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Additionality in Carbon Projects: Evidence from the Brazilian Amazon

Dissertação de Mestrado

Masters dissertation presented to the Programa de Pós–graduação em Economia, do Departamento de Economia da PUC-Rio in partial fulfillment of the requirements for the degree of Mestre em Economia.

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Co-advisor: Prof. Leonardo Rezende

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To the Brazilian biodiversity,
for inspiring me and fueling my passion
for life, knowledge, and exploration.

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Abstract

Ferreira Arbache,João Pedro; Assunção, Juliano (Advisor); Rezende, Leonardo (Co-Advisor). **Additionality in Carbon Projects: Evidence from the Brazilian Amazon.** Rio de Janeiro, 2024. 63p. Dissertação de Mestrado – Departamento de Economia, Pontifícia Universidade Católica do Rio de Janeiro.

Carbon markets offer a promising avenue for tackling climate change, yet their advancement encounters challenges, notably in accurately measuring emissions avoidance from forest-related activities. This paper introduces a dynamic discrete choice model tailored for assessing such emissions, using a novel database of panel data on private property land use, characteristics, and carbon project participation. Our analysis reveals that approximately 23% of carbon stocks within forestry carbon projects on private properties in the Brazilian Amazon lack exposure to deforestation risks and should therefore not be tradable as carbon credits. Through simulated scenarios, we demonstrate that elevated carbon prices or reduced participation costs in these projects could substantially augment the supply of avoided carbon emissions. Interventions such as cost reductions, price subsidies or regulatory improvements could bolster supply and contribute to climate change mitigation efforts. Lastly, we identify suitable properties for future project participation, aiming to mitigate investment risks and optimize expected returns.

Keywords

Carbon Markets; Additionality; Amazon; Dynamic Discrete Choice Model.

Resumo

Ferreira Arbache,João Pedro; Assunção, Juliano; Rezende, Leonardo. **Adicionalidade em Projetos de Carbono: Evidência da Amazônia Brasileira**. Rio de Janeiro, 2024. 63p. Dissertação de Mestrado – Departamento de Economia, Pontifícia Universidade Católica do Rio de Janeiro.

Os mercados de carbono oferecem uma promissora abordagem para enfrentar as mudanças climáticas. No entanto, seu avanço encontra desafios, especialmente na medição precisa da redução de emissões provenientes de atividades relacionadas à floresta. Este artigo apresenta um modelo dinâmico de escolha discreta adaptado para avaliar tais emissões, utilizando uma nova base de dados de dados em painel sobre o uso da terra em propriedades privadas, contendo suas características e participação em projetos de carbono. Nossa análise revela que aproximadamente 23% dos estoques de carbono dentro de projetos de carbono florestal em propriedades privadas na Amazônia brasileira não têm exposição a riscos de desmatamento e, portanto, não devem ser negociados como créditos de carbono. Através de cenários simulados, demonstramos que maiores preços de carbono ou menores custos de participação nesses projetos poderiam aumentar substancialmente a oferta de emissões de carbono evitadas. Intervenções como redução de custos, subsídios de preço ou melhoras regulatorias poderiam recrudescer a oferta e contribuir para os esforços de mitigação das mudanças climáticas. Por fim, identificamos propriedades adequadas para participação futura em projetos, com o objetivo de mitigar os riscos de investimento e otimizar os retornos esperados.

Palavras-chave

Mercados de Carbono; Adicionalidade; Amazônia; Modelo Dinâmico de Escolha Discreta.

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Nesses tempos de céus de cinzas e chumbos,
nós precisamos de árvores desesperadamente verdes.

Mário Quintana, *Poesias*.

1
Introduction

Climate change poses one of the most significant challenges of the 21st century. The scale and reach of its associated consequences require all types of solutions. One of them comes from carbon markets, which price CO2 emissions and create market mechanisms to reach optimal levels of emissions. Notably, voluntary carbon markets (VCM) have gained prominence in recent years, with over 2.3 billion credits traded by 2022. Firms purchase carbon credits to offset their emissions, financing projects that have so far removed or avoided the emissions of 2.3 Gt of CO2[1], equivalent to Brazil's total emissions in 2022. The practice of purchasing carbon credits is becoming increasingly prevalent among firms, driven by consumer/investor pressures and the desire to contribute to mitigation efforts. Transactions in this market reached nearly US$2 billion in 2022, with forecasts projecting a surge to US$100 billion by 2030. The significance of the VCM is evident, yet uncertainties and risks persist in its operation.

In the development of carbon projects, stakeholders must quantify the amount of CO2 removed from the atmosphere or the emissions avoided. While measuring removals is relatively straightforward, assessing avoidance requires projections and counterfactuals in the absence of the project. A carbon credit is deemed **additional** if its associated avoidance/removals are feasible only through carbon credit revenues. In other words, without carbon projects, maintaining such mitigation activities would be economically unviable for project stakeholders.

A pressing concern in the VCM is the predominance of credits originating from avoidance projects, which are subject to questionable methodologies for measuring avoided emissions. This uncertainty has led to a decrease in the issuance of new credits, as buyers shy away from the market to avoid accusations of greenwashing[2]. Buyers are reluctant to purchase non-additional credits, as they would make no tangible contributions to mitigating climate change. The primary issue lies in project developers utilizing methodologies and measurements that inflate the amount of avoided CO2 emissions. Consequently, the integrity of these markets is jeopardized, prompting efforts from industry players to enhance the quality of supply and facilitate the identification of credible products on the demand side.

[1] One carbon credit corresponds to the avoidance/removal of one ton of $CO2$.

[2] See e.g. <https://www.ecosystemmarketplace.com/publications/state-of-the-voluntary-carbon-market-report-2023/>

The Brazilian Amazon stands as one of the world's largest carbon sinks, storing huge amounts of carbon in its biomass. This region also hosts numerous carbon projects, which generate credits under the pretext of avoided deforestation. Landowners sell carbon credits because they perceive this activity to be more profitable than potential agricultural revenues, which require clearing these areas. However, this possibility of land use has been exclusive to large landowners, exacerbating income inequalities related to land ownership, bringing with it significant distributive consequences.

Forecasting deforestation in this context is challenging, involving numerous determinants such as transport infrastructure, agricultural prices, rural credit, soil quality, climate, and economic growth (e.g. (CHOMITZ; THOMAS, 2003), (FOSTER; ROSENZWEIG, 2003), (ASSUNçãO; GANDOUR; ROCHA, 2015), (ASSUNçãO et al., 2019), (ARAUJO; ASSUNÇÃO; BRAGANÇA, 2023)). Historical trends or land use models are typically employed for such projections. However, recent evidence (e.g. (WEST et al., 2020) and (WEST et al., 2023)) suggests that these estimates may overstate deforestation, thereby maximizing credit generation.

In this paper, we develop a model to assess additionality in REDD projects (Reduce Emissions from Deforestation and Degradation) scattered throughout the Brazilian Amazon. We also examine the distributive consequences that such projects have in this region. Additionally, we investigate how various carbon prices, taxes and participation costs - including those linked to the regulatory environment - could impact the supply of additional forest carbon in the VCM. To this end, we propose a dynamic discrete choice model where profit-maximizing farmers choose the land use based on the flow returns from alternative land uses, which vary across properties. A unit of carbon is considered additional if it would have been deforested in the absence of carbon projects.

Our model is inspired in the works of (ARAUJO; COSTA; SANTANNA, 2022) and (SCOTT, 2018), which develop dynamic models that generate land use transition probabilities that depend on observed and unobserved state variables and parameters. We derive a structural regression equation in which the land use transition probabilities form the dependent variable. Utilizing the observed land use choices of 13,224 private properties, we estimate the model's structural parameters. We select properties that are suitable to participate in REDD projects, combining multiple datasets to model agriculture, forest and REDD returns at the property level. Specifically, we obtain property land use across time, together with agricultural productivity, carbon stock, area, and transportation costs. Our analysis spans the period from 2010 to 2022, a period marked by the increasing significance and prevalence of REDD projects in the Amazon.

Our findings reveal that nearly one-quarter of the carbon stored in current REDD properties faces no risk of deforestation. That is, around 0.16 Gt of carbon stored in private properties is not additional. This is an expressive share, which highlights the need of adopting better methods to measure avoided emissions. Improving additionality measures is essential for reducing the financial risks associated with investing in carbon markets.

We then move to investigate the effects of carbon prices on the supply of additional carbon in REDD projects. We find that higher prices have the potential to substantially reduce emissions linked to deforestation, leading landowners to shift from agriculture to REDD. Consequently, higher prices augment the supply of additional carbon, increasing its share to as high as 90%. We also find that the most likely entrants across various carbon price scenarios are large properties with above-average carbon stocks and below-average agricultural productivity, located predominantly in the states of Acre, Amazonas, and Mato Grosso. While this is good for preservation efforts, the distributional consequences of REDD projects entail the exclusion of small landowners, likely due to prohibitive participation costs. As a result, such properties are inclined to deforest and engage in agricultural activities, with carbon revenues flowing exclusively to large landowners and perpetuating existing disparities.

We further explore the impact of a carbon tax on reducing emissions and expanding CO_2 supply. We find that a carbon tax has a low effect in reducing emissions and agricultural area. Carbon supply is almost inelastic to such policy, as most of the areas that decide to forfeit agricultural activities due to tax costs end up remaining idle. These results underscore the efficacy of market mechanisms such as REDD projects in promoting preservation and emissions avoidance compared to taxes.

In our final counterfactual analysis, we explore the impact of reducing participation costs on carbon supply. We highlight that such costs may be capturing regulatory complexities that increase transaction and development costs. We find that lowering participation costs has a similar effect to increasing carbon prices, resulting in a substantial increase in carbon supply. Reducing costs associated with REDD projects emerges as the most efficient approach for expanding participation in carbon projects, as the associated cost of increasing supply is lower compared to subsidizing prices.

Considering our findings, several policy interventions could enhance participation in carbon markets. A primary focus should be on reducing costs, which can be achieved through the creation of stable regulatory frameworks that reduce uncertainty and transaction costs. Alternatively, governments could directly subsidize entry and participation costs for landowners. Subsidizing carbon prices through additional payments for each carbon credit is another option, albeit with higher associated costs. Measures that stimulate demand for carbon credits, such as regulations on emissions and the implementation of cap-and-trade systems, could also bolster the market. On the private market side, adopting technologies to reduce certification, transaction, and operational expenses could increase supply. Additionally, using assessments to identify investment opportunities in suitable properties could further reduce project costs.

Related Literature. This paper belongs to a recent literature that evaluates the effectiveness of Payment for Ecosystem Services (PES) programs. Prior studies in this field have employed reduced form techniques, such as Differences-In-Differences and Synthetic Controls, to assess program outcomes, yielding mixed results. For instance, (ALIX-GARCIA; WOLFF, 2014), (JAYACHANDRAN et al., 2017), (SIMONET et al., 2019) and (GUIZAR-COUTIñO et al., 2022) find small but positive impacts in terms of avoiding emissions. Conversely, (WEST et al., 2020) and (WEST et al., 2023) find that the ex ante deforestation baselines of REDD projects are substantially higher than their counterfactuals, suggesting minimal additionality in such projects.

Our paper advances in this literature by introducing an economic model of land use, enabling us to explain deforestation and conservation choices beyond statistical means. Our main contribution is to measure additionality in current REDD projects and to assess various price and cost scenarios that may materialize in the future. We also identify private areas that are most suitable for developing *additional* REDD projects. Besides, we show the distributive consequences of such projects, which may exacerbate income inequalities related to land ownership. We also find mechanisms that could enhance the effectiveness of these activities, such as reducing costs and establishing a more stable regulatory framework.

Moreover, we relate to a literature that employs discrete choice models to study land use (e.g (SCOTT, 2018); (SOUZA-RODRIGUES, 2019); (ARAUJO; COSTA; SANTANNA, 2022); (HSIAO, 2022); (ARAUJO, 2023); (ASSUNçãO et al., 2023); (DOMíNGUEZ-IINO, 2023)). Our paper is closest to (ARAUJO; COSTA; SANTANNA, 2022) which estimates the carbon-efficient level of forestation in the Brazilian Amazon using a dynamic model. We depart from this model and innovate by explicitly incorporating the option of joining carbon projects. This inclusion enables us to investigate the impact of carbon payments on farmers' decisions and aggregate land use in the Brazilian Amazon in a more explicit manner compared to implicit model derivations commonly found in the literature. We also contribute to this literature by proposing a model wherein the unit of decision-making is the property, as opposed to pixels or municipalities.

The paper proceeds as follows. Chapter 2 provides an overview of carbon markets and carbon projects. Chapter 3 describes our model and the strucutural regression equation used to recover the parameters. Chapter 4 describes the data. Chapter 5 presents our estimation strategy and results. Counterfactual exercises and analyses are discussed in Chapter 6. Chapter 7 concludes.

2
Background

We begin with a brief overview of carbon markets and projects to contextualize our empirical setting. Carbon markets can be categorized into two main types: regulated and voluntary markets. Regulated markets, also known as compliance markets, operate within a legal framework where participants must adhere to local regulations through mechanisms such as cap-and-trade or carbon taxes. These markets are highly regulated with clear rules governing their operation. In contrast, we focus on voluntary markets, where firms voluntarily offset their emissions by purchasing carbon credits. Each carbon credit corresponds to one ton of avoided or removed CO2. Voluntary markets have seen significant growth in recent years, with the market value exceeding US$2 billion in 2022, and forecasts indicating it may reach US$100 billion by 2030. Unlike compliance markets, voluntary markets are unregulated, with credibility and standards set by market participants. Recently, concerns about the credibility of these markets have arisen, supported by academic evidence (e.g. (WEST et al., 2020), (WEST et al., 2023)) and journalistic investigations, leading to a decline in carbon credit demand and, consequently, in fewer projects being released[1].

Given the absence of a central regulator in voluntary markets, it is crucial that the supply meets specific requirements for carbon credits to be valid. These requirements include measurability, additionality, permanence, and leakage. Measurability ensures that carbon credits are quantifiable, allowing for verification against accredited methodologies. Additionality is a key aspect of carbon credits, referring to the notion that a carbon project is only financially viable due to revenues from selling carbon credits. In other words, without carbon revenues, the associated emission reduction or avoidance activities would not be feasible. Permanence requires that emission reductions or removals from mitigation activities endure or are fully compensated in the event of reversal risks. Finally, leakage pertains to the idea that emission reductions from carbon credits should not be offset by increased emissions elsewhere.

In theory, these requirements are assessed in the carbon credit creation process, which involves several lengthy and costly steps. Initially, a carbon project developer plans and organizes the project, submitting documents and

[1] See e.g. <https://www.ecosystemmarketplace.com/publications/state-of-the-voluntary-carbon-market-report-2023/>

calculating the amount of removed or avoided carbon emissions. Projects undergo evaluation against quality criteria defined in project-specific methodologies and are validated and reviewed by independent auditors to ensure compliance with selected standards. Once registered with a registry operator (e.g., Verra or Gold Standard), projects begin operation and credit issuance. Registry operators establish standards for credit quality, certify and issue credits, and maintain a registry to track certified projects and credit issuance and retirement. Throughout the project's operational phase, emission savings are monitored and re-verified at regular intervals.

A significant issue concerning recent criticisms of voluntary carbon markets relates to their business model. Registry operators, which function as market centralizers and regulators, earn revenue through registered credits, incentivizing them to accept inflated estimates of carbon removals or avoidance. Similarly, project developers earn per credit, preferring projects that generate millions rather than thousands of credits. Validators, as third-party auditors, face the risk of not being engaged in future projects if they dispute project estimates, potentially leading to leniency in their assessments to maintain business relationships.

The Brazilian Amazon hosts over 70 carbon projects, primarily focusing on land use and deforestation. The most prevalent projects in the region are known as REDD projects (Reducing Emissions from Deforestation and Degradation), all registered under the Verra registry with the VCS (Verified Carbon Standard) stamp. These projects commonly use methodologies focused on avoided deforestation. The process of creating REDD credits involves an initial partnership between landowners and project developers. Properties must comply with local regulations, and are required to have high forest cover and substantial carbon stocks to produce a profitable number of credits. Ideally, these properties should also be located in regions facing deforestation pressures. Given the complexity and high fixed implementation costs of developing projects, REDD projects often involve multiple properties.

Project developers employ Verra methodologies to project deforestation in both the project area and adjacent regions, utilizing tools such as historical changes and land use models. Verra determines that projections must be conservative and realistic. However, recent research suggests that these methodologies tend to overestimate deforested areas (e.g. (WEST et al., 2020), (WEST et al., 2023)).

Once projections are completed, and all methodology steps are fulfilled, a validator confirms compliance before the project can be registered with Verra and carbon credits can be sold. Each year, a project can sell credits equivalent to the amount of avoided carbon emissions related to projected deforestation levels. Any unsold credits can be carried over to subsequent years. Implicit in this process is the assumption that landowners choose to sign REDD contracts because they anticipate carbon credit revenues to exceed profits from deforestation and associated activities, such as cattle grazing or cash crops. Typically, project developers retain a portion of each carbon credit sold, with landowners' REDD profit tied to the amount of carbon stock preserved in a given year. To address permanence requirements, REDD projects typically span 30 years or more, with severe financial penalties for early termination, making REDD contracts a binding commitment that discourages landowners from deforesting their lands.

This overview highlights the intricacies of the carbon credit creation process, its associated challenges, and the decision-making context of landowners in the Brazilian Amazon concerning the possibility of selling carbon credits. This decision, coupled with multiple land use choices, motivates our model, which we detail in the following Section.

3
Model

We depart from the work of (ARAUJO; COSTA; SANTANNA, 2022) to formulate a dynamic discrete choice model where every year a profit-maximizing landowner chooses how to allocate the land inside its property. In this section, we describe the model, the choice revenues, and derive the structural regression equation that serves as the basis of our estimation approach.

3.1
Setup

The basic unit of decision in the model is a property, denoted by m. Each property m is run by a rational agent that chooses the profit-maximizing land use. In our setup, we only consider formally registered properties in the SIGEF database[1], implying that agents hold property rights over the land and receive the cash flow from any economic activity performed inside the property. Agents can choose among two possible land uses: $agriculture$[2] or $forest$. Forested properties have the possibility to participate in REDD contracts. Hence, the choice set of economic uses for a property m consists of $j \in J = \{agriculture, forest, REDD\}$. That is, landowners can either deforest they property for agricultural purposes, maintain it as forested land with native vegetation, or sign a REDD contract and earn carbon credit revenues. This choice is repeated every year $t = 1, 2, ..., \infty$.

We diﬀerentiate from (ARAUJO; COSTA; SANTANNA, 2022) by considering that both $agriculture$ and $REDD$ are absorbing states. That is, once an agent chooses one of the above options, this decision is permanent and the property remains locked in that state indefinitely. Hence, the only possible transitions in this model are $forest$ to $agriculture$ and $forest$ to $REDD$. We motivate this hypothesis based on the nature of REDD contracts, which typically involve long-term commitments lasting at least 30 years. While it is true that we observe regeneration in a fraction of deforested areas in the Amazon, a specific requirement in REDD contracts - that the area must have been

[1]REDD projects require strong property rights within land parcels, and the SIGEF database serves as a proxy for evaluating this requirement.

[2]Given that approximately 90% of the deforested land in the Amazon Biome is presently utilized for pasture, in this paper, we equate agriculture with cattle farming and use the two terms interchangeably (see e.g. (ASSUNçãO et al., 2023)).

forested for at least 10 years - motivates us to discard a possible *agriculture* to *forest* to *REDD* transition.

The transition to *REDD* is directly observed in the data, so it is straightforward to model when this decision has been taken. Typically, the share of a property inside a *REDD* project is close to 100%. We need, though, to formulate a definition for the transition to *agriculture*, since deforestation decisions within properties are lumpy. We define the transition to *agriculture* to happen in the year when more than 5% of the property area has been deforested[3].

Each land use choice generates a profit flow $\pi_j^m(w_{mt}, \varepsilon_{mtj})$ in year t that depends on a vector of property-specific state variables $w_{mt} \in \mathbb{R}^L$ encompassing both observable (e.g., prices, land characteristics, transportation costs) and unobservable (to the econometrician) variables – as well as $\varepsilon_{mtj} \in \mathbb{R}$, which represent property, choice and time specific shocks that are unobservable to the econometrician. We assume a separable structure for the profit function:

$$\pi_j^m(w_{mt}, \varepsilon_{mtj}) = r_j^m(w_{mt}; \alpha) + \varepsilon_{mtj}, \tag{3-1}$$

where $r(\cdot; \alpha)$ is a known function up to parameters α.

Assumption 1 *The evolution of property-specific state variables follows a Markov process and it is conditionally independent from property-level information (decisions and characteristics) - i.e., $F(w_{m,t+1}|w_{m,t}, \varepsilon_{mtj}, j) = F(w_{m,t+1}|w_{m,t})$.*

Assumption 1 implies that property-level decisions and characteristics do not influence the dynamics of market-level variables. This is consistent with the idea that landowners are price takers in competitive final product markets

Assumption 2 *Property level shocks ε_{mtj} are independent over time and choices conditional on property characteristics and market-level state variables, with type-I extreme value distribution.*

Assumption 2 is standard in the dynamic discrete choice literature. Assumptions 1 and 2 enable us, under usual regularity conditions, to write the agent's dynamic land use choice problem with Bellman equations. The problem of an agent in period t, with land use $k = forest$ in period $t-1$ is:

$$V(k, w_{mt}, \varepsilon_{mt}) = \max_{j \in J} \left\{ r_j(w_{mt}; \alpha) + \varepsilon_{mjt} + \rho E\left[\bar{V}(j, w_{m,t+1}) \mid w_{mt} \right] \right\}, \tag{3-2}$$

where $\bar{V}(j, w_{mt}) = \begin{cases} E_\varepsilon[V(j, w_{mt}, \varepsilon_{mt})], & \text{if } j = \text{forest} \\ \frac{r_j(w_{mt};\alpha)}{1-\rho}, & \text{otherwise} \end{cases}$, $\varepsilon_{mt} \in \mathbb{R}^3$ is the vector of shocks ε_{mjt} for each choice $j \in J$, and ρ is the discount rate.

[3]For robustness, we apply 10% and 15% thresholds and find similar results across all scenarios.

Assumption 3 *Future carbon and cattle prices are assumed to be constant and equal to those of 2022.*

Assumption 3 is necessary for computing the present values for both REDD and agriculture revenues. Though strong, this assumption could be perceived as a conservative estimate of expectations, considering that forecasts and reputable sources typically anticipate upward trends in both REDD and agriculture prices over time. Nonetheless, given the nature of discounting future revenues, this hypothesis carries more weight for revenues closer to the present rather than those further into the future. Given the relatively stable nature of prices in the short term, as illustrated in Figure 4.4, it is reasonable to argue that this assumption is valid.

We denote the non-random component of equation 3-2 as

$$v(j, forest, w_{mt}) = r_j(w_{mt}; \alpha) + \rho E\left[\bar{V}(j, w_{m,t+1}) \mid w_{mt}\right]. \tag{3-3}$$

We can then re-write the agent's problem as

$$V(forest, w_{mt}, \varepsilon_{mt}) = \max_{j \in J} \{v(j, forest, w_{mt}) + \varepsilon_{mjt}\}. \tag{3-4}$$

The distributional assumption on property level shocks (Assumption 2) implies the logit conditional choice probability:

$$p(j|forest, w_{mt}) = \frac{\exp v(j, forest, w_{mt})}{\sum_{j' \in J} \exp v(j', forest, w_{mt})}, \text{ for } j, j' \in J. \tag{3-5}$$

This is the probability a property transitions from land use $k = forest$ to land use j conditional on w_{mt}. The formulation above yields the (HOTZ; MILLER, 1993) inversion:

$$\log\left(\frac{p(j|forest, w_{mt})}{p(j'|forest, w_{mt})}\right) = v(j, forest, w_{mt}) - v(j', forest, w_{mt}), \text{ for } j, j' \in J. \tag{3-6}$$

That is, the ratio of conditional choice probabilities of different alternatives is directly related to the difference between the non-random components of returns from these alternatives.

We can decompose the property-specific w_{mt} into its observable and unobservable components. That is, $w_{mt} = (x_{mt}, \xi_{mt})$, where $x_{mt} \in \mathbb{R}^{L-3}$ represents a vector of observed variables and $\xi_{mt} \in \mathbb{R}^3$ represents a vector of choice specific unobserved state variables. We require $r_j(\cdot; \alpha)$ to be linear in α with an additive property and choice specific unobservable:

$$r_j(w_{mt}; \alpha) = \bar{\alpha}_j + \alpha_j R_j(x_{mt}) + \xi_{jmt}, \text{ for } j \in J, \tag{3-7}$$

where $R_j(x_{mt})$ is a choice specific known function of observables, and $\bar{\alpha}_j$ is an intercept. The specific formulation for $R_j(\cdot)$ will be determined by data availability and discussed in detail in the next Subsection.

We let the $\bar{\alpha}_j$ absorb choice-specific components which are constant across properties and time - it captures present value costs related to land use j. This implies ξ_{jmt} is mean zero across properties and time.

Structural regression equation. We select $j = REDD$ and $j = agriculture$ in (3-6) to obtain our structural regression equation. The diﬀerence between the returns of REDD and agriculture yields a specification in which all α_j can be estimated:

$$\log\left(\frac{p(REDD|forest, w_{mt})}{p(agri|forest, w_{mt})}\right) = v(REDD, forest, w_{mt}) - v(agri, forest, w_{mt}) \tag{3-8}$$

Substituting (3-3) in the equation above, we obtain:

$$\begin{aligned}\log\left(\frac{p(REDD|forest, w_{mt})}{p(agri|forest, w_{mt})}\right) &= \frac{r_{REDD} - r_{agri}}{1-\rho} \\ &= \frac{\bar{\alpha}_{REDD} - \bar{\alpha}_{agri} + \alpha_{forest}R_{forest}(x_{mt})}{1-\rho} + \\ &\quad \frac{\alpha_{REDD}R_{REDD}(x_{mt}) - \alpha_{agri}R_{agri}(x_{mt}) + \xi_{REDD,m,t} - \xi_{agri,m,t}}{1-\rho}\end{aligned} \tag{3-9}$$

The left-hand side depends only on conditional choice probabilities that can be estimated directly from the data. On the right hand side, we have regressors $R_{forest}(x_{mt})$, $R_{REDD}(x_{mt})$ and $R_{agri}(x_{mt})$ and aggregate shocks $\xi_{REDD,m,t}$ and $\xi_{agri,m,t}$. With this formulation, we estimate the coeﬃcients that minimize the diﬀerence between the ratio of conditional choice probabilities and the diﬀerence between the returns of the two selected choices.

3.2 Flow of Profits

We will now delve into our formulation of flow profits $r_j(\cdot;\alpha)$ for each land use option. These formulations primarily stem from contextual and data-driven considerations. In this discussion, we will introduce several covariates that inform our analysis. Further details regarding the data are provided in Chapter 4.

Agriculture. As previously mentioned, agriculture activity in this paper is represented by cattle farming. Hence, the choice for agriculture is equivalent to converting the property to pasture. The cattle produced on each property could be transported to destination markets and sold at market prices. The net revenue from this operation is equal to:

$$r_{agri}(w_{mt};\alpha) = \alpha_{agri}(p_{pt} - z_{pm})y_{m,p}area_m + \bar{\alpha}_{agri} + \xi_{agri,m,t} \tag{3-10}$$

where y_{mp} is a productivity measure of beef in kg/ha on property m, p_{pt} is the cattle price in destination markets, z_{pm} is the transportation cost from property m to destination markets, $area_m$ is property m's size in hectares, and $\bar{\alpha}_{agri} + \xi_{agri,m,t}$ is a fixed cost associated with agricultural land use, encompassing costs related to inputs, wages and other unobserved factors that may vary across properties and time. Specifically, we allow $\xi_{agri,m,t}$ to be correlated with potential yields y_{pm} and transportation costs. This consideration is particularly relevant in contexts where transportation costs significantly influence land use decisions. In our context, the placement of roads may be correlated with unobserved factors aecting agricultural returns.

Forest. We adopt a forest return specification similar to that of (ARAUJO; COSTA; SANTANNA, 2022), in which the return of leaving a property m unused will depend on the carbon stock of native vegetation per hectare h_m in that property:

$$r_{\text{forest}}(w_{mt};\alpha) = \alpha_{\text{forest}}h_m area_m + \xi_{\text{forest},m,t}, \tag{3-11}$$

The coecient α_{forest} encapsulates a combination of two elements. Firstly, it reflects the influence of environmental protection policies aimed at conserving forests, often correlated with forest density. This coecient quantifies the extent to which such policies assist farmers in internalizing the value of maintaining standing forests. Secondly, it accounts for the private costs and benefits associated with forest density. Higher carbon stocks may entail costs to landowners, as areas of dense forest tend to be more susceptible to encroachment. Conversely, they may also yield benefits, such as the safeguarding of water springs.

We have normalized the intercept α_{forest} to zero. Consequently, any additional costs and benefits associated with forest conservation that are not directly tied to forest density will be accounted for by the intercept of agriculture returns and by the structural error $\xi_{\text{forest},m,t}$.

REDD. Finally, we model the return of keeping property m's forest cover and signing a REDD contract. We can specify the REDD revenue as a sum of the forest revenue and the pecuniary value received in REDD contracts:

$$r_{REDD}(w_{mt};\alpha) = \alpha_{\text{forest}} h_m area_m + \alpha_{REDD} p_{REDD,t} h_m area_m + \bar{\alpha}_{REDD} + \xi_{REDD,m,t} \tag{3-12}$$

With this specification, we assume annual deforestation for the entire property, in contrast to REDD contracts that project deforestation within a property over time. REDD projects generate credits for each year's projected deforestation, which are subsequently sold in the VCM. We anticipate that the coe□cient α_{REDD} will adjust for this disparity between (3-12) and actual carbon revenues.

4
Data

We have assembled a novel property-year panel dataset that integrates information on carbon projects, property characteristics, and commodity prices. To the best of our knowledge, this is the first dataset to encompass all REDD projects in Brazil, incorporating data at the property level. Our analysis focuses on the time frame spanning from 2010 to 2022, the period when such projects began to gain significance.

4.1
Project Data

The project data comes from the Verra Registry. Verra is one of the world's main carbon offset programs. Together with Gold Standard, American Carbon Registry (ACR), and Climate Action Reserve (CAR), they account for nearly 90% of the credits in the voluntary markets. None of these three standards had REDD projects located in Brazil.

As of December 2022, there were 77 REDD projects in the Brazilian Amazon. The main data retrieved from the Verra Registry is the KML file for the polygon of the projects, which enables us to know their exact locations. We also obtain the date when projects started issuing credits.

4.2
Property Data

We obtain property polygons from the IMAFLORA's Atlas of Brazilian Agriculture, restricting our sample for units located in the Amazon biome and registered in the Land Management System (SIGEF). We make this selection because this database is a proxy for properties that comply with national land regulations and property rights requirements, as required for participation in REDD projects. Subsequently, we subset this sample to find properties that were suitable to join REDD projects in 2010, setting a minimum threshold of 80% of forest cover[1] [2]. Using the property polygons, we compute property area. We further remove properties with less than 5 hectares, and properties

[1] The average forest cover of REDD properties upon entry is 99%.

[2] Properties in the Amazon are required to maintain a minimum of 80% forest cover (Reserva Legal). Thus, those exceeding 80% are opting to retain forests in regions susceptible to change. However, there is a lack of compliance and enforcement with this regulation, with 99% of deforestation in the Amazon exhibiting some degree of irregularity.

with zero carbon stock, leaving us with 20,375 observations. In our estimation, we also remove properties in the 1st and 100th percentiles of area.

Cross-referencing project and property polygons allows us to identify units that entered into REDD contracts. We classify properties with more than 20% overlap with project areas as REDD properties, totaling 433 entrants up to 2022. As described in Section **??**, we classify agriculture properties as those that have deforested more than 5% of their area, resulting in a total of 4,527 properties until 2022. Since our analysis starts in 2010, we eliminate properties that transitioned to one of the absorbing states prior to this year. This leaves us with a total of 13,224 properties for analysis.

4.3 Land Use

We collect land use information for suitable properties from MapBiomas[3]. This dataset uses Landsat images to annually categorize the use of each 30-meter resolution pixel in Brazil into various land use classifications. We aggregate land use into three categories: agriculture, forest, and other (i.e., non-classified pixels, urban areas, and water). For our purposes, we consider agriculture pixels as deforested pixels.

To build the dependent variable in our regression equation (3-9), we need to obtain the conditional choice probability $p(j|forest, w_{mt})$ - that is, the probability of transitioning from $forest$ to j conditional on property and time. Differently from (ARAUJO; COSTA; SANTANNA, 2022), we estimate this conditional probability using a multinomial logit with pooled data. If a property chooses $j \in J = \{agriculture, REDD\}$ in t, we only keep its observations up to year t. Our preferred specification consists of:

$$
\begin{aligned}
transition_{m,r,t} = {} & \alpha^j + \beta_1^j lat_m + \beta_2^j lon_m + \beta_3^j lat_m \times lon_m \\
& + \beta_4^j transportCost_m + \beta_5^j roadDistance_m \\
& + \beta_6^j carbon_{mt} + \beta_7^j soy_{mt} + \beta_8^j pasture_{mt} \\
& + \theta_r^j + \varphi_t^j + \varepsilon_{mr}^j, \\
& \text{for } transition, j \in J = \{agriculture, REDD, forest\}.
\end{aligned} \tag{4-1}
$$

Where θ_r is an immediate region (IR) fixed effect, and φ_t represents year fixed effects. $carbon$, soy and $pasture$ represent measures of property productivity, in which:

[3]Project MapBiomas - Collection 8.0 of Brazilian Land Cover & Use Map Series, accessed on 20/12/2023 through the link: <http://mapbiomas.org>.

$$
\begin{aligned}
carbon_{mt} &= log(carbonStock_m) \quad carbonPrice_t \quad log(area_m),\\
soy_{mt} &= log(soyY_m) \quad soyPrice_t \quad log(area_m),\\
pasture_{mt} &= log(pastureY_m) \quad cattlePrice_t \quad log(area_m).
\end{aligned}
$$

lat_m and lon_m denote the latitude and longitude of property m's centroid. The remaining variables are described in the following subsections. Results are described in Table 9.1. The distribution of the estimated conditional choice probabilities are depicted in Figures 9.1 and 9.2.

4.4 Carbon Stock and Potential Agriculture Returns

Carbon stock. Carbon stock data is key for our paper, since it dictates both forest and REDD revenues. We obtain this data from the Woodwell Climate Research Center, which provides values for above-ground live woody biomass at a 30-meter resolution. We then convert these values to the potential CO2 release ((ZARIN et al., 2016)[4]).

Figure 4.1 shows the amount of carbon stored in the suitable properties in 2000. As mentioned before, we remove properties with 0 carbon stock from our sample. Similar to (ARAUJO; COSTA; SANTANNA, 2022), we treat the measure of carbon stock in each property as the maximum attainable carbon density that piece of forest may accumulate. Carbon stock per property is obtained by selecting a random point[5] inside each property, for which we extract the Woodwell carbon data. We then multiply this value by the property area. We follow this procedure for the agriculture productivity variable.

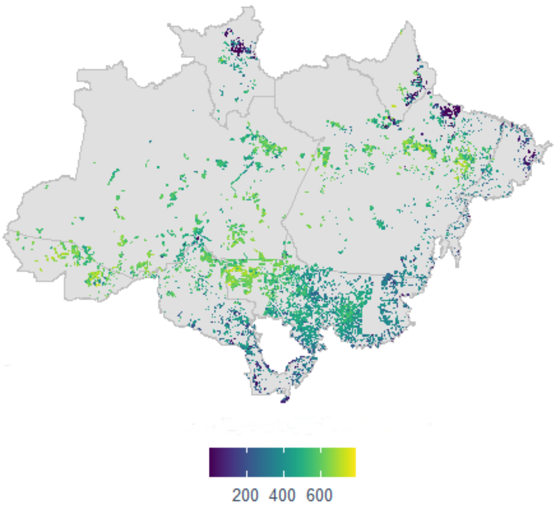
Potential agriculture returns. As mentioned before, we represent agriculture with cattle farming in this paper. Agriculture returns are specified in equation (3-10). The agriculture return in property m in year t is represented by the expected revenue of cattle, net of transportation costs to the nearest port.

y_{mp} is a modified version of the Pasture Suitability Index, provided from the Food and Agriculture Organization's (FAO) project Global-Agroecological

[4]This dataset follows the methodology outlined in (BACCINI et al., 2012). The unit in the original data is megagram of Biomass per hectare. To convert biomass to CO2 per hectare, this value must be divided by 2 – providing a measure of carbon (C) – and then multiplied by 44/12 – yielding a measure of carbon dioxide (CO2). Accessed through Global Forest Watch Climate on 31/10/2023. <https://data.globalforestwatch.org/datasets/aboveground-live-woody-biomass-density> .

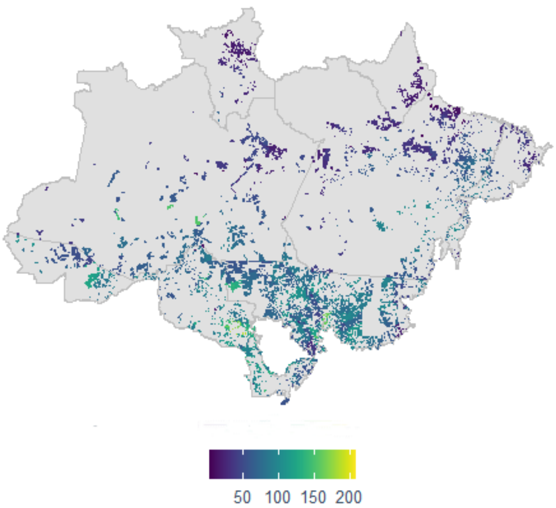
[5]Carbon stock and potential yield variables present a smooth variation in space, so this approach is a reasonable one.

Figure 4.1: Carbon Stock (t/ha)



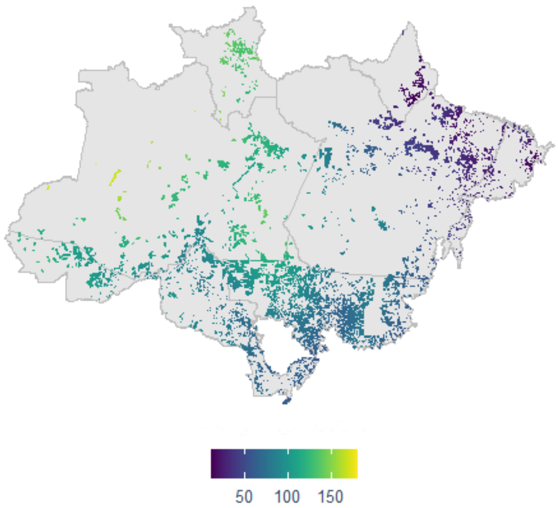
This map plots carbon stock density (tons of CO_2 per hectare) at 30 meter resolution. The values vary from blue (less carbon) to yellow (more carbon).

Figure 4.2: Agriculture Productivity (kg/ha)



This map plots agriculture productivity (kg/ha). The values vary from blue (lower) to yellow (higher).

Figure 4.3: Transportation Costs (R$/t)



This map plots minimum transportation costs of cattle from every property to the international market in Brazilian reais (R$) per ton. The values vary from blue (lower) to yellow (higher).

Zones. This data is not a cardinal measure, i.e., it is not measured directly in units of output per hectare. Hence, we follow a procedure similar to (DOMíNGUEZ-IINO, 2023) and (ASSUNçãO et al., 2023) to transform it in a measure in kg/ha.

For such purposes, we cross all pasture pixels in 2017 with the FAO data. That is, we obtain the pasture suitability index for each pasture pixel in the Brazilian Amazon. Further, we group this data by municipality, obtaining a mean index for each municipalities' pasture area. We then get data from the 2017 Agricultural Census, specifically the cattle weight per hectare and cattle farm gate price variables (which are in the municipality level) to estimate the following model by OLS, wheighted by municipality pasture area:

$$\begin{aligned}\log(cattle\_kgPerHa_i) = \log(mean\_pastureIndex_i) &+ lat_i + lat_i^2 + \\ &lon_i + lat_i \quad lon_i + distance_i + distance_i^2 + \\ &historicalTemp_i + \log(historicalPrecip_i) + \\ &\log(farmGatePrice_i) + \quad {}_i\end{aligned}$$

Where $distance_i$ is the distance from municipality i to its state capital, and $historicalTemp_i$ and $historicalPrecip_i$ are respectively municipality i's historical mean temperature and precipitation (for the 1970-2000 period). Results are reported in Table 9.2. The R^2 of this regression is 0.44. With the estimated parameters, we transform the index for each property into a measure of kg/ha. Results are plotted in Figure 4.2. It is clear that areas deeper in the forest have lower agriculture productivity, while those in the forest fringe have a higher potential for agriculture.

4.5 Transportation Costs

We estimate the cost z_{mp} of transporting cattle from each property to the nearest export port following the procedure adopted in (ARAUJO; COSTA; SANTANNA, 2022) and (ARAUJO; ASSUNÇÃO; BRAGANÇA, 2023). For our purposes, we only consider transport by roads, and obtain cattle freight cost data from the Group of Research and Extension in Agroindustrial Logistics at ESALQ to perform the procedure. Estimated costs are depicted in Figure 4.3. We see that properties located deep inside the forest face the highest costs, while those closer to the coast, or located in consolidated areas - such as the Southern Amazon -, display lower costs.

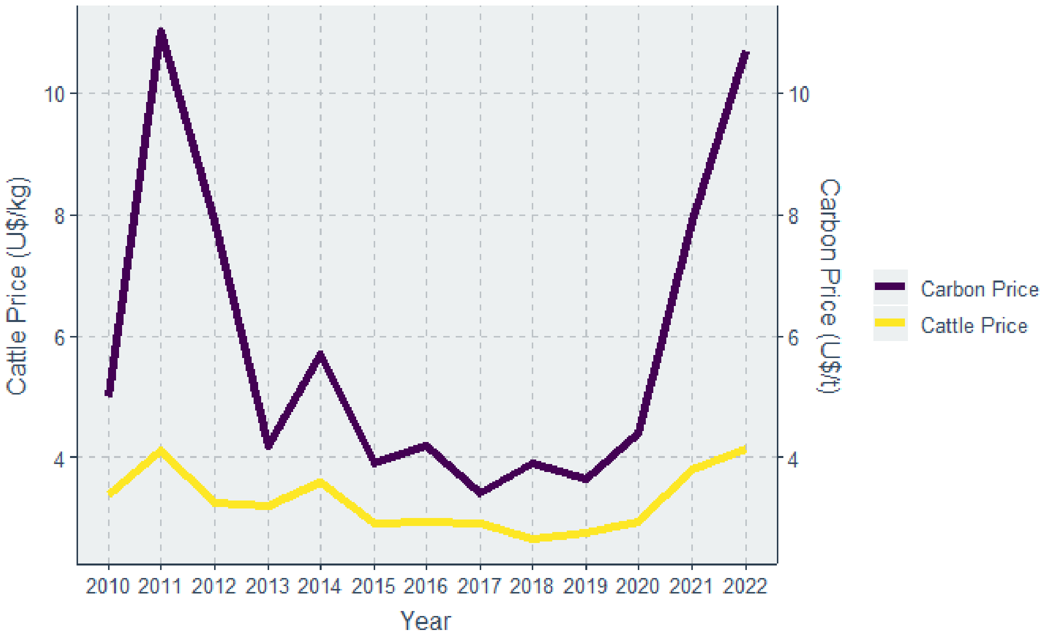
4.6 Prices

We obtain cattle price data from College of Agriculture Luiz de Queiroz (ESALQ). Carbon credit prices are obtained from the Ecosystem Marketplace reports. As each carbon project sells its credits for a different price, reflecting the monopolistic competition nature of this market, the price data we obtain represents the mean of REDD projects located in South America. To deflate prices, we get inflation data from IBGE, using 2020 as the base year in our analysis. Figure 4.4 displays carbon and cattle prices in the period of study.

4.7 Summary Statistics

We conclude this section by providing summary statistics for the main cross-sectional variables used in the model estimation. Table 4.1 illustrates substantial cross-section variation in area, carbon stock, agricultural productivity and transportation costs. This variability is significant as we aim to explore counterfactual scenarios involving long-term shifts in REDD and agricultural returns. In our model, a sustained increase in REDD prices, for instance, corresponds to an increase in carbon stocks. Therefore, the variation in cross-sectional net returns from agriculture and REDD plays a crucial role in computing price elasticities based on the model.

Figure 4.4: Carbon and Cattle Prices



This figure plots carbon and cattle prices over time.

Table 4.1: Descriptive Statistics

Variable:	Area	Carbon Stock	Agriculture Productivity	Transport Cost
Model analog:	$area_m$	h_m	$y_{m,p}$	z_{pm}
Unit:	(ha)	(t/ha)	(kg/ha)	(R$/t)
Mean	996.15	447.91	65.95	80.16
Std	1925.63	156.36	28.56	30.33
Min.	5.83	1.83	3.25	12.35
1st Qu.	53.26	368.50	45.73	66.91
Median	252.98	473.00	66.22	80.06
3rd Qu.	1116.30	564.67	85.62	101.11
Max.	19938.40	788.33	207.46	180.85

This table shows descriptive statistics for the property characteristics used in the model's estimation. Transportation costs are in Brazilian reais (R$) as of 2008, the first year we have data on transportation costs.

5
Estimation

We estimate the structural equation (3-9), which relates the conditional choice probabilities and the potential returns of REDD and agriculture in two steps. We use a non-linear least squares approach to first estimate the revenue coe□cients α_j, and then obtain the $\bar{\alpha}_j$. By substituting regressors $R_j(x_{mt})$ in (3-9)[1], we obtain the final specification for our structural regression equation:

$$\log\left(\frac{p(REDD|forest, w_{mt})}{p(agri|forest, w_{mt})}\right) = \frac{\bar{\alpha}_{REDD} - \bar{\alpha}_{agri}}{1-\rho} + \alpha_{forest}\frac{h_m area_m}{1-\rho} + \alpha_{REDD} h_m area_m PV_{REDD} - \alpha_{agri} y_{m,p} area_m [PV_{agri} - \frac{z_{pm}}{1-\rho}] + \xi_{mt}, \qquad (5\text{-}1)$$

5.1
First Step: OLS Estimation

Our first step is to estimate equation (5-1) by pooled OLS. We leverage two distinct sources of variation to identify our parameters. While prices represent the sole observed state variables that exhibit temporal variation, this variation is amplified by considerable variability in the cross-sectional distribution of potential agriculture returns and carbon stocks across properties.

Table 5.1 presents the results of estimating the structural regression equation (5-1). As expected, we obtain positive estimates for all coe□cients. A positive α_{agri} means that an increase in agricultural returns increases the likelihood of land being converted to pasture. A positive α_{REDD} means that an increase in the returns associated to REDD contracts increases the likelihood of a forested property joining this kind of projects.

Finally, a positive α_{forest} indicates that a higher stock of carbon in a given property decreases the likelihood of this area being deforested[2]. We can monetize the carbon stock coe□cient by dividing it by $\hat{\alpha}_{agri}$ to obtain the landowner's perceived value of preserving carbon in the forest. Our estimates fall in the range of R\$0.94, or US\$0.18 per ton of CO2[3]. This perceived value reflects the impact of environmental regulation, whereby agents partially

[1]The derivation of the final regression equation is available in Appendix 9.1.

[2]Note that α_{forest} is part of both REDD and forest revenues, which are related to maintaining the land unused.

[3]We use the exchange rate of USD \$ 0.19 per R\$ from December 2022. Note that this benefit is already at the present value, as our coe□cients are estimated discounting REDD and agriculture revenues.

internalize the social value of carbon stored in the forest, in addition to net preservation private benefits and costs unrelated to REDD activities.

These estimates are lower than those reported in (ARAUJO; COSTA; SANTANNA, 2022) or (ASSUNçãO et al., 2023), which find a shadow value of around US$5.6 - US$7.6. This difference may be partly attributed to the estimation window. While the former calculates this value for a period ending in 2017 and the latter extends up to 2008, we investigate such prices until 2022. The gap period between our study and theirs was marked by an increase in deforestation rates, resulting in reduced carbon stocks and, consequently, a lower perceived value. Nonetheless, all of these estimates are considerably lower than most estimates of the social value of carbon, which are centered around US$50/t ((EPA, 2016)). These figures suggest that farmers do not fully account for the social cost of deforestation.

Table 5.1: Estimation Results

Model Parameter (1)	Estimate (2)
α_{REDD}	0.013 (0.001)
α_{forest}	0.153 (0.058)
α_{agri}	0.162 (0.011)
Constant	−31.106 (0.139)
Observations	171,899
R^2	0.007
Adjusted R^2	0.007
Residual Std. Error	51.918 (df = 171895)
F Statistic	379.543 (df = 3; 171895)
Note:	$p<0.1$; $p<0.05$; $p<0.01$

This table shows the OLS estimates of α_j obtained in the first step of the estimation (equation 5-1). Column 1 reports model parameters, while Column 2 displays the corresponding estimates. Revenues are divided by 10^6 to improve parameter visualization.

5.2 Second Step: Non-Linear Least Squares

We use the estimated $\hat{\alpha}_j$ to estimate the remaining parameters in equation (5-1) using a non-linear least squares procedure. Specifically, we estimate $\bar{\alpha}_{agri}$ by choosing the parameter that minimizes the distance:

$$e = \sum_m [\log(\frac{p(agri|forest, w_{mt})}{p(forest|forest, w_{mt})}) - (V(agri, w_{mt}; \hat{\alpha}_j, \bar{\alpha}_{agri}) - V(forest, w_{mt}; \hat{\alpha}_j, \bar{\alpha}_{agri}))]^2,$$

$$\text{for } t = 2010, ..., 2022. \tag{5-2}$$

Where $V(forest, w_{mt}; \hat{\alpha}_j)$ is computed by iteration. Table 5.2 shows the results.

Table 5.2: Alpha Bar Estimates

Model Parameter	Estimate	$/\alpha_{agri}$
(1)	(2)	(3)
$\bar{\alpha}_{REDD}$	−29.74	−183.08
$\bar{\alpha}_{agri}$	1.36	8.37

This table presents the estimates of $\bar{\alpha}_j$, using $\hat{\alpha}_j$ estimated in equation (5-1) using OLS. Column 1 reports model parameters, while Column 2 displays the corresponding estimates, and Column 3 monetizes the coefficients. We report the estimates divided by $(1-\rho)$ to be consistent with the other parameters, which are displayed in present value terms.

The second and third rows monetize the cost coefficients. We can see that REDD properties have an associated average present value cost of US$35.61 million[4]. This figure includes entry costs (e.g. certification costs), maintenance expenses (such as surveillance and continuous verification), transaction costs, and the proportion of credits allocated to project developers. Besides that, $\bar{\alpha}_{REDD}$ may be capturing information and regulatory costs that increase the costs of implementing REDD projects. This may be one of the reasons why the adoption to such projects is still low. Despite the positive perspective regarding carbon prices and markets, high participation costs[5] and complex regulatory environments may deter landowners from engaging in these initiatives. This highlights that changes in the regulatory environment may be a powerful tool to increase REDD participation.

[4]Recall that we divided revenues by 10^6 in the first step of the estimation.

[5](United Nations Environment Programme, 2023) and the references therein report a cost range of US$30-US$50/t. Our estimates are around US$80/t.

On the other hand, we get a positive estimate for $\overline{\alpha}_{agri}$, meaning that, relative to forest (remember that we set $\overline{\alpha}_{forest} = 0$), this land use option provides landowners with an additional present value of US$1.59 million. That is, among the three possible options, agriculture has a negative cost, which can be translated as a surplus that this activity offers to those who pursue it. This surplus is capturing benefits related to agriculture that are not explicit in our specification (3-10).

6
Counterfactuals

In this chapter, we use our estimated model to assess additionality in carbon projects and project different scenarios considering a range of carbon prices, taxes and participation costs. The value function for each alternative scenario is the key ingredient that needs to be computed to obtain the counterfactual conditional choice probabilities using equation (3-5). Just as in the model, we remove all uncertainty about prices by assuming they remain constant from 2022 onwards. Regarding the property-specific state variables w_{mt}, we assume they remain constant over time[1] (i.e., carbon stock, productivity and transportation costs are constant over time, and hence $w_m = \frac{1}{T}\sum_t w_{mt}$). The logit errors assumption implies that the integrated Bellman equation for forest returns has a convenient expression:

$$\bar{V}(forest, w_m) = \log\Big(\sum_{j \in J} \exp(r_j(w_m;\alpha) + \rho\bar{V}(j, w_m))\Big) + \gamma, \tag{6-1}$$

where γ is the Euler constant.

After computing $\bar{V}(forest, w_m)$ by iteration[2], we use expression (3-5) to recover the associated CCPs $p^t_{j,m}$ for each option and year. We then compute the expected probability of property m being in a specific state between 2010 and $T = 2050$[3]: $A_m(j, w_m)$. That is, we obtain the expected probability of property m being in state j by the period T. Aggregating for all properties (weighting by property area), we obtain the total 2050 land use, which we call $A(j, w)$, where $w = \{w_m\}_m$. These objects are the basis for our counterfactual exercises, and are, respectively, given by:

$$A_m(agri, w_m) = p^{2010}_{agri,m} + \sum_{t=2011}^{T}\Big(\prod_{s=2010}^{t-1} p^s_{\text{forest,m}}\Big) \times p^t_{\text{agri,m}} \tag{6-2}$$

[1] We believe this assumption is reasonable in our context since these variables change very slowly with time, and we are interested in investigating a time horizon of around 40 years, during which they would likely change little.

[2] Note that, since there is no uncertainty in the REDD and agriculture revenues, we can compute them by simply bringing their associated revenues to present value.

[3] We select 2050 as our reference year because it marks the conclusion of the last project in our dataset. The most recent project started in 2020 and is scheduled to conclude in 2050, with the potential for renewal. Consequently, our analysis focuses on examining the probability of project areas being deforested or remaining intact throughout their existence period. This approach allows us to scrutinize project additionality.

$$A_m(REDD, w_m) = p^{2010}_{REDD,m} + \sum_{t=2011}^{T} \left(\prod_{s=2010}^{t-1} p^s_{\text{forest,m}} \right) \times p^t_{\text{REDD,m}} \tag{6-3}$$

Specifically, equation (6-2) provides the expected probability that property m will transition to agriculture between 2010 and 2050, while equation (6-3) outlines the expected probability of property m participating in carbon projects during the same period.

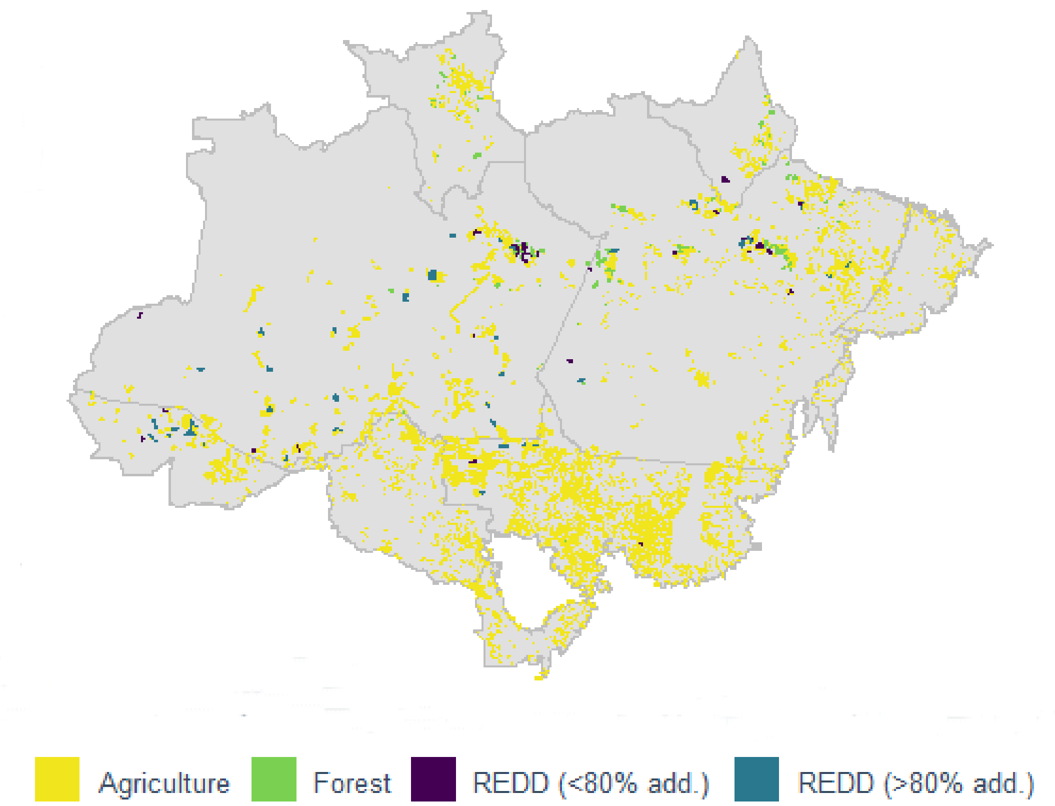
6.1 Additionality in Carbon Projects

We analyze 13,224 properties in the Amazon, totaling 13.1 million hectares—an area equivalent to Greece—and storing approximately 6.4 Gt of carbon, equivalent to the US' total CO2 emissions in 2022. Out of this total, an area of around 3.2 million hectares has already been deforested, releasing 1.45 Gt of CO2 to the atmosphere. Despite these negative figures, this shows that there's still room to preserve the remaining 77% of the carbon stock inside private properties. However, it is necessary to investigate to what extent this stock would be eligible to participate in REDD projects, and which properties would keep their land idle in any scenario.

In a business-as-usual (BAU) scenario, where carbon prices remain constant at US$10.70 per ton from 2022 onwards, the model forecasts that 0.66 Gt of carbon would be preserved in REDD projects, covering an area of 1.1 million hectares, as depicted in Figure 6.1. That is, by 2050, the model forecasts that 8% of the total private land area in the Brazilian Amazon Biome (registered in the SIGEF database) would engage in such activities. Out of this total, the additionality share would be 83.7%. This implies that most of the carbon stock protected in these projects would be facing deforestation risks in a scenario without REDD contracts. However, a 16.3% share is still high, indicating that a significant proportion of REDD projects are not effectively contributing to their goals of mitigating climate change through market mechanisms. Besides that, the model forecasts that around 80% of the property areas, totaling of 10.4 million hectares, would be deforested for agriculture purposes. This would result in emissions totaling 5 Gt of CO2, a significant and concerning amount that could be avoided through higher carbon prices or taxes - or lower costs -, as demonstrated in the following Subsections.

We can use our model to investigate the ongoing REDD projects, and check whether their participating properties are actually facing deforestation risks in the 2010-2050 horizon. We find that, out of the 0.65 Gt of CO2 inside REDD properties, 77.4% could be considered additional. This means

Figure 6.1: 2050 Land Use Forecast - BAU Scenario



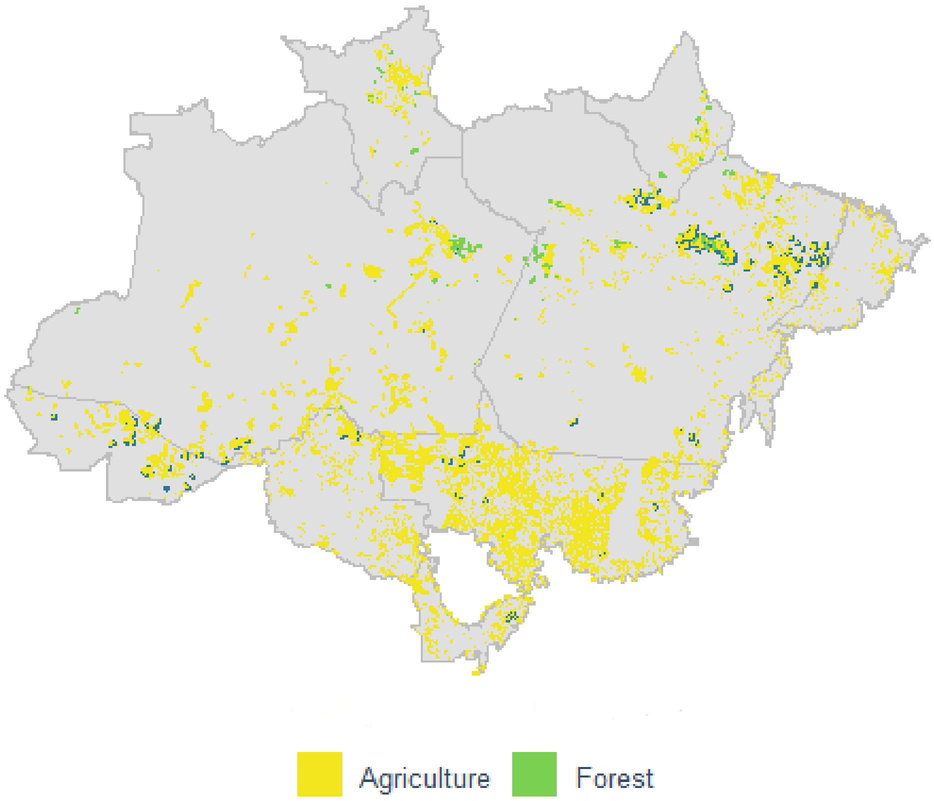
This map plots the expected 2050 land use for each property in the BAU scenario. We plot the land use with the highest expected probability in 2050. Property polygons were bu□ered to improve visualization. REDD properties with more than 80% of additional carbon are coloured in blue.

that nearly a quarter[4] of the carbon stock *protected* in REDD projects are actually not facing any risk of deforestation and, therefore, should neither be considered additional nor be sold in the market.

Figure 6.2 depicts the 2050 land use scenario without REDD projects, outlining properties that already participate in such contracts in blue. It is evident from this map that a significant portion of the supply of non-additional CO2 comes from projects in the Northeast of Para, particularly in the Portel municipality region. The dissemination of questionable products undermines confidence in carbon markets, posing a potential obstacle to market development. These findings highlight the need of employing more robust and suitable techniques for forecasting deforestation and other land use decisions in carbon markets. This approach is crucial for fostering better

[4](WEST et al., 2020), for instance, finds that around 40% of credits in Brazilian projects are not genuinely additional.

Figure 6.2: 2050 Land Use Forecast - No REDD Scenario

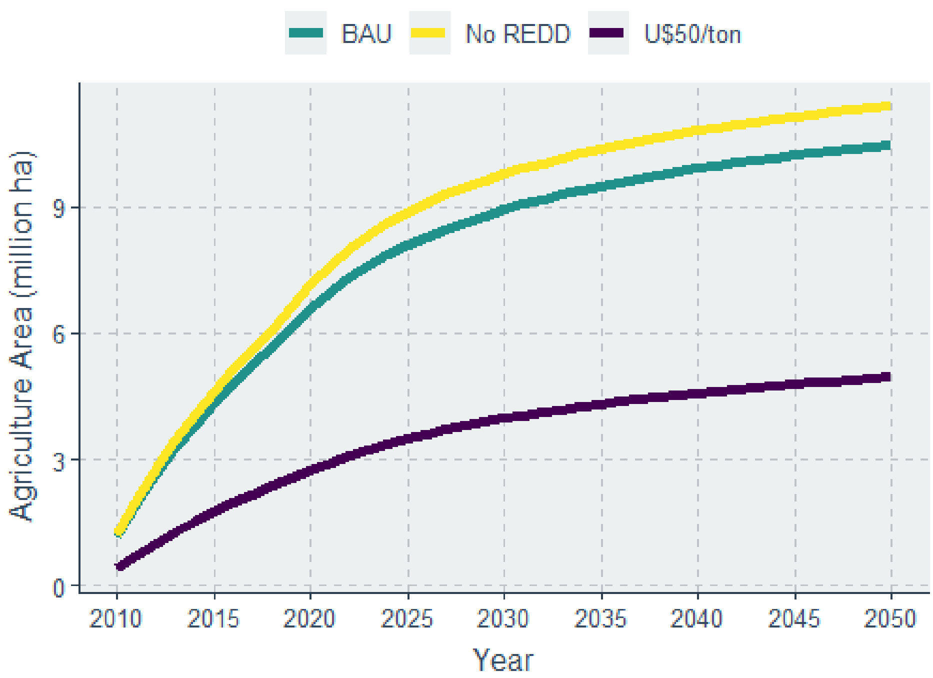


This map plots the expected 2050 land use for each property in the No REDD scenario. We plot the land use with the highest expected probability in 2050. Property polygons were buffered to improve visualization. Properties inside REDD projects are contoured by a blue line.

practices and inspiring confidence in this growing market.

We can have a dimension of the dynamics of the model by analyzing the evolution of the land use and carbon emissions over time. Figure 6.3 illustrates the total agriculture area in scenarios with a BAU carbon price, without REDD contracts, and with a US$50 carbon price. The difference between the no REDD line and the BAU and US$50 lines is the *additional* area that is joining carbon projects in these scenarios. We also plot in Figure 6.4 the evolution of carbon emissions in these three scenarios. Note again that the additional carbon supply in each scenario is given by the difference between the no REDD line and the two others. These areas represent the avoided CO2 emissions that were due to the existence of REDD contracts, which incentivize landowners shift from deforestation decisions to preserving forests and earning carbon credit revenues. Figure 6.5 depicts carbon supply over time. Obviously, there is no carbon supply in a scenario without REDD contracts. In the BAU

Figure 6.3: Agriculture Area Dynamics



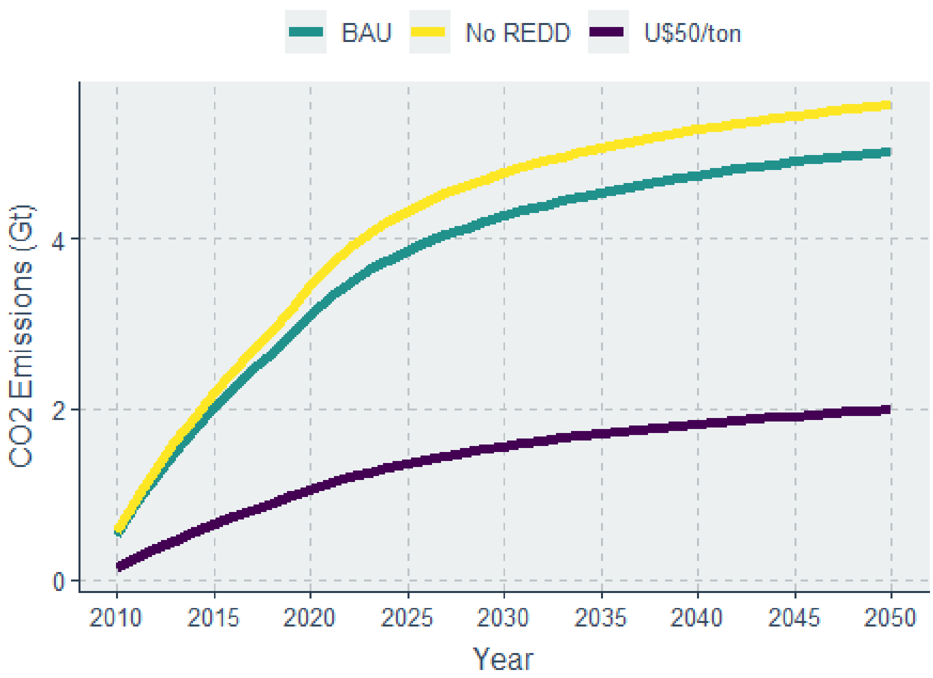
This figure plots the agriculture area dynamics in the BAU, No REDD, and US$50 scenarios.

scenario, we observe a smooth growth in supply over time, while in the US$50 scenario, most agents wait for prices to reach the US$50 level to make their decisions. A great share of properties opt for REDD after prices reach this level.

Finally, we analyze certain property characteristics of the most likely entrants in REDD projects under both the BAU and the US$50 price scenarios, comparing them with the entire sample of properties. Table 6.1 highlights that, in the BAU scenario, REDD properties tend to be the largest in terms of area. These properties benefit from their extensive size, which harbors a considerable amount of above-average carbon stocks, thereby rendering the commercialization of carbon credits more valuable. Participation in such contracts entails fixed costs; hence, the scale e□ects o□ered by large areas can facilitate participation. In contrast, we observe that such properties exhibit below-average agricultural productivity.

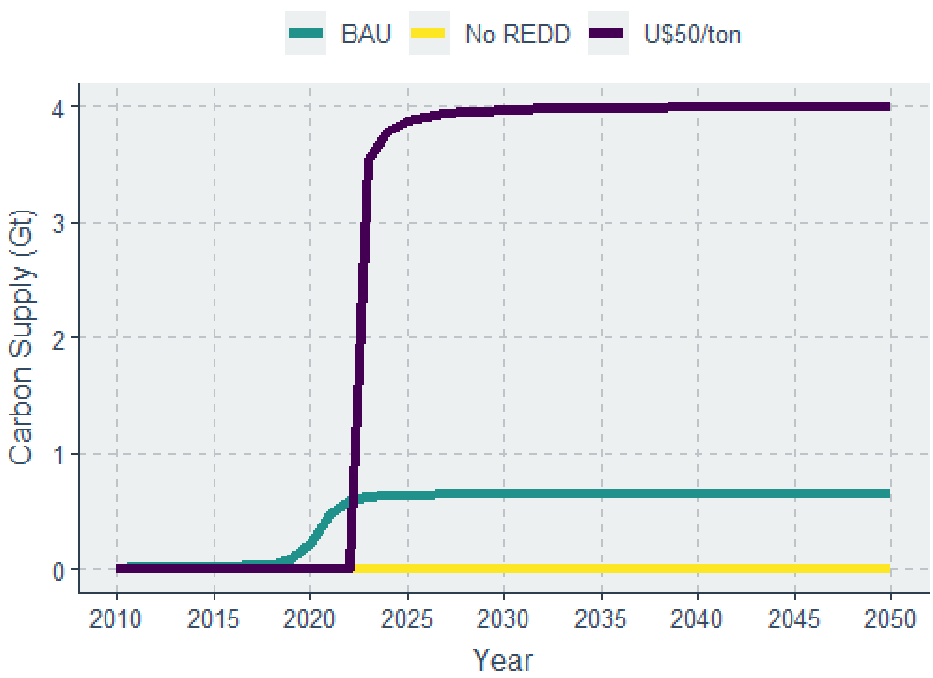
When examining the most probable entrants in the US$50 price scenario, we still observe a prevalence of large properties with rich carbon stocks, albeit smaller in size and stocks compared to those in the BAU scenario. However, the potential agricultural productivity of such properties is higher than that of the BAU scenario but still below the average of the entire sample. This suggests that higher prices introduce greater heterogeneity in the profile of

Figure 6.4: Carbon Emission Dynamics



This figure plots the carbon emission dynamics in the BAU, No REDD, and US$50 scenarios.

Figure 6.5: Carbon Supply Dynamics



This figure plots the carbon supply dynamics in the BAU, No REDD, and US$50 scenarios.

REDD properties. Higher prices can translate into increased REDD profits, which may offset high fixed costs, leading to the participation of properties with higher agricultural productivity and lower carbon stocks. As we will explore in the subsequent subsections, prices serve as a mechanism to enhance the quality of carbon supply (in terms of additionality).

It's essential to acknowledge the distributional effects resulting from the opportunity to preserve forests through REDD projects. The likely entrants are predominantly large properties, leaving little room for small participants, who may not be able to bear REDD participation costs. Consequently, the influx of predominantly international capital into Brazil to fund such activities will benefit large landowners, while excluding smaller ones from this opportunity. Carbon markets risk exacerbating distributive inequalities in forested countries, as large property owners stand to gain wealth while smaller ones are left behind. This widening income disparity related to land ownership could lead to the deforestation of small properties or their acquisition by larger landowners. Therefore, it is imperative to reconsider the structure of such projects to promote greater inclusion and maximize the social benefits derived from these activities.

Table 6.1: REDD Property Characteristics

Variable:	Area			Carbon Stock			Agriculture Productivity		
Sample:	All	BAU	US$ 50	All	BAU	US$ 50	All	BAU	US$ 50
Mean	996.15	13576.06	4589.61	447.91	599.96	569.34	65.95	46.75	63.52
Std	1925.63	3245.19	3432.33	156.36	61.21	90.90	28.56	15.15	24.75
Min.	5.83	8167.74	1512.37	1.83	452.83	139.33	3.25	19.99	3.25
1st Qu.	53.26	11148.62	2513.69	368.50	557.33	518.38	45.73	34.94	47.78
Median	252.98	13573.30	3084.35	473.00	599.50	586.67	66.22	50.16	63.06
3rd Qu.	1116.30	16075.72	4869.65	564.67	646.25	638.00	85.62	55.94	75.96
Max.	19938.40	19938.40	19938.40	788.33	740.67	748.00	207.46	81.94	152.80

This table presents area, carbon stock, and agriculture productivity statistics for properties that would join REDD projects in the BAU and US$50 scenarios. We also display these statistics for the whole sample for comparison reasons.

6.2 Carbon Supply with Different REDD Prices

Carbon prices are one of the main determinants for landowners to choose whether to join REDD projects. If prices are high enough, they may choose to preserve their forests and earn carbon credit revenues, instead of clearing their properties for cattle ranching. In this subsection, we investigate how different carbon prices could change the CO2 supply in the VCM. As of 2022, REDD prices for Brazilian projects were set at around US$10.70/t. In our model, we project future revenues assuming that this price remains constant indefinitely (referred to as the BAU scenario). In our counterfactual analyzes, we examine scenarios where this price undergoes permanent changes for future periods (starting from 2023 onwards).

We inspect a price range of US$0 to US$200 per ton of CO_2. As we can see in Figure 6.7, the CO_2 supply grows monotonically with prices. For lower prices, carbon supply is modest, but it grows fast with marginal price increments. At current prices, supply is projected to be around 0.66 Gt. A US$50 price scenario, anticipated to be achieved in the next 10 to 20 years by specialized sources[5], and considered to be the social cost of carbon ((EPA, 2016)), could increase the supply sixfold to 4 Gt. We plot the forecasted land use for this price scenario in Figure 6.6. We see that a significant portion of private areas opt for REDD projects, with minimal choice for forest.

The shape of the supply curve is intuitive: low price increments (between the US$10 - US$50 range) would make REDD more profitable than agriculture for 54% of private areas, encompassing 67% of the carbon stock stored in such regions. This indicates that these price increases would attract landowners with high carbon density and moderate agriculture productivity. Hence, farmers are responsive to carbon prices in the steeper part of the curve.

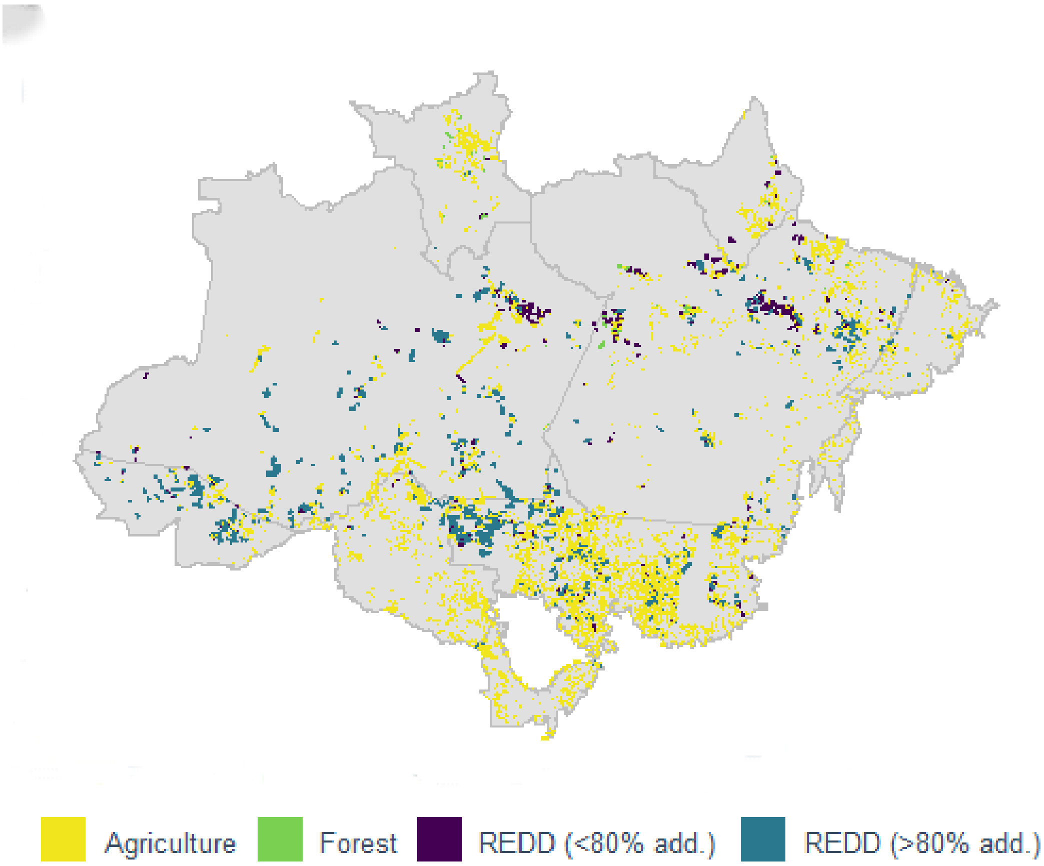
For a US$200 price, 86% of private areas and 91% of the carbon stored in such areas would opt to sign REDD contracts. However, even at such elevated levels of carbon prices, some properties would still remain in agriculture, driven by their relatively high potential returns and low carbon stocks. So the flat portion of the curve, to the right, is attributed to capacity constraints: with higher prices, farmers would be inclined to maintain almost all private land forested (under REDD projects).

While values may differ due to modeling assumptions, methodologies, regions, and time periods covered, the shape of this curve mirrors findings from other studies (see, e.g., (NEPSTAD et al., 2007), (KINDERMANN et al., 2008), (LUBOWSKI; ROSE, 2013), and (SOUZA-RODRIGUES, 2019)), underscoring the significant potential for emissions reduction through avoided deforestation.

We can see the price effect shifting the landowners' choices in Figure 6.8, where we depict the agriculture area as a function of carbon prices. This convexity is intuitive: small price changes would be sufficient to turn REDD more attractive than cattle farming for many agents. The effect on CO_2 emissions is substantial: a US$50 carbon price, instead of the current

[5] See, for example, <https://about.bnef.com/blog/carbon-credits-face-biggest-test-yet-could-reach-238-ton-in-2050
> , <https://www.statista.com/statistics/1284060/forecast-carbon-offset-prices-by-scenario/
>

Figure 6.6: 2050 Land Use Forecast - US$50 Scenario



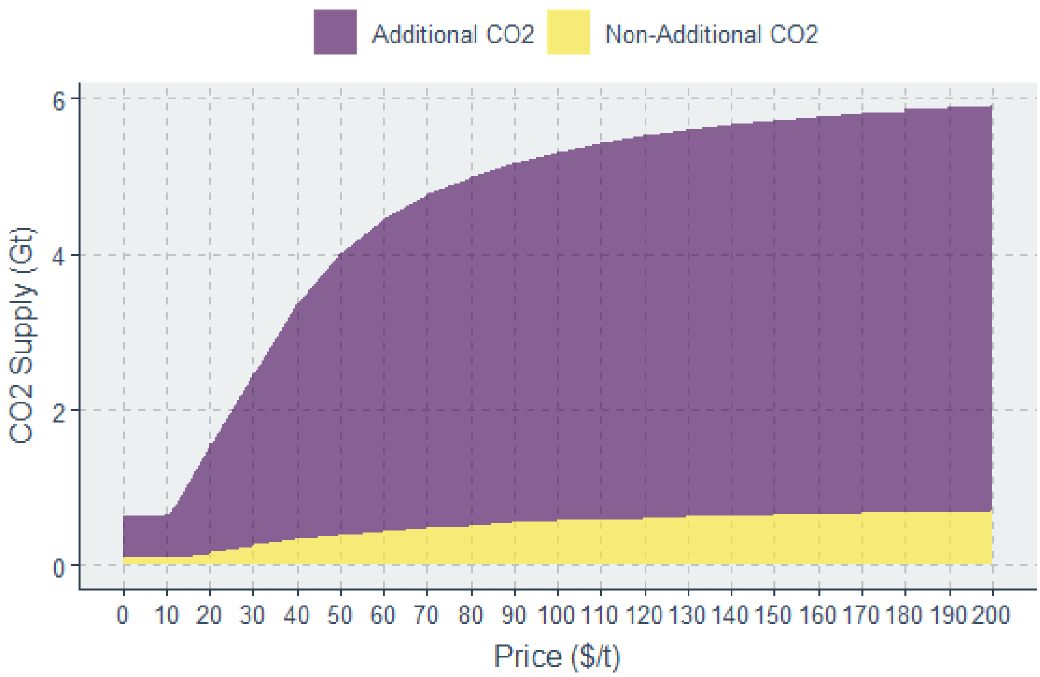
This map plots the expected 2050 land use for each property in the US$50 scenario. We plot the land use with the highest expected probability in 2050. Property polygons were buffered to improve visualization. REDD properties with more than 80% of additional carbon are coloured in blue.

US$10.70, could avoid the release of 3 Gt into the atmosphere[6] as a consequence of deforestation.

In terms of additionality, Figure 6.9 illustrates that the additional CO2 supply share initially increases with prices, reaching a maximum at the US$50 scenario, where 90.3% of the carbon stock in REDD properties would be additional. Subsequently, it begins to decline, reaching an 88.3% share for a US$200 price scenario. This trend is explained by the fact that, up to US$50, REDD becomes attractive to landowners who would opt for agriculture in a no REDD scenario. However, as prices rise above this threshold, REDD starts to attract properties that would remain forested in a scenario without REDD. These higher prices make REDD viable for properties with lower carbon stocks, which would otherwise be unable to participate in scenarios with lower prices

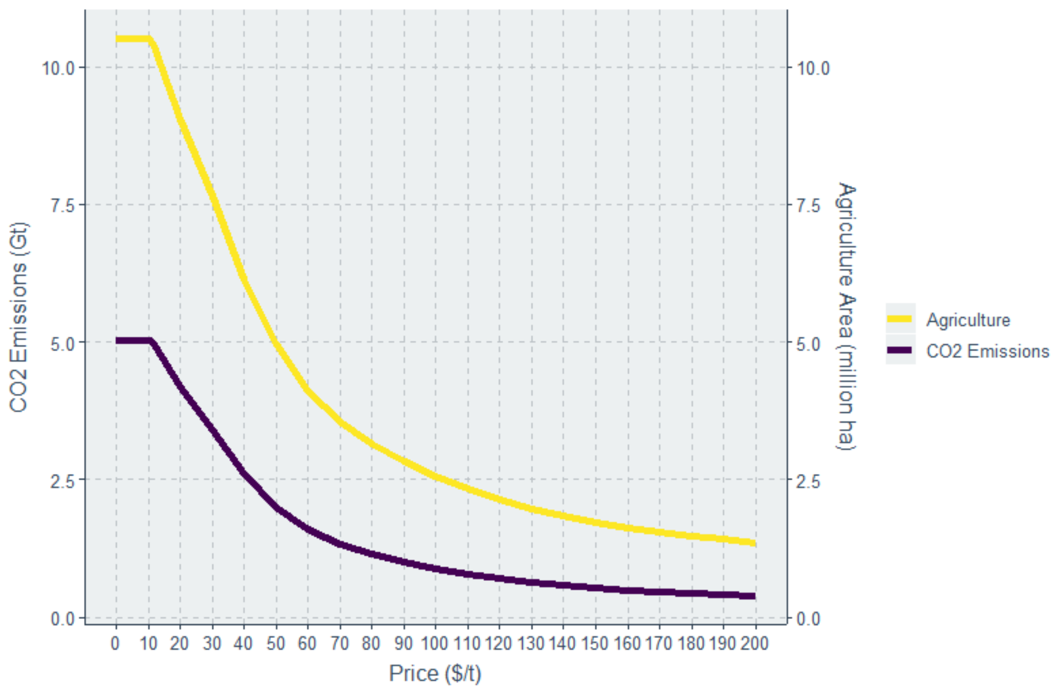
[6] These results are consistent with recent studies, e.g. (GRISCOM et al., 2017) which find that "natural climate solutions" could potentially capture/avoid about 11.3 Gt of CO2 per year globally with costs no greater than US$100/t.

Figure 6.7: Carbon Supply for Different REDD Prices



This figure plots the 2050 carbon supply considering different future carbon prices (prices are assumed to be constant from 2023 onwards).

Figure 6.8: Carbon Emissions and Agriculture Area for Different REDD Prices



This figure plots the 2050 agriculture area and carbon emissions considering different future carbon prices (prices are assumed to be constant from 2023 onwards).

and higher costs.

Figure 6.9 also underscores the importance of considering average results when evaluating REDD projects. Rather than focusing solely on additionality forecasts at the individual project level, it is crucial to examine aggregate outcomes across different scenarios. Estimating additionality measures at a granular level may be challenging or even impractical, making an aggregate approach more appropriate. While some projects may have to accommodate others lacking in additionality, the aggregate benefits are likely to outweigh the associated costs. For instance, a scenario with a US$200 price and 6Gt of carbon supply with 88% additionality may be preferable to a US$50 scenario with higher additionality shares but lower supply levels. Despite potential supply issues, the overall outcomes are superior in the former case.

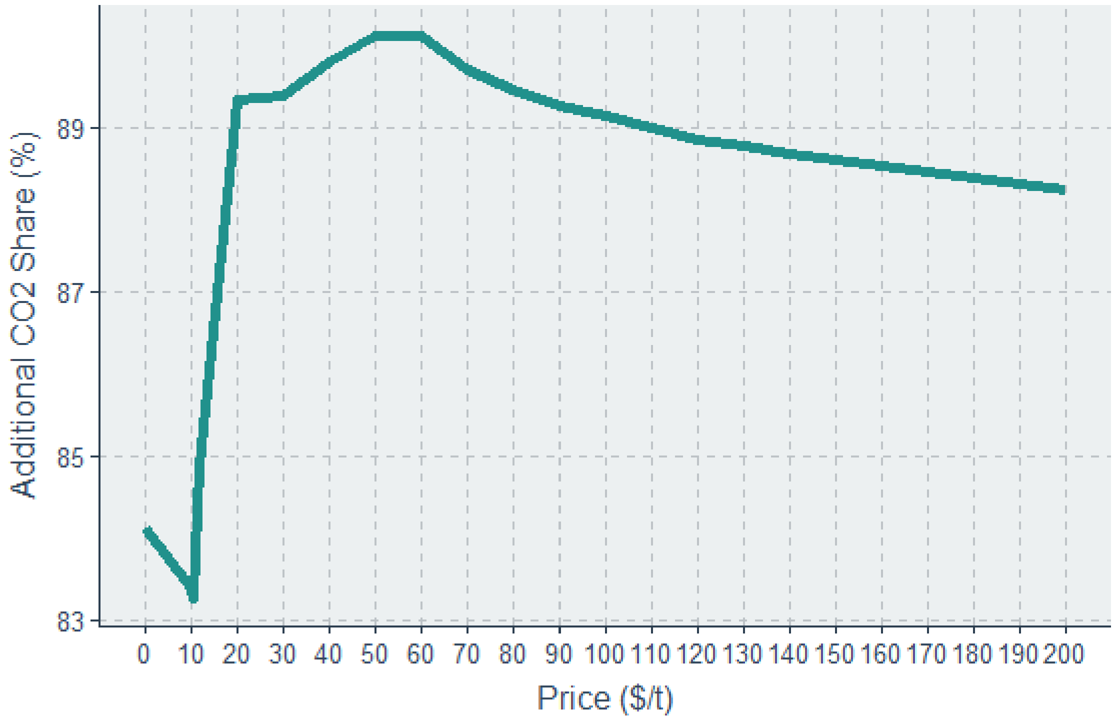
Considering these findings, there is an opportunity for policy interventions aimed at influencing the pricing dynamics of carbon markets to enhance participation. Potential policies include subsidizing carbon prices through additional payments for each carbon credit. Alternatively, measures that stimulate demand could also be effective. Implementing regulations on emissions and introducing carbon pricing mechanisms such as carbon taxes or cap-and-trade systems could directly raise the cost of emitting CO2, thus incentivizing emission reductions and potentially boosting demand for carbon credits.

6.3 Carbon Supply with Different Carbon Taxes on Agriculture

We now investigate the effects of a carbon tax on agriculture into the entrance in REDD projects and agriculture. Carbon taxes have a low impact in REDD supply. Even for high carbon tax values, landowners still choose to deforest and engage in agriculture, with a low adoption to REDD. We see this clearly in Figure 6.10, which illustrates that the CO2 supply in REDD is almost perfectly inelastic to a carbon tax - supply varies from 0.662Gt to 0.669Gt in the considered tax range. This phenomenon can be attributed to the limited impact of taxes on the present value revenues of agriculture[7]. Essentially, the tax only affects landowners once, during the transition from forest to agriculture, when carbon is released through deforestation. In subsequent periods, there is no further tax incidence. Thus, the tax can be viewed as a fixed conversion cost. Higher tax values may potentially have a more significant

[7] In this paper, our focus is primarily on present value revenues. Therefore, a tax that impacts only a single stream of profits may not have the ability to alter the overall present value associated with agriculture for a particular property, thereby failing to influence its decision.

Figure 6.9: CO2 Supply Additionality Share



This figure plots the 2050 CO2 supply additionality share considering different future carbon prices (prices are assumed to be constant from 2023 onwards).

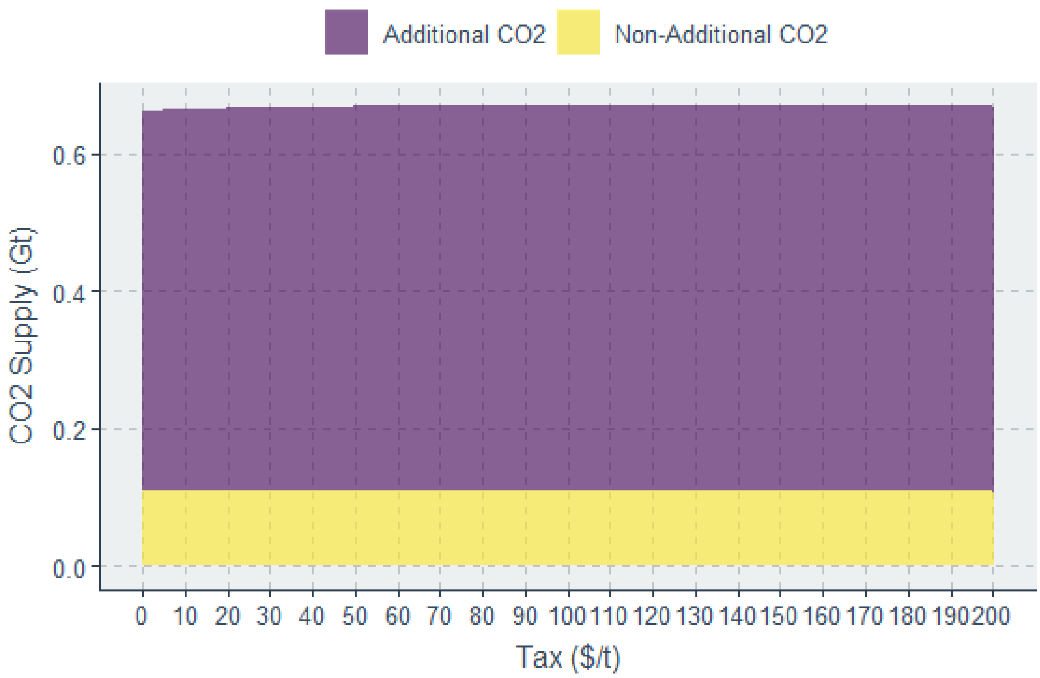
impact on reducing deforestation by incentivizing the preservation of densely forested properties.

Although, as depicted in Figure 6.11, a carbon tax has an effect on reducing carbon emissions and the agriculture area in the Brazilian Amazon. Implementing a carbon tax at a rate of $200/ton can lead to a total reduction of 0.67 Gt of CO2 emissions, resulting in a decrease in agriculture area by 1.2 million hectares. Still, this is a modest figure for a high tax[8]. In this scenario, small properties with high carbon stocks are the ones that are most deterred from engaging in agriculture due to the higher costs associated with the carbon tax. However, despite having carbon stocks above the average, these properties do not transition to REDD projects. This is because the costs associated with participating in REDD are too high for them to bear.

These findings underscore the limited effectiveness of a carbon tax compared to a market mechanism that incentivizes landowners to conserve their forests. They emphasize the importance of establishing a more conducive

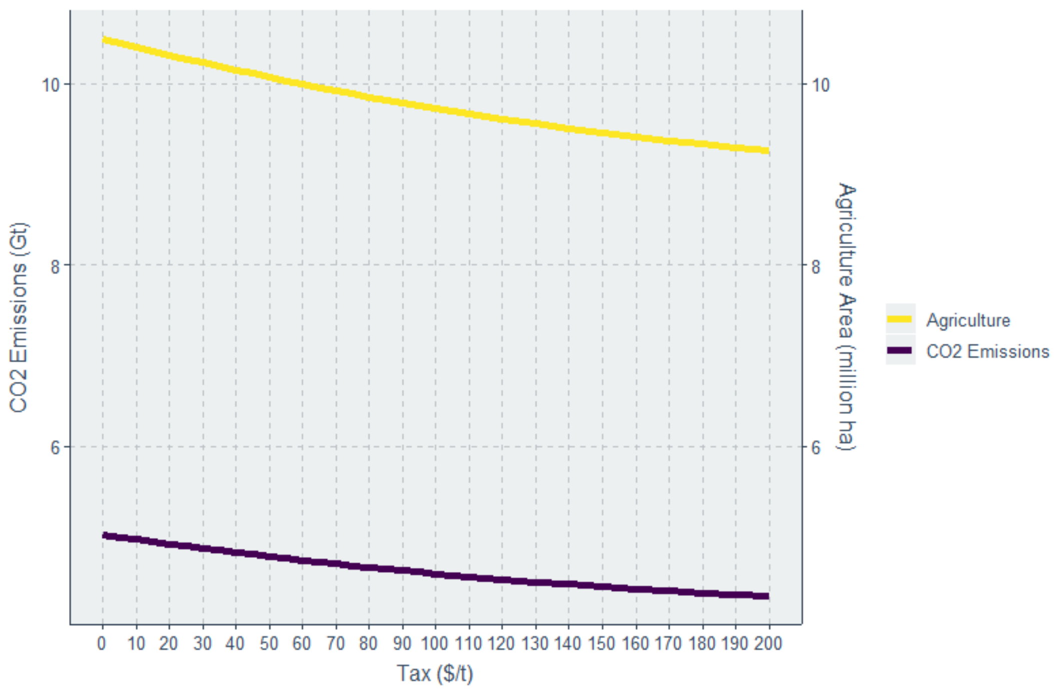
[8]Our results are different and lower than those of other studies, e.g. (SOUZA-RODRIGUES, 2019) and (ARAUJO; COSTA; SANTANNA, 2022), because here we consider that the tax is charged only once, while they consider a tax that is charged every year when a plot of land is not forested.

Figure 6.10: Carbon Supply for Different Carbon Taxes



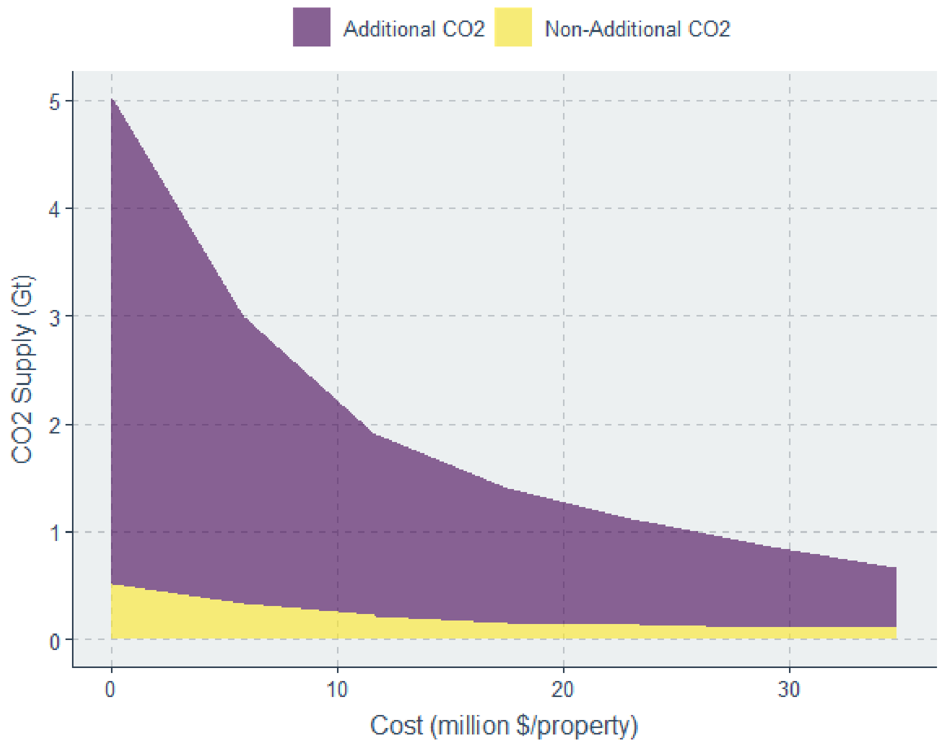
This figure plots the 2050 carbon supply considering different carbon taxes on agriculture.

Figure 6.11: Carbon Emissions and Agriculture Area for Different Carbon Taxes



This figure plots the 2050 agriculture area and carbon emissions considering different carbon taxes on agriculture.

Figure 6.12: Carbon Supply with Different Participation Costs



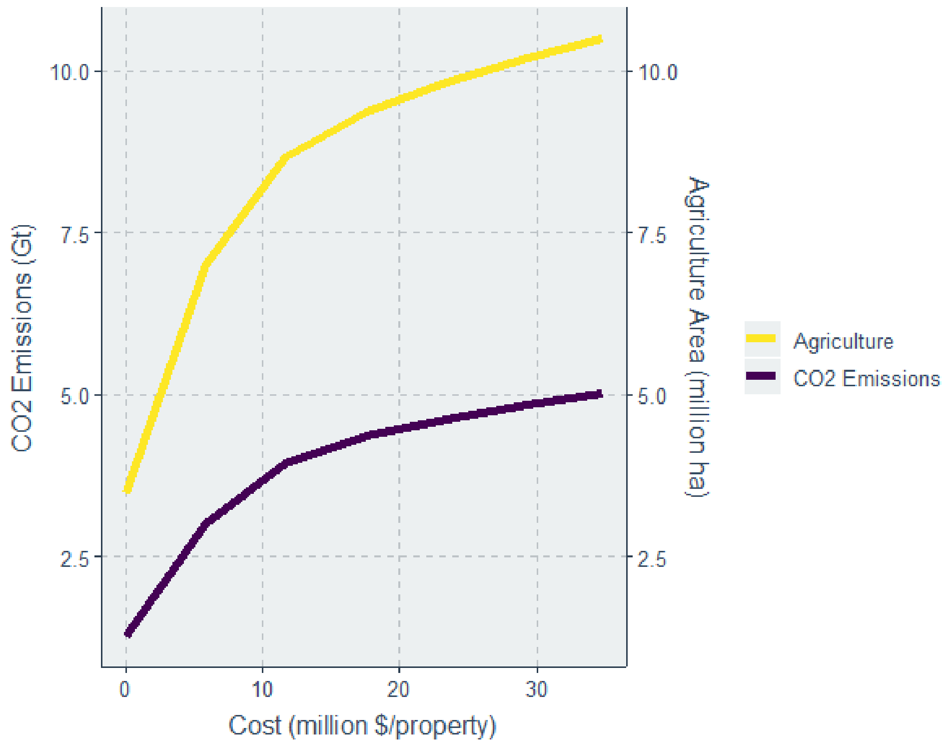
This figure plots the 2050 carbon supply considering different participation costs in REDD projects (we change the value of the $\bar{\alpha}_{REDD}$).

environment for carbon markets, characterized by credible methodologies and robust governance, which could significantly enhance efforts to combat climate change. By implementing improved techniques, carbon markets could attract more investments and bolster the prices of carbon credits. Consequently, this would further incentivize landowners to participate in initiatives aimed at preserving carbon stocks, thereby increasing the overall supply of protected carbon and avoided emissions.

6.4
Carbon Supply with Different REDD Costs

Participation costs play a crucial role in landowners' decisions regarding REDD project participation. Here, we investigate how different costs could change carbon supply. Our estimate for $\alpha_{\bar{REDD}}$ stands at US$35.61 million/property. Therefore, we examine how lowering this cost down to US$0 could change the supply of avoided emissions under the BAU price scenario. Figure 6.12 illustrates the carbon supply curve under different participation costs. It is clear that reducing costs could significantly increase carbon supply. In a scenario with no participation costs (US$0), the supply would match that of a US$80/t scenario, totaling 5 Gt. Figure 6.12 also depicts that the

Figure 6.13: Carbon Emissions and Agriculture Area with Dierent Participation Costs



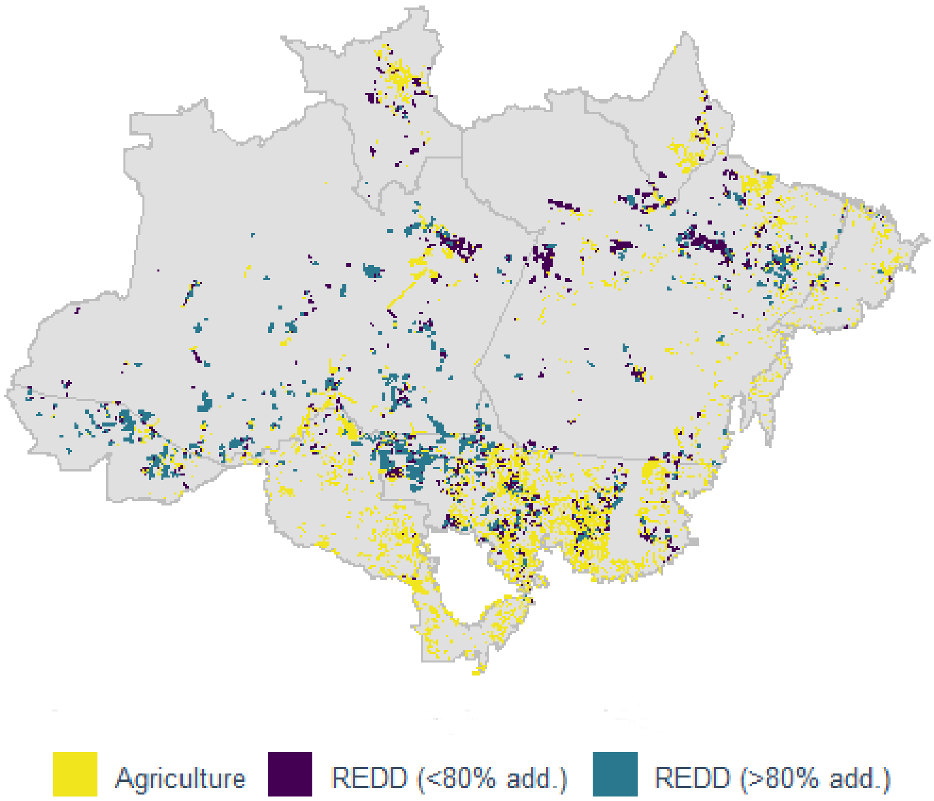
This figure plots the 2050 agriculture area and carbon emissions considering dierent participation costs in REDD projects (we change the value of the $\bar{\alpha}_{REDD}$).

additionality share in a lower cost scenario would be approximately 88%.

As Figure 6.13 shows, bringing costs to zero would result in a reduction of agricultural area by 7 million hectares, avoiding the emission of 3.7Gt of CO2. These numbers align with results found in previous research (e.g. (SOUZA-RODRIGUES, 2019), (ARAUJO; COSTA; SANTANNA, 2022) and (ASSUNçãO et al., 2023)), highlighting the significant emission reduction potential of modest carbon payments under a zero-cost structure. Moreover, reducing costs could enable the entry of smaller properties compared to other scenarios. In the zero-cost scenario, there would be no choice for forest land use; landowners would opt for either REDD or agriculture, as depicted in Figure 6.14.

Subsidizing entry through higher prices would result in a cost of $80 - 10.7 =$US$69.3/ton per year, or US$693/ton (using a 10% discount rate and targeting a supply of 5 Gt), while subsidizing entry through participation costs would entail a fixed cost of US$80/ton. This highlights the eectiveness of reducing costs as a strategy to incentivize participation in carbon markets. This can be achieved by reducing intermediaries in carbon credit trading to minimize transaction costs or by lowering certification, verification, and monitoring

Figure 6.14: 2050 Land Use Forecast - Zero Participation Cost Scenario



This map plots the expected 2050 land use for each property in the zero participation cost scenario. We plot the land use with the highest expected probability in 2050. Property polygons were buffered to improve visualization. REDD properties with more than 80% of additional carbon are coloured in blue.

expenses—e.g., through technology adoption that streamlines these processes. Additionally, establishing stable regulatory frameworks can reduce bureaucracy, uncertainty and transaction costs for project developers. Examples include aligning REDD-related policies at both state and federal levels, as well as establishing the Regulatory Framework for the Brazilian Carbon Market. Such measures offer a cost-effective approach for both governments and private entities to promote participation in carbon projects.

6.5 Long-run Effects of Higher Carbon and Cattle Prices

In our last counterfactual exercise, we assess how variations in cattle and carbon prices affect land use and carbon release. Here, we compare the 2050 land use with ($\tilde{w}$) and without (w) a $100 \times \Delta\%$ price change and compute a long-run elasticity of land use with respect to agricultural and carbon prices:

Table 6.2: Long-run Land Use Elasticities with Respect to Carbon and Cattle Prices

Forest Cover (1)	Agriculture Area (2)	REDD Area (3)	Carbon Released (4)	REDD Carbon (5)
Panel A. Carbon price elasticities				
-0.03	-0.11	1.15	-0.14	1.19
Panel B. Cattle price elasticities				
-1.10	0.17	-0.10	0.19	-0.10

This table presents the long-run elasticity of forest cover, agriculture area, REDD area, carbon released, and REDD carbon with respect to carbon price (Panel A) and with respect to cattle price (Panel B). Elasticities calculated with Δ = 10% (eq. 6-4) price increase.

$$\partial_{j,\Delta} = \frac{A(j,\tilde{w}) - A(j,w)}{A(j,w)} \frac{1}{\Delta} \tag{6-4}$$

Table 6.2 Panel A reports elasticities with respect to carbon prices. We estimate an own land-use price elasticity of 1.15, while the estimated elasticity for the carbon supply is of 1.19. This means that, when there is an increase in carbon prices, the area dedicated to carbon projects increases, but less than the carbon stock entering such projects. This suggests that increases in carbon prices attract properties with relatively high carbon stocks to participate in REDD contracts. Notably, the shift in decisions primarily arises from agriculture areas (-0.11), with a smaller contribution from properties that were previously idle (-0.03). Consequently, the new carbon supply predominantly originates from areas that would have been deforested otherwise, which bodes well for the additionality of carbon projects. When splitting the supply between additional and non-additional CO2, we observe own-price supply elasticities of 1.39 and 0.12, respectively. This provides further evidence that an increase in prices attracts a relatively larger amount of additional carbon to the market.

Following (ARAUJO; COSTA; SANTANNA, 2022), we also examine the e□ects of price increases on the quantity of carbon released, assuming that all carbon stock in aboveground biomass is released through deforestation. This involves aggregating the carbon stock of all properties weighted by the probability that each property will transition from forest to agriculture in the counterfactual scenario. We estimate that the elasticity of carbon released with respect to carbon prices is -0.14, showing how carbon markets can have an impact in reducing carbon emissions. Specifically, a 10% increase in prices would result in the avoidance of emissions equivalent to 0.07 Gt.

Table 6.2 Panel B reports elasticities with respect to cattle prices. We estimate a positive, but inelastic own price elasticity (0.17). This is also valid for the elasticity of carbon released (0.19). These low values may reflect capacity constraints, as most of the area in the BAU scenario is already allocated to agricultural use. We see that most of the change in land use comes from the conversion of forests (-1.10), but there is still a share of new agriculture areas coming from carbon projects (-0.10). The e□ects of higher cattle prices are more novice than the benefits coming from an increase of carbon prices (in terms of carbon released), meaning that increases in agricultural prices could be an obstacle for the development of new carbon projects.

7
Conclusion

This paper addresses the issue of additionality in carbon projects in the Brazilian Amazon, particularly those related to forest conservation through avoided deforestation. Using a novel database, we employ a dynamic discrete choice model to estimate land-use decisions made by farmers. Our analysis reveals that approximately 77% of the carbon stock within private properties participating in REDD projects is additional. However, nearly one quarter of the total supply does not face actual deforestation risks. This substantial proportion highlights the necessity for improved assessments in project development to enhance the supply of genuine emission reductions and bolster the integrity of the voluntary carbon market.

Our model reveals that elevated carbon prices have the potential to improve the CO2 supply quality, resulting in decreased carbon emissions and expanded forest areas within REDD projects. In contrast, carbon taxes in agriculture demonstrate minimal impact on these outcomes. Ultimately, reducing costs emerges as the most cost-effective approach for increasing the supply of additional carbon within the VCM.

To achieve these objectives, policymakers may consider implementing policies such as subsidizing entry costs or carbon prices, along with initiatives to reduce market uncertainty through stable regulatory frameworks. Stimulating demand can be achieved through emissions regulation and the adoption of cap-and-trade mechanisms, which could elevate prices.

Market-based strategies involve embracing technologies and practices that lower certification, transaction, and operational expenses. Furthermore, identifying suitable properties could mitigate investment risks and decrease project costs. Our model highlights that the most promising areas for REDD project development are in Acre, Amazonas, and Mato Grosso, particularly on large properties. This finding poses a warning on REDD projects, which could benefit exclusively large landowners, generating distributive consequences that exacerbate land-related disparities.

The findings presented in this paper offer insights into enhancing the resilience and effectiveness of carbon markets, fostering reduced risk and improved quality and supply. Equipped with this knowledge, market participants and policymakers can make more informed evaluations of carbon projects, attracting increased investment to such activities. This, in turn, aids in climate change mitigation and accelerates decarbonization efforts, all while minimizing associated social and economic costs.

8
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9
Appendix

9.1
Regression Equation Derivation Details

Here we provide more details on the derivation of the regression equation. We substitute regressors $R_j(x_{mt})$ in (3-9), obtaining the following:

$$\log\left(\frac{p(REDD|forest, w_{mt})}{p(agri|forest, w_{mt})}\right) = \frac{\bar{\alpha}_{REDD} - \bar{\alpha}_{agri} + \alpha_{forest} h_m area_m}{1-\rho} + \frac{\alpha_{REDD} p_{REDD,t} h_m area_m - \alpha_{agri}(p_{pt} - z_{pm}) y_{mp} area_m}{1-\rho} + \frac{\xi_{REDD,m,t} - \xi_{agri,m,t}}{1-\rho} \tag{9-1}$$

Since prices vary with time, and we assume them to become constant from $\tau = 2022$ onwards, note that:

$$PV_{REDD,t} \equiv \frac{p_{REDD,t}}{1-\rho} = \sum_{s=t}^{\tau-1} \rho^{s-t} p_{REDD,s} + \frac{\rho^{\tau-t} p_{REDD,\tau}}{1-\rho}, \tag{9-2}$$

$$PV_{agri,t} \equiv \frac{p_{agri,t}}{1-\rho} = \sum_{s=t}^{\tau-1} \rho^{s-t} p_{p,s} + \frac{\rho^{\tau-t} p_{p,\tau}}{1-\rho} \tag{9-3}$$

Substituting the above in (9-1), we finally obtain:

$$\log\left(\frac{p(REDD|forest, w_{mt})}{p(agri|forest, w_{mt})}\right) = \frac{\bar{\alpha}_{REDD} - \bar{\alpha}_{agri}}{1-\rho} + \alpha_{forest} \frac{h_m area_m}{1-\rho} + \alpha_{REDD} h_m area_m PV_{REDD} - \alpha_{agri} y_{m,p} area_m \left[PV_{agri} - \frac{z_{pm}}{1-\rho}\right] + \xi_{mt}, \tag{9-4}$$

where $\xi_{mt} = \frac{\xi_{REDD,m,t} - \xi_{agri,m,t}}{1-\rho}$.

9.2
Figures and Tables

Table 9.1: CCP Results

	REDD	Agriculture
log(carbon)*$*log(area)	0.001	−0.002
	(0.001)	(0.0002)
log(soy)*$*log(area)	−0.002	0.00001
	(0.001)	(0.0003)
log(pasture)*$*log(area)	0.0002	0.00004
	(0.00001)	(0.00000)
transportCost	−0.019	−0.016
	(0.002)	(0.001)
roadDistance	0.002	0.00004
	(0.0001)	(0.00003)
lat	−1.898	−0.909
	(0.0001)	(0.00002)
lon	−0.049	−0.118
	(0.003)	(0.001)
lat*lon	−0.023	−0.016
	(0.0004)	(0.0001)
Constant	−24.627	−6.222
	(0.0001)	(0.00002)
Year FE	Yes	Yes
IR FE	Yes	Yes
AIC	42,047.000	42,047.000

This table presents the results for the CCP estimates using a multinomial logit with pooled data.

Figure 9.1: CCP Distribution - REDD

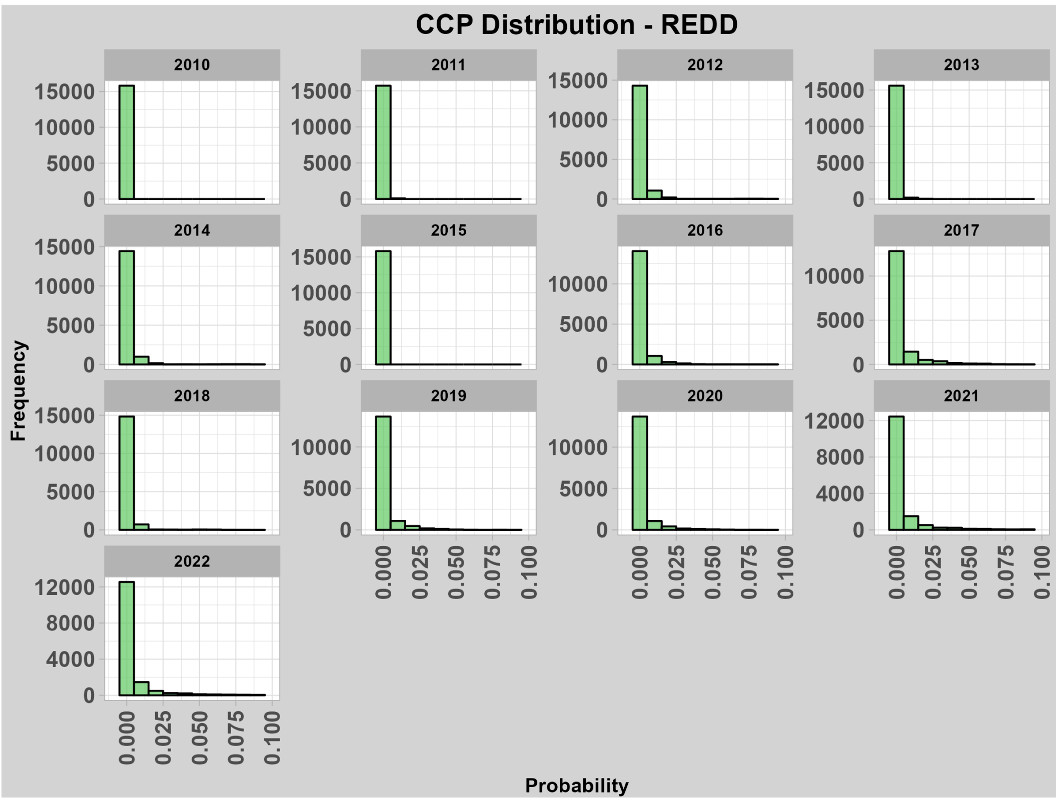

Figure 9.2: CCP Distribution - Agriculture

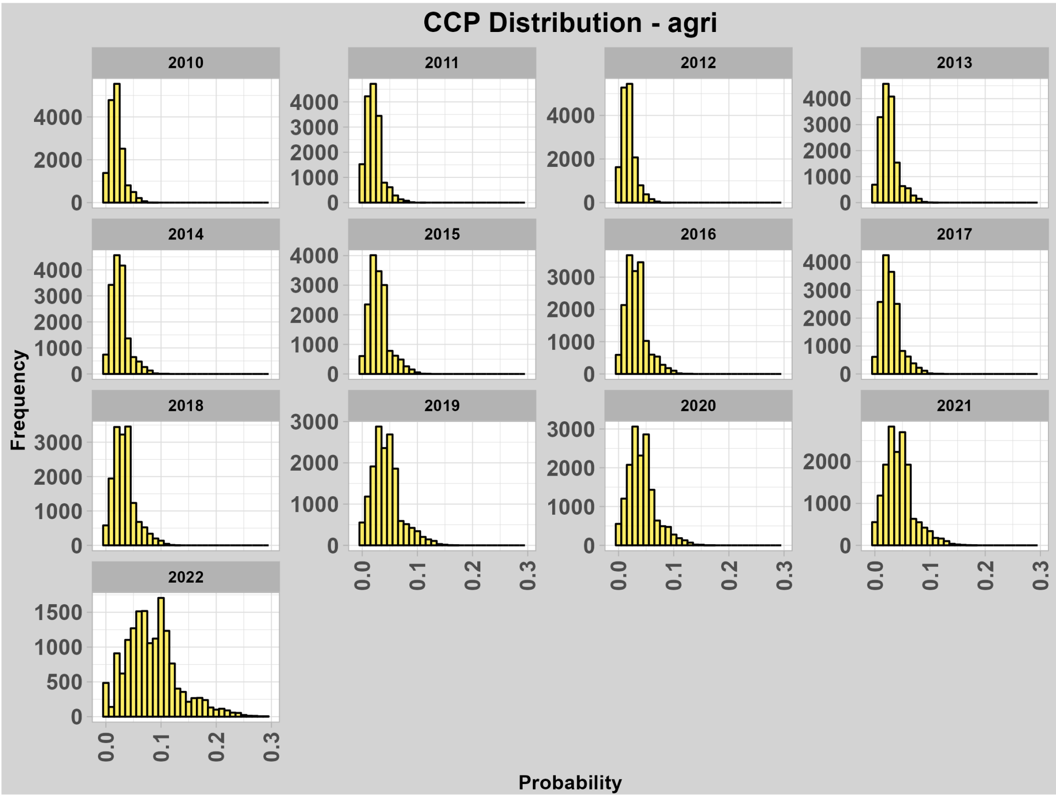

Table 9.2: Cattle Productivity - Index to kg/ha

Variable	Estimate
log(mean_pasture_y)	0.197
	(0.081)
lat	0.211
	(0.094)
lon	0.024
	(0.012)
lat^2	−0.006
	(0.001)
distance	0.00000
	(0.00000)
$distance^2$	−0.000
	(0.000)
historical_temp	−0.150
	(0.045)
log(historical_precip)	−0.138
	(0.026)
log(cattleSlaughter_farmGatePrice_2017)	1.702
	(0.167)
lat*lon	0.005
	(0.002)
Constant	1.929
	(1.578)
Observations	435
R^2	0.449
Adjusted R^2	0.436
Residual Std. Error	161.050 (df = 424)
F Statistic	34.523 (df = 10; 424)
Note:	$p<0.1$; $p<0.05$; $p<0.01$

This table presents the results for the regression that transforms the Pasture Suitability Index into a productivity measure in kg/ha.