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Green Finance and Deforestation Reduction in Brazil: a PVAR Analysis of the Amazon Fund

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Abstract

The Amazon rainforest is emitting more carbon dioxide than it can absorb due to deforestation since 2021, leading to significant impacts on global warming. The loss of biodiversity due to land use change in the Amazon biome is also a major issue. Legal Amazon is an administrative area in Brazil that encompasses 64% of the Amazon biome and nine federal states. The Amazon Fund is the main international climate finance vehicle that operates in Legal Amazon. However, its disbursements have recently dropped due to disagreements between donors and the Brazilian government up to 2022. This paper aims to assess the impact of the Amazon Fund's projects in reducing deforestation along with other factors, such as the national environmental agency sanctions and agricultural production. Using satellite observations and microeconomic data, a panel dataset has been constructed to analyze the evolution of various environmental features, climate finance, regulation, and production from 2002 to 2020 across 760 municipalities in Legal Amazon. A Panel Vector Auto Regression (PVAR) is used to model a stylized economic system in which variables can affect each other at different lags. Our main findings suggest that the Amazon Fund's disbursements significantly reduce deforestation rates. Federal-managed projects are more effective than those led by states or municipalities. The most efficient projects are those devoted to land use planning, which involves the development and the protection of local autochthonous communities. Overall, we estimate that the Amazon Fund operates with a low abatement cost (between 0.4 and 1.1 EUR per saved ton of CO2).

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

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

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Non-Technical Summary

This paper investigates whether green finance—specifically through the Amazon Fund—has helped reduce deforestation in the Brazilian Amazon. The Amazon rainforest is crucial for regulating Earth's climate, but rising deforestation, especially since 2019, has turned parts of it into a net source of carbon emissions rather than a carbon sink. To fight rainforest clearing, the Amazon Fund was set up in 2009 as Brazil's main international climate finance tool. Primarily funded by Norway and Germany, it supports projects in Brazil's Legal Amazon region. Its disbursements have been steadily increasing up to 2017, then have sharply declined.

We use economic and satellite data from 760 municipalities between 2002 and 2020 to assess how Amazon Fund disbursements, government enforcement actions, and agricultural activity affect deforestation. We apply an econometric method (PVAR—Panel Vector Auto Regression) that enable capture the complex interactions between these variables over time. Our empirical findings yield insights for policy-makers and green funders.

The first set of policy implications is related to the role of agricultural activities. Agricultural output growth entails higher rates of rainforest clearing. When analysing the separate role of agricultural commodities, wood production shows a more clear-cut impact on deforestation than cattle ranching or soybean production. Controlling illegal logging and wood smuggling and, ultimately, promoting alternative materials to reduce the international demand for timber is crucial in the fight for deforestation.

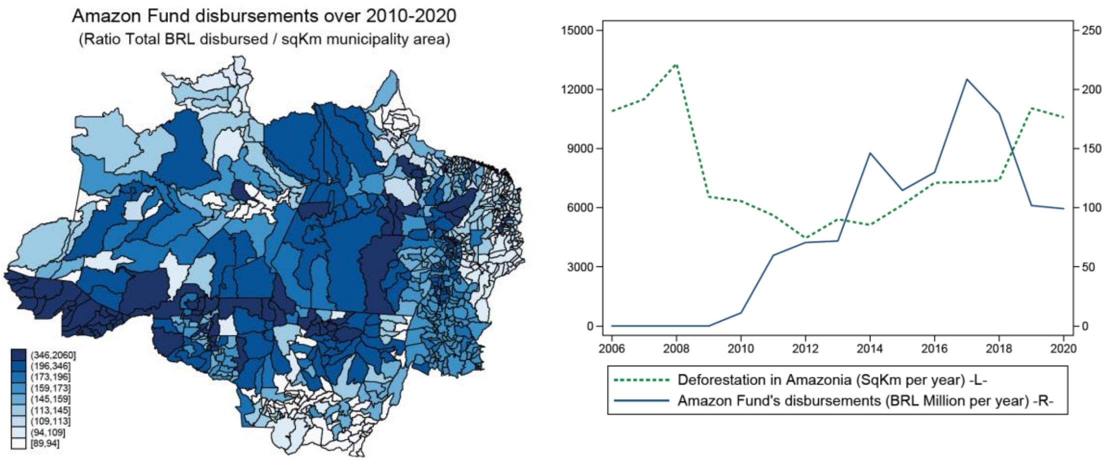
Second, monitoring efforts need proper law enforcement mechanisms to be effective against deforestation. Blacklisting municipalities, combined with economic incentives to exit the blacklist, helps to slow down deforestation.

Third (and main) set of policy conclusions: properly designed green finance manages to reduce significantly deforestation rates. The action of the Amazon Fund interacts with (and works through) other key factors. Green finance, agricultural productivity, and law enforcement may benefit from important synergies. i/ Promoting agricultural productivity (in terms of per capita agricultural output) rather than extensive use of new lands helps to enhance the efficacy of green finance in fighting deforestation. This has to be balanced by a control of local pollution, to the extent that biodiversity may be harmed by pesticides, fertilizers, etc. ii/ Some of the Funds' main successful projects, such as those related to monitoring and control systems or to the enforcement of the Forest code through the Rural Environmental Registry (CAR), facilitate the action of environmental agencies. iii/ At a more disaggregated level, some types of projects need relatively less funding to fight deforestation. By recipient, projects managed at the federal or state level are more efficient than those managed by municipalities. This is probably due to the taxonomy of the projects, rather than to the level of governance. Federal government and states' projects are to a large extent related to actions that yield immediate gains against deforestation, such as monitoring, enforcing environmental regulation (CAR) and fighting illegal fires. In turn, tools that fight deforestation rather in the long run or that specifically target the recovery of biodiversity, such as fostering sustainable production or science & innovation activities, are typically led by the third sector (eg. NGOs, foundations) and universities. Our findings do not call for a public top-down approach in the allocation of disbursements, though. Land use planning, which is the most efficient axis, corresponds to projects most often led by the third sector and aimed at empowering local autochthonous communities in protected areas. Strengthening the social roots in indigenous lands is thus a highly efficient way to fight against rainforest clearing

Last the Amazon Fund is a relatively "cheap" green finance tool: ultimately, it manages to reduce emissions from deforestation at a low cost per saved ton of carbon dioxide.

In all, this research fills a key gap by providing the first overall quantitative evidence that the Amazon Fund works, and that international climate finance can support effective environmental protection—if backed by political will.

Figure 1. Amazon Fund disbursements and deforestation in Brazilian Amazon



Source: BNDES, INPE, and authors' calculations. Note: The Amazon Fund disbursements focus (dark blue areas) on the so-called "arc of deforestation"

Finance verte et réduction de la déforestation au Brésil : une analyse PVAR du Fonds Amazonien

Résumé

Depuis 2021, la forêt amazonienne émet plus de dioxyde de carbone qu'elle ne peut en absorber en raison de la déforestation, ce qui entraîne des impacts significatifs sur le réchauffement climatique. La perte de biodiversité due au changement d'affectation des terres dans le biome amazonien constitue également un problème majeur. L'Amazonie légale est une zone administrative du Brésil qui couvre 64 % du biome amazonien et neuf États fédéraux. Le Fonds Amazonien est le principal mécanisme international de financement climatique qui opère dans l'Amazonie légale. Cependant, ses décaissements ont récemment diminué en raison de désaccords entre les donateurs et le gouvernement brésilien jusqu'en 2022. Cet article vise à évaluer l'impact des projets du Fonds Amazonien dans la réduction de la déforestation, ainsi que d'autres facteurs tels que les sanctions de l'agence environnementale nationale et la production agricole. À l'aide d'observations satellitaires et de données microéconomiques, un panel de données a été constitué pour analyser l'évolution de divers paramètres environnementaux, du financement climatique, de la réglementation et de la production entre 2002 et 2020 dans 760 municipalités de l'Amazonie légale. Un modèle de régression vectorielle autorégressive sur données de panel (PVAR) est utilisé pour capter l'interaction dynamique entre les variables. Nos principaux résultats suggèrent que les décaissements du Fonds Amazonie réduisent significativement les taux de déforestation. Les projets gérés au niveau fédéral sont plus efficaces que ceux pilotés par les États ou les municipalités. Les projets les plus efficients sont ceux consacrés à la planification de l'utilisation des terres, qui impliquent le développement et la protection des communautés autochtones locales. Dans l'ensemble, nous estimons que le Fonds Amazonien opère avec un faible coût d'abattement (entre 0,4 et 1,1 EUR par tonne de CO_2 économisée).

Mots-clés : finance verte, déforestation, forêt amazonienne, PVAR

1 Introduction

According to the IPCC Special Report on Climate Change and Land (2019) [39], 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. The trend is not getting better as parts of the Amazon rainforest are beginning to act as net carbon emitters, failing to fully 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 a key driver of biodiversity loss, according to the IPBES (Watson et al., 2019). Furthermore, the pandemic that the world experienced in 2020 should act as a reminder that the deforestation process also increases the risk of releasing infectious agents (IPBES 2020; Ellwanger et al., 2020). In all, deforestation exacerbates physical and transition risks. Reducing it can significantly contribute to mitigate climate change.

Green finance is a major tool for fighting deforestation. Evaluating the related policies is key for preserving economic resilience and palliating systemic risks, eg. by promoting sustainable land use. Moreover, assessing the efficiency of different types of projects provides insights to refine the green taxonomy and to avoid *greenwashing*.

From a global perspective, since the late 2000s several international funds have been established within the United Nations REDD+ framework (Reducing emissions from deforestation and forest degradation in developing countries), in which "developing countries can receive results-based payments for emission reductions when they reduce deforestation". Among them, the Amazon Fund, which operates only in Brazil, is the most active, with an overall disbursement of more than 600 million USD since 2009 (Table 9).

Since its establishment in 2009, the Amazon Fund has been managed 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. Up to May 2021, 534 million USD have been disbursed 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 have respectively financed 14% and 5% of REDD+ projects in Brazil. The fund allocation process is summarized in Figure 22.

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 Amazon. On the other hand, the government unilaterally suspended the board of directors

[1] One project has been abandoned, since Climate Funds Update last update of Table 9

[2] Climate Funds Update, May 2022

and the technical committee of the fund[3]. During the period 2019-2022, the Fund decided to stop making new pledges and 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], while some other countries expressed their willingness to become shareholders and contribute for the first time (The United Kingdom[5], France[6], and the United States)[7]. As a result of this new political impulse, the number of projects supported has risen from 102 to 124 between 2022 and 2025.

Officially, the main objective of the Fund is to reduce the annual deforestation rate in the Amazon rainforest. While the assessments on the Fund's efficacy have been carried out either qualitatively or at very local level, so far no empirical studies have addressed its effectiveness in a quantitative and comprehensive way. To echo this fact, in the 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 other policies of the 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 Environment and Climate Change publishes annually a "black list" of the municipalities responsible for the largest contributions to aggregate deforestation in the Legal Amazon. 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 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

[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

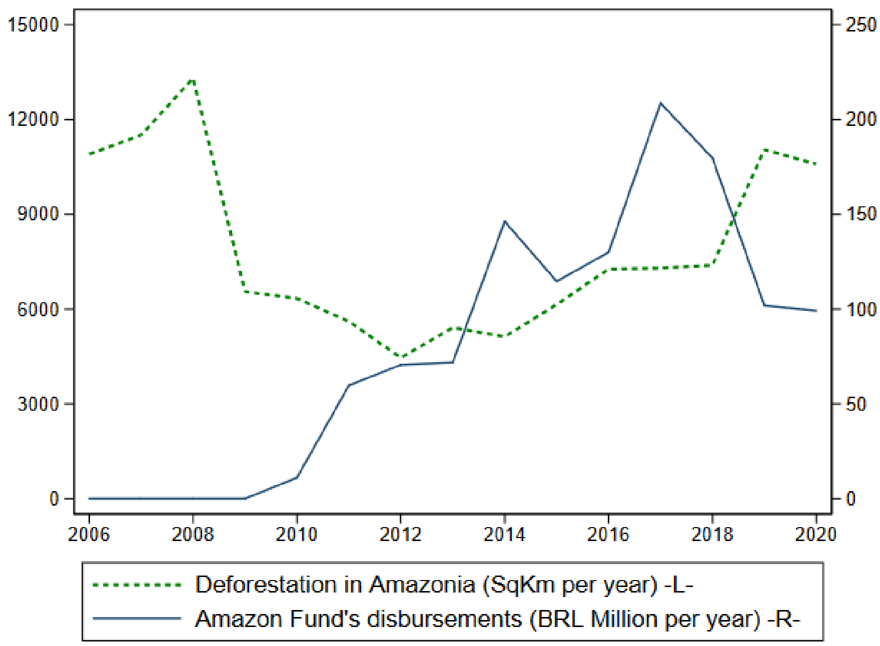
[7]https://www.bbc.com/portuguese/articles/cp90rzygp0lo

[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

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, "Brazilian Institute of Environment and Renewable Natural Resources"), and they tend to have lower market values than those registered in the CAR.

In the same vein as 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. 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 actions of the Brazilian Ministry of Environment (blacklisting and fines) 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.

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.

[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.

The contribution of this article is threefold.

First, to our knowledge, this is the first paper to achieve a quantitative assessment of 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 the 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. Several 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). Whereas existing studies commonly employ difference-in-differences or synthetic control methods, our benchmark analysis takes a different approach. 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 purely 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; Faria et al., 2024). 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 improved law enforcement with satellite teledetection (Assunção et al., 2014). Along with climate finance and deforestation, our study encompasses two other endogenous variables: law enforcement (proxied by the government blacklisting decisions - then by the sanctions by the national environmental agency -IBAMA- in robustness checks) and agricultural production (GDP -then commodities production for robustness). We also control for exogenous factors such as agricultural prices. Last, we find that rural credit at the local level is a valid instrument variable, which makes our PVAR GMM estimations more reliable. 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 dynamics that provides some theoretical foundations for the empirical work. Section 3 presents the data and provides 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. Section 6 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 dynamics 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 or de Souza Batista et al., 2023). 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:

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

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 keeps the rain-forest clearing under a cap level $\overline{d}$ (in km^2). [10] The planner discounts the future using a factor β.

The constrained intertemporal maximization problem can be written as:

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

s.t.

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

The Lagrangian is:

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

where λ_t is the shadow value associated to land.

The first order condition with respect to d_t leads to:

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

So that,

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

Rearranging,

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

[10] Since the Amazon Fund follows a staggered disbursement procedure aimed at ensuring that funds are effectively used to combat deforestation, our framework captures quite accurately the incentives faced by local policymakers.

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

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

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

Denote $S = \sum_{\tau=0}^{\infty} \beta^\tau d_\tau$ the discounted sum of deforestation areas, we get that:

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

At the optimum, S is:

- an increasing function of the total stock of land $\overline{T}$, the agricultural prices p (Hypothesis 1) and the intrinsic yields r;
- a decreasing function of the international donation amount per year R (Hypothesis 2), the unit *production* cost of deforestation c, and the stringency of law enforcement s (Hypothesis 3).

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 24 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.

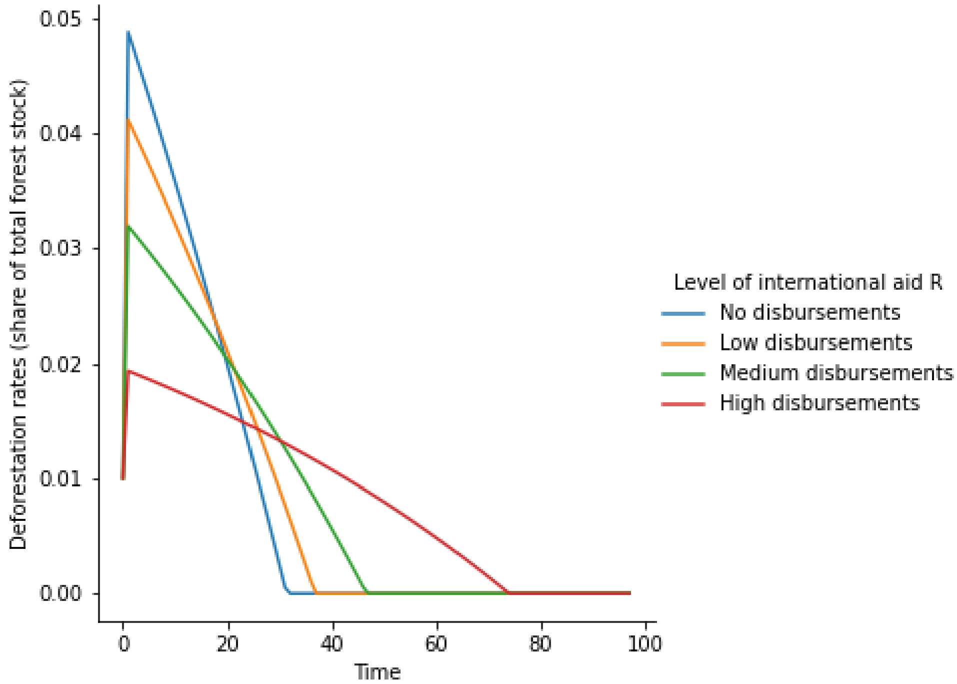


Figure 2: Optimal deforestation path for different values of R

In addition, we have that:

$$\frac{\partial^2 S}{\partial r\, \partial R} = \frac{\bar{T}}{2} \cdot \frac{1-\beta}{pr^2} > 0$$

Namely, the higher the agricultural yields, the less negative the marginal impact of international finance on the reduction of deforestation (so the lower its efficacy in absolute terms - Hypothesis 4). This is quite intuitive: *a priori*, the larger the yield r, the higher the opportunity cost of not deforesting and benefitting from international aid. Note that this stylized model cannot capture alternative patterns stemming from changes in the agricultural output dynamics. Notwithstanding, in practice international finance could be more efficient as agriculture becomes more intensive and the use of new lands is less needed (ie. in areas where a higher agricultural productivity makes reducing deforestation easier for green projects).

We then investigate how the marginal impact of the Fund on the accumulation of deforestation S varies as a function of $\bar{T}$.

$$\frac{\partial^2 S_t}{\partial \bar{T}\, \partial R} = -\frac{1-\beta}{2pr} < 0$$

The higher the initial stock of forest $\bar{T}$, the greater the marginal efficiency of the fund (Hypothesis 5). This results from the combined effect of two assumptions: (i) the feedback loop effect weakens as $\bar{T}$ increases, and (ii) the reward is based on absolute deforestation avoidance, regardless of the municipality's size or the initial deforestation stock. When $\bar{T}$ is high, the agricultural planner has little incentive to conserve forest to benefit from the positive externalities of the feedback loop; the main benefit from conservation becomes the reward from international aid. As a result, this reward has a stronger marginal impact on optimal deforestation decisions. Note that if we had defined R as a reward based on relative deforestation, $\frac{\bar{d}-d_t}{\bar{T}}$, the cross-derivative would be zero, and the impact of the fund would no longer depend on the initial stock of deforestation (Hypothesis 5 bis).

3 Data and main variables

Economic, regulatory, and environmental data were gathered from several sources to build a panel database. The dataset encompasses a sample of 760 municipalities[11] spread over 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

Our study focuses on the path of rainforest clearing as the main explained variable. Every year, the Brazilian National Institute of Space Research (INPE) publishes estimates of the rainforest clearing commonly called deforestation rates (in km^2). This measure corresponds to the surface that has suffered a 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 the Legal Amazon, in English). For technical reasons (there are fewer clouds and therefore better visibility during the dry seasons), the flow in year t actually corresponds to the deforestation occurring between August of year $t-1$ and July of year t. This increase is disclosed at a local level for the 760 municipalities of the dataset. As the INPE disclaims that data on 2000 and 2001 are not consistent with other years, we restrict the panel from 2002 to 2020.

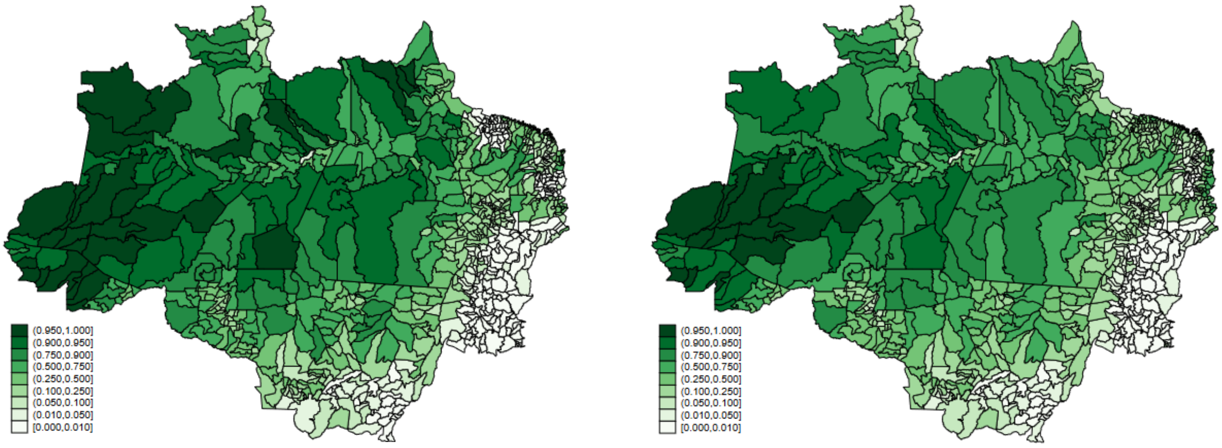
Some caveats stem from the measurement of rainforest evolution. The PRODES detection system only takes into account gross deforestation increments and not net deforestation. In other words, data capture to what extent an area has been deforested but do not tell us whether it has been partially or fully 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 rainforest. 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 p.p. in the Legal Amazon (Figure 3). Yet, over time, aggregate deforestation has significantly varied, in connection with the envrionmental public policies and the degree of enforcement of environmental regulations mentioned above. After reaching 22 242

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

km^2 on yearly average between 2000 and 2004, forest clearing notably declined between 2005 and 2009 (-41% on average, between the two periods), and did even more between 2010 and 2014, when aggregate deforestation dropped to 5 778 km^2 (-56% compared to the previous 5-year period). However, this trend has reverted. Forest clearing has been increasing since 2015, particularly between 2019 and 2021 (+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 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 Green finance: the Amazon Fund

We are primarily interested in the role of green finance in deforestation dynamics. A major contribution of this paper is to build a comprehensive 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 econometrically infer the role of the main drivers of deforestation.

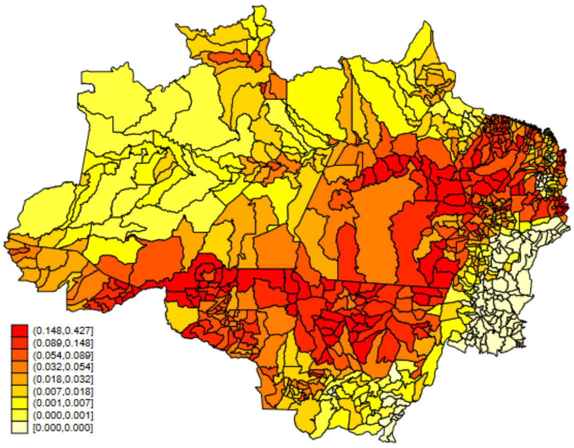
Two main sources of information were used to obtain variables that describe the action of the Amazon Fund in the 760 municipalities of the Amazon biome:

- 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 to May 2021). At the end of this step, we got the disaggregation of disbursements at the state level. The information obtained is summarized in Table 10 (in Appendix).

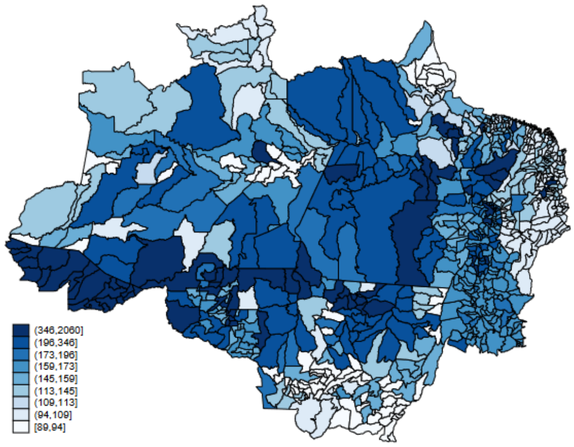
- In order to disaggregate disbursements at the municipality level, we used a second source of information: the Brazilian manager of the Amazon Fund (the BNDES). Exchanges with the Fund's managers made it possible to identify more precisely the geographical areas that received funds from the 102 projects and the group of municipalities that benefited from each of them. As we did not know the exact amount of money going to each municipality, we applied a simple rule to allocate resources from one project: the distribution was made on a pro rata basis of the area of each municipality (this corresponds to the "area criteria" depicted in Figure 23).

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

We got a more granular decomposition of the Amazon Fund's projects, split by recipient, axis and theme.

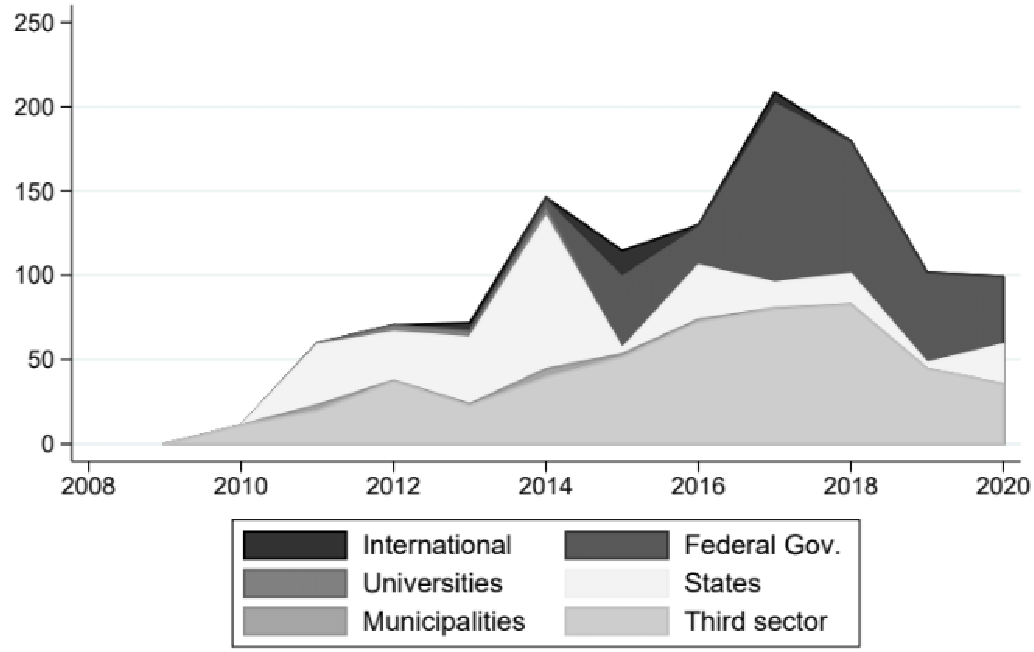
Six types of recipients, both in the public and private spheres, act within different geographical perimeters and have received funding from the Amazon Fund: the international sphere, the Brazilian federal government, states, municipalities, the third sector, and universities (Figure 5). Among these 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 and non-governmental organizations.

- Brazilian states are responsible for 25.7% of disbursements, most of which have occurred before 2015. Among the 22 projects carried out by the states, 14 are allocated to the support of 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, allocated through 8 projects. These funds have been disbursed mainly after 2015 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 (BRL millions per year)



Source: BNDES and authors' calculations

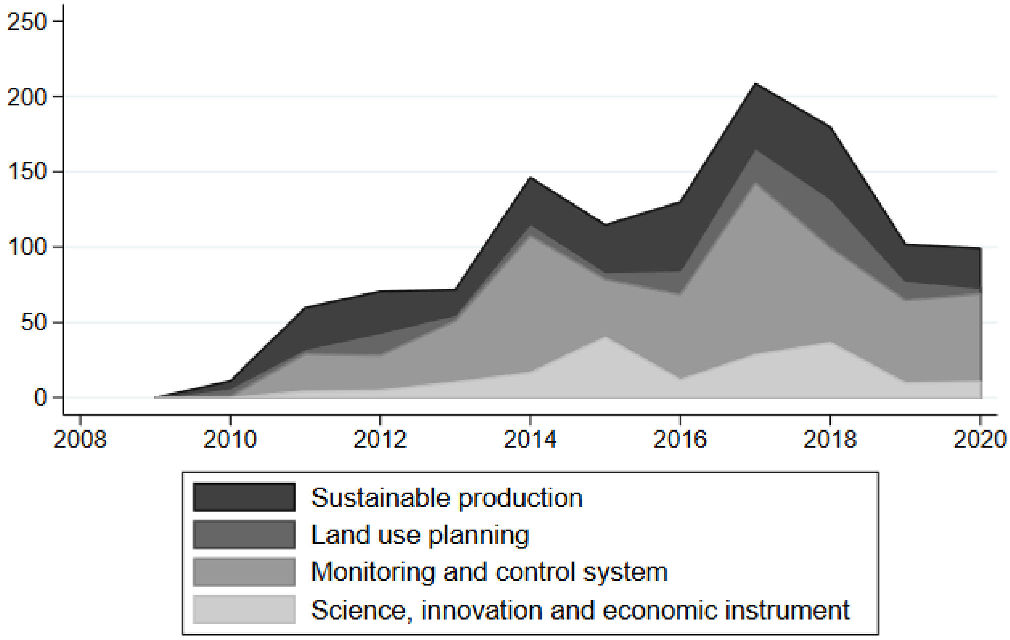
For each project, the Amazon Fund defines one or more axes and themes of action in which the project fits. The four axes correspond to those defined by the PPCDAm launched in 2004. They are described in the last edition of the plan[12].

- 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 estimated weight of each axis for each of the 102 projects. The breakdown is provided in the Appendix (Table 11).

[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 (BRL millions per year)



Source: BNDES and authors' calculations

Since 2010, the Amazon fund has devoted 42% of ressources to the "Monitoring and Control" axis. Thereby, the fund has massively financed the states to recruit and train teams devoted 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. [13] Almost a third of the fund's disbursements (29%, 154 million USD) have been allocated to support the "sustainable production" axis of action of the PPCDAm. [14]

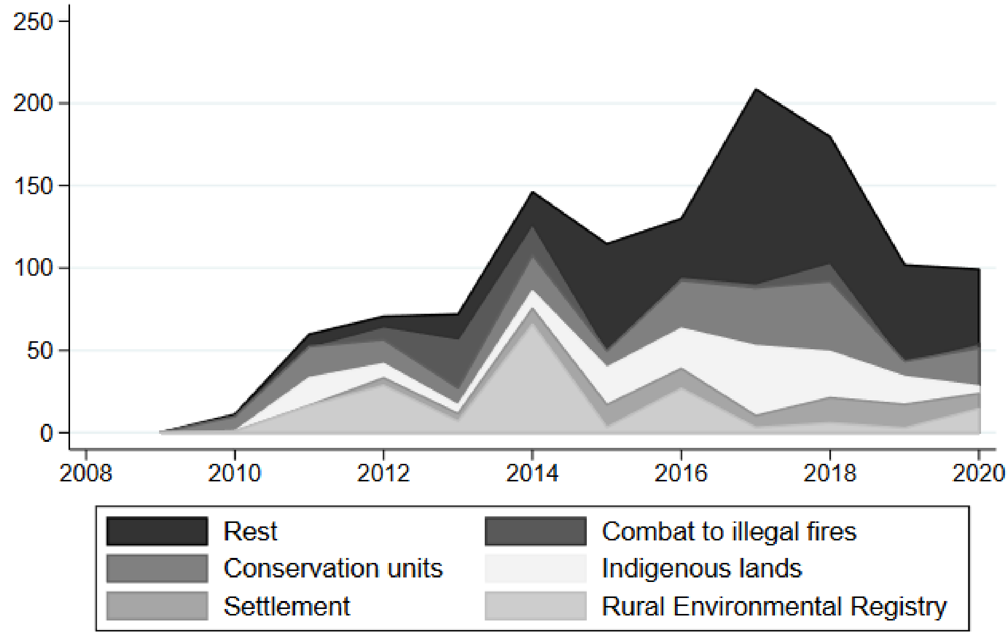
In addition, the Amazon Fund defines its own projects split by theme. The main themes covered by the Amazon Fund activities are:

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

[13] 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)

[14] Sustainable production projects have been much less studied in the empirical literature.

Figure 7: Annual Amazon Fund disbursements by theme between 2008 and 2020 (BRL millions per year)



Source: BNDES and authors' calculations

As Figures 7 and 3.2 show, not all projects have necessarily a thematic allocation.

Table 1: Project counts by Axis, Theme, and Recipient

	Category	**Count**
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

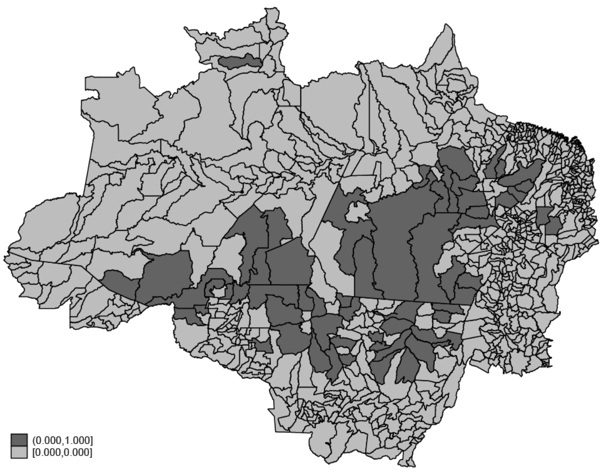
Note: Unlike for the recipients, axes and themes are not mutually exclusive: a single project can be devoted to several themes. For example, among the 102 projects, 59 were devoted (at least) to sustainable production.

3.3 Law enforcement

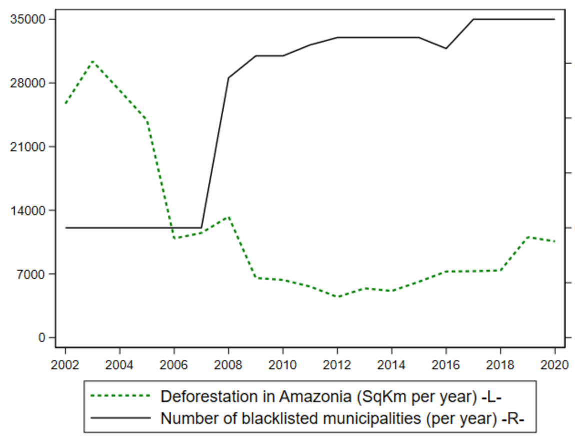
Law enforcement actions, mainly through blacklisting and sanctions on infractors, have been a key factor in reducing deforestation in the Legal Amazon (Assunção and Rocha, 2019).

The Action plan for the Prevention and Control of Deforestation in the Legal Amazon (PPCDAm) encompassed two major sequential components. Launched in 2004, the first plan sets up new procedures and resources to improve the monitoring and control of the rainforest, including the intensive use of the satellite-based Real-Time Detection of Deforestation System (DETER). Implemented from late 2007 on, the second component focused on actions aimed at strengthening law enforcement, in particular the Forest Code. One of the main measures was the creation and the publication by the Ministry of the Environment of a blacklist of municipalities (called *Municípios Prioritários* - MPs). The criteria for entering and exiting the list are related to the recent evolution of local deforestation. After entering the blacklist, MPs are more closely monitored and more likely to be fined by the IBAMA (see below), which can even put some farms under embargo. Other actions on MPs are related to economic incentives, such as access restrictions to subsidized rural credit. At the end of 2008, there were 41 MPs. With some occasional drops, the total number has increased to 57 in 2020.

Figure 8: Law enforcement: Blacklisting



(a) Municipalities having entered the blacklist at least once in 2008-2020 (dark grey)



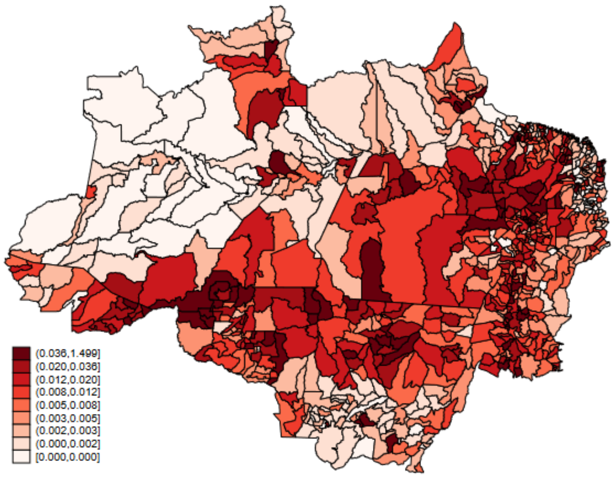
(b) Number of municipalities in the blacklist and deforestation

Source: MMA and authors calculations

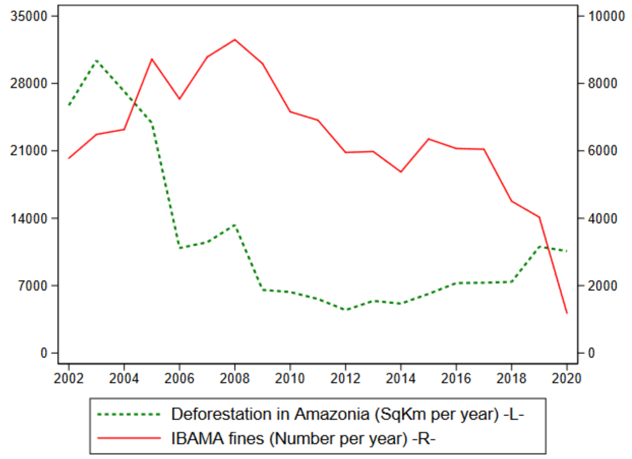
The administrative arm of the Brazilian Ministry of Environment is the Brazilian Institute of the Environment and Renewable Natural Resources (IBAMA). It regularly updates a public census of environmental infractions detected by the authorities since 1980[15]. The file describes more than 700 000 infractions committed all over Brazil. It is possible to aggregate the number and amount of infractions at the municipal level for each year.

[15]https://dadosabertos.ibama.gov.br/dataset/fiscalizacao-auto-de-infracao

Figure 9: Law enforcement: IBAMA fines



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



(b) Number of infractions in the Legal Amazon and deforestation

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

Historically, the enforcement of fines has faced huge challenges and a relatively small fraction has been collected. In practice, less than 5% are paid by offenders. We thus use the blacklisting decisions as a proxy for law enforcement in our baseline models, and leave the IBAMA's sanctions for robustness checks.

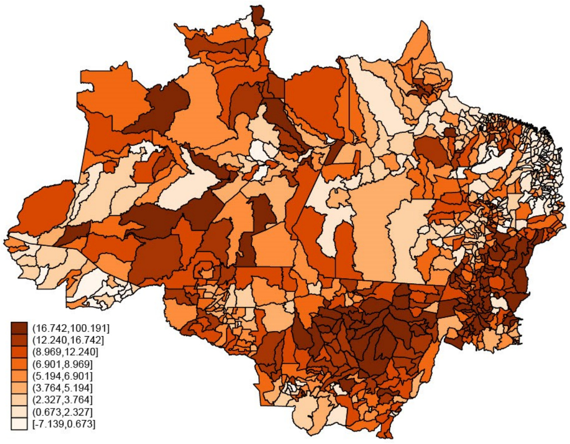
3.4 Agricultural activities

3.4.1 Local agricultural GDP

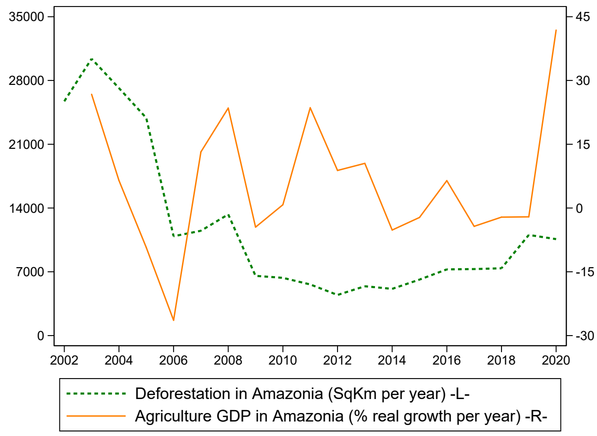
Agricultural activity is recognized as another key driver of deforestation in the Brazilian Amazon rainforest (Assunção et al., 2015; da Silva et al., 2010).

When using production valued at market prices, aggregate agriculture GDP growth and deforestation look positively correlated up to the late 2000s. From 2018 on, the jump in deforestation seems to precede a skyrocketing rise in agriculture GDP.

Figure 10: Annual real growth (%) of agriculture GDP



(a) Average annual real growth (%) of agriculture GDP (2003-2020)



(b) Agriculture GDP Real Growth and deforestation

Source: IBGE and authors calculations

3.4.2 Agricultural commodities' production in volume

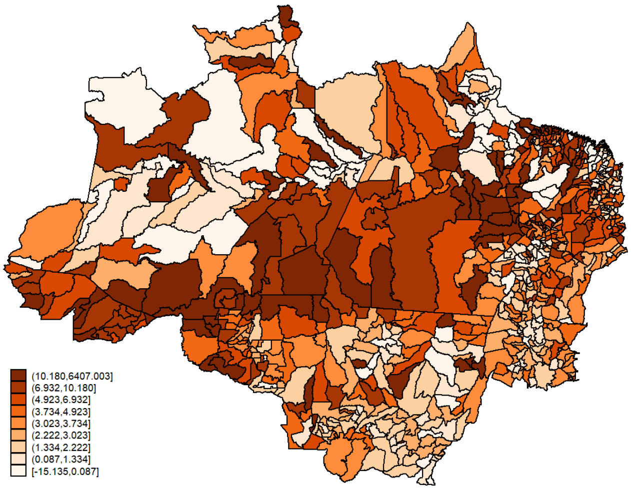
Using IBGE data, we also get three types of agricultural production in volume :(i) the steer livestock[16], measured as cattle size (the number of heads of beefs is reported each December 31st); (ii) the soybean production[17] in tons; (iii) the volume of wood production (in m^3 of extracted logs).

As put forward by WWF, illegal logging has been widespread for a longtime in Brazil. It is suspected to be a major driver of deforestation, pushed by domestic and foreign demand for timber products. Moreover, cleared areas often lead to "subsequent conversion for agriculture or pasture". Figure 11 suggests that wood extraction has mainly occurred all along the central areas of Legal Amazon, from South to North. In addition, the maps show that beef farms settle much further into the forest than soybean farms. This corresponds to the agricultural transition described by WWF: "Soy developers then capitalize on the cattle ranchers and take over their land, pushing cattle ranching (and deforestation) towards new pioneer areas."

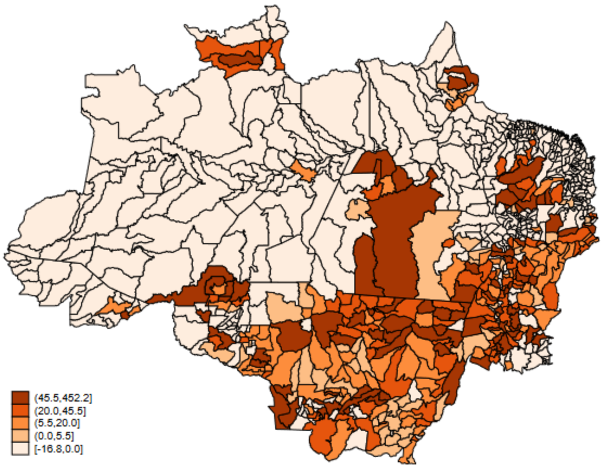
The above measures of commodities' production have the advantage of not being affected by prices. However, data on soybean quantities entail too many zero observations. Data on cattle (specified as steer stock growth, below) are much more balanced, but show extreme dispersion. To get a more comprehensive and reliable picture of agricultural production, we use agricultural GDP in our baseline model, while controlling for commodities' national market prices in domestic currency. We leave physical wood production and the export price of timber in USD for robustness checks.

[16] https://sidra.ibge.gov.br/tabela/3939
[17] https://sidra.ibge.gov.br/tabela/1612

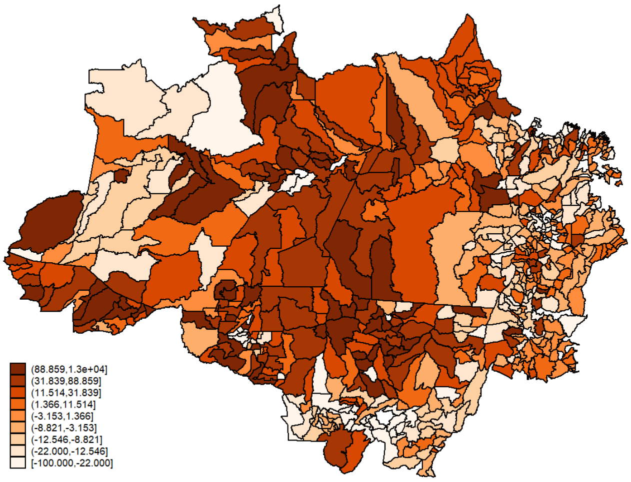
Figure 11: Average annual growth (%) of commodities production in volume (2001-2020)



(a) Steer livestock (number of heads)



(b) Soybean production (tons)



(c) Wood production (logs in m3)

Source: IBGE and authors calculations

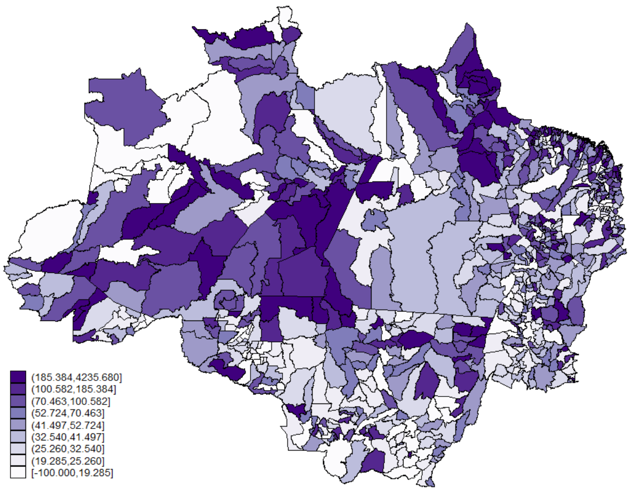
3.4.3 Local credit to agriculture

Rural credit is a variable that may be either positively or negatively correlated with deforestation, depending on the biome and the loans' earmarked purpose (Faria et al., 2024).

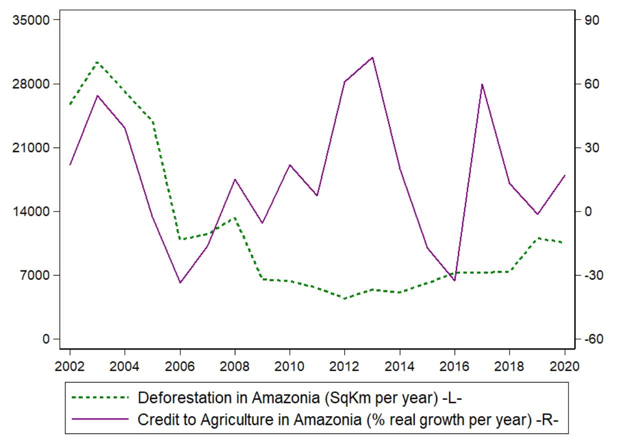
To get a measure of the evolution of rural credit in Brazil at the municipality level in the Legal Amazon we use the series and the definition made available by Banco Central de Brasil (BCB). Within the *Sistema Nacional de Crédito Rural* (SNCR), the BCB is the supervisor of rural credit, the regulation 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 sectoral allocation of the latter is legally predetermined and 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. [18]

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. As shown in Figure 12b, aggregate rural credit's real growth tends to comove with the deforestation rate up to 2010 then both variables look decorrelated. During the period 2010-2013, rural credit experiences a remarkable hike, in line with the government's strategy of financing economic development. Then it drops hugely in the onset of the 2015-16 crisis, reflecting the scaling-back of subsidized credit adopted by subsequent governments. In turn, rural credit is likely to be correlated with some of the main variables in our analysis, eg. blacklisting or agriculture GDP. The potential channels of transmission to rainforest clearing are thus rather indirect. We therefore use rural credit for robustness checks, particularly as an instrumental variable.

Figure 12: Annual growth (%) of agriculture credit



(a) Average annual real growth of agriculture credit (2001-2020)



(b) Agriculture credit real growth and deforestation

Source: BCB and authors' calculations

3.4.4 Agricultural prices at the national level

Assunção et al. (2015) show that deforestation responds to agricultural output prices. We include two exogenous price variables in our model: soybean and beef prices. Using data from CEPEA (Centro de Estudos Avançados em Economia Aplicada), we gather daily prices of soy[19] and cattle[20], 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

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

[19]https://www.cepea.esalq.usp.br/br/indicador/soja.aspx

[20]https://www.cepea.esalq.usp.br/br/indicador/boi-gordo.aspx

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).

4 Methodology

4.1 PVAR Specification and estimation

Public policies evaluation using panel data is often based on static approaches such as differences in differences (*Diff in Diff* - or DiD) estimations. Yet, they rely on a strong assumption: the treatment is supposed to be exogenous. Moreover, while the treatment can be staggered across panel units, it is usually assumed to happen once. Last, DiD methods may suffer from omitted variables and reverse causality bias. As suggested by the discussion above, our main variables of interest can interact with each other. While the Amazon Fund aims at reducing deforestation in the future, observed rainforest clearing (the outcome of its action) affects in turn its disbursement decisions. The same happens with law enforcement policies, applied in priority in areas where illegal forest clearing has been observed in order to slow it down. Moreover, the Amazon Fund decisions are likely to be influenced by the (negative) "signalling effect" of blacklisting or IBAMA sanctions on a given municipality. Last, agricultural production is not only related to deforestation, but may also affect policy-making when it is in breach with the Forest code.

In order to capture these kind of dynamics we fit, as baseline approach, 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 regressors. A PVAR model is rather data-intensive and relies on strong identification assumptions to infer causality. However, there are several pros. 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). Last, unlike traditional DiD methods, the PVAR enables cross-section units (municipalities) to experience randomly and continuously assigned treatments (the Amazon Fund disbursements), the intensity of which may vary over time.

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 $i = 1, \ldots N$ municipalities, and $t = 1, \ldots T$ 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 exogenous 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 maximum 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 [21]. Also called Helmert procedure, the transformation consists in subtracting from each variable Y_{it} the average of all future available observations as follows:

$$\tilde{Y}_{it} = \sqrt{\frac{T-t}{T-t+1}} \left(Y_{it} - \frac{1}{T-t} \sum_{s=t+1}^{T} Y_{is} \right) \tag{2}$$

Where the term $\sqrt{\frac{T-t}{T-t+1}}$ ensures that the transformed errors are, under certain conditions, homoskedastic and uncorrelated with the original errors (Arellano, 2003)

[21]Compared to other transformation methods, such as first differences, FOD save observations from being dropped when there are data gaps. Moreover, FOD help reduce GMM-estimators' bias as N and T increase (see Phillips, 2022)

Our baseline PVAR encompasses four endogenous variables with panel dimension: deforestation rates, the Amazon Fund disbursements, blacklisting municipalities, and agricultural production. Besides, the prices of two major commodities (beef and soybean) are added as exogenous regressors, varying over time but common to all municipalities. The various PVAR specifications we tested became often unstable when using two or more lags. We thus fit a one-lag model. We use the most parsimonious set of GMM-type instruments:[22] we instrument the first lag of the FOD-transformed endogenous variables by the first lag of the untransformed endogenous variables as well as the contemporaneous untransformed exogenous variables. Thereby, our baseline one-lag model is estimated using 6 instruments. As the number of parameters to estimate equals in this case the number of moment conditions, the system is exactly identified. The statistic generally used to test the validity of instruments (Hansen J-stat test) has zero degrees of freedom and yields no exploitable values. As far as past realizations are excluded from the transformed data, the lagged instrumented regressors become orthogonal with errors and are theoretically valid.[23]

Both in the baseline PVAR and in robustness tests we specify the variables as ratio of flows and rates of growth (see Table 12). The aim is to avoid panel unit roots and ultimately to get a stable structural VAR. All are continuous variables except blacklist, which takes value +1 when a municipality is blacklisted, -1 when it exits the list, and 0 otherwise. Following Hamilton (2020), stationarity [24] 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 circle.

For the sake of efficiency, once FOD-transformed, the equations of the GMM system (1) are jointly estimated (see Holtz-Eakin et al.,1988). Table 2 displays the estimates of our baseline PVAR.

4.2 SVAR Identification scheme

The coefficients of the estimated unrestricted VAR do not necessarily imply causality. For the impulse-response functions (IRFS) to have a causal interpretation, we need to simulate "primitive" orthogonal innovations of endogenous variables, so that they are contemporaneously uncorrelated. We identify such 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. Thereby, the most "exogenous" variable (ordered first) is assumed to be able

[22] Adding further lags to our GMM-type instruments proved also to make the PVAR system quickly instable. Moreover, the proliferation of lags in instrumental variables are likely to make them "weak" (see Roodman(2009)

[23] An application of this GMM estimator to PVAR can be found in Love and Zicchino (2006). For more detail on the statistical package used in PVAR estimation with panel data, see Abrigo and Love (2016)

[24] 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.

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.

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 [25], 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.

As far as agricultural production is concerned, the common wisdom is that logging, raising cattle or setting soybean farms are drivers 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. As described by WWF[26], deforestation leads in the short term to a local increase in the size of the cattle herd, then in the medium term to an increase in crop volumes (which benefit from the organic matter deposited by the cattle).[27] To complete the identification of agricultural shocks, we rely on Granger tests using two lags. Rainforest clearing does Granger-cause both steer growth and soybean production. For a given price of these commodities (which we control for), this pattern suggests that deforestation precedes a large part of agricultural production.

As discussed above, the short-term causality of our law enforcement variables, vis-à-vis deforestation may be bidirectional. On the one hand, satellite support is crucial for monitoring deforestation, allowing policy decisions to be taken on short notice. Since 2004, IBAMA has

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

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

[27]This is also consistent with the spacial distribution highlighted in Figures 11a and 11b. The latter suggest that cattle farms precede soybean crops in the agricultural expansion from the South towards the North of Legal Amazon.

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. Thereby, the Ministry of the Environment and IBAMA are enabled to blacklist and sanction a municipality shortly after infractions are observed. On the other hand, the expected effects of law enforcement are likely to occur rapidly after public injunctions. The interdiction of keeping crops or cattle raising, the forced destruction or the unavailability of heavy equipment and, more generally, the command-and-control component of the blacklisting policy are likely to have a contemporaneous impact on deforestation (Assunção et al., 2014; Assunção and Rocha, 2019). Granger causality tests suggest to place the proxy of law enforcement before deforestation in the pre-ordering.

Our baseline SVAR orders therefore first policy-decisions, then environmental and economic variables: Amazon Fund, blacklisting, deforestation, agricultural production.

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. Our baseline complete specification (column 3) sets four endogenous variables and one lag. As there is a structural break in deforestation data in 2001 (see above) estimations are performed for the sample 2002-2020. Since data on local agricultural GDP is unavailable before 2002 and we specify this variable in rate of growth, in our complete specification (3) to (5) the maximum T is 16 years. The statistical significance of estimates is considered using the usual levels of confidence.

The results from simpler models are consistent with those yield by our baseline specification. As expected, deforestation shows positive autocorrelation, suggesting some inertia in the rainforest clearing. Our main variable of interest, the (lagged) action of the Amazon Fund, is negatively correlated with deforestation rates. Anything else being equal, one additional BRL disbursed per km^2 is related to drop in the deforestation rate of this area the following year. Besides, one year after entering the blacklist, the deforestation rate declines in the average municipality. Agricultural output is in turn positively related to deforestation.

With regards the exogenous variables, the steer price is positively correlated with deforestation rates, as predicted by the model in Section 2. In turn, soybean prices are negatively correlated with contemporaneous deforestation. While this seems at odds with hypothesis 1 in Section 2, we should have in mind that in the model the effect is entirely driven by supply, whereas the observed data reflect an equilibrium price that also embeds demand-side dynamics.

Table 2: Estimation of baseline PVAR - GMM exactly identified system

Response: Deforestation rate (ratio/km^2)	(1)	(2)	(3) Baseline	(4) High Prod. (>50% pct)	(5) Low Prod. (<50% pct)	(6) Dense For. (>75% pct)	(7) Sparse For. (<25% pct)
Endogenous variables [lags]:							
Deforestation rate (ratio/SqKm) [-1]	0.0355***	0.0355***	0.322***	0.425***	0.229***	0.426***	0.0336
	(3.90)	(3.90)	(7.17)	(6.26)	(4.41)	(6.40)	(0.98)
Amazon Fund disbursements (BRL/SqKm) [-1]	-0.000845***	-0.000847***	-0.00108***	-0.00140**	-0.000641**	-0.00115*	-0.000109**
	(-3.35)	(-3.35)	(-3.80)	(-2.35)	(-2.48)	(-1.93)	(-2.55)
Blacklist (enter/exit) [-1]		-0.0675	-0.183***	-0.254***	-0.0843	-0.255***	
		(-1.50)	(-4.09)	(-4.16)	(-1.55)	(-4.91)	
Local agricultural GDP (growth) [-1]			0.000481***	0.000588***	0.000252**	0.000348**	0.0000123
			(4.04)	(3.73)	(2.07)	(2.07)	(1.32)
Exogenous variables:							
Steer price (real growth)	0.000254	0.000227	0.00127***	0.00118**	0.00162***	0.00149*	-0.00000643
	(0.65)	(0.57)	(3.05)	(2.16)	(2.60)	(1.71)	(-0.11)
Soybean price (real growth)	0.000378	0.000382	-0.00181***	-0.00182***	-0.00162***	-0.000743**	-0.000112***
	(1.21)	(1.22)	(-8.48)	(-5.71)	(-5.97)	(-2.54)	(-2.74)
N. observations.	13680	13680	12154	6074	6080	3037	3040
N. municipalities	760	760	760	380	380	190	190
Average N. of years	18	18	15.99	15.98	16	15.98	16
GMM-type instruments	4	5	6	6	6	6	5

Estimation sample: 2002-2020; t statistics in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

All the PVAR models are estimated through GMM a la Arellano and Bover (1995), removing cross-section fixed effects from data by FOD.

Our baseline specification assumes that, for a given level of rainforest clearing inertia, law enforcement, and agricultural output, the impact of the Amazon Fund on deforestation is spatially homogeneous. We extend our baseline results by clustering municipalities according to geographical and economic factors that might matter for green finance efficiency. Both are put forward by the stylized model in section 2.

First, we check the role of agricultural yields in the Amazon Fund's ability to slow down deforestation. For the sake of comparability, the measure of agricultural productivity is generally built from the market value of the output. Due to data limitations in panel, we use the 2010-20 average ratio of local agriculture GDP (in nominal BRL) over the total municipality population as an imperfect proxy of agricultural "productivity". The lowest quartile of the municipalities' distribution has received very few disbursements from the Amazon Fund, making the interquartile comparison non exploitable. We therefore split the cross-section sample into the 50% municipalities above/below the median "productivity" (2.19 BRL/person per year). The columns (4) and (5) of Table 2 show significant and different estimates.

Second, we investigate the role of the rainforest density (see Figure 3). We use the ratio of forest over the total municipality area in 2009 (just before the Amazon Fund started its projects). Thereby, we split the sample into the quartiles of municipalities with higher/lower forest density (respectively, higher or equal than 46.2%/lower than 3.08%). The columns (6) and (7) of Table 2 suggest again a significantly heterogeneous efficiency of green finance depending on whether the rainforest is initially dense or sparse in the treated area.

In all, the unrestricted PVAR estimation underpins the IRFs analysis below.

5.2 Structural VAR (SVAR) analysis

5.2.1 Overall effects on the average municipality

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 13 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 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 (OIRF) tends to vanish, suggesting that the specified variables have no unit roots in panel.

With regards the response of deforestation (Column 3 of Figure 13), the 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 being blacklisted lead both to a significant reduction in deforestation rates in the average

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

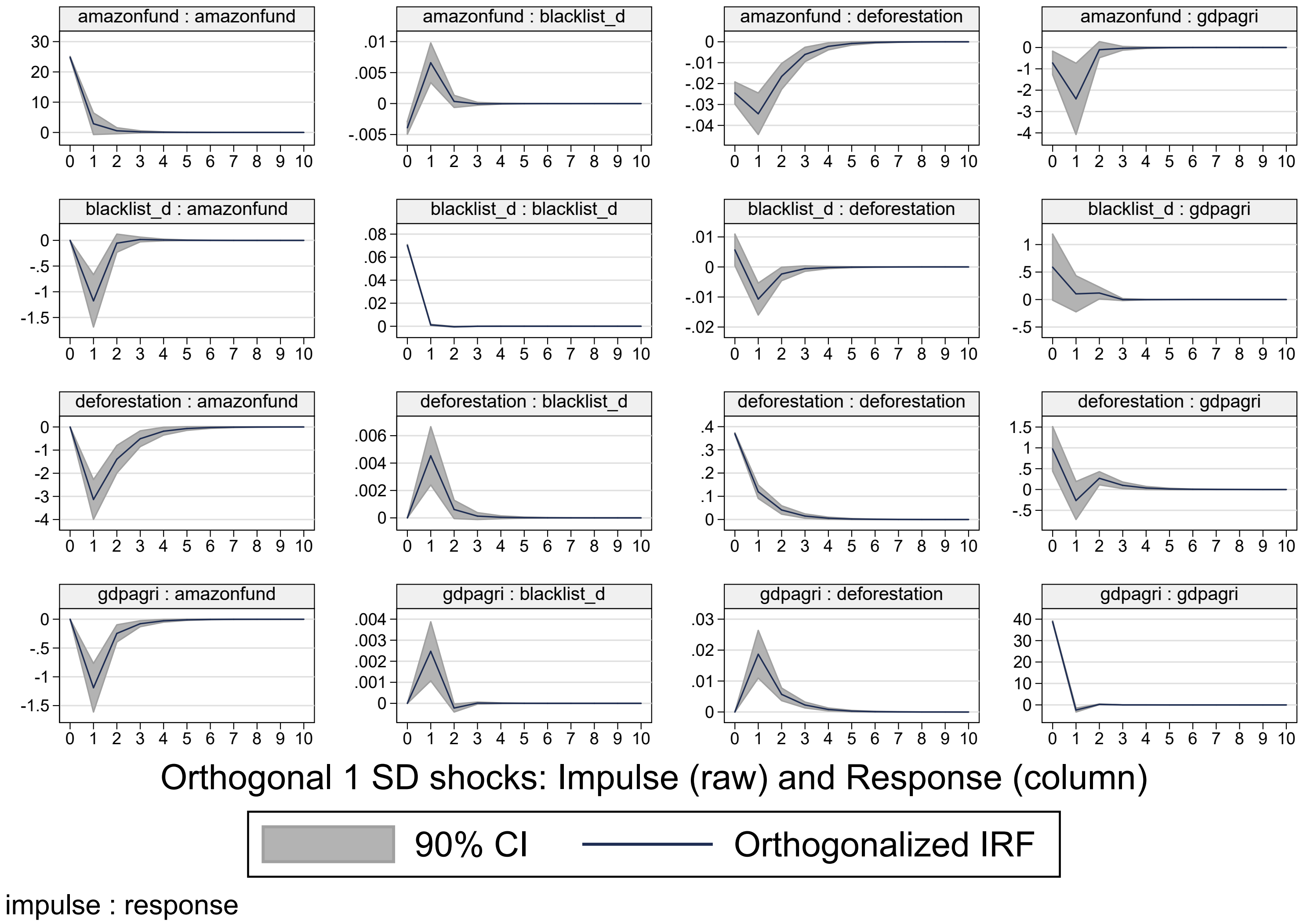
Variables	1 S.D.
Deforestation rate (% ratio/km^2 per Year)	0.369
Amazon Fund disbursement (BRL/km^2 per Year)	24.837
Blacklist (enter/exit)	.0702
Local agricultural GDP (% Y/Y growth)	38.79

Note: The table displays the value of one standard deviation used by IRFs to simulate a shock on each endogenous variable. As series for GDP growth begin in 2003 and we use one additional lag for instruments the sample used in the baseline PVAR estimation and in IRFs is two years shorter than the whole dataset. SD values may thus differ from those in Table 12.

municipality. This is in line with Hypothesis 2 and 3 of the Section 2. The beneficial effect of green finance is smaller but 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 0,00138% of its area from deforestation the following year. This means that the Amazon Fund needs to disburse 721 BRL per km^2 for saving 1% of a municipality area from deforestation in t+1. Entering the blacklist saves 0.152% of the average municipality area from clearing in t+1, but the effect dies out in the next years. Last, +1 pp. in agricultural GDP real growth entails an increase of 0.00048 pp. in the % ratio of deforestation in the average municipality one year after the shock. This effect is modest and has has to be read with the statistical distribution of the variable in mind: with an important time and cross-section dispersion (see Figure 11), over the whole sample agricultural GDP has grown by more than 8% per year in the average municipality (see Table 12). This means that barely 0.004% of deforested area every year may be imputable to the previous year agricultural GDP growth on average. The effect of agricultural output is diluted by the magnitude of the aggregate variable, measured in BRL value, but it is robust to all specifications (see Table 4)

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 13). In particular (line 3 of IRFs), 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 agricultural GDP growth entails a similar effect, leading to a drop in Amazon Fund disbursements. Both a rise in deforestation and in agricultural output make the average municipality more likely to enter the blacklist (column 2). Consistently with the support to public policies characteristic of the Amazon Fund's projects, *ceteris paribus* with a one year lag the Ministry of Environment's sanctions (captured by the blacklisting decision) positively react to the Fund's disbursements. Law enforcement seems therefore to be strengthened by green finance.

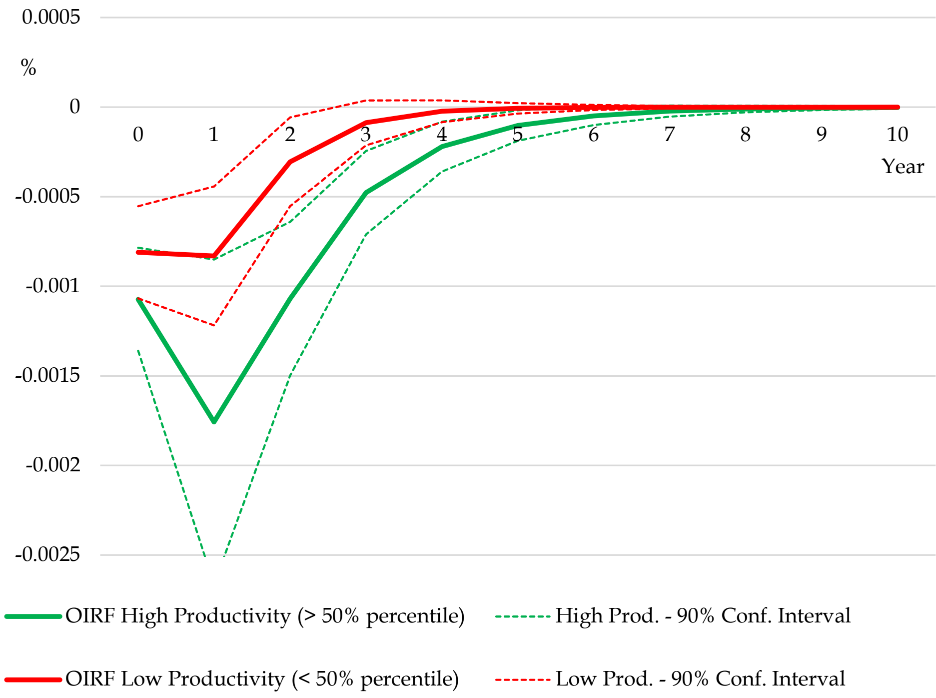
Figure 13: IRFs - all endogenous variables



5.2.2 Spatial heterogeneity: clustering municipalities according to economic and geographic features

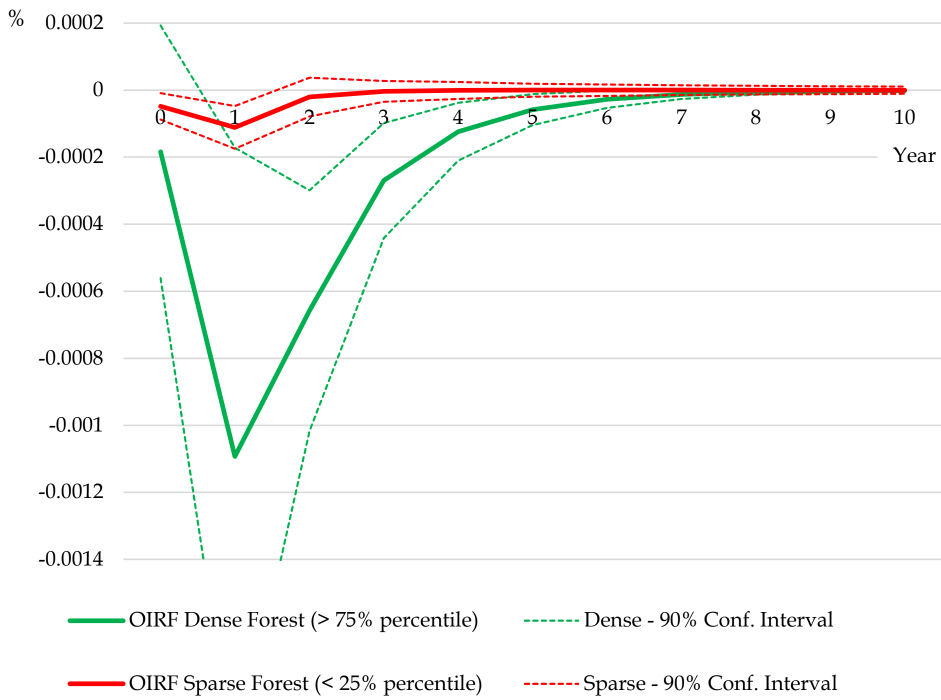
In the subsequent analysis, we normalize the OIRFs by one standard deviation to get a readable response in terms of BRL disbursed. When splitting the sample of municipalities by low/high agricultural productivity (see Section 5.1), the IRFs in Figure 14 show that the Amazon Fund is more efficient within the more productive cohort of municipalities on average for the period 2010-2020. This is at odds with Hypothesis 4 in Section 2. We find two alternative interpretations: i/ green finance manages to reduce deforestation particularly in municipalities where the growth of agricultural production is based in more intensive lands' use, rather than in clearing new areas; ii/ while a municipality may face larger opportunity costs when its productivity is high, its institutions may also be better equipped to receive funding from the Amazon Fund and BNDES. Both the agricultural dynamics and the institutional dimension are overlooked in the model.

Figure 14: IRFs - Impact of +1 BRL/km^2 of Amazon Fund disbursements on % deforestation/km^2 by **local agricultural productivity**



Moreover, the Figure 15 shows that the impact of the Amazon Fund on deforestation reduction is much stronger (up to ten times in year $t+1$) and long-lasting within the quartile of municipalities with higher rainforest density, compared to the quartile of municipalities where the rainforest is sparse. This appears consistent with Hypothesis 5 of section 2, although the underlying explanation may differ: municipalities that have managed to conserve a high level of forest are likely to have institutions better equipped to use the Amazon Fund disbursements effectively, regardless of the incentive mechanisms linked to environmental feedback suggested by the model.

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



5.2.3 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 precisely, for a green taxonomy: 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. We normalize again the responses' trajectories by the standard deviation of each type of project's series, to get readable results in terms of units.

By axis (Figure 16), projects devoted to land use planning (27 of the 103 projects at least focus on this axis) rank first in terms of efficiency, followed by projects allocated to monitoring and control systems. Somewhat surprisingly, sustainable production projects are less efficient than the average (represented by the dotted line).

The difference in impact between the various themes (Figure 17) is less clear than in the case of the axes. In the first year after a shock, projects aimed at fighting illegal fires are more efficient than the other ones. Yet, only 6 projects were conducted in this theme, compared to more than 20 for the other categories (Figure 3.2). This result should therefore be taken with caution. In the very short run, projets related to the Rural Environment Registry are the most efficient ones. Settlement projects, aimed at areas that have presented high deforestation rates, are less efficient than the average. This is consistent with our above finding: at the aggregate level, the deforestation reduction related to Amazon Fund disbursements is higher in areas where the rainforest is more dense.

Figure 16: IRFs - Impact of +1 BRL/km^2 of Amazon Fund disbursements on % deforestation/km^2 by project's **axis**

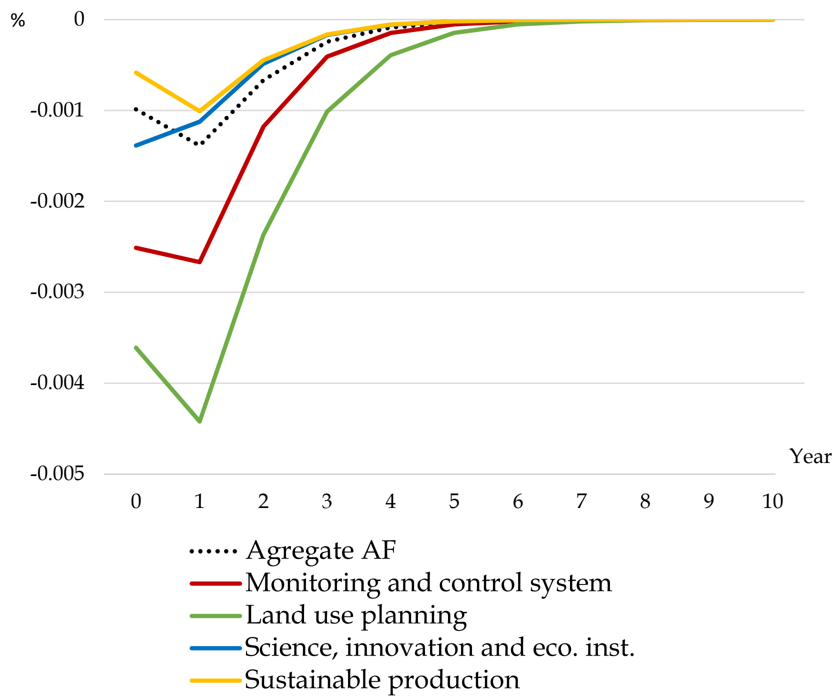
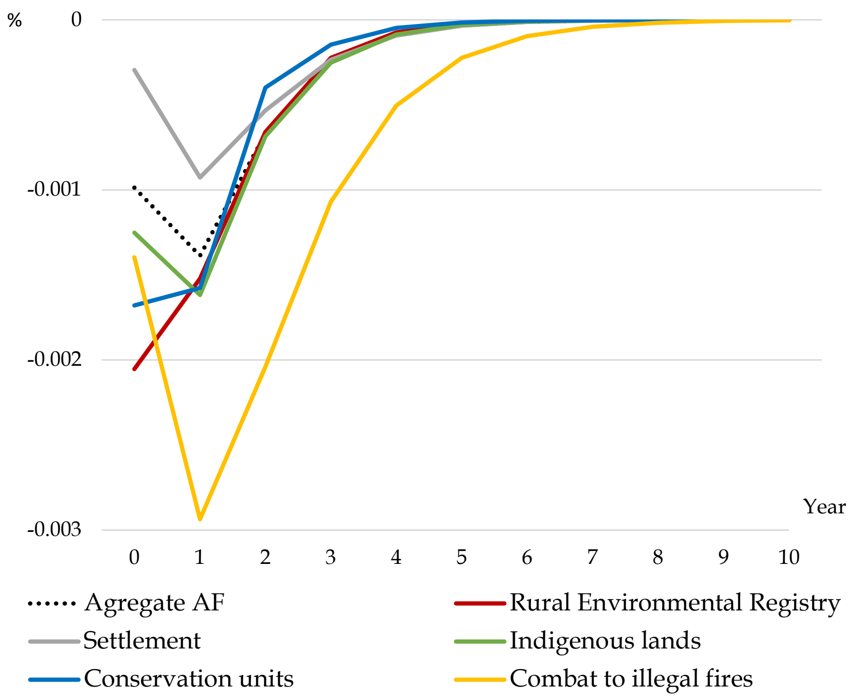
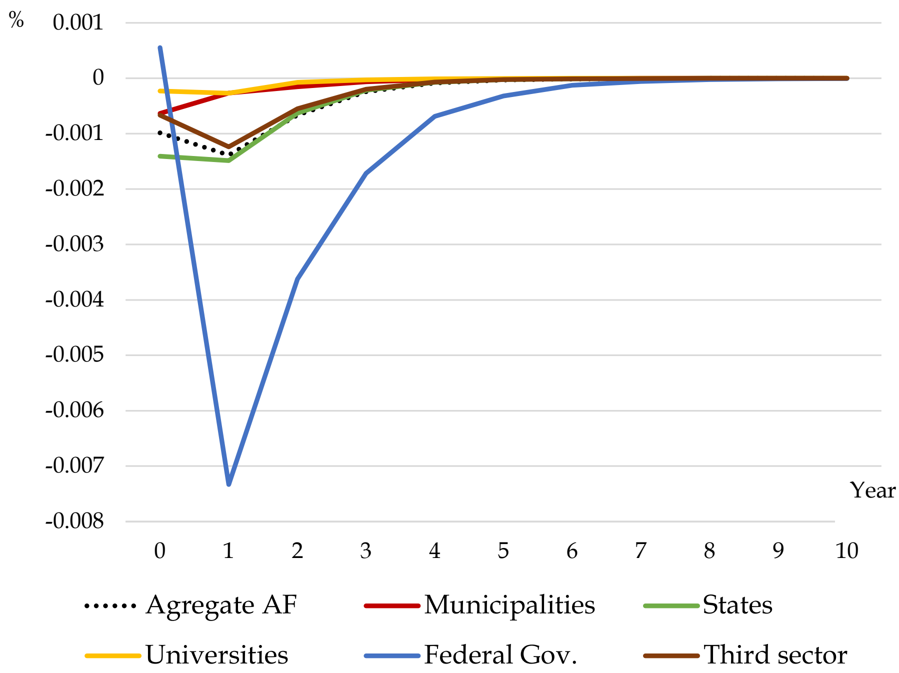


Figure 17: IRFs - Impact of +1 BRL/km^2 of Amazon Fund disbursements on % deforestation/km^2 by project's **theme**



When broken down by recipient (Figure 18), a clear pattern emerges: the higher the level of government within the federal structure the greater the efficiency. Projects led by the federal government tend to be more efficient than those led by states, which are in turn more efficient than those managed by municipalities or universities (the latter account only for 7 and 6 projects, respectively). As most of the projects are conducted by a third sector recipient (59 of them), the average aggregate response is driven by the results for this subset.We provide further interpretation of our findings in terms of policy implications in section 6.

Figure 18: IRFs - Impact of +1 BRL/km^2 of Amazon Fund disbursements on % deforestation/km^2 by **recipient** body



5.3 Robustness tests

5.3.1 Alternative specifications and estimation methods

We carry out a number of sensitivity checks using different samples, alternative variables and specifications, and other estimation methods. Table 4 displays the main results, compared to our baseline model (column 1). We estimate our PVAR restricted to the sample period in which the Amazon Fund has been operating, ie. from 2008 on (col. 2). To check the validity of instruments, we run the regression adding to our GMM-type instruments the contemporaneous and one-lag rural credit growth, so that we get an over-identified system. Thereby the moment conditions exceed the number of parameters to estimate (which corresponds to the degrees of freedom of the J-Statistic), and the Hansen test becomes exploitable. We do so starting from our PVAR baseline model (col. 3) and specifying as well a single equation model estimated through 2SLS, with the data FOD-demeaned and the instruments added the same way as in the baseline PVAR (col. 9). We then replace several variables in our baseline specification by alternative measures (also with panel dimension). Blacklist is replaced by the value of IBAMA fines (col. 4). In order to test a physical measure of agricultural output instead of the local agriculture GDP, we use the wood production while controlling for export timber-prices (col. 5). [28] Local rural credit is added as another endogenous variable to our baseline specification (col.

[28]As soybean production has too many zero observations, we tested as alternative commodity production the growth of the steer stock. While the latter turned out to be non-statistically significant, our main results

6). We remove the cross-sectional mean before estimating our baseline PVAR to expunge the results from common time fixed effects (col 7). Last, along with 2SLS, we estimate a standard OLS with fixed-effects by municipalities (col. 8). All regressions are set to yield standard errors robust to intra-group correlation. In both over-identified models (3 and 9), the Hansen J-stat p-value suggests that our instruments are uncorrelated with the error term. The alternative and additional variables in models 4 to 6 are not statistically significant. Yet the negative correlation of deforestation rates with the Amazon Fund disbursements remains significant in all the models (around -0.001). Its absolute value increases when restricting the sample to the more recent period (2) and drops notably when removing time-FE (7).

remained unchanged. For the sake of space, the Table 4 only displays the estimation with wood production, which shows the best fit of the commodities tested.

Table 4: Alternative specifications and estimation methods

	Panel VAR							Single Equation Model	
Response: Deforestation rate (ratio/km^2)	(1) Baseline	(2) t >2008	(3) Overid.	(4) IBAMA	(5) Wood	(6) CredAgri.	(7) Time FE	(8 OLS FE	(9) 2SLS Overid.
Endogenous variables [lags]:									
Deforestation rate (ratio/SqKm) [-1]	0.322***	-0.0741**	0.331***	0.322***	0.0302***	0.331***	0.259***	0.259***	0.341***
	(7.17)	(-2.16)	(7.09)	(7.17)	(3.50)	(6.83)	(6.23)	(6.74)	(9.34)
Amazon Fund disburs. (BRL/SqKm) [-1]	-0.00108***	-0.00186***	-0.00126***	-0.00108***	-0.00244***	-0.00103***	-0.000393***	-0.000825***	-0.00078***
	(-3.80)	(-6.53)	(-4.59)	(-3.78)	(-6.08)	(-3.41)	(-3.95)	(-5.00)	(-3.98)
Blacklist (enter/exit) [-1]	-0.183***	-0.0733	-0.210***		-0.137***	-0.185***	-0.137***	-0.264***	-0.177***
	(-4.09)	(-1.57)	(-4.51)		(-2.89)	(-4.11)	(-3.11)	(-5.64)	(-4.04)
Local agricultural GDP (growth) [-1]	0.000481***	-0.000282***	0.000599***	0.000471***		0.000614***	0.000191**	0.000344***	0.00061***
	(4.04)	(-4.46)	(4.37)	(3.99)		(4.50)	(2.18)	(3.43)	(4.65)
Ibama fines (BRL/SqKm) [-1]				-0.00000117					
				(-1.07)					
Wood extraction (m3 per year) [-1]					0.00000119***				
					(4.43)				
Local credit to agri. (real growth) [-1]						-0.00000073			
						(-0.26)			
Exogenous variables:									
Steer price (real growth)	0.00127***	-0.00119***	0.00138***	0.00135***	0.00189***	0.00143***		0.000979***	0.00120***
	(3.05)	(-3.28)	(3.43)	(3.22)	(4.50)	(3.18)		(4.12)	(4.84)
Soybean price (real growth)	-0.00181***	-0.000770***	-0.00183***	-0.00183***	0.000687**	-0.00181***		-0.00181***	-0.00172***
	(-8.48)	(-5.00)	(-8.50)	(-8.58)	(2.21)	(-7.57)		(-10.19)	(-9.49)
Timber wood - export price in USD (growth)					0.00341***				
					(16.34)				
N. observations.	12154	8360	11442	12090	13179	11395	12154	12914	11442
N. municipalities	760	760	757	756	760	755	760	760	757
Average N. of years	15.99	11	15.11	15.99	17.34	15.09	15.992	17.0	15.11
Adj. R2							0.151	0.151	
GMM-type instruments	6	6	6	6	7	7	4		6
Other instruments			2						2
J-stat DF	0	0	8	0	0	0	0		2
Hansen J-stat p-value			0.919						0.456

Estimation sample: 2002-2020 except col. (2); t statistics in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

All the PVAR models are estimated through GMM a la Arellano and Bover (1995), removing cross-section fixed effects from data by FOD.

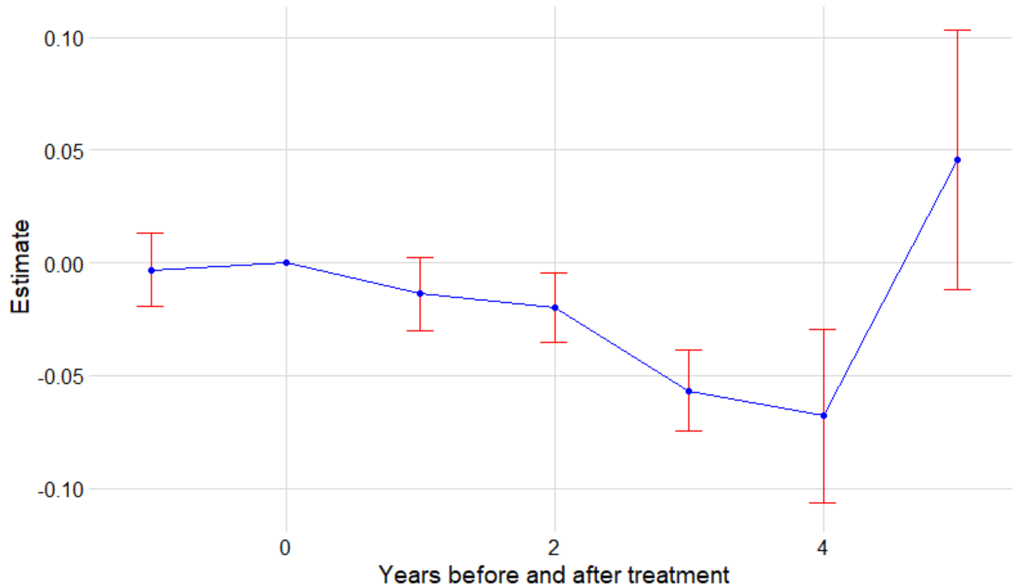
OLS FE estimation includes a constant not reported in the table; Adj. R2 *within* for OLS FE estimation, and *uncentered* for 2SLS

5.3.2 Difference-in-Differences Estimator and Event study

In this section, we estimate the effect of Amazon Fund disbursements on deforestation using a Difference-in-Differences (DiD) framework. Specifically, we follow the methodology of De Chaisemartin and d'Haultfoeuille (2024)[29], which accommodates non-binary treatments that can vary in intensity over time.

We define the treatment as the maximum of two values: (i) the difference between the actual disbursement and the median disbursement over the period 2010–2020 (10.6 reais/year/km^2) and (ii) zero. Namely, a municipality is considered untreated until its disbursement exceeds the median level. This assumption is reasonable given that the distribution of disbursements is highly right-skewed (see Figure 26). We control for the blacklisting of municipalities, their agricultural GDP and the intensity of law enforcement. We check the effects both weighting the estimation by the area of municipalities (Figure 19) and not weighting it (Figure 20).

Figure 19: Event study: effect of the Amazon Fund disbursements (reais per km^2) on annual deforestation rates in p.p.



Consistent with our baseline results, Figure 19 shows that the Amazon fund has a negative impact on deforestation.

Table 5: Estimation of Treatment Effects: Event-Study Effects

	Estimate	SE	LB CI	UB CI	N	Switchers	N.w	Switchers.w
Effect_1	-0.01378	0.00833	-0.03010	0.00254	3,418	405	21,680,038	2,755,909
Effect_2	-0.01979	0.00788	-0.03523	-0.00434	2,492	232	16,081,801	2,179,152
Effect_3	-0.05686	0.00913	-0.07475	-0.03897	1,643	89	10,269,083	945,612
Effect_4	-0.06794	0.01957	-0.10630	-0.02958	937	54	5,689,905	488,870
Effect_5	0.04551	0.02930	-0.01193	0.10294	362	7	2,358,707	46,568
Test of joint nullity of the effects: p-value = 0.0000								

[29]We use the R package DIDmultiplegtDYN.

The temporality of the effect differs from that observed in IRFs: the most significant negative impact is observed between 3 and 4 years after the shock (Table 8), compared with 1 year in the case of IRFs. This can be explained by the fact that the notion of shock is not exactly the same in both cases. In the case of the event study, the shock necessarily occurs when disbursements first exceed the median value of 10.6 reais/year/km^2, while IRFs display a synthetic shock of one standard deviation that is not a priori set in time.

Table 6: Average Cumulative (Total) Effect per Treatment Unit

	Estimate	SE	LB CI	UB CI	N	Switchers	N.w	Switchers.w
Average	-0.00072	0.00020	-0.00111	-0.00032	3,800	787	25,340,240	6,416,111
Average number of time periods over which a treatment effect is accumulated: 1.8902								

As shown in Table 6, the order of magnitude of the cumulative effect appears smaller, but not far from those observed with the macroeconometric exercise.

Table 7: Testing the Parallel Trends and No Anticipation Assumptions

	Estimate	SE	LB CI	UB CI	N	Switchers	N.w	Switchers.w
Test	-0.00328	0.00824	-0.01943	0.01288	3,418	405	21,680,038	2,755,909

The pre-trend estimated coefficient ($\beta = 0.00328$) is small in magnitude, and its confidence interval includes zero. Namely, there is no evidence of pre-trends or anticipatory effects. Following De Chaisemartin and d'Haultfoeuille (2024), this ensures that treatment effect estimates are not driven by violations of the parallel trends assumption.

Figure 20: Event study: effect of the Amazon Fund disbursements (reais per km^2) on annual deforestation rates in p.p. (non-weighted)

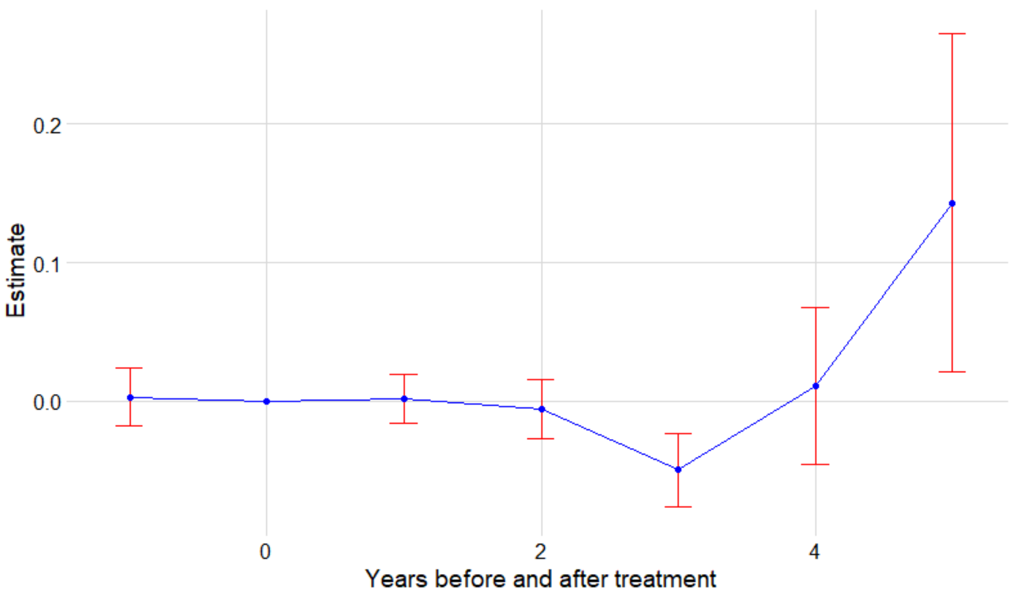


Table 8: Estimation of treatment effects

	Estimate	SE	LB CI	UB CI	N	Switchers
Effect_1	0.00171	0.00900	-0.01592	0.01934	3,418	405
Effect_2	-0.00547	0.01086	-0.02676	0.01582	2,492	232
Effect_3	-0.04976	0.01340	-0.07601	-0.02350	1,643	89
Effect_4	0.01113	0.02897	-0.04566	0.06792	937	54
Effect_5	0.14322	0.06214	0.02142	0.26502	362	7

5.4 Counterfactual analysis and abatement cost

Beyond knowing to what extent the Amazon Fund disbursements are effective overall in reducing deforestation, we seek to find out whether they are efficient. To this end, we use a classic environmental economics tool: the abatement cost. We first 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[30]. 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 367 tCO2[31].

In order to estimate the abatement cost we build a counterfactual aggregate deforestation curve. 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. Since the GMM approach demeans by FOD all the variables before estimation (see section 4), after the initial forecast we undo the transformation described in the expression 2 to get predictions non-centered around zero.

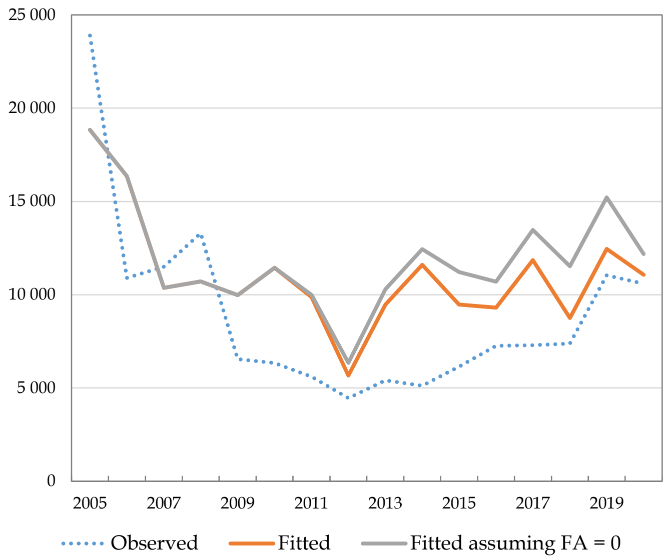
According to the counterfactual run from our baseline PVAR (Table 4, col.1), between January 1, 2010 and December 31, 2020, the cumulative difference between the two predicted deforestation rates amounts to 13848 km^2 (Figure 21 a). In the very same period, 1280 million BRL were disbursed by the Amazon 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 2.52 BRL/tCO2 (about 0.42 EUR). We complete this figure using a more conservative estimation: when removing time-fixed effects (Table 4, col.7) our counterfactual yields an abatement cost of 6.95 BRL/tCO2 (about 1.12 EUR).

[30]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)

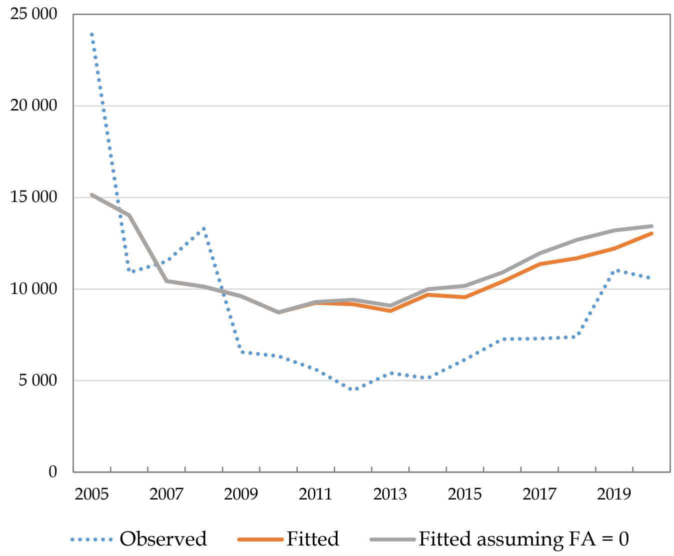
[31]As confirmed by the "Ministério do Meio Ambiente" (Nota Técnica n.22 / 2011 / DPCD / SECEX. Technical note, Departamento de Políticas para o Combate ao Desmatamento)

Note that in both cases the data sample starts in 2002. The high deforestation rates observed at the beginning of the sample make appear a strong degree of inertia in our estimation. Hence the upward bias of the predictions displayed in Figure 21 (a, b). Since the bias affects the forecast both including and removing the Amazon fund action, the counterfactual exercise remains reliable. For the sake of comparability, we run a counterfactual based on an estimation sample from 2008 on (Table 4, col.2). The predictions 21 (c) match better the observed deforestation in levels, but look more inaccurate in terms of variations.

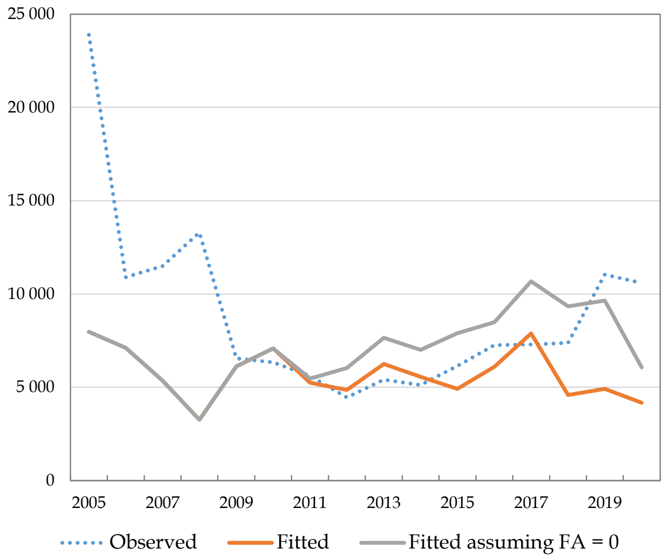
Figure 21: Counterfactual - Deforestation in Legal Amazonia (total km^2/year)



(a) Baseline PVAR



(b) PVAR (7) - Time-FE



(c) PVAR (2) - t >2008

Source: Amazon Fund and authors' calculations

We can take these figures as an upper bound on the average abatement cost for two main reasons:

- 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, 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.

Our results should be taken with 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 blacklisting policies by the Ministry of Environmentand and IBAMA fines. Yet this is a noisy measure of the evolution of the authorities' ability and willingness to enforce the law aiming at fighting deforestation. Sanctions 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.

It is also important to highlight that the ecological benefits of the Amazon Fund—alongside its social co-benefits—extend beyond carbon storage. The fund also helps reduce the leading driver of biodiversity loss, as identified by IPBES: land-use change (2019). Effective conservation policies require a precise understanding of the costs of preserving natural habitats (Strassburg et al., 2020). By estimating the conservation costs associated with the Amazon Fund's actions, this paper moves beyond the commonly used agricultural opportunity costs, offering a more comprehensive basis for prioritizing conservation efforts.

6 Conclusion and policy implications

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 Amazon, such as the one conducted in this paper, can serve as a support for other initiatives around the world and shed some light on the type of projects to be prioritized in green taxonomies. 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 insights for policy-makers and green funders.

The first set of policy implications is related to the role of agricultural activities in deforestation in Brazilian Amazon. As expected, the municipalities where agricultural production grows experience a rise in rainforest clearing. Yet, the dynamics of the main agricultural commodities differ. The spatial distribution shows that cattle farms tend to precede crops at the local level. Notwithstanding, public policies should continue to target soy as well. The 2006 Soy Moratorium is likely to have helped slow down deforestation. Both cattle and soybean tend to be produced in the wake of logging. Local wood production, in parallel with international timber prices, appear as the most significant driver of rainforest clearing among the main agricultural commodities. Controlling illegal logging and wood smuggling and, ultimately, promoting alternative materials to reduce the international demand for timber is crucial in the fight for deforestation.

Second, monitoring efforts need proper law enforcement mechanisms to be effective against deforestation. Blacklisting municipalities, combined with economic incentives to exit the blacklist, helps to slow down deforestation.

Third (and main) set of policy conclusions: properly designed green finance manages to reduce significantly deforestation rates. The action of the Amazon Fund interacts with (and works through) other key factors. i/ Promoting agricultural productivity (in terms of per capita agricultural output) rather than extensive use of new lands helps to enhance the efficacy of green finance in fighting deforestation. Yet, it is worth noting that, while increasing agricultural productivity can save land, it can also create local pollution (pesticides, fertilizers) that is harmful to biodiversity. ii/ Some of the Funds' main successful projects, such as those related to monitoring and control systems or to the Rural Environmental Registry (CAR) enforcement, facilitate the action of environmental agencies. Green finance, agricultural productivity, and law enforcement may thus benefit from important synergies. iii/ At a more disaggregated level, some types of projects need relatively less funding to fight deforestation. By recipient, projects managed at the federal or state level are more efficient than those managed by municipalities. This is probably due to the taxonomy (axis and theme) of the projects, rather than to the level of governance. Federal government and states' projects are to a large extent related to actions that yield immediate gains against deforestation, such as monitoring, enforcing environmental regulation (CAR) and fighting illegal fires. In turn, tools that fight deforestation in a more indirect way or rather in the long run, such as fostering sustainable production or science

& innovation activities, are typically led by the third sector (eg. NGOs, foundations) and universities. Our findings do not call for a public top-down approach in the allocation of disbursements, though. Land use planning, which is the most efficient axis, corresponds to projects most often led by the third sector and aimed at empowering local autochthonous communities in protected areas. Strengthening the social roots in indigenous lands is thus a highly efficient way to fight against rainforest clearing.

In all, the Amazon Fund appears to be an efficient tool to slow down deforestation. Moreover, by estimating the conservation costs associated with the Amazon Fund's actions, this paper moves beyond the commonly used agricultural opportunity costs, offering a more comprehensive basis for prioritizing conservation efforts. After converting the number of km^2 of saved deforestation into the number of avoided tCO_2 emissions, we obtain a low abatement cost (between 0.42 and 1.12 EUR per tonne of CO_2). Yet, these figures are 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 beneficial effect attributed *ceteris paribus* to the Amazon Fund might be overestimated.

Last but not least, the fund also helps reduce the leading driver of biodiversity loss, as identified by IPBES: land-use change (2019). Effective conservation policies require a precise understanding of the costs of preserving natural habitats (Strassburg et al., 2020). Some projects' axis, such as science, innovation and economic instruments, the efficiency of which in terms of deforestation reduction are slightly lower than the average, specifically target "the recovery, conservation, and sustainable use of biodiversity". Further research should address the ecological benefits of the Amazon Fund—alongside its social co-benefits—beyond carbon storage.

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A Additional figures

Figure 22: Amazon Fund Allocation Process: From Donors to Municipalities (ann example)

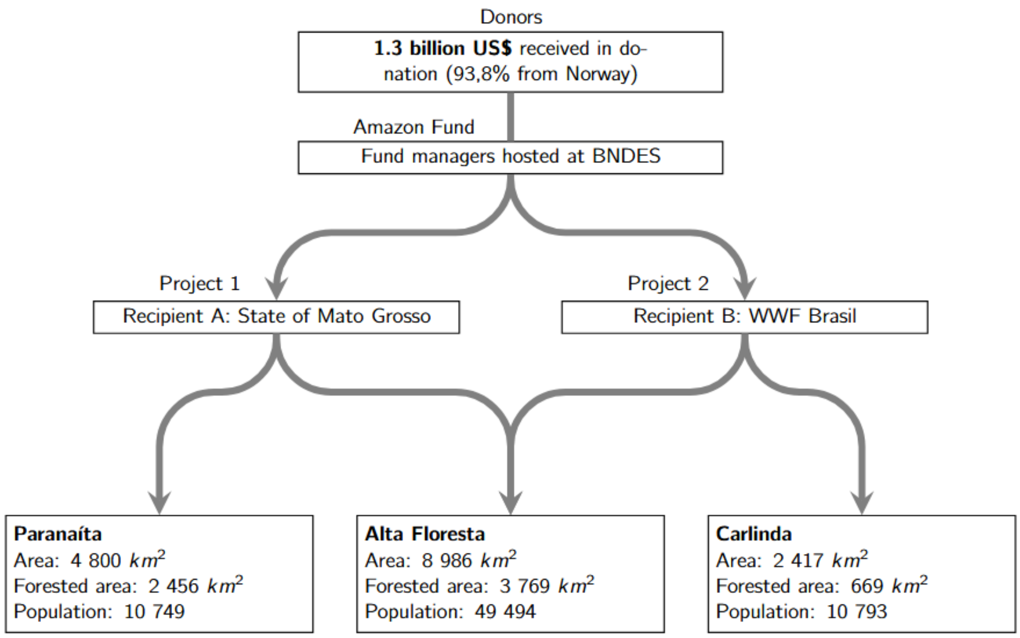


Figure 23: Proxy Allocation of Funds to Municipalities

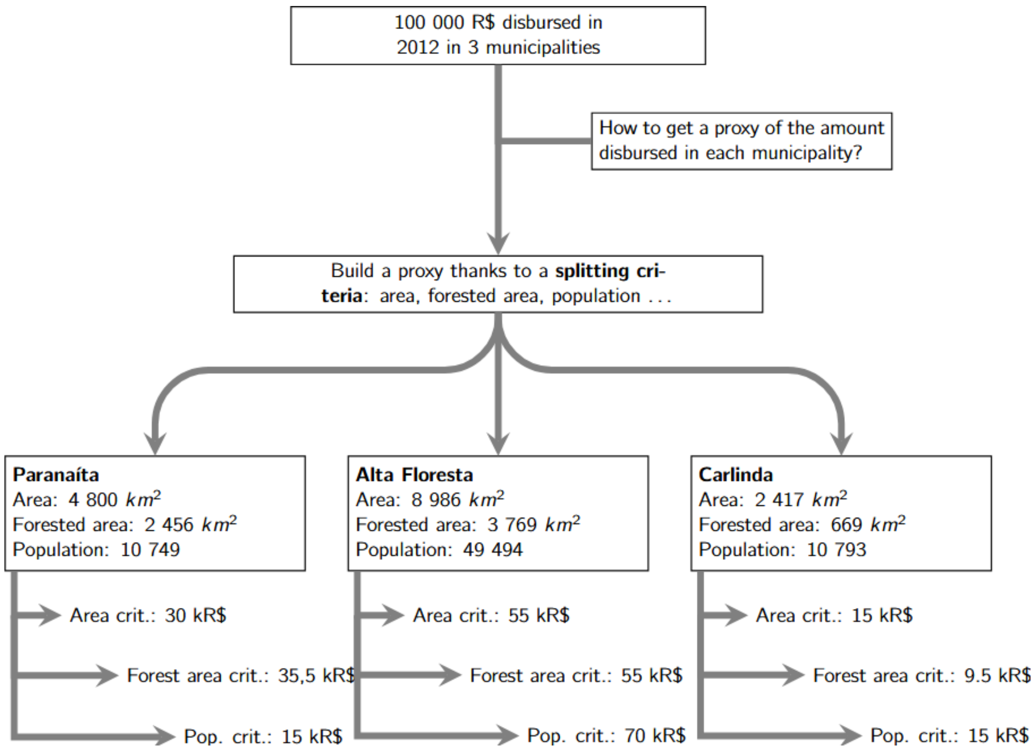


Figure 24: Optimal deforestation stock path for different values of R

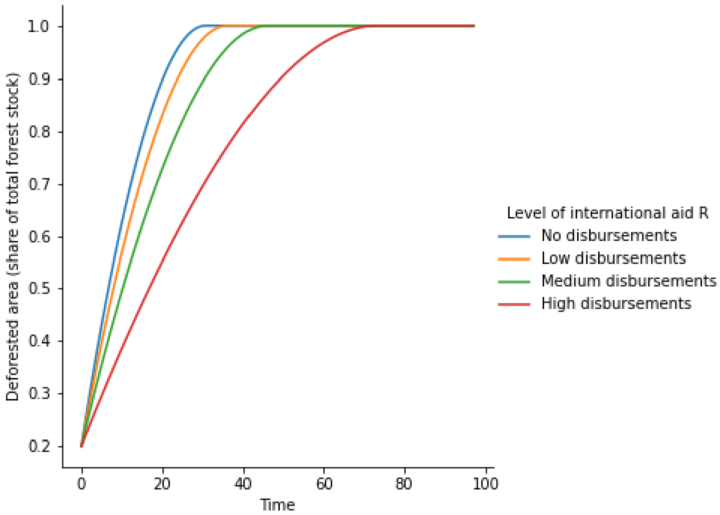


Figure 25: Spatial concentration of projects per type of recipient

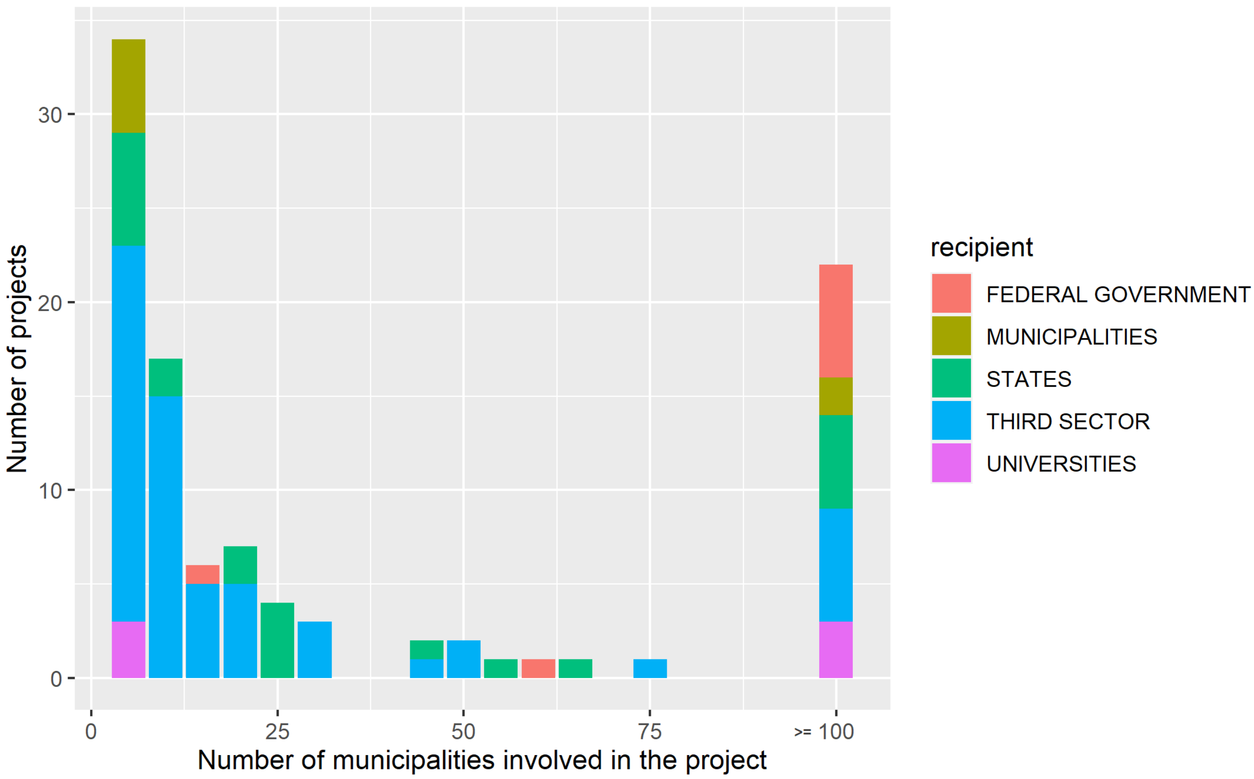
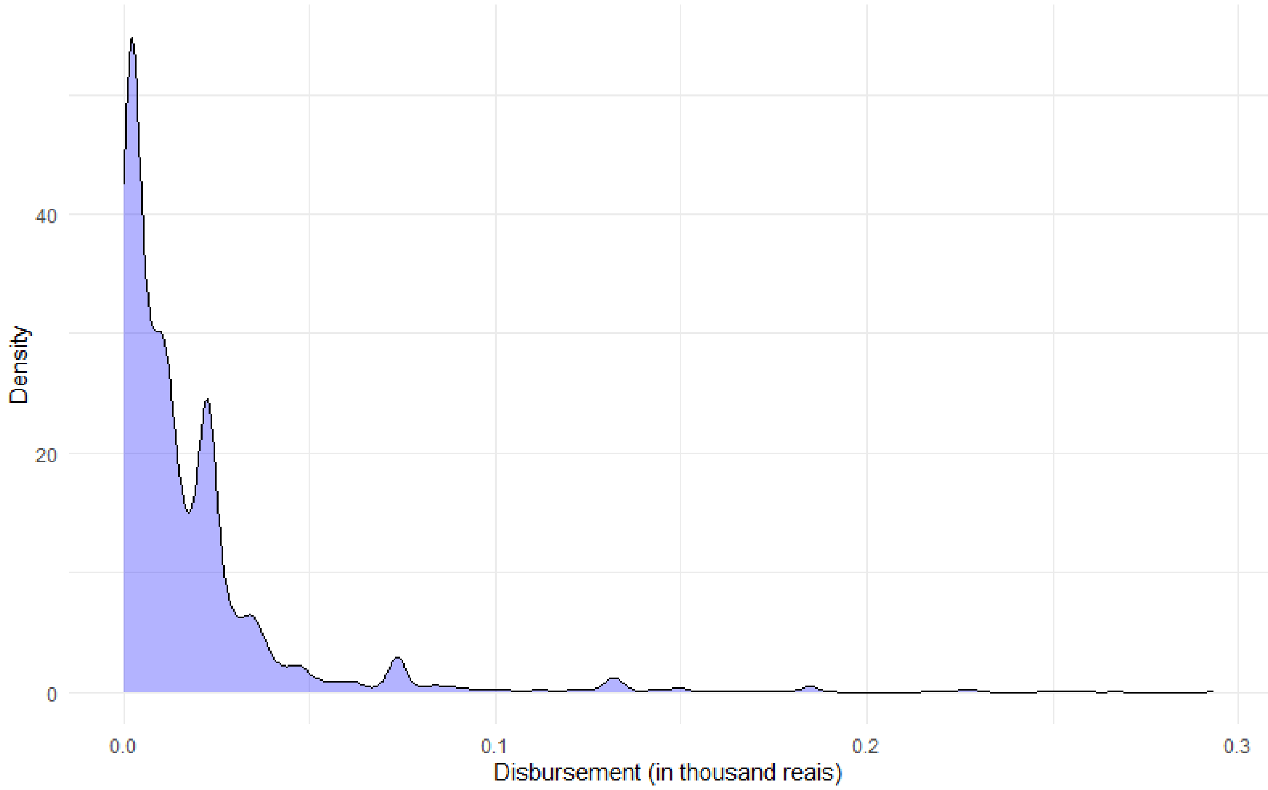


Figure 26: Density of disbursments on the period 2010-2020.



B Additional tables

Table 9: 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.

Table 10: List of the 102 projects and their main features

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	2010
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 11: Breakdown of each project by axis

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 12: Variables used in estimations and main descriptive statistics of the sample (2002-2020)

Variables	(1) N. obs	(2) Mean	(3) S.D.	(4) Min	(5) Max
Endogenous panel variables used in baseline specification					
Deforestation rate (% ratio/SqKm per Year)	14,440	0.282	0.725	0	20.65
Amazon Fund disbursement (BRL/SqKm per Year)	14,440	10.82	27.14	0	615.5
Blacklist (enter =1; exit =-1; no change =0)	14,440	0.00395	0.0659	-1	1
Agriculture GDP (% Y/Y real growth)	13,674	8.218	43.49	-96.34	1,805
Endogenous panel variables used in robustness tests					
Ibama fines (BRL/SqKm per Year)	14,364	380.3	2,568	0	122,215
Wood extraction (m3 per year)	14,026	1,7384.16	71,035.86	0	1,521,233
Local credit to agriculture (% Y/Y real growth)	13,682	112.3	1,215	-100	73,082
Exogenous (aggregate) variables					
Steer price (% Y/Y real growth)	19	2.443	12.97	-15.30	33.02
Soybean price (% Y/Y real growth)	19	2.914	19.43	-30.88	44.34
Timber wood - export price in USD (% Y/Y growth)	19	15.07	47.122	-44.995	139.58

Note: The table displays the transformation of variables used in our regressions (before taking FOD). A lower number of observations may be used in estimation due to lags in the VAR system and in GMM-type instruments (see Table 2)

Figure 27: 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"