and their deforestation is not reported by INPE.

[18]This corresponds to 484 municipalities out of the 783 municipalities of the Legal Amazon; availability of control variables further restricts the sample to 457 municipalities. Results are robust to the selection of the threshold, although the inclusion of regions with almost no forest considerably worsens the fit of the data.

[19] With the 10% filter, we eliminate a considerable part of the municipalities of the States of Pará (38%), Mato Grosso (45%), Maranhao (48%), and Tocantins (78%), but almost none of Acre and Amapá (0%), and only few of Amazonas (2%), Roraima (13%), and Rondônia (2%).

[20] Alternative specifications treating the rate of deforestation as dependent variable yielded comparable results, and are not reported.

[21] In order to contain the number of instruments and to reduce the potential for endogenous feedback, we only use third and fourth lags to estimate the first differences of endogenous variables. Depending on specification, this results in 15 to 22 instruments.

[22] When including state-year effects jointly with agricultural GDP in specifications 5 and 6, we also cannot disentangle the effects of soy price variation any more. This is not surprising as agricultural GDP is affected by variation in product prices and hence will capture part of the price effects as well.

[23] We recognize that the new policy from Conselho Monetário Nacional (Resolution No. 3545 of February 29, 2008) represents a step in this direction and are looking forward to be able to measure its effects.