Three essays on Brazil's deforestation control policies and their potential effects: Conflicts, Compliance, and Secondary Forest recovery

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ABSTRACT

Brazil reduced its annual deforested area from 27772 km^2 to 4571 km^2 from 2004 to 2012. This phenomenal achievement resulted from multiple government initiatives, most notably the Action Plan for the Prevention and Control of Deforestation in the Legal Amazon (PPCDAm). However, these ambitious deforestation control policies yield multiple spillover effects. This dissertation examines the effects of the two initiatives from the PPCDAm program, namely the Forest Code of 2012 and the Green Municipality Program. Chapter one provides causal evidence that land registration abates conflicts in Pará. The chapter discusses policy implications in three discussions, prospective deforestation control, potential agricultural growth, and livelihoods promotion within CAR and its related policies. The results from this chapter provoke a question about the drop in land conflicts that stimulates forest conservation on private landholdings. Thereon, my second chapter deals with the dynamic land clearing decision of private landholders in the Brazilian Amazon. The results suggest that the persistence of compliance, thus forest conservation on privately held land, is driven mainly by past compliance and municipality-level incentives. As these two chapters established that land registration abates conflicts, and private landholders are driven by specific incentives to preserve the forest on their land. My third chapter investigates the impact of the provincial governance promotion program on secondary forest recovery. Municipalities participating in the local government improvement program steadily observe an expansion in secondary forest areas. To sum up, my dissertation explores the spillover effects of the deforestation control policy, starting with achieving fewer land conflicts and investigating the local incentives to promote forest protection on private land. Lastly, I provide evidence that the governance promotion program will result in secondary forest recovery.

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GENERAL AUDIENCE ABSTRACT

Brazil reduced its annual deforested area from 27772 km^2 to 4571 km^2 from 2004 to 2012. This phenomenal achievement resulted from multiple government initiatives, most notably the Action Plan for the Prevention and Control of Deforestation in the Legal Amazon (PPCDAm). This dissertation presents the unintended consequences of two policies under PPCDAm, namely the Forest Code of 2012 and the Green Municipality Program, on land conflicts, environmental policy compliance, and secondary forest recovery. The first chapter provides robust evidence that perceived land tenure security (via land registration) effectively reduces land conflicts. Further, the chapter invokes if the drop in land conflicts stimulates forest conservation on private landholdings. Subsequently, my second chapter deals with the dynamic land clearing decision of private landholders in the Brazilian Amazon. The results suggest that the persistence of compliance, thus forest conservation on privately held land, is driven mainly by past compliance and municipality-level incentives. As these two chapters established that land registration abates conflicts, and private landholders are driven by specific incentives to preserve the forest on their land. My third chapter investigates the impact of the provincial governance promotion program on secondary forest recovery. Municipalities participating in the local government improvement program steadily observe an expansion in secondary forest areas. In summary, the dissertation begins with a study of the unintended consequences of the deforestation control policy, starting with achieving fewer land conflicts. Then, I present a study of the local incentives to promote forest protection on private land. Lastly, I present that the local governance promotion program will result in secondary forest recovery.

Dedication

During my master's, I met several smallholder families from Mato Grosso, Minas Gerais, and Bahia. Their stories were inspiring, provoking, and relatable.

To Landless Peasants of Brazil

The memory and lessons I learned from

Dr. Narendra Dabholkar

(1945 –2013)

And

Comrade Sharad Patil

(1925–2014)

Acknowledgment

One's experience in Ph.D. is full of tales; some of the tales are funny, a few are tragic, but they are all either amusing or gratifying. And the last bit depends on your version of Ph.D. My tale can be summarized in the eternal words of Maya Angelou, "anything that works against you can also work for you once you understand the Principle of Reverse." I spent a significant decade after completing my undergrad in engineering—traveling, working, and learning—first with students and then with labor unions in India and Brazil. While I earned valuable knowledge, insight, and experience, my partial academic training in economics failed to meet the demands of first-year grad students. This drove me into recurring despair, anxiety, and more. The pandemic did not help. More than half of this dissertation is thought, prepared, and perhaps first written while I was on phone calls to India, scavenging for medication, oxygen tanks, and eventually for hope. During this, I began reminiscing about my travel & experiences of encountering new languages, people-places, and their tales. And I uncovered the rationale for pursuing the research— for me; it is about striving against the odds of my circumstances, identity, and society. So, I am thankful for the opportunity. In my father's words, "Getting a Ph.D. is simply an entry pass; once you are in, you should accomplish valuable scholarship, so equip yourself for that." I am excited about the prospect of serving, participating, and learning more tales.

Thank you, Dr. Schons, for your guidance, support, and opportunity. I am glad to have you as a doctoral advisor. Dr. Gori, your advice made me achieve this goal. Thank you for believing in me and this dissertation's ideas. Dr. Amacher, I appreciate my time learning with you in the classroom and your comments on this dissertation. Dr. Thomas, I appreciate your timely input and advice in developing the geospatial and remote sensing data.

I want to thank my family. As a first-generation student, I am sincerely aware that I am standing on the giant shoulders of my father, Nivrutti Shinde, and my mother, Suman Shinde, née Karanjkar. Your unwavering belief in education, first as a way out of poverty and second as a lifelong goal, empowered us to pursue higher education. Equally, my sisters, Smita, Madhuri, and Meenakshi, believed in this goal with patience, appreciation, and unconditional love. Mangesh, for lifelong friendship, joy, and advice. I am excited to share the stories, books, and anecdotes with my niece, Diya. Finally, Poonam, your support, determination, and love kept it together.

Ph.D. is an individual's degree earned collectively. The contributions of friends are ample in this journey. I thank my dear friends and colleagues from union days, Vishal, and ViKa, for exemplifying that research is a function of activism. In Blacksburg, I met Smridh, who ascertained that to have an unconditional friend is to be one. Gaurav stood firm with me during the pandemic and beyond. Both of you are true friends, in need and deed. Sakshi, Shreya, and Abhinaba believed in my ability as a researcher and provided consistent encouragement, conversations, and delight. Pedro, for offering the courage to speak & stand up. All of you are retelling us that all good or bad times shall pass; after that, people stay on in their tales.

Lastly, I sincerely appreciate the staff and faculty at ICTAS for providing doctoral fellowship, mentorship, and many opportunities. ICTAS doctoral scholarship lightened my financial responsibility, which allowed me to focus more on the most critical aspect of grad school: learning. Your generosity has inspired me to help others and give back to the community.

Epigraph

ईशें केलें नाहीं तुजसाठीं सर्व ।। करूं नको गर्व ।। प्राण्यांमध्ये ।। १।।
देह देवूनीया बुद्‌धिमान केला ।। धनीपणा दिला ।। सर्वांमध्ये ।।२।।
जगाच्या कल्याणा कष्टवावा ।। कारणीं लावावा ।। सत्यासाठी ।।३।।
अशा वर्तमाना जन्माचे सार्थक ।। संतोषी निर्मीक ।। जोती म्हणे ।।४।।

Jyotirao Phule, on The Religion of Humanity

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Chapter 1

Introduction

Since the beginning of this century, Brazil's municipal level deforestation rate decreased from an average of 18 to 7 km^2 from 2004 to 2014 because of a mixture of command-and-control and incentive-based policy measures (Boucher et al., 2013; Arima et al., 2014). The Brazilian policy response to control the rapid deforestation beckoned as a comprehensive lesson for other tropical countries (Arima et al., 2014; Burgess et al., 2019; Neeff and Piazza, 2020). A substantial portion of this success is credited to a comprehensive set of policies under the Action Plan for Prevention and Control of Deforestation in the Brazilian Amazon (PPCDAm) (Mello and Artaxo, 2017; West and Fearnside, 2021).

This dissertation focuses on two policy measures from PPCDAm: 1) Forest Code of 2012 via Rural Environmental Registry (CAR) and 2) the Green Municipality Program (PMV) of 2010. The dissertation design encompasses the PPCDAm era from 2001 to 2019. The program interventions occurred for CAR in 2008 (CAR-Pará), 2009 (CAR-Mato Grosso), and 2012 (CAR-Brazil), whereas the Green Municipality Program began from 2010 to 2017 in Pará. I employ robust program-evaluation approaches, namely staggered difference-in-difference, synthetic control, and panel data methods, to describe the causation between the program interventions and the outcome of interests.

Chapter (1) evaluates the impact of the land registration program (via CAR) on land conflicts. Using the quasi-experimental method, I provide causal evidence that land registration improves perceived land tenure security, which abates land conflicts in the state of Pará. To improve the study to explore if the period which expressed weakening of land conflicts also stimulates forest conservation on private landholdings. Subsequently, my second chapter deals with the dynamic land clearing decision of private landholders in the Brazilian Amazon. The results suggest that the persistence of compliance, thus forest conservation on privately held land, is driven mainly by past compliance and municipality-level incentives. As these two chapters established that land registration abates conflicts, and private landholders are driven by specific incentives to preserve the forest on their land. My third chapters investigate the impact of provincial governance promotion program on secondary forest recovery. I find that municipalities participating in the local government improvement program steadily observe an expansion in a secondary forest areas. To sum up, my dissertation explores the spillover effects of the deforestation control policy, starting with perpetrating fewer land conflicts and investigating the local incentives to promote forest protection on private land. Lastly, I provide evidence that the governance promotion program will result in secondary forest recovery.

PPCDAm program

PPCDAm was launched in 2004. It results from an inter-ministry working group followed by the infamous June 2003 report by the National Institute for Space Research (INPE) on soaring deforestation rates in previous years (Mello and Artaxo, 2017; West and Fearnside, 2021). PPCDAm involved government and non-governmental agencies, expert groups, and civil society members (Mello and Artaxo, 2017). PPCDAm has three key objectives; land planning, monitoring & controlling, and sustainable development. The objectives are unified in their broad aim of controlling deforestation while creating sustainable livelihoods.

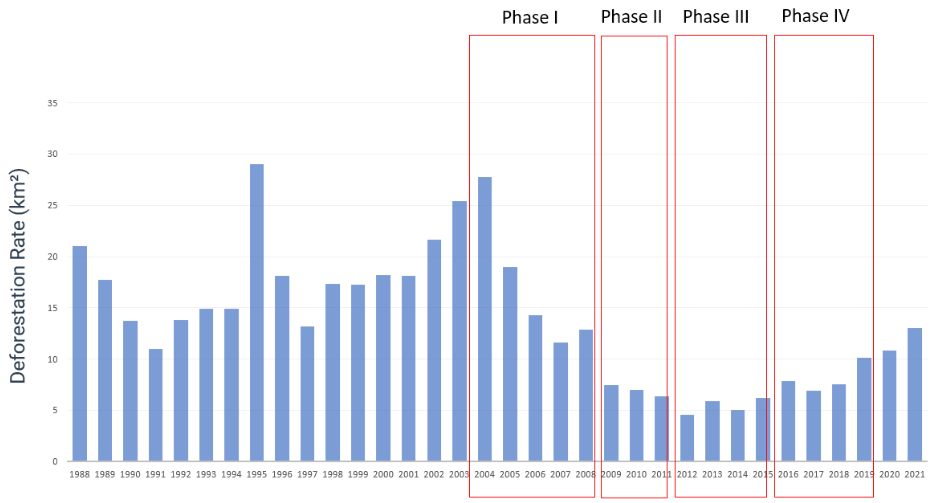

Figure 1 Deforestation in Legal Amazon

The figure observes a u-shaped slide back to the early 2000s deforestation level post-Bolsonaro years since 2019. The figure shows that PPCDAm phases efficiently controlled the surging deforestation rates in the pre-PPCDAm era across the Legal Amazon. However, the last phase of PPCDAm has significantly increased deforestation rates. Source: Authors' construction from TerraBrasilis portal[1].

Figure (1) illustrates that pre-PPCDAm deforestation was 18 km^2; it was reduced to 10 km^2 in the PPCDAm Phase I-IV (2004 to 2019) in Legal Amazon[2]. In the context of soring deforestation rate, the drastic change since 2004 is considered a result of efficient implementation of legal, technological, and administrative policies in Legal Amazon.

Phase I (2004 to 2008) has seen a higher deforestation rate than other phases. It was twice the average yearly deforestation rate at 18 km^2 compared to 7 km^2 in Phase II, 5 km^2 in Phase III, and 8 km^2 in Phase IV. I observe that PPCDAm phases I to IV have a u-shaped deforestation rate due to limitations of existing policies, local and federal government changes, and technological barriers to detecting small patches of Deforestation (Araujo et al., 2009; Boucher et al., 2013; Heilmayr et al., 2020).

[1] http://terrabrasilis.dpi.inpe.br/en/home-page/

[2] According to IBGE, Legal Amazon corresponds to the area under the responsibility of the Superintendence of the Amazon Development – SUDAM established by Article 2 of Complementary Law no. 124, of 03/01/2007. The region is formed by the states of Acre, Amapá, Amazonas, Pará, Rondônia, Roraima, Tocantins and Mato Grosso, and also by the municipalities of the state of Maranhão located west of the 44th meridian. (IBGE, 2020)

As illustrated in Figure (2), PPCDAm has accomplished four distinct phases of three sets of policies: land planning, monitoring & control, and sustainable development produced to control, monitor, and reduce Deforestation in Legal Amazon.

The set of policies includes;

- Land planning: policies targeted land-use change due to increasing population pressure, economic demand, and contention between the indigenous population with private landholders and the federal-state government.
- Monitoring & control: a set of policies focused on improving the technical, administrative, and jurisdictive response to illegal deforestation and encroachments on indigenous, conservation, and reserved forest lands.
- Sustainable development: a feature of policy aimed at integrating land planning and monitoring with local livelihoods promotion and sustainable development.

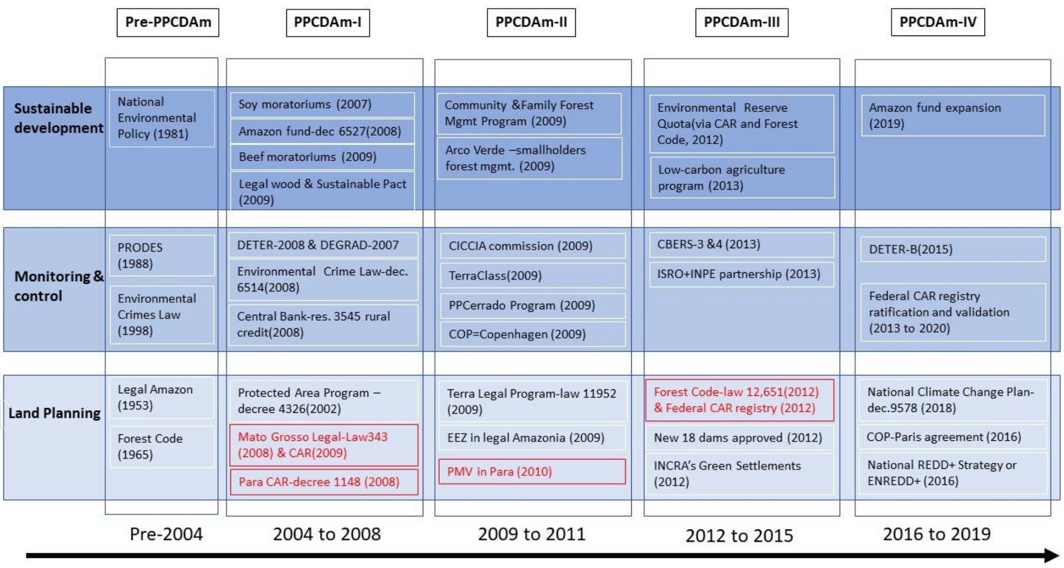

Figure 2 Phases of PPCDAm

The figure illustrates a detailed summary of the PPCDAm phases from 2004 to 2019, when the current government abandoned the project. There are four phases; Phase I from 2004 to 2008. This phase focused on assertively monitoring illegal *d*eforestation via an efficient satellite-based survey and simultaneously curbing credit access—increasing the environmental fines.

Phase II, from 2009 to 2011, focused on critical land-use planning and monitoring, where a program like Terra Legal and Terra Class laid the foundation for future ambitious revisions of the Forest Code. Phase III from 2012 to 2015 marked a long-debated revision of the Forest Code of 2012. Recently, Phase IV from 2016 to 2019 observed updates in DETER-B and REDD+ strategies. Although, this dissertation focuses on red highlighted programs. The PPCDAm's land-planning objective focuses on the author's understanding of the critical purpose behind specific policy programs. In practice, the programs may serve all three objectives. For example, CAR, via the Forest Code of 2012, has integrated the objective of sustainable land use planning and monitoring. Source: Authors' construction from various sources.

All three goals of PPCDAm worked in alliance with state, federal, and municipal governments. However, the foundational planning happened mainly in the federal government (West and Fearnside, 2021). Neeff and Piazza (2020) suggest that Brazil's effectiveness in controlling deforestation relied heavily on adequate long-term, transferable and sustained forest monitoring.

However, the source of these novel policies has been an open topic for research. I understand that a few of these policies emerged from political pressure from international and national media and built a case for punitive policy for surging deforestation rates. For example, in 2008, the Brazilian government blacklisted municipalities in the Amazon to better target efforts to prevent deforestation. As a result, the law enforcement and monitoring activities were intensified, and economic sanctions and political pressures were imposed on those municipalities (Assunção and Rocha, 2019). A few other policy responses were built upon post-colonial era legislations. For example, the Forest Code of 2012 was significantly built from the older forest code of 1965, environmental criminal law, and Legal Amazonia definitions from 1955.

The expansion of PPCDAm included a significant component of technological innovation in satellite-driven land use monitoring. These policies are derived from the pre-PPCDAm era

Program to Calculate deforestation in the Amazon (PRODES) project. It has the collaboration of the Ministry of the Environment (MMA) and the Brazilian Institute of the Environment and Renewable Natural Resources (IBAMA). It is part of an action by the Ministry of Science, Technology, Innovation, and Communications (MCTIC) in the Permanent Inter-ministerial Work for reducing deforestation rates in the legal Amazon, created by the presidential decree of July 3, 2005.

The Brazilian federal government considers effective land-use planning fundamental to controlling deforestation. Thus, the core focus of PPCDAm programs is efficient land-use planning. As a result, the decades-long PPPCDAm overlapped with revisions and the establishment of multiple land registries such as Terra Legal and Sistema de. Gestão Fundiária (SIGEF). Brazilian federal and state governments legislated numerous decrees, resolutions, and laws addressing various aspects of land planning ranging from the Indigenous Territory to Special-Economic Zone (SEZs) within Legal Amazon. These statutory obligations are built upon pre-existing constitutional dictates such as the Forest Code of 1965 and the National Environmental Policy of 1981.

Since Phase-I of PPCDAm, the state government and federal agencies reemphasized land planning by enacting the state-level Cadastro Ambiental Rural (CAR), first in Pará in 2008 and then in Mato Grosso in 2009. In 2012, these registries were consolidated into a national Rural Environmental Registry (CAR) under the revised Forest Code of 2012 in Phase III of PPCDAm.

Forest Code of 2012

In 2012, Congress in Brazil revised its Native Vegetation Protection Law (No. 12,651/2012), also known as the Forest Code, as primary legislation regulating private rural land use. The Forest Code established the federal Rural Environmental Registry (Cadastro Ambiental Rural, CAR). The Forest Code represents a transition of the government's approach to concrete efforts to implement the law for forest conservation. It provides specific tools to manage and implement remote sensing technology to monitor the conserved, cleared, and restored forest. The Forest Code mandates that all landowners follow a series of rules, such as: (i) establish and preserve riparian areas called Permanent Protection Areas (Portuguese acronym, APP) as defined by the law, (ii) maintain a legally established land cover under native vegetation called Legal Reserve (Portuguese acronym, RL), and (iii) enroll the landholding in the Rural Environmental Registry (Portuguese acronym, CAR), a public database that includes spatial information regarding the location, size, and condition of APP and RL within every landholding.

Green Municipality Program (PMV)

The Green Municipality Program (Portuguese: Programa Municípios Verdes, PMV) is a policy by the Government of Pará developed in partnership with municipalities, civil society, and private initiatives. PMV aims to combat deforestation in the state, reinforce sustainable rural production through strategic actions of environmental & land ordering, environmental management via implementation of CAR, and structure the environmental management of the participating municipalities (PMV, 2021).

Dissertation Summary

The dissertation begins with an objective to evaluate three associated spillover effects of PPCDAm. Broadly, I contend that the reduced land conflicts and persistent compliance post-Forest Code of 2012 constructed a micro-foundation for provincial governance promotion programs like PMV, which fostered secondary forest expansion in the Brazilian Amazon.

Firstly, the Brazilian Amazon has a persistent crisis of low-intensity land conflicts. Chapter (1) shows causal evidence that land registration offers perceived tenure security, reducing land conflicts in Pará. Using a cross-sectional panel of 808 municipalities from 2001 to 2012 in staggered difference-in-differences (DID) and dynamic event study design, I found that the number of conflicts reduced by 33%, whereas the number of escalations by 28%. These results are consistent for two robustness test mechanisms using a two-way fixed effect (TWFE) imputation estimator and an alternative data source.

Secondly, if the land conflicts are mitigated from 2001 onwards, what factors foster compliance with the Forest Code of 2012 and further the goal of protecting native vegetation on private land? Chapter (2) explores the persistence of compliance with the Forest Code of 2012 and the municipality-level factors affecting it in Mato Grosso and Pará in the Brazilian Amazon. Previous studies have aimed at understanding the factors affecting compliance using a static model of landholders' decision to clear land. However, the land use decision to comply or not is inherently dynamic. I propose an empirical evaluation and extension of Schons et al. (2019) 's dynamic land clearing under constraints established by the Forest Code of 2012. I extend their framework to include a decision to reforest the land besides land clearing. I found that the true state dependence only explains about half of the persistent behavior of landholders.

Additionally, the municipality-level factors affect compliance differently depending on the property size, state, and regional variations. The chapter has four policy implications. Firstly, I provide novel insight into how local socio-economic factors affect compliance under selection bias and state dependence. This provides a policy insight on sustaining persistence in forest conservation on private landholdings. Secondly, I include various factors such as land conflicts or forest fires, which diverge impact on compliance in the two states. This suggests the need for tailored policy to address the restoration of deforested lands.

Thirdly, I demonstrate how the extensive geospatial and secondary economic data can be utilized to provide local inputs for policy implementation. The first two chapters established that land registration abates conflicts and specific municipality-level incentives are as important as past compliance to promote forest conservation on private land. Now I turn towards whether the region with reduced land conflicts and known factors influencing the persistence of compliance will have increased secondary forest expansion in the case of local governance. Chapter (3) presents causal evidence that local policy intervention successfully added 14 to 27 $km^2$of secondary forest in the state of Pará. Using novel econometric tools such as generalized synthetic control and matrix completion, I evaluated the self-participation in treatment, i.e., the Programa Municípios Verdes (PMV) fostered secondary forest recovery in the treated municipality. These results are consistent with multiple econometric methods; generalized synthetic control, matrix completion, and staggered differences-in-difference. PMV strengthens sustainable rural production via strategic actions of environmental-land ordering and environmental management, focuses on local pacts, monitors deforestation, implements the CAR, and structures environmental management at the participating municipalities (PMV, 2021). This robust local policy intervention led to increased monitoring and secondary forest recovery.

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Chapter 2

Does self-declared and mandatory environmental registration of landholdings reduce land conflicts? Evidence from the state of Pará in the Brazilian Amazon

Abstract

This chapter shows causal evidence that land registration offers perceived tenure security, reducing land conflicts in Pará. Using a cross-sectional panel of 808 municipalities from 2001 to 2012 in staggered difference-in-differences (DID) and dynamic event study design, I found that the number of conflicts reduced by 33%, whereas the number of escalations by 28%. These results are consistent for two robustness test mechanisms using a two-way fixed effect (TWFE) imputation estimator and an alternative data source. In exploring the mechanisms behind the decline of land conflicts in post-CAR periods, I propose four channels of conflicts abatement, obtainability of newly cleared land (by forest fire per 1000 population), in-migration effects (by families involved in conflicts), increased monitoring effect (by IBAMA fine intensity) and climatic effects (by conflict by drought index). Firstly, newly cleared land (by forest fire per 1000 population) ensures the continual opportunity for expansion of the non-forested economic activity. Together with in-migration effects (estimated using families involved in land

conflicts), I suggest that the recent influx of families contributes to new land clearing patterns in Pará. Thus, resulting in abating the conflicts over remaining limited non-forested land. Additionally, increased monitoring increases the cost of 'getting caught' for illegal deforestation, subsequently increasing the cost of new land clearing. This indicates a more significant opportunity cost of conflict over existing land. To conclude, I explore the channels of conflict-stricken by the local drought index. The preliminary results suggest that CAR registration lessened conflicts. However, after the inclusion of the drought index, the conflicts intensified in Pará. Finally, the chapter discusses policy implications in three discussions, prospective deforestation control, potential agricultural growth, and livelihoods promotion within CAR and its related policies.

Keywords: land conflicts, escalations, environmental land registration, CAR, and Legal Amazon

Introduction

Between the years 1988 to 2019, the annual average land conflicts propagated from 356 to 798 even though the annual average deforestation rate dropped from 18 to 9 km^2in the Brazilian Amazon. The deforestation rate dropped because of wholesome public policy measures (Arima et al., 2014; Tacconi et al., 2019). However, the ever-increasing conflicts present a puzzling dilemma for policymakers.

In this chapter, I evaluate the underlying question of mandatory and self-declared land registration capacity to abate land conflicts. The chapter builds on the hypothesis that CAR registration, at best, provides perceived tenure security to landholders via a steady stream of benefits emerging from the local, state, and federal governments. These benefits stream, in turn, guarantees the perceived tenure security that lowers land conflicts.

The dilemma around insecure property rights has been extensively discussed within the context of the Brazilian Amazon, given that it has been identified as the primary factor contributing to the deforestation of the most extensive rainforest in the world (Mendelsohn, 1994; Araujo et al., 2009; Alston & Mueller, 2010). Moreover, property rights insecurity has been shown to cause land conflicts (De Oliveira, 2008; Hidalgo et al., 2010; Fetzer & Marden, 2017). In Brazil, the evolution of property rights insecurity and land conflicts' is historically founded on coexisting state-led expropriation of "non-productive" land for agrarian reform and non-state-led appropriation of land from the landholders. Both have led to inefficient investments in the land as a productive asset and high investments in labor to watch over it (Araujo et al., 2009; Alston & Mueller, 2010).

Land registration programs are one of the cost-intensive policy measures. By legal mandate, the state of Pará in 2008 and Mato Grosso in 2009 made these programs a forerunner to the federal policy later enacted by the Forest Code of 2012. In this chapter, I propose a conceptual framework where land registration safeguards the expected utility of land use in a twofold path, first by imposing land use constraints on rural landholders and then via providing a streamlined benefit of the registration. The purpose of registration paves a path towards conservation goal, i.e., compliance with the Forest Code of 2012. Ultimately, the land conflicts blend externalities due to the conservation mandate. Within this framework, I propose a causal empirical analysis where the CAR registration is a binary treatment to evaluate the shift in land conflict outcome.

Using staggered difference-in-differences (DID) and dynamic event study design, I provide reliable evidence that land conflicts declined by 33% and escalations by 28% in Pará. I consider four main mechanisms impacting land conflict abatement within Pará, specifically recently cleared land (by forest fire), in-migration effects (by families involved in conflicts), increased monitoring effect (by IBAMA fine intensity), and climatic effects (by conflict by drought index). These mechanisms push the overall estimated reduction of land conflicts in Pará.

The chapter is organized as follows. First, I establish a brief background on land conflicts and land registration within the Brazilian Amazon. This is followed by the conceptual framework building on the hypothesis that perceived tenure security via CAR abates land conflicts in Pará. The following section introduces data sources, descriptions, and summary statistics. Then empirical frameworks using dynamic DID and event study model are presented. It is followed by results, mechanisms, and policy implications. Last, of all, I provide a conclusion and future direction for the research.

Background

This section provides an overview of two background information about the Legal Amazon[3]. The first is a summary of land conflicts. Second, an overview of the environmental land registration policy in Legal Amazon.

A brief overview of land conflicts in Brazil

There is a reciprocal relationship between deforestation and land conflicts in Brazil. Figure (3) shows the decades of higher deforestation complemented by consistent land conflicts from 1988 to 2004. Later from 2005 to 2020, the land conflicts were elevated while the deforestation rate declined due to comprehensive control policies (Arima et al., 2014; Tacconi et al., 2019). This section provides an overview of land conflicts in the Brazilian Amazon using the two periods.

[3] Legal Amazon corresponds to the area under the responsibility of the Superintendence of the Amazon Development – SUDAM established by Article 2 of Complementary Law no. 124, of 03/01/2007. The region is formed by the states of Acre, Amapá, Amazonas, Pará, Rondônia, Roraima, Tocantins and Mato Grosso, and also by the municipalities of the state of Maranhão located west of the 44th meridian (IBGE-Legal Amazon, 2021).

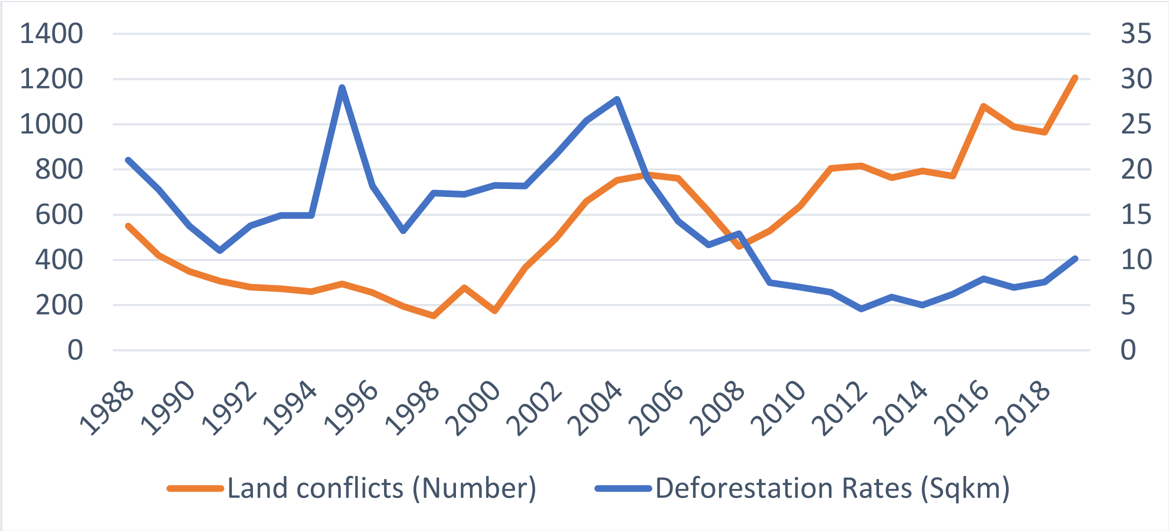

Figure 3 Trends in land conflicts and deforestation rate

Source: Author's estimation using PRODES and CPT data

Phase I 1990 to 2004: Low intensity and high deforestation

The low intensity and high deforestation regime can be explained by mounting agricultural and pastoral activity in this region, increasing number of encampments, possessions, and occupation of freshly deforested land, and land invasions by small and family-led landholders (Alston et al., 2009; Alston and Mueller, 2010). Since 2000, the new economic opportunities have opened avenues for higher soy and beef activities via deforestation in Mato Grosso and Pará. The conflicts increased due to the growing number of squatting and renewed land invasions (Ondetti, 2010).

It was supplemented by demographic upheaval within Brazil's domestic policies. Carr (2004) illustrates a practical problem: it is commonly agreed that population drives land use changes, yet the empirical evidence that population led to deforestation at a local scale is scant. Carr (2004) reviewed four channels affecting frontier forest conversion: population density, fertility, household demographic composition, and in-migration. These factors also aid land conflicts in the region. For example, Alston et al. (2009) provide empirical evidence that potential land rents associated with land conversion, local norms, and policies aggravate land violence in the Brazilian Amazon. The authors suggest that the absence of de jure property rights in the Brazilian forest frontier has incentivized surplus benefits associated with newly deforested land and securing the land via violent invasions.

Phase II 2004 to 2019: High intensity and high deforestation

The demi-decade of 1999 to 2004 witnessed elevated land conflicts and deforestation. As a result, the then Brazilian government succeeded with long-term planning, decentralized, and targeted goals of monitoring and controlling deforestation (West and Fearnside, 2021). The comprehensive intervention of the Action Plan for the Prevention and Control of Deforestation in the Legal Amazon (PPCDAm), launched in 2004, advocated a radical conservation reform in Brazil (West and Fearnside, 2021).

From 2004 to 2008, the first phase of PPCDAm -led environmental monitoring led to a spillover effect in lessening land conflicts (De Oliveira, 2008). However, the PPCDAm phases II (2009–2011), III (2012–2015), and IV (2016–2020) all have followed the peak of land conflicts recorded in recent years. Scholars have yet again attributed this rise in land conflicts to property rights insecurity, land invasions, and expansion of mining activity (Hidalgo et al., 2010; Fetzer and Marden, 2017). However, the current government's approach in favor of weaponizing the land rights toward big landholders, mining companies, and land prospectors can be the reason for an unprecedented rise in land conflicts (da Silva and Bampi, 2019).

Environmental registration program

In this section, I emphasize the deforestation control policy that enacted a mandatory and self-declaratory land registration program. In 2012, the federal government announced a national registry consolidation under the Native Vegetation Protection Law (No. 12,651/2012), also known as the Forest Code, and created the Rural Environmental Registry—CAR (Cadastro Ambiental Rural). CAR aims to create, maintain, and monitor private landholdings in the Brazilian Amazon. However, before the federal program began in 2012, two states, namely Mato Grosso and Pará, preceded the federal rural environmental registry by four years. Both states began self-declared and targeted environmental registration programs for landholdings in the Brazilian Amazon. These early registries were later consolidated into the federal registry.

Environmental land registration before the Forest Code of 2012

CAR program was initiated in Pará in 2004 for rural properties involved in the economic enterprise. It was reconfigured in 2008[4] and became obligatory for all landholdings in the state under Pará's rural environmental registry—CAR (Cadastro Ambiental Rural) (Alix-Garcia et al., 2018; West and Fearnside, 2021). The state of Mato Grosso followed suit with the codification of State Law 343 of 2008, which established a land tenure and environmental regularization program in 2009[5] for rural landholdings in the state, the Mato Grosso Legal (Alix-Garcia et al., 2018; West and Fearnside, 2021).

[4] Please refer to CAR, State Decree 1148, 17 July 2008. Here, the CAR made compulsories for all rural properties and separated from the environmental licensing process (Alix-Garcia et al., 2018; West and Fearnside, 2021).

[5] Please refer to State Decree 2238, 13 Nov. 2009. Here, the CAR legislated in Mato Grosso, but remains technically voluntary; registrants offered incentive of protection from new fines for old deforestation and a 90%

The implementation of the CAR was different in the two states; Pará's CAR was provisional as it was self-declared, unverified, and yet mandatory (after 2008), whereas Mato Grosso's CAR was self-declaratory, (moderately) well-reviewed, and legally binding plan to achieve compliance with the later Forest Code (Alix-Garcia et al., 2018; West and Fearnside, 2021). The critical difference between the two states' programs was that Pará's CAR was mandatory while Mato Grosso's CAR was voluntary (Alix-Garcia et al., 2018; West and Fearnside, 2021).

Both states had similar goals behind the environmental land registration program. The primary aim was twofold, for the state government to achieve reduced deforestation and for private landholders to qualify for rural activity licenses and credit programs. Both states actively promoted registration using several channels. For instance, in Mato Grosso, the registered landholdings were exempted from the environmental fine for illegal deforestation before the registration time (Alix-Garcia et al., 2018). In Pará, the municipality-level incentives such as licensed rural economic activity such as tree plantations were promoted.

In the state of Pará, the CAR was promoted as the pivotal program under many other environmental monitoring policies. The Green Municipality Program—PMV (Programa Municípios Verdes) strongly endorsed not only the registration but also compliance with the environmental land registration and later with provisions of the Forest Code of 2012 (Sills et al., 2020; Moz-Christofoletti et al., 2022). The policy of Priority Municipalities—PM (Municípios Prioritários) since 2008[6] encouraged CAR registration in Pará and Mato Grosso.

discount on old fines under the program MT Legal (which ultimately ran from Dec. 2008-2012 in Mato Grosso) (Alix-Garcia et al., 2018; West and Fearnside, 2021).

[6] Please refer to Decree 6321, 21 December 2007. From 2008 to 2018, 62 municipalities on the periphery of Legal Amazon were targeted into increased monitoring and control of deforestation.

National Rural Environmental Registry

Brazil's National Rural Environmental Registry System – SICAR (Sistema Nacional de Cadastro Ambiental Rural) process resembles Pará's CAR. The CAR is an electronic public record of all rural properties and landholdings in an online repository, SICAR. A vital purpose of the CAR is to maintain environmental information on rural properties and landholdings. The environmental information refers to Permanent Preservation Areas – APP (Áreas de Preservação Permanente), restricted use, Legal Reserve—LR (Reserva Legal), forest remnants, and other forms of native vegetation and consolidated areas.

According to the Forest Code of 2012, registration in CAR is primarily necessary for environmental regularization (Regularidade Ambiental do Imóvel) under Environmental Regularization Programs – PRA (Programas de Regularização Ambiental). By regularization, the database includes information on the owner, landholder directly responsible for the given property, documents of ownership or possession, and georeferenced information on the perimeter, location, area under native vegetation, APP, consolidated area, and LR.

The database comprises geospatial and property (or landholding) level information (SICAR, 2020). The Federal CAR database connects with a geospatial database using a unique registration id. The combination of the Federal CAR (SICAR, 2020) and geospatial CAR (CAR, 2020) delivers exhaustive details on individual private landholdings, a self-declared area under LR, APP, and consolidated areas, dates of registration, and willingness to participate in environmental regularization program.

Direct Benefits of CAR registration

CAR has three direct benefits, set up an environmental regularization, access to rural credit, and rural environmental activity licenses. Registration in CAR is the first step to environmental regularization, which permits environmental, economic planning, and possession of the property. Moreover, registration in CAR (and PRA) ensures that rural producers access lower interest rates for credit [7] (Assunção et al., 2020) and agriculture insurance (Souza et al., 2020). Furthermore, the CAR acts as a precondition of environmental easements and Environmental Reserve Quota—CRA (Cota de Reserva Ambiental) in consolidated rural areas until July 22, 2008, located in Permanent Preservation Areas and Legal Reserves (Chiavari and Lopes, 2015; Chiavari and Lopes, 2021). Ultimately, an exemption for properties or landholdings that have deforested vegetation in areas of permanent preservation, Legal Reserve, and restricted use is committed until 07/22/2008 (Chiavari and Lopes, 2015).

Several other benefits in terms of exemption from registration in the Real Estate Registry—CRI (Cartório de Registro de Imóveis), potentially generating tax credits from APP and LR land area, and exemption on taxes for pieces of equipment utilized in the protection of APP and LR land (SICAR, 2020; Chiavari and Lopes, 2015). Furthermore, the CAR is a precondition for several governmental policies and programs, such as practicing aquaculture and silviculture on private landholdings and approving LR & APP proportions on given landholdings (SICAR, 2020; Chiavari and Lopes, 2015).

[7] Mainly after December 2017 the CAR is prerequisite to access rural credit program (Souza et al., 2020)

Indirect Benefits of CAR registration

Besides the direct benefits of registration in CAR, the private rural landholder collects indirect political, social, and economic benefits. This section highlights two key indirect benefits of the CAR registration: perceived tenure security and political-economic agency.

Perceived tenure security

CAR registration offers direct economic benefits to the landholder, thus paving a potential benefit for securing tenure or property rights in the future. The registration in CAR ensures the landholder's claim on the occupation or encampment of the landholding without granting legal tenure, i.e., legal titles for the ownership. Although the registration in CAR does not exempt legal tenure, the registration recognizes landholdings' use, occupation, and encampment. Likewise, the landholders' clearing of native vegetation prior to 2008 is exempted from the environmental crime associated with the clearing. In doing so, the state recognizes the de facto tenure security.

Following a framework in Van Gelder (2010), I suggest that the CAR registration ensures the landholder's perceived and de facto tenure security, not legal tenure. Similar to the de facto–de jure property rights framework (Mueller, 2016; Mueller, 2018), where the Forest Code of 2012 through CAR raised a dilemma of, on the one hand, uniting the de facto property claims into the CAR registry while on the other hand left the legality of claims in an indeterminate state. Currently, the CAR ensures the perceived tenure security by facilitating tangible social and economic benefits for landholders registered in the CAR.

Political-economic agency

Land occupation, encampment, holding, or legal tenure determines an individual's access to a social, economic, and political agency (Andersson and Ostrom, 2008). The direct benefits of CAR registration create landholders' social and economic agency as the Brazilian Amazon is one of the decisive subjects in the country's domestic (and international) politics. Therefore, the rural landholder is directly associated with domestic politics and indirectly associated with international politics. I consider that the CAR registration enables new and old claimants to access land and its associated connections with non-governmental, social, religious, and governmental associations within given municipalities.

Although there is scarce evidence if the CAR registration gets impacted by local and national elections in Brazil, there is plenty of evidence suggesting that deforestation gets adversely impacted by several channels from the local and national electoral, resource, and social politics. For instance, local and national elections increase the resource rent and exacerbate the deforestation cycle (Klomp and de Haan, 2016). In Brazil, episodic deforestation rise is associated with elections and the weakening of forest monitoring due to the change in political regime (Rodrigues-Filho et al., 2015). Moreover, the land tenure concentration, weak monitoring, and electoral rhetoric against conservation suggest that the CAR may become a tool of local political and economic control that may influence local elections and resource depletion (Rodrigues-Filho et al., 2015; Azevedo et al., 2017; Yanai et al., 2020).

Conceptual framework

I propose a conceptual framework based on direct and indirect benefits from the landholder's registration in CAR. It ensures perceived tenure security via a de facto benefits stream—firstly via resource extraction activity (Demsetz, 1974; Mendelsohn, 1994) and secondly via indirect benefit of perceived and expected tenure security (Benin et al., 2005; Arnot et al.,2011). This conceptual framework builds on hypotheses that the CAR registration led to higher perceived tenure security which lowers land conflicts.

Following Demsetz's (1974) thesis that property rights have emerged in the prearranged context of the law, regulation, and norm, this conceptual framework builds on perceived land tenure security and its spillover effects in controlling land conflicts within the context of the Brazilian Amazon. There are three characteristics of perceived tenure security emerging from literature. Firstly, to link the perceived tenure security with tangible benefits. In the case of CAR registration, the landholders receive a direct and indirect benefits stream. As it is challenging to measure tenure security, it can only be estimated via its components (Van Gelder, 2010). For example, Carter and Olinto (2003) argue that tenure security materializes in access to credit and investment opportunities. However, Arnot et al. (2011) highlighted comprehensive literature on how and why a definition of tenure security needs our attention. The author suggests that multiple researchers have relied on defining tenure security via its components. For example, the length of tenure (landholding) is often seen as tenure security. Nevertheless, this component-based definition of tenure security fails to address a few questions like the link between perceived tenure and investment (mainly endogenous).

Tenure security is a bundle of assurance (legal or social binding agreement) of tenure and substance (a set of attributes such as use, occupation, fencing, and so on). CAR registration imposes a legally mandating constraint on land use to award the rights to use, occupy, fence, and till the land. By doing this, the landholder's expected utility of land use gets swayed by formal & informal institutions and the local political economy. Together, these construct a degree of tenure security. I refer to this as expected utility evolving from direct and indirect benefits of CAR registration. This framework builds on linking the intervention (CAR registration) with the expected utility of land-use choices. The intervention ensures two outcomes, one human-welfare outcome (such as the distributional effect of land registration via CAR to smallholder families) and the second conservation outcome (such as restoring and protecting APP & LR). Finally, the conflict is a spillover effect of the conservation outcome of registration.

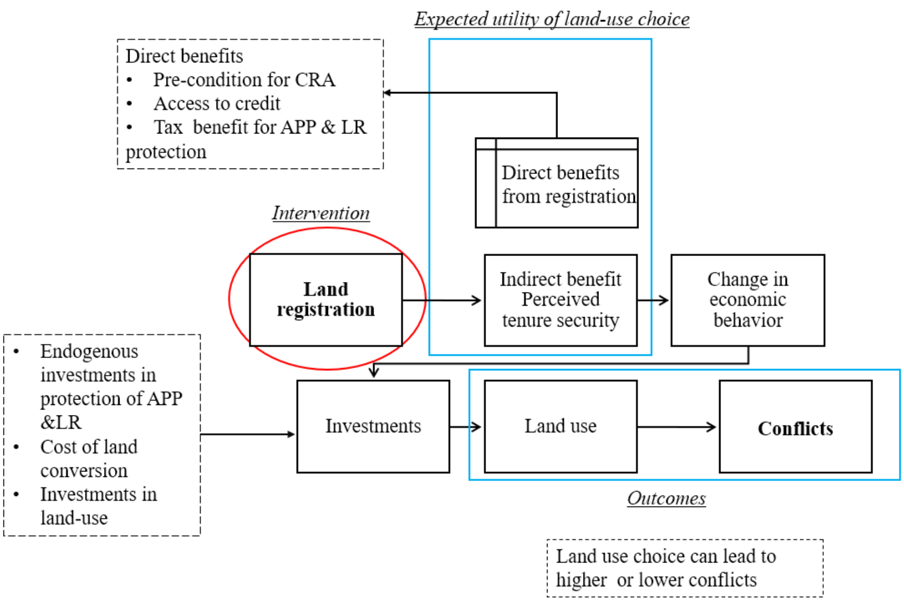

Figure 4 Conceptual framework linking land registration to conflicts

The figure is a comprehensive framework (from Arnot et al., 2011; Benin et al., 2005) where the effect of an intervention (CAR) is linked to an outcome (land conflicts) via an expected utility of land use associated with land registration (perceived land tenure security). Source: Author’s construction

Step 1 is to link it with the economic behavior of individuals. CAR links landholders' economic behavior, such as land-use constraints, to their perceived tenure security. Step 2 is to link assurance (of property rights) in the context of perceived tenure security. In the registration, the landholder expected benefits include the future legal tenure and the existing tenure security. Lastly, to link the perceived tenure security to investments. Once the landholder registers in CAR, the land use decisions are endogenous to their consumption and investment choices. For example, CAR is the first step in the environmental regularization program, which demands APP and LR protection (and restoration). The protection constructs a consumption for equipment such as fences or gates. One key benefit of CAR is tax cuts awarded to landholder fences and protect native vegetation.

To summarize, I propose to evaluate this framework using an empirical model as shown below;

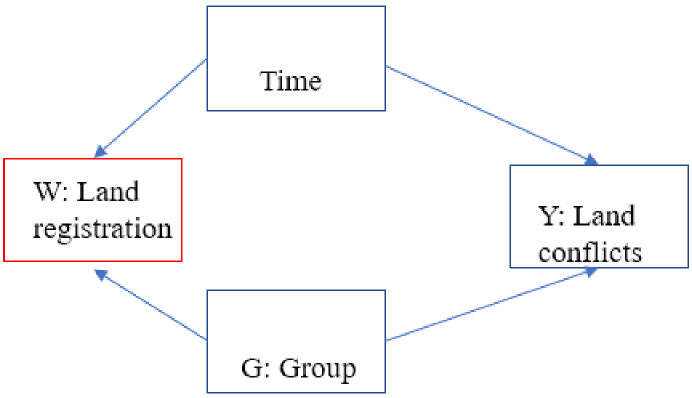

Figure 5 DAG for the difference in difference (DID)

In the empirical framework, from Figure (4), I propose to estimate the causal impact of mandatory and self-declared land registration on land conflicts. The expected outcome is that increased land tenure security due to land registration may reduce the likelihood of land conflicts.

Data and descriptive statistics

This section summarizes the study area, data, and empirical methods employed in this chapter.

Study area

Figure (6) illustrates a map of our study area. I utilized a cross-sectional panel on 808 municipalities in states of 808 municipalities in Brazil's Legal Amazon states from 2001 to 2012. It includes the states of Acre, Amapá, Amazonas, Pará, Rondônia, Roraima, Tocantins and Mato Grosso, and Maranhão.

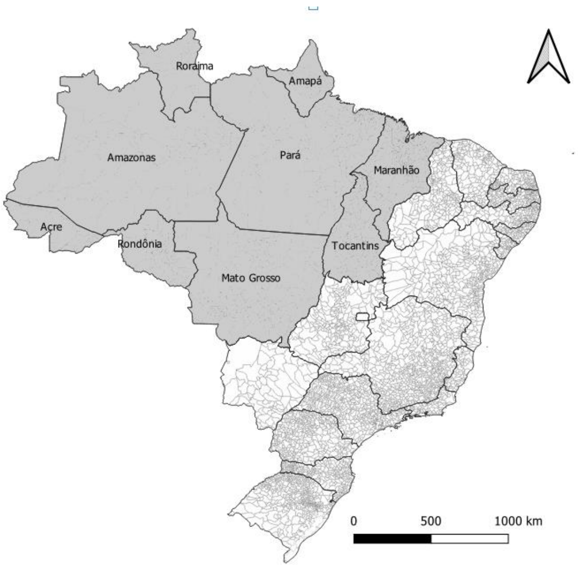

Figure 6 Study area includes states in Legal Amazon

The treatment occurred in Pará (in 2008), Mato Groos (in 2009), and the rest of the Brazilian Amazon (in 2012). I included the Paráand the rest of the states from Legal Amazon as primary cross-sectional data.

Data

I collected data from an open-source repository, secondary data sources, and official statistics. I employed various data collection tools and techniques ranging from Python data conversion and cleaning from scanned PDF files to Google Big-Query to collect and clean data from Base dos Dados (Dahis et al., 2022) and land use data from the Google Earth Engine (GEE). This section provides a breakdown of data sources, types, and other details.

Dependent variables: a measure of land conflicts

This chapter employs two estimates of municipality-by-year land conflicts; 1) Number of land conflicts: it is an aggregated measure of the number of conflicts over land, occupations, and camps; and 2) Number of escalations: it is an aggregated level of violent outcomes in the land conflicts, i.e., the sum of murders + attempted murders + death threats.

The land conflicts data was collected from the Pastoral Land Commission—CPT (Comissão Pastoral da Terra). CPT defines land conflicts as actions of resistance and confrontation for the possession, use, and ownership of land (posse, uso e propriedade) and the access to natural resources (acesso aos recursos naturais)[8]. Additionally, the occupations/retakes (ocupações/retomadas) and the encampments (acampamentos) are also classified within the scope of land conflicts. CPT's definition of conflict is thorough and incorporates two critical aspects of human—resource (land) interactions: land possession, ownership, and resource use & access.

CPT provides yearly books titled Conflicts in Brazil (Conflitos no Campo Brasil). I constructed a municipality-by-year aggregation of a number of land conflicts, families involved in conflicts, murders, attempted murders, and death threats. I utilized the IBGE shapefile of

[8] Natural resource includes (but not limited to) the rubber plantations, babassu or chestnut plantations, among others (which guarantee the right to extractivism), when they involve squatters, settlers, quilombolas, geraizeiros, indigenous people, small tenants, peasants, landless people, rubber tappers, peasants in the background and pastures, babassu coconut breakers, chestnut trees, faxinalenses, etc. Please refer "Conflitos no Campo Brasil'' books from 1988 onwards

municipalities to match municipal-level changes in 2001. Following suit by earlier researchers[9], I prefer to aggregate the conflicts in the parent municipality in case of the formation of new municipalities during the study period.

Treatment intervention: Data on CAR registrations

I collected data on CAR registration at the municipal level from the public repository National Rural Environmental Registry System – SICAR (Sistema Nacional de Cadastro Ambiental Rural) maintained by Brazil's Forest Service—SFB (Serviço Florestal Brasileiro)[10].

I employ binary CAR as a treatment intervention. I constructed a cross-sectional panel with binary treatment variables for municipalities with CAR registration in Pará in 2008 and Mato Grosso in 2009.

Covariates

I collected data on control variables using several official repositories. Using MapBiomas collection 5 in Google Earth Engine (GEE), I estimated the municipality-by-year native forest area (km^2). To construct the annual deforestation increment (ADI), I followed the procedure laid out by Assunção et al. (2015). ADI estimates yearly deforestation increment for each municipality by year. The herd density is estimated using the Municipal Livestock Research—PPM (Pesquisa Pecuária Municipal). The PPM provides a number of cows per municipality. The herd density includes cattle ranching activity. The government monitoring is controlled by an environmental fine (adjusted to 2019$). It is estimated using the data from the Brazilian Institute of the Environment and Renewable Natural Resources—IBAMA (Instituto Brasileiro

[9] Hidalgo et al. (2010); Fetzer and Marden (2017); and Albertus et al. (2018)

[10] I downloaded data in December 2020 for municipalities across Brazil in ESRI-Shapefile format.

do Meio Ambiente e dos Recursos Naturais Renováveis). To control for municipal level protected land, I include yearly protected area per municipality using the World Database on Protected Areas (WDPA). Exogenous price indices are estimated using the steps illustrated in Assunção et al. (2019). I include price indices for rice, sugarcane, corn, and cassava. Indices for soy are dropped as it has a high correlation with the corn price index. I control for non-agriculture value added (adjusted to 2019$). The data is collected from Brazil's Gross Domestic Product—PIB (Produto Interno Bruto do Brasil). Lastly, I constructed municipality-by-year precipitation (mm) and Palmer Drought Severity Index (PDSI) from TerraClimate in GEE (Abatzoglou et al., 2018).

Descriptive statistics

Table (1) presents group-wise descriptive statistics for cohort 2008, and the control group includes all the states in Legal Amazon except Mato Grosso.

Table 1 Descriptive statistics

	Before weighting						After weighting					
	Treat			Control			Treat			Control		
	mean	variance	skewness	mean	variance	skewness	mean	variance	skewness	mean	variance	skewness
Number of land conflicts	0.7975	2.713	3.408	0.5366	3.038	7.847	0.7975	2.713	3.408	0.7975	2.714	4.186
Number of attempted murders	0.19	1.062	9.113	0.02822	0.1033	22.2	0.19	1.062	9.113	0.19	1.062	8.514
Number of murders	0.1	0.2155	6.515	0.03502	0.08417	14.66	0.1	0.2155	6.515	0.1	0.2155	7.029
Number of death threats	0.5025	1.845	3.48	0.2036	1.378	10.26	0.5025	1.845	3.48	0.5025	1.845	3.547
Number of families involved in conflicts	85.73	67001	4.816	40.54	29293	10.82	85.73	67001	4.816	85.74	67003	5.162
Annual deforestation increment (sqkm)	48	4729	3.768	29.71	5006	7.811	48	4729	3.768	48	4730	2.187
Herd density (N/sqkm)	34.72	965.3	1.292	30.51	1318	1.93	34.72	965.3	1.292	34.72	965.3	0.8882
Total amount of environmental fine (2019R$	2.79E+07	8.94E+15	5.717	4504530	2.04E+15	37.83	2.79E+07	8.94E+15	5.717	2.79E+07	8.94E+15	4.934
ppa rice	6251	2.48E+07	0.3883	7475	2.90E+07	0.4287	6251	2.48E+07	0.3883	6251	2.48E+07	0.5777
ppa corn	5143	8971852	0.5734	4146	6270643	0.5026	5143	8971852	0.5734	5143	8971857	0.5053
ppa cane	347.7	2324687	6.276	251.5	1727529	11.99	347.7	2324687	6.276	347.7	2324720	8.867
ppa cassava	8961	4.65E+07	0.937	5497	4.03E+07	1.585	8961	4.65E+07	0.937	8961	4.65E+07	0.6783
Precipitation (mm)	188.6	1488	0.5282	159.3	2125	0.5917	188.6	1488	0.5282	188.6	1488	0.2889
Non-agriculture value added (2019R$)	7.09E+08	6.66E+18	9.6	4.05E+08	7.34E+18	17.12	7.09E+08	6.66E+18	9.6	7.09E+08	6.67E+18	6.666
Aggregated sum of protected area (sqkm)	3547	1.77E+08	5.281	1067	2.52E+07	8.063	3547	1.77E+08	5.281	3547	1.77E+08	4.896

The table shows the descriptive statistics for treated (Pará) and control (rest of states in Legal Amazon) before and after entropy matching. The table was generated using the Stata package ebalance provided by Hainmueller's (2012) entropy balancing approach.

Empirical framework

In this section, I present the primary methodology to estimate the treatment effect of CAR registration policy intervention on land conflicts along with the robustness checks strategy.

Methodology

I present an econometric strategy using a binary treatment intervention in municipalities in Pará (in 2008) and Mato Grosso (in 2009) in the cross-sectional panel of 2001 to 2012 for 808 municipalities in the Brazilian Amazon. To estimate the treatment effect of CAR registration, I exploit the heterogeneity in treatment intervention using the staggered difference-in-difference (DID).

I began by following the static DID model to estimate the treatment effect τ of treatment intervention $W_{i,t}$ where $W_{i,t} \in \{0,1\}$ as.

$$Y_{it} = \alpha_i + \beta_t + \tau W_{i,t} + \epsilon_{i,t}$$

Equation 1

Y_{it} is dependent variable and α_i and β_t are municipality and time fixed effects. The above econometric estimation employs a workhorse two-way fixed effects (TWFE) model to estimate the treatment effects. The treatment effect is interpreted as an overall effect of participating in the treatment across groups and time periods.

Alternatively, I explore the dynamic DID model to estimate τ, which is interpreted as determining the effect of participating in the treatment at different lengths of exposure.

$$\left(\widehat{\tau^{did}}, \hat{\mu}, \hat{\alpha}, \hat{\beta}\right) = arg\ min\ \alpha, \beta, \mu, \tau \left\{ \sum_{i=1}^{N} \sum_{t=1}^{T} (Y_{it} - \mu - \alpha_i - \beta_t - W_{it}\tau)^2 \right\}$$

Equation 2

However, recent literature has emphasized that TWFE produces a weighted average of treatment effects with a few negative weights (Borusyak and Jaravel, 2017; Goodman-Bacon, 2020; Sun and Abraham, 2020; Callaway and Sant'Anna, 2021) (De Chaisemartin and d'Haultfoeuille, 2020). The negative weights may estimate the incorrect treatment effects; for example, Callaway and Sant'Anna (2021) suggest that negative weights may result in negative τ when all treatment effects are positive. Moreover, in the case of staggered DID, the conventional TWFE may produce misleading results by comparing the already treated units with those not yet treated.

I suggest that Callaway and Sant'Anna's (2021), colloquially referred to as CSDID, is an appropriate methodology for this chapter due to three advantages. First, the CSDID provided a dynamic event study and staggered DID for $group \times time$ heterogeneity to estimate the group-by-year average treatment effect on treated units (ATT). Second, the dynamic event study allows one to evaluate the causal Parámeter with heterogeneity and dynamic effects. Furthermore, the underlying estimation strategy in CSDID relies on the doubly robust (DR) DID estimator proposed by Sant'Anna and Zhao (2020). By doubly robust DID estimation, the author suggests that DR-DID designs ATT that is consistent when either a working (Parámetric) model for the propensity score or a working (Parámetric) model for the outcome evolution for the comparison group is correctly specified (Sant'Anna and Zhao, 2020). To summarize, the CSDID provides three unique estimation strategies to estimate the group-by-year ATT, the dynamic event study ATT and aggregated average ATT across the group-by-year.

Assumptions in CSDID

I estimate the following CSDID specification with conditional Parállel trend assumptions (PTA) and conditional no-anticipation (NA). Following Heckman et al. (1997), CSDID determined that the conditional PTA is an apt estimation when the role of covariates is crucial for treatment assignments. Hence, CSDID proposed a conditional (on covariates) PTA. I test these assumptions using a dual approach. First, I provide an estimate for the chi-square test hypothesis that all pre-treatment is equal to zero. Tables (2) and (3) show that our main model specification for cohort—2008 satisfies the pre-trend test, i.e., the pre-trend is absent[11]. Lastly, concerning NA, I suggest that the pilot registry in Pará (in 2008) and Mato Grosso (in 2009) does not entail an anticipated registry across the legal amazon states.

Covariate balancing

Callaway and Sant'Anna (2021) demonstrated an approach for staggered DID and dynamic event study with the flexible inclusion of covariates. However, this chapter employs a diverse control group with all municipalities from legal amazon except Pará and Mato Grosso. I

[11] Additionally, I provide a lternative estimate using did imputation, please see Table (14)

understand that these municipalities have different levels of covariates. Therefore, I utilize two strategies to balance the cross-sectional panel for the control and treated groups.

First, I employ Hainmueller's (2012) entropy balancing approach. It is a set of balance conditions (weights) constructed using the matching mean. For example, variable A must be matched between treated and control groups. I follow,

$$\sum_{i|D_i=0} w_i A_i = \sum_{i|D_i=1} A_i$$

where D_i indicates treatment status and w_i are the matching weights. Hainmueller (2012) provides matching for three moments: mean, variance and skew. I choose variance moments to match our sample.

Second, I analyzed population weights as shown in Cheng and Hoekstra (2013). The inclusion of population weight addresses two crucial issues in our model specification. First, I constructed a measure of land conflicts from primary source data, which did not include population-adjusted measures of the rate of murders, land conflicts, or other indicators. By using population weight for a model, I provide population-adjusted estimates. Second, the population is a crucial factor influenced by conflicts and influences conflicts. In order to tackle this circular channel, I include the mean population of the municipality in the study period.

Robustness checks

The role of robustness checks is to reevaluate primary model specifications and results. In this chapter, I employ two robustness check strategies:

Firstly, using alternate econometric estimation for Equation (2): I employ Borusyak and Jaravel's (2017) imputation form when treatment-effect heterogeneity in the dynamic event study. To extend the CSDID, the dynamic event study by Borusyak and Jaravel (2017) takes the mean overall lags using a linear combination of all point estimates, and this approach exploits the advantages of two-fixed effects to control for unobserved confounders. I find that in Pará, conflicts and escalations reduced by 9.4 and 10.1%, respectively.

Secondly, to test the main model specification in Equation (2) with seParáte data from Mortality Information System – SIM (Sistema de Informação sobre Mortalidade). I estimated the municipality-by-year mortality rate per 1000 population for overall men and women mortalities. Using the CSDID specification, I show that overall mortality was reduced in Pará in post-intervention periods.

Results

Tables (2) and (3) show results for the CSDID model for "Number of land conflicts" and "Number of escalations." Control variables include ADI: Annual deforestation increment (km^2), Herd density: Cattle herd density (Number of cattle/Municipal area), Fine amount: Total Amount in Real of Environmental Fines(adjusted for 2019R$), Non-ag value: Non-agriculture gross value added at current prices is measured by subtracting the Gross value added at current agricultural prices from the Gross added value at total current prices at the municipality level (adjusted for 2019R$), Protected area: Cumulative WDPA protected area (km^2), and Yearly mean precipitation (mm).

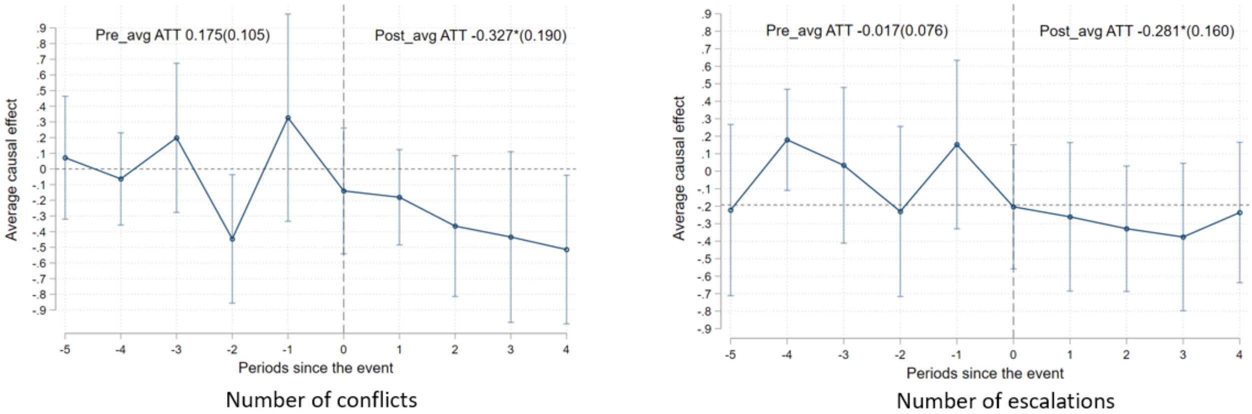

Figure 7 Dynamic event study plot

This plot is generated using the Callaway and Sant'Anna (2021) implementation in Stata.

Figure (7) illustrates that the dynamic event study for "Number of conflicts" and "Number of escalations" has declined since CAR intervention in Pará. I find that the state of Pará (Cohort 2008) shows consistent results across the sample. Both the conflicts and escalations declined by 33% and 28% in Pará. In other words, the conflicts are reduced by 1/3rd while escalations are reduced by slightly more than 1/4th after policy intervention[12].

[12] Columns (2) and (6) in Table (2) show that these results reject the pre-trend chi-square test at 17 and 10%, respectively. Therefore, it suggests that these results satisfy the assumption of PTA.

Table 2 DID with dependent variable "Number of conflicts"

	ATT for Pará (Dropping Mato Grosso)		ATT for Mato Grosso (Dropping Pará)		ATT (All states in legal amazon & staggered CAR)	
	667 municipalities & 12 years		664 municipalities & 12 years		808 municipalities & 12 years	
	1	2	3	4	5	6
ATT					-0.228** (0.101)	-0.115 (0.0963)
G2008	-0.470*** (0.112)	-0.327* (0.190)			-0.475*** (0.111)	-0.246** (0.114)
G2009			0.260* (0.154)	-0.056 (0.431)	0.213* (0.121)	0.0404 (0.162)
Population weight	Yes	No	Yes	No	Yes	No
Entropy Balancing	No	Yes	No	Yes	No	Yes
Pretrend Test. H0 All Pre-treatment are equal to 0						
Chi2	12.6808	7.6496	12.8471	6.1875	33.0824	16.9897
p-value	0.0266	0.1766	0.0455	0.4025	0.0005	0.1082
Obs.	7310	7310	7272	7272	8839	8839

NOTE: Significance levels: *10%, **5%, ***1% and Std. Errors in brackets.
The Table shows average treatment effects using Callaway and Sant'Anna's (2021) framework of estimating group-time treatment effects for three group-cohorts Pará (in 2008), Mato Grosso (in 2009), and the rest of the federal states (in 2012) from Legal Amazon. Control variables include The variables are ADI: Annual deforestation increment (km^2), Herd density: Cattle herd density (Number of cattle/Municipal area), Fine amount: Total Amount in Real of Environmental Fines(adjusted for 2019R$), Non-ag value: Non-agriculture gross value added at current prices is measured by subtracting the Gross value added at current agricultural prices from the Gross added value at total current prices at the municipality level (adjusted for 2019R$), Protected area: Cumulative WDPA protected area (km^2), Yearly mean precipitation (mm) and agriculture price indices for rice, corn, sugarcane, and cassava are measured using the calculation of agricultural output prices, illustrated by Assunção et al. (2015). The estimation was done in the Stata CSDID package using seed number 0687 with 1000 bootstrapping iterations for the "not-yet-treated" specification. All models are with importance weights (iweight) at the municipality level.

Table 3 DID with the dependent variable as "Number of escalations"

	ATT for Pará (Dropping Mato Grosso)		ATT for Mato Grosso (Dropping Pará)		ATT (All states in legal amazon & staggered CAR)	
	667 municipalities & 12 years		664 municipalities & 12 years		808 municipalities & 12 years	
	1	2	3	4	5	6
ATT					-0.268** (0.107)	-0.106 (0.162)
G2008	-0.313* (0.165)	-0.281* (0.160)			-0.317*** (0.165)	-0.068 (0.126)
G2009			-0.205* (0.121)	-0.0829 (0.1441)	-0.181* (0.103)	-0.151 (0.324)
Population weight	Yes	No	Yes	No	Yes	No
Entropy Balancing	No	Yes	No	Yes	No	Yes
Pretrend Test. H0 All Pre-treatment are equal to 0						
Chi2	13.3806	5.1002	6.2141	1.3864	19.2302	13.3555
p-value	0.0201	0.4038	0.3996	0.9667	0.0571	0.2707
Obs.	7310	7310	7272	7272	8839	8839

NOTE: Significance levels: *10%, **5%, ***1% and Std. Errors in brackets.
The Table shows average treatment effects using Callaway and Sant'Anna's (2021) framework of estimating group-time treatment effects for three group-cohorts Pará (in 2008), Mato Grosso (in 2009), and the rest of the federal states (in 2012) from Legal Amazon. Control variables include The variables are ADI: Annual deforestation increment (km^2), Herd density: Cattle herd density (Number of cattle/Municipal area), Fine amount: Total Amount in Real of Environmental Fines (adjusted for 2019R$), Non-ag value: Non-agriculture gross value added at current prices is measured by subtracting the Gross value added at current agricultural prices from the Gross added value at total current prices at the municipality level (adjusted for 2019R$), Protected area: Cumulative WDPA protected area (km^2), Yearly mean precipitation (mm) and agriculture price indices for rice, corn, sugarcane, and cassava are measured using the calculation of agricultural output prices, illustrated by Assunção et al. (2015). The estimation was done in the Stata CSDID package using seed number 0687 with 1000 bootstrapping iterations for the "not-yet-treated" specification. All models are with importance weights (iweight) at the municipality level.

Mechanisms

In this section, I provide intuition behind the results from Tables (2) and (3). I suggest that the reduction in conflicts and escalations in the state of Pará is driven by four mechanisms, newly cleared land (by forest fire), in-migration effects (by families involved in conflicts), increased monitoring effect (by IBAMA fine intensity), and climatic effects (by conflict by drought index).

Mechanism I

This mechanism suggests that in post-CAR registration periods, the municipality with newly deforested land creates further opportunities for non-forested land use. This abates contentions over existing non-forested land and thereby reduces conflicts. I utilized the CSDID specification from Equation (2) to estimate the "Forest fire per 1000 people" as an indicator of land clearing activity in Pará and Mato Grosso. The results suggest land clearing fires were reduced in Mato Grosso by 20%, while they increased in Pará by 9.7%. This indicates that in Pará, the CAR intervention resulted in newly cleared land that reduced the opportunity cost for new land invasions and increased benefits of non-forested land use expansion.

Mechanism II

In this mechanism, I study the number of families in land conflicts reduced in Pará by 35%, indicating the in-migration effects. By in-migration, I suggest inward migration within Legal Amazon or Brazil. Using a measure of "Families in (land) conflicts per 1000 people", I suggest that the number of families involved in land conflicts has reduced since the CAR intervention. With newly deforested land, the decrease in families in conflicts subsided the land conflicts in Pará.

Mechanism III

This mechanism is called the increased monitoring effect (by IBAMA fine intensity). I suggest expanding environmental monitoring; since CAR intervention, the state of Pará has witnessed an increase in "Environmental fine (2019R$) per 1000 people". The higher fine indicates a higher likelihood of 'getting caught' for illegal land invasions, deforestation, and other activities. It may explain the direct effect of conflict reduction in Mato Grosso. However, in the case of Pará, I observed an increase in forest fire; therefore, the increased environmental fine may be associated with the newly deforested land in the region.

Mechanisms IV

Tables (2) and (3) show the preliminary results of the chapter; I observe that land conflicts and escalations declined in post-CAR intervention. In this mechanism, I employ normalized drought index adjusted conflicts and escalations measures to test the effect of regional dry and wet seasons on land conflicts. I employ the palmer drought severity index, which has a negative value for the dry season and positive values for the wet season. The dependent variables "Escalations by drought index" and "Conflicts by drought index" indicate the wet and dry season adjusted measure of conflicts. I refer to this mechanism as a climatic effect (by conflicts by drought index). I find reverse effects to our main model specifications; escalations and conflicts increased in Pará post-CAR intervention[13].

[13] Using a similar framework, I test the model if the “Fire in dry season” vs “Fire in wet season” have any effects due to CAR intervention. Both results show no treatment effects. Furthermore, no treatment effect exists in case of using drought index as a dependent variable.

Table 4 Mechanisms for declining land conflicts

	Mechanism 1	Mechanism 2	Mechanism 3	Mechanism 4	
	Forest Fires per 1000 people	Families in conflicts per 1000 people	Environmental fine (2019R$) per 1000 people	Escalation by drought index	Conflicts by drought index
G2008	0.097*	-0.354***	0.086**	0.0217**	0.0373*
	(0.056)	(0.0995)	(0.041)	(0.0103)	(0.0209)
Chi2	22.1530	5.5270	2.91	5.5951	2.9426
p-value	0.005	0.3550	0.7139	0.3476	0.788
Observations	7310	7310	4105	7307	7306
G2009	-0.203**	0.254	-0.218***	0.0118	0.006
	(0.0844)	(0.241)	(0.075)	(0.0087)	(0.0208)
Chi2	15.6882	5.8390	8.8788	7.6879	15.3742
p-value	0.0155	0.4415	0.1805	0.2619	0.0175
Observations	7272	7272	4114	7271	7265

NOTE: Significance levels: *10%, **5%, ***1% and Std. Errors in brackets.

The Table shows average treatment effects using Callaway and Sant'Anna's (2021) framework of estimating group-time treatment effects for three group-cohorts Pará (in 2008), Mato Grosso (in 2009), and the rest of the federal states (in 2012) from Legal Amazon. Control variables include The variables are ADI: Annual deforestation increment (km^2), Herd density: Cattle herd density (Number of cattle/Municipal area), Fine amount: Total Amount in Real of Environmental Fines(adjusted for 2019R$), Non-ag value: Non-agriculture gross value added at current prices is measured by subtracting the Gross value added at current agricultural prices from the Gross added value at total current prices at the municipality level (adjusted for 2019R$), Protected area: Cumulative WDPA protected area (km^2), Yearly mean precipitation (mm) and agriculture price indices for rice, corn, sugarcane, and cassava are measured using the calculation of agricultural output prices, illustrated by Assunção et al. (2015). The drought index is Palmer Drought Severity Index (PDSI) estimated using TerraClimate data. The estimation was done in the Stata CSDID package using seed number 0687 with 1000 bootstrapping iterations for the "not-yet-treated" specification. All models are with mean-population weights (iweight) with municipality-level yearly population.

Limitations

I suggest that there are two fundamental limitations of this chapter. First deals with data limitations, second deals with equivalence between treatment and control groups (or selection bias), and lastly, the relationship between outcome variable and treatment intervention (selection into treatment).

Firstly, this research intends to investigate how land registration affects land conflicts. The data available on the study of land conflicts is limited and may suffer from under-estimation bias, i.e., the actual level of land conflicts may not be estimable using the current data. In addition, the number of land conflicts and escalations is counted as data measures. Thus, they include zero as a valid observation. Following earlier research using this data, I analyzed the log-transformed variables with linear DID assumptions (Alston et al., 2009; Hidalgo et al., 2010; Alston and Mueller, 2010; Fetzer and Marden, 2017; Albertus et al., 2018; Rajão et al., 2020). Therefore, the results are at best an approximation of the actual level of conflicts, and they may suffer from estimation bias. I propose to resolve this using twofold strategies. Firstly, I employ additional data source mortality rate (number of overall mortalities*1000/ population) to revisit the main model specifications. Second, I built an aggregate measure of violent conflicts referred to as the "Number of escalations." This measure indicates a violent conflict level which shows the approximate level of actual violence in the given municipality (Fetzer and Marden, 2017; Albertus et al., 2018). I show that the results for the main model specification are robust to these two strategies.

Secondly, the equivalence between the treatment and control group is addressed using the entropy balance covariates matching (Hainmueller, 2012). Tables (2) and (3) show that the primary model specification for Pará satisfies the Parállel trends' assumption. To add to CSDID results, I present Borusyak and Jaravel's (2017) estimation for pre-trend. The results shown in Table (14) suggest no pre-trend in the dynamic event study.

Lastly, one key question is that CAR registrations are not correlated with land conflicts. The data suggest that the binary treatment of CAR registration in Pará (since 2008) and Mato Grosso (since 2009) has no strong correlation with the number of land conflicts and escalations. Moreover, CAR registration is mandatory, even though it is self-declaratory. This dissolves the selection into a treatment issue. Further, I suggest that covariate matching enables us to address the question of equivalence and selection into treatment.

Policy implication

Policy implication I: CAR registration and deforestation control

The primary goal of CAR registration is to control deforestation on private landholdings in the Legal Amazon. However, the results suggest that CAR registrations do not warrant that goal. Deforestation (annual deforestation increment) has been declining in the study period of this chapter. The decline, however, stemmed from local decentralized and robust governance policies. For example, Moz-Christofoletti et al. (2022) provide evidence that decentralized policies like the green-municipality program (PMV) implementation effectively control deforestation in Pará. Similar results can be seen in the case of the property municipalities (MP) program by Assunção and Rocha (2019). This chapter finds that CAR registration's impact on land conflicts via perceived tenure security gets actualized via different channels like increasing forest fire, intensifying deforestation. I suggest that registration should be supplemented by a stringent mandate of safeguarding and restoring APP and LR on private properties.

Policy implication II: alignment of agricultural growth and resource protection

In addition to monitoring the deforestation on private landholdings, the CAR can also aid agriculture growth. Chiavari and Lopes (2021) suggest that Brazil can double its agricultural yields while utilizing already cleared forested land. In an empirical study, Szerman et al. (2022) show that conservation benefits can be comparable to agricultural land use in improving crop yield and streamlined credit constraints for rural producers' cultivation of deforested land. To add on Szerman et al. (2022), this chapter's results suggest that rural producers can generate value-addition to already deforested land via reduced land conflicts.

Policy implication III: livelihoods promotion and CAR

One key limitation of CAR (and the Forest Code of 2012) has been the lack of a robust framework addressing the livelihoods promotion for registered rural producers. Although registration in CAR entitles a stream of benefits, strengthening those benefits may not outweigh the constraints imposed by CAR registration. For example, Jung et al. (2017) suggest that CAR does not have explicit livelihoods impact goals. However, it affects local livelihoods considerably. The authors argue that CAR registration should merge with poverty reduction goals. This chapter's results show that the extended goal of reduced land conflicts is directly associated with peace-building and livelihoods in peacetime. The narrative on sustainable livelihoods is not complete until the policy addresses the peace-building process.

Conclusion

The chapter began with the hypothesis that land registration permits rural producers 'perceived tenure security. Therefore, land registration should reduce land conflicts in the region. I present a causal inference using primary evidence of the DID model, robustness checks using an alternative estimation strategy, and data on mortality. The results suggest that the CAR intervention reduced land conflicts and conflict escalations, the number of families in conflicts, and the overall mortality rate in Pará. Further, the chapter offers a mechanism via which these lowered conflicts get realized. I focus on four mechanisms, namely newly cleared land (by forest fire), in-migration effects (by families involved in conflicts), increased monitoring effect (by IBAMA fine intensity), and climatic effects (by conflict by drought index). Lastly, I suggest three broad policy implications of this analysis, the potential abatement of land conflicts via land registration gives rise to a critical limitation of CAR in expanding the benefits to rural producers.

Future research

I consider two potential areas for improvement: the expansion of the analysis timeframe to include post-2012 CAR registration as treatment and the inclusion of all municipalities in the Legal Amazon sample. Secondly, the treatment variables CAR is a continuous variable indicating registration level at the municipality level. In future research, I propose to develop a continuous DID framework to reassess the findings of this study.

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Chapter 3

Evaluating landholder's true state dependence and municipality-level factors affecting the compliance with the Forest Code of 2012

Abstract

This chapter explores the persistence of compliance with the Forest Code of 2012 and municipality-level factors affecting it in Mato Grosso and Pará in the Brazilian Amazon. Previous studies have aimed at understanding the factors affecting compliance using a static model of landholders' decision to clear land. However, the land use decision to comply or not is inherently dynamic. I propose an empirical evaluation and extension of Schons et al. (2019) 's dynamic land clearing under constraints established by the Forest Code of 2012. I extend their framework to include a decision to reforest the land besides land clearing. I suggest that the landholder's decision to comply with the Forest Code of 2012 can be dynamic as s/he can jump in & out of the compliance threshold, i.e., 1/5th land clearing in the Brazilian Amazon. I am using remote sensing and GIS to address the question of modeling dynamic compliance using a large-cross sectional panel of 12711 landholdings in Pará across ten years and 4813 landholdings in Mato Grosso across nine years. I employ recent advances in bias-corrected high-dimensional fixed effects to estimate the true state dependence (compared with the random-effect model). I found that the true state dependence only explains about half of the persistent behavior of landholders. Additionally, the municipality-level factors affect

compliance differently depending on the property size, state, and regional variations. The chapter has four policy implications. Firstly, I provide novel insight into how local socio-economic factors affect compliance under selection bias and state dependence. This provides a policy insight on sustaining persistence in forest conservation on private landholdings. Secondly, I include various factors such as land conflicts or forest fires, which have a diverging impact on compliance in the two states. This suggests the need for tailored policy to address the restoration of deforested lands. Thirdly, I demonstrate how the extensive geospatial and secondary economic data can be utilized to provide local inputs for policy implementation.

Keywords: dynamic compliance, persistence, bias-corrected fixed effect modeling, the Forest Code of 2012, and Pará& Mato Grosso

Introduction

Similar individuals make different decisions when faced with the same set of options. Moreover, these decisions become an interesting question when decision-makers repeatedly face the same set of options. I study one such scenario: what is the dynamic compliance for landholders when they are obliged to comply with land-use constraints to promote forest conservation?

In 2012, The Native Vegetation Protection Law (No. 12,651/2012), also known as the Forest Code, was enacted as a significant step in promoting Brazil's efforts in deforestation control. The law limits the expansion of production on private landholdings in Permanent Preservation Areas (Áreas de Preservação Permanente – APP) and Legal Forest Reserves (Reserva Legal—LR). APP is an area around water bodies, while LR is the proportion of private landholdings that is legally protected (or to be restored) under native vegetation. As such, the law constrains rural producers' land use to 1/5th of their landholding area in the Amazon biome[14]. In other words, landholders abiding by the 1/5th rule are *compliant* with the Forest Code.

To conduct functional implementation, the Forest Code of 2012 enacted a federal land registration program to collect, maintain and monitor georeferenced information on all private landholdings in the Brazilian Amazon. To promote registration, the government contends that this law acts as a mutual benefit stream for rural producers and society. For the former, in case of registration, landholders receive a stream of benefits in terms of credit access, exemptions

[14] IBGE divides Brazilian territory into six different types of biomes defined in Brazil: Amazon, Atlantic Forest, Cerrado, Caatinga, Pampa, and Pantanal. The Forest Code puts land use constraints on the biome of rural producer's residency. In Amazon, the landholder is required to maintain 4/5th of their land under native vegetation (IBGE, 2021).

from past environmental crime, tax benefits on equipment to protect native vegetation, and licenses to operate silviculture or aquaculture activities (SICAR, 2020; Chiavari and Lopes, 2015). For the latter, safeguarding native vegetation on private landholdings produces net social benefits, albeit at the private cost to landholders. However, the registration does not ensure that the landholder will comply with the Forest Code provisions. In this chapter, I present a novel perspective on landholders' declared preference to participate in environmental regularization programs, laying out the path to *becoming* compliant with the Forest Code.

The chapter focuses on private landholdings in Pará and Mato Grosso. These two states were selected for dual purposes. First, although the federal registry was enacted in 2012, two states studied here, Pará in 2008 and Mato Gross in 2009,[15] implemented their land registration and environmental regularization programs. I utilize these nearly decade-long land-use decisions available for studying dynamic compliance. Second, although both states are on the historical forest frontier of the Brazilian Amazon (Chiavari and Lopes, 2015), their development paths differ. Mato Grosso's deforestation path was mainly export-oriented, whereas Pará's was driven by small landholder's agricultural and allied activities expansion. They offer a unique case study to evaluate forest conservation policies on private landholdings.

This chapter analyzes large cross-sectional panels with private landholding and their municipalities. I studied 12711 landholdings in 141 municipalities in Pará for ten years, while Mato Grosso had 4813 landholdings in 86 municipalities for nine years[16]. I present two

[15] Both Pará and Mato Grosso began their land registration program to foster forest conservation & restoration on private landholdings before the federal registry was enacted in 2012 (Alix-Garcia et al., 2018; West and Fearnside, 2021).

[16] The sample was carefully narrowed down considering four step criteria: First, I include the sample of municipalities within the same compliance threshold of land clearing: 1/5th of total landholding is legally permitted. Secondly, I remove landholdings that have analysis status as 'pending' or 'rejected'. And Third, I include landholders who explicitly stated their choice of participating in the environmental regularization program. Finally, I include the landholdings exhibit dynamic land-use pattern. Please refer the Figure (8)

objectives using recent advances in econometrics with high-dimensional and nonlinear fixed effects modeling. Firstly econometric evaluation of persistence (i.e., state dependence), and secondly, determining the impact of observed factors at the municipality-level influencing landholder's compliance decision.

Past compliance has a structural impact on the probability of compliance in future periods, commonly referred to as 'true state dependence.' However, several landholder-specific attributes are crucial in determining whether the compliance decision is stable over time and varies across landholders. Additionally, these attributes are inaccessible in commonly available data sets, or in general, they are unobserved for each landholder. This presence of unobserved landholder-specific dissimilarities leads to serial correlation in compliance. Therefore, the past compliance experience may appear to have a structural effect on the probability of future compliance; in fact, it does not, thus producing spurious state dependence. Consequently, studying dynamic decision-making is an empirical econometric challenge. In this chapter, I use a dynamic econometric model allowing for the presence of unobserved effects to disentangle true state dependence from the spurious one.

The chapter begins with a conceptual framework of a dynamic land clearing model from Schons et al. (2019). The conceptual framework extends a dynamic land clearing model to include a reforestation path. The chapter illustrates two approaches to disentangle true state dependence (to understand persistence): first, I estimate spurious state dependence using a random effect (RE) dynamic probit model. This approach poses a strong condition on the underlying structure of the unobserved heterogeneity. To correct the biased estimates, I revisit the RE estimates using the recent advances in econometric literature using analytical bias corrected probit fixed effects (FE) estimation. This approach suggests that unobserved heterogeneity considerably impacts state dependence; however, it is half that it was with the RE approach. Additionally, I present policy mechanisms via covariates in the model to explore the factors affecting dynamic compliance.

Lastly, I propose three contributions to current literature; firstly, I show robust evidence of state dependence in the persistence of compliance vs. noncompliance with the land use constraints under the Forest Code of 2012. Additionally, I control for the municipal-level factors such as population density, agricultural crop prices (for Rice, Sugarcane, Cassava, Soy, and Cattle), and year-fixed effects as exogenous control, whereas area under protection, fine density, GDP per capita, and credit density that are treated as endogenous. These estimates of covariates suggest crucial policy insights on the local government scale to promote compliance. Secondly, the results illustrate that dynamic land clearing decisions are not a one-directional from the forest to non-forested land; they can go from non-forest to forested land. This has implications for understanding the critical step of the forest restoration activity on private landholdings. Lastly, the chapter demonstrates advanced remote sensing and GIS tools to provide a novel insight into the landholder's decision modeling using high-dimension econometric approaches.

The chapter is organized as follows; first, I elaborate on background information, then a conceptual framework, data & descriptive statistics, empirical framework, results, and policy implications.

Background

In this section, the chapter introduces background information on the land registration program, its shortcomings, and theoretical challenges to evaluating dynamic compliance.

CAR registration is not a sufficient condition for compliance

The Forest Code consolidated and created a federal land registration program called National Rural Environmental Registry System - SICAR (Sistema Nacional de Cadastro Ambiental Rural). The registry maintains a sizeable geospatial dataset of landholdings across the Legal Amazon[17]. For instance, the registry includes 220573 landholdings in Pará (N= 93118) and Mato Grosso (N=127455)[18] as of December 2020. However, the registration in CAR is not a sufficient condition for the landholder's willingness to comply with the provisions of the Forest Code.

CAR registration is the first and required step toward landholder's enrollment in Environmental Regularization Program—PRA (Programa de Regularização Ambiental). Enrollment into PRA ensures that landholders promise to oblige to the provisions of the Forest Code of 2012. This exempts the landholder from the sanctions or fines for illegal land clearing (which occurred before July 2008[19]). The sanctions or fines are reversed in regeneration, recovery, and environmental compensation action. To sum up, the Forest Code of 2012 sets out the three critical steps toward compliance as follows, step (1) is to register into an online georeferenced database of landholdings, and step (2) if registered landholding is validated, then confirm the

[17] Legal Amazon corresponds to the area under the responsibility of the Superintendence of the Amazon Development – SUDAM established by Article 2 of Complementary Law no. 124, of 03/01/2007. The region is formed by the states of Acre, Amapá, Amazonas, Pará, Rondônia, Roraima, Tocantins, and Mato Grosso, and also by the municipalities of the state of Maranhão located west of the 44th meridian (IBGE-Legal Amazon, 2021).

[18] Based on the author's data collection from the CAR (2020) database: https://www.car.gov.br/; please refer to Appendix for more information on the municipality-wise registration pattern in Pará and Mato Grosso.

[19] According to the Forest Code 2012, landholders who have environmental liabilities related to the clearing of remnants of native vegetation, which took place until July 22, 2008, in APP, Legal Reserve and restricted use area, who are registered in the CAR may apply for membership in the PRA of the state in which they are located so that the environmental regularization of their property can continue (Chiavari and Lopes, 2015).

landholder's "willingness to join the PRA[20]" and step (3) deals with the execution by landholder's path to restoring the LR and APP.

Previous studies[21] have expressed concern about equating land registration into CAR to the "willingness to comply." I propose a solution; the CAR registration documents responses from the registered landholder's "willingness to join PRA." In this chapter, I exploit this information to construct a sample of landholdings with a declared preference to participate in PRA. I suggest that declared preference participation in PRA warrants a prima facie assumption of utilizing a subset of landholdings (that agreed to participate in PRA) to evaluate a dynamic compliance model.

In a recent comprehensive report, Chiavari and Lopes (2021) acknowledge that CAR registrations have increased in all states in the last decade. CAR enrollment and (preliminary) analysis have progressed steadily. However, the data validation is much slower than expected across the states[22]. Furthermore, the report highlights that the final stage of CAR is ensuring that all landholdings declare the PRA is the most challenging policy task for the local government. Therefore, the selection of landholding in the empirical analysis is a significant challenge to address.

I propose four-step criteria to narrow down the dynamic land-use sample employed in this chapter. Figure (8) illustrates an approach to narrow down the sample to evaluate the dynamic compliance. I am using data[1] from the Sistema de Cadastro Ambiental Rural (SICAR, 2020).

[20] In SICAR (2020) each registered landholder was asked if s/he wants to participate in PRA (Aderiu ao Programa de Regularização Ambiental), the options were Sim (1), Não(2) and Não informado(3).

[21] Mueller, 2016; Azevedo et al., 2017; Jung et al., 2017; Santiago et al., 2018; Schons et al., 2019; Jung et al., 2021

[22] A notable exception is State of Espírito Santo has completed all three core steps, enrollment, preliminary analysis and data validation till late 2021.

Steps (1 & 2) concerned with the legal land-clearing threshold. The Forest Code of 2012 mandates different thresholds for maintaining LR and APP depending on the biome of the landholder's residence. I selected municipalities from the Legal Amazon, 141 in Pará and 86 in Mato Grosso. Step (3) was to narrow down the validated landholdings. I found that 96% (7294 out of 7583) of landholdings in Mato Grosso while 91% (26049 out of 28593) of landholdings in Pará are not yet analyzed by local officials. Therefore, the sample was reduced to 33343 landholdings. The last criteria to limit the sample was "if landholders prefer to participate in PRA." I found that 76 % (5529 out of 7294) in Mato Grosso while 50% (12937 out of 26049) of landholdings in Pará declared their willingness to participate in environmental regularization.

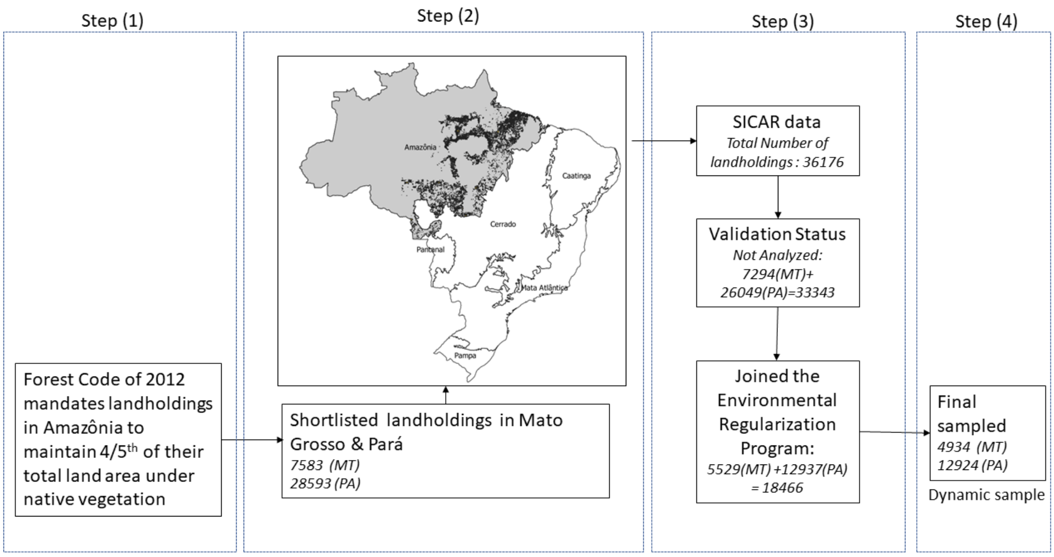

Figure 8 Approach to getting dynamic compliance landholdings sample

The figure shows the strategy to narrow down the sample of properties following the standard compliance threshold, i.e., they are from Legal Amazon. Thus, they fall in 4/5th landholdings to be maintained under the native vegetation threshold. Furthermore, I narrow down the landholdings ‘validated’ and ‘joining PRA.’ Finally, considering the dynamic land use, I narrow down the sample of 17858 landholdings across the decade-long cross-sectional panel dataset.

In the following section, I present an extension of the conceptual framework based on Schons et al.(2019) 's dynamic land clearing model for a smallholder. The extension includes dynamic land clearing and forest restoration on private land. I suggest that empirically the question of policy compliance becomes a selection bias problem by including lag-dependent variables, potentially endogenous covariates, and fixed effects. The following conceptual framework introduces these issues from the theoretical perspective.

Conceptual framework

I propose a conceptual framework suggested by Schons et al.(2019) ‘s dynamic land clearing model for a smallholder who can clear land and sell the harvested timber to make way for agriculture or grazing and sell wood from uncleared land. Three critical insights from Schons et al.(2019) are helpful for this chapter; 1) unobserved assessment of risk (of being caught) affects compliance 2) this risk is endogenous, and therefore, there is nonrandom self-selection into compliance or noncompliance (empirically, there is selection bias), lastly 3) dynamic land clearing (and compliance) is affected by observed & unobserved factors (Schons et al., 2019).

However, in a dynamic model of land clearing decisions for the smallholder, Schons et al., 2019 assumed that land clearing in one direction, i.e., forested land, is cleared and not reforested. In this conceptual framework, I extend the Schons et al.(2019) dynamic model to include land clearing and restoring, i.e., deforestation and reforestation. Additionally, I extend it to analytically evaluate the selection bias, i.e., self-selection into compliance or noncompliance, using recent econometric methods.

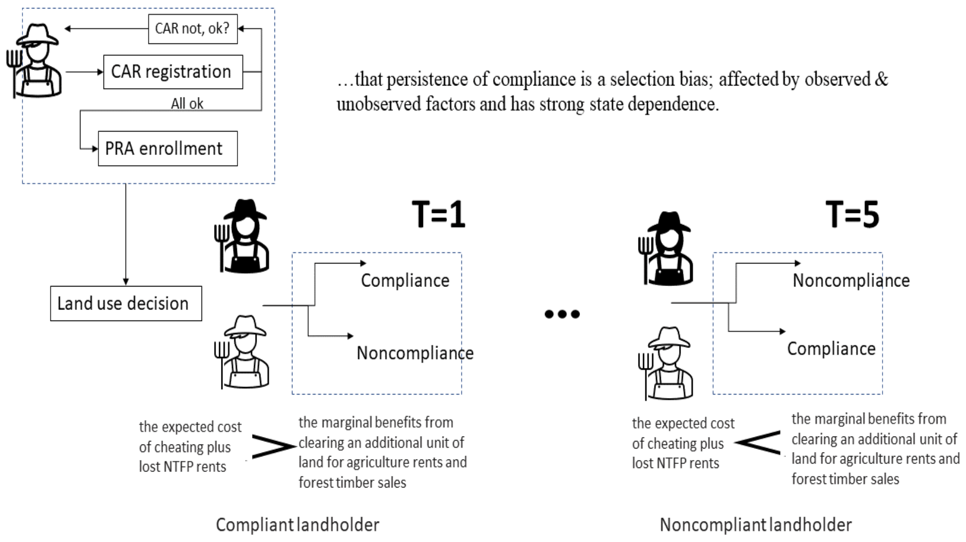

Figure 9 Overview of conceptual framework

The figure extends the dynamic land clearing framework from Schons et al.(2019) to include landowner's reforestation efforts. This enables us to have dynamic compliance with the Forest Code of 2012. I narrow down 17858 landholdings in Pará and Mato Grosso.

Figure (9) shows a two-stage conceptual framework. Stage(1) deals with narrowing down the landholder's willingness to participate in PRA and thereby comply or noncomply with the Forest Code of 2012. Stage(2) deals with dynamic land clearing decisions where the landholder's clearing path depends on the expected cost of cheating & lost non-timber forest products (NTFP) rents compared to the marginal benefit of clearing additional land units (Schons et al., 2019). I suggest that the expected cost of cheating and rents can change over time, and therefore the landholder's compliance can change to noncompliance. This conceptual framework raises two key empirical questions; first, the persistence of compliance progress with respect to past compliance. Second is the impact of initial endowment heterogeneity on future compliance of landholders.

I consider two conceptual challenges; first, land registration is not analogous to "willingness to comply." The landholder's current incentives drive their probability of land registration. However, the probability (and later persistence) of compliance is driven by the landholder's initial endowments, unobserved factors (such as perception of enforcement of the law), and the marginal benefit of clearing additional land. Accordingly, this chapter utilizes the sample of landholdings that have stated their willingness to participate in PRA and have a moderately large T to evaluate the impact of initial endowments on compliance.

Moreover, I suggest that initial endowments have temporal effects on outcomes, as initial endowments are heterogeneous. This effect is heterogenous and can be serially correlated with compliance. Schons et al.(2019) considered this an effect of unobserved and observed factors affecting the decision to clear additional land. For example, the authors build their model including an unobserved perceptive of the risk of 'getting caught' for noncompliance. In this chapter, I consider that municipal-level environmental fine intensity captures this unobserved perception. It determines the local law enforcement and its impact on compliance.

Further, the initial endowments affect subsequent endowments and, therefore, compliance. Schons et al.(2019) consider these as; first, the authors suggest that the 'perception of getting caught' evolves dynamically, and then the heterogeneous endowments at the household level. These changes determine future compliance. Secondly, the non-constant prices and rents affect future compliance.

To sum up, I suggest a conceptual framework extending Schons et al.(2019) to include reforestation and local (municipality-level) factors that account for both observed (such as exogenous agricultural price shocks) and unobserved (such as fine intensity) channels impacting dynamic compliance. Finally, I propose an approach to evaluate true state dependence and the influence of initial, existing endowments and time-fixed effects on future compliance.

Empirical framework

The empirical framework intends to explain the suitability of the fixed effects (FE), random effects (RE), and bias-corrected fixed effects (BCFE) dynamic nonlinear (probit) model to estimate the relationship between compliance, lag-compliance, and covariates. I conducted the conventional dynamic random effect model (Wooldridge, 2005; Rabe-Hesketh and Skrondal, 2013) and the bias-corrected fixed effect model (Fernández-Val and Weidner, 2016; Cruz-Gonzalez et al.,2017; Stammann, Amrei, 2017). These two models are evaluated in their ability to model unobserved heterogeneity and state dependence.

Few econometric concerns with a nonlinear dynamic model

Previous research has discussed the shortcomings of nonlinear dichotomous outcomes models with unobserved heterogeneity and lag-dependent variables. (Heckman, 1987; Heckman, 2007; Wooldridge, 2005). The dynamic specification aims to account for the state dependence process and heterogeneity.

I begin with compliance as the proportion of landholding is 1= if 4/5th or more land is under forest cover or 0 otherwise. Consider the following model specifications where Y_{it} where $Y_{it} \in [0,1]$ is compliance at the time t and Y_{it-1} is compliance at time $t-1$;

$$Y_{it} = 1\{\rho Y_{it-1} + X_{it}'\theta + c_i + \varepsilon_{it} > 0\},$$

where X_{it} denotes a vector of strictly exogenous covariates, and distributional assumptions are imposed on the error term ε_{it} in order to account for the nonlinearity of this model. Further, these models assume that $\varepsilon_{it} \mid Y_{i0}, \dots, Y_{it-1}, X_i, c_i \sim NIID(0,1), where X_i = (X_{i1}, \dots, X_{iT})$ denotes the time series of explanatory variables and Y_{i0} is the initial condition (Wooldridge,2005). Thus, the dynamic probit model is as follows;

$$P(Y_{i0}, \dots, Y_{it-1}, X_i, c_i) = \Phi(\rho Y_{it-1} + X_{it}'\theta + c_i).$$

Equation 1

The main econometric challenges in the estimation of the parameters in the model are as follows;

1) To account for the dependence on the initial condition (for which assuming independence of the unobserved heterogeneity c_i is often unreasonable) and
2) To disentangle the estimation of ρ (which measures the structural impact of past innovation experience on future innovation activity) from the effect of c_i.

Heckman (1987; 2007) argues that in understanding dynamic decision-making, the initial endowments have a continual effect on the outcome, described as heterogeneity c_i. Moreover, the effect of initial endowments attenuates the subsequent experience, thereby altering the outcome, described as state dependence ρ. Further, Heckman (1987; 2007) and Wooldridge (2005) underlined that problems might occur if the initial observation and unobserved factors are correlated, referred to as the initial condition problem[23].

[23] Please refer Rabe-Hesketh and Skrondal (2013) for an overview of these econometric problems. For original argument by Prof. Heckman, please refer https://eml.berkeley.edu/~mcfadden/discrete/ch4.pdf

In the following two subsections, I discuss how these shortcomings are tackled using the RE and BCFE models. To conclude, I suggest that the bias-corrected fixed effect is the suitable methodology to resolve all the issues discussed earlier.

Fixed effects (FE) model

In general, the unobserved heterogeneity c_i can be accounted as the fixed effects, as suggested by Heckman (1987); this would resolve the restriction imposed by the distribution of unobserved heterogeneity. However, many landholdings in the sample develop in individual intercepts for each fixed effect, thus resulting in an incidental parameter problem (IPP). To tackle the bias due to IPP, i.e., the relationship between lag-variable and unobserved parameters leads to bias in estimating true state dependence. Conventional FE modeling can help resolve this but requires a unique condition where the number of observations is significantly larger than the number of periods. These conditions are rarely tackled in practice due to a lack of availability of the data with N>>T. Therefore, I move to alternative solutions to the RE model.

Random Effect (RE) Model

The initial condition problem can be resolved by explicitly modeling the initial response jointly with the subsequent response, as illustrated by Heckman (2007). Wooldridge (2005) recommended conditioning the response at the initial period and the time-varying explanatory variables at each period (excluding the initial period). This is known as Wooldridge's simple RE dynamic nonlinear modeling problem solution. In theory, this is a robust approach, including initial period values and time-averaged values of variables contributing to the unobserved heterogeneity. Implementing the RE with large N and small T was a computational issue. Recently, to implement the *simple solution* in Stata, Grotti and Cutuli (2018) offered a tool to estimate the dynamic random-effects probit models with unobserved heterogeneity. The Stata module xtpdyn (Grotti and Cutuli, 2018) utilizes the algorithm that Rabe-Hesketh and Skrondal (2013) proposed. I provide estimates of the RE model as a reference to compare with BCFE using this implementation.

However, the RE model does not fully address the econometric issues highlighted at the beginning of this section. The intended 'simple solution to initial condition problem' by conditioning on y^{i0}, partially allows a dependence between unobserved heterogeneity parameters and initial conditions. However, it does not fully account for the time-varying covariates structure. Further, Rabe-Hesketh and Skrondal (2013) recommended that the 'initial condition problem' can be solved by including the initial period of an explanatory variable X_{i0}. This incorporates a limited bias correction. Moreover, applying Wooldridge (2005), I understand that the use of RE is suitable in cases where modeling specification is fully parametric, i.e., a specification is conditional distribution is assumed to include the risk of misspecification, which leads to inconsistent estimates for the parameters of interest.

I understand that the unobserved heterogeneity depends on the number of landholdings. Therefore, unobserved factors such as initial endowments of large landholders are significantly different from small landholders. Additionally, heterogeneous landholders' unobserved perception risk depends on their race and social-political background[24]. At best, I conclude that

[24] Indigenous people's land & forest rights are widely studied topics (Baragwanath and Bayi, 2020; BenYishay et al., 2017; Mueller, 2022). The race and land relationships are comparatively less explored in assessing the Forest Code.

the RE model provides spurious estimates of state dependence when using endogenous and exogenous covariates.

Bias Corrected Fixed-Effects Model (BCFE)

Recent literature in econometric methods has reviewed the key challenges in modeling nonlinear dynamic models. Czarnowske and Stammann (2019) summarized the benefits of using BCFE; RE models suffer from the unobserved effects stemming from the distributional assumptions on error terms, while FE estimates suffer bias due to incidental parameter problems. BCFE is a recent econometric tool to handle the shortcomings of RE and FE models.

Fernández-Val and Weidner (2016) proposed a methodology to permit the estimation of dynamic nonlinear panel data with individual and time FE with arbitrary dependence of the initial condition on the FE. The author has utilized stochastic expansions to derive additive correction terms for the FE and maximum likelihood for estimation and average partial effects (APE). Given the inclusion of high-dimensional fixed effects, the computation of these estimators becomes a limitation of their prevalent acceptance. However, recent advances in multi-way fixed effect modeling (Stammann, 2017; Czarnowske and Stammann, 2019) enable us to evaluate these models for high-dimensional data.

I utilize high-dimensional probit panel two-way fixed effects: time and individual fixed effects using Stammann's (2017) algorithm for a generalized linear model with k-fixed effects. The authors provide R-package alpaca: Fit GLM's with High-Dimensional k-Way Fixed Effects

(Stammann, 2017; Czarnowske and Stammann, 2019). I utilized this package on Google Colab[25].

Stammann (2017) and Czarnowske and Stammann (2019) provide a practical implementation of analytical correction using a post-estimation routine that can be used to substantially reduce the incidental parameter bias problem present in nonlinear fixed-effects models (see Fernández-Val, Iván, and Martin Weidner, 2016 for an overview). The command applies the analytical bias correction derived by Fernández-Val and Weinder (2016) and Hinz, Stammann, and Wanner (2020) to obtain bias-corrected estimates of the structural parameters. It is currently restricted to logit and probit models with two- and three-way fixed effects (Stammann, 2017). Further, I estimate average partial effects (APE) on bias-corrected models.

Advantages of BCFE over RE

BCFE models overcome the limitation of RE (and FE) models to include time-invarying variables. For instance, I include 'protected area' in municipalities as covariates as its important determinant of forest restoration and conservation. Moreover, the RE model imposes distributional assumptions (i.e., normality) on unobserved heterogeneity. This resulted in an inability to distinguish partial effects on time-invarying factors separately. Wooldridge (2005) recommends that the estimates of parameters of time-invariant variables that

cannot be identified in a FE specification are reported for the RE specification. However, they

[25] https://colab.research.google.com/?utm_source=scs-index

should not be interpreted in isolation from the effect of the unobserved heterogeneity. In using BCFE, Fernández-Val and Weidner (2016) suggested that the main interest lies in estimating the APE, not estimates. Unlike in RE, where increasing T does not solve the bias associated with state dependence, the BCFE model is more suitable for moderately large T.

To summarize, I provide estimates using the RE and BCFE model to explore the dynamic compliance, state dependence, and covariates. The results show that the RE model estimates the state dependence twice that of BCFE.

Data and descriptive statistics

I constructed a sample using a large-cross sectional panel of 12711 landholdings in Pará across ten years and 4813 landholdings in Mato Grosso across nine years. The data was collected using various tools such as web-scrapping using Python, remote sensing data using Google Earth Engine, and secondary data sources.

Dependent variable: binary compliance

I define compliance based on the land-use constraints under the provision of the Forest Code of 2012 for landholders residing in the Brazilian Amazon. Compliance is defined as the proportion of landholding is 1= if 4/5th or more land is under forest cover or 0 otherwise. Land-use constraint determines landholder's LR, the most common LR requirement of 80% of the property in the Amazon, 35% in the Cerrado, and 20% in the Pantanal, though some landholdings ' requirements may be lower (Soares-Filho et al. 2014). This chapter employs landholdings from the state of Pará and Mato Grosso.

To estimate the compliance for each landholding, I utilize land-use classification data from the Brazilian Annual Land Use and Land Cover Mapping Project—Mapbiomas collection[26] (Azevedo Sr et al., 2020) and shapefile for sampled landholdings from geospatial data from the CAR (2020). The Mapbiomas provides annual land cover and land use maps from 1985 to 2020 (and subsequent annual updates) (Azevedo Sr et al., 2020). For all the Mapbiomas-related, estimates were constructed on the open-source platform of Google Earth Engine—GEE (Gorelick et al., 2017).

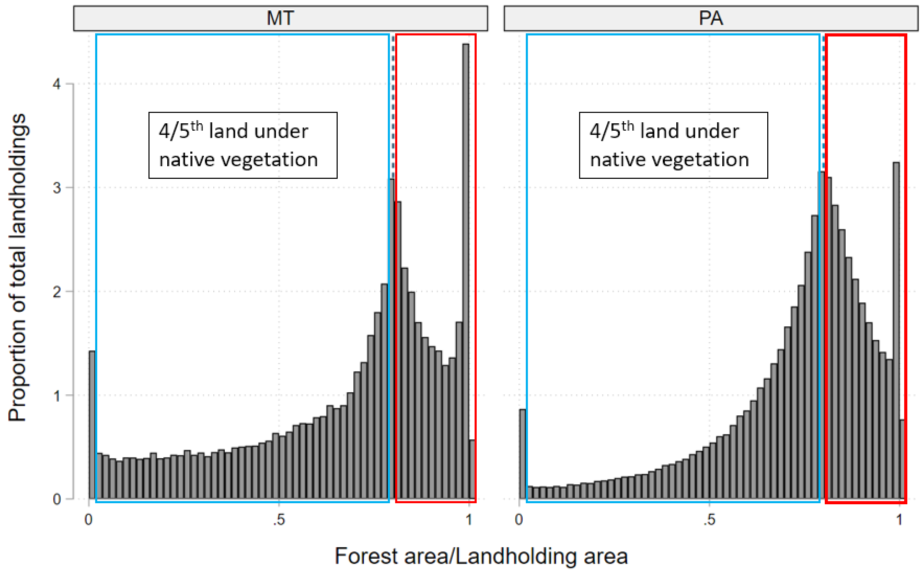

Figure 10 Native forest proportion on landholdings

The figure shows the distribution (1= fully forested, 0= entirely deforested) of native forest (estimated from Mapbiomas collection 5) on private landholdings in two states. There are a significant number of landholders complying with the 4/5th threshold.

Covariates: municipal level control variables

[26] I employed yearly land-use classification rasters from Collection 5 - covering the period 1985-2019 (published in August 2019). Their methodology for classification is explained in their technical handbook; please refer MapBiomas (2021). These raster datasets can be called into the GEE interface using ID: projects/mapbiomas-workspace/public/collection6/mapbiomas_collection50_integration_v1

The dataset includes landholding level information and municipality level covariates. I control for the municipal-level factors such as population density, agricultural crop prices (for Rice, Sugarcane, Cassava, Soy, and Cattle), and year-fixed effects as exogenous control, whereas area under protection, fine density, GDP per capita, and credit density that are treated as endogenous.

Population density and GDP per capita were estimated using Instituto Brasileiro de Geografia e Estatística – IBGE's population projection for municipalities and GDP dataset, respectively. The exogenous agricultural crop price indices are estimated using the method discussed in Assunção et al. (2015; 2019). These exogenous price shocks determine the local agricultural incentives affecting the dynamic compliance. I include municipality-level precipitation using the TerraClimate database from GEE (Abatzoglou et al., 2018). Furthermore, I built fine intensity using the method illustrated by (Hargrave and Kis-Katos, 2013), where I divided the total amount of fine imposed by Instituto Brasileiro do Meio Ambiente e dos Recursos Naturais Renováveis—IBAMA (2020) by an area of natural vegetation in 2007 from Mapbiomas. Credit density is estimated using a municipality's total financial value of rural credit by the area under cropping from Mapbiomas. The area of protected indigenous land was estimated by QGIS using the data from WDPA (UNEP-WCMC, 2020). Lastly, I include a municipal-level measure of land conflicts constructed from the dataset from Comissão Pastoral da Terra—CPT(2020). Finally, I constructed the number of forest fires using (the Fire Information for Resource Management System—FIRMS dataset (2021) superimposed on Mapbiomas to distinguish forest fires from other fires like agriculture fires.

Table 5 Municipality descriptive statistics

	Mato Grosso			Pará		
	N	mean	sd	N	mean	sd
Population Density (N/ km^2)	1692	6.948	25.461	1716	56.455	260.24
Precipitation (mm)	1692	2.094	0.44	1728	2.466	0.627
PPA Rice	1692	0.821	1.446	1728	0.296	0.562
PPA Sugarcane	1692	0.758	2.616	1728	0.043	0.104
PPA Cassava	1692	0.346	0.868	1728	5.642	10.797
PPA Corn	1692	0.556	1.441	1728	0.233	0.499
PPA Soy	1692	7.892	12.951	1728	0.281	0.213
PPA Cattle	1692	81.768	85.684	1728	54.738	79.114
Fine intensity (R$/ km^2)	1692	18.474	83.167	1728	41.979	236.33
WDPA protected (km^2)	1692	1205.642	2598.065	1728	4675.507	16321.19
Credit density (R$/ km^2)	1692	321.115	308.763	1720	343.451	1736.819
GDP per capita	1692	29.849	25.15	1716	12.191	14.325
Avg. CAR landholdings size (ha)	1692	1160.433	1948.194	1728	683.47	3735.505
Number of land conflicts (N)	1692	0.265	0.792	1728	0.749	2.285
Forest fires (N)	1668	153.39	204.251	1716	123.505	273.691

NOTE: all descriptive statistics are for municipality-level variables.

Results

RE model shows that state dependence is about 69% and 67%, whereas the BCFE models put this at 45% and 35% in Pará and Mato Grosso. This suggests that the BCFE model corrected the true state dependence. In both states, I find that the probability of property-level compliance is associated with compliance level in the past and is also associated with the set of coefficients of the variable capturing unobserved heterogeneity (UH). The initial condition, initial value, and within-unit average of time-varying explanatory variables (like GDP per capita and credit density at the municipal level) have statistically significant effects on the initial condition of compliance. Thus, indicating that these characteristics are correlated and unobserved factors positively associated with compliance.

In Mato Grosso, I found that the property-level probability of compliance is positively driven by population density, precipitation, and average parcel size in CAR at the municipality level, population density, precipitation, and average parcel size in CAR lag-compliance and initial level of compliance at the property-level. However, factors that lower the probability of compliance are a multi-commodity price index, GDP per capita, fine intensity, protected area size, credit density, and land conflict number at the municipality level.

Moreover, in Pará, compliance is positively driven by lag-compliance, population density, and soy price index. In contrast, rice, cassava, and cattle price index, GDP per capita, indigenous protected area size, Number of fire incidents, and land conflict level negatively affect the probability of compliance. Our results show that command-and-control is an essential policy instrument, but incentive-based programs are essential in controlling deforestation on private properties and encouraging continued compliance. Further, effective CAR implementation and civil actions such as the roundtable of the soy and cattle are essential in increasing compliance. I recommend that a combination of socio-economic incentives for restoration, protected areas, and monitoring via environmental fines are essential to increase compliance. Likewise, the land conflicts at the municipality level negatively affect compliance and fire incidence. Therefore, the policies to promote compliance shall consider the likelihood of success via curbing fire activity and land conflicts.

Table 6 Avg. partial effects (APE)—Random Effects (RE) utilizing Wooldridge's (2005) method

VARIABLES	Pará (1)	Mato Grosso (2)
Lag Compliance	0.691***	0.670***
	(0.00237)	(0.00655)
Population Density (N/ km^2)	-5.77e-05**	0.00397***
	(2.53e-05)	(0.000451)
Precipitation (mm)	-0.00118	0.0348***
	(0.00189)	(0.00694)
PPA Rice	-0.0240***	-0.0138***
	(0.00329)	(0.00161)
PPA Sugarcane	-0.00841	-0.000646
	(0.0149)	(0.00170)
PPA Cassava	-0.000971***	-0.00888**
	(8.98e-05)	(0.00415)
PPA Soy	0.0188***	-0.00151***
	(0.00542)	(0.000354)
PPA Cattle	-0.000365***	-0.000308***
	(3.03e-05)	(3.80e-05)
Protected indigenous land (km^2)	-4.31e-07***	-2.13e-06***
	(8.19e-08)	(4.95e-07)
Fine intensity (2017 R$)	1.89e-05**	-0.000173***
	(7.66e-06)	(3.89e-05)
GDP per capita (2017 R$)	-0.000862*	0.000157
	(0.000448)	(0.000200)
Credit density (2017 R$/ km^2)	-3.24e-06	-5.95e-05***
	(4.47e-06)	(1.01e-05)
CAR avg parcel size (ha)	7.33e-07*	6.48e-06***
	(4.14e-07)	(1.56e-06)
Number of land conflicts (N)	-0.00288***	0.00333*
	(0.000706)	(0.00183)
Number of fire incidence (N)	-9.18e-06***	0.000108***
	(2.77e-06)	(1.28e-05)
Initial condition compliance at time 0	-0.0313***	0.0401***
	(0.00226)	(0.00477)
Initial period of fine intensity	2.60e-05	0.000160***
	(2.29e-05)	(4.89e-05)
Initial period of GDP per capita	0.000847**	0.000159
	(0.000389)	(0.000371)
Initial period of credit density	5.19e-06	8.99e-05**
	(3.17e-06)	(4.54e-05)

Initial period of CAR avg parcel size	-2.98e-06***	-1.26e-05***
	(3.92e-07)	(1.47e-06)
Initial period of Number of land conflict	-0.000757	-0.00141
	(0.00125)	(0.00362)
Initial period of Number of fire incidence	-3.04e-05**	-9.93e-05***
	(1.46e-05)	(3.14e-05)
Time average of fine intensity	-4.53e-05	-0.000201
	(3.03e-05)	(0.000139)
Time average of GDP per capita	0.000915	0.000810***
	(0.000559)	(0.000310)
Time average of credit density	2.37e-05***	9.31e-05***
	(8.79e-06)	(1.69e-05)
Time average of CAR avg parcel size	-1.83e-06	8.90e-06**
	(1.60e-06)	(4.37e-06)
Time average of Number of land conflict	-0.000139	-0.00874
	(0.00178)	(0.00533)
Time average of Number of fire incidence	2.80e-05	-9.50e-05***
Constant	(2.63e-05)	(3.03e-05)
Observations	114,399	38,504

NOTE: Table shows average partial effects (APE). The estimates use Stata command xtpdyn, which implemented RE from Wooldridge's (2005) using an algorithm by Rabe-Hesketh and Skrondal (2013). Please refer Appendix for regression outcomes. Robust standard errors in parentheses, significant levels are ***1%, **5%, and *10%

Table 7 Avg. partial effects (APE)—Bias corrected fixed effects (RE) utilizing Fernández-Val and Weidner's (2016) method

	(1)	(2)
VARIABLES	Pará	Mato Grosso
Lag Compliance	0.4497***	0.3493***
	(0.002723)	(0.004968)
Population Density (N/ km^2)	0.0002427	0.001348
	(0.0002271)	(0.00653)
Precipitation (mm)	-0.04289***	-0.000519
	(0.005372)	(0.01217)
PPA Rice	-0.007513	-0.01005**
	(0.007958)	(0.00382)
PPA Sugarcane	-0.06189	0.00967*
	(0.04473)	(0.00403)
PPA Cassava	-0.000485**	0.00583
	(0.0001794)	(0.008232)
PPA Soy	-0.07736***	-0.002361#
	(0.01496)	(0.001221)
PPA Cattle	-0.00006699	0.0004038***
	(0.00006235)	(0.00007437)
Protected indigenous land (km^2)	-0.00001685***	0.0001667
	(4.019e-06)	(0.001068)
Fine intensity (2017 R$)	0.00002503***	-0.0002065***
	(6.652e-06)	(0.00003516)
Credit density (2017 R$/ km^2)	-2.604e-06	0.0000508***
	(4.124e-06)	(0.00001409)
GDP per capita (2017 R$)	-0.0003843	0.00122***
	(0.000474)	(0.000217)
CAR avg parcel size (ha)	-7.965e-07*	2.794e-07
	(3.355e-07)	(1.299e-06)
Number of land conflicts (N)	-0.0011	0.00335#
	(0.00066)	(0.001818)
Number of fire incidence (N)	7.175e-08	0.0000499***
	(3.383e-06)	(0.00001474)

NOTE: The table shows average partial effects (APE). Please refer Appendix for regression outcomes. The estimates use the R package alpaca, which implemented BCFE from Fernández-Val and Weidner's (2016) algorithm employing GLMs with high-dimensional k-way fixed effects provided by Stammann (2017). Please refer Appendix for regression outcomes. Robust standard errors in parentheses, significant levels are ***0%, **1%, *10%, and #5%.

Mechanism

Role of state dependence

The results show that the persistence of compliance can be explained by state dependence. However, the RE estimates show that state dependence explains compliance at about 69% and 67%, which is twice the estimated state dependence using the BCFE model's 45 % and 35 % in Pará and Mato Grosso. I suggest that true state dependence is about half the spurious state dependence. These results indicate that the state dependence, although significantly high, still does not explain the persistence. The municipality-level factors are crucial in sustaining forest conservation on private landholdings.

Exogenous price shocks

I found that exogenous agriculture price shocks work differently in these states. With historical export-oriented deforestation and land use, Mato Grosso exhibits the negative impact of soy expansion incentives on compliance. Furthermore, the soy price shock decreased the probability of compliance by 7% in Pará and 0.2% in Mato Grosso. This indicates that exogenous shocks in Soy production provide local incentives for land clearing, thus reducing compliance. On the contrary, the smallholder cropping in Pará stemmed from an expansion of agricultural activity across the BR230 highway. Subsequently, the price shock to daily consumption-based crops like cassava marginally reduces compliance probability in Pará but not in Mato Grosso. Finally, the export-oriented economic activity in Mato Grosso with Sugarcane and Cattle ranching fosters the likelihood of compliance by small margins. I suggest that this indicates the existing cleared land abates the need for new expansions of these activities. This could reflect increasing compliance.

Protected indigenous land

The results indicate that having protected indigenous land in the landholder's municipality affects compliance with the Forest Code negatively. Together with land invasion on protected indigenous territory, this effect can be attributed to causing an increase in compliance on private lands. The private landholding in indigenous territories holds higher initial endowments in terms of native vegetation compared to outside ones. This could be one of the reasons for this effect.

Fine intensity and enforcement of the Forest Code

The results suggest that the fine intensity has diverging effects in these two states. In Pará, increasing fine intensity enforcement fosters compliance, while in Mato Grosso, the impact is contrary. I suggest that in Pará, the monitoring and enforcement are driven by local governmental schemes like the Green Municipality Program. This may foster compliance with private landholding.

Limitations

I consider four limitations of this study. The first is the lack of landholder-level data. Although, the chapter demonstrates that the advanced GIS and remote sensing tools are useful in conducting high-dimensional econometric analysis. The lack of variables like landholder's race and income (and thereby benefits coming from welfare schemes like Bolsa Floresta or Bolsa

Familia) affect the land-clearing decision. Second, the conceptual framework to include reforestation incentives are endogenous to landholder's land size, income, and much more.

Conclusion

The chapter began with a dual objective, firstly to evaluate the true state dependence in continuous compliance with the Forest Code of 2012. Secondly, to estimate the impact of municipality-level factors on landholder compliance. The results suggest that compliance persistence is half that estimated using the conventional RE modeling. This suggests that landholders' past compliance plays a significant but lower role in sustaining forest conservation on private landholdings. Moreover, I suggest that the role of exogenous factors such as agricultural crop prices and population density matters as much as endogenous factors such as forest fires and land conflicts. Thus, providing critical insights into the means of intervention at the local government level besides monitoring.

Future research

I propose to extend the current analysis by including a few additional results to extend the policy implications. For instance, I plan to conduct a separate analysis of BCFE by a land-size group. I content that smallholder (less than one fiscal-module land size) vs. large landholder (greater than one fiscal-module land size) may provide insights into the role of smallholder land clearing and persistence under the Forest Code. Furthermore, I plan to include indicators for local policy impact on forest compliance under the Green Municipality Program (PMV).

The PMV was proposed to foster the complaint by intervening in municipal governance and monitoring mechanisms. I suggest the chapter may improve by explicitly incorporating dynamic reforestation mechanisms on private landholdings. Further, the BCFE shows robust evidence for state dependence; however, the impact of municipality-level vs. landholding level factors needs to be disaggregated using factors like soil quality for each landholder. Soil quality is an essential indicator of land conversion decisions. This chapter can be extended to understand these factors.

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Chapter 4

Does investing in local government capacity promote secondary forest growth? Evidence from the Green Municipality Program in the Brazilian Amazon

Abstract

Restoration of the Amazon rainforest is one of the most critical objectives for sustaining global climate action. In this Chapter, I present causal evidence that local policy intervention successfully added 14 to 27 km^2 of secondary forest in the state of Pará. Using novel econometric tools such as generalized synthetic control and matrix completion, I evaluated the self-participation in treatment, i.e., the Programa Municípios Verdes (PMV) fostered secondary forest recovery in the treated municipality. I utilize a robust quasi-experimental approach that compares a municipality's outcome with a weighted synthetic control group generated from nonparticipating municipalities to handle self-selection. The treated cohort average treated effects on treated (ATT) shows a 27 km^2 increase in a secondary forest area. Moreover, the young secondary forest (age 1 to 8 years) expanded faster at 26 km^2 than mature secondary forests (9 to 24 years) at 15 km^2. Although the treated cohort exhibits a 1.5 km^2 loss of secondary forest per year, it has a 7 km^2 increase. Lastly, I conduct robustness checks using the matrix-completion technique, which shows improved matching of pre-treatment trends in the area of the secondary forest and ATT of a 14 km^2 increase. These results are consistent with multiple econometric methods; generalized synthetic control, matrix completion, and staggered differences-in-difference. PMV strengthens sustainable rural production via strategic actions of environmental-land ordering and environmental management, focuses on local pacts, monitors deforestation, implements the CAR, and structures environmental management at the participating municipalities (PMV, 2021). This robust local policy intervention led to increased monitoring and secondary forest recovery.

Keywords: secondary forest growth, generalized synthetic control, matrix completion, Pará and Programa Municípios Verdes-PMV

Introduction

Concerns over forest ecosystem fragmentation, biodiversity loss, and environmental degradation, by and large, have recently expanded the focus of the international conservation community from the reduction of deforestation and forest degradation to forest cover expansion and restoration expressed through efforts such as the creation of the UN Decade on Ecosystem Restoration in 2020 (United Nations, 2022). In Brazil, however, such efforts have started to be legally tackled since the enactment of the 2012 Forest Code, the federal-level legislation regulating land use within private lands and introducing the legal structure for reporting reforestation and the provision of reforestation and forest restoration incentives. In this Chapter, I investigate the effects of a state-level program called Green Municipalities Program (herein PMV from the Portuguese name of the Program: Programa Municípios Verdes) on secondary forest growth in the state of Pará, in the Brazilian Amazon.

Although native vegetation cover in the Brazilian Amazon has decreased by 18% between 1985 and 2018 (from 582 million hectares to 507 million hectares, respectively), the net secondary forest area has expanded from 635,044 hectares to 45,538,393 hectares in that same period[27]. Secondary forests provide enhanced ecosystem services in areas where human disturbances have entirely removed old-growth forests (Chokkalingam and Jong, 2001; Silva Junior et al., 2020). For example, secondary forests provide a stream of ecosystem benefits, such as air quality control, improving soil fertility, rainfall water management, and timber & non-timber provisioning (Zeng et al., 2019). In particular, the trade-off between regulating and provisioning services boosts with expansion in the young and intermediate secondary forests,

[27] Authors estimates using MapBiomas (2020).

providing greater additionality (of services), opportunities for management, and climate mitigation (Naime et al., 2020).

Moreover, the Brazilian Amazon's secondary forest offers several opportunities beyond the ecosystem restoration goals. For instance, the secondary forest can provide a potential avenue for carbon sequestration and nature-based climate solutions (Heinrich et al., 2021), persistent drought shocks (Anderson et al., 2018), and livelihood opportunities (Alves-Pinto et al., 2018). Additionally, secondary forest recovery presents a novel avenue for extension and integration of welfare and livelihoods promotions within the development policies in Brazil. For instance, Jung et al. (2017) developed a comprehensive framework to address the lack of livelihoods promotion via environmental interventions such as the Forest Code of 2012. The chapter presents *mediating factors* linking forest conservation policies to household livelihoods and increased ecosystem provisions.

PMV can be seen as one such mediating factor. It was initiated to foster the rural property's Rural Environmental Registration (Portuguese: Cadastro Ambiental Rural, CAR) to combat deforestation and forest degradation in the state of Pará. PMV strengthens sustainable rural production via strategic actions of environmental-land ordering and environmental management, focuses on local pacts, monitors deforestation, implements the CAR, and structures environmental management at the participating municipalities (PMV, 2021). Although, PMV's primary goal is to maintain low deforestation in the participant municipality. By the time PMV was enacted in 2010, deforestation was already reduced in this region (Assunção and Rocha, 2019; Sills et al., 2020; Moz-Christofoletti et al., 2022). Thus, the primary responsibility of PMV navigated toward expanding CAR registration and sustaining rural credit, tax benefits, and additional funding sources such as The Amazon Fund[28].

This chapter suggests two secondary forest dynamics within the Brazilian Amazon. First, as discussed before, the secondary forest contributes to enhanced ecosystem provisions which can further improve the financial, health, and human capital (Perz and Skole, 2003a). I suggest that secondary forest recovery is strongly aligned with the goals of the PMV. Second, the secondary forest provides a socioeconomic opportunity to mitigate the long-term effects of poverty on the environment and vice versa. Perz and Skole (2003a; 2003) studied social determinants of secondary forests, suggesting that longstanding settlement and traditional activities positively impact secondary forests, whereas in-migration and non-traditional land use accelerate deforestation along with secondary forests in some areas. The PMV aided the combination of these two dynamics by linking the rural producers with community efforts to control deforestation. The PMV provided collective benefits for rural producers via land registration (for example, streamlined rural credit access) and a share in local environmental action[29].

In this Chapter, I investigate the causal relationship between PMV participation and the municipality level's recovery of secondary forest areas. I employ a cross-sectional panel dataset of 760 municipalities from 2001 to 2019 constructed using secondary forest and land-use classification data from Silva Junior et al. (2020) and MapBiomas (2020). I evaluate the

[28] Municipalities with high engagement in controlling deforestation and implementing environmental management can also receive higher tax revenues from the Green Tax Fund (ICMS Verde). In 2015, R$ 82 millions reais (USD 21 million) was transferred from the Amazon Fund to municipalities to support CAR registration as part of the program (Moz-Christofoletti et al., 2022).

[29] The PMV governance structure comprises government institutions (such as the Federal Prosecution Service, the Brazilian environmental enforcement agency, and the Pará State Public Prosecution Service), the private sector, non-governmental organizations, and rural producers (mainly from the agribusiness sector). They conducted average 3 to 4 meetings per year which involved all stakeholders untill 2017—moreover, a vast audience, which in some cases reached almost 300 people (Moz-Christofoletti et al., 2022, PMV, 2021).

hypothesis that municipalities participating in the PMV in the State of Pará present a higher secondary forest expansion than nonparticipating municipalities. The municipality's self-participation in the PMV to spillover effect in expanding the secondary forest area's area (in km^2 at the municipal level). I utilize a robust quasi-experimental approach of generalized synthetic control that compares a municipality's outcome with a weighted synthetic control group generated from nonparticipating municipalities to handle self-selection. The results show that PMV fostered the growth of the secondary forest area in participating municipalities. The treated cohort's average effects on treated (ATT) shows 27 km^2 of secondary forest.

The Chapter is organized as follows; I begin with a detailed background, then dive into data, empirical strategies, results, and discussion.

Background

Since the early 2000s, Brazil has set an example of robust policy-led deforestation control (Nepstad et al., 2014; Tacconi et al., 2019). While deforestation increased in the post-2014 years, the decline from 2002 to 2014 recognized the innovative public policy measures to control deforestation. These policies extended from converging on credit constraints (Assunção et al., 2020), sustainable supply-chain agreements (Lambin et al., 2018) and, improving monitoring & local government capacity ((Piketty et al., 2015; Tacconi et al., 2019), and targeted deforestation supervision (Antonaccio et al., 2018). These efforts culminated in a land-use policy to consolidate property registration, deforestation monitoring, and sustainable certification with private and rural land use. The law enforcement capacity increased deforestation control by engaging satellite monitoring; IBAMA led enforcement structure and expanded the protected areas at the federal and state levels. At the municipality level, local actors consolidated these efforts into an initiative to eliminate deforestation and support green supply chains at the territorial level (Piketty et al., 2015).

The PMV is one of those innovative policies to curb deforestation. The government of Pará developed in partnership with municipalities, civil society, private initiatives, the Brazilian Institute for the Environment and Renewable Natural Resources (Portuguese: Instituto Brasileiro do Meio Ambiente e dos Recursos Naturais Renováveis, IBAMA), and the Federal Public Ministry (Portuguese: Ministerio Publico Federal, MPF) (PMV, 2021). PMV chiefly aims to combat deforestation in the state, reinforce sustainable rural production through strategic actions of environmental and land ordering and environmental management, focus on local pacts, monitor deforestation, implement the CAR, and structure the environmental management of the participating municipalities (PMV, 2021).

Considering that PMV is a program targeted at high deforestation municipalities, Table (8) summarizes the deforestation in PMV vs. non-PMV municipalities across the Brazilian Amazon. It compares all the municipalities within Legal Amazon[30] vs. municipalities in PMV. The PMV municipalities are primarily in Pará, whereas the non-PMV municipalities are in Legal Amazon. I observed that all current deforestation measures estimate that PMV participant municipalities have twice the deforestation rate compared to non-PMV municipalities. Brazil's official estimates by PRODES show that PMV participants have almost thrice the deforestation rate as non-PMV municipalities. The estimated deforestation increment from the official source PRODES consistently underestimated the values, while GFW shows

[30] In 2004, the Brazilian Institute for Geography and Statistics (IBGE) divided the country into six biomes on the basis of the predominant original vegetation. For Amazonia, different government policies, laws, and statistics vary as to which definition of the region is used. The “Amazon biome” (bioma Amazônia) is contained entirely within the “Legal Amazon” except for a tiny area in the state of Maranhão (West and Fearnside, 2021).

higher estimates due to the upgraded methodology in 2017. I believe that MapBiomas estimated deforestation increments are closer to actual "land cover change" as the only database considering land-use change relationships to validate the forest area[31].

Table 8 Deforestation in municipalities participating in PMV vs. non-PMV

	Non-PMV (629 municipalities)	PMV (129 municipalities)
	Mean (SD) N= 11951	Mean (SD) N=2451
Deforestation increments from MapBiomas	26.39 (52.90)	53.37 (104.04)
Deforestation increments from GFW	24.41 (51.66)	57.62 (121.99)
Deforestation increments from PRODES	14.33 (55.42)	39.45 (110.56)

NOTE: Values in km^2. Author's calculation using MapBiomas, Global Forest Watch (GFW), and Programa Pará Calcular o Desmatamento na Amazônia (PRODES) in Google Earth Engine (GEE) for municipalities shapefile from IBGE for the year 2001.

The PMV was anticipated as a follow-up to the Action Plan for the Prevention and Control of Deforestation in the Legal Amazon (PPCDAm)[32], launched in 2004 (Assunção and Rocha, 2019; West and Fearnside, 2021). PPCDAm devised a "priority municipalities list" strategy where municipalities were "blacklisted" based on the official reported deforestation level[33]. The municipalities with a higher-than-average deforestation level of state were "blacklisted." The PMV program emerged to strengthen PPCDAm—specifically priority municipalities list

[31] GFW used the improved satellite data causing better detections of tree cover loss, which is likely due to the algorithm adjustments and other variability that directly impact how trends in tree cover loss appear over time (GFW Blog#A2021, 2021; GFW Blog#J2020, 2020). Also, there are some significant differences in the way PRODES and the GFW data detect changes, for example, the UMD spikes in primary forest loss in Brazil in 2016 and 2017 were due to understory fires that are not monitored by PRODES. (PRODES , 2021; GFW, 2021; Azevedo Sr et al. 2020)

[32] PPCDAm has been implemented in four distinct phases: PPCDAm-I (2004–2008), II (2009–2011), III (2012–2015), and IV (2016–2020). Please refer West and Fearnside (2021) for more details. Note that PPCDAm is not a single policy but it is a collection of policies.

[33] Recently the favored name is “Critic List” (Zwick and Calderón, 2022). I employ the name “blacklist” following the citations used in this context.

strategy. A few PMV municipalities were also part of the 'blacklisted' list. However, compared to PMV, the 'blacklisted' list had a more nuanced purpose of superior monitoring to curb deforestation. In contrast, the PMV is a wide-ranging program that builds economic opportunities while curbing deforestation.

Sills et al. (2020) present a comprehensive standpoint on PMV where environmental governance capacities of local government with local as well as federal incentives structure. The chapter illustrates the implementation of PMV against the backdrop of blacklisting of municipalities under Priority Municipalities (Portuguese: Municípios Prioritários, MPs), where federal command-and-control policy designated municipalities with unusually higher rates of deforestation for improved targeting and law enforcement. Subsequently, the MPs created a local incentive structure where enlisted municipalities were rewarded for their adoption to control excessive deforestation. Sills et al. (2020) find that the PMV has a significant positive impact on economic activity, although it fails to reduce deforestation beyond what federal policy has achieved. Assunção and Rocha (2019) provide robust evidence that blacklisting significantly reduced deforestation. The chapter suggests that the monitoring and law enforcement channel primarily drove this effect, and there is no effect on agricultural production or credit concessions.

Benchmarks of PMV

PMV is a rating of participating municipalities where each municipality receives a gets placed in one of five categories. The five rating categories are as follows; 1) Embargoed: these are the municipalities from the blacklisted list of the Ministry of Environment (MMA), 2) Under pressure: these municipalities had high deforestation in earlier years and have pressure from local economic projects such as hydropower dams, 3) Consolidated: these municipalities hold less than 60% native vegetation by 2010 but have actively participated in land registration drive under the Forest Code of 2012, 4) Forested: these are municipalities with more than 60% forest cover and lastly, 5) Municipality under control: this is the Green Municipality, meaning it has controlled deforestation.

Municipalities join the PMV by signing up the Term of Commitment (TAC) with MPF or signing the Term of Adhesion (TA) directly with the PMV at the state level in Pará. Both agreements provide legal and political stability to the commitment signed. PMV allows the municipality to receive incentives ranging from environmental clearance licenses, tax breaks, training for local officials, local government restructuring, and CAR implementation. These incentives aim to achieve a broad goal of supporting regulations for the financial sustainability of local environmental and resource management.

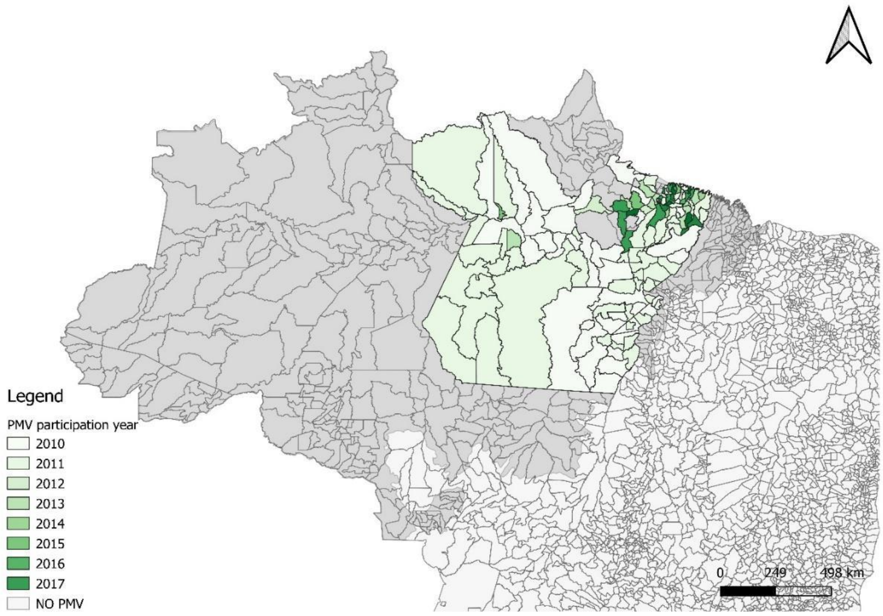

Figure 11 Staggered treatment of PMV since 2010

The figure illustrates the municipal enrollment in PMV Program from 2010 onwards; grey-colored municipalities are part of Legal Amazon. I observed that enrollment began in central and western municipalities and moved towards north-eastern municipalities. The blue color outline represents Legal Amazon (or Legal Amazonia). I consider the staggered enrollment into PMV by municipalities as "treatment," and from Legal Amazon, the synthetic "control" or "untreated" cohort was constructed.

PMV is a multi-stakeholder program involving the federal government, state government, civil society, and rural producers. The PMV is steered by a central committee referred to as the Coges: twenty-five members, with ten representatives from the government and twelve representatives from civil society, in addition to the Federal Public Ministry (MPF), the Public Ministry of the State of Pará (MPE) and the Brazilian Institute for the Environment and Natural Resources Renewables (IBAMA), which plays an essential role in command-and-control actions and information on critical deforestation areas. There are two primary commitments: Firstly, each participant municipality must maintain the annual deforestation rate below 40 km^2 (based on Prodes/INPE criteria). Secondly, more than 80% of the municipal area is registered in the Rural Environmental Registry (CAR). In doing this, the PMV ensures that the municipality develops a local governance system that carries out field verifications of illegal deforestation hotspots if they occur and report to the Program. To create accountability, the PMV ensures that the municipal working group combats illegal deforestation or environmental monitoring with aid from the IBAMA and Municipal Environmental Agency.

The adhesion of municipalities to the PMV is voluntary and brings participants mainly competitive and long-term advantages. The participant municipality receives legal, market, and administrative infrastructure security. Regarding legal security, the PMV brings stability to a rural economic activity where rural producers are free from sanctions or economic embargoes. PMV reduces the collective cost of fines and embargoes at the municipality level and should encourage municipal-level economic development. Regarding market security, sustainability certification (like the Soy moratorium) imposes an apt socioeconomic origin. Lima et al. (2019) present that soy importing countries have restricted products that harm the environment. In Brazil, large retail chains, such as Walmart, Carrefour, and Pão-de-Açúcar, have declared that they will no longer buy products from illegal deforestation and work in conditions analogous to slavery. In addition, some slaughterhouses (such as JBS and Marfrig) signed the Conduct Adjustment Term (TAC), pledging to purchase only from environmentally regular suppliers (Lambin et al. 2018). The Federal Government has prioritized access to credit, development, and rural technical assistance regarding credit access security by changing the municipality's position concerning environmental and social issues. Rural credit is an effective deforestation control policy (Assunção et al., 2020). In addition, the State of Pará plans to reduce taxes for producers with environmental regularity and a priority on land regularization in the state.

In summary, PMV provides a set of socioeconomic incentives for participant municipalities. Although, the participant municipality has not exhibited an additional decrease in forest loss beyond the federal policies intent (Sills et al., 2020). The PMV has contributed positively to increased economic activity within and between municipalities across the state. I hypothesize a positive spillover effect of PMV participation on increasing secondary forest growth at the municipal level.

Deforestation control and Secondary Forest growth

Figure (12) shows that secondary forest area has grown from 2001 to 2019 while native forest cover has deteriorated. In 2005, I observed an increase in secondary forest areas crossing over the forest area. I suggest that the PPCDAm effectively contributed to reducing deforestation of native forests from 2004 to 2015; it can be said that the growth in secondary forest areas was motivated by curbing deforestation activity and improved monitoring and enforcement in the Brazilian Amazon.

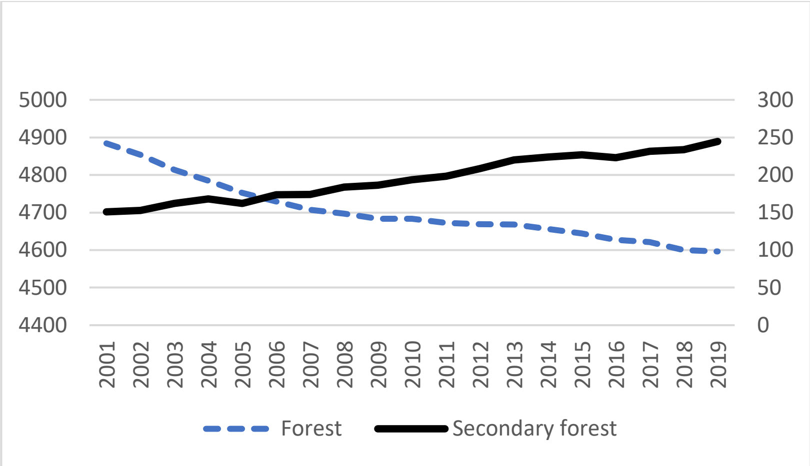

Figure 12 Dynamics between secondary and native forest

The figure that estimates from the MapBiomas secondary forest area and (native) forest formations using GEE shows that since 2005 there has been a cross-over between the two. In Legal Amazon, the average municipality area under the secondary forest area grew from 150 to 250 km^2 while (native) forest formations declined from 4900 to 4600 km^2.

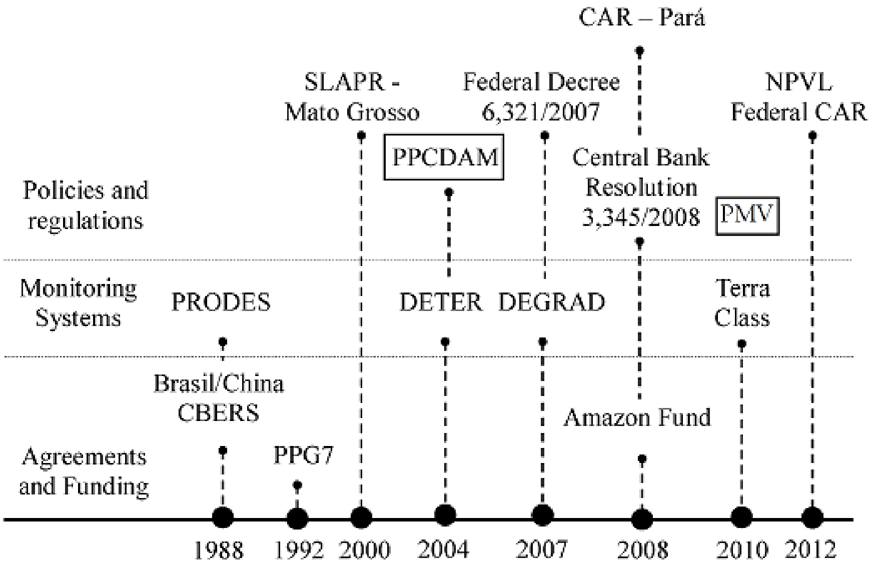

Figure 13 Timeline of PPCDAm

The figure shows that since 1985, the Brazilian government has enacted policies to tackle rising deforestation in Legal Amazon. Figure13 illustrates the three categories of policies: 1) Agreements and Funding (like Amazon Fund), 2) Monitoring systems (like PRODES), and 3) Policies and regulations (like PPCDAM). I believe that policies and regulations were largely effective and consolidated under the Action Plan for the Prevention and Control of Deforestation in the Legal Amazon (PPCDAm), launched in 2004, a long-term program that successfully controlled forest loss till 2014-15. PMV can be considered a byproduct of PPCDAm-type policies. PMV emerged in 2008 and was consolidated at the state level in Pará in 2010. Source: Authors illustration using Roitman et al. (2018)

Figure (13) outlines the short history of Brazil's deforestation control policy. I observe three types of deforestation control policies (West and Fearnside, 2021; Roitman et al., 2018).

- Type I: Agreements and Funding: These include policies like the Amazon Fund. These policies build upon international cooperation to sustain livelihood promotion, ecological protections, and deforestation controls.
- Type II: Monitoring systems include the advanced satellite-based technology led by Brazil's Instituto Nacional de Pesquisas Espaciais (INPE) and Forest Service. The monitoring systems focused on federal cooperation between states and federal agencies within brazil to better monitor, punish and deter the deforestation of Amazon and other native vegetations.
- Type III: Policies and regulations: These are consolidated policy measures like The Action Plan for the Prevention and Control of Deforestation in the Legal Amazon (PPCDAM) and PMV. The policies and regulations build on the other two types of policies.

West and Fearnside (2021) explain that PPCDAm phase I (2004 to 2008) to PPCDAm phase II (2009 to 2011) observed a twofold decline in deforestation rates. The authors attributed the success of PPCDAm to improved land planning, monitoring & control, and sustainable development schemes under the policy. Phase I actively targeted the "arc of deforestation" municipalities; for instance, the case of Parágominas is widely studied in the literature (Piketty et al., 2015; Assunção and Rocha, 2019; West and Fearnside, 2021; Zwick and Calderón, 2022). In 2008, the Parágominas became Brazil's first "green municipality" as it was infamous for deforestation, an area larger than one-third of its size (Piketty et al., 2015).

Moreover, PPCDAm (Phase 1) was the creation of 50 million ha of protected areas as part of the Protected Areas Program (ARPA) that had been established by Decree 4326 of 2002, mainly located along deforestation frontiers, the "homologation" of 10 million ha of indigenous territories and declaring invalid ≈60,000 illegal land titles (West and Fearnside, 2021). Also noteworthy was Mato Grosso's State Law 343 of 2008, which established a land-tenure and environmental regularization program for rural landholdings in the state, the Mato Grosso Legal (Alix-Garcia et al. 2018). The policy influenced a similar initiative launched in the state of Pará in the same year (State Decree 1148 of 2008), establishing what would later result in the national Rural Environmental Registry (CAR) system, a spatially explicit database for registering (legally and illegally) cleared areas in each landholding and determining forest (Alix-Garcia et al. 2018). Ultimately, the 2012 Forest Code (Law 12,651 of 2012) retained the constraints on land use from the erstwhile Forest Code of 1965 and strengthened the protection of native vegetation. Note that registration and abiding by the Forest Code is the key provision of PMV. Together, these legal and policy provisions contributed to the increase in secondary forest areas across the Brazilian Amazon.

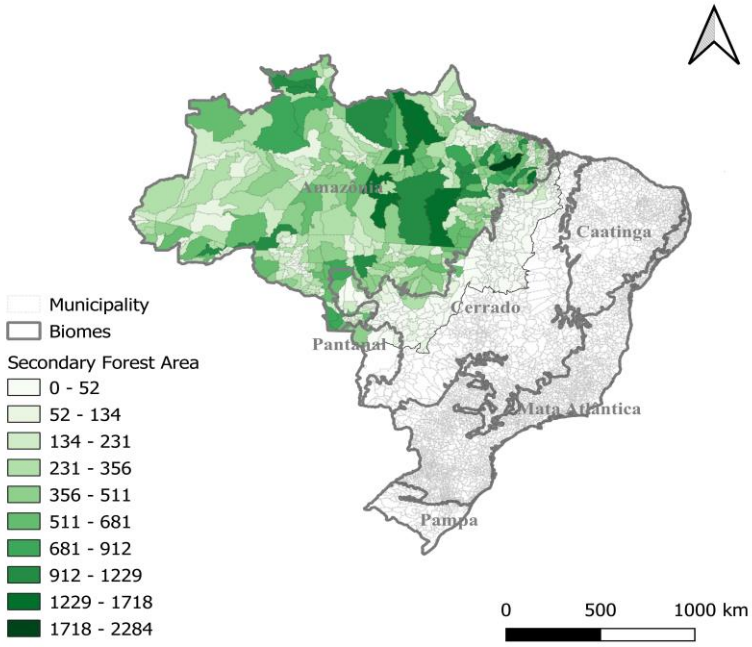

Figure 14 Municipality-level secondary forest

The figure illustrates aggregated secondary forest area in km^2 at the municipality level from 2001 to 2019. I observe that periphery municipalities on the "arc of deforestation" also exhibit growth in a secondary forest area. The municipalities outside Legal Amazon are not included in the sample. The area in square kilometers was estimated using the GEE zonal statistics from the secondary forest growth and area measurements in Silva Junior et al. (2020)

I consider that PMV membership since 2010 has covered more than 90% of municipalities in Pará. This provides a case study of a consolidated public policy agenda contributing to diminishing deforestation during the last two decades[34]. In this chapter, I plan to test the hypothesis that PMV participation fostered the growth of secondary forest areas. Our central hypothesis exploits the causal evaluation method to evaluate the impact of the municipality's self-selection into PMV on secondary forest growth.

[34] Please refer West and Fearnside (2021) and Mello and Artaxo (2017) for recent overview of the policy and its impact.

Data

I built a cross-sectional panel using data from various sources to answer our research question on the causal effect of municipality participation in the PMV program on secondary forest cover[35]. The dataset contains variables for 758 municipalities located in the Legal Amazon of Brazil, spanning 19 years, from 2001 to 2019.

Dependent variable

The outcome variables are measures of the area under secondary forest cover calculated using Silva Junior et al. (2020): area of secondary growth (km^2), increment, loss (km^2), and area of the secondary forest by age (km^2) at the municipality level. The treatment variable is "the municipality has to choose to participate in the PMV program" and takes a value of 1 if the municipality has decided to join the Program and zero if it has not. Since its inception, the PMV has gradually attracted 129 municipalities composing the "treatment" group, all located in Pará. The "untreated group" comprises 629 municipalities located throughout the Brazilian Amazon.

Covariates

The covariates include exogenous municipality-level annual agricultural crop price indices for rice, sugarcane, soy, and cassava,[36] and nonagricultural gross value added in 2019 Brazilian Currency (R$) values. I also include the environmental fines (2019R$) enforced by IBAMA to consider the command-and-control mechanisms at the local government level. To control for property enrollment in CAR, I include the total area of CAR-enrolled properties by year (km^2).

[35] Please refer Appendix (1) for details on sources.

[36] I measure exogenous price variation using the method applied in Assunção et al. (2019) and Assunção et al. (2015)

Furthermore, I include herd density (number of cattle heads per km^2) to include the impact of cattle ranching economic activity. Finally, I control municipality-level precipitation (mm) and temperature (K). Last, I estimated deforestation at the municipal level to evaluate the impact of PMV on deforestation control. However, given the high correlation between secondary forest area and deforestation, I decided to drop it from the covariates.

Table 9 Descriptive Statistics

If the unit joined PMV/MPF dummy	Non-PMV (629 municipalities)		PMV (129 municipalities)		
Variable	N	Mean	N	Mean	F-Test
Secondary Forests (km^2)	11951	153.37 (208.806)	2451	399.49 (418.205)	1868.49***
Environmental Fines (2019R$)	11951	4,086,001 (28090697)	2451	13,767,393 (77025434)	114.55***
Herd Density (N/ km^2)	11951	37.13 (38.925)	2451	28.29 (32.023)	111.15***
Nonagricultural value added(2019R$)	10693	2.98E+08 (1.96E+09)	2193	5.26E+08 (2.02E+09)	24.51***
PPA Rice	11951	9,031.26 (6976.90)	2451	5,975.55 (5826.32)	411.32***
PPA Corn	11951	4797.537 (3487.291)	2451	4612.225 (3290.11)	5.85**
PPA Soy	11951	2715.606 (6627.256)	2451	29.673 (130.941)	402.54***
PPA Sugarcane	11951	663.276 (3262.276)	2451	336.664 (1475.254)	23.58***
PPA Cassava	11951	5899.701 (9202.058)	2451	11247.79 (10597.6)	650.86***
Precipitation (mm)	11951	151.674 (43.683)	2451	196.805 (46.586)	2121.37***
Maximum temperature (K)	11951	317.763 (9.372)	2451	315.759 (6.396)	102.39***
Protected Areas (km^2)	11951	144247.2 (572380.9)	2451	215784.3 (898660.1)	25.43***
CAR properties (km^2)	11951	11740.72 (95103.36)	2451	279.188 (5596.941)	35.57***

Statistical significance: * 5%, 1% ** and 0.1%***.

NOTE: Please refer to Appendix (1) for data sources.

Empirical strategy

To deal with the self-selection problem, I follow Xu (2017) and Gobillon and Magnac (2016) and develop a generalized synthetic control model as this approach enables the selection of a robust untreated or control group from the combination of weighted traits of the never-treated municipalities in our sample to serve as the counterfactual in this analysis. The synthetic control methodology formalizes the selection of the comparison units using a data-driven procedure (Abadie, 2021; Abadie et al., 2010). Furthermore, this type of approach is robust against specification searches as the synthetic control weights are calculated before the post-treatment outcome is realized (Abadie, 2021). Thereon the synthetic control method constructs a transparent counterfactual using a combination of the "untreated " group that matches efficiently with "treated" units.

Unlike standard difference-in-difference (DiD), the generalized synthetic control method does not rely on the Parállel trends assumption, according to which the difference in outcome between the treated and untreated group in the absence of treatment would be constant. In theory, the violation of the Parállel trends assumption occurs due to unobserved time-varying confounders. A solution to the failure of the Parállel trends assumption has been offered by Abadie (2005), which is to condition pre-treatment observables using matching methods before estimating the ATT using DiD. However, this procedure does not ensure that the Parállel trends assumption holds in pre-treatment periods.

Abadie et al. (2010) offered a method to match pre-treatment covariates and outcomes between the treated and the untreated group using a pre-treatment match as criteria for a good match. The "synthetic control" method constructs a synthetic control unit from a set of untreated (control) units. This approach permits a comparison between treated and synthetic control units to offer a flexible and robust against violation of Parállel trends assumptions. An additional solution to the assumption violation on DiD is explicitly to model the unobserved time-varying heterogeneities. Bai (2009) utilizes an interactive fixed effects (IFE) model, including unit-specific intercepts interacting with time-varying coefficients. These time-varying coefficients are latent factors, while unit-specific intercepts are factor loadings (Xu, 2017). Generalized

Synthetic Control employs both solutions to address the violation of parallel trends assumption by unifying the synthetic control method with an interactive fixed-effects model (IFE).

This is a specific case of DiD, where step one estimates the IFE model using control group data and obtaining a fixed number of latent factors. Step two estimates factor loadings for each treated unit by linearly projecting pre-treatment treated outcomes onto the space spanned by these factors (Xu, 2017). Finally, the combined method imputes the treated counterfactuals based on the estimated factors and factor loadings (Xu, 2017). I estimate the following model:

$$\mathrm{Y_{it}} = \delta_{\mathrm{it}}\mathrm{D_{it}} + \mathrm{x'_{it}}\beta + \lambda'_{\mathrm{i}}\mathrm{f_t} + \varepsilon_{\mathrm{it}}$$

Equation 1

where Y_{it} is a vector containing the outcome of interest, i.e., secondary forest area and forest loss, for each municipality i in year t, and D_{it} is a vector containing information on whether municipality i participates in the PMV program in year t, in that case taking the value equal to 1, or zero otherwise. The vector δ_{it} contains the heterogeneous treatment effect of municipality i participation in the PMV program in year t, to be estimated. The term $\lambda'_i f_t$ is a factor component model that takes linear, additive form by assumption. The vector x'_{it} contains a series of municipal-level observed covariates, including herd density (number of cattle heads per km^2), exogenous crop price indices for rice, sugarcane, and cassava in 2019 Brazilian currency values, precipitation (mm), nonagricultural gross value added (in 2019 Brazilian currency values), total protected area extension (km^2), and total area of CAR-enrolled properties by year (km^2).

Covariates matching

The generalized synthetic control method utilizes a two-step approach to create synthetic control municipalities. First, it begins with an interactive fixed effects model using the control municipalities. Following that, the method predicts factor loadings for treated and control groups. Figure (15) shows the factor loadings employed in estimating the main results in Table (10).

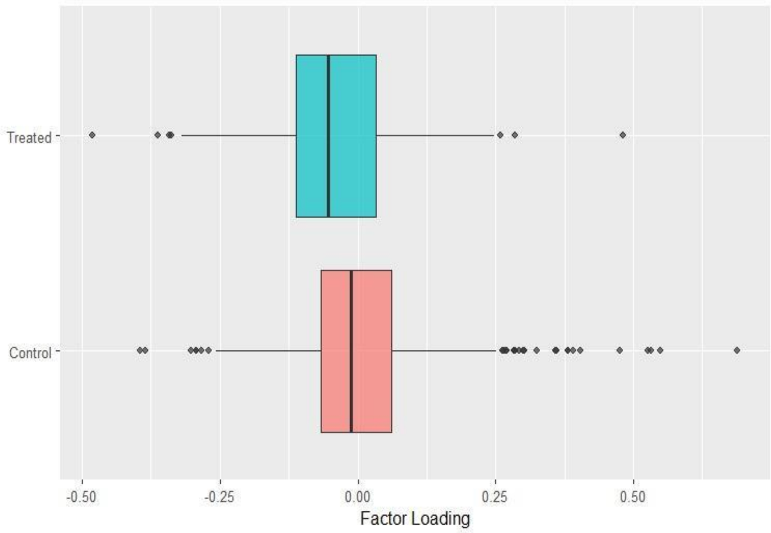

Figure 15 Latent factor loadings

The figure illustrates latent factor loadings behind the matching method used in estimating the main results in Table (10). The estimation was done in R gysnth, MC, and EM algorithms using seed numbers 282006 and 1000 bootstrapping iterations.

The generalized synthetic control presents matching using dimension reduction (to estimate latent factors) and conventional synthetic control as it considers the pretreated treatment group as a reference for matching. Given that, I do not have a "never-treated" control group, and states in Legal Amazon are not comParáble. I believe using this approach provides us with several advantages. First, it matches treated and control units using multiple cohorts and staggered treatment. This allows us to estimate the uncertainty estimates and provides an improved model specification to the conventional fixed effects method. Second, it selects the factor loadings based on data structure; in other words, the flexibility of estimation includes the underlying data structure. This improves the matching; as shown in Figure (15), the treated and control covariates are almost identical.

Challenges to identification

Our primary identifying assumptions deal with two essential aspects. First, treatment participation is endogenous to municipality-level controls due to self-selection or participation in PMV. Second, treatment occurred in the state of Pará, where gradually, all municipalities get treated. Therefore, I do not have control of municipalities. Pará is the forest's socioeconomic and political frontier that has evolved in the last decades.

Results

Figure (15) and Table(10) show that the treated cohort average treated effects on treated (ATT) shows a 27 km2 increase in a secondary forest area.

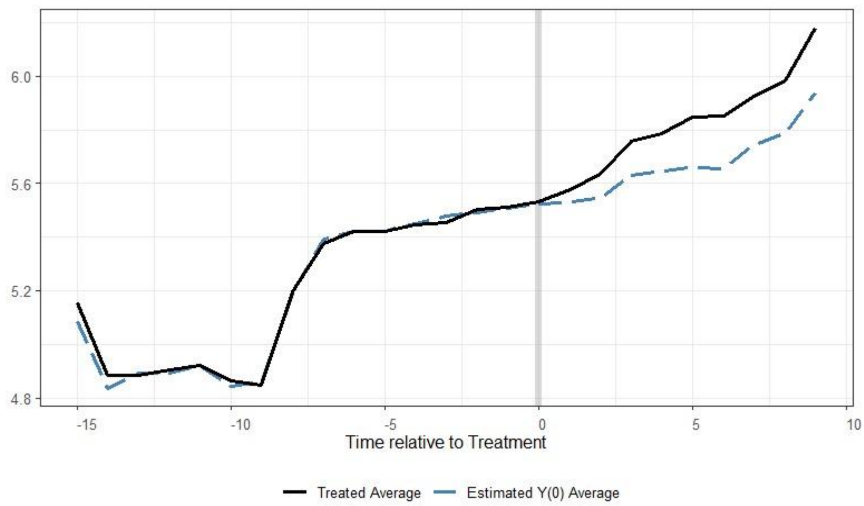

Figure 16 Generalized Synthetic Control plot

The figure shows estimated ATT with the dependent variable 'secondary forest area' using the Generalized synthetic control. Control variables include Land conflicts (N), Herd density (N/ km^2), Fine amount (2019R$), Non-ag value (2019R$), Protected area (km^2), Fire count at municipality-level, temperature (degree K), and rainfall (mm), CAR area (km^2), and

Agricultural prices for rice, sugarcane, and soybean. All price indices are measured using agricultural output prices calculation steps illustrated by Assunção et al. (2015). The estimation was done in R gysnth, MC, and EM algorithms using seed numbers 282006 and 1000 bootstrapping iterations.

The young secondary forest (age 1 to 8 years) expanded faster at 26 km2 than mature secondary forests (9 to 24 years) at 15 km2. Although the treated cohort exhibits a 1.5 km2 loss of secondary forest per year, it has a 7 km2 increase.

Table 10 Main results: secondary forest area using Generalized Synthetic Control

Average ATT	Generalized Synthetic Control Method
Secondary forest area (km^2)	0.1445*** (0.03263)
Secondary forest loss (km^2)	0.06574** (0.02523)
Secondary forest increment (km^2)	0.2411*** (0.02708)
Secondary forest by age group (in years):	
Young (1 to 8 years age)	0.2243 *** (0.05203)
Mid-mature (9 to 16 years age)	0.1094 (0.08165)
Mature (17 to 24 years age)	-0.7063 (0.3159)
Old (25 to 34 years age)	0.6285** (0.302)
Municipality fixed effects	Yes
Year fixed effects	Yes
Observations	12886
Treated municipalities	129

Control municipalities	629

NOTE: Std error statistics in parentheses and *5%, 1% ** and 0.1%***. Control variables include; Land conflicts, Herd density, Fine amount (2019R$), Non-ag value (2019R$), Protected area (km^2), Fire count at municipality-level, temperature (degree K) and rainfall (mm), CAR area (km^2), and Agricultural prices for rice, sugarcane, and soybean. All price indices are measured using agricultural output prices calculation steps illustrated by Assunção et al. (2015). The estimation was done in R gysnth, mc and em algorithms using seed numbers 282006 and 1000 bootstrapping iterations.

Robustness checks

An essential purpose of the robustness check is to validate our treatment effect estimation. A classic strategy in a quasi-experimental setup is to change the treatment intervention time to test the violation of the "no anticipation" assumption at the unit level. However, the treatment is anticipated in our study, and there is self-selection into a unit-level treatment. Additionally, the treatment occurs progressively; hence, the treatment time change may not prove a valid strategy.

I provide evidence of robustness using a non-Parámetric estimation approach strategy called matrix completion (Athey et al., 2021). The results corroborate the hypothesis that PMV participation supported an expansion of secondary forest growth. I also provide evidence from a staggered difference-in-difference (DiD) following Callaway and Sant'Anna (2021). Whereas the matrix completion non-parametric does not require the Parállel trends assumption, as is the case with the generalized synthetic control model I applied, the quasi-experiment design of the analysis where self-selection assigns treatment in a non-random manner may weaken the causal hypotheses. Even though the staggered DiD method in Callaway and Sant'Anna (2021) assumes conditional Parállel trends and anticipation, the results of the application of this model to the constructed dataset support the significance and the direction of the treatment effects found using the synthetic control model shown above. Table(11) shows the results from the robustness check strategy. I revisited the main model specification and found that secondary forest grew by 14 to 21 km2.

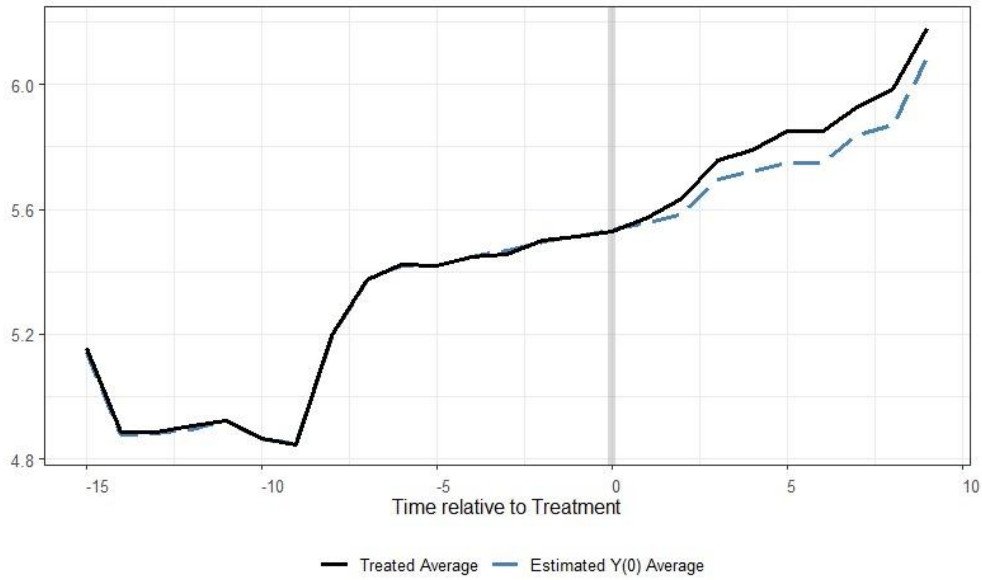

Figure 17 Matrix completion plot

The figure shows estimated ATT with the dependent variable 'secondary forest area' using the Matrix completion method. Control variables include; Land conflicts (N), Herd density(N/, Fine amount (2019R$), Non-ag value (2019R$), Protected area (km^2), Fire count at municipality-level, temperature (degree K), and rainfall (mm), CAR area (km^2), and Agricultural prices for rice, sugarcane, and soybean. All price indices are measured using agricultural output prices calculation steps illustrated by Assunção et al. (2015). The estimation was done in R gysnth, MC, and EM algorithms using seed numbers 282006 and 1000 bootstrapping iterations.

Table 11 Alternative results

Average ATT	Matrix completion method	Difference-in-Difference (TWFE without factors)
Total secondary forest area (km^2)	0.07305** (0.01886)	0.1145*** (0.03491)
Secondary forest loss (km^2)	0.07394** (0.02575)	0.06574** (0.02523)

Increment (km^2)	0.2335*** (0.02903)	0.2411*** (0.02708)
Age (in years):		
Young (1 to 8 years age)	0.1209*** (0.02915)	0.1145** (0.03491)
Mid-mature (9 to 16 years age)	-0.009001 (0.04278)	-0.0194 (0.04789)
Mature (17 to 24 years age)	-0.01633 (0.04835)	-0.03295 (0.05257)
Old (25 to 34 years age)	1.001*** (0.1063)	1.173*** (0.1136)
Municipality fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
Observations	12886	12886
Treated municipalities	129	129
Control municipalities	629	629

NOTE: Std error statistics in parentheses and *5%, 1% ** and 0.1%***.. Control variables include; Land conflicts, Herd density, Fine amount (2019R$), Non-ag value (2019R$), Protected area (km^2), Fire count at municipality-level, temperature (degree K) and rainfall (mm), CAR area (km^2), and Agricultural prices for rice, sugarcane, and soybean. All price indices are measured using agricultural output prices calculation steps illustrated by Assunção et al. (2015). The estimation was done in R gysnth, mc and em algorithms using seed numbers 282006 and 1000 bootstrapping iterations.

Mechanisms

This section presents channels of impact through which the secondary forest area increase can be explained. I show these results for mechanisms in Table (12).

Table 12 Mechanisms behind secondary forest recovery

	PRODES Deforestation increment (km^2)	PPRODES Deforestation Area (km^2)	Pasture area (km^2)	Forest per people	Fires per 1000	Fine per 1000 people
	1	2	3	4		5

Avg. ATT	-0.387***	0.000345	-0.0527***	-0.09404***	0.5683***
	(0.0474)	(0.00446)	(0.0177)	(0.02477)	(0.1958)
Municipality fixed effects	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	12886	12886	12886	12886	12886
Treated municipalities	129	129	129	129	129
Control municipalities	629	629	629	629	629

NOTE: Std error statistics in parentheses and *5%, 1% ** and 0.1%***. For Columns (1) & (2), the control variables include; Land conflicts, Herd density, Fine amount (2019R$), Non-ag value (2019R$), Protected area (km^2), Fire count at municipality-level, temperature (degree K), and rainfall (mm), CAR area (km^2), and Agricultural prices for rice, sugarcane, and soybean. All price indices are measured using agricultural output prices calculation steps illustrated by Assunção et al. (2015). For Column (3) model, all controls above, except Herd density and deforestation increment. For Column (4) model, all controls above, except Fire count and deforestation increment. For Column (5) model, all controls above, except Fine amount(2019R$) and deforestation increment. The estimation was done in R gysnth, mc, and em algorithms using seed numbers 282006 and 1000 bootstrapping iterations.

Firstly, the PMV effectively controlled deforestation increment and did not affect deforested areas (given by official estimates) in participating municipalities. This indicates that the PMV may have a spillover effect in fostering secondary forest recovery by controlling deforestation. I suggest that deforestation control is primarily a mechanism through which secondary forest was allowed to recover. Previous researchers have suggested that the gap between deforestation and secondary forest recovery is narrowing in neotropical zones (Nunes et al., 2020; Poorter et al., 2016). The recovery of secondary forests is driven by local land use and socioeconomic factors; for instance, Perz and Skole (2003) suggested that the Brazilian Amazon does not follow prolonged depletion (of native vegetation) to steady recovery (of secondary forest) pattern perceived in forest transition literature. However, the pattern is more analogous to the localized cycles of depletion-recovery. Similar to Caviglia-Harris et al. (2016), deforestation in Brazilian Amazon follows a boom-bust cycle driven by local economic incentives and migration patterns. I suggest that the recovery of secondary forests due to PMV results from two simultaneously evolving phenomena. To summarize, the deforestation decline can also have spillover effects in escalating deforestation in neighboring municipalities to PMV. This suggests a shift in the deforestation frontier, as indicated by Moz-Christofoletti et al. (2022) 's recent findings that neighborhood municipalities from Pará observed more deforestation than PMV municipalities in Pará.

Second is the decline of new cattle rearing activity in the PMV municipalities. The collective effort to create a sustainable beef industry affected deforestation control (Nepstad et al., 2014; Lambin et al., 2018). This corresponds with the results that deforestation declined, as did pasture activity. Thus, paving the way for secondary forest recovery. Similarly, I suggest that new forest fire activity declined in PMV municipalities. The results show a significant decline in forest fires. This further supports the argument that a decline in new pasture expansion and new land clearing may have supported the secondary forest recovery.

Lastly, I suggest that forest monitoring plays a crucial role in secondary forest expansion. However, the IBAMA fine per 1000 people declines in the PMV municipality. This indicates that the PMV's approach of integrating land registration (and associated stream of benefits) with local government intervention has resulted in fewer fines along with the newly cleared native forest. Collectively, these resulted in improved monitoring through incentives instead of fines.

Limitations

This study's two fundamental limitations, first dealing with limitations of remotely sensed secondary forest data. Although, Junior et al.(2020) presented a detailed use of Mapbiomas collection 4 to estimate the secondary forest area. The dataset can be improved by assessing the deforested area's probability of reforesting (in other words, the probability that the deforested pixel switches back to forest). Regarding policy evaluation, the consequences of reforestation can be measured using these pixel-level probability data. Second, to consider the staggered implementation of synthetic control, I suggest the control can be constructed using boundary thresholds, such as municipalities on the boundary region and indigenous territory can have prior spillover effect of deforestation control and secondary forest growth.

Conclusion

The results provide causal evidence that the municipality participating in PMV resulted in the recovery of the secondary forest by 27 km^2. I test these results for robustness using two different estimation strategies, which show the change in magnitude, but the sign and significance of the change, i.e., expansion of secondary forest area, is consistent with the main model specification. I present novel findings that local multi-stakeholders-based deforestation control policy like PMV has a robust spillover effect in developing the secondary forest. Furthermore, the chapter also presents robust evidence that official estimates for deforestation (by PRODES) decreased in post-PMV periods.

Future research

I consider two avenues for future research expansion. Firstly, I suggest that these estimates can be improved by using strict assumptions of regression discontinuity. The regression discontinuity can also be helpful in terms of selecting a control group near the boundary of the state. Secondly, I suggest mechanisms where CAR implementations are tested for spillover effect in secondary forest growth.

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Chapter 5

Conclusion

By 2012, the annual deforested area reduced to 16% of its peak in 2004 (27772 km^2 to 4571 km^2). Previous research has accredited this monumental accomplishment to multi-government and stakeholders policy, mainly the Action Plan for the Prevention and Control of Deforestation in the Legal Amazon (PPCDAm). Nonetheless, these enterprising deforestation control policies deliver numerous spillover effects. This dissertation studied the effects of the two initiatives from the PPCDAm program, namely the Forest Code of 2012 and the Green Municipality Program. Moreover, the dissertation examined if their spillover effects abate land conflicts, foster forest conservation on private landholdings, and expand secondary forests at the municipal level. Each dissertation chapter deals with one effect: land conflicts, compliance, and secondary forest recovery.

The dissertation conducted twofold research—the first stage with formulating a conceptual framework, hypothesis, and empirical strategy. As a part of PPCDAm, two critical policy interventions occurred. Firstly, the massive federal land registration began in 2012 (following the enactment of the Forest Code of 2012). Based on the perceived tenure security framework, I hypothesized that land registration ensures perceived tenure security for landholders, which may reduce land conflicts in the region. Once the land conflicts are lowered, the landholder in the region may respond to robust incentives enacted by the Forest Code of 2012 to protect native vegetation on privately held lands. I tested this hypothesis using an empirical framework of a dynamic model of land clearing. The model extends the current theoretical model by Schons et al. (2019) to include the path to reforestation on private landholdings. I proposed a primary hypothesis to test the persistence of compliance along with the impact of municipality-level attributes on dynamic land use. After that, I explored if the state of Pará has seen subsided land conflicts and persistence of compliance with the Forest Code of 2012. I explored whether there is any effective increase in a secondary forest area. My last chapter subsequently investigated this question. I hypothesized that municipalities participating in local governance promotion schemes like PMV may have increased secondary forest area.

This stage deals with data collection; I began collecting land registration data from SICAR for more than 35k landholdings across 285 municipalities in Mato Gross and Pará. Step two dealt with collecting specific land use patterns, such as native and secondary forest areas, for two decades, from 2001 to 2020, at three levels, private landholdings, municipality, and state-level. Second, I collected detailed land conflicts at the municipality level. Both these datasets were supported by additional datasets from Instituto Brasileiro de Geografia e Estatística - IBGE's livestock, population, economic, and agriculture data. To include the impact of climatic variables, I collected data at the municipality level from TerraClimate. The data on rural credit provisions (Banco Central do Brasil), environmental fines (nstituto Brasileiro do Meio Ambiente e dos Recursos Naturais Renováveis, IBAMA) and protected area (World Database on Protected Areas) were collected at the municipality level. Finally, I included exogenous agricultural shocks by price indices for rice, cassava, sugarcane, soy, and beef.

The dissertation is summarized as follows; Chapter (1) provides causal evidence that land registration abates conflicts in Pará. The chapter discusses policy implications in three discussions, prospective deforestation control, potential agricultural growth, and livelihoods promotion within CAR and its related policies. The results from this chapter provoke a question about the drop in land conflicts that stimulates forest conservation on private landholdings. Thereon, my second chapter deals with the dynamic land clearing decision of private landholders in the Brazilian Amazon. The results suggest that the persistence of compliance, thus forest conservation on privately held land, is driven mainly by past compliance and municipality-level incentives. The first two chapters established that land registration abates conflicts, and private landholders are driven by specific incentives to preserve the forest on their land. My third chapter investigates the impact of provincial governance promotion programs on secondary forest recovery. Municipalities participating in the local government improvement program steadily observe an expansion in secondary forest areas. To sum up, my dissertation explores the spillover effects of the deforestation control policy, starting with achieving fewer land conflicts and investigating the local incentives to promote forest protection on private land. Lastly, I provide evidence that the governance promotion program will result in secondary forest recovery.

Appendix A
Chapter 1

Table 13 Data sources and descriptions for Chapter 1

Variable	Description	Units	Source of the data	Links
Dependent	Conflicts = the CPT "Conflicts over Land, Occupations, and Camps." variable	Count	The author's calculation uses data from the Comissão Pastoral da Terra (CPT)	For CPT data: https://www.cptnacional.org.br/index.php/publicacoes-2/conflitos-no-campo-brasil
	Conflict events: the "Escalations" variable, = murders + attempted murders + death threats.	Count	Same as above	
	Murders attempted: the "Violence" variable, = murders + attempted murders.	Count	Same as above	
Covariates	Municipality level other variables			
	ADI: Annual deforestation increment	Km^2 area	The author's calculation uses data from the MapBiomas collection 5.	For shapefiles: https://www.ibge.gov.br/geociencias/organizacao-do-territorio/malhas-territoriais/15774-malhas.html For Mapbiomas landuse: ID: projects/mapbiomas-workspace/public/collection5/mapbiomas_collection50_integration_v1 For GEE: https://earthengine.google.com/
	Fine amount: Total Amount in Real of Environmental Fines	Amount adjusted for 2019R$	The author's calculation uses data from the Instituto Brasileiro do Meio Ambiente e dos Recursos Naturais	https://dadosabertos.ibama.gov.br/ 1. Collection of Environmental Fines

		Renováveis (IBAMA)	Protected Property 2. Environmental Fines Distributed by Protected Property
Non-ag value: non-agriculture gross value added at current prices is measured by subtracting the Gross value added at current agricultural prices from the Gross added value at total current prices at the municipality level	Amount adjusted for 2019R$	The author's calculation uses data from the Produto Interno Bruto do Brasil (PIB)	For IBGE data: https://www.ibge.gov.br/explica/pib.php For shapefiles: https://www.ibge.gov.br/geociencias/organizacao-do-territorio/malhas-territoriais/15774-malhas.html
Protected area: Cumulative WDPA protected area	Km^2 area	The author's calculation uses data from the World Database on Protected Areas (WDPA)	For shapefiles: https://www.protectedplanet.net/country/BRA
Population density	Number of people/ area of municipalities	Brazilian census	For IBGE pop data: https://www.ibge.gov.br/estatisticas/sociais/populacao/9109-projecao-da-populacao.html?=&t=downloads
Herd density: Cattle herd density	Number of cattle/Municipal area	The author's calculation uses data from the Pesquisa Pecuária Municipal (PPM)	For IBGE PPM data: https://www.ibge.gov.br/estatisticas/economicas/agricultura-e-pecuaria/9107-producao-da-pecuaria-municipal.html?=&t=downloads
Annual index of crop prices	Price indices	The author's calculation uses data from the method given by Assunção et al. (2015)	For Parana Price data: https://www.agricultura.pr.gov.br/ For Mapbiomas landuse to get cropping area:

	ID: projects/mapbiomas-workspace/public/collection5/mapbiomas_collection50_integration_v1 For GEE: https://earthengine.google.com/

NOTE: Data was compiled from various sources for municipal boundaries of Brazil in 2001. We employed an IBGE municipal code for merging and creating cross-sectional panel data.

Robustness Checks (1)

Table 14 Using the DID imputation method (Borusyak and Jaravel, 2017)

	(1) Number of Conflicts	(2) Number of escalations
Treatment effect (tau0)	-0.0943*	-0.101*
	(-2.90)	(-2.99)
Pre-trend (pre1)	-0.0752	-0.102
	(-1.41)	(-1.51)
Annual deforestation increment (Km^2)	0.00612	0.00439
	(0.98)	(0.78)
Herd density (N/ Km^2)	0.0616+	0.0249
	(1.79)	(0.84)
IBAMA fine (2019R$)	0.000239	-0.000177
	(0.19)	(-0.18)
PPA Rice	-0.145+	-0.135+
	(-1.70)	(-1.67)
PPA Sugarcane	0.0524	0.0555
	(0.89)	(1.20)
PPA Corn	0.570*	0.380+
	(3.85)	(1.69)
PPA Cassava	0.0360	0.0466
	(0.50)	(0.89)
Precipitation (mm)	-0.0278	-0.0130
	(-0.72)	(-0.40)
Non-agriculture value added (2019R$)	0.0287	0.0502
	(0.64)	(1.14)
Agg. protected area (Km^2)	0.0175*	0.00122
	(3.04)	(0.30)
N	7310	7310

NOTE: significance levels are + 10% & *5% and t statistics in parentheses.
All variables are log-transformed. Did_imputation was conducted using the Stata package "did_imputation" provided by Borusyak and Jaravel (2017) with all horizons and auto sample options. I included the pre-trend estimated for five periods, and errors are clustered at the municipality level.

Robustness Checks (2)

Table 15 Using the SIM data with CSDID

	ATT for Pará (dropping Mato Grosso) 667 municipalities & 12 years					
	1	2	3	4	5	6
	Mortality rate (Overall)		Mortality rate (Men)		Mortality rate (Women)	
ATT or ATT for G2008	-0.0624*** (0.0229)	-0.134** (0.056)	-0.0746 (0.0482)	-0.0117 (0.0913)	-0.108** (0.049)	-0.0981 (0.0716)
Population weight	Yes	No	Yes	No	Yes	No
Entropy Balancing	No	Yes	No	Yes	No	Yes
Pretrend Test. H0 All Pre-treatment are equal to 0						
Chi2	5.4288	4.0611	2.0045	8.1509	5.9563	10.5936
p-value	0.3658	0.5407	0.8485	0.1481	0.3105	0.0601
Obs.	7310	7310	7272	7272	8839	8839

NOTE: Significance levels: *10%, **5%, ***1% and Std. Errors in brackets.
The Table shows average treatment effects using Callaway and Sant'Anna's (2021) framework of estimating group-time treatment effects for three group-cohorts Pará (in 2008), Mato Grosso (in 2009), and the rest of the federal states (in 2012) from Legal Amazon. Control variables include The variables are ADI: Annual deforestation increment (Km^2), Herd density: Cattle herd density (Number of cattle/Municipal area), Fine amount: Total Amount in Real of Environmental Fines(adjusted for 2019R$), Non-ag value: Non-agriculture gross value added at current prices is measured by subtracting the Gross value added at current agricultural prices from the Gross added value at total current prices at the municipality level (adjusted for 2019R$), Protected area: Cumulative WDPA protected area (Km^2), Yearly mean precipitation (mm) and Agriculture price indices for rice, corn, sugarcane, and cassava are measured using the calculation of agricultural output prices, illustrated by Assunção et al. (2015). The estimation was done in the Stata CSDID package using seed number 0687 with 1000 bootstrapping iterations for the "not-yet-treated" specification. All models are with importance weights (iweight) with municipality-level yearly population.

Additional results

Table 16 Two-Way Fixed Effects (TWFE) OLS

	(1) Number of conflicts	(2) Number of escalations	(3) Mortality Rate	(4) Mortality Rate of Men	(5) Mortality Rate of Women
Annual deforestation increment (Km^2)	0.00137 (0.08)	-0.0207 (-0.76)	0.00486^{+} (1.95)	0.00349 (1.26)	0.00714* (2.28)
Herd density (N/Km^2)	-0.00539 (-0.04)	0.0765 (1.18)	-0.0201 (-1.53)	-0.0184 (-1.32)	-0.00309 (-0.24)
Total amount of environmental fine (2019R$)	0.00763^{+} (1.75)	0.00474 (1.15)	0.000409 (0.65)	0.000684 (0.92)	0.000105 (0.12)
ppa rice	-1.223*	-0.732*	0.0228	0.0354	-0.0266
	(-3.36)	(-3.82)	(0.88)	(1.35)	(-0.73)
ppa cane	0.337	-0.181	-0.0174	0.00265	-0.0196
	(1.19)	(-0.40)	(-0.68)	(0.11)	(-0.78)
ppa corn	1.285*	0.600	-0.108*	-0.148*	0.0420
	(3.86)	(1.60)	(-2.25)	(-3.80)	(0.31)
ppa cassava	0.676*	0.502*	0.00157	0.0227	0.0120
	(5.12)	(3.72)	(0.09)	(1.52)	(0.49)
Precipitation (mm)	-0.247* (-2.25)	-0.0790 (-0.41)	0.0159 (1.20)	0.0177 (0.96)	-0.0167 (-0.67)

Non-agriculture value added (2019R$)	-0.123 (-0.71)	-0.157 (-0.71)	-0.105* (-4.58)	-0.114* (-4.59)	-0.0990* (-4.26)
Aggregated sum of Protected area (Km^2)	0.0125 (0.72)	0.00997 (0.53)	-0.00143 (-0.52)	-0.00168 (-0.60)	-0.00267 (-0.84)
constant	-3.098	0.754	4.328*	4.135*	2.835*
	(-0.79)	(0.19)	(7.94)	(7.53)	(3.03)
N	7310	7310	7304	4487	2782

t statistics in parentheses
$^{+}$ $p < 0.10$, * $p < 0.05$

Table 17 TWFE Poisson model

	(1)	(2)	(3)	(4)	(5)
	Number of conflicts	Number of escalations	Mortality Rate	Mortality Rate of Men	Mortality Rate of Women
Annual deforestation increment (Km^2)	0.0724* (2.28)	0.0958 (1.56)	0.000918 (0.22)	0.00494 (0.85)	0.00637 (0.69)
Herd density (N/ Km^2)	0.0974 (0.65)	0.0543 (0.22)	-0.00865 (-0.40)	-0.00436 (-0.17)	0.0147 (0.38)
Total amount of environmental fine (2019R$)	0.00598 (0.79)	-0.00965 (-0.59)	0.000864 (0.90)	-0.000766 (-0.57)	-0.000223 (-0.12)
ppa rice	-1.773*	-1.888*	0.147*	0.244*	0.0927
	(-4.17)	(-2.20)	(2.20)	(2.62)	(0.81)
ppa cane	0.801*	0.495	0.0499	0.0259	0.107
	(2.78)	(1.10)	(1.39)	(0.65)	(1.56)
ppa corn	8.747*	5.842	0.0340	-0.236+	0.477
	(2.48)	(0.92)	(0.12)	(-1.66)	(0.57)
ppa cassava	0.439 (0.71)	0.297 (0.24)	-0.106 (-1.21)	-0.0773 (-1.09)	-0.0598 (-0.40)
Precipitation (mm)	-0.207 (-1.08)	-0.231 (-0.53)	-0.00364 (-0.12)	-0.0198 (-0.55)	0.00188 (0.03)
Non-agriculture value added (2019R$)	-0.233 (-1.04)	0.124 (0.31)	-0.190* (-5.06)	-0.186* (-3.95)	-0.289* (-4.50)

Aggregated sum of Protected area (Km^2)	0.0114	-0.0778*	-0.00256	-0.000541	-0.0105
	(0.44)	(-2.16)	(-0.59)	(-0.12)	(-1.13)
constant	-67.28*	-47.59	-5.598*	-4.868*	-8.296
	(-2.62)	(-1.06)	(-3.04)	(-3.81)	(-1.37)
N	4461	2475	7304	4487	2782

t statistics in parentheses
$^{+}$ $p < 0.10$, * $p < 0.05$

Agricultural output prices calculation steps (Assunção et al. 2015)

We use the Parána price series to build two variables of interest. Parána prices come from, http://www.agricultura.pr.gov.br/deral/precos

1. The first of these variables, an annual index of crop prices, is constructed in three steps.
2.

a. In step one, we construct nominal annual price series by averaging nominal monthly price series for each calendar year and culture. Annual prices are deflated to the year 2000 Brazilian Reais and are expressed as an index with the base year 2000.

b. In step two, we calculate a weighted real price for each of the crops according to the following expression:

$$PPAitc = PPtc * Aic, 2000-2001 \qquad (1)$$

where PPAitc is the weighted real price of crop c in municipality i and year t; PPtc is the Parána-based real price of the crop c in year t expressed as the index with the base year 2000; and Aic, 2000−2001 is the share of the municipal area used as farmland for crop c in municipality i averaged over 2000 through 2001 period. This latter term captures the relative importance of crop c within municipality i's crop production in the years immediately preceding the sample period. It thus serves as a municipality-specific weight that introduces cross-sectional variation in the commodity price series.

c. In the third and final step, we use principal component analysis on the weighted real crop prices to derive the annual index of crop prices. This technique allows the price variations common to the five selected crops to be represented in a single measure. The resulting index of crop prices captures the first principal component of the five weighted real prices. The first principal component explains approximately 38 percent of the variation in the series, driven mainly through soybean, rice, and corn. As the index maximizes the price variance captured by our variable of interest, it represents a more comprehensive measure of the agricultural output price scenario within our empirical setup than the individual prices themselves.

2. The second variable of interest is an annual index of cattle prices, which is derived analogously to PPAitc in Equation (1). However, as annual data on land pasture are not available, the index uses the ratio of heads of cattle to municipal area in municipality i averaged over the 2000 through 2001 period as the municipality-specific weight Aci, 2000−2001. Using the annual indices of agricultural prices addresses our model's first empirical implication, which establishes that agricultural output prices should be included in conservation policy evaluation.

Appendix B

Chapter 2

Table 18 Data source and description

	Variable	Description	Source	Hyperlinks
Y	Dependent	Binary (=1 complying with Forest Code and 0 otherwise)	Author's calculation using GEE and R	For shapefiles: https://www.car.gov.br/publico/imoveis/index For Mapbiomas landuse: ID: projects/mapbiomas-workspace/public/collection5/mapbiomas_collection50_integration_v1 For GEE: https://earthengine.google.com/
X	Controls			
		CAR avg. parcel size	CAR and authors' calculations	For shapefiles: https://www.car.gov.br/publico/imoveis/index For QGIS: https://www.qgis.org/en/site/
		Precipitation	TerraClimate	For GEE: https://developers.google.com/earth-engine/datasets/catalog/IDAHO_EPSCOR_TERRACLIMATE
		Fine intensity (2017R$)	Author's calculation using IBAMA and Mapbiomas	For IBAMA open data: https://dadosabertos.ibama.gov.br/ 1. Collection of Environmental Fines Protected Property 2. Environmental Fines Distributed by Protected Property
		Credit density (2017R$)		For rural credit data: https://www.bcb.gov.br/estabilidadefinanceira/micrrural 1. Financing Granted to Producers and Cooperatives 2. Pronaf - National Program for Strengthening Family Agriculture
		Municipality GDP	PIB	For IBGE data: https://www.ibge.gov.br/explica/pib.php For shapefiles: https://www.ibge.gov.br/geociencias/organizacao-do-territorio/malhas-territoriais/15774-malhas.html
		Protected indigenous land	The author's calculation uses data from	For shapefiles: https://www.protectedplanet.net/country/BRA

	the World Database on Protected Areas (WDPA)	
Population density	IBGE	For IBGE pop data: https://www.ibge.gov.br/estatisticas/sociais/populacao/9109-projecao-da-populacao.html?=&t=downloads For Parana Price data: https://www.agricultura.pr.gov.br/
Annual index of cattle prices	Author's calculation using SEAB-PR	For Mapbiomas landuse to get cropping area: ID: projects/mapbiomas-workspace/public/collection5/mapbiomas_collection50_integration_v1 For GEE: https://earthengine.google.com/ For Parana Price data: https://www.agricultura.pr.gov.br/
Annual index of crop prices (Rice, Sugarcane, Cassava, and Soy)	Author's calculation using SEAB-PR	For Mapbiomas landuse to get cropping area: ID: projects/mapbiomas-workspace/public/collection5/mapbiomas_collection50_integration_v1 For GEE: https://earthengine.google.com/
Number of land conflicts	CPT	For CPT data: https://www.cptnacional.org.br/index.php/publicacoes-2/conflitos-no-campo-brasil
Number of Forest Fires	FIRMS	For fire data: https://developers.google.com/earth-engine/datasets/catalog/FIRMS For Mapbiomas landuse: ID: projects/mapbiomas-workspace/public/collection5/mapbiomas_collection50_integration_v1 For GEE: https://earthengine.google.com/

NOTE: all covariates are at Municipality-level variables.

Additional Background on CAR

What is the Rural Environmental Registry – CAR, and what is its purpose?

The Rural Environmental Registry - CAR is a national electronic public registry, mandatory for all rural properties, to integrate environmental information on rural properties and possessions, composing a database for control, monitoring, environmental and economic planning, and combating logging. It was created by Law 12.651/2012, art. 29.

Who must be registered for the CAR?

Registration in the CAR is mandatory for all rural properties in the country, including areas and territories for collective use, titled or granted to traditional peoples or communities, and rural properties of the Agrarian Reform Program characterized as settlements, regardless of title and exploitation of the rural property.

What is the Rural Environmental Registry System - SICAR?

The Rural Environmental Registration System – SICAR is responsible for issuing the Registration Receipt of the rural property in the CAR, confirming the registration, and submission of the documentation required to analyze the location of the Legal Reserve area and is defined as a nationwide electronic system for managing environmental information on rural properties throughout the country. This information is intended to support policies, programs, projects, and activities for control, monitoring, environmental and economic planning, and combating deforestation.

It was created through Decree No. 7.830/2012, art. 3rd, with the following objectives:

1. Receive, manage and integrate CAR data from all federative entities
2. Register and control information on rural properties, referring to their perimeter and location, remnants of native vegetation, areas of social interest, public utility areas, Permanent Preservation Areas, Restricted Use Areas, consolidated areas, and to Legal Reserves;
3. Monitor the maintenance, restoration, regeneration, compensation, and suppression of native vegetation and vegetation cover in the Permanent Preservation, Restricted Use, and Legal Reserve areas inside rural properties;
4. Promote environmental and economic planning of land use and environmental conservation in the national territory, and make public information available on the Internet on the environmental regularization of rural properties in the national territory.

What is the purpose of registering a rural property in the CAR?

The registration of rural property in the CAR serves to comply with the mandatory declaration and registration of environmental information for all rural properties in Brazil and issue the "Rural Property Registration Receipt in the CAR." It serves to inform them;

1. Register the Legal Reserve area with the competent environmental agency, and as a requirement for approval of its location;
2. Proceed with environmental regularization through adherence to the Environmental Regularization Programs of the States and the Federal District – PRA;
3. Access to government support programs;
4. Request authorization for the practice of aquaculture and associated infrastructure in rural properties with up to 15 (fifteen) rural modules located in areas of permanent preservation;
5. Request authorization for the removal of a forest or other forms of native vegetation on the rural property;
6. Request the calculation of Permanent Preservation Areas in the calculation of the property's Legal Reserve;
7. Request authorization for the economic exploitation of the Legal Reserve through sustainable management;
8. Request the constitution of environmental easements and Environmental Reserve Quota on a rural property and to access the Legal Reserve compensation mechanisms;
9. Request authorization for intervention and removal of vegetation in Areas of Permanent Preservation and Legal Reserve for activities with low environmental impact; and
10. Request authorization to continue agroforestry, ecotourism, and rural tourism activities in consolidated rural areas until July 22, 2008, located in Permanent Preservation Areas and Legal Reserve; is for
11. Access agricultural credit, in any of its modalities, after December 31, 2017,

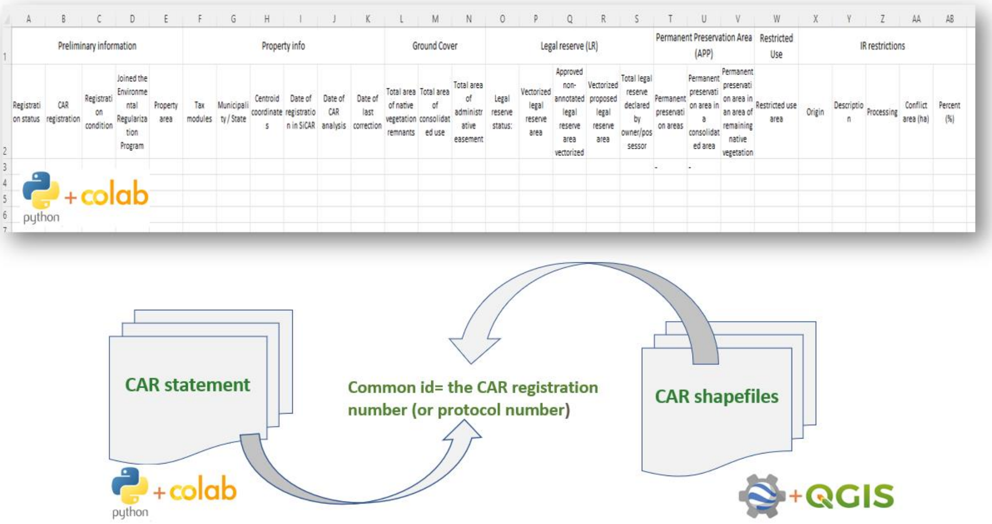
What is the CAR Status Statement?

The CAR Situation Statement is a document made available by SICAR that presents information on the rural property registry regarding:

1. Registration status (active, pending, or canceled);
2. The status of the progress of the registration analysis process (awaiting analysis, under analysis, analyzed with pending issues, etc.);
3. The data declared in the car regarding land cover, legal reserve, permanent preservation areas, and restricted use areas; and
4. To the status of the legal reserve.

It can be consulted on the SICAR, at the link https://www.car.gov.br/#/consultar , or by the Owner/Possessor Center, at the link https://www.car.gov.br/#/central/acesso .

Merging SICAR and CAR databases



We collected GIS shapefiles data from Sistema de Cadastro Ambiental Rural –SICAR:

https://www.car.gov.br/publico/imoveis/index

Until December 31, 2020, 7.02 million rural properties were registered, totaling 539,327,533.1 hectares inserted in the system's database (Brazilian Forest Service, 2021). We download 864791 rural properties from Acre (AC), Amapá(AP), Amazonas(AM), Maranhão(MA), Mato Grosso(MT), Mato Grosso do Sul(MS), Pará (PA), Rondônia(RO), Roraima(RR), and Tocantins(TO).

Following Shapefiles of properties, we extracted unique ids by dropping duplicates in Arc GIS pro and summarized 864826 properties. Here, 34 ids have no information available. Hence we dropped them.

We began extracting dates and other available information from Sistema de Cadastro Ambiental Rural –SICAR v3.0.0 consultation website:

https://www.car.gov.br/#/consultar

Web scraping is python code that allows users to extract information from websites in python array and later in CSV files. We designed a web scraping tool that employs selectolax 0.2.11HTML parser and TwoCaptcha to bypass the captcha to extract the years of CAR enrollment. Please follow, https://pypi.org/project/TwoCaptcha/

Finally, the merged data was used to create a sample of properties in Mato Grosso and Pará.

Table 19 Municipality level CAR registration

IBGE_7 Municipality Code	Municipality Name	State	Number Of Landholdings In SICAR
Lowest registrations			
1507706	São Sebastião da Boa Vista	PA	11
1504505	Melgaço	PA	15
1502608	Colares	PA	26
1504109	Magalhães Barata	PA	33
1501105	Bagre	PA	37
1504422	Marituba	PA	38
1500800	Ananindeua	PA	41
1506302	Salvaterra	PA	44
1506203	Salinópolis	PA	47
Highest registrations			
5103205	Colíder	MT	2439
5100250	Alta Floresta	MT	2719
5105150	Juína	MT	2829
5102504	Cáceres	MT	3156
1507300	São Félix do Xingu	PA	3271
1504703	Moju	PA	3543
1505064	Novo Repartimento	PA	3544
1504802	Monte Alegre	PA	3612

NOTE: The table summarizes CAR registration inParáand Mato Grosso; for illustrative purposes, it summarizes the lowest and highest number of landholdings by a municipality in the two states. The data was collected from the (SICAR: https://www.car.gov.br/#/consultar) in December 2020. Please refer to the Appendix for more information.

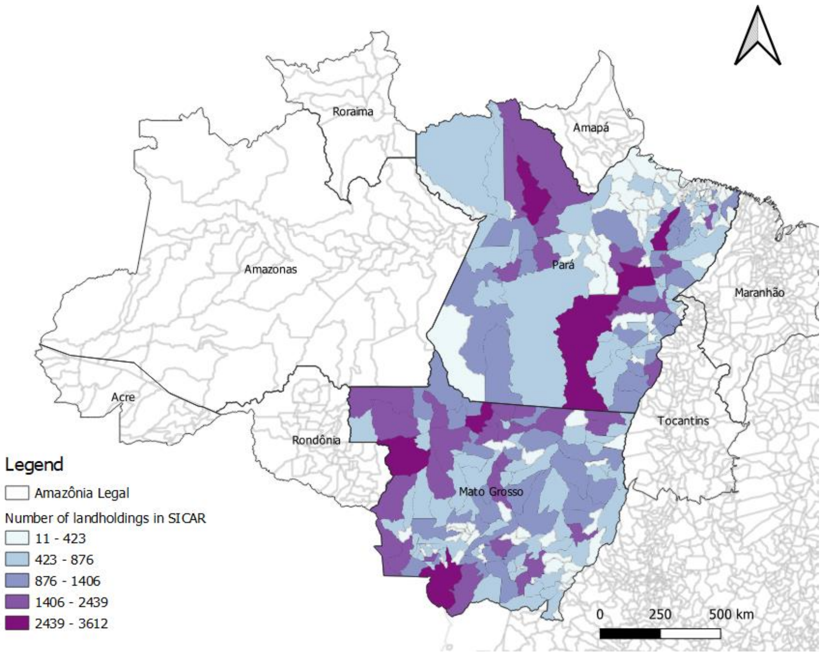


Figure 18 Municipality level CAR registration

CAR registration in Pará and Mato Grosso until December 2020 for dynamic land-use sample. The data was collected from the (SICAR: https://www.car.gov.br/#/consultar) in December 2020.

Detailed regression results

Table 20 Random Effects (RE) with Wooldridge's (2005) method

	Pará	Mato Grosso
	(1)	(2)
VARIABLES		
Lag Compliance	2.128***	2.280***
	(0.0106)	(0.0252)
Population Density (N/ Km^2)	-0.000260**	0.0249***
	(0.000114)	(0.00284)
Precipitation (mm)	-0.00534	0.218***
	(0.00852)	(0.0434)
PPA Rice	-0.108***	-0.0864***
	(0.0148)	(0.0101)
PPA Sugarcane	-0.0379	-0.00405
	(0.0672)	(0.0106)
PPA Cassava	-0.00437***	-0.0556**
	(0.000405)	(0.0260)
PPA Soy	0.0847***	-0.00945***
	(0.0244)	(0.00222)
PPA Cattle	-0.00164***	-0.00193***
	(0.000137)	(0.000239)
Protected indigenous land (ha)	-1.94e-06***	-1.33e-05***
	(3.69e-07)	(3.10e-06)
Fine intensity (2017 R$)	8.50e-05**	-0.00108***
	(3.46e-05)	(0.000244)
GDP per capita (2017 R$)	-0.00389*	0.000982
	(0.00202)	(0.00125)
Credit density (2017 R$/ Km^2)	-1.46e-05	-0.000372***
	(2.01e-05)	(6.30e-05)
CAR avg parcel size (ha)	3.30e-06*	4.06e-05***
	(1.86e-06)	(9.79e-06)
Number of land conflict (N)	-0.0130***	0.0209*
	(0.00318)	(0.0115)
Number of fire incidence (N)	-4.14e-05***	0.000677***
	(1.25e-05)	(8.00e-05)
Initial condition compliance at time 0	-0.144***	0.233***
	(0.0108)	(0.0260)
Initial period of fine intensity	0.000117	0.000999***
	(0.000103)	(0.000307)
Initial period of GDP per capita	0.00382**	0.000998
	(0.00175)	(0.00232)
Initial period of credit density	2.34e-05	0.000563**
	(1.43e-05)	(0.000284)
Initial period of CAR avg parcel size	-1.34e-05***	-7.88e-05***
	(1.77e-06)	(9.29e-06)
Initial period of Number of land conflict	-0.00341	-0.00880
	(0.00562)	(0.0227)
Initial period of Number of fire incidence	-0.000137**	-0.000622***
	(6.57e-05)	(0.000197)

Time average of fine intensity	-0.000204	-0.00126
	(0.000136)	(0.000869)
Time average of GDP per capita	0.00412	0.00507***
	(0.00252)	(0.00194)
Time average of credit density	0.000107***	0.000583***
	(3.97e-05)	(0.000106)
Time average of CAR avg parcel size	-8.24e-06	5.57e-05**
	(7.20e-06)	(2.73e-05)
Time average of Number of land conflict	-0.000628	-0.0547
	(0.00802)	(0.0334)
Time average of Number of fire incidence	0.000126	-0.000595***
	(0.000119)	(0.000190)
Constant	-1.080***	-2.020***
	(0.0244)	(0.110)
Observations	114,399	38,504
Number of groups	12,711	4,813

NOTE: Robust standard errors in parentheses, significant levels are ***1%, **5%, and *10%
The estimates use Stata command xtpdyn, which implemented RE from Wooldridge's (2005) using an algorithm by Rabe-Hesketh and Skrondal (2013).

Table 21 Bias corrected fixed effects (BCFE) using Fernández-Val and Weidner's (2016) method

VARIABLES	(1) Pará	(2) Mato Grosso
Lag Compliance	1.68***	1.695***
	(0.013)	(0.03008)
Population Density (N/ Km^2)	0.00121	0.008814
	(0.00151)	(0.05436)
Precipitation (mm)	-0.214***	-0.003398
	(0.0331)	(0.0988)
PPA Rice	-0.03748	-0.06571*
	(0.04916)	(0.03198)
PPA Sugarcane	-0.3088	0.06319
	(0.2806)	(0.04037)
PPA Cassava	-0.00242*	0.03812
	(0.00101)	(0.06217)
PPA Soy	-0.386***	-0.01544
	(0.0976)	(0.01017)
PPA Cattle	-0.0003338	0.00264***
	(0.0003763)	(0.0006435)
Protected indigenous land (ha)	-0.000084***	0.00109
	(0.0000232)	(0.01131)
Fine intensity (2017 R$)	0.000125**	-0.00135***
	(0.0000468)	(0.0002984)
Credit density (2017 R$/ Km^2)	-0.000013	0.000332**
	(0.000024)	(0.0001218)
GDP per capita (2017 R$)	-0.00192	0.007978***
	(0.00186)	(0.00205)
CAR avg parcel size (ha)	-3.974e-06	1.828e-06
	(2.542e-06)	(1.383e-05)
Number of land conflicts (N)	-0.00502	0.0219
	(0.0045)	(0.01538)
Number of fire incidence (N)	3.581e-07	0.0003264*
	(2.538e-05)	(0.0001356)
Number of Obs.	80883	23160
Number of Groups	8987	2895
Time (years)	9	8
Residual deviance	68673.64	15928.11
Null deviance	112058.48	31982.85

The table shows robust standard errors in parentheses; significant levels are ***0%, **1%, *10% and #5%. The estimates use the R package alpaca, which implemented BCFE from Fernández-Val and Weidner's (2016) algorithm employing GLMs with high-dimensional k-way fixed effects provided by Stammann (2017).

Appendix C

Chapter 3

Table 22 Data sources and descriptions

	Variable	Description	Source	Hyperlinks
Y	Dependent	Secondary Forest Area (km^2) Age (in years since 1985) Increment (km^2) Loss (km^2)	MapBiomas (Silva Junior et al., 2020)	For shapefiles: https://www.ibge.gov.br/geociencias/organizacao-do-territorio/malhas-territoriais/15774-malhas.html For Mapbiomas landuse: ID: projects/mapbiomas-workspace/public/collection5/mapbiomas_collection50_integration_v1 For raster files of the secondary forest: https://zenodo.org/record/3928660
X	Covariates	Environmental Fines(2019 R$)	IBAMA	https://dadosabertos.ibama.gov.br/ 1. Collection of Environmental Fines Protected Property 2. Environmental Fines Distributed by Protected Property
		Area of CAR properties by year (km^2)	CAR	SICAR shapefiles: http://www.car.gov.br/publico/imoveis/index
		Herd density (Number per km^2)	IBGE	For IBGE PPM data: https://www.ibge.gov.br/estatisticas/economicas/agricultura-e-pecuaria/9107-producao-da-pecuaria-municipal.html?=&t=downloads
		Annual index of crop prices (Rice, Corn, Sugarcane, Cassava, and Soy)	SEAB-PR and author's calculation	For Parana Price data: https://www.agricultura.pr.gov.br/ For Mapbiomas landuse to get cropping area: ID: projects/mapbiomas-workspace/public/collection5/mapbiomas_collection50_integration_v1 For GEE:

		https://earthengine.google.com
Precipitation (mm)	TerraClimate	For GEE: https://developers.google.com/earth-engine/datasets/catalog/IDAHO_EPSCOR_TERRACLIMATE
Protected area (km^2)	IBGE	For shapefiles: https://www.protectedplanet.net/country/BRA
Number of fire incidences (N)	FIRMS	https://developers.google.com/earth-engine/datasets/catalog/FIRMS
Number of land conflicts (N)	CPT	For CPT data: https://www.cptnacional.org.br/index.php/publicacoes-2/conflitos-no-campo-brasil

Source: Author's data collection from various sources.

Deforestation increments in non-PMV vs. PMV municipalities from 2001 to 2019

Table 23 Deforestation using three sources

	NO PMV (629 municipalities)			PMV (129 municipalities)		
Year	MapBiomas	GFW	PRODES	MapBiomas	GFW	PRODES
2001	31.75312	21.69969	61.62859	54.89167	52.49607	125.5775
2002	48.64375	31.17303	27.15594	94.9	63.58504	69.46083
2003	56.91094	30.12017	30.21922	96.525	50.9422	91.98917
2004	35.57031	34.18788	28.56313	77.9	79.62	74.05167
2005	33.04219	29.19191	24.73547	74.06667	76.62147	67.17084
2006	23.61563	21.69954	9.245781	79.06667	62.23553	41.5175
2007	22.73281	18.85066	9.479062	59.49166	54.00988	45.29417
2008	19.51563	16.05106	12.205	56.09167	56.96335	45.75417
2009	19.6	11.57246	4.845469	46.65	38.25157	28.75417
2010	16.74063	20.55174	4.888594	43.60833	44.68168	26.72917
2011	18.90625	13.81895	5.177344	34.31667	35.41017	19.1225
2012	21.34219	20.76323	4.31875	43.20833	45.85964	14.0975
2013	20.2375	14.89231	5.245625	33.8	35.77569	17.115
2014	17.44062	21.8863	5.350312	37.95833	48.05086	14.1875
2015	20.5375	19.68243	6.190312	28.075	41.26865	18.1825
2016	23.24375	46.56302	7.380781	55.79167	126.0761	21.1925
2017	22.25156	38.50552	7.640313	37.075	112.4824	20.07833
2018	24.27656	25.3714	7.500469	60.63334	70.40925	21.5475
2019	21.35781	24.82291	10.69531	50.10833	60.65828	34.99083

NOTE: All estimates in square kilometers of area deforested using 758 municipalities in Brazilian Amazon for respective yearly average from 2001 to 2019. Author's estimations using GEE from various sources.

Secondary and planted forest

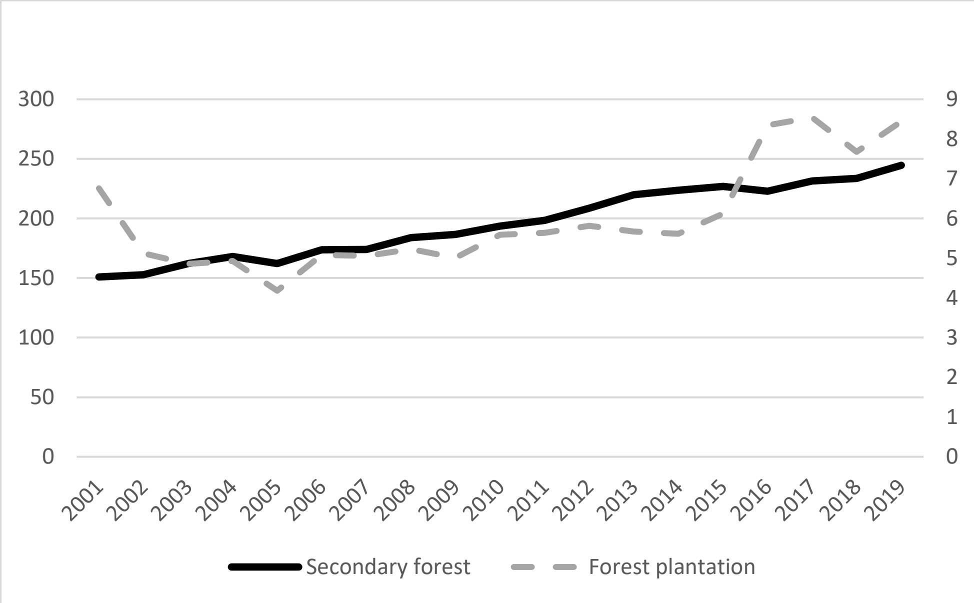
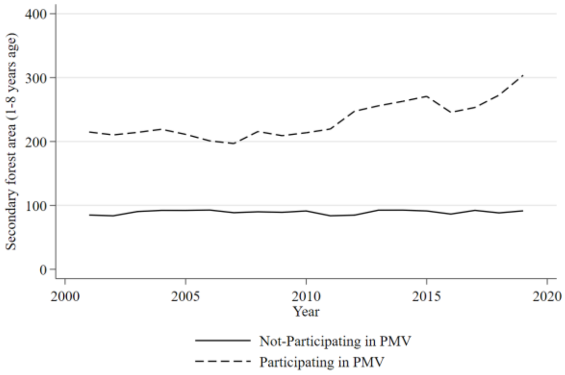
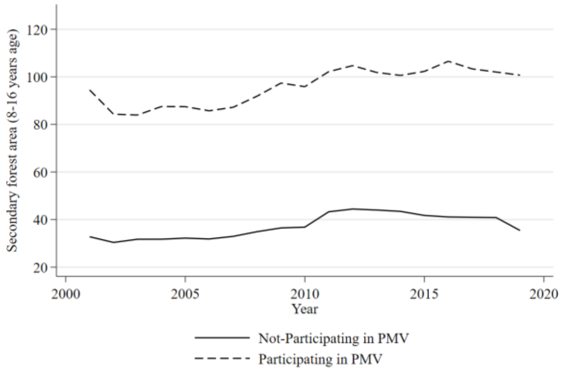


Figure 19 Forest plantation and secondary forest growth

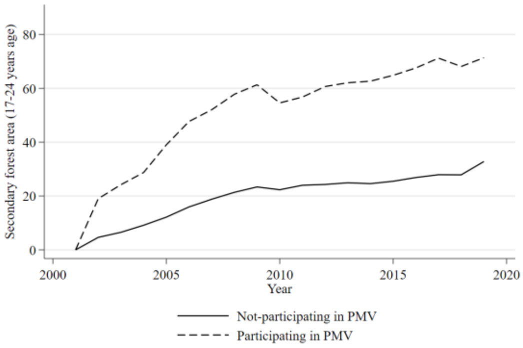
The secondary forest growth is when a pixel classified as anthropic cover (e.g., pasture or agriculture) in a given year is replaced in the following year by a pixel of forest cover (excluding mangroves and plantations) (Silva Junior et al. 2020). Forest plantations are tree species planted for commercial purposes (e.g., Pinus, Eucalyptus, Araucaria) (MapBiomas, 2020). We observe a consistent growth in both secondary and plantation (Silvicultura); the Figure shows secondary forest growth is much higher than plantation forest, where on average secondary forest grew from 150 to 250 km^2 while plantation forest from 5 to 9 km^2 in Legal Amazon.

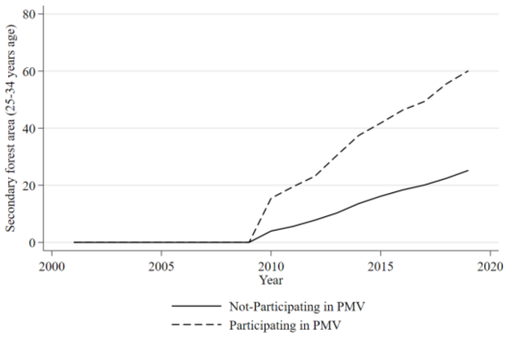
Age of secondary forest area since 1986





1 to 8 years old secondary forest area
8 to 16 years old secondary forest area





17 to 24 years old secondary forest area
25 to 34 years old secondary forest area

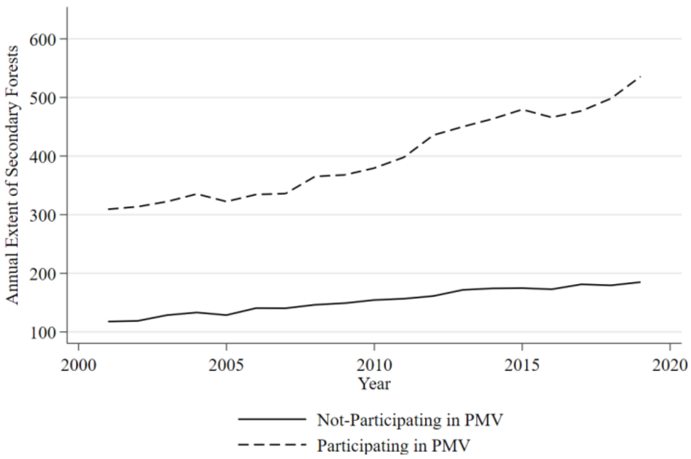


Figure 20 Trends in secondary forest recovery

The figures show secondary forest area under PMV municipalities is higher than the non-PMV municipalities in our sample. Figures (a) to (d) show that newer growth forest (1 to 16 years age) is more consistent over the years whereas comParátively mature growth forest (17-24 years age) emerges recently in 2001-2002 while older growth forest (25-34 years age) emerges from 2009-2010 onwards.

Detailed results using Generalized synthetic control with secondary forest area (km²)

Table 24 Detailed results from the generalized synthetic control

Dependent: Secondary Forest Area (km²)	Generalized Synthetic Control (gsynth algorithm)	Generalized Synthetic Control (EM algorithm)	Matrix Completion Method	DID TWFE
Average ATT	0.1445***	0.07624***	0.07305***	0.06869***
	(0.03263)	(0.003525)	(0.01886)	(0.02548)
Environmental Fines(2019R$)	- 0.0001922	-1.971e-06	3.806e-05	9.374e-05
	(0.0003461)	(0.0002128)	(0.0004234)	(0.0005348)
Herd density (Number per km²)	-0.0391946 #	7.626e-03	7.943e-03	1.312e-02 (0.0205042)
	(0.0142498)	(0.0030310)	(0.0203360)	
PPA Rice	- 0.0147976	-1.125e-02*	-1.096e-02	-6.774e-03 (0.0653816)
	(0.0366748)	(0.0057112)	(0.0244576)	
PPA Sugarcane	0.0021862	3.379e-02***	3.385e-02 (0.0260095)	3.025e-02 (0.0261017)
	(0.0164444)	(0.0015866)		
PPA Soy	- 0.0391964*	7.759e-02***	7.785e-02 (0.0376919)	7.652e-02 (0.0326878)
	(0.0189524)	(0.0023423)		
Precipitation (mm)	0.0297222#	4.239e-02***	4.493e-02 (0.0122332)	5.383e-02 (0.0140221)
	(0.0107927)	(0.0063196)		
Max. temperature (K)	0.3724443	-4.244e-01**	-4.264e-01 (0.3760366)	-3.627e-01 (0.3645746)
	(0.2523858)	(0.0849438)		
Non-ag gross value added (R$)	- 0.0137580	2.472e-02	2.483e-02	2.250e-02 (0.0208128)
	(0.0141171)	(0.0031088)	(0.0184995)	
Protected area (km²)	- 0.0022657	-4.080e-03	-3.931e-03 (0.0084585)	-6.922e-03 (0.0078094)
	(0.0050707)	(0.0027916)		
Area of CAR properties by year (km²)	0.0026425*	1.391e-03	9.768e-04 (0.0015654)	6.628e-04 (0.0016527)
	(0.0011408)	(0.0003934)		
Number of land conflicts	0.0011325	3.107e-03	5.814e-03 (0.0053074)	6.604e-03 (0.0070341)
	(0.0040136)	(0.0022395)		

Number of fire incidences	- 0.0069842* (0.0027910)	-1.403e-02 (0.0013693)	-1.608e-02 (0.0035208)	-1.700e-02 (0.0048518)
Federal roads length				

NOTE: #10%, *5%, 1% ** and 0.1%***
The results used the Generalized Synthetic Control Method with two-way fixed effects (municipal and year fixed effects) and cross-validation with 1000 bootstrapping with seed number 282006.

Additional results from Table (24) for different dependent variable

Avg Treatment effects in secondary forest increment as dependent variable.

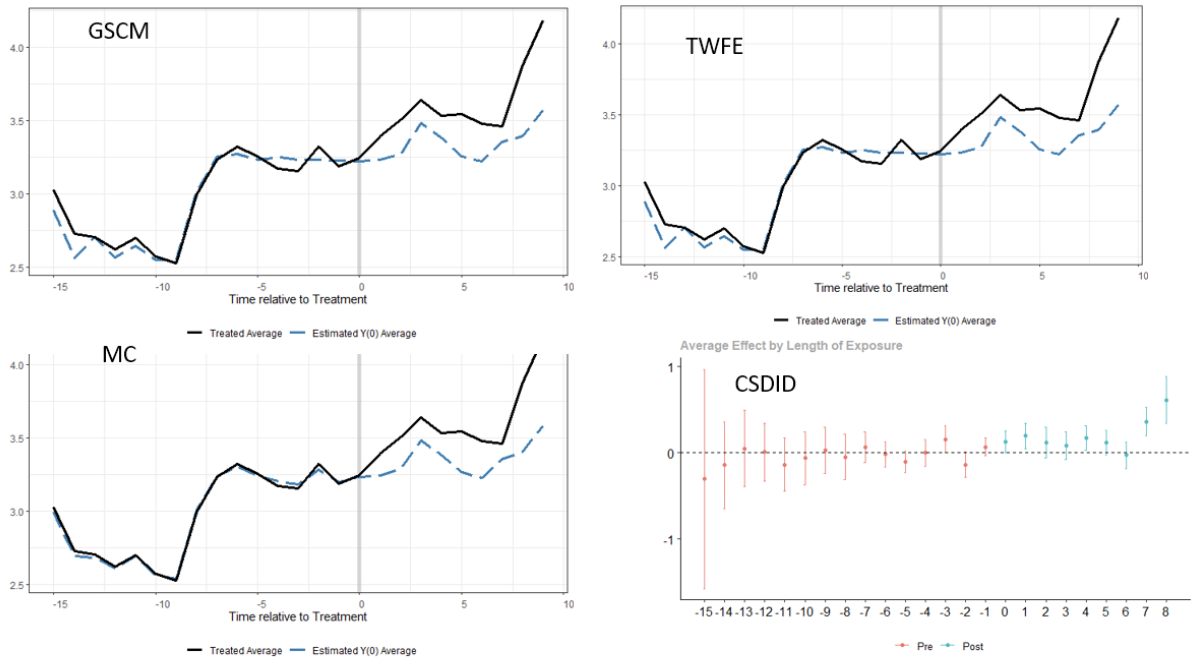


Figure 21 Secondary forest increment results

The figure shows estimated ATT with the dependent variable 'secondary forest area increment' using the Generalized synthetic control (GSCM), Matrix completion (MC), Two-way fixed effects (TWFE), and Callaway and Sant'Anna (2021) method. Control variables include; Land conflicts, Herd density, Fine amount (2019R$), Non-ag value (2019R$), Protected area (km^2), Fire count at municipality-level, temperature (degree K) and rainfall (mm), CAR area (km^2), and Agricultural prices for rice, sugarcane, and soybean. All price indices are measured using agricultural output prices calculation steps illustrated by Assunção et al. (2015). The estimation was done in R gysnth, MC, and EM algorithms using seed numbers 282006 and 1000 bootstrapping iterations.

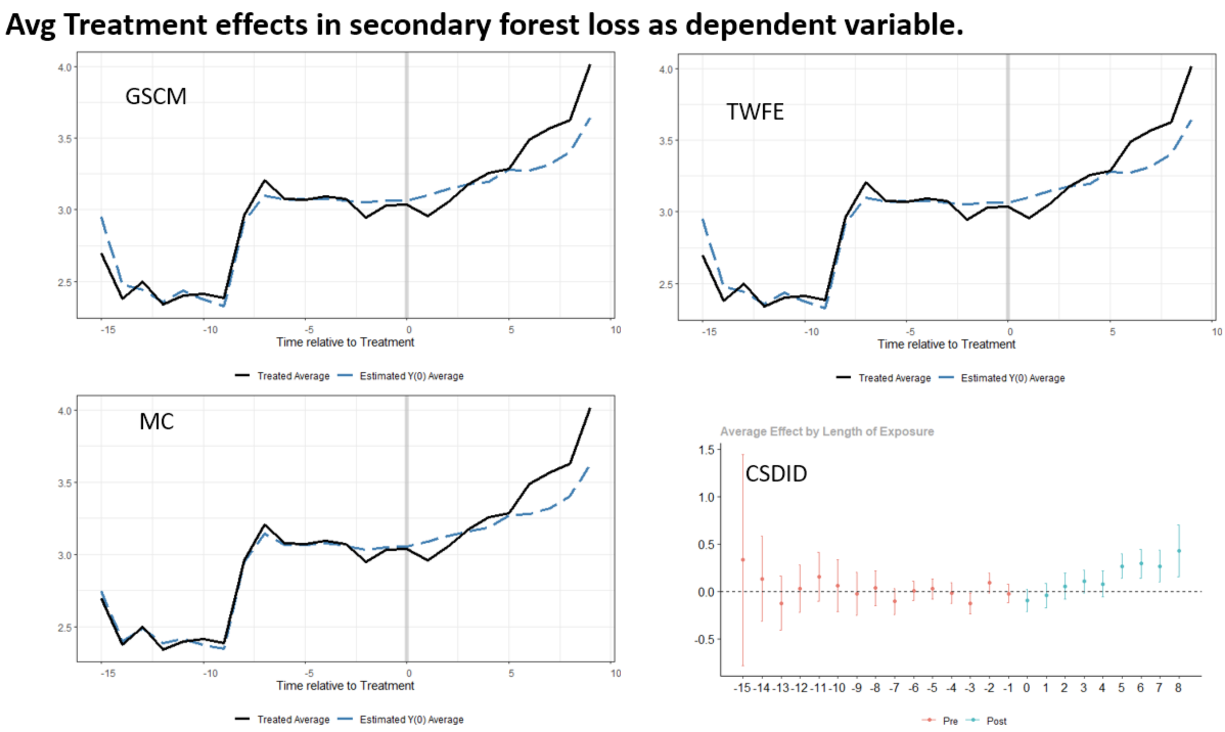


Figure 22 Secondary forest loss results

The figure shows estimated ATT with dependent variable 'secondary forest area loss' using the Generalized synthetic control (GSCM), Matrix completion (MC), Two-way fixed effects (TWFE), and Callaway and Sant'Anna (2021) method. Control variables include; Land conflicts, Herd density, Fine amount (2019R$), Non-ag value (2019R$), Protected area (km^2), Fire count at municipality-level, temperature (degree K) and rainfall (mm), CAR area (km^2), and Agricultural prices for rice, sugarcane, and soybean. All price indices are measured using agricultural output prices calculation steps illustrated by Assunção et al. (2015). The estimation was done in R gysnth, MC, and EM algorithms using seed numbers 282006 and 1000 bootstrapping iterations.

Avg Treatment effects in secondary forest area (age 1 to 9) as dependent variable.

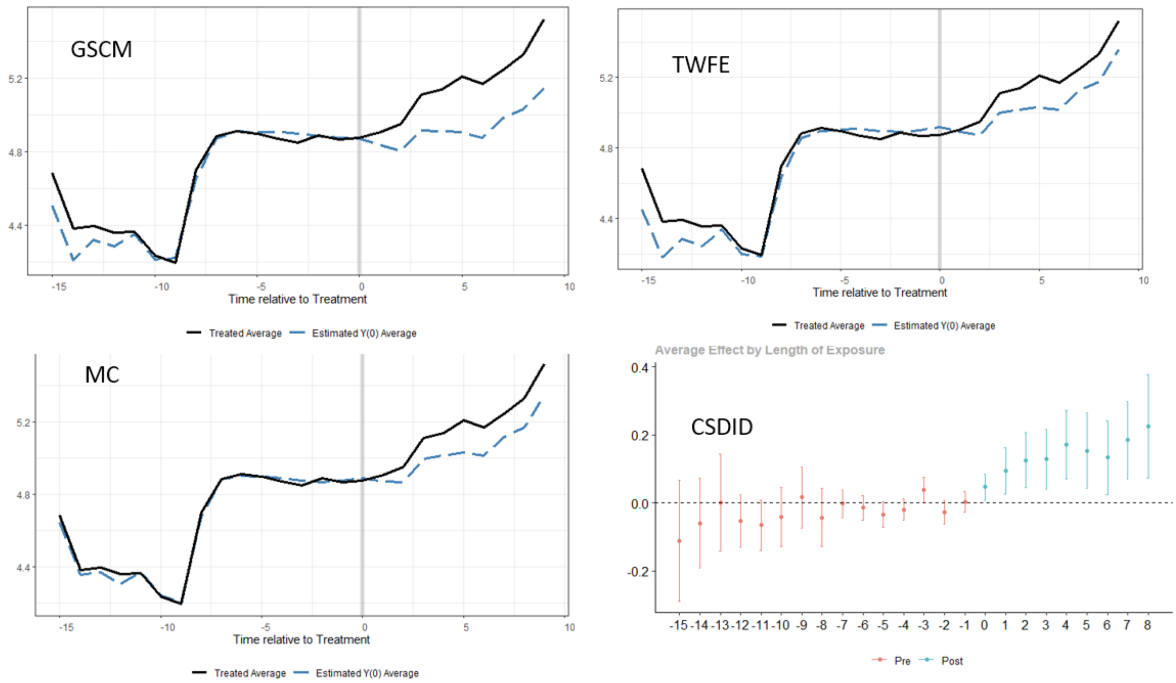


Figure 23 Secondary young forest results

The figure shows estimated ATT with the dependent variable 'secondary forest area age 1 to 9' using the Generalized synthetic control (GSCM), Matrix completion (MC), Two-way fixed effects (TWFE), and Callaway and Sant'Anna (2021) method. Control variables include; Land conflicts, Herd density, Fine amount (2019R$), Non-ag value (2019R$), Protected area (km^2), Fire count at municipality-level, temperature (degree K) and rainfall (mm), CAR area (km^2), and Agricultural prices for rice, sugarcane, and soybean. All price indices are measured using agricultural output prices calculation steps illustrated by Assunção et al. (2015). The estimation was done in R gysnth, MC, and EM algorithms using seed numbers 282006 and 1000 bootstrapping iterations.

Detailed results of two-way fixed effect regression with secondary forest area as a dependent variable

Table 25 TWFE regression results

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Secondary forest area in km^2	Secondary forest areas aged 1 to 8 in km^2	Secondary forest areas aged 9 to 16 in km^2	Secondary forest areas aged 17 to 24 in km^2	Secondary forest areas aged 25 to 34 in km^2	Secondary forest areas loss in km^2	Secondary forest areas increment in km^2
Fine (2019R$)	-0.000231	-0.000528	0.00210*	0.00224*	-0.00161	0.0000113	-0.000197
	(-0.49)	(-0.76)	(2.27)	(2.06)	(-0.75)	(0.01)	(-0.21)
Herd density	0.0166	0.0483	0.0705*	0.00576	-0.0558	0.0390	-0.00790
	(0.93)	(1.89)	(2.15)	(0.13)	(-0.83)	(1.93)	(-0.32)
Non-ag value (2019R$)	0.0233	0.0660*	0.0562	-0.119*	0.0130	0.0445*	0.0429
	(1.44)	(2.54)	(1.71)	(-2.35)	(0.16)	(2.17)	(1.85)
PPA rice	0.0376	0.0764	0.467***	0.267*	-1.237***	-0.300***	-0.0939
	(1.46)	(1.61)	(4.25)	(2.28)	(-5.63)	(-4.27)	(-1.69)
PPA cane	0.0472*	0.0588	-0.0887	-0.00505	0.397***	0.0832**	0.0689**
	(2.03)	(1.84)	(-1.86)	(-0.09)	(3.64)	(3.27)	(2.58)
PPA corn	0.0794	0.188*	0.0440	0.329	-0.0854	-0.0124	0.0547
	(1.10)	(2.33)	(0.21)	(1.54)	(-0.12)	(-0.13)	(0.34)
PPA soy	0.0438	0.0591	-0.0248	-0.0801	-0.599***	0.0254	-0.0643
	(1.26)	(1.26)	(-0.42)	(-1.17)	(-4.30)	(0.82)	(-1.85)
PPA cassava	-0.234**	-0.319***	-0.0806	0.174	1.033***	-0.0919	-0.0531
	(-3.02)	(-4.25)	(-1.01)	(1.70)	(3.90)	(-1.09)	(-1.41)
Rainfall (mm)	0.0520***	0.0833***	-0.138***	0.0270	0.443***	-0.0287	0.107***
	(4.14)	(4.47)	(-5.63)	(0.76)	(8.06)	(-1.07)	(3.52)
Temp (K)	-0.469	3.266***	-4.518***	-8.405***	-19.14***	1.473**	0.391
	(-1.32)	(6.27)	(-7.46)	(-10.17)	(-13.33)	(2.76)	(0.70)
Ag. Protected area (km^2)	-0.0000192	0.00929	-0.00600	0.0187	-0.0333	0.0187	-0.00716
	(-0.00)	(1.77)	(-0.23)	(0.68)	(-1.74)	(1.01)	(-0.68)
CAR (km^2)	-0.00142	-0.000761	0.000104	-0.0109**	-0.0508***	-0.00328	0.00421*
	(-1.02)	(-0.37)	(0.04)	(-3.09)	(-7.80)	(-1.68)	(2.22)

Constant	6.816**	-16.89***	25.11***	46.58***	112.2***	-4.142	-0.492
	(3.13)	(-5.39)	(6.29)	(9.05)	(10.92)	(-1.31)	(-0.14)
Observations	12886	12886	12886	12886	12886	12886	12886
Adjusted R^2	0.992	0.981	0.961	0.929	0.768	0.943	0.927
Log-likelihood	5426.2	379.1	-3107.3	-5977.7	-12582.9	-3851.4	-5883.0
aic	-10828.3	-734.3	6238.5	11979.4	25189.8	7726.8	11789.9
bic	-10738.7	-644.7	6328.1	12069.0	25279.4	7816.3	11879.5
Municipality FE	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y

NOTE: t statistics in parentheses
#10%, *5%, 1% ** and 0.1%***.
All variables are log-transformed.