Green finance and deforestation reduction in Brazil: a PVAR analysis of the Amazon Fund *

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[Preliminary version]

Abstract

Owing to deforestation, since 2021, the Amazon rainforest is emitting more CO2 than it is able to absorb, with a crucial impact on global warming and biodiversity loss. Legal Amazonia is an administrative area in Brazil that accounts for 64% of the whole Amazon rainforest in South America. With 5.2 million km^2, it represents 61% of the entire Brazilian territory, encompassing 9 federal states. The Amazon Fund is one of the main vehicles of international climate finance operating in Legal Amazonia. Its disbursements have dramatically dropped in recent years following important disagreements with the Brazilian government. The goal of this paper is to assess the impact of the Amazon Fund's projects in reducing deforestation, along with some other key factors, such as the national environmental agency's sanctions and agricultural production. Using satellite observations and microeconomic data, we build a panel dataset on the evolution of variables capturing environmental features, climate finance, regulation and production over 2002-2020 across the 760 municipalities of Legal Amazonia. We use a Panel Vector AutoRegression (PVAR) to replicate a stylized economic system where variables can influence each other at different lags. Our main empirical findings entail interesting policy implications: i) the Amazon Fund disbursements significantly reduce deforestation rates; ii) by recipient body, projects managed at the states level are more efficient than those managed by municipalities or universities; iii) by type of project, those related to land use planning, which involve the development and protection of local autochthonous communities, are the most efficient.

JEL Codes: C33, C81, F35, Q20, Q54, Q56

Keywords: Green finance, Deforestation, Amazon rainforest, Panel-VAR

*Any views expressed represent those of the authors and not necessarily those of the Banque de France or the Eurosystem. We are grateful to [...] Any remaining errors are our own.

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1 Introduction

According to the IPCC Special Report on Climate Change and Land (2019) [32], green house gas emissions from land use and land use change in the world averaged nearly 5.2 $GtCO_2/year$ between 2007 and 2016, slightly more than the European Union's emissions over the same period. These emissions are mainly due to deforestation. Thus, reducing deforestation can contribute significantly to mitigate climate change. The trend is not getting better as parts of the Amazon rainforest are beginning to act as net carbon emitters, failing to play its historical role as a regulator of the global carbon cycle (Gatti et al., 2021). The process of land use change (in which deforestation in the Amazon rainforest is largely involved) is also the primary source of biodiversity loss, according to the IPBES (Watson et al., 2019). Furthermore, the pandemic that the world has just experienced should act as a reminder that the deforestation process increases the risk of releasing infectious agents (IPBES 2020; Ellwanger et al., 2020).

From a global perspective, the efforts made by some countries have resulted in the creation of several bilateral and multilateral funds, which have joined the unosian REDD+ initiative (Reducing Emissions from Deforestation and Forest Degradation). Among them, the Amazon Fund, which operates only in Brazil, is the most active in terms of disbursement (Table 1).

Table 1: REDD funds over the world

Fund	Fund Type	Pledge	Deposit	Approval	Disbursement	Nb proj.
Amazon Fund	Multi Donor National	1288.23	1288.23	719.69	528.89	103
BioCarbon Fund ISFL	Multilateral	349.898	219.35	107	0	5
Central African Forest Initiative (CAFI)	Multi Donor Regional	478.76	319.59	182.24	182.24	11
Congo Basin Forest Fund (CBFF)	Multi Donor Regional	186.021	164.6525	83.11	58.91	37
FCPF-RF	Multilateral	466.54	466.54	311.24	253.47	46
FCPF-CF	Multilateral	874.5	874.5	0	0	0
Forest Investment Program (FIP)	Multilateral	735.86	735.86	573.73	249.18	48
UN-REDD Programme	Multilateral	329.04	323.94	323.52	315.56	35

Source: Climate Funds Update.

Notes: All figures are in USD mn. Updated in March 2021.
NB. BioCarbon Fund ISFL : BioCarbon Fund Initiative for Sustainable Forest Landscapes, FCPF-RF: Forest Carbon Partnership Facility - Readiness Fund, FCPF-CF: Forest Carbon Partnership Facility - Carbon Fund.

The Amazon Fund was created in 2009 and has been managed since then by the *Banco Nacional de Desenvolvimento Econômico e Social* (BNDES, the Brazilian publicly-owned development bank). The fund is mainly financed by the Norwegian government, up to 93,8%. Germany, through its development agency (5,7%) and Petrobras (0,5%) - the main state-owned Brazilian corporation in the petroleum industry - complete the funding. Since 2009, 534 million USD have been disbursed (up to May 2021) to support 102 projects[1] (Figure 1). The Amazon Fund is by far the largest fund operating in Brazil in the context of the fight against deforestation, with 81% of total REDD+ disbursements[2]. Two other funds, the Green Climate Fund and the Forest Investment Program finance respectively 14% and 5% of REDD+ projects in Brazil.

[1] One project has been abandoned, since Climate Funds Update last update of Table 1
[2] Climate Funds Update, May 2022

From 2019 on, the fund's activities were jeopardized by Bolsonaro's government. On the one hand, according to the Norwegian and German donors, Brazilian authorities were no longer giving sufficient guarantees on their real willingness to reduce deforestation in Legal Amazonia. On the other hand, they unilaterally suspended the board of directors and the technical committee of the fund[3]. During the period 2019-2022, the Fund decided to stop making new pledges and stopped funding new projects, limiting itself to honor disbursements for projects already contracted. A few days after taking power on January 1, 2023, Lula da Silva's government reactivated the board of the fund. Since then, a number of countries have expressed their willingness to make new pledges : Germany wishes to enlarge its participation in the Fund [4], whereas some other countries are willing to become shareholders and contribute for the first time (The United Kingdom[5], France[6], and the United States[7].

Officially, the main objective of the Fund is to reduce the annual deforestation rate in the Amazon rainforest. While qualitative assessments tend to show that the Fund has been effective at a very local level, so far no scientific studies have addressed its effectiveness in a quantitative way. To echo this fact, in a recent annual report of the Amazon Fund [1] (2019), its president stated: "Although there is clear evidence that the Amazon Fund has contributed to reducing deforestation in the Amazon rainforest, it is a great challenge to estimate this contribution quantitatively".

From an empirical standpoint, disentangling the impact of the Amazon fund from the Brazilian government's agenda on deforestation is a major challenge. A number of public policies have been implemented since the Plan of Action for the Prevention and Control of Deforestation in the Legal Amazonia (PPCDAm) was launched in 2004 by the Brazilian federal government. Along with new public forestry policies, subsequent measures have enhanced the enforcement of existing regulation (particularly the Forest Code) and, to some extent, aligned the interest of municipal authorities and the business sector with the goal of reducing deforestation rates. Since 2007, the Ministry of the Environment publishes annually a "black list" of the municipalities responsible for the largest contributions to aggregate deforestation in Legal Amazonia. Among others, land use in these municipalities is particularly monitored, so that business not in compliance with environmental laws are cut from rural credit and are exposed to commercial embargoes on their production. In 2009, the Rural Environmental Cadastre (CAR) was launched as a key tool for controlling forest clearing in private landholdings. [8] Private holders have been encouraged to register their properties in the CAR to be in compliance

[3]https://www.climatechangenews.com/2023/01/04/first-day-office-lula-revives-1-billion-fund-amazon/

[4]https://www.reuters.com/business/environment/germany-pledges-funds-help-brazil-defend-amazon-rainforest-2023-01-30/

[5]https://www.reuters.com/business/environment/britain-could-join-amazon-fund-help-brazil-control-deforestation-uk-minister-2023-01-03/

[6]https://www1.folha.uol.com.br/ambiente/2023/02/franca-e-uniao-europeia-estudam-contribuir-para-fundo-amazonia-diz-chanceler-francesa.shtml

[7]https://www.bbc.com/portuguese/articles/cp90rzygp0lo

[8]The CAR is a system of georeferenced identification of rural properties. It enables the monitoring and control of remaining native vegetation within the areas protected by law (APP and LR). It is not in force in public lands, such as areas reserved for indigenous settlements, national and state parks and other sustainable reserves

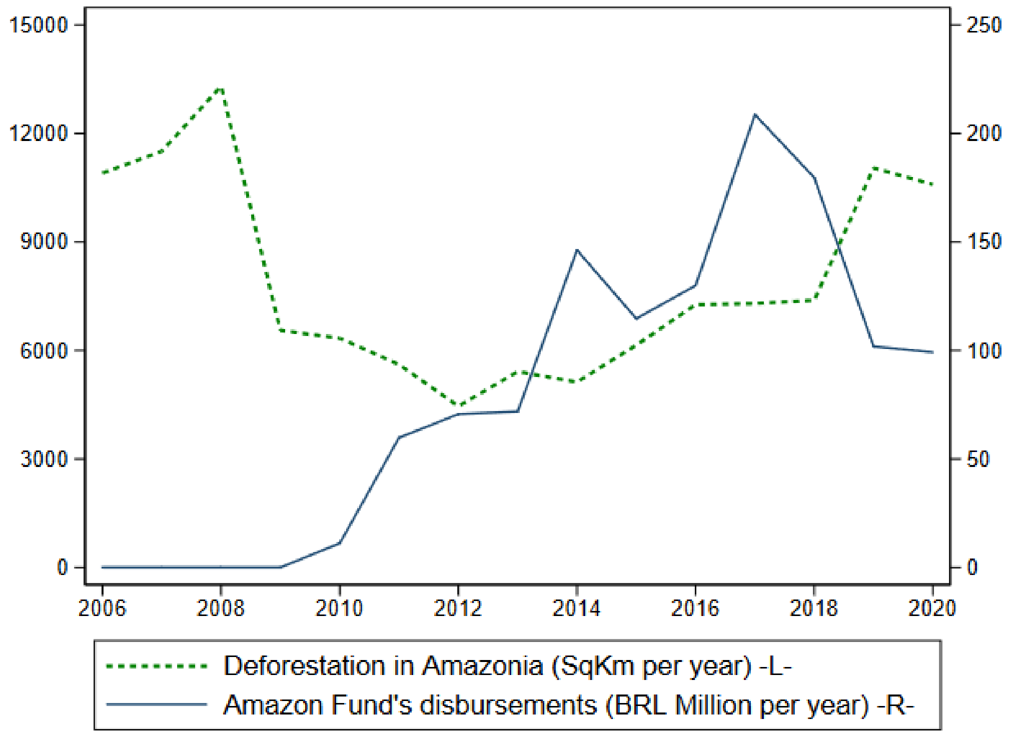
with the Forest Code. Thereby, rural landholders are required to keep a large share of native vegetation aside as Area of Permanent Preservation (APP - mainly hilltops and river banks) or as Legal Reserve (LR - areas proposed by the landholder to be legally under conservation or recovery). [9] On the one hand, municipalities blacklisted as main contributors to deforestation tend to encourage landholders to adhere, as reaching at least 80% of rural properties registered in the CAR is a necessary condition to exit the black list. On the other hand, landholders have strong incentives to register in the CAR, as this is required for obtaining a license for rural economic activity as well as for accessing rural (subsidized) credit. Unregistered properties are exposed to sanctions from previous deforestation by the federal environmental agency (IBAMA), and they tend to have lower values than those registered in the CAR.

As for other climate projects funded by international creditors, the action of the Amazon Fund has explicitly supported many of the above public policies since 2009. The findings of this empirical work can thus be read as a case study on the effectiveness of international climate finance in supporting the Brazilian regulatory environmental framework. While the latter was progressively improved between 2004 and 2014, from 2015 on the economic crisis and drastic changes in the government environmental approach have significantly undermined the willingness and the ability of public policies to fight deforestation. The assessment of the Amazon Fund's action cannot be totally disentangled from these developments.[10]. Rather, to address the determinants of rainforest clearing, in this paper we take into account the intertwined action of climate finance, public policies, and commodities' production and markets. In particular, we use the sanctions by the national environmental agency (IBAMA) as a proxy for the willingness and the ability of authorities to enforce environmental regulation. This way we can assess the action of the Amazon Fund for a given stance of public policy.

[9] In the Amazon biome, the Forest Code generally requires the addition of APP and LR to represent at least 80% of the private landholding. The rest of the area can be authorized for deforestation under certain conditions.

[10] As an illustration, the Fund's main owners have stopped their contribution following serious irritants with Bolsonaro's government. From 2019 on, the Amazon Fund's disbursements correspond to the implementation of projects previously approved, but there has not been further funding for new projects.

Figure 1: Deforestation and disbursements of the Amazon Fund in Legal Amazonia between 2006 and 2020



Sources: INPE for deforestation rates; BNDES and authors calculations for Amazon Fund's disbursements.

The contribution of this article is threefold.

First, to our knowledge, it is the first paper to achieve a quantitative assessment on the effectiveness and efficiency of the Amazon Fund. Several papers have conducted political and organizational qualitative analyses of the Amazon Fund, as an example of a results-based funding (RBF) mechanism. These papers raise concerns about the lack of overall strategy of the fund due to its governance (Correa et al., 2019), and the *de facto* disagreement, between donor countries (which seek to obtain proof of additionality and performance of their new funding) and Brazil (which wants to receive cash for its past efforts) (van der Hoff et al., 2018). Correa et al. (2020) attempt to quantitatively assess the environmental performance of the Amazon Fund in some specific areas. Yet they find no evidence of a causal effect on deforestation of the Amazon Fund's financing of sustainable production chains in Alta Floresta, in the state of Mato Grosso. In turn, this paper presents a quantitative analysis of the performance of the Amazon Fund as a whole. Not only we estimate the Fund's effectiveness, but we also assess its efficiency through the calculation of an abatement cost of greenhouse gas emissions related to deforestation. Moreover, for the sake of public policy recommendations, we assess the Fund's performance according to its different axes of intervention, projects' themes, and recipient bodies.

Second, our quantitative study adds to the literature on empirical evaluations of REDD+ projects around the world. A number of studies have been carried out in areas containing tropical forests, such as Guyana (Roopsind et al., 2019), Mexico (Ellis et al. 2020) or Uganda (Jayachandran et al., 2017). Several works have also been conducted in Brazil with contrasting results (Carrilho et al., 2022; West et al. 2020 and Simonet et al. 2019). All these approaches use difference in differences or synthetic control techniques. In this paper, we depart from these traditional methods. Drawing on empirical tools from financial economics, we use a Panel Vector AutoRegressive method (PVAR). While PVAR models are applied in a wide range of topics in macroeoconomics and finance (see Canova and Ciccarelli 2013) for a survey), this methodology is still barely exploited for analyzing climate issues. Ciccarelli and Marotta,2021) use a PVAR model to analyse the mutual effects of climate change, climate policies and the macroeconomy in a global framework. Yet, to our knowledge so far this methodology has not been exploited to address the relationships between climate finance and deforestation at the microeconomic level.

Third, this paper extends the literature on the economic determinants of deforestation in the Brazilian Amazon rainforest. Since the major decline in deforestation in the late 2000s, a great amount of research has focused on the causes of variations in deforestation levels. These variations can be the result of both economic phenomena and public policies with environmental objectives. Assunção et al. (2015) and da Silva et al. (2010) show that the prices of agricultural commodities such as beef or soybeans have an exogenous impact on deforestation rates. Similarly, the conditions of access to rural credit can significantly influence deforestation (Assunção et al., 2020). Many of the PPCDAm policies mentioned above are found to be effective in reducing deforestation: blacklisting municipalities (Assunção and Rocha, 2019 and Cisneros et al., 2015), land registration (Alix-Garcia et al., 2018), areas protection (Soares-Filho et al., 2010) and enhanced law enforcement with satellite teledetection (Assunção et al., 2014). Along with climate finance and deforestation, our study encompasses other endogenous variables such as law enforcement (proxied by the Brazilian regulator - IBAMA - sanctions) and agricultural production (soybean and cattle), as well as exogenous variables such as agricultural prices and rural credit. As the PVAR enables to replicate a stylized economic system, this paper sheds light on the role of the determinants of deforestation in the Brazilian Amazon rainforest covered by the aforementioned studies, while taking into account possible feedback effects among the main factors.

The remainder of the article is organized as follows. Section 2 describes a simple model of deforestation patterns that provides some theoretical foundations for the empirical work. Section 3 presents the data along with a discussion of the institutional context. Section 4 addresses the empirical strategy (panel VAR) and identification hypothesis. Section 5 presents our main findings, putting some emphasis on the dynamic effects of green finance, law enforcement and agricultural production on deforestation, as well as on the efficiency of the different types of Amazon Fund's projects. Section6 briefly concludes the paper, discussing the main policy implications and suggesting some future research avenues.

2 A stylized model of deforestation

In order to provide the main economic intuitions behind our empirical work, this section describes a simple model of deforestation patterns encompassing an environmental feedback loop, law enforcement and international "green" finance. We consider an agricultural planner that maximizes her intertemporal profits and operates within a bounded space of area $\overline{T}$. At each period t, the agricultural planner chooses to deforest an amount d_t of land. The accumulated deforested area (in km^2) over time is $D_t = \sum_{\tau=0}^{t} d_\tau$. The planner produces an agricultural commodity on the area D_t. To simplify our analysis, we assume that it is not possible to reforest (i.e. we impose $d_t > 0$ for all t). Thus, for all t, D_t necessarily increases through time. This constraint is consistent with the deforestation data available in Brazil (see Section 3).

The planner takes into account a negative externality of deforestation: the depletion of forest stocks has an impact on its future agricultural yields through the degradation of climate regulation (Strand et al., 2018). Denoting p the price of the agricultural good (in monetary units per tons) and r the intrinsic agricultural yield (in tons per km^2), the planner's agricultural income can be written as:

$$I_t \ = prD_t \left(1 - \frac{D_t}{\overline{T}}\right)$$

Where we draw on Ollivier (2012) and Clark (1974) for the mathematical form of the environmental feedback loop.

The agricultural planner faces a *production* cost of deforesting c (in monetary units per km^2). As far as most of its deforestation is illegal, its *total* cost increases with the level of sanctions due to law enforcement s (expressed as a premium on the production cost). As proposed by Ollivier (2012), an international donor is willing to give to the agricultural planner a monetary compensation R (in monetary units per km^2 of saved deforestation) if she clears the rain-forest under a cap level $\overline{d}$ (in km^2). The planner discounts the future using a factor β.

The constrained intertemporal maximization problem can be written as:

$$\max_{\{d_t\}_t} \sum_{t=0}^{\infty} \beta^t \left[prD_t \left(1 - \frac{D_t}{\overline{T}}\right) - c(1+s)d_t + R\left(\overline{d} - d_t\right)\right]$$

s.t.

$$\forall t \geq 0, d_t \geq 0$$

The Lagrangian is:

$$\mathcal{L} = \sum_{t=0}^{\infty} \beta^t \left[prD_t \left(1 - \frac{D_t}{\overline{T}}\right) - c(1+s)d_t + R\left(\overline{d} - d_t\right) - \lambda_t d_t\right]$$

where λ_t is the shadow value associated to land.

The first order condition with respect to d_t leads to:

$$\beta^t \left(pr - 2\frac{pr}{\overline{T}} D_t - c(1+s) - R - \lambda_t \right) + \sum_{q=t+1}^{\infty} \beta^q \left(pr - 2\frac{pr}{\overline{T}} D_q \right) = 0$$

So that,

$$\left(pr - 2\frac{pr}{\overline{T}} D_t - c(1+s) - R - \lambda_t \right) + \sum_{q=1}^{\infty} \beta^q \left(pr - 2\frac{pr}{\overline{T}} D_{q+t} \right) = 0$$

Rearranging,

$$\frac{pr}{1-\beta} - c(1+s) - R - \lambda_t = 2\frac{pr}{\overline{T}} \sum_{q=0}^{\infty} \beta^q D_{q+t}$$

Evaluating at $t = 0$, we finally get,

$$\sum_{q=0}^{\infty} \beta^q D_q = \sum_{\tau=0}^{\infty} d_\tau \sum_{q=\tau}^{\infty} \beta^q = \frac{\overline{T}}{2(1-\beta)} - \frac{\overline{T}}{2pr} \left(R + \lambda_0 + c(1+s) \right)$$

$$\sum_{\tau=0}^{\infty} d_\tau \sum_{q=\tau}^{\infty} \beta^q = \frac{\overline{T}}{2} \left(\frac{1}{1-\beta} - \frac{1}{pr} \left(R + \lambda_0 + c(1+s) \right) \right)$$

At the optimum, the (adjusted) discounted sum of deforestation areas are:

- an increasing function of the total stock of land $\overline{T}$ (provided β is high enough), the agricultural prices p and the intrinsic yields r;
- a decreasing function of the international donation amount per year R, and unit *production* cost of deforestation c and the stringency of law enforcement s.

We obtain the optimal deforestation path as the numerical solution of the maximization problem above (Figure 2). It is noteworthy that the higher the level of international aid, the lower the deforestation rates in the short run. However, assuming lower disbursements from the beginning of the simulation leads to lower forest clearing rates in the long run. This stems simply from the fact that, with no green finance disbursements, the stock of forest depletes faster, and less forest is "available" for deforestation (Figure 16 in appendix). Owing to the discount factor, whatever the level of R, the optimal deforestation path leads to a full depletion of the forest in the very long run.

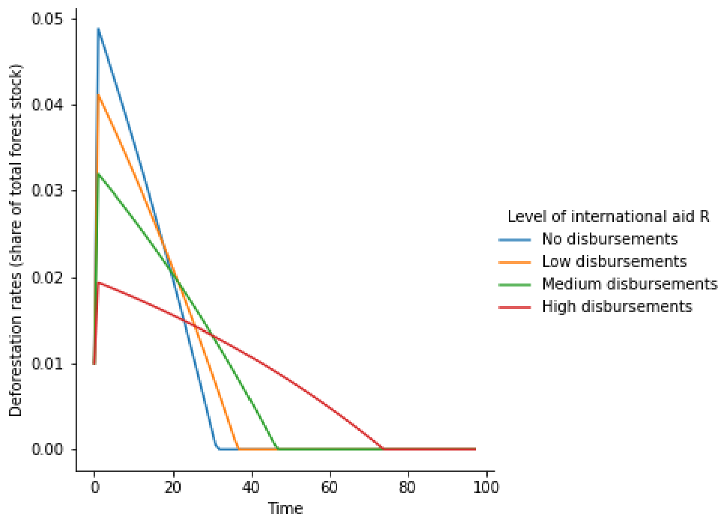


Figure 2: Optimal deforestation path for different values of R

3 Data

Economic, regulatory and environmental data were gathered from several sources in order to build a panel database. The dataset encompasses a sample of 760 municipalities[11] spread over all the nine states of the Amazon biome: Acre, Amapá, Amazonas, Maranhão, Mato Grosso, Pará, Rondônia, Roraima, Tocantins. Panel data span from 2002 to 2020 on a yearly basis.

3.1 Deforestation

Every year, the Brazilian National Institute of Space Research (INPE) publishes estimates of the deforestation increment, commonly called deforestation rates (in km^2). This measure corresponds to the surface that has suffered clear-cut over the past twelve months. The related calculations are carried out using satellite images from the PRODES program (Satellite Project to Monitor Deforestation in Legal Amazon, in English). For technical reasons (there are fewer clouds and therefore better visibility during the dry seasons), the increment of year t actually corresponds to deforestation occurring between August of year $t-1$ and July of year t. This increment is disclosed at the very local level, for the 760 municipalities of the data set. As the INPE disclaims that data on 2000 and 2001 are not consistent with other years, we restricted the panel from 2002 to 2020.

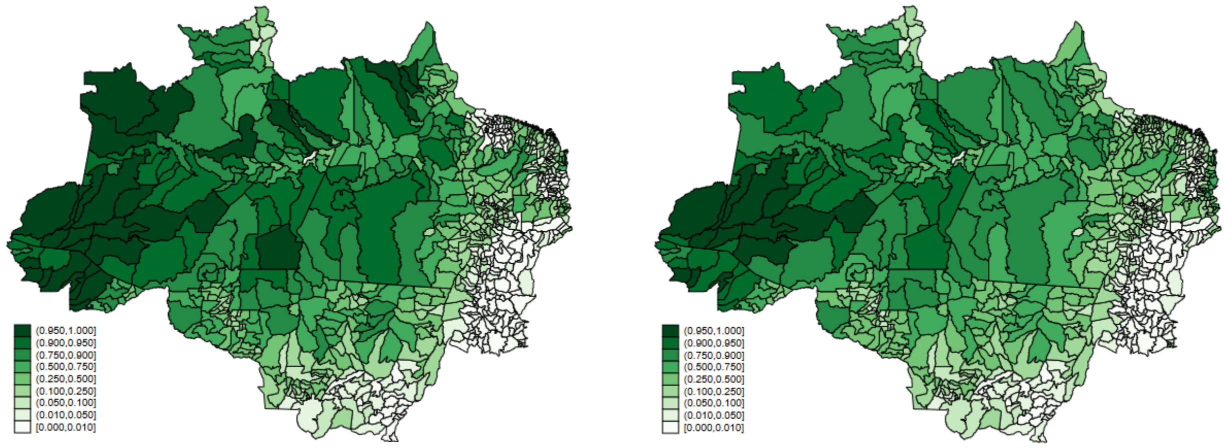
Some caveats stem from the measurement of the rain-forest evolution. The PRODES detection system only takes into account gross deforestation increments and not net deforestation. In other words, data capture to what extent an area has been deforested, but do not tell us whether it has been partially or fully reforested later on, even if it has been in practice. This may have an impact on the study: while several Amazon Fund projects aim at reforesting some areas, it is only possible to assess their impact in terms of gross loss of rain-forest. Moreover, the PRODES system only detects clear-cutting, and therefore does not take into account the simple degradation of the forest. Our baseline results must therefore be interpreted carefully, in light of measurement limitations.

Between 2002 and 2020, the density of primary forest over the municipality area has shrunk on average by almost 7.5% in Legal Amazonia (Figure 3). Yet, over time, aggregate deforestation has significantly varied, in connection with the forestry public policies and the degree of enforcement of environmental regulation mentioned above. After reaching 22 242 km^2 on annual average in 2000-04, forest clearing notably declined in 2005-09 (-41%), and did even more in 2010-14, when aggregate deforestation dropped to 5 778 km^2 (-56% compared to the previous 5-year period). However, this trend has reverted and forest clearing has been increasing during the last 8 years, particularly in 2019-21, when it rose by 59% relative to the previous 4-year period, to reach 11 397 km^2 on annual average. The area where deforestation has been more intense forms an arc of municipalities from Rondonia to northern Para, through

[11] according to the IBGE nomenclature (Brazilian Institute of Geography and Statistics)

northern Mato Grosso (Figure 4a).

Figure 3: Amazon rainforest density (remaining share of primary forest)



(a) in 2002 (b) in 2020

Source: INPE and authors calculations

3.2 Measuring the action of the Amazon Fund

A major contribution of this paper is to build a clean database of Amazon Fund disbursements between 2009 and 2020 in the Brazilian Amazon rainforest, disaggregated at the municipal level. Correa et al. (2019) have reconstructed the Fund's municipal disbursements up to 2017. Yet they limit themselves to a descriptive analysis. In turn, we use such a level of granularity to infer causality on deforestation while controlling for structural factors, constant over time but varying across municipalities.

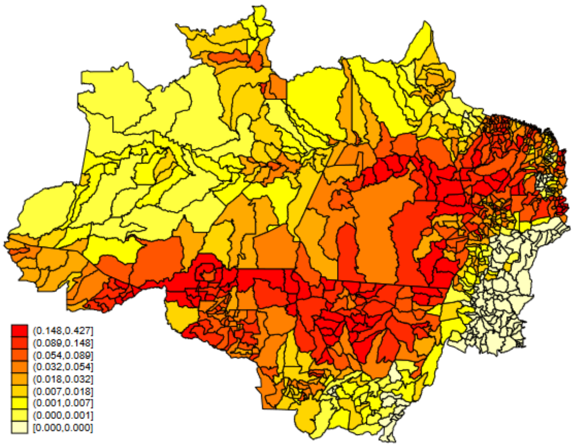
Two main sources of information were used to obtain variables that describe the action of the Amazon Fund in the 760 municipalities of the Amazon biome:

- The first source of information is the Amazon Fund website. Using the *BeautifulSoup* package of Python, 102 web pages of the Amazon Fund's projects were scrapped to gather the information needed for an empirical assessment: the title, the beneficiary organisation and its type, the status of the project (approved, contracted or concluded), the states in which the project occurs, the axis, the theme, the total value of the project, the total estimated support, and the effective support disbursed on a yearly basis (up tp May 2021). At the end of this step, we get the disaggregation of disbursements at the state level. The information obtained is summarized in Table 5 (Annex).

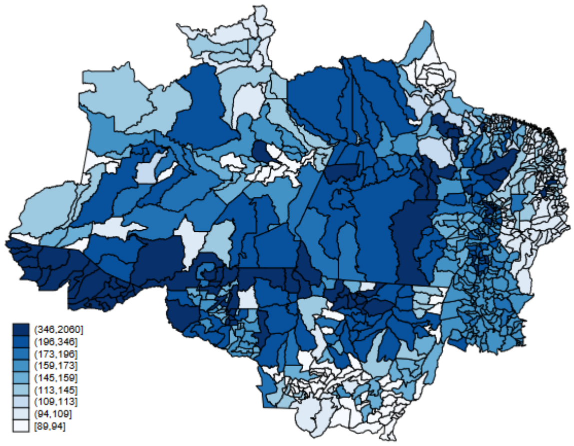
- In order to disaggregate disbursements at the municipality level, we used a second source of information: the Brazilian manager of the Amazon Fund (the BNDES). Exchanges with the Fund's managers made it possible to identify more precisely the geographical areas that received funds from the 102 projects. For each of the 102 projects, we got information about the group of municipalities that benefited from it. As we did not know the exact amount of money going to each municipality, we applied an arbitrary rule to allocate resources from one project: the distribution is made on a pro rata basis of the area of each municipality.

On an aggregate and spatial basis, Figure 4b suggests that the action of the Amazon Fund tends to focus on the deforestation arc.

Figure 4: Deforestation and Amazon Fund disbursements



(a) Deforestation (share of deforested area between 2002 and 2020)



(b) Amazon Fund disbursements (in $R\$/km^2$)

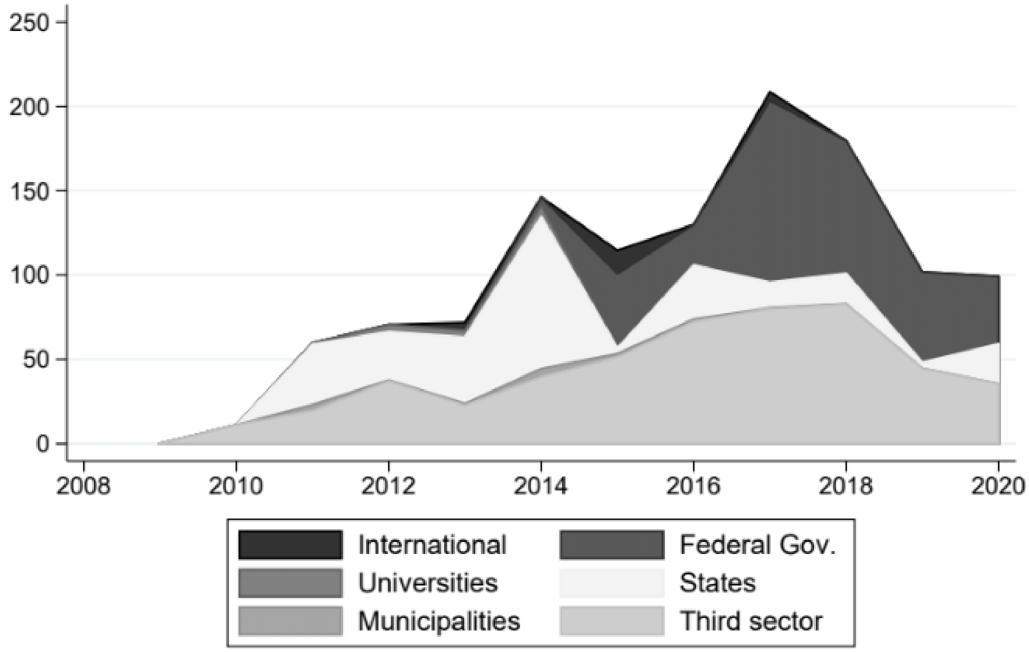
Source: INPE and authors calculations for deforestation; BNDES and authors calculations for Amazon Fund disbursements

A more granular decomposition by recipient, axis and theme makes it possible to disentangle the effects of each component and to formulate policy recommendations.

Six different types of recipients, both in the public and the private sphere and acting within different geographical perimeters, have received funding from the Amazon fund: the international sphere, the Brazilian federal government, states, municipalities, the third sector, and universities (Figure 5). Among these six types of recipients, three of them concentrate 95.8 % of the Fund's disbursements up to December 2020:

- The third sector receives 43.1% of disbursements. It includes charities, social enterprises, co-operatives, community interest companies or non-governmental organizations.
- Brazilian states are responsible for 25.7% of disbursements. Most of these disbursements have occurred before 2015. Among the 22 projects carried out by the states, 14 are allocated to the support of the 9 CAR plans, which represent 57.4% of the disbursements made by the states on funds donated by the Amazon fund.
- The Federal government receives 27% of disbursements that are shared by 8 projects. It mainly disburses funds after 2015 in order to support federal agencies such as the INPE (2 projects) or the IBAMA (3 projects).

Figure 5: Annual Amazon Fund disbursements by recipient between 2008 and 2020 (in millions of reais per year



Source: BNDES and authors' calculations

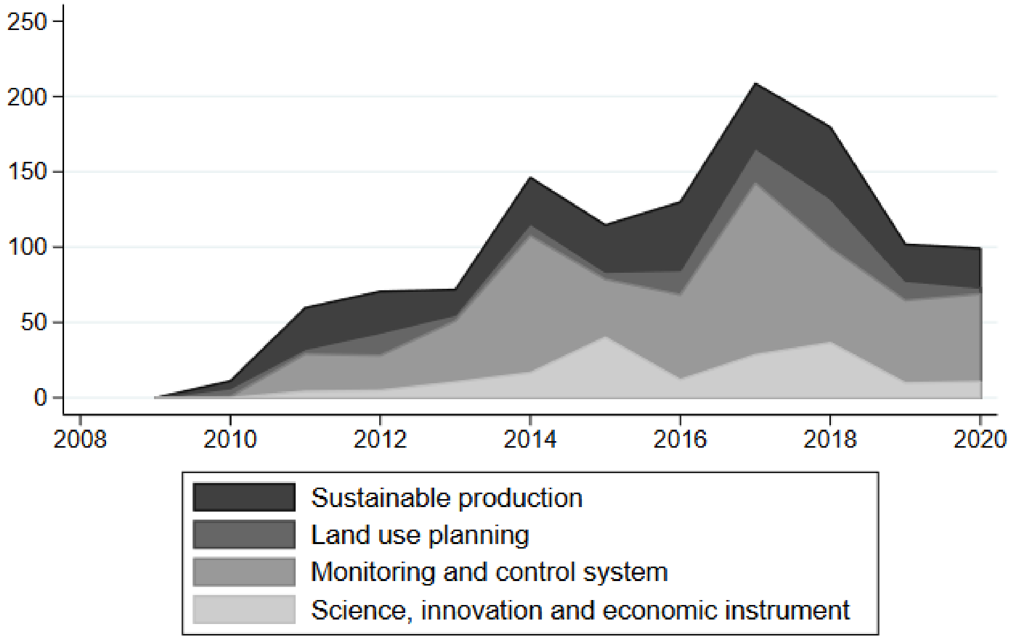
For each project, the Amazon Fund defines one or more axes and themes of action in which the project fits. The four axes correspond to those defined by the PPCDAm launched in 2004 (the Action Plan for the Prevention and Control of Deforestation in the Legal Amazon). They are described in the last edition of the plan[12]:

- sustainable productive activities: promoting sustainable forest management and agricultural production systems ;
- environmental monitoring and control: (i) promoting accountability for environmental crimes and infractions, (ii) putting shared forest management into effect, (iii) preventing and fighting forest fires and (iv) improving and strengthening the monitoring of vegetation cover ;
- land-use planning: promoting land regularization and reinforcing protected areas ;
- normative and economic instruments for the control of illegal deforestation.

The BNDES provided us with the contribution of each project for each axis. The breakdown is provided in the Annex of this paper (Table 6).

[12] http://combateaodesmatamento.mma.gov.br/images/conteudo/Livro-PPCDam-e-PPCerrado_WEB_1.pdf

Figure 6: Annual Amazon Fund disbursements by axis between 2008 and 2020 (millions of BRL per year)



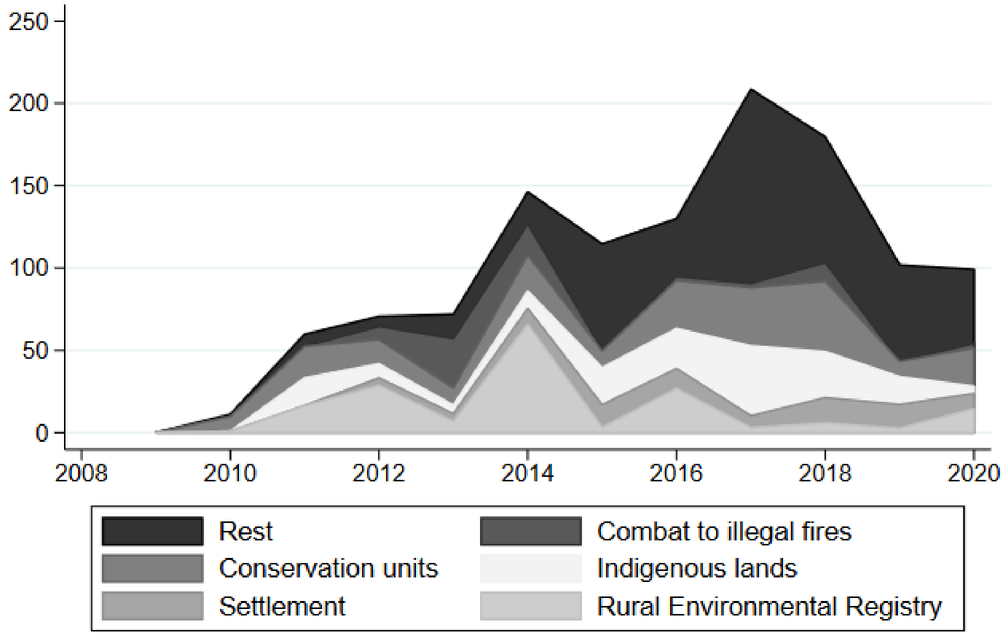
Source: BNDES and authors' calculations

Since 2010, the Amazon fund has devoted 42% of ressources to "Monitoring and Control" axis. Indeed, the fund has massively supported the states in financing teams dedicated to the registration of land holdings in the Amazon rainforest in the *Cadastro Ambiental Rural* (CAR) The CAR enables authorities to enforce the application of the Forest Code. Property rights programs aimed at combating deforestation have been studied quite extensively, both in Brazil (Costa et al., 2018; L'Roe et al., 2016) and in other tropical forests (see for example Wren-Lewis et al., 2020). Almost a third of the fund's disbursements (29%, 154 million USD) were made to support the "sustainable production" axis of action of the PPCDAm. Sustainable production projects have been much less studied in the empirical literature.

In addition to fitting into the PPCDAm axis decomposition, the Amazon Fund has formulated its own theme decomposition. The main themes covered by the Amazon Fund activities are:

- Indigenous lands
- Conservation units
- Rural Environmental Registry – CAR
- Settlement
- Combating illegal fires and burn-offs.

Figure 7: Annual Amazon Fund disbursements by theme between 2008 and 2020 (in millions of reais per year



Source: BNDES and authors' calculations

As Figures 7 and 8 show, not all projects have necessarily a thematic allocation.

Figure 8: Number of projects per axis, theme and recipient

AXIS	Monitoring and control systems	42
	Science, innovation and economic instruments	25
	Land use planning	27
	Sustainable production	59
THEME	Rural Environmental Registry (CAR)	19
	Settlement	16
	Indigenous lands	28
	Conservation units	28
	Combat to illegal fires and burn-offs	6
RECIPIENT	Third Sector	58
	Federal Government	8
	States	22
	Municipalities	7
	Universities	6
	International	1

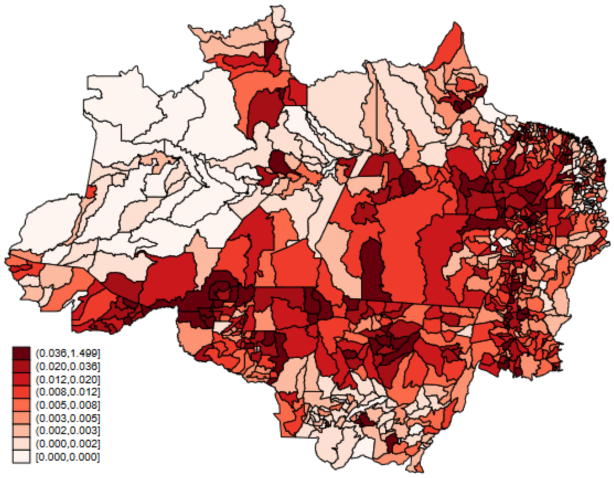
Source: BNDES and authors' calculations

Note: Unlike for the recipients, axes and themes are not mutually exclusive: a single project can be devoted to several themes. For example, among the 102 projects, 59 were devoted (at least) to sustainable production.

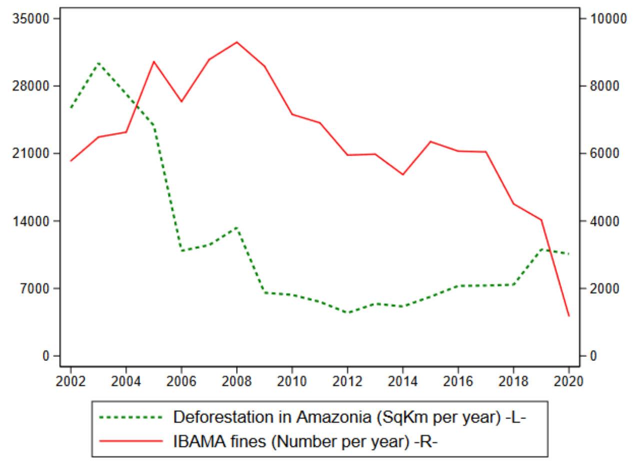
3.3 Law enforcement

The administrative arm of the Brazilian Ministry of Environment, i.e. the Brazilian Institute of the Environment and Renewable Natural Resources (IBAMA), regularly updates a public census of environmental infractions detected by the authorities since the 1980's[13]. The file describes more than 700 000 infractions committed all over Brazil. It is possible to aggregate the number and amount of infractions at the municipal level for each year.

Figure 9: Law enforcement



(a) Number of infractions per km^2 between 2010 and 2020



(b) Number of infractions in the Legal Amazon between 2002 and 2020

Source: IBAMA and authors calculations

Disclaimer: according to the IBAMA, the data on infractions committed in 2019 and 2020 are not complete due to a change in the data collection application

Not all crimes are necessarily related to the destruction of primary forest. We extract infractions concerning environmental administration, federal technical cadastre, environmental control, environmental emergency, flora, granting of authorizations (licensing), and conservation units.

Several stylized facts are noteworthy:

- As expected, the selected infractions are concentrated in the deforestation arc (Figure 9a). Besides, it appears that the arc of infractions is somewhat upstream of the arc of Amazon Fund disbursements (Figure 4b).
- The number of infractions increased significantly during the environmental effort of the late 2000s, before declining continuously until 2020 (Figure 9b).

3.4 Agricultural activities

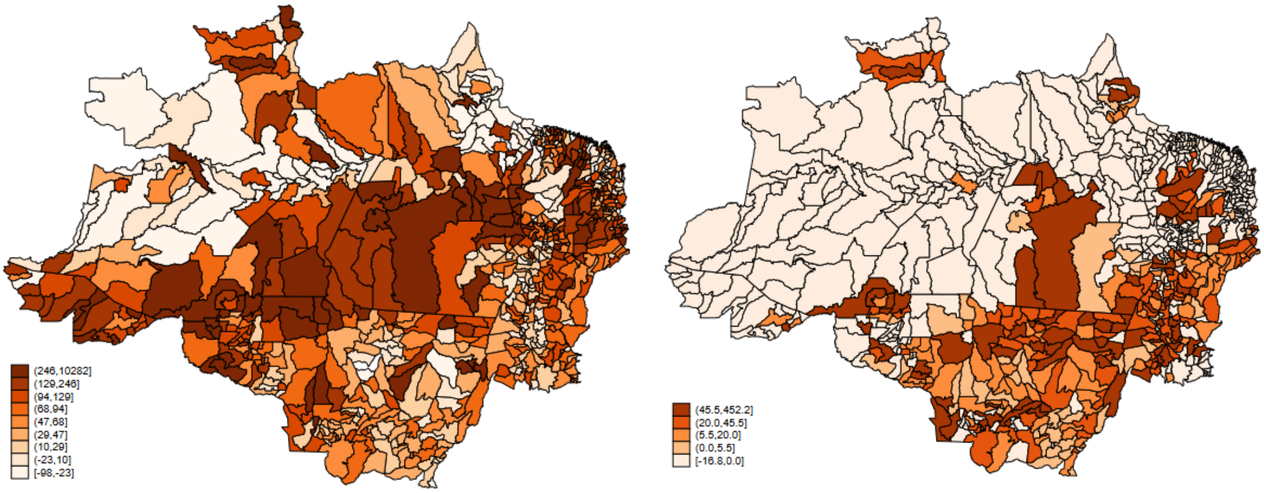
3.4.1 Livestock and crops at the municipality level

Agricultural activity is recognized as a key driver of deforestation in the Brazilian Amazon rainforest (Assunção et al., 2015 or da Silva et al., 2010). Using IBGE data, two types of agricultural production are included in the panel :(i) the steer livestock[14], which corresponds

[13]https://dadosabertos.ibama.gov.br/dataset/fiscalizacao-auto-de-infracao
[14]https://sidra.ibge.gov.br/tabela/3939

to cattle size (the number of heads of beefs is reported each December 31st) and (ii) the soy bean production[15] in tonnes.

Figure 10: Growth (%) of agricultural production between 2001 and 2020



(a) Steer livestock (number of head) (b) Soybean production (tons)

Source: IBGE and authors calculations

In Figure 10, we can notice that beef farms settle much further into the forest than soybean farms. This corresponds to the agricultural transition described by WWF[16]: "Soy developers then capitalize on the cattle ranchers and take over their land, pushing cattle ranching (and deforestation) towards new pioneer areas."

3.4.2 Agricultural prices at the national level

Assunção et al. (2015) show that deforestation responds to agricultural output prices. In line with this finding, we include two exogenous price variables in our model: soybeans and beef prices. Using data from CEPEA (Centro de Estudos Avançados em Economia Aplicada), we gather daily prices of soy[17] and cattle[18], and we transform them into annual prices. These prices are respectively those prevailing in the states of Parana and Sao Paulo, which are not Amazonian states. As these prices do not depend directly on the volumes produced in the Legal Amazon, we use them as exogenous indicators (as in Assunção et al. (2015)). Expressed in local currency, agricultural prices in levels tend to have an upward trend. To get stationary series, in the econometric analysis we use these variables in real growth (by expunging the GDP deflator from the nominal annual rate of variation).

[15] https://sidra.ibge.gov.br/tabela/1612
[16] https://wwf.panda.org/discover/knowledge_hub/where_we_work/amazon/amazon_threats/unsustainable_cattle_ranching
[17] https://www.cepea.esalq.usp.br/br/indicador/soja.aspx
[18] https://www.cepea.esalq.usp.br/br/indicador/boi-gordo.aspx

3.4.3 Aggregate rural credit

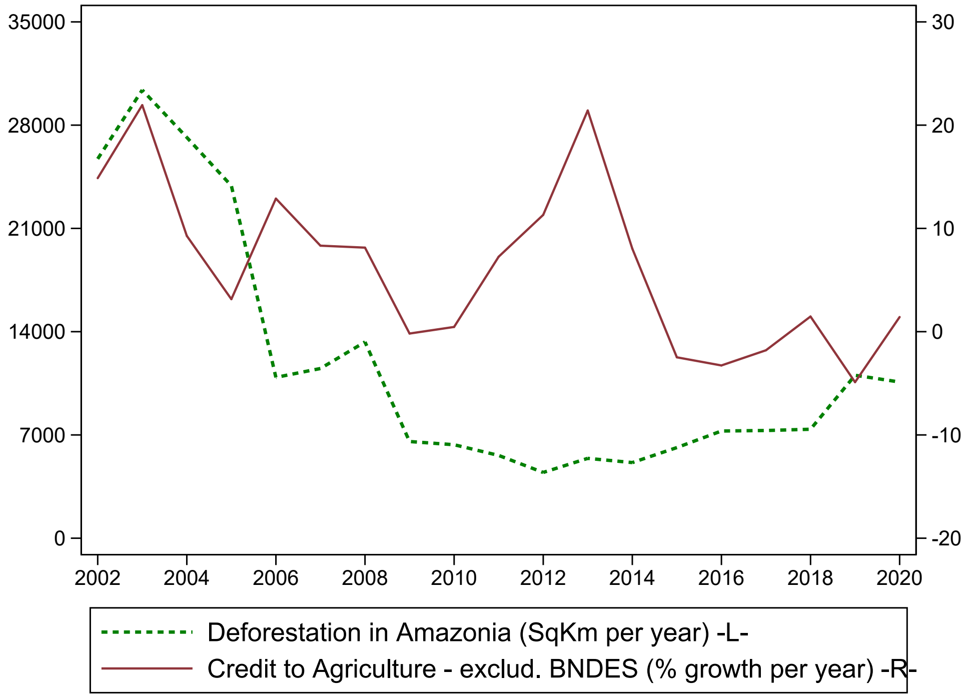
To get a measure of the aggregate evolution of rural credit in Brazil we use the series and the definition made available by Banco Central de Brasil (BCB). Within the *Sistema Nacional de Crédito Rural* (SNCR), the BCB is the supervisor of rural credit, the regulation of which is set in terms of agricultural development by public authorities. The activities considered are agricultural cultivation, animal husbandry and production, cultivation of forest species, pisciculture and aquaculture. The operations encompass funding, commercialization and investment purposes. Agro-industrial loans granted by BNDES are categorized by the BCB as industrial credit and are therefore excluded from our measure. Rural lending in Brazil uses earmarked resources, ie. subsidized funds, the sector's allocation of which is legally predetermined, granted either at market or at regulated interest rates. Rural credit is granted by commercial banks, and development and cooperative agencies. Most of them are publicly-owned, notably Banco do Brasil (which holds around 70% of outstanding lending), Banco da Amazônia, and Banco do Nordeste do Brasil. [19]

Using the BCB data warehouse, we add outstanding rural credit to both individuals and corporations to build our series. Series used in our empirical analysis are transformed into real growth rates using the GDP deflator. [20]. As shown in Figure 11, rural credit's real growth tends to comove downwards with the deforestation rate up to 2010. During the period 2010-2013, rural credit experiences a remarkable hike, in line with the government's strategy of financing economic development. Then it stagnates from the onset of the 2015-16 crisis on, reflecting the scaling-back of subsidized credit adopted by subsequent governments.

[19] For more detail on the rural credit framework in Brazil, see *Manual do Crédito Rural* (https://www3.bcb.gov.br/mcr/completo).

[20] The outstanding rural credit corresponds to the addition of series 20597 and 20609. As they are not available before March 2007, our measure for the period 2000 - 2007 is computed by backwards projection, using the old (now disabled) series 7519. All series are gathered on https://www3.bcb.gov.br/sgspub/localizarseries/localizarSeries.do?method=prepararTelaLocalizarSeries

Figure 11: Growth in outstanding agricultural credit between 2002 and 2020



Sources: INPE and authors calculations for deforestation; BCB and authors calculations for credit to agriculture

4 Methodology

4.1 PVAR Specification and estimation

To investigate the impact of the Amazon Fund on deforestation, along with the role of other variables of interest such as law enforcement and agricultural production, we use a Vector Autoregressive model estimated with panel data (PVAR). The dynamic VAR structure replicates a stylized economic system where the variables treated as endogenous can influence each other at different lags, while not precluding the inclusion of exogenous variables. This way, potential endogeneity (simultaneity) bias, characteristic in static approaches, are ruled out. Moreover, the panel-data structure makes it possible to account for unobserved structural heterogeneity among cross-sections (e.g. the effect of different social structures or levels of education at the local level on deforestation rates).

In reduced autoregressive form, the system of equations of the p order-PVAR can be written as follows:

$$Y_{it} = \mathbf{A}_p(L)Y_{it} + \mathbf{B}X_{it} + f_i + e_{it} \tag{1}$$

Where $i = 1, \dots N$ municipalities, and $t = 1, \dots T$ years.

Y_{it} denotes a vector of m endogenous variables, $\mathbf{A}_p(L)$ is an $m \times m$ invertible matrix containing the vectors of coefficients $a^j_{kp}(L)$ of lagged endogenous variables. (L) is a lag polynomial, such that each endogenous variable y^j_{it} enters the equation of k variable with p lags: $a^j_{kp}(L)y^j_{it} = a^j_{k1}y^j_{it-1} + ... + a^j_{kp}y^j_{it-p}$. X_{it} is a vector of n exogenous variables, with an associated $m \times n$ matrix of coefficients $\mathbf{B}$. For the sake of parcimony, we assume that exogenoues variables may have only a contemporaneous effect on Y_{it}.

In equations estimated with panel data, the error can be split into two components: f_i is a vector of m panel-specific effects; e_{it} is a vector of m reduced-form idiosyncratic innovations, with an associated $m \times m$ variance-covariance matrix $\mathbf{\Sigma}_e$.

In standard time-series VAR, as long as series do not have a unit root, the equation system (1) can be estimated by Ordinary Least Squares (OLS). Yet, the potential presence of unobserved panel-specific effects, rather constant over time but differing across municipalities, poses the risk of omitted variable bias: if the latter is correlated with the observed explanatory variables, pooled OLS estimates are biased and inconsistent (see Wooldridge, 2010).

The fixed effects (FE) estimator is a usual way to get consistent estimates in the presence of unobserved time-constant cross-section heterogeneity effects. This method allows for an arbitrary correlation between f_i and the explanatory variables (a hypothesis that precludes the use of pooled OLS or random effects estimators). The FE estimator uses some transformation of equations to remove the unobserved effect, typically by subtracting from data on every variable Y_{it}, X_{it}, as well as from fi and the idiosyncratic error, its individual's mean over the time span. However, this demeaning of the original panel data (called *within* transformation) may give rise to an important issue in dynamic models such as (1). The demeaned error term becomes correlated with the transformed lagged dependent variables in the PVAR, yielding biased estimates particularly when the number of cross-sections N is much larger than the time span T (Nickell, 1981, 1981). This is the case of our analysis, in which the cross-sectional dimension (760 municipalities) strongly outnumbers the number of periods (18 years after expressing some variables in growth rates).

To correct the dynamic panel bias, we apply the Generalized Method of Moments (GMM) proposed by Arellano and Bover (1995), which uses forward orthogonal deviations (FOD) for transforming the data, then lagged regressors as instruments. Also called Helmert procedure, the transformation consists in subtracting from each variable the average of all future available observations. As far as past realizations are excluded from the transformed data, the lagged instrumented regressors become orthogonal with errors. An application of this GMM estimator to PVAR can be found in Love and Zicchino (2006) . [21]

The data used in the PVAR are transformed in order to get suitable variables (see Table 7). Deforestation, the Amazon fund disbursements in BRL, and the IBAMA fines in BRL are annual "flows" normalized by the municipality area in $/km^2$. The steer stock (in heads) and the annual production of soybean (in tons) are expressed in year-on-year nominal rates of growth. As for the exogenous aggregate variables, agricultural credit, steer price, and soybean price are specified in real rates of growth. Expressing variables in ratios and rates of growth seeks to avoid panel unit roots and ultimately to get a stable structural VAR. Following Hamilton (2020), stationarity [22] is checked by computing the eigenvalues of the matrix of coefficients of the VAR(1) form of our p-order model, VAR(p). We only keep models for which all eigenvalues lie inside the unit cercle.

The PVAR order is selected using the three model and moment selection criteria (MMSC) proposed by Andrews and Lu (2001) for GMM estimations. The MMSC are based on the J-statistic for testing over-identifying restrictions and are analogous to three usual information criteria founded on the loglikelihood function: Akaike (AIC), Bayesian (BIC), and Hannan and Quinn (HQIC). We ruled out PVAR models with order higher than two, as they proved to be unstable. We fit a two-lag PVAR, which minimizes two out of the three information criteria.

4.2 SVAR Identification scheme

The coefficients of the estimated unrestricted VAR do not necessarily imply causality. For the impulse-response functions (IRFS) and Forecast Error Variance Decomposition (FEVD) to have a causal interpretation, we need to simulate "primitive" orthogonal innovations of endogenous variables, so that they are contemporaneously uncorrelated. We identify such

[21] For more detail on the statistical package used in PVAR estimation with panel data, see Abrigo and Love (2016)

[22] A VAR(p) is considered to be stable, and thus covariance stationary, if the first and second moments of the vector process are not dependent on the period t, so that the effects of an innovation on the error term die out over time.

shocks by imposing a standard Cholesky factorization of the variance-covariance matrix of reduced form errors, so that we get a structural VAR (SVAR) with recursive structure. This amounts to impose a triangular block of restrictions on the contemporaneous impacts (i.e. within one year) among variables, some of which are assumed to be nil ex ante. This way, the most "exogenous" variable (ordered first) is assumed to be able to affect contemporaneously the whole rest and can only be affected by the others with at least one year lag. In turn, the most "endogenous" variable (ordered last) can be contemporaneously affected by all the other, but an innovation on it can have an impact on the rest of the variables only after one year. The same block of symmetric restrictions is imposed on each cross-section. While this scheme implies a strong homogeneity in the dynamics of responses to shocks across municipalities, it helps preserve some parsimony in the number of identification restrictions (see Canova and Ciccarelli, 2013). As the ordering of variables in the recursive structure may potentially affect the IRFs outcome, we choose it based on economic foundations. When the latter do not enable a clear identification of the ex-ante ordering of shocks, we rely on additional empirical evidence based on pairwise Granger causality tests.

First, we take the disbursements from the Amazon Fund as the most exogenous variable. As a matter of fact, the activation of any disbursement by the Amazon Fund takes several years after the environmental or economic necessity of a project has been established. Indeed, the project manager must first apply to the Amazon Fund to obtain disbursements, then co-construct the project with the Fund in order to be eligible before receiving the first funding. While a project leader's decision may be the result of immediate observation of changes in local deforestation, law enforcement or agricultural variables, this observation cannot influence disbursements in the short term (less than a year). In the other way around, during the course of a project, the Amazon Fund does not disburse the whole funding at the beginning. It rather ensures, nearly on an annual basis [23], that the disbursements have been used in accordance with the terms of a project contract. This staggered payment schedule intends to affect environmental practices within a funded community in the short-term. We can thus assume that the outcome of the Fund's action is observable within a year. In all, we find strong support for ranking disbursements from the Amazon Fund first in the preorder.

In order to establish the rest of the pre-ordering, we need to clarify what we mean by short-term causality. In the context of deforestation, it is undeniable that the will to raise cattle or soybean farms is a driver of deforestation. Yet this takes some time to occur. In turn, there is enough evidence that deforestation rather precedes, at least temporally, new agricultural land uses. More precisely, deforestation leads in the short term to a local increase in the size of the cattle herd, and only in the medium term to an increase in crop volumes (which benefit from the organic matter deposited by the cattle) as described by WWF[24]. This suggests that deforestation directly precedes the cattle herd (the variable steer growth), but not necessarily the crops (the variable soybean production growth). To complete the identification of agricultural shocks, we rely on Granger tests using two lags, which by construction check

[23] See projects' pages on the: Amazon Fund website

[24] https://wwf.panda.org/discover/knowledge_hub/where_we_work/amazon/amazon_threats/unsustainable_cattle_ranching

whether some causality may be inferred either in $t+1$ or $t+2$. They suggest that deforestation and steer growth cause soybean production, while only deforestation causes steer growth. If we consider that causality in the medium term makes more likely causality within a year t, the Granger tests suggest ordering steer growth before soybean production, and both after deforestation. This is also consistent with the spacial distribution highlighted in Figures 10a and 10b, which suggest that cattle farms precede soybean crops in the agricultural expansion from the South towards the North of Legal Amazon.

With regards the proxy of law enforcement, the short-term causality vis-à-vis deforestation may be bidirectional. On the one hand, satellite support helps speed-up most of IBAMA's forest actions. Since 2004 (a large part of the sample considered in this paper), IBAMA has used the DETER system to monitor nearly in real time the endangered biomes, empowering its capacity to intervene in the area under consideration. Thereby, offenders can be caught almost red-handed and IBAMA is enabled to sanction shortly after infractions are observed. On the other hand, the expected effects of law enforcement are likely to occur rapidly after IBAMA's injunctions: the interdiction of keeping crops or cattle raising, the forced destruction or the unavailability of heavy equipment, etc. are likely to have a contemporaneous impact on deforestation (Assunção et al., 2014). While short term causality is plausible in both directions, we choose to place the proxy of law enforcement before deforestation in the pre-ordering. This is coherent with Granger causality tests and prevents the negative contemporaneous correlation between the two variables to be interpreted as a reduction of IBAMA sanctions when an increase of deforestation is observed. The intuitive causal effect is indeed the opposite: an increase in IBAMA fines, likely to be accompanied by legal injunctions, helps reduce deforestation within one year.

The baseline pre-ordering used in our SVAR is therefore: Amazon Fund, Ibama, deforestation, steer, soybean.

5 Results

5.1 Baseline unrestricted PVAR

Table 2 shows our baseline estimation results. We perform forward regressions, departing from a two variables VAR and adding endogenous variables one by one up to our baseline complete specification, which sets five endogenous variables and two lags. Due to some missing observations for IBAMA and agricultural production variables, the sample used in our baseline PVAR estimation includes 755 municipalities. As there is a structural break in deforestation data in 2001 (see above) estimations are performed for the sample 2002-2020. We use some variables in rate of growth, so that one year is dropped. The average estimation period per municipality is almost 18 years. The statistical significance of estimates is considered using the usual levels of confidence (with at least 90%).

The results from simpler models are consistent with those yield by our baseline specification. As expected, deforestation shows positive autocorrelation, (unfortunately) suggesting some inertia in the rainforest clearing. Our main variable of interest, the action of the Amazon Fund, is negatively correlated with deforestation rates, both one and two years after the disbursement occurs. Anything else being equal, one additional BRL disbursed perkm^2 is related to a 0.0037% drop in deforestation of this area the following year. Law enforcement, captured by the ratio of IBAMA fines in BRL per km^2, appears also to be negatively correlated with deforestation rates, both one and two years after the fines are filed. This is consistent with previous empirical findings (e.g. Assunção et al. (2015)). With regard to agricultural output, cattle breeding is positively related to deforestation only two years after its stock has grown, while growth in soybean production shows no significant correlation. The latter result is to be interpreted in light of the aforementioned stylized fact: cattle farms tend to be settled in recently deforested areas, and soybean farms follow only later on, with an important lag. Last, all the three exogenous variables have a significant contemporaneous relationship with rainforest clearing. As in Assunção et al. (2015), rural credit is positively correlated with deforestation. In turn, the prices of agricultural commodities are negatively correlated with deforestation rates. The result is not necessarily counterintuitive: as far as increases in beef and soybean prices are driven by declines in those commodities' production and supply, rather than by demand expansions, they may be related to a reduction in deforestation rates.

5.2 Structural VAR (SVAR) analysis

5.2.1 Overall effects

To the extent that the identification scheme described above is well-founded, IRFs imply some causality relationships, ceteris paribus, among endogenous variables. For the sake of comparability, Figure 12 shows the response of deforestation over a ten years horizon to *one standard deviation* (S.D.) orthogonal shock on each of the other endogenous variables. To be interpreted

Table 2: Estimation of baseline PVAR

Response: Deforestation rate (ratio/km^2)	(1)	(2)	(3)	(4)
Endogenous variables [lags]:				
Deforestation rate (ratio/km^2) [-1]	0.0302***	0.0299***	0.0290***	0.0290***
	(3.47)	(3.38)	(3.29)	(3.29)
[-2]	0.0136***	0.0138***	0.0132***	0.0132***
	(4.57)	(4.53)	(4.51)	(4.51)
Amazon Fund disbursement (BRL/km^2) [-1]	-0.00374***	-0.00372***	-0.00370***	-0.00369***
	(-7.08)	(-7.14)	(-7.12)	(-7.11)
[-2]	-0.00223***	-0.00222***	-0.00221***	-0.00220***
	(-4.84)	(-4.86)	(-4.87)	(-4.85)
Ibama_fines (BRL/km^2) [-1]		-0.00000766***	-0.00000751***	-0.00000744***
		(-3.73)	(-3.68)	(-3.66)
[-2]		-0.00000689***	-0.00000676***	-0.00000672***
		(-2.96)	(-2.93)	(-2.92)
Steer stock (growth) [-1]			9.51e-08	0.000000109
			(0.10)	(0.11)
[-2]			0.00000144***	0.00000144***
			(7.81)	(7.80)
Soybean tons (growth) [-1]				0.0000511
				(1.43)
[-2]				-0.000000206
				(-0.73)
Exogenous variables:				
Credit to agriculture (real growth)	0.0118***	0.0118***	0.0114***	0.0115***
	(8.26)	(8.21)	(7.99)	(8.01)
Steer price (real growth)	-0.000949**	-0.000938**	-0.000870**	-0.000848**
	(-2.45)	(-2.41)	(-2.24)	(-2.19)
Soybean price (real growth)	-0.000876***	-0.000877***	-0.000927***	-0.000923***
	(-3.08)	(-3.08)	(-3.30)	(-3.28)
N. observations.	13680	13608	13522	13522
N. municipalities	760	756	755	755

Estimation sample: 2002-2020; t statistics in parentheses; confidence levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.
All the PVAR models are estimated through GMM à la Arellano and Bover (1995), removing cross-section fixed effects from data by FOD.

in terms of units, impulses and responses must therefore be normalized by the S.D. magnitude of the corresponding variable, displayed in Table 3. The IRFs confidence intervals, set at 90%, are computed through Monte Carlo simulations (200 draws) of the estimated baseline model (4) in Table 2. As pointed out by Lütkepohl (2005), a stable PVAR implies stationarity. Within our horizon of analysis, the effect described by the orthogonalized impulse-response functions (IRF) tends to vanish, suggesting that the specified variables have no unit roots in panel.

With regards the response of deforestation, IRFs trajectories are in line with the predictions derived from the model in section 2. and remain fully consistent with the correlation analysis drawn from Table 2. Additional Amazon Fund disbursements and a rise of sanctions fined by IBAMA lead both to a significant reduction in deforestation rates. The beneficial effect of green finance is larger and more long-lasting than that of law enforcement. Once normalized by their S.D., we find that 1 additional BRL disbursed by the Amazon Fund on the average municipality saves 0,002% of its area from deforestation within the same year. Its effect shows a peak around 0.0038% in the first and the second year following the shock, and remains still significant in the third year. The effect of IBAMA fines appears to be much more modest: an additional BRL of fines saves 0.00001138% deforestation in that area within the same year, then it progressively drops to die out after two years. Taking the effect one year after the shock in both cases for comparison, this means that the Amazon Fund needs to disburse 266 BRL per km^2 for saving 1% of a municipality area from deforestation, while IBAMA needs to fine almost 128,000 BRL per km^2 to do the same. This statistical gap in efficacy may stem from two reasons. First, the variable IBAMA fines shows a strong dispersion over time and across municipalities, which makes its standard deviation and thus the simulated shock needed for a given effect much larger than the Amazon Fund disbursements' one. Second, the degree of enforcement of IBAMA sanctions is very low: less than 5% are paid by offenders in practice. With regards agricultural production, + 1 pp. in the % growth of cattle farms entails an increase of 0.000002 pp. in the % ratio of deforestation in the average municipality two years after the shock. In other words, +490% annual growth in livestock leads to +1% of deforestation in the same area. Again, this effect is at first glance modest. Yet, it has to be read with the statistical distribution of the variable in mind: over the whole sample, steer stock has grown more than 170% per year in the average municipality (see Table 7), with a huge time and cross-section dispersion reflected in very high S.D. (see Figure 10).

With regards the dynamics of other endogenous variables, it is noteworthy that some features of the theoretical model from section 2 do capture what we find empirically trough the IRFs (Figure 17). In particular, the Amazon Fund responds to a positive shock on deforestation by reducing the amount of its disbursements with one to three years lag. This is consistent with the staggered payment schedule used in practice by the Fund, which may be revised-down ex post if projects' goals are not fully achieved. A rise in cattle growth entails a similar effect, leading to a drop in Amazon Fund disbursements and to a parallel rise in IBAMA sanctions. Consistently with the support to public policies characteristic of the Amazon Fund's projects, *ceteris paribus* IBAMA sanctions positively react to the Fund's disbursements. Law enforcement seems therefore to be strengthened by green finance.

Table 3: Magnitude of simulated IRF shocks (in-sample 1 standard deviation)

Variables	(1) 1 S.D.
Deforestation rate (% ratio/km^2 per Year)	0.6156
Amazon Fund disbursement (BRL/km^2 per Year)	22.501
Ibama fines (BRL/km^2 per Year)	2325.828
Steer stock (heads, % Y/Y growth)	1076.717
Soybean production (tons, % Y/Y growth)	191.6104

Note: The table displays the value of one standard deviation used by IRFs to simulate a shock on each endogenous variable. As the sample used in the PVAR estimation and in IRFs is smaller relative to the whole dataset, SD values may differ from those in Table 7

Forecast Error Variance Decomposition (FEVD) completes the SVAR overall analysis provided by IRFs, in terms of relative contributions of the endgenous variables to changes in the variable of interest (see Table 4). As expected, over a 10 years horizon, past deforestation accounts for the largest part of current rainforest clearing (almost 92%). Then, consistently with the magnitude of IRFs coefficients, the Amazon fund ranks as the second most important factor in terms of explanatory power, as it is responsible for 7.5% of a given variation in deforestation rates.

Figure 12: IRFs - Response of deforestation

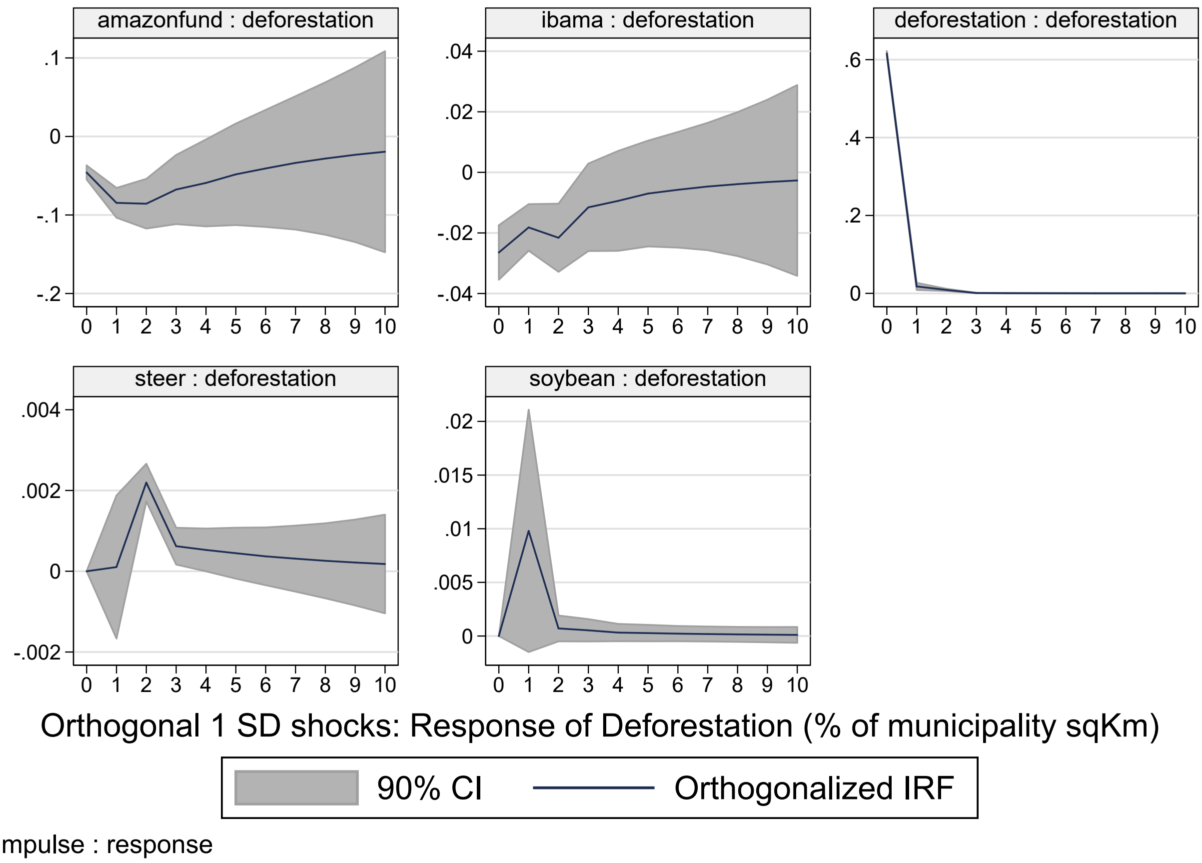


Table 4: Forecast Error Variance Decomposition

Response variable	Forecast horizon	Impulse variable: Amazon Fund	Ibama	Deforestation	Steer	Soybean
Amazon Fund	1	100	0	0	0	0
	5	99.5491	0.4406	0.0021	0.0065	0.0017
	10	99.4174	0.5716	0.0025	0.0067	0.0018
Ibama	1	0.0126	99.9874	0	0	0
	5	3.5736	96.4208	0.0002	0.0051	0.0003
	10	4.9365	95.0578	0.0003	0.0051	0.0003
Deforestation	1	0.5515	0.1834	99.2652	0	0
	5	6.0733	0.4235	93.4780	0.0014	0.0239
	10	7.5392	0.4481	91.9877	0.0015	0.0236
Steer	1	0.0061	0.0011	0.0168	99.9760	0
	5	0.4622	0.0130	0.0168	99.5077	0.0002
	10	0.5763	0.0148	0.0168	99.3919	0.0002
Soybean	1	0.0014	0.0129	0.0004	0.0002	99.9851
	5	0.0863	0.0226	0.0006	0.0051	99.8855
	10	0.1126	0.0232	0.0006	0.0051	99.8586

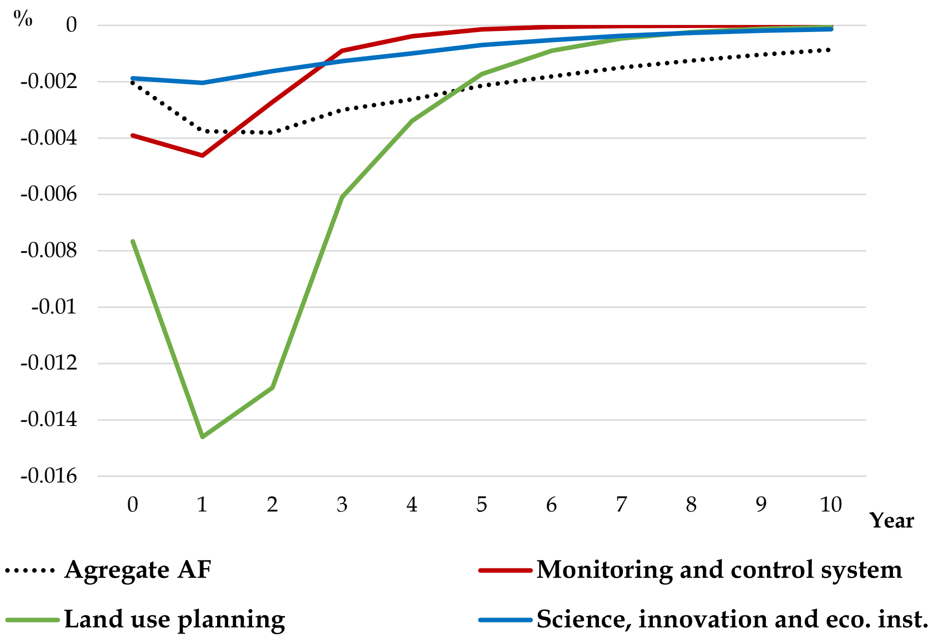
Contribution (%) of each impulse variable to the h-step ahead forecast-error variance of the response variable, where the forecast horizon h is expressed in years.
200 Montecarlo draws are used to estimate standard errors. The order of variables corresponds to the one in Cholesky decomposition used to identify orthogonal shocks..

5.2.2 Efficiency by type of project

The results above show evidence on the aggregate efficacy of the Amazon Fund at the meso-economic level. Next, we use more granular data to address an important issue for sustainable finance and, more generally, for the financing of development: the efficiency of the different types of projects. We split the series of Amazon Fund disbursements over time and across municipalities following the aforementioned projects' categories. As granular series within a municipality may present strong breaks and be much more volatile than the aggregate Amazon fund's disbursements in panel, some PVARs are found to be unstable. The corresponding IRFs are not displayed in that case, as they become unreliable. For the reliable IRFs we normalize again responses' trajectories by the standard deviation of each type of project's series, to get readable results in terms of units.

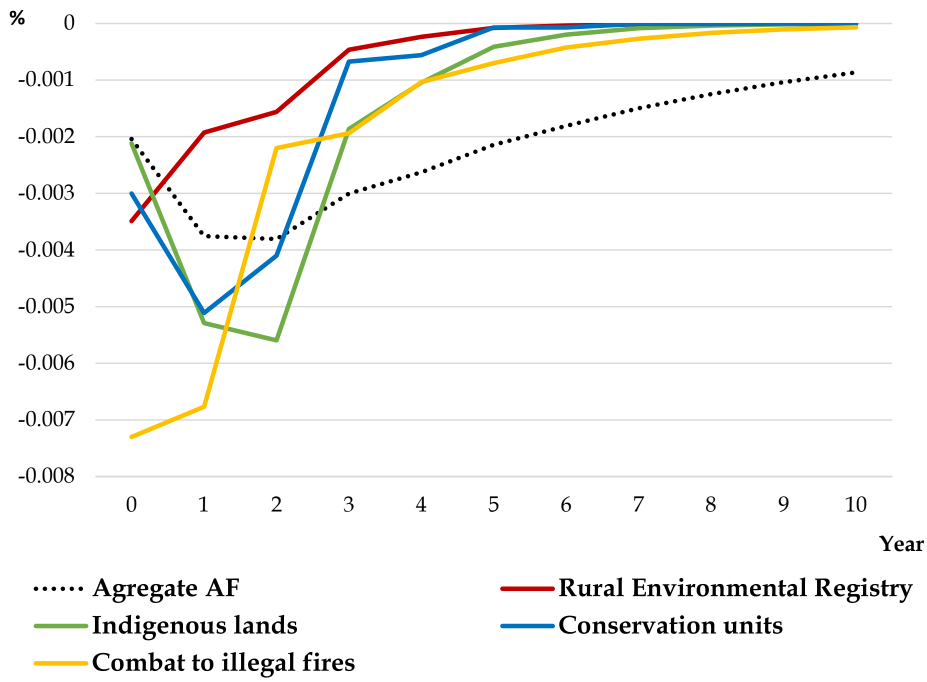
By axis, projects devoted to land use planning appear to be much more efficient than those allocated to monitoring and control systems and those related to science, innovation and economic instrument.

Figure 13: IRFs - Impact of +1 BRL/km^2 of Amazon Fund disbursements on % deforestation/km^2 by project's **axis**



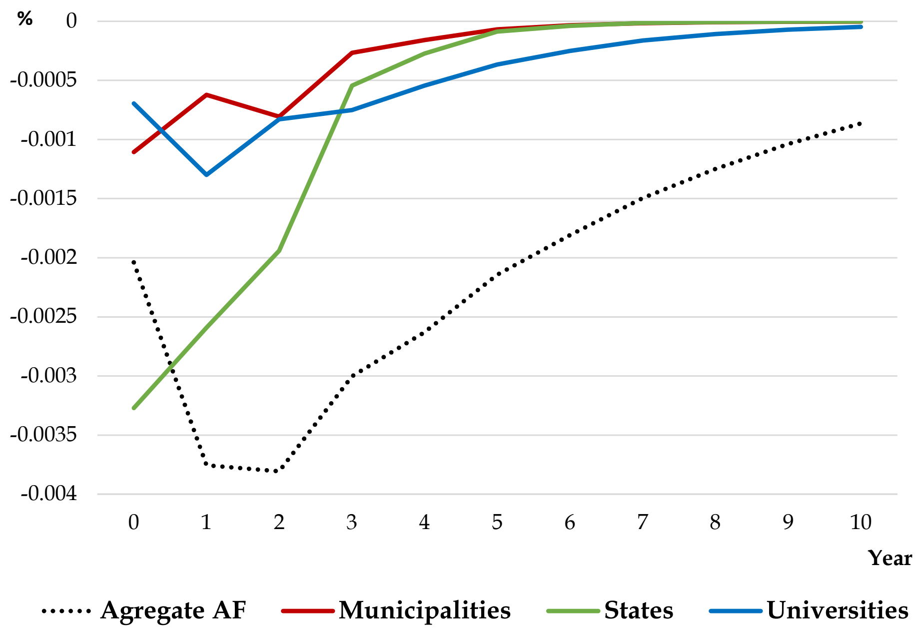
The difference in impact between the various themes is less clear than in the case of the axes. In the very short term, projects aimed at fighting illegal fires are more efficient than others (Figure 14). However, only 6 projects were conducted in this theme, compared to more than 20 for the other categories (Figure 8): this result should therefore be taken with caution. Within a one or two year horizon, the projects operating in indigenous lands or conservation units are more efficient than those aimed at supporting the implementation of the rural environmental register (CAR).

Figure 14: IRFs - Impact of +1 BRL/km^2 of Amazon Fund disbursements on % deforestation/km^2 by project's **theme**



With regard to the break-down by recipient, the simulations are stable in only 3 out of 6 categories. State-led project are more efficient than those conducted by municipalities and universities (only 7 and 6 projects, respectively). However, they are less efficient than the aggregate effect. Unfortunately, the PVAR run on projects led by the third sector is not stable. Thus, only partial conclusions can be drawn from Figure 15 because (i) a majority of projects are conducted by the third sector (Figure 8) and (ii) projects led by the third sector are usually more targeted than the other ones (Figure 19).

Figure 15: IRFs - Impact of +1 BRL/km^2 of Amazon Fund disbursements on % deforestation/km^2 by **recipient** body



5.3 Robustness tests

[Subsection in progress]

5.4 Abatement cost

[Subsection in progress, to be potentially revised]

Beyond knowing whether the Amazon Fund disbursements are effective overall in reducing deforestation, we seek to know whether they are efficient. To this end, we use a classic environmental economics tool: the abatement cost. The goal is to estimate the impact of a monetary unit spent by the Amazon fund on deforestation. From there, it is possible to convert the number of deforested hectares avoided into tons of CO2 avoided. The calculation yields an abatement cost in monetary unis (in this case BRL) per ton of CO2 avoided.

We know the carbon content of the biomass of one hectare of primary forest. While estimates in the literature can vary, at the time of its creation the Amazon Fund adopted the very conservative assumption that one hectare of primary forest contained 100tC[25]. The conventional unit for expressing abatement costs is $/tCO2eq, so we use molar mass to convert the Amazon Fund convention: clearing one hectare of primary forest results in the release of

[25]This value appears in the midterm evaluation report on the effectiveness of the Amazon Fund (https://www.fundoamazonia.gov.br/export/sites/default/en/.galleries/documentos/monitoring-evaluation/Independent-evaluations/Amazon-Fund-Mid-Term-Evaluation-Report-Effectiveness.pdf)

367 $tCO2$[26]. In this paper, we use two different methods for estimating the abatement cost: exploiting IRFs and building a counterfactual aggregate deforestation curve.

5.4.1 Estimation through IRFs

The IRFs obtained in Section 5.2.1 make it possible to calculate how many BRL disbursed by the Amazon Fund are needed to save one hectare of primary forest from clearing.

We assume that the environmental benefit of 1 standard deviation (24.5 BRL) disbursed by the Amazon Fund on a square kilometer is the (undiscounted) sum of the significant impacts on deforestation in the years following the disbursement. According to our baseline estimation, disbursements have a significantly negative impact over four periods: from the contemporary impact to the third year after disbursement. Within this time interval, anything else being equal, 24.5 BRL spent on a square kilometer leads to the sustainable preservation of 0.004% of this area. Therefore, it is necessary to spend 64 BRL to preserve 1ha. Using the emissions convention mentioned above, we obtain an abatement cost of 0.17 BRL/tCO2.

5.4.2 Estimation through counterfactual analysis

From Table 2, we calculate (i) a deforestation rate forecasted in-sample by our model, as well as (ii) a counterfactual annual deforestation rate, forecasted in-sample assuming that the Amazon Fund makes no disbursements. Between January 1, 2010 and December 31, 2020, the cumulative difference between the two predicted deforestation rates amounts to 14 200 km^2. In the very same period, 1280 million BRL were disbursed by the Amazon Fund for projects in the Legal Amazon. After converting the number of square kilometers of deforestation saved into the number of tCO2 avoided, we obtain an abatement cost of 2.45 BRL/tCO2.

5.4.3 Interpretation of the abatement cost

Several factors lead us to believe that these figures are an upper bound on the average abatement cost:

- First, the assumption on the value of the carbon content of a hectare of primary forest is very conservative.
- Second, greenhouse gases other than CO2 (in particular methane and nitrous oxide) are not taken into account.

Furthermore, it should be noted that the approach taken here ignores all the social and economic co-benefits of the Amazon Fund, which by themselves could justify the relevance of the fund, even if we had found no environmental effectiveness.

[26] As confirmed by the "Ministério do Meio Ambiente" (Nota Técnica n.22 / 2011 / DPCD / SECEX. Technical note, Departamento de Políticas para o Combate ao Desmatamento)

Nevertheless, these results have to be taken with much caution. As we highlight in the introduction, the Amazon fund's action is part of a broader public strategy to fight deforestation, which the fund helps to support. It is challenging to expunge the estimation of the fund's impact from the whole set of public policies. As a proxy of the latter, we used the sanction policies by IBAMA. Yet this is an noisy measure of the evolution of authorities' ability and willingness to enforce the law aiming at fighting deforestation, as IBAMA fines are also driven by private agents' decisions to commit infractions. To the extent that the role of public policies is only partially captured, the effect attributed to the Amazon fund might be overestimated.

6 Conclusion

At a time when the world is facing climate change, massive biodiversity loss and increasing zoonotic diseases, conserving the integrity of tropical forests appears to be crucial. An empirical analysis of the role of multilateral green financing policies in Brazilian Amazonia, such as the one conducted in this paper, can serve as a support for other initiatives around the world. The quality and the granularity of the data that we exploit at the local level, as well as the causal inference enabled by the panel SVAR, yield interesting insights for policy-makers and green funders. First, our study addresses the role of (enhancing or palliating) factors of deforestation in Brazilian Amazonia. As expected, the municipalities where agricultural production grows experience a rise in rainforest clearing. Since cattle farms tend to precede crops at the local level, beef appears to cause primarily deforestation, rather than soybean. Its effects on rainforest clearing are however lagged around two years, which opens some room for public policies to implement corrective or preventive actions. Our findings show that, overall, the Amazon Fund disbursements help to reduce significantly deforestation rates, and suggest that properly designed green finance may be more efficient than environmental agencies when sanctions are not sufficiently enforced. Moreover, at a more disaggregated level, some types of projects need relatively less funding to fight deforestation. By recipient, projects managed at the regional level by federal states are more efficient than those managed by municipalities or universities. By axis, projects related to land use planning, which involve the development and protection of local autochthonous communities, are the most efficient. By theme, projects aimed at fighting illegal fires appear to be the most efficient in the very short term, whereas those acting in indigenous lands last two years to reach their maximum efficacy. In all, the Amazon Fund appears to be an efficient tool to make deforestation slow down. After converting the number of km^2 of deforestation saved into the number of tCO_2 emissions avoided, we obtain a low abatement cost (between 0.22 and 0.56 BRL/tCO_2). Yet, this figure is to be taken cautiously : to the extent that the role of public policies and agencies is only partially captured, and that their effects are intertwined with those of green finance (the projects of which support actually public policies), the beneficial effect attributed to the Amazon Fund might be overestimated. Further research should address those caveats, by better capturing government environmental policies implemented in parallel to green finance projects. Potential spatial spillovers of the latter across municipalities is another promising topic to investigate.

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7 Appendix

Title	Responsible	Organization type	Total Support	Approval Date
forest assistance program +	amazonas sustainable foundation (fas)	Third Sector	31518490	2016
car bahia	institute of environment and hydric resources in the state of bahia (inema) - bahia state/state secretariat for environmental development	States	31671000	2014
sustainable northern corridor	institute of agriculture and forest management and certification (imaflora)	Third Sector	3312877	2014
car mato grosso do sul	environmental institute from mato grosso do sul state (imasul)	States	8789800	2014
public policy incubator in the amazon	federal university of para (ufpa) and the research development and support foundation (fadesp)	Universities	2660567	2011
mamiraua	mamiraua sustainable development institute (idsm)	Third Sector	8504678	2012
jacunda, green municipality economy	municipality of jacunda	Municipalities	199352	2011
irehi - taking care of territory	native amazon operation (opan)	Third Sector	8160140	2015
going green	environmental conservation institute - the nature conservancy of brazil (tnc brazil)	Third Sector	16000000	2009
car parana	parana environmental institute (iap)	States	2079332	2016
value chains in indigenous lands in acre	comissao pro indio do acre (cpi-acre)	Third Sector	3091111	2015
sustainable fishing	wwf brazil	Third Sector	3205943	2013
preserving porto dos gauchos	municipality of porto dos gauchos, in the state of mato grosso	Municipalities	120655	2011
indigenous experiences of territorial and environmental management in acre	acre pro-indigenous people commission (cpi-acre)	Third Sector	5823061	2018
sustainable mato grosso	state of mato grosso	States	35015970	2013
the state of acre: zero forest fires	state of acre/state of acre military firefighters (cbmac)	States	13280709	2012
protected areas in the amazon - phase 2	brazilian biodiversity fund (funbio)	Third Sector	19949058	2009
forest assistance program	sustainable amazon foundation (fas)	Third Sector	19107547	2009
socioenvironmental management in municipalities of para	institute of people and the environment of the amazon (imazon)	Third Sector	9736473	2009
belem islands	federal university of para (ufpa) and the research development and support foundation (fadesp)	Universities	1138083	2012
management and governance of indigenous lands in the rio negro and xingu basins - pgtas	socioenviromental institute (isa)	Third Sector	11712000	2016
productive sociobiodiversity in the xingu	socioenvironmental institute (isa)	Third Sector	8023856	2013
semas para	state of para	States	15923230	2010
portal seeds	ouro verde institute (iov)	Third Sector	5397778	2009
dissemination and improvement of sustainable forest management techniques	tropical forest institute (ift)	Third Sector	7449000	2010
forest firefighters of mato grosso	state of mato grosso	States	12518230	2011
amazon bioactive compounds	federal university of para (ufpa) and research development and support foundation (fadesp)	Universities	1352368	2012
consolidating territorial and environmental management in indigenous lands	indigenous work center (cti)	Third Sector	11934540	2016
car: lawful tocantins	state of tocantins	States	26800000	2013
car roraima	state of roraima (fundacao estadual do meio ambiente e recursos hidricos de roraima - femarh)	States	3075205	2014
ethno-environmental protection of isolated and recently contacted indigenous peoples in the amazon	center for indigenous work (cti)	Third Sector	19043330	2014
forest protection in the state of tocantins	state of tocantins, having as executor the state of tocantins military firefighters (cbmto)	States	4958910	2012
reforestation in the southern part of amazonas state	state of amazonas	States	17575286	2010
amazon backyards	center for studies on culture and the environment in the amazon (rioterra)	Third Sector	8837852	2013
recovering marcelandia	municipality of marcelandia	Municipalities	551556	2010
biodiversity	federal university of para (ufpa) and the research development and support foundation (fadesp)	Universities	4639706	2012
family farming value chains in the state of mato grosso	alternative technology center association (cta)	Third Sector	3238032	2014
new social mapping in the amazon	amazonas state university (uea) and the muraki institutional support foundation	Universities	4614587	2010
amazon water springs - phase 2	municipality of alta floresta, in the state of mato grosso	Municipalities	7146563	2013
buriti springs	municipality of carlinda	Municipalities	1875500	2011
amazon's water springs	municipality of alta floresta, in the state of mato grosso	Municipalities	2781340	2010
satellite environmental monitoring of the amazon biome	national institute of space research (inpe) - science, applications and space technology foundation (funcate)	Federal Government	66952436	2014
monitoring forest coverage in the regional amazon	amazon cooperation treaty organization (acto)	International	23693641	2013
mangrove forests	federal university of para (ufpa) and research development and support foundation (fadesp)	Universities	1982143	2012
empowering environmental monitoring and control in order to combat illegal deforestation in the brazilian amazon	brazilian institute of environment and renewable natural resources (ibama)	Federal Government	56295964	2016
tapajos active forest	center for advanced studies in social and environmental promotion - ceaps (health and joy project)	Third Sector	12493011	2018
amazonia agroecologica project	federation of agencies for social and educational assistance (fase)	Third Sector	17547560	2018
everlasting forest	institute of people and the environment of the amazon (imazon)	Third Sector	14293105	2017
forest cities	institute for the conservation and sustainable development of the amazon (idesam)	Third Sector	12055534	2017
kayapo fund	brazilian biodiversity fund (funbio)	Third Sector	16900000	2011
environmental regularization	the brazilian foundation for sustainable development (fbds)	Third Sector	9267000	2018
car ceara	state superintendence for the environment in the state of ceara (semace)	States	24583420	2016
car acre	state of acre	States	16838000	2013
small eco-social projects in the amazon	society, population and nature institute (ispn)	Third Sector	12814691	2012
amazonia sar	federal government/defense ministry - operations and management center of the amazonian protection system (censipam)	Federal Government	47958727	2015
communal forests	tropical forest institute (ift)	Third Sector	8100000	2017
preserving the babassu forest	interstate association of the movement of women babassu coconut breakers (amiqcb)	Third Sector	9222739	2017
more sustainability in the countryside	state of maranhao	States	40476077	2017
integrated environmental socioeconomic development project (pdseai)	state of rondonia - state secretariat for environmental development (sedam-ro)	States	31227392	2014
environmental management qualification program	brazilian institute of municipal administration (ibam)	Third Sector	18853482	2012
kayapo territory, culture and autonomy	protected forest association (afp)	Third Sector	9089870	2017
strengthening the forest based sustainable economy	extraction commercialization central cooperative for the state of acre (cooperacre)	Third Sector	4981614	2014
new paths in cotriguacu	municipality of cotriguacu	Municipalities	1567845	2014
ppp-ecos in the amazon - phase 2	society, population and nature institute (ispn)	Third Sector	22766000	2018
sustainable indigenous amazon	association in defense of ethno-environmental kaninde	Third Sector	7352757	2015
arapaima: production networks	native amazon operations (opan)	Third Sector	6364730	2014
importance of forest environmental assets	state of acre	States	52930867	2010
high jurua	association of the ashaninka of the amonia river (apiwtxa)	Third Sector	6597581	2015
materialize	association of small agro-farmers in the reca project	Third Sector	6422748	2014
strengthening environmental management in the amazon	institute of man and environment of the amazon (imazon)	Third Sector	12104865	2015
para combating forest fires and unauthorized burn-offs	state of para/state of para military firefighters (cbmpa)	States	16830280	2012
sustainable bem viver	institute of research and indigenous education (iepe)	Third Sector	11858793	2015
value chains of nontimber forest products	sos amazonia association	Third Sector	9938777	2015
sustainable settlements in the amazon	amazon environmental research institute (ipam)	Third Sector	23401624	2011
use of social technologies to reduce deforestation	interstate agricultural development association (adai)	Third Sector	9059718	2017
training to conserve	amazon conservation team (ecam)	Third Sector	1404360	2014
portal seeds - phase ii	ouro verde institute (iov)	Third Sector	16086000	2013
banco do brasil foundation - amazon fund	fundacao banco do brasil (fbb)	Third Sector	14515520	2012
banco do brasil foundation - amazon fund / phase 2	banco do brasil foundation (fbb)	Third Sector	12000000	2014
pact for the forest	elaboration and development of socioenvironmental projects (pacto das aguas)	Third Sector	8700000	2018
national forest inventory - the amazon	federal government/brazilian forest service (sfb)	Federal Government	65000555	2012
strengthening territorial and environmental management of indigenous lands in the amazon	environmental conservation institute - the nature conservancy of brazil (tnc brazil)	Third Sector	15487682	2014
greener rondonia	state of rondonia, military fire department of the state of rondonia (cbmro)	States	15040500	2012
knowing to preserve	the amazon museum (musa)	Third Sector	9984629	2009
amazon's nectar	peabiru institute	Third Sector	2030000	2014
adding value to amazon socioproductive chains	life center institute (icv)	Third Sector	16405000	2017
sustainable tapajos	conservation international of brasil (ci-brasil)	Third Sector	18835139	2017
green municipalities program	the state of para	States	45591647	2013
prevfogo / ibama	brazilian institute of the environment and renewable natural resources (ibama)	Federal Government	14717270	2013
valuable forests - new business models for the amazon	institute of agriculture and forest management and certification (imaflora)	Third Sector	17369442	2017
car espirito santo	institute of agricultural and forestry defense of espirito santo (idaf)	States	13889440	2018
car amazonas	state of amazonas	States	29867722	2018
forest sentinels	vale do amanhecer farmers cooperative (coopavam)	Third Sector	5175522	2014
apl babassu	association of settlement areas in the state of maranhao (assema)	Third Sector	4897085	2014
environmental monitoring of brazilian biomes	space science, applications and technology foundation (funcate) and national institute of space research (inpe)	Federal Government	49778000	2017
integrated legacy of the amazon region ("lira")	institute of ecological research (ipe)	Third Sector	45000000	2018
sowing rondonia	center for studies on culture and the environment in the amazon (rioterra)	Third Sector	25305337	2017
indigenous territorial management in the south of amazonas state	international institute of education of brazil (ieb)	Third Sector	11448505	2016
land regularization	mato grosso state - office of articulation and regional development (gdr/mt)	States	72900000	2018
amazon integrated project	brazilian agricultural research corporation (embrapa) and eliseu alves foundation (fea)	Federal Government	33691380	2015
profisc i-b	brazilian institute of environment and natural resources (ibama)	Federal Government	1,4E+08	2018
dema fund	federation of agencies for social and educational assistance (fase)	Third Sector	6601699	2011

Table 5: List of the 102 projects and their main features

Name of the project	Monitoring and control systems	Science, innovation and economic instruments	Land use planning	Sustainable production
Socioenvironmental Management in Municipalities of Pará	61%	0%	19%	20%
Going Green	100%	0%	0%	0%
Protected Areas in the Amazon - Phase 2	0%	0%	100%	0%
Forest Assistance Program	0%	0%	15%	85%
Portal Seeds	0%	0%	0%	100%
Amazon's Water Springs	3%	0%	0%	97%
Importance of Forest Environmental Assets	41%	3%	7%	49%
New Social Mapping in the Amazon	0%	100%	0%	0%
Knowing to Preserve	0%	92%	0%	8%
Recovering Marcelândia	30%	0%	0%	70%
Reforestation in the southern part of Amazonas State	11%	0%	0%	89%
Dissemination and Improvement of Sustainable Forest Management Techniques	0%	25%	0%	75%
Semas Pará	100%	0%	0%	0%
Preserving Porto dos Gaúchos	100%	0%	0%	0%
Forest Firefighters of Mato Grosso	100%	0%	0%	0%
Public Policy Incubator in the Amazon	0%	100%	0%	0%
Jacundá, Green Municipality Economy	82%	0%	15%	4%
Dema Fund	0%	0%	0%	100%
Sustainable Settlements in the Amazon	10%	0%	9%	81%
Buriti Springs	13%	0%	0%	87%
Kayapó Fund	0%	0%	50%	50%
Mangrove Forests	0%	100%	0%	0%
Biodiversity	0%	100%	0%	0%
Environmental Management Qualification Program	100%	0%	0%	0%
Pará Combating Forest Fires and Unauthorized Burn-offs	100%	0%	0%	0%
Forest Protection in the State of Tocantins	100%	0%	0%	0%
The State of Acre: Zero Forest Fires	100%	0%	0%	0%
Belém Islands	0%	100%	0%	0%
Amazon Bioactive Compounds	0%	100%	0%	0%
National Forest Inventory – The Amazon	0%	100%	0%	0%
Mamirauá	0%	100%	0%	0%
Banco do Brasil Foundation – Amazon Fund	0%	0%	0%	100%
Greener Rondônia	100%	0%	0%	0%
Small Eco-Social Projects in the Amazon	0%	0%	0%	100%
Sustainable Fishing	0%	0%	0%	100%
Portal Seeds – Phase II	0%	5%	0%	95%
Amazon Backyards	0%	32%	0%	68%
Monitoring Forest Coverage in the Regional Amazon	70%	30%	0%	0%
Green Municipalities Program	100%	0%	0%	0%
Sustainable Mato Grosso	74%	0%	26%	0%
CAR Acre	100%	0%	0%	0%
CAR: Lawful Tocantins	100%	0%	0%	0%
Amazon Water Springs - Phase 2	23%	0%	0%	77%
Productive Sociobiodiversity in the Xingu	0%	0%	0%	100%
Prevfogo / Ibama	100%	0%	0%	0%
Amazon's Nectar	0%	0%	0%	100%
ethno-environmental protection of isolated and recently contacted indigenous peoples in the amazon	0%	100%	0%	0%
Arapaima: Production Networks	0%	0%	0%	100%
Family Farming Value Chains in the State of Mato Grosso	0%	0%	0%	100%
Materialize	0%	0%	0%	100%
Strengthening Territorial and Environmental Management of Indigenous Lands in the Amazon	0%	0%	87%	13%
New Paths in Cotriguaçu	17%	0%	0%	83%
CAR Roraima	100%	0%	0%	0%
Forest Sentinels	0%	0%	0%	100%
Banco do Brasil Foundation – Amazon Fund / Phase 2	0%	0%	0%	100%
Sustainable Northern Corridor	0%	0%	0%	100%
Strengthening the Forest Based Sustainable Economy	0%	0%	0%	100%
apl babassu	0%	0%	0%	100%
CAR Bahia	100%	0%	0%	0%
Integrated Environmental Socioeconomic Development Project (PDSEAI)	73%	0%	19%	8%
Training to Conserve	0%	0%	100%	0%
CAR Mato Grosso do Sul	100%	0%	0%	0%
satellite environmental monitoring of the amazon biome	53%	47%	0%	0%
Sustainable Indigenous Amazon	0%	0%	72%	28%
Value Chains of Nontimber Forest Products	0%	0%	0%	100%
Amazonia SAR	97%	3%	0%	0%
Amazon Integrated Project	0%	100%	0%	0%
High Juruá	0%	0%	62%	38%
Value Chains in Indigenous Lands in Acre	0%	0%	0%	100%
Strengthening environmental management in the Amazon	60%	24%	16%	0%
Sustainable Bem Viver	0%	0%	93%	7%
IREHI – Taking Care of Territory	0%	0%	74%	26%
CAR Paraná	100%	0%	0%	0%
Forest Assistance Program +	0%	0%	16%	84%
Consolidating Territorial and Environmental Management in Indigenous Lands	0%	0%	79%	21%
CAR Ceará	100%	0%	0%	0%
Empowering Environmental Monitoring and Control in Order to Combat Illegal Deforestation in the Brazilian Amazon	100%	0%	0%	0%
management and governance of indigenous lands in the rio negro and xingu basins - pgtas	0%	0%	83%	17%
Indigenous Territorial Management in the South of Amazonas State	0%	0%	69%	31%
Adding Value to Amazon Socioproductive Chains	0%	0%	0%	100%
Kayapó Territory, Culture and Autonomy	0%	0%	93%	7%
Environmental Monitoring of brazilian Biomes	37%	63%	0%	0%
Forest Cities	83%	17%	0%	0%
Sowing Rondônia	31%	12%	0%	57%
Use of Social Technologies to Reduce Deforestation	0%	0%	0%	100%
Sustainable Tapajós	0%	0%	13%	87%
Valuable Forests - New business models for the Amazon	0%	0%	0%	100%
Everlasting Forest	0%	54%	0%	46%
More sustainability in the countryside	100%	0%	0%	0%
Preserving the Babassu Forest	0%	0%	100%	0%
Communal Forests	0%	0%	0%	100%
Land Regularization	0%	0%	100%	0%
Tapajós Active Forest	0%	19%	0%	81%
PPP-ECOS in the Amazon – Phase 2	0%	0%	0%	100%
CAR Amazonas	100%	0%	0%	0%
Integrated Legacy of the Amazon Region ("Lira")	0%	11%	33%	56%
Indigenous Experiences of Territorial and Environmental Management in Acre	0%	0%	75%	25%
Amazônia Agroecológica Project	0%	0%	0%	100%
Environmental Regularization	50%	50%	0%	0%
Profisc I-B	100%	0%	0%	0%
Pact for the Forest	0%	0%	0%	100%
car espirito santo	100%	0%	0%	0%

Table 6: Breakdown of each project by axis

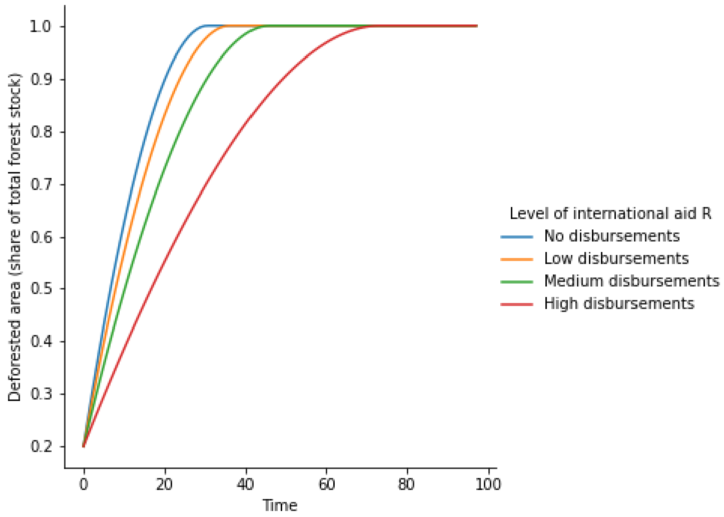

Figure 16: Optimal deforestation stock path for different values of R

Table 7: Variables used in estimations and main descriptive statistics of the dataset (2000-2020)

Variables	(1) N. obs	(2) Mean	(3) S.D.	(4) Min	(5) Max
Deforestation rate (% ratio/km^2 per Year)	15,960	0.451	3.137	0	97.50
Amazon Fund disbursement (BRL/km^2 per Year)	15,960	9.791	26.01	0	615.5
Ibama fines (BRL/km^2 per Year)	15,876	353.8	2,486	0	122,215
Steer stock (heads, % Y/Y growth)	15,893	170.2	7,702	-100	720,528
Soybean production (tons, % Y/Y growth)	15,960	25.58	1,251	-100	155,803
Credit to agriculture (BRL, % Y/Y real growth)	20	5.230	8.793	-12.77	21.94
Steer price (BRL, % Y/Y real growth)	20	2.221	12.66	-15.30	33.02
Soybean price (BRL, % Y/Y real growth)	20	3.516	19.10	-30.88	44.34

Note: The table displays the transformation of variables used in our regressions. While the descriptive statistics refer to the whole available dataset, a lower number of observations are used in estimation due to lags in the VAR system (see Table 2

Figure 17: IRFs - all endogenous variables

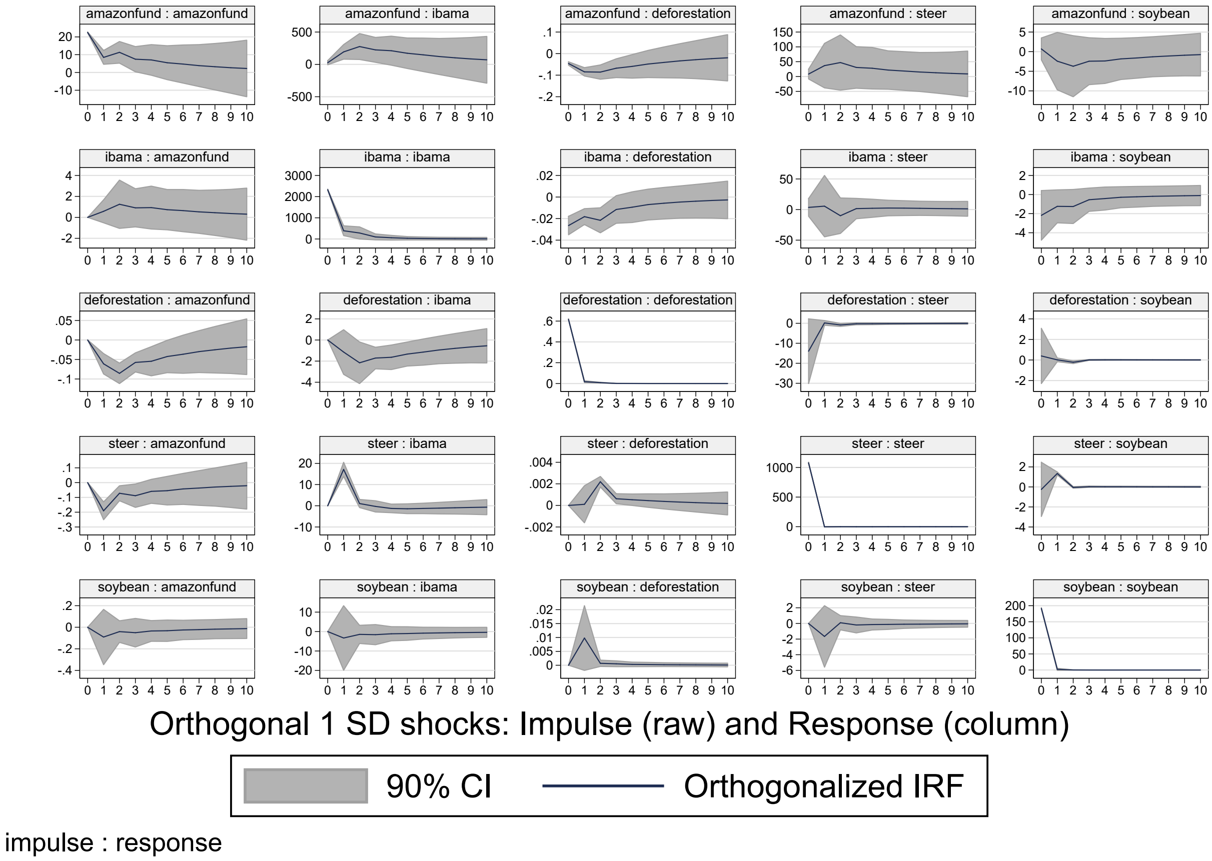

Figure 18: Correlation between recipients, axis and themes

		AXIS				THEME					RECIPIENT					
		Monitoring and	Science, Innova	Land use plann	Sustainable pro	Rural Environm	Settlement	Indigenous lan	Conservation u	Combat to illeg	Third Sector	Federal Govern	States	Municipalities	Universities	International
AXIS	Monitoring and control systems	100,0%	19,0%	16,7%	28,6%	45,2%	2,4%	2,4%	9,5%	14,3%	16,7%	14,3%	50,0%	16,7%	0,0%	2,4%
	Science, innovation and economic instruments	32,0%	100,0%	12,0%	40,0%	4,0%	16,0%	12,0%	32,0%	0,0%	48,0%	20,0%	4,0%	0,0%	24,0%	4,0%
	Land use planning	25,9%	11,1%	100,0%	77,8%	7,4%	7,4%	55,6%	44,4%	0,0%	81,5%	0,0%	14,8%	3,7%	0,0%	0,0%
	Sustainable production	20,3%	16,9%	35,6%	100,0%	8,5%	27,1%	44,1%	35,6%	0,0%	84,7%	0,0%	5,1%	10,2%	0,0%	0,0%
THEME	Rural Environmental Registry (CAR)	100,0%	5,3%	10,5%	26,3%	100,0%	0,0%	0,0%	5,3%	0,0%	15,8%	0,0%	73,7%	10,5%	0,0%	0,0%
	Settlement	6,3%	25,0%	12,5%	100,0%	0,0%	100,0%	31,3%	50,0%	0,0%	100,0%	0,0%	0,0%	0,0%	0,0%	0,0%
	Indigenous lands	3,6%	10,7%	53,6%	92,9%	0,0%	17,9%	100,0%	39,3%	0,0%	92,9%	0,0%	3,6%	0,0%	3,6%	0,0%
	Conservation units	14,3%	28,6%	42,9%	75,0%	3,6%	28,6%	39,3%	100,0%	0,0%	82,1%	3,6%	10,7%	0,0%	3,6%	0,0%
	Combat to illegal fires and burn-offs	100,0%	0,0%	0,0%	0,0%	0,0%	0,0%	0,0%	0,0%	100,0%	0,0%	16,7%	83,3%	0,0%	0,0%	0,0%
RECIPIENT	Third Sector	12,1%	20,7%	37,9%	86,2%	5,2%	27,6%	44,8%	39,7%	0,0%	100,0%	0,0%	0,0%	0,0%	0,0%	0,0%
	Federal Government	75,0%	62,5%	0,0%	0,0%	0,0%	0,0%	0,0%	12,5%	12,5%	0,0%	100,0%	0,0%	0,0%	0,0%	0,0%
	States	95,5%	4,5%	18,2%	13,6%	63,6%	0,0%	4,5%	13,6%	22,7%	0,0%	0,0%	100,0%	0,0%	0,0%	0,0%
	Municipalities	100,0%	0,0%	14,3%	85,7%	28,6%	0,0%	0,0%	0,0%	0,0%	0,0%	0,0%	0,0%	100,0%	0,0%	0,0%
	Universities	0,0%	100,0%	0,0%	0,0%	0,0%	0,0%	16,7%	16,7%	0,0%	0,0%	0,0%	0,0%	0,0%	100,0%	0,0%
	International	100,0%	100,0%	0,0%	0,0%	0,0%	0,0%	0,0%	0,0%	0,0%	0,0%	0,0%	0,0%	0,0%	0,0%	100,0%

Source: BNDES and authors' calculations

Note: The table should be read as follows: among projects allocated to "Monitoring and control systems", 16,7 % were also allocated to "Land use planning" and 50,0 % were conducted by "States"

Figure 19: Spatial concentration of projects per type of recipient