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SHAI OLIVEIRA VAZ

CAN PASTURE RECOVERY CURB DEFORESTATION IN BRAZIL?

EVIDENCE FROM A DYNAMIC MODEL

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Trabalho de conclusão de curso apresentado para a Escola Brasileira de Economia e Finanças (FGV/EPGE) como requisito para o grau de bacharel em Ciências Econômicas.

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Abstract

This paper examines whether pasture recovery can effectively curb deforestation in Brazil, using a structural dynamic model to analyse land-use decisions. The model incorporates both the extensive margin, where improved pasture quality is linked to lower conversion rates, and the intensive margin, where increased productivity incentivizes greater land conversion. By disentangling these effects, I empirically assess their net impact on deforestation and carbon emissions. Employing detailed data on pasture degradation, land-use changes, and livestock systems, I estimate model parameters and evaluate two counterfactual policy scenarios. The first examines a pasture recovery policy, while the second assesses a carbon tax that internalizes the social cost of emissions. The results indicate that while pasture recovery reduces deforestation, a significant portion of its benefits is offset by increased economic incentives for land conversion. In contrast, even modest carbon taxes achieve substantial reductions in deforestation and emissions. These findings underscore the limited effectiveness of pasture recovery as a stand-alone solution and suggest that policy approaches integrating carbon pricing may offer greater potential for mitigating deforestation and achieving climate goals.

Keywords: Deforestation; Cattle Ranching; Pasture Recovery; Carbon Taxes; Dynamic Discrete Choice Model.

Resumo

Este artigo analisa a recuperação de pastagens e seu potencial de reduzir o desmatamento no Brasil, utilizando um modelo dinâmico estrutural para analisar as decisões de uso da terra. O modelo incorpora tanto a margem extensiva, onde a melhoria da qualidade das pastagens está associada a menores taxas de conversão, quanto a margem intensiva, onde o aumento da produtividade incentiva uma maior conversão de terra. Ao desagregar esses efeitos, avalio empiricamente seu impacto líquido no desmatamento e nas emissões de carbono. Utilizando dados detalhados sobre degradação de pastagens, mudanças no uso da terra e sistemas de pecuária, estimo os parâmetros do modelo e avalio dois cenários contrafactuais. O primeiro analisa uma política de recuperação de pastagens, enquanto o segundo avalia um imposto sobre o carbono que internaliza o custo social das emissões. Os resultados indicam que, embora a recuperação de pastagens reduza o desmatamento, parte significativa de seus benefícios é diminuída pelos incentivos decorrentes do aumento dos retornos da conversão de terra. Em contraste, impostos sobre o carbono, mesmo modestos, alcançam reduções substanciais no desmatamento e nas emissões. Esses resultados destacam a eficácia limitada da recuperação de pastagens como solução isolada e sugerem que abordagens que integrem a precificação de carbono podem oferecer maior potencial para mitigar o desmatamento e alcançar as metas climáticas.

Palavras-chave: Desmatamento; Pecuária; Recuperação de Pastagens; Imposto de Carbono; Modelo Dinâmico de Escolha Discreta.

List of Figures

List of Tables

Contents

1 Introduction

Agriculture in Brazil serve as a key driver of the country's economy and contribute substantially to the global food supply chain (Calil; Ribera, 2019). However, the expansion of the agricultural frontier has converted large areas of natural vegetation into pastures and crop fields. Land use changes respond for the majority of Brazilian greenhouse gas emissions, accounting for half of the emissions of the recent years (Clima, 2023). Deforestation also causes the degradation of vital ecosystems, loss of biodiversity, and drop in carbon sequestration potential.

Cattle ranching practices are central in this process. Just in the Amazon, where the majority of the Brazilian carbon biomass stock is located, 75% of the land-use emissions are due to pasture activities. When all emissions caused by cattle ranching are jointly considered, aggregating pasture maintenance fires and enteric fermentation to land-use change, these activities account for approximately half of *all* Brazilian emissions (Bustamante et al., 2012). With global demand expected to rise (FAO, 2017), the sustainability and productivity of the Brazilian agricultural sector is a pressing matter. A critical issue in this context is pasture degradation, which is associated with reduced carrying capacity, diminished productivity, and greater reliance on additional land.

The relationship between agricultural productivity and land-use change has long been debated in the literature, with two opposing theoretical frameworks shaping the discussion. On the one hand, the *Borlaug hypothesis* argues that productivity gains reduce the pressure to convert natural land by enabling more output from existing farmland. On the other hand, the *Jevons paradox* highlights the possibility that efficiency improvements may increase resource use by lowering production costs and incentivising further expansion. These frameworks are particularly relevant for understanding the role of pasture recovery in curbing deforestation, as improving pasture quality could have both land-saving and land-expanding effects.

While the potential for productivity increases in Brazilian farming has been abundantly documented (Arantes et al., 2018; Cerri et al., 2018; Strassburg et al., 2014), particularly through pasture recovery (Carlos et al., 2022; Dias-Filho, 2012; Feltran-Barbieri; Féres, 2021; Santos et al., 2022), and despite its prominence in policy discussions[1], the effectiveness of pasture recovery as a deforestation mitigation strategy remains largely untested[2].

[1] E.g. the National Program for the Conversion of Degraded Pastures (Brazil, 2023)

[2] As far as I am aware, this is one the first works to test this hypothesis in economics, particularly leveraging recent methods of empirical industrial organization. Some ecological research has also studied this topic, suggesting intensification policies may be ineffective to curb deforestation (Müller-Hansen et al., 2019).

The literature often assumes that restoring degraded pastures reduces pressure for additional land conversion and discourages deforestation in frontier regions. However, such assumptions overlook the possibility that higher pasture quality could increase land returns, thereby incentivising expansion. This gap highlights the need for rigorous empirical analysis to disentangle these competing effects and assess their implications for policy outcomes.

This paper addresses the gap in the literature by developing an economic model that explicitly accounts for the dual effects of pasture quality on land-use decisions. I employ a structural econometric approach, widely used in empirical industrial organisation and environmental economics. Specifically, I develop a dynamic discrete-continuous choice model in which landowners simultaneously make decisions on two margins: a discrete choice on land use (extensive margin) and a continuous choice on herd stocking rates (intensive margin). By estimating the parameters of this model, I am able to evaluate how improvements in pasture quality influence both margins and estimate the relative magnitudes of the Borlaug and Jevons effects, quantifying their net impact on deforestation and carbon emissions.

Using the estimated model, I conduct counterfactual analyses to evaluate two policy scenarios. The first scenario considers a widespread pasture recovery policy, which mandates a minimum share of high-quality pastures in each municipality. The second scenario explores the impact of carbon-efficient land use, achieved through the internalization of the social cost of carbon emissions via a carbon tax. These scenarios are designed to capture contrasting mechanisms and assess their relative effectiveness: the first emphasises land quality improvements, while the second directly targets the externalities associated with land conversion.

This study contributes to the literature by presenting a preliminary empirical exploration of the competing effects of pasture recovery on deforestation, offering a nuanced perspective on the associated trade-offs. The structural dynamic approach provides a framework for understanding the mechanisms driving land-use decisions and assessing the potential impacts of policy interventions. While these findings are specific to Brazils context of livestock expansion and tropical forest conservation, they may provide valuable insights for policymaking aimed at balancing agricultural productivity, environmental sustainability, and climate objectives.

2 Literature Review

2.1 Productivity and deforestation

This research contributes to the ongoing debate on the impact of agricultural productivity improvements on deforestation. The relationship is theoretically ambiguous (Balboni et al., 2023; Jayachandran, 2022; Kaimowitz; Angelsen, 1998), with empirical evidence supporting both mitigating and exacerbating effects.

On the one hand, the *Borlaug hypothesis* suggests that advancements in agricultural productivity reduce the pressure to convert natural land into agricultural use by increasing yields on existing farmland. For instance, Szerman et al. (2022) found that rural electrification in Brazil improved crop yields, prompting farmers to shift from cattle ranching to crop farming, which ultimately reduced deforestation. Similarly, Abman et al. (2024) showed that an agricultural extension program for small-scale farmers in Uganda led to the adoption of intensification technologies, curbing forest loss. These exercises are grounded on similar theoretical models in which opposing effects on the intensive and extensive margins yield an ambiguous net outcome. In both instances, constraints on input availability strengthened the land-saving effects, encouraging farmers to allocate more resources to existing farmland.

On the other hand, the *Jevons paradox* highlights how efficiency gains can increase resource demand, as lower production costs raise equilibrium outputs and attract additional inputs. In agriculture, this can lead to higher rates of land conversion. Supporting this perspective, Carreira, Costa, and Pessoa (2024) demonstrated that productivity gains from the introduction of genetically engineered soy seeds in Brazil induced cropland expansion in areas exposed to the technology, which favours large-scale farmers with fewer capital constraints. Similarly, community-driven development programs in The Gambia (Hess; Jaimovich; Schündeln, 2021) and the Philippines (Pagel, 2022) facilitated investments in infrastructure, agricultural equipment, and draft animals, raising agricultural yields but also accelerating deforestation.

Here, I develop a structural model that estimates both the intensive and extensive margins of production in cattle ranching, specifically in the context of productivity improvements from degraded pasture recovery. By incorporating these two dimensions of decision-making, the model captures the competing mechanisms at play: on the intensive margin, productivity gains lead to higher output per unit of land, constrained by factor availability, potentially reducing deforestation; on the extensive margin, higher returns from improved productivity raise expected profits, incentivizing land expansion and, consequently, deforestation. This framework separates these effects and enables the analysis of counterfactual scenarios of widespread pasture recovery.

2.2 Cattle cycles

This research contributes to the economic literature on cattle cycles, pioneered by Jarvis (1974). Their seminal work conceptualizes cattle as capital goods and ranchers as portfolio managers, emphasizing the inherently dynamic nature of cattle production. They highlight the complex and often ambiguous responses of producers to price shocks, where short-term and long-term elasticities can differ in sign. For example, a perceived long-term price increase raises the opportunity cost of early slaughter, prompting producers to postpone sales and retain cattle.

Building on these foundations, Paarsch (1985) explore behavioural variations among ranchers under alternative management assumptions. Rosen (1987) provide a conceptual framework that underscores herd inventory management as a key driver of dynamic supply responses. Further advancing this perspective, Rosen, Murphy, and Scheinkman (1994) apply time-series techniques to study herd demographics, offering empirical insights into cattle inventory management in the United States. More recently, Goel (2020) adopt a Generalized Method of Moments approach to examine the dynamic effects of beef prices on land use, demonstrating that temporary and permanent price shocks can yield effects of opposite signs on deforestation rates.

I integrate several aspects from the cattle cycles literature in my analysis. In particular, the model developed here incorporates dynamic responses to price shocks, assuming inter-temporally optimizing agents. By treating cattle as capital goods, the model employs a law of motion for cattle stock that accounts for demographic herd management, enabling the analysis of how price shocks influence herd size adjustments and slaughter decisions over time.

2.3 Land use and deforestation

This study aligns with a growing body of research employing discrete choice models to analyse land use dynamics and their environmental impacts. Seminal works, such as Chomitz and Gray (1996) and Pfaff (1999), focus on the drivers of tropical deforestation, particularly the role of transportation networks in shaping land use patterns. Expanding on this foundation, Souza-Rodrigues (2019) compares the cost-effectiveness of different policies to limit deforestation in the Brazilian Amazon, finding that incentive-based policies are significantly less costly than command-and-control approaches. These studies primarily rely on static models to assess land use decisions[1].

[1] Other econometric approaches have also highlighted the influence of commodity prices and market access on deforestation (e.g. Araujo; Assunção; Bragança, 2023; Assunção; Gandour; Rocha, Rudi,

Recent advancements have introduced dynamic discrete choice models[2] to better capture the inter-temporal decision-making processes of landowners and farmers, representing a significant methodological evolution. Scott (2014) was the first to apply these models to agriculture, introducing a framework that accounts for unobserved heterogeneity and employs flexible specifications. Using remote sensing data on U.S. land use, Scott demonstrated that long-term cropland-price elasticities are substantially higher than those estimated with static models.

Building on this theoretical framework, Sant'Anna (2024) applied a similar approach to analyse ethanol supply in Brazil, disentangling the contributions of acreage expansion and yield improvements. With a focus on environmental policy, Araujo, Costa, and Sant'Anna (2020) extended the models choice set and specifications to explore carbon-efficient forest conservation in the Amazon, accounting for landowners' internalisation of social costs. Additionally, Hsiao (2024) utilized a dynamic discrete-continuous choice approach within a partial equilibrium model to evaluate the effects of policy on palm oil production and emissions. Finally, Barrozo (2024) investigated the role of market power in the beef cattle sector, examining its impact on production and emissions through both static and dynamic discrete choice models.

Finally, this research is related to recent master's theses at my institution[3], such as those by Pacheco (2021) and Pimentel (2021). The former examines the effects of price and climate change on crop supply in agriculture using a random-coefficients approach, while the latter uses a short panel and a static model to explore the impact of the Soy Moratorium on livestock intensification and deforestation in the Brazilian Cerrado.

In this study, I analyse cattle ranching production using a dynamic discrete-continuous model that draws on elements from the recent literature, particularly Hsiao (2024) and Araujo, Costa, and Sant'Anna (2024). In the model, a farmer managing a plot of land faces a dynamic discrete choice between maintaining natural vegetation or converting the plot to pasture. The expected returns from maintaining natural vegetation depend on the carbon biomass stock, while the returns from pasture are determined by the farmer's dynamic, continuous decisions regarding herd demographic management.

2015). Additionally, studies have evaluated the effectiveness of environmental targeting policies in reducing forest loss, including the use of satellite-based monitoring and enforcement programmes (e.g. Assunção; Gandour; Rocha, Romero, 2023; Assunção; Rocha, 2019).

[2] This extension builds on the dynamic framework established by Rust (1987), with important theoretical contributions from Hotz and Miller (1993), Aguirregabiria and Mira (2007, 2002), and Arcidiacono and Miller (2011).

[3] FGV EPGE

3 Model

I conceptualize the cattle farmer's decision-making problem as three-fold: (i) a land-use decision, where they determine whether to convert natural vegetation into pasture; (ii) an intensive margin decision regarding stocking rates (i.e., the number of animals kept in the field); and (iii) short-run consumption decisions, such as the number of animals to be sent for slaughter and the timing of these actions. While interdependent, these decisions represent distinct aspects of the production process. In this framework, stage (i) corresponds to the extensive margin, while stages (ii) and (iii) are jointly considered within the intensive margin.

The model's treatment of the intensive margin draws on methods for continuous optimization in dynamic settings (Hall, 1978; Stokey; Lucas; Prescott, 1989). Farmers solve a problem based on observable stocks and an unobservable consumption function, which remains latent to the econometrician. However, the optimization process yields an Euler equation defined over observable variables, made possible by a law of motion that links consumption decisions to total stock dynamics.

For the extensive margin, I employ a dynamic discrete choice framework with a terminal choice structure, inspired by Hsiao (2024) and Araujo, Costa, and Sant'Anna (2024). This approach adheres to the principles outlined by Arcidiacono and Ellickson (2011) and Aguirregabiria and Mira (2010), relying on theoretical advancements by Hotz and Miller (1993) and Arcidiacono and Miller (2011). The model compares land conversion decisions at time t and $t+1$. With forward-looking optimization for herd management, finite dependence holds, enabling the derivation of a discrete analogue to an Euler equation.

The use of Euler equation estimation for dynamic discrete choice models is advantageous because it eliminates the need to directly compute continuation values, a task required by other recursive methods. This approach sidesteps the complexity of deriving conditional choice probabilities (CCPs) from the value functions and allows the model to be estimated using standard linear techniques.

3.1 Intensive margin

I start with the problem of a rancher i who manages a plot of land already covered in pastures, in municipality m, located in region g. They start period t with animal stock h_{it} inherited from the previous period. Their dynamic problem consists of a profit maximization at every period. I write it as the following dynamic programming problem:

$$\mathcal{V}(h_{it}; \boldsymbol{s_{mt}}) = \max_{c_{it}} \{r(c_{it}; \boldsymbol{s_{mt}}) - \psi(h_{it}; \boldsymbol{s_{mt}}) + \beta\ \mathbb{E}_t[\mathcal{V}(h_{it+1}; \boldsymbol{s_{mt+1}})]\}$$

Where $r(\cdot)$ is a revenue function and $\psi(\cdot)$ are the costs. The control variable c_{it} represents consumption from the stock, h_{it}. It can be seen as sales of cattle for slaughter, breeding, and fattening, net of purchases of new animals[1].

The vector $\boldsymbol{s_{mt}} = \{p_{mt}, \boldsymbol{x_{mt}}, \xi_{mt}, \varepsilon_{mt}, g\}$ bundles the state variables at time t. I include local prices p_{mt} and a vector of cost-factors $\boldsymbol{x_{mt}}$. I assume ranchers as price takers. I also include market-level shocks ξ_{mt} and ε_{mt}, related to the extensive and intensive margins. Finally, g denotes the region of farmer i.

Assumption 1. The size of the herd h_{it+1} follows a law of motion given by:

$$h_{it+1} = (1 + \phi)h_{it} - c_{it}$$

I assume the rancher's herd at the end of period t follows a law of motion that depends on a biological growth rate of the inherited herd, and on levels of consumption during t. The parameter ϕ is defined as a biological growth rate of the herd. It can be considered the net result of birth and mortality rates at optimal reproductive practices, whose analysis I abstain from.

In particular, I specify the following functional forms for $r(\cdot)$ and $\psi(\cdot)$. Revenues are taken to depend linearly on consumption c_{it} and local prices p_{mt}. And I take costs to be increasing and convex on the inherited herd h_{it}. I also tackle unobserved heterogeneity with the employment of region fixed effects and a time trend as cost factors.

$$\begin{gathered} r(c_{it}; \boldsymbol{s_{mt}}) = \alpha_p p_{mt} c_{it} \\ \psi(h_{it}; \boldsymbol{s_{mt}}) = \left[\frac{1}{2}\delta h_{it} + \boldsymbol{x_{it}}\gamma_x + \gamma_g + \gamma_t t + \varepsilon_{it}\right] h_{it} \end{gathered} \tag{3.1}$$

3.1.1 Structural regression equation for the intensive margin

I solve the intensive margin problem as usual for continuous dynamic programming problems. First, I assume an interior solution, leveraging the structure of convex costs and linear revenues. Then, I take the first order condition for the right-hand maximization problem, and the envelope condition of the value function. Combining these two, I can derive an Euler equation on the observables. I assume rational expectations to retrieve a regression model in h_{mt+1}, considering realised values as noisy measures of expectations.

[1] This means we allow for consumption to be either positive or negative. If consumption is negative, the farmer incurs costs, paying p_{mt} for each (net) animal bought. And if consumption is positive, they extract revenues selling each (net) animal at the same price p_{mt}

The derivation can be found in Appendix G.1.

$$\boxed{\begin{aligned} h_{mt+1} &= \alpha_p \frac{(1+\phi)}{\delta}\, p_{mt+1} - \alpha_p \frac{1}{\delta}\frac{1}{\beta}\, p_{mt} \\ &- \boldsymbol{x_{mt+1}} \frac{\gamma_x}{\delta} - \frac{\gamma_g}{\delta} - (t+1)\frac{\gamma_t}{\delta} \\ &+ \eta_{mt} + \mu_{mt} \end{aligned}} \tag{3.2}$$

Where η_{it} is an expectational error, defined as the difference between expected and realised values of observables. And μ_{it} is the structural error. They are given by:

$$\begin{aligned} \eta_{mt} &= \alpha_p \frac{(1+\phi)}{\delta}\left[\mathbb{E}_t[p_{mt+1}] - p_{mt+1}\right] \\ &- \frac{\gamma_x}{\delta}\left[\mathbb{E}_t[\boldsymbol{x_{mt+1}}] - \boldsymbol{x_{mt+1}}\right] \\ &- \frac{1}{\delta}\left[\mathbb{E}_t[\varepsilon_{mt+1}] - \varepsilon_{mt+1}\right] \\ \mu_{mt} &= -\frac{1}{\delta}\varepsilon_{mt+1} \end{aligned} \tag{3.3}$$

3.2 Extensive margin

Now I proceed to describe the land use decision of a rancher. Current land use in a plot is given by $k \in \{0,1\}$, where 0 represents natural vegetation and 1 represents pastures. If $k = 0$, the plot starts t forested and the agent faces a discrete choice $j \in J = \{0,1\}$, deciding on their extensive margin. When agents decide on this margin, they face unobservable shocks $\boldsymbol{\nu_{it}} = \nu_{ijt},\ j \in \{0,1\}$. For simplicity, here I bundle vectors $\boldsymbol{\omega_{it}}$ and $\boldsymbol{\varepsilon_{it}}$, of observable and unobservable variables, in a single state vector $\boldsymbol{s_{mt}}$.

If ranchers choose $j = 0$, they extract returns from forest activities and face the same choice next period. Alternatively, if they choose $j = 1$, the plot is deforested and converted to pastures. Agents pay a conversion cost and extract returns from cattle raising, for which they face intensive margin choices, first on initial herd size, then on consumption rates every period. Deforestation is a terminal action and ends the discrete choice problem.

I assume random utility, conditional independence and extreme value errors. These assumptions are detailed below, and are standard in the dynamic discrete choice literature (Arcidiacono; Ellickson, 2011).

Assumption 2. The agent's conditional payoffs $\pi(j, \boldsymbol{s_{mt}}, \boldsymbol{\nu_{it}})$ for the extensive margin are additively separable in the unobservable shock $\boldsymbol{\nu_{it}}$.

Assumption 3. State variables follow a Markov process and are independent from unobservable extensive-margin shocks, conditional on current state.

$$F(\boldsymbol{s_{mt+1}} \mid \boldsymbol{s_{mt}}, j, \boldsymbol{\nu_{it}}) = F(\boldsymbol{s_{mt+1}} \mid \boldsymbol{s_{mt}})$$

Assumption 4. Extensive margin shocks ν_{ijt} are independent and identically distributed over time and choices, following a Type I Extreme Value distribution.

I consider the following specifications for the flow of conditional payoffs. When keeping native vegetation, payoffs depend on the carbon stock of above-ground biomass b_m. And for pastures, the payoffs serve as the link between the extensive and intensive margin decisions. I assume land conversion imply costs Ψ, to which I add the intensive-margin value function of starting period t with inherited herd $h_{mt} = 0$.

$$\begin{aligned} \pi(j=0, \boldsymbol{s_{mt}}, \boldsymbol{\nu_{it}}) &= \alpha_b b_m + \xi_{mt} + \nu_{i0t} \\ \pi(j=1, \boldsymbol{s_{mt}}, \boldsymbol{\nu_{it}}) &= -\Psi(\boldsymbol{s_{mt}}) + \mathcal{V}(h_{mt}=0, \boldsymbol{s_{mt}}) + \xi_{mt} + \nu_{i1t} \end{aligned} \tag{3.4}$$

Here I employ Bellmans principle of optimality, and also define the extensive margin value function recursively as a dynamic programming problem. Note that the choice $j = 1$ is terminal in the extensive margin, so there is no continuation value afterwards.

$$\begin{aligned} V(k=0,\ \boldsymbol{s_{mt}}, \boldsymbol{\nu_{it}}) = \max_j \Big\{ &\alpha_b b_m + \xi_{mt} + \nu_{i0t} + \beta\, \mathbb{E}\Big[V(j_t = 0,\ \boldsymbol{s_{mt+1}}, \boldsymbol{\nu_{it_1}}) \mid \boldsymbol{s_{mt}} \Big],\ \text{if } j = 0; \\ &-\Psi(\boldsymbol{s_{mt}}) + \mathcal{V}(h_{mt}=0, \boldsymbol{s_{mt}}) + \xi_{mt} + \nu_{i1t},\ \text{if } j = 1 \Big\} \end{aligned}$$

3.2.1 Structural regression equation for the extensive margin

A detailed derivation for the following condition can be found in Appendix G.2. The right-hand side denotes the cut-off value above which the farmer favours converting the plot to pasture at t instead of keeping it forested and converting at $t + 1$.

$$\log\left(\frac{\rho_{mt}}{1-\rho_{mt}}\right) - \beta\log(\rho_{mt+1}) + \beta\gamma = -\Psi(\boldsymbol{s_{mt}}) + \beta\Psi(\boldsymbol{s_{mt+1}}) \tag{3.5}$$

$$- \alpha_b b_m + \delta\frac{\beta}{2}(h_{mt+1})^2 \tag{3.6}$$

$$+ \eta^e_{it} + \mu^e_{it} \tag{3.7}$$

Where η^e_{it} is an expectational error, and μ^e_{it} a structural error, given by:

$$\begin{aligned} \eta^e_{mt} = \beta \Bigg[&\mathbb{E}_t[\log(\rho_{mt+1})] - \log(\rho_{mt+1}) \\ &+ \mathbb{E}_t\Big[\Psi(\boldsymbol{s_{mt+1}})\Big] - \beta\Psi(\boldsymbol{s_{mt+1}}) \\ &- \Big[\mathbb{E}_t[\xi_{mt+1}] - \xi_{mt+1}\Big] \Bigg] \end{aligned} \tag{3.8}$$

$$\mu^e_{mt} = -\beta\xi_{mt+1}$$

Next, I provide more structure to the extensive margin cost function, explicitly incorporating factors analogous to those used in the intensive margin cost specification. It serves two key purposes. First, it captures the impact of higher pasture quality on the use of limited inputs, such as fertilisers or credit, which influences land conversion costs. This tests the Borlaug hypothesis that productivity improvements can reduce land expansion. Second, it provides controls for other determinants of conversion costs, improving consistency across the model. Specifically, I define the $\Psi(\cdot)$ function as:

$$\Psi(\boldsymbol{s_{mt}}) = \boldsymbol{x_{it}}\gamma_x^e + \gamma_g^e + \gamma_t^e t$$

Therefore, the term $-\Psi(\boldsymbol{s_{mt}}) + \beta\Psi(\boldsymbol{s_{mt+1}})$ can be written as follows:

$$\begin{aligned} -\Psi(\boldsymbol{s_{mt}}) + \beta\Psi(\boldsymbol{s_{mt+1}}) = & \Big[\beta\boldsymbol{x_{it+1}} - \boldsymbol{x_{it}}\Big]\gamma_x^e \\ & + \Big(\beta - 1\Big)\gamma_g^e \\ & + \gamma_t \Big(\beta + (\beta - 1)t\Big) \end{aligned}$$

Finally, I get the following regression equation for the extensive margin.

$$\boxed{\begin{aligned} \log\left(\frac{\rho_{mt}}{1-\rho_{mt}}\right) - \beta\log(\rho_{mt+1}) + \beta\gamma = & \Big[\beta\boldsymbol{x_{it+1}} - \boldsymbol{x_{it}}\Big]\gamma_x^e \\ & + \Big(\beta - 1\Big)\gamma_g^e + \gamma_t^e \Big(\beta + (\beta - 1)t\Big) \\ & - \alpha_b b_m + \delta\frac{\beta}{2}(h_{mt+1})^2 \\ & + \eta_{it}^e + \mu_{it}^e \end{aligned}} \tag{3.9}$$

4 Data

In this section I describe the land use and pasture quality data employed. Refer to Appendix H for a detailed description of further sources of data utilized, such as time-consistent municipality polygons, cattle herd, cattle prices, product-level international trade flows, aboveground carbon biomass, weather controls, transportation costs, market access and pasture suitability.

4.1 Land use

Land-use data is sourced from the *MapBiomas Project* (Souza et al., 2020), which provides annual 30-meter resolution maps derived from Landsat imagery. Using a random forest classifier, spatial-temporal filters to minimize noise, and thorough accuracy assessments, MapBiomas classifies each pixel into predefined land-use categories. Year-on-year transition matrices are created by comparing pixel classifications between consecutive years, enabling detailed tracking of land-use changes over time.

I aggregate land-use statistics and transitions into four categories: agriculture, pasture, natural vegetation, and other (e.g., non-classified pixels, urban areas, and water). My analysis focuses on transitions from natural vegetation to pasture. The conditional choice probabilities ρ_{mt} are estimated non-parametrically as the share of natural vegetation pixels converted to pasture in each municipality for each pair of successive years.

4.2 Pasture quality

For this study, I use high-resolution data on the quality of Brazilian pastures developed as part of the *MapBiomas Project* (Santos et al., 2022). This dataset is constructed based on the Normalized Difference Vegetation Index (NDVI), a widely used metric for assessing vegetation health and productivity. The NDVI is derived by comparing the reflectance of electromagnetic radiation in the red and near-infrared portions of the spectrum, utilising imagery from Landsat satellites. It serves as an effective proxy for vegetative vigour, with higher values generally indicating healthier, more productive vegetation.

Pasture quality is inherently influenced by local environmental conditions, meaning that a pasture considered degraded in one biome might still perform adequately in another (Dias-Filho, 2014). To account for this geographical heterogeneity, the dataset normalizes the median NDVI values using biome-specific maximum and minimum percentiles. This normalization ensures that comparisons are made relative to the optimal vegetation conditions within each biome. After normalization, the NDVI values are categorised into three classes of vegetative vigour, corresponding to the states of high, medium and low vigour.

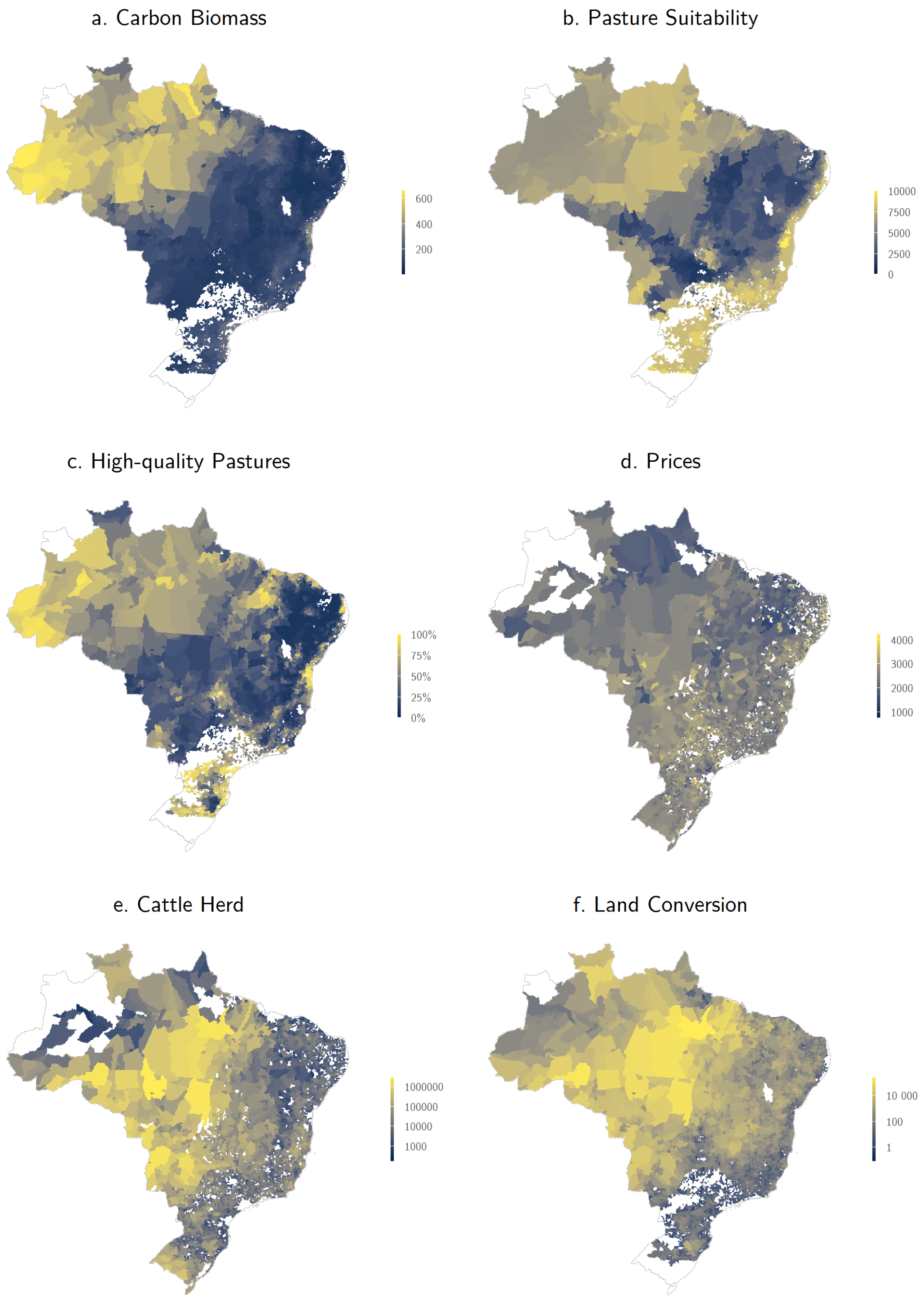
The use of NDVI as an indicator of pasture quality is grounded in its ability to reflect biological degradation by capturing the health of vegetation and its forage productivity. However, this measure is less effective at detecting agricultural degradation, which involves increased weed presence that competes pastures out (Lapig; Inpe; Embrapa, 2023). As such, while the data is highly suited to assessing the biological quality of pastures, it may underestimate the full extent of degradation in areas where agricultural degradation is more prevalent.

By employing this dataset, my analysis focuses on the counterfactual scenarios of improving the *biological* quality of pastures. For a broader discussion on the distinctions between biological and agricultural degradation, as well as the causes and consequences of pasture degradation, see Appendix F.

To construct an indicator of pasture quality for each municipality, I calculate the share of its pasture area classified with high vegetative vigour. This approach offers the advantage of producing a continuous variable, which provides greater granularity in capturing variations in pasture quality across municipalities and over time. By focusing on the share of high-vigour pastures, the measure inherently accounts for the quality of all remaining pasture areas, implicitly classifying those with lower vigour as degraded. This includes areas identified as either mildly or severely degraded based on their vegetative state.

This indicator offers a more flexible metric for evaluating policy changes in pasture quality and their potential impacts compared to a categorical variable. In counterfactual scenarios, it enables the assessment of gradual increases in the share of high-quality pastures. These improvements represent a hypothetical recovery or restoration of degraded pasture areas, encompassing the entire spectrum of degradation, from mild to severe.

Figure 1 – Geographical Distribution of Main Variables



This figure plots for each municipality in sample, **(a)** the carbon biomass density, measured in tons of CO_2 per hectare; **(b)** the index of pasture suitability from FAO-GAEZ; **(c)** the share of pastures with high quality, in 2017; **(d)** the average per capita price of cattle sold for slaughter in 2017, measured in R$ of 2022; **(e)** the herd of cattle at the end of 2017; **(f)** total area converted from natural vegetation to pasture in 2006 and 2007, measured in hectares.

5 Identification and Estimation

5.1 General setting

This chapter details the identification strategy and estimation approach for the structural (Euler) equations of the model. The equations are estimated at the municipality level, focusing on both intensive and extensive margins of cattle ranching. The identification of parameters relies on a combination of fixed effects, instrumental variables, and calibration, with key assumptions grounded in the literature.

For the **intensive margin**, I estimate the following regression equation, developed in the structural model (3.2).

$$
\begin{aligned}
h_{mt+1} = \alpha_p \frac{(1+\phi)}{\delta}\, p_{mt+1} - \alpha_p \frac{1}{\delta}\frac{1}{\beta}\, p_{mt} \\
- \boldsymbol{x_{mt+1}} \frac{\gamma_x}{\delta} - \frac{\gamma_g}{\delta} - (t+1)\frac{\gamma_t}{\delta} \\
+ \eta_{mt} + \mu_{mt}
\end{aligned}
$$

In this equation, h_{mt+1} denotes the herd size at the beginning of time $t+1$, capturing the stock of cattle available for future production. The terms p_{mt} and p_{mt+1} correspond to the local cattle prices at times t and $t+1$, respectively, reflecting market conditions that influence ranchers' decisions. The variable $\boldsymbol{x_{mt+1}}$ represents a vector of observable covariates – such as temperature, market access, transportation cost and pasture quality – that affect production costs. The term γ_g captures biome fixed effects, which account for differences in herd management costs and constraints across ecosystems, mitigating biases from unobserved regional heterogeneity. The parameter γ_t captures a time trend to reflect temporal dynamics. Lastly, η_{mt} and μ_{mt} represent an expectational error and a structural error that captures idiosyncratic shocks, respectively.

For the **extensive margin**, I estimate the structural equation 3.9 from the model, as follows.

$$
\begin{aligned}
\log\left(\frac{\rho_{mt}}{1-\rho_{mt}}\right) - \beta \log(\rho_{mt+1}) + \beta\gamma = \Big[\beta \boldsymbol{x_{it+1}} - \boldsymbol{x_{it}}\Big]\gamma_x^e \\
+ \Big(\beta - 1\Big)\gamma_g^e + \gamma_t^e \,\Big(\beta + (\beta-1)t\Big) \\
- \alpha_b b_m + \delta \frac{\beta}{2}(h_{mt+1})^2 \\
+ \eta_{it}^e + \mu_{it}^e
\end{aligned}
$$

In this equation, ρ_{mt} represents the probability that a plot of land is converted to pasture at time t within the municipality. The variable $\boldsymbol{x_{it}}$ is the same vector of covariates influencing ranchers' costs, including factors such as pasture quality. The term b_m measures the density of carbon biomass in the municipality as measured in the year 2000. The optimal herd size for the subsequent period, h_{mt+1}, connects the extensive margin to forward-looking expectations in herd management derived from the intensive margin. Finally, η^e_{it} and μ^e_{it} account for the expectational error and the idiosyncratic shocks in land-use decisions.

The expectational errors, which capture the gap between expectations and realizations, call for the use of instruments to address potential endogeneity. For the intensive margin, as outlined in equations 3.3, expectational errors are inherently correlated with prices and time-varying cost factors, particularly pasture quality. In the extensive margin, as indicated in equations 3.8, endogeneity arises solely from the correlation between expectational errors and cost factors. To address these issues, I instrument for prices using a shift-share variable derived from exogenous shocks to Chinese agricultural imports. For pasture quality, I employ the minimum monthly values of the Palmer Drought Severity Index (PDSI) from the previous year as an instrument, which serves both margins. Further details on the construction of these instruments are provided in the subsequent section.

5.2 Instruments

5.2.1 Prices

To address the potential endogeneity of cattle prices in my regression, I employ a Shift-Share Instrumental Variable (SSIV) approach based on exogenous shocks to Chinese meat imports. This method leverages the substantial and well-documented increase in China's demand for agricultural products over the past decades, particularly since its accession to the World Trade Organization (WTO) in 2001. The instrument is constructed following the methodology of Carreira, Costa, and Pessoa (2024), which itself is theoretically grounded in the framework of Borusyak, Hull, and Jaravel (2022). This approach isolates exogenous variation in local outcomes by combining national-level shocks with initial shares of production at the regional level.

The first step in constructing the instrument involves estimating the exogenous shock component of Chinese import growth. Using detailed product-country-year trade data, I estimate an auxiliary regression to identify China-specific import growth rates for each product category[1] j. This regression excludes Brazilian data to ensure that the

[1] A product is identified by its 6-digit code in the World Customs Organization's (WCO) "Harmonized System" classification. The data used here pertains to fresh, chilled, or frozen meat from bovine animals (HS Chapter 02, Headings 01 and 02).

shocks are not influenced by domestic factors. The regression takes the following form:

$$G_{cj,t} = \gamma_{j,t} + \psi_{\text{China},\, j,t} + \epsilon_{cj,t}$$

Here, $G_{cj,t}$ denotes the growth rate of country c's imports of product j in year t, measured relative to a base year. The term $\gamma_{j,t}$ captures year-product fixed effects, varying across both products and years, to account for time-specific characteristics of each product that are invariant across countries. And $\psi_{\text{China},\, j,t}$ represents China-product-specific dummies, which isolate the component of import growth uniquely attributable to Chinese demand for product j in year t. The residual term $\epsilon_{cj,t}$ reflects any unexplained variation. I set the base year to 2000, just prior to China's World Trade Organization (WTO) accession in 2001, following Carreira, Costa, and Pessoa (2024), to ensure that the base period accurately reflects pre-treatment conditions, unaffected by subsequent policy changes.

After obtaining the estimated China-specific import growth rates ($\widehat{\psi}_{\text{China},\, j,t}$), I construct the Shift-Share Instrument as:

$$\widehat{x}_{m,t} = \sum_{j} S_{mj,\bar{t}} \cdot x_{j,\bar{t}} \cdot \widehat{\psi}_{\text{China},\, j,t} \tag{5.1}$$

In this expression, $S_{m,\bar{t}}$ represents the share of production in municipality m in the base year $\bar{t}$. This share is derived from the 1995 agricultural census, ensuring it predates the base year and is unaffected by subsequent shocks. $x_{j,\bar{t}}$ is the volume of Brazilian exports of product j to China in the base year. Lastly, $\widehat{\psi}_{\text{China},\, j,t}$ denotes the predicted China-specific import growth rates for product j in year t, as estimated in the auxiliary regression.

This Shift-Share variable combines the exogenous national-level shocks $\widehat{\psi}_{\text{China},\, j,t}$ with initial regional production shares $S_{m,\bar{t}}$, ensuring that the instrument captures variation in regional outcomes that stems from China's demand growth rather than from endogenous local factors. The base year values for shares and exports ensure that the comparison baseline for the shocks is pre-determined and independent of the key policy changes that triggered the shock. The use of this instrument is particularly strong for the analysis of cattle prices because Chinese meat imports have been a major driver of global demand shifts, particularly for beef. By isolating the exogenous component of this demand, the Shift-Share instrument acts as a demand shifter (Angrist; Krueger, 2001), providing a credible strategy to address the endogeneity of prices on the supply side.

5.2.2 Pasture Quality

To address the potential endogeneity in pasture quality, I use the Palmer Drought Severity Index (PDSI) from the previous year as an instrument. Specifically, I take the lowest monthly observation within the year to capture the driest conditions experienced, which have the greatest impact on pasture quality.

The PDSI is a widely used metric for measuring drought severity by comparing current moisture levels to historical averages. I rely on monthly PDSI values calculated by Abatzoglou et al. (2018) in the TerraClimate dataset. These values are derived from a modified Thornthwaite-Mather climatic water-balance model, which incorporates precipitation (moisture supply), reference evapotranspiration (moisture demand), and soil water storage. The reference evapotranspiration is estimated using the FAO's Penman-Monteith energy balance approach, which accounts for air temperature, solar radiation, air humidity, and wind speed.

The PDSI is a strong instrument for pasture quality because it measures soil moisture availability – a critical factor for vegetation growth and forage production. By reflecting the effects of climatic variability, the PDSI captures how droughts influence vegetation health and productivity. Its standardized design also allows for consistent comparisons of climatic stress on pasture quality across municipalities, regions, biomes, and time.

The use of minimum PDSI values focuses on the most severe drought conditions, such as the driest months or the most intense dry spells. These extreme events are particularly important for pasture quality, as they represent periods when vegetation is most stressed and forage availability is at its lowest. Using lagged values ensures the instruments exogeneity, as past climatic conditions are predetermined and not influenced by current agricultural decisions or land-use changes.

The key assumption is that drought conditions, as measured by the PDSI, influence herd management and land-use decisions only indirectly through their effect on pasture quality. For example, severe droughts can lead to reduced forage availability, prompting farmers to adjust herd sizes (Skidmore, 2023) or clear additional land for grazing (Desbureaux; Damania, 2018). This indirect relationship supports the validity of the PDSI as an instrument for addressing the endogeneity of pasture quality in the regression framework.

5.3 Results

Table 1 presents the second-stage estimation results for the instrumental variable regression of the intensive margin structural equation, incorporating biome fixed effects and a full set of controls. The corresponding first-stage results are provided in Appendix A. As a robustness check, Appendix B includes results from two additional specifications that employ municipality fixed effects, with and without instrumentation. The coefficients in these alternative specifications maintain the same sign as the main results, but their magnitudes are attenuated.

Table 1: Intensive Margin IV Regression Results

	h_{mt+1}	Parameters
p_{mt}	-0.0188*** 0.0071	$-\frac{\alpha_p}{\delta\beta}$
p_{mt+1}	0.0198*** 0.0071	$\frac{\alpha_p(1+\phi)}{\delta}$
Pasture Quality (x_{mt+1})	1.3111** 0.5629	$-\frac{\gamma_{pasture}}{\delta}$
Year	0.2904** 0.1324	$-\frac{\gamma_t}{\delta}$
Num.Obs.	6487	
Controls	Temp.; Past.Suit.; Mkt.Acc.; Transp.Cost.	
Fixed Effects	Biome	
F (2nd stage)	108.51	
F (1st stage: p_{mt})	49.9809	
F (1st stage: p_{mt+1})	47.7408	
F (1st stage: Past. Qual.)	38.0575	
Clustered SE	Yes (Municipality)	

* p < 0.1, ** p < 0.05, *** p < 0.01

Standard errors clustered at the municipality level. Biome fixed effects. Controls: Pasture suitability, market access, transportation cost, average minimum and average maximum temperatures. Shift-share variables used as instruments for prices. Palmer drought severity index (PDSI) used as instrument for pasture quality.

The second-stage results from the estimation of the extensive margin structural equation can be seen in Table 8, also with biome fixed effects and controls. Appendix C exhibits the first-stage results for this model. Alternative empirical exercises[2] with a less precise but higher-frequency survey data described in section H.2 are shown in Appendix D, with and without instruments. The results are close to the main specification, particularly when instruments are employed.

The full structural regression model is under-identified in its parameters. Identification is achieved by calibration of the inter-temporal discount factor β. This is a common practice in the literature, as the discount factor is generally unidentified in dynamic models (Magnac; Thesmar, 2002). I assume $\beta = 0.9$. With this calibration, the intensive margin

[2] Note that for the extensive margin a core parameter (α_b) is estimated from a time-invariant municipality-specific variable (b_m). Therefore, an exercise with municipality fixed effects is not viable for the extensive margin as it was for the intensive margin, because the carbon biomass parameter would be absorbed by the fixed effects.

Table 2: Extensive Margin IV Regression Results

	$\log\left(\frac{\rho_{mt}}{1-\rho_{mt}}\right) - \beta\log(\rho_{mt+1}) + \beta\gamma$	Parameters
$\frac{\beta}{2}(h_{mt+1})^2$	0.2964** (0.1469)	δ
Pasture Quality $(\beta x_{mt+1} - x_{mt})$	6.8196*** (0.7412)	$\gamma^e_{pasture}$
b_m	0.0011*** (0.0002)	$-\alpha_b$
$(\beta + (\beta - 1)t)$	-0.0762*** (0.0234)	γ^e_t
Num.Obs.	6210	
Controls	Temp.; Past.Suit.; Mkt.Acc.; Transp.Cost.	
F (2nd stage)	15.7038	
F (1st stage: Past. Qual.)	715.7339	
Clustered SE	Yes (Municipality)	

* p < 0.1, ** p < 0.05, *** p < 0.01

Standard errors clustered at the municipality level. Controls: Pasture suitability, market access, transportation cost, average minimum and average maximum temperatures. All time varying controls have been calculated as an inter-temporal difference of the form $\beta x_{mt+1} - x_{mt}$. Palmer Drought Severity Index (PDSI) used as instrument for the intertemporal difference in pasture quality.

estimates allow me to identify the parameters $\left(\phi, \alpha_p/\delta, \gamma_x/\delta, \gamma_g/\delta, \gamma_t/\delta\right)$. And from the extensive margin estimates, I identify $\left(\delta, \alpha_b, \gamma^e_x, \gamma^e_g, \gamma^e_t\right)$. I then use δ to extract $\left(\alpha_p, \gamma_x, \gamma_g, \gamma_t\right)$ in levels, and divide by α_p to calculate all relevant parameters in monetary terms. The results are presented in Table 3.

5.4 Comments

The estimated price coefficients align with the predictions from the cattle cycles literature. The coefficient for p_{mt} is negative, whereas the coefficient for p_{mt+1} is positive. This indicates that a temporary increase in current prices p_{mt}, not expected to persist into the following year, motivates producers to increase herd consumption in the present, thereby reducing the herd size in the subsequent period. Conversely, if producers in t anticipate a price increase only in $t+1$, they are incentivized to decrease current herd

Table 3 – Structural Parameters

Parameter	Value	Scaled by α_p (R$)
ϕ	0.1684	
δ	0.2964	
α_p	0.0050	
α_b	-0.0011	-0.22
Intensive margin cost factors		
$\gamma_{pasture}$	-0.3887	-77.29
γ_t	-0.0861	-17.12
$\gamma_g : g =$ amazonia	174.7659	34755.92
$\gamma_g : g =$ caatinga	174.8613	34774.89
$\gamma_g : g =$ cerrado	174.8432	34771.29
$\gamma_g : g =$ mata atlantica	174.8058	34763.86
$\gamma_g : g =$ pampa	174.8677	34776.17
$\gamma_g : g =$ pantanal	174.7419	34751.14
Extensive margin cost factors		
$\gamma^e_{pasture}$	6.8196	1356.22
γ^e_t	-0.0762	-15.16
$\gamma^e_g : g =$ amazonia	157.3413	31290.67
$\gamma^e_g : g =$ caatinga	154.0151	30629.18
$\gamma^e_g : g =$ cerrado	155.2466	30874.09
$\gamma^e_g : g =$ mata atlantica	156.0026	31024.44
$\gamma^e_g : g =$ pampa	156.1444	31052.64
$\gamma^e_g : g =$ pantanal	153.6928	30565.09

consumption to capitalize on higher prices later, resulting in a larger herd size for the following year. Additionally, I estimate a biological growth rate ϕ of 16.84%, which is consistent with the aggregate volumes of slaughter with respect to the national herd[3].

A negative coefficient for pasture quality ($\gamma_{pasture}$) in the intensive margin indicates that lower pasture quality in a municipality raises marginal herd management costs, thereby reducing the optimal stocking rates. Conversely, an improvement in pasture quality decreases these marginal costs, enabling higher optimal stocking rates. This relationship aligns with economic intuition, as better-quality pastures support greater forage production and reduce input requirements per unit of livestock.

For the extensive margin, the coefficient for pasture quality ($\gamma^e_{pasture}$) is positive, suggesting a different dynamic. A reduction in pasture quality incentivizes higher land conversion rates, possibly as farmers seek to expand the land available for grazing to compensate for reduced productivity on existing pastures. Conversely, improvements in

[3] For rough estimates, one can employ the Law of Motion of cattle stock to national aggregate data from the *Pesquisa da Pecuária Municipal* and *Pesquisa Trimestral do Abate de Animais*, both from IBGE, yielding similar growth rate results.

pasture quality raise the effective cost of land conversion. This could reflect increased demand for complementary inputs or greater reliance on credit, both of which make expansion less profitable.

The coefficients for the time trend cost parameters (γ_t, γ_t^e) are both negative, indicating that herd management and land conversion costs have declined between 2006 and 2017. This likely reflects technological advancements, improvements in infrastructure, or policy changes that have reduced costs over time. The decline in conversion costs could also stem from the expansion of transportation networks or other developments that have lowered barriers to land use changes, such as loosened environmental regulations.

The near-zero and negative coefficient for carbon biomass (α_b) suggests that, on average, Brazilian farmers place no implicit monetary value on carbon stocks. This finding underscores the notion that, in the absence of effective policy incentives, carbon conservation plays a negligible role in farmers' land-use decisions. It presents an even bleaker outlook than the results of Araujo, Costa, and Sant'Anna (2024), who find a small but positive carbon valuation for properties in the Amazon, where command-and-control policies have had some success in curbing deforestation. Both in my findings and theirs, the implicit valuation of stored carbon biomass by farmers is far below the efficient level – one that would align with the social cost of carbon (SCC). A recent estimate by Barrage and Nordhaus (2024) puts the SCC at \$66.00 per tonne (in 2019 dollars), exposing the substantial gap between farmers' private valuations and the broader externality cost of carbon release.

Finally, the parameter δ which represents the leading coefficient in the intensive margin cost function, is positive. This indicates an upward quadratic relationship for marginal costs in the intensive margin, which is consistent with the model's expectation of convex costs. In other words, as stocking rates increase, marginal herd management costs rise at an accelerating rate, reflecting the diminishing returns to stocking density.

In the extensive margin, δ interacts with the squared optimal stocking rates, a regressor that captures the expected differential profits from land conversion at time t relative to $t + 1$. A positive δ in this context supports the structural model, as higher optimal stocking rates correspond to greater land productivity and higher yields per unit of land. This increases the incentive for land conversion, as the potential returns from expanding pastureland become more attractive.

In the following section, I perform two counterfactual exercises using the results from the structural model estimation. The parameters $\gamma_{pasture}, \gamma_{pasture}^e$ and δ are used to simulate the effects of a hypothetical set of pasture recovery policies, disentangling their competing impacts on the intensive and extensive margins. Additionally, by modifying the α_b parameter, I assess the implications of increasing farmers' valuation of carbon biomass, through mechanisms such as a carbon tax, up to the social cost of carbon.

6 Counterfactuals

6.1 General approach

In this section, I evaluate two sets of counterfactual policies and their impacts on land conversion and carbon emissions. These scenarios are compared to baseline model-predicted values, which serve as a benchmark, allowing for the analysis of potential reductions in land conversion and carbon emissions (abatements). The counterfactuals represent hypothetical alternative policy scenarios of pasture recovery and carbon taxes applied during the study period to the sample under investigation.

Unlike stable settings where a steady-state scenario can be computed from a stationary distribution of CCPs, as in Araujo, Costa, and Sant'Anna (2024), the non-stationary nature of this study requires a different methodology to estimate the counterfactuals. I adopt the approach outlined by Hsiao (2024), which is designed for a similar non-stationary context.

Using this method, I introduce short-term policy perturbations while holding long-term market conditions constant. Since agents are forward-looking and the model assumes no path dependency, long-term CCPs remain unchanged. The counterfactual policy impacts are estimated directly from the models Euler equations. From these, I calculate new short-term CCPs, working backwards from the unchanged future CCPs. These revised CCPs are then used to estimate counterfactual land conversion rates (by multiplying the new CCPs by the municipality area) and counterfactual carbon emissions (by multiplying the new land conversion by the carbon density per hectare).

To validate the model, I apply the same estimation approach without introducing any policy changes, producing baseline predictions for land conversion and emissions. This benchmark exhibits 4.3 million hectares of natural vegetation converted to pastures and 1.2 billion tons of CO_2 emitted. These predictions align closely with observed values, demonstrating the model's robustness. Table 4 presents the model-predicted baselines alongside the observed data, with their relative errors. The model slightly overestimates land conversion by 4.9% and carbon emissions by 4.6%, indicating a good degree of predictive accuracy.

6.2 Pasture recovery

For the first counterfactual exercise, I evaluate the impacts of policies designed to promote widespread pasture recovery. These policies are implemented by imposing a

Table 4 – Baseline scenario

Variable	Predicted	Observed	Relative error
Land conversion ($10^4 km^2$)	4.3169	4.1160	0.0488
Carbon emissions (Gt CO_2)	1.1724	1.1211	0.0458

minimum threshold for the share of high-quality pastures in each municipality. Specifically, municipalities where the share of high-quality pastures falls below the policy-mandated minimum undergo recovery efforts to meet the threshold. The policy gradually escalates this minimum in 1% increments, from 0% to 100%, culminating in a scenario where all pastures across the study area are fully restored to high quality.

For each policy scenario, I calculate the counterfactual land conversion rates and CO_2 emissions, and compare them to the baseline model-predicted values. The baseline serves as a benchmark, representing the estimated land conversion in the absence of policy intervention. Panel A of Table 5 summarises the total land conversion reductions and carbon abatement across the range of recovery scenarios.

The structural model's separation of intensive and extensive margins allows for the identification of the competing effects of pasture quality on land conversion rates. The results of the estimation reveal two opposing dynamics:

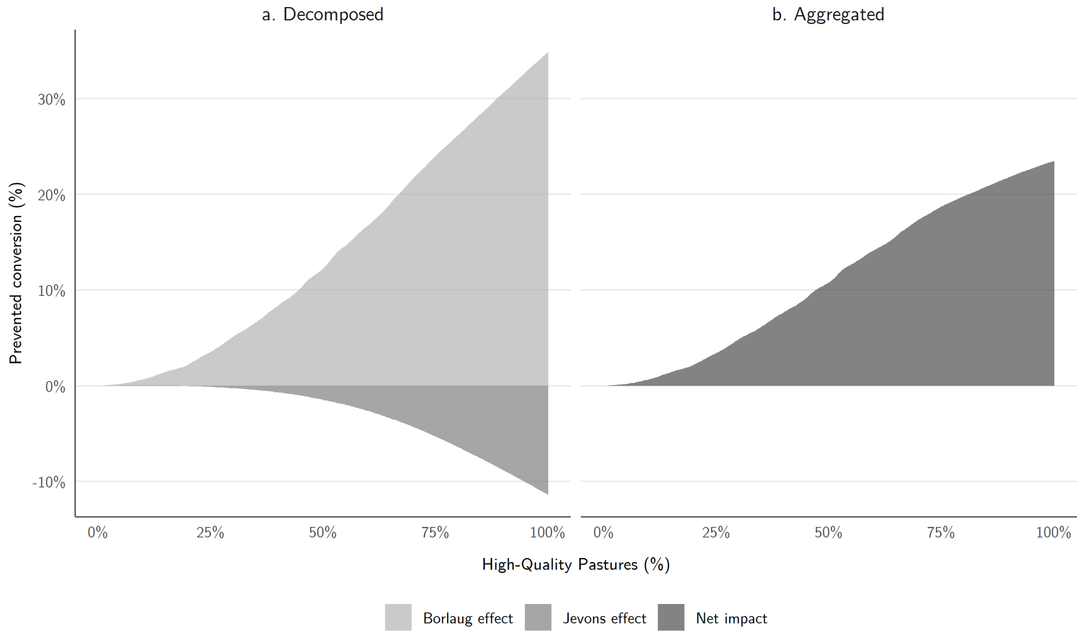
Borlaug Effect: Higher pasture quality is associated with increased conversion costs, as indicated by the positive $\gamma^e_{pasture}$ in the extensive margin. Improved pasture quality discourages land conversion by making expansion less profitable, potentially due to increased reliance on complementary inputs or greater credit constraints. This aligns with the *Borlaug hypothesis*, which suggests that gains in productivity reduce pressure for land expansion.

Jevons Effect: On the intensive margin, a negative $\gamma_{pasture}$ indicates that improved pasture quality lowers marginal costs, raising optimal stocking rates. Additionally, a positive δ implies that higher optimal stocking rates amplify the returns to land use, incentivizing land conversion. This mirrors the *Jevons Paradox*, where efficiency gains can lead to increased resource use.

I estimate the impact of pasture recovery disaggregated into the Borlaug and Jevons effects, as well as its net result. The **Borlaug Effect** is isolated by estimating the counterfactual impact of increased pasture quality exclusively through the extensive margin, without considering the indirect impacts from the intensive margin. This represents the maximum potential land conversion reduction achievable if only the land-saving effects of pasture recovery were at play. Whereas the **Jevons Effect** is calculated as the difference between the Borlaug effect and the net impact of pasture recovery policies. It is equivalent to computing only the indirect impact of $\gamma_{pasture}$ through δ.

This decomposition is illustrated in Figure 2, which shows how the Borlaug and Jevons effects evolve as the policy-mandated minimum share of high-quality pastures increases. Additionally, Appendix E presents a similar analysis, focusing on the decomposition of the carbon abatement potential under these policy scenarios.

Figure 2 – Pasture recovery counterfactual



This figure shows the potential prevented land conversion from a pasture recovery counterfactual. The X-axis shows the minimum share of high-quality pastures set by the policy in each municipality. The Y-axis shows the prevented conversion relative to the baseline for each policy level. Panel **(a)** shows the disaggregation between Borlaug and Jevons effects, while panel **(b)** exhibits the net effect.

The results indicate that a hypothetical policy achieving complete recovery of pastures to high quality could have prevented up to 23.5% of the land conversion to pasture observed during the study period. This outcome aligns with the Borlaug hypothesis, as improvements in pasture quality reduce the pressure for land expansion. However, a closer examination of the disaggregated effects reveals an important nuance. While the maximum potential reduction in land conversion from the *Borlaug effect* is estimated at 33%, approximately one-third of this reduction is offset by the opposing *Jevons effect*. In other words, the conversion incentives driven by higher land productivity and returns substantially attenuate the land-saving potential of this policy.

6.3 Carbon efficient land use

The second counterfactual scenario evaluates carbon-efficient land use, where agents fully internalize the externality costs of carbon emissions, following the approach of Araujo, Costa, and Sant'Anna (2024). This is achieved by aligning the private perceived

Table 5 – Summary of prevented land conversion and CO_2 emissions in policy counterfactuals

	Prevented Land Conversion		Prevented CO_2 Emissions	
Policy	Area ($10^4 km^2$)	vs. Baseline (%)	Volume (Gt CO_2)	vs. Baseline (%)
A: Pasture Recovery				
25%	0.15	3.4%	0.01	1.2%
50%	0.47	10.8%	0.07	6.0%
75%	0.81	18.7%	0.18	15.0%
100%	1.01	23.5%	0.26	21.8%
B: Carbon Tax				
\$0.5	1.10	25.5%	0.42	36.1%
\$1	1.81	42.0%	0.68	57.7%
\$2	2.62	60.6%	0.93	79.1%
\$5	3.46	80.1%	1.11	94.5%
\$10	3.86	89.4%	1.15	98.2%
\$20	4.09	94.8%	1.17	99.4%
\$66	4.27	98.9%	1.17	99.9%

This table presents results for prevented land conversion of natural vegetation to pasture and prevented CO_2 emissions for different levels of pasture recovery and different rates of carbon tax. The columns (3) and (5) represent, respectively, the prevented conversions and prevented emissions with respect to baseline conversion and emission estimates.

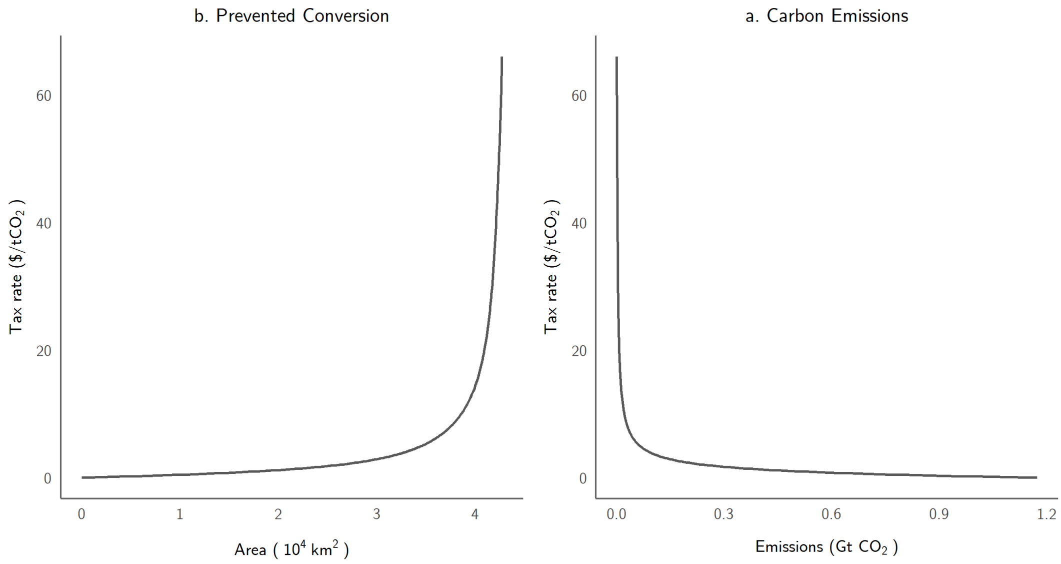
value of carbon stocks ($^{\alpha_b}/_{\alpha_p}$) with the social cost of carbon, estimated at \$66.00 per tonne of CO_2 (Barrage; Nordhaus, 2024). Conceptually, this corresponds to implementing a first-best, perfectly enforceable carbon tax on land-use changes[1]. Conversely, the heightened perceived value of carbon can also be interpreted as the private monetary valuation of stronger environmental policies.

I simulate several scenarios where a carbon tax is applied, ranging from \$0/tCO_2 to \$66/tCO_2, the value at which carbon efficiency is achieved. The results are summarised in Table 5, Panel B. In the carbon-efficient scenario, 98.9% of the predicted land conversion and 99.9% of carbon emissions would have been avoided. Notably, the impact of the carbon tax is highly convex. While achieving full preservation requires imposing high costs, the majority of land conservation and carbon abatement is achieved at relatively modest tax levels. For instance, with a carbon tax of just \$10/ton, 89% of land conversion and 98% of carbon emissions would be prevented. These results are illustrated in Figure 3, which highlights the convex relationship between the tax rate and the reductions in land conversion and emissions. This pattern is highly consistent with the findings of Araujo,

[1] The SCC estimate is a present value measured in 2019 dollars. I first calculate its annuity equivalent with a 10% annual interest rate ($1 - \beta$). Then, I convert it to R\$ with the average exchange rate of 2019, R\$3.9445 per dollar. Finally, I update this to R\$ of 2022 using the Extended National Consumer Price Index (IPCA).

Costa, and Sant'Anna (2024) for the Amazon.

Figure 3 – Carbon taxes counterfactual



This figure shows the impact of different levels of carbon tax on prevented land conversion and carbon emissions. In Panel **(a)**, the X-axis represents area with natural vegetation, in $10^4 km^2$ (million hectares), while in Panel **(b)**, the X-axis represents CO_2 emissions. In both panels, the Y-axis shows the tax rate, in \$/tCO_2.

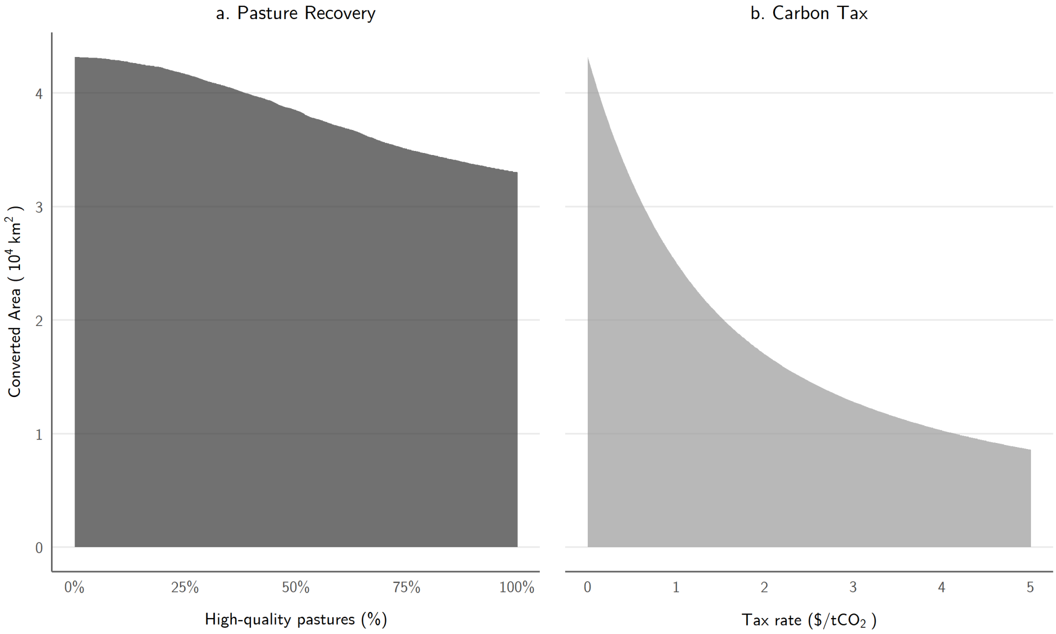
6.4 Comparison

In this section, I compare the potential impacts of the two counterfactual policies: pasture recovery and carbon-efficient land use. Figure 4 provides a visual comparison of the total converted area in each policy scenario. The left panel illustrates the outcomes of a pasture recovery policy, where recovery rates vary from 0% to 100%. The right panel depicts the effects of a carbon tax policy, ranging from \$0 to \$5/tCO_2, at which point 80% of land conversions are already avoided.

The comparison reveals that carbon taxes are significantly more effective in preventing land conversion. The maximum reduction achieved through a pasture recovery policy caps at 23.5%, even at full recovery (100% high-quality pastures). By contrast, this level of avoided conversion is reached with a carbon tax below \$1/tCO_2. This stark difference highlights the greater efficiency of carbon taxes in aligning private incentives with socially optimal land-use outcomes.

These findings underscore the relative limitations of policies targeting productivity improvements alone. While pasture recovery can mitigate some land-use pressures, it is subject to diminishing returns and competing economic incentives, such as those captured by the *Jevons effect*. In contrast, carbon taxes directly internalize the externality cost of emissions, making them a far more potent tool for addressing deforestation and associated carbon emissions.

Figure 4 – Counterfactual comparison



This figure shows a comparison of the two counterfactual scenarios under analysis. The Y-axis represents the total converted area, in $10^4 km^2$ (million hectares). Panel **(a)** shows the results of a pasture recovery policy, X-axis varying between 0% and 100% recovery. Panel **(b)** shows the impact of a carbon tax policy, X-axis varying from \$0 to \$5/tCO_2.

7 Conclusion

This paper analyses the economic drivers of land-use decisions in Brazilian agriculture, focusing on the impacts of agricultural productivity improvements and carbon efficiency on deforestation and carbon emissions. Using a dynamic structural model, I explore both the intensive and extensive margins of land-use decisions, shedding light on the economic incentives behind land conversion and the interplay between productivity gains and carbon valuation.

The structural model developed in this study captures forward-looking behaviour, convex costs, and the competing effects of productivity improvements. In particular, I analyse the productivity increasing channel of pasture recovery. On the one hand, higher pasture quality increases conversion costs, reducing deforestation – a dynamic consistent with the Borlaug hypothesis. On the other hand, productivity improvements also raise land profitability, incentivising further conversion – a mechanism reflecting the Jevons paradox.

The results from the model estimation also indicate that farmers place little to no implicit monetary value on carbon stocks, underscoring the absence of private incentives for carbon conservation. This finding suggests a significant gap between private land-use incentives and socially optimal outcomes, given the externality cost of carbon emissions.

I conducted two counterfactual analyses. First, a pasture recovery policy, aimed to increase the share of high-quality pastures in municipalities. Results showed that full recovery could prevent up to 23.5% of land conversion during the study period. However, a disaggregated analysis revealed that one-third of the potential reduction from the Borlaug effect was offset by the opposing Jevons effect. This demonstrates that while productivity-driven policies can reduce deforestation, their land-saving potential is significantly attenuated by increased economic returns from land conversion.

Next, I examined the impacts of a carbon-efficient land-use policy, where agents internalize the social cost of carbon emissions through a carbon tax. Results show that a tax of \$66/tCO_2 – equivalent to the estimated social cost of carbon – could prevent 98.9% of land conversion and 99.9% of emissions. Moreover, the impact of the tax is highly convex: most of the conservation and abatement benefits can be achieved with a low tax rate of \$10/tCO_2.

A comparison of the two policies underscores the superior effectiveness of carbon taxes in addressing land conversion and emissions. While the maximum impact of pasture recovery is notable, it is equivalent to the effect of a carbon tax below \$1/tCO_2. This demonstrates that policies directly targeting carbon emissions, such as carbon pricing, are far more effective and efficient in achieving environmental objectives.

These findings have important implications for policy design. First, productivity-improving policies, while beneficial in reducing deforestation under certain conditions, are limited by competing economic incentives. Second, carbon pricing offers a direct mechanism for aligning private incentives with social welfare goals, providing a highly effective tool for sustainable land-use management. Finally, the convexity of the tax impact suggests that significant environmental benefits can be achieved at relatively low cost, making carbon pricing a politically and economically viable solution.

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Appendix

A – Intensive margin: first stage results

Table 6 – Intensive margin first stage results

Dependent Variables:	p_{mt}	p_{mt+1}	Pasture Quality (x_{mt+1})
Variables			
$ssiv_{mt}$	-19.93***	-21.23***	0.0140***
	(3.417)	(3.645)	(0.0021)
$ssiv_{mt+1}$	13.23***	14.08***	-0.0092***
	(2.261)	(2.411)	(0.0014)
pdsi_min	0.1117***	0.1100***	5.68×10^{-5}***
	(0.0201)	(0.0207)	(1×10^{-5})
Year	79.05***	59.88***	0.0075***
	(0.9454)	(0.9916)	(0.0003)
Temperature	✓	✓	✓
Past. Suit.	✓	✓	✓
Mkt. Acc.	✓	✓	✓
Transp. Cost	✓	✓	✓
Fixed-effects			
Biome	✓	✓	✓
Fit statistics			
Observations	6,487	6,487	6,487
F-test	309.45	173.59	98.484
F-test (1st stage)	49.981	47.741	38.057

Clustered (Municipality) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

B – Intensive margin with municipality fixed effects

Table 7 – Intensive margin FE regression results

Dependent Variable:	h_{mt+1}	
	OLS	IV
Variables		
p_{mt}	-0.0004***	-0.0004***
	(6.4×10^{-5})	(0.0002)
p_{mt+1}	0.0004***	0.0004**
	(6.18×10^{-5})	(0.0002)
Pasture Quality (x_{mt+1})	0.0953***	0.3666***
	(0.0155)	(0.0658)
Year	0.0047***	0.0069***
	(0.0014)	(0.0024)
Temperature	✓	✓
Past. Suit.		
Mkt. Acc.	✓	✓
Transp. Cost		
Fixed-effects		
Municipality	✓	✓
Fit statistics		
Observations	6,487	6,487
F-test	5,689.8	7,821.2

Clustered (Municipality) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

C – Extensive margin: first stage results

Table 8 – Extensive margin first stage results

Dependent Variable:	Pasture Quality ($\beta x_{mt+1} - x_{mt}$)
Variables	
pdsi_min	$-5.9 \times 10^{-5***}$
	(2.07×10^{-6})
$\frac{\beta}{2}(h_{mt+1})^2$	-0.0301***
	(0.0072)
b_m	-0.0002***
	(9.17×10^{-6})
$(\beta + (\beta - 1)t)$	0.0005
	(0.0010)
Temperature	✓
Past. Suit.	✓
Mkt. Acc.	✓
Transp. Cost	✓
Fixed-effects	
Biome	✓
Fit statistics	
Observations	6,210
F-test	106.02
F-test (1st stage)	715.73

Clustered (Municipality) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

D – Extensive margin exercise with survey data

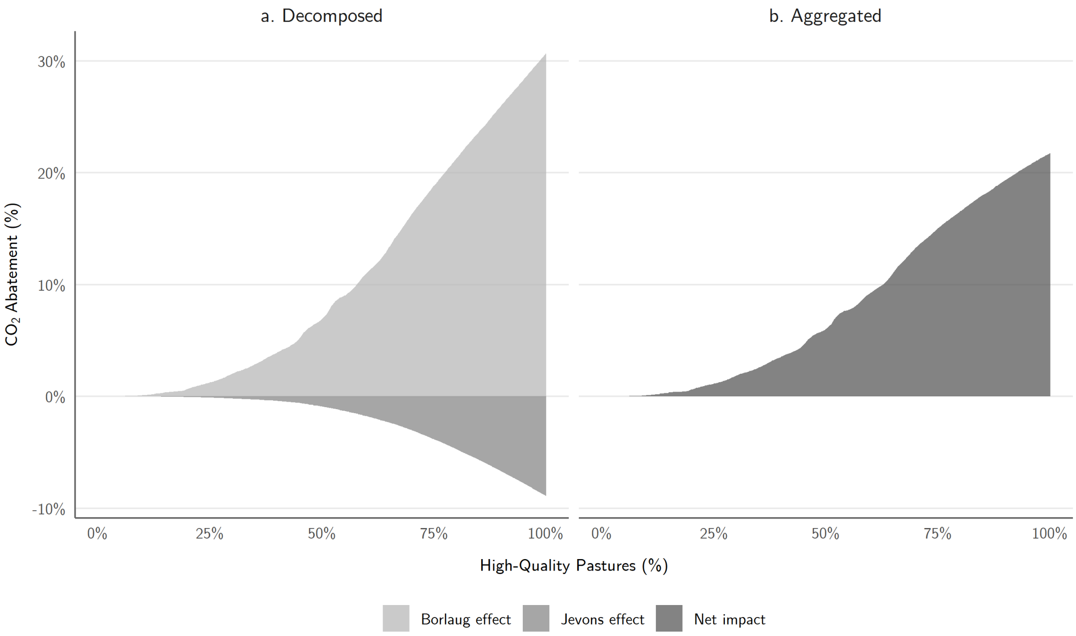
Table 9 – Extensive margin regression with survey data

Dependent Variable:	$\log\left(\frac{\rho_{mt}}{1-\rho_{mt}}\right) - \beta\log(\rho_{mt+1}) + \beta\gamma$	
	OLS	IV
Variables		
$\frac{\beta}{2}(h_{mt+1})^2$	0.1171***	0.3427***
	(0.0331)	(0.1006)
Pasture Quality ($\beta x_{mt+1} - x_{mt}$)	1.382***	10.76***
	(0.0860)	(0.8078)
b_m	-0.0004***	0.0013***
	(6.79×10^{-5})	(0.0002)
$(\beta + (\beta - 1)t)$	-0.0424***	-0.0660***
	(0.0047)	(0.0054)
Temperature	✓	✓
Past. Suit.	✓	✓
Mkt. Acc.	✓	✓
Transp. Cost.	✓	✓
Fixed-effects		
Biome	✓	✓
Fit statistics		
Observations	64,736	64,736
F-test	6.6588	6.7972

Clustered (Municipality) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

E – Pasture recovery effect on abatements

Figure 5 – Pasture recovery counterfactual (CO_2 Abatement)



This figures plots the potential CO_2 abatement from a pasture recovery counterfactual. The X-axis shows the minimum share of high-quality pastures set by the policy in each municipality. The Y-axis shows the carbon abatement relative to the baseline emissions for each policy level. Panel **(a)** shows the disaggregation between Borlaug and Jevons effects, while panel **(b)** exhibits the net effect.

F – Details on pasture degradation

Pasture degradation refers to the decline in a pasture's capacity to support livestock. This phenomenon is characterised by a progressive loss of pasture vigour and resilience, impairing its ability to recover after grazing or adverse environmental conditions. As a result, pasture degradation poses a significant challenge to the sustainability of livestock production systems. Pasture degradation can be broadly categorised into two main types: agricultural degradation and biological degradation (Dias-Filho, 2014).

Agricultural degradation is primarily associated with the encroachment of invasive plant species and the proliferation of weeds. These competing plants reduce the availability of high-quality forage for livestock, making grazing increasingly inefficient. Over time, the dominance of weeds further suppresses pasture productivity, creating a feedback loop of reduced forage availability, decreased livestock performance, and declining agricultural output.

Biological degradation, in contrast, arises from soil deterioration. It manifests as a reduction in vegetation cover, leading to soil erosion, loss of organic matter, and the depletion of critical nutrients needed to sustain plant growth. This form of degradation is more severe than agricultural degradation because it undermines the fundamental capacity of the soil to support any vegetation, further exacerbating environmental and productivity challenges.

The drivers of degradation include a combination of improper grazing practices and external environmental factors. Inadequate grazing management – such as overgrazing, poor rest period planning, neglect of soil fertility restoration, and excessive reliance on fire – contributes significantly to both agricultural and biological degradation. Additionally, factors like pest infestations, plant diseases, and adverse environmental conditions (e.g., low rainfall or poor soil fertility) amplify the degradation process.

Recovery efforts typically involve interventions such as soil fertility restoration, reseeding with high-quality forage species, and implementing rotational grazing systems. These measures not only address the symptoms of degradation but also tackle its root causes, including improper grazing management and nutrient imbalances (Dias-Filho, 2015).

In Brazil, pasture degradation remains a pervasive issue, affecting both the environmental health of grazing lands and the economic viability of livestock farming. Although recent improvements have been documented, degraded pastures still constitute a substantial share of total pastureland. For instance, in 2018, 58.9% of pastures in Brazil exhibited some level of degradation (Santos et al., 2022).

The recovery of degraded pastures is often presented in the literature as a key component of agricultural intensification strategies, with the potential to enhance productivity while reducing pressure on natural ecosystems. By improving the productive capacity of existing pastures, some argue that pasture recovery could discourage the need for additional land conversion and thus help curb deforestation (Carlos et al., 2022; Dias-Filho, 2012; Feltran-Barbieri; Féres, 2021).

However, while this premise is widely cited, it remains largely untested in the context of comprehensive economic models of land use. As demonstrated in this paper, the interplay between pasture quality and land conversion is complex. While higher-quality pastures can indeed reduce deforestation through increased conversion costs (the Borlaug effect), the associated productivity gains may simultaneously incentivise land conversion by raising the economic returns to grazing (the Jevons effect). These countervailing forces suggest that the potential of pasture recovery as a deforestation mitigation strategy must be carefully scrutinised, particularly in policy discussions aimed at achieving sustainable agricultural development.

G – Demonstrations

G.1 Intensive Margin

G.1.1 Derivation of the optimality condition

The first order condition states that, at the optimum, marginal revenue equals the discounted future marginal value of the herd.

$$\begin{aligned}\frac{\partial r(c_{it}; \boldsymbol{s_{mt}})}{\partial c_{it}} &= -\beta\,\mathbb{E}_t\left[\frac{\partial \mathcal{V}(h_{it+1}; \boldsymbol{s_{mt+1}})}{\partial h_{it+1}}\frac{\partial h_{it+1}}{\partial c_{it}}\right] \\ &= \beta\,\mathbb{E}_t\left[\frac{\partial \mathcal{V}(h_{it+1}; \cdot)}{\partial h_{it+1}}\right]\end{aligned} \tag{G.1}$$

And by the envelope theorem, at the optimum, the marginal value equals the discounted future marginal value, increased by ϕ, minus marginal costs.

$$\begin{aligned}\frac{\partial \mathcal{V}(h_{it}; \boldsymbol{s_{mt}})}{\partial h_{it}} &= -\frac{\partial \psi(h_{it}; \boldsymbol{s_{mt}})}{\partial h_{it}} + \beta\,\mathbb{E}_t\left[\frac{\partial \mathcal{V}(h_{it+1}; \boldsymbol{s_{mt+1}})}{\partial h_{it+1}}\frac{\partial h_{it+1}}{\partial h_{it}}\right] \\ &= -\frac{\partial \psi(h_{it}; \cdot)}{\partial h_{it}} + \beta(1+\phi)\,\mathbb{E}_t\left[\frac{\partial \mathcal{V}(h_{it+1}; \cdot)}{\partial h_{it+1}}\right]\end{aligned} \tag{G.2}$$

Substituting G.1 in G.2 yields:

$$\frac{\partial \mathcal{V}(h_{it}; \cdot)}{\partial h_{it}} = -\frac{\partial \psi(h_{it}; \cdot)}{\partial h_{it}} + (1+\phi)\frac{\partial r(c_{it}; \cdot)}{\partial c_{it}}$$

Forwarding it one period, and substituting back into G.1, we reach the optimality condition of the problem, given by the following Euler equation:

$$\frac{\partial r(c_{it}; \cdot)}{\partial c_{it}} = \beta\,\mathbb{E}_t\left[(1+\phi)\frac{\partial r(c_{it+1}; \cdot)}{\partial c_{it+1}} - \frac{\partial \psi(h_{it+1}; \cdot)}{\partial h_{it+1}}\right] \tag{G.3}$$

That means optimal slaughter c_{it} is that which equates marginal revenue from a sale at t to the discounted expected marginal opportunity cost of the forgone sale at $t+1$. Each new animal sold increases revenues at t, but reduces the herd for the next period, reducing potential revenues but also reducing the herd carrying cost.

Note that for every plot i in municipality m, the farmers face the same optimality condition. Therefore, I can denote the optimal choice $h^{\star}_{it}$ for every plot in municipality m

as simply h_{mt}. From the specified functional forms, marginal revenues and costs are given by:

$$\frac{\partial r(c_{it};\cdot)}{\partial c_{it}} = \alpha_p p_{mt}$$

$$\frac{\partial r(c_{it+1};\cdot)}{\partial c_{it+1}} = \alpha_p p_{mt+1}$$

$$\frac{\partial \psi(h_{mt+1};\cdot)}{\partial h_{mt+1}} = \delta h_{mt+1} + \boldsymbol{x_{it+1}}\gamma_x + \gamma_g + \gamma_t(t+1) + \varepsilon_{it+1}$$

With this, I can write the Euler equation G.3 as follows.

$$\frac{1}{\beta}\alpha_p p_{mt} = \alpha_p(1+\phi)\,\mathbb{E}_t[p_{mt+1}] - \mathbb{E}_t\Big[\delta h_{mt+1} + \boldsymbol{x_{it+1}}\gamma_x + \gamma_g + \gamma_t(t+1) + \varepsilon_{it+1}\Big] \tag{G.4}$$

Note that, from the law of motion, the process of deciding on c_{it} at period t also defines h_{mt+1}. Hence, I can write $\mathbb{E}_t[h_{mt+1}] = h_{mt+1}$.

$$\delta h_{mt+1} = \alpha_p(1+\phi)\,\mathbb{E}_t[p_{mt+1}] - \frac{1}{\beta}\alpha_p p_{mt} - \mathbb{E}_t[\boldsymbol{x_{it+1}}\gamma_x] - +\gamma_g - \gamma_t(t+1) - \mathbb{E}_t[\varepsilon_{it+1}]$$

Which can be then rewritten as 3.2.

G.2 Extensive Margin

G.2.1 Derivation of the optimality condition

I further define the ex-ante value function, which is the expected value of being in state $\boldsymbol{s_{mt}}$ before the realization of shocks $\boldsymbol{\nu_{it}}$.

$$\bar{V}(0,\, \boldsymbol{s_{mt}}) \equiv \mathbb{E}_{\boldsymbol{\nu}}\Big[\, V(0,\, \boldsymbol{s_{mt}}, \boldsymbol{\nu_{it}})\,\Big]$$

And the conditional value functions, which are the present value of choosing j in period t and behaving optimally afterwards. Here, consider $\pi_{mt}(j)$ to mean the payoffs $\pi(j, \boldsymbol{s_{mt}}, \boldsymbol{\nu_{it}})$ net of the idiosyncratic shocks ν_{ijt}.

$$v(0, \boldsymbol{s_{mt}}) = \pi_{mt}(0) + \beta\,\mathbb{E}\Big[\,\bar{V}(0,\, \boldsymbol{s_{mt+1}}) \mid \boldsymbol{s_{mt}}\Big] \tag{G.5}$$

$$v(1, \boldsymbol{s_{mt}}) = \pi_{mt}(1) \tag{G.6}$$

Assumption 4 of EV1 extensive margin shocks implies the conditional choice probabilities have closed-form logit solutions. That is to say, the probability of observing a choice of land conversion from forest to pastures ($j_t = 1$), is given by:

$$\rho(1 \mid \boldsymbol{s_{mt}}) = \frac{\exp\Big[\,v(1, \boldsymbol{s_{mt}})\,\Big]}{\exp\Big[\,v(0, \boldsymbol{s_{mt}})\,\Big] + \exp\Big[\,v(1, \boldsymbol{s_{mt}})\,\Big]}$$

To lighten notation, I denote henceforth $\rho(1 \mid \boldsymbol{s_{mt}}) = \rho_{mt}$ and $\rho(0 \mid \boldsymbol{s_{mt}}) = 1-\rho_{mt}$, which follows from the binary choice set. Using the Hotz and Miller (1993) inversion, I can rearrange the conditional choice probabilities and relate their ratio to the difference in conditional value functions:

$$\log\left(\frac{\rho_{mt}}{1-\rho_{mt}}\right) = v(1, \boldsymbol{s_{mt}}) - v(0, \boldsymbol{s_{mt}}) \tag{G.7}$$

And applying Arcidiacono and Miller (2011)'s *Lemma 1* to the EV1 case, the ex-ante value function can be rewritten with respect to the conditional value function of any arbitrary choice:

$$\bar{V}_{it}(0) = v(1, \boldsymbol{s_{mt}}) - \log(\rho_{mt}) + \gamma \tag{G.8}$$

Where γ is the Euler-Mascheroni constant. In equation G.7, I substitute the conditional value functions with G.5 and G.6, and apply equation G.8 forwarded one period:

$$\begin{aligned}\log\left(\frac{\rho_{mt}}{1-\rho_{mt}}\right) &= \pi_{mt}(1) - \pi_{mt}(0) - \beta\,\mathbb{E}_t\Big[\bar{V}_{it+1}(0)\Big] \\ &= \pi_{mt}(1) - \pi_{mt}(0) - \beta\,\mathbb{E}_t\Big[\pi_{mt+1}(1) - \log(\rho_{mt+1}) + \gamma\Big]\end{aligned}$$

Now, I open $\pi_{mt+1}(1)$ to include the intensive margin value function.

$$\begin{aligned}&\log\left(\frac{\rho_{mt}}{1-\rho_{mt}}\right) = -\Psi(\boldsymbol{s_{mt}}) + \mathcal{V}(h_{mt}=0, \boldsymbol{s_{mt}}) + \xi_{mt} - \pi_{mt}(0) \\ &- \beta\,\mathbb{E}_t\Big[-\Psi(\boldsymbol{s_{mt+1}}) + \mathcal{V}(h_{mt+1}=0, \boldsymbol{s_{mt+1}}) + \xi_{mt+1} - \log(\rho_{mt+1}) + \gamma\Big]\end{aligned} \tag{G.9}$$

Before advancing, I first develop the following difference of intensive-margin value functions. From now on, I denote optimal decisions in the path where the plot is deforested at t using one-asterisk-variables $(*)$, and where it was deforested at $t+1$ using two-asterisk-variables $(**)$.

$$\begin{aligned}&\mathcal{V}(h_{mt}=0, \boldsymbol{s_{mt}}) - \beta\,\mathbb{E}_t\Big[\mathcal{V}(h_{mt+1}=0, \boldsymbol{s_{mt+1}})\Big] \\ &\quad = r(c^*_{it}; \cdot \mid h_{mt}=0) + \beta\,\mathbb{E}_t\Big[\mathcal{V}(h^*_{mt+1}; \cdot)\Big] \\ &\quad - \beta\,\mathbb{E}_t\Bigg[r(c^{**}_{it+1}; \cdot \mid h_{mt+1}=0) + \beta\,\mathbb{E}_{t+1}\Big[\mathcal{V}(h^{**}_{mt+2}; \cdot)\Big]\Bigg]\end{aligned}$$

And developing further:

$$\begin{aligned}&\mathcal{V}(h_{mt}=0, \boldsymbol{s_{mt}}) - \beta\,\mathbb{E}_t\Big[\mathcal{V}(h_{mt+1}=0, \boldsymbol{s_{mt+1}})\Big] \\ &\quad = r(c^*_{it}; \cdot \mid h_{mt+1}=0) + \beta\,\mathbb{E}_t\Bigg[r(c^*_{it+1}; \cdot) - \psi(h^*_{mt+1}; \cdot) + \beta\ \mathbb{E}_{t+1}[\mathcal{V}(h^*_{mt+2}; \cdot)]\Bigg] \\ &\quad - \beta\,\mathbb{E}_t\Bigg[r(c^{**}_{it+1}; \cdot \mid h_{mt+1}=0) + \beta\,\mathbb{E}_{t+1}\Big[\mathcal{V}(h^{**}_{mt+2}; \cdot)\Big]\Bigg]\end{aligned}$$

The revenues $r(c^*_{it+1};\cdot)$ and $r(c^{**}_{it+1};\cdot \mid h_{mt+1}=0))$ are not equal, because the latter comes from the initial herd allocation at $t+1$. In these initial allocations, it can be shown using the law of motion that the consumptions alone define the herd that is left for the next period. That is:

$$\begin{aligned} c^*_{it\,|\,h_{mt}=0} &= -h^*_{mt+1} \\ c^{**}_{it+1\,|\,h_{mt+1}=0} &= -h^{**}_{mt+2} \end{aligned} \tag{G.10}$$

More importantly, it can be shown that $h^*_{mt+2} = h^{**}_{mt+2}$. It happens because the optimal choice of next-period herd follows from the intensive-margin Euler condition (equation G.3) and is only forward-looking. Regardless of inherited herd, the rancher will consume optimally so that they end the period with the herd defined by the same optimality condition.

It means that, whether the rancher deforests at t or at $t+1$, at the end of $t+1$ they have herd size $h^*_{mt+2} = h^{**}_{mt+2}$. It follows then, that $\mathcal{V}(h^*_{mt+2};\cdot) = \mathcal{V}(h^{**}_{mt+2};\cdot)$. That is to say, the property of finite dependence holds and I can difference out the continuation values. Therefore, we can write the difference as:

$$\begin{aligned} &\mathcal{V}(h_{mt}=0,\boldsymbol{s_{mt}}) - \beta\,\mathbb{E}_t\Big[\mathcal{V}(h_{mt+1}=0,\boldsymbol{s_{mt+1}})\Big] \\ &\qquad = r(c^*_{it};\cdot \mid h_{mt}=0) + \beta\,\mathbb{E}_t\Bigg[r(c^*_{it+1};\cdot) - \psi(h^*_{mt+1};\cdot)\ - r(c^{**}_{it+1};\cdot \mid h_{mt+1}=0)\Bigg] \end{aligned}$$

Now we can return to the equation G.9 and substitute this difference.

$$\begin{aligned} \log\left(\frac{\rho_{mt}}{1-\rho_{mt}}\right) &= -\Psi(\boldsymbol{s_{mt}}) + \xi_{mt} - \pi_{mt}(0) - \beta\,\mathbb{E}_t\Big[-\Psi(\boldsymbol{s_{mt+1}}) + \xi_{mt+1} - \log(\rho_{mt+1}) + \gamma\Big] \\ &\quad + r(c^*_{it};\cdot \mid h_{mt}=0) + \beta\,\mathbb{E}_t\Bigg[r(c^*_{it+1};\cdot) - \psi(h^*_{mt+1};\cdot)\ - r(c^{**}_{it+1};\cdot \mid h_{mt+1}=0)\Bigg] \end{aligned}$$

Now, using the specified functional forms for intensive margin revenues and costs(3.1), extensive margin payoffs (3.4), and the results from G.10.

$$\begin{aligned} \log\left(\frac{\rho_{mt}}{1-\rho_{mt}}\right) + \beta\gamma &= -\Psi(\boldsymbol{s_{mt}}) + \xi_{mt} - \alpha_b b_m - \xi_{mt} \\ &\quad - \beta\,\mathbb{E}_t\Big[-\Psi(\boldsymbol{s_{mt+1}}) + \xi_{mt+1} - \log(\rho_{mt+1})\Big] \\ &\quad - \alpha_p p_{mt} h^*_{mt+1} + \beta\alpha_p\,\mathbb{E}_t\Big[p_{mt+1}(c^*_{it+1} + h^*_{mt+2})\Big] \\ &\quad - \beta\,\mathbb{E}_t\Bigg[\Big[\tfrac{1}{2}\delta h^*_{mt+1} + \boldsymbol{x_{it+1}}\gamma_x + \varepsilon_{it+1}\Big]\,h^*_{mt+1}\Bigg] \end{aligned}$$

From the law of motion, it holds that $c^*_{it+1} + h^*_{mt+2} = (1+\phi)h^*_{mt+1}$. And from the intensive margin Euler equation specified in G.4, the following also holds:

$$\mathbb{E}_t\left[\tfrac{1}{2}\delta h^*_{mt+1} + \boldsymbol{x_{it+1}}\gamma_x + \varepsilon_{it+1}\right] = -\frac{1}{\beta}\alpha_p p_{mt} + \alpha_p(1+\phi)\,\mathbb{E}_t[p_{mt+1}] - \mathbb{E}_t\left[\tfrac{1}{2}\delta h^*_{mt+1}\right]$$

Therefore, I can rewrite the equation as:

$$
\begin{aligned}
\log\left(\frac{\rho_{mt}}{1-\rho_{mt}}\right) + \beta\gamma = -\Psi(\boldsymbol{s_{mt}}) + \xi_{mt} - \alpha_b b_m - \xi_{mt} \\
- \beta\, \mathbb{E}_t\Big[-\Psi(\boldsymbol{s_{mt+1}}) + \xi_{mt+1} - \log(\rho_{mt+1})\Big] \\
- \alpha_p p_{mt} h^*_{mt+1} + \beta\alpha_p(1+\phi)\, \mathbb{E}_t\Big[p_{mt+1} h^*_{mt+1}\Big] \\
- \beta\, \mathbb{E}_t\Bigg[\Big[-\tfrac{1}{\beta}\alpha_p p_{mt} + \alpha_p(1+\phi)p_{mt+1} - \tfrac{1}{2}\delta h^*_{mt+1}\Big]\, h^*_{mt+1} \Bigg]
\end{aligned}
$$

Which can be easily simplified and rearranged to:

$$
\begin{aligned}
\log\left(\frac{\rho_{mt}}{1-\rho_{mt}}\right) + \beta\gamma = -\Psi(\boldsymbol{s_{mt}}) - \alpha_b b_m \\
+ \beta\, \mathbb{E}_t\Big[\, \Psi(\boldsymbol{s_{mt+1}})\Big] - \beta\, \mathbb{E}_t\Big[\xi_{mt+1}\Big] \\
+ \beta\, \mathbb{E}_t\Big[\log(\rho_{mt+1})\Big] + \frac{\beta}{2}\delta(h^*_{mt+1})^2
\end{aligned}
$$

I rearrange the previous equation and employ rational expectations, allowing me write expected values as the sum of realizations and an expectation error, to yield the equation in 3.5.

H – Data description

H.1 Municipalities

The number and area of municipalities – the smallest administrative divisions in Brazil – change over time due to the creation of new municipalities or the annexation of existing ones. To address this issue, I use the concept of *minimum comparable areas* (AMCs), which are time-consistent regions enabling the construction of municipality panel data. I follow the methodology of Ehrl (2017), who developed AMCs for the period 18722010, and extend it to account for municipal boundary changes between 2010 and 2022.

All official statistics at the municipality level are aggregated to the AMC level. Additionally, I calculate the predominant biome in each AMC, defined as the biome occupying the largest share of its area, based on the methodology from IBGE (2024). Hereafter, I refer to these minimum comparable areas simply as municipalities.

H.2 Cattle herd

I use two data sources to estimate the herd of cattle per municipality per year. The primary source is the *Agricultural Census* for the years 1995, 2006, and 2017 (IBGE, 1995, 2006, 2017). The census collects detailed data on agricultural establishments and their activities, with each production unit serving as the observation unit. The second source is the annual livestock production surveys (*Pesquisa da Pecuária Municipal*) (IBGE, 2022). This dataset is primarily derived from administrative records of the Foot-and-Mouth Disease Vaccination Campaigns[1], compiled by state and local inspectorates as well as veterinary posts.

To approximate h_{mt}, which is a theoretical measure of livestock per plot of land, I normalize the municipality's head of cattle by its total area. This normalization ensures a temporally and spatially consistent measure of livestock density across municipalities of varying sizes. It then facilitates cross-sectional and temporal comparisons, as it accounts for differences in land availability that could otherwise confound the relationship between herd size and other variables of interest.

[1] *Campanha de Vacinação contra a Febre Aftosa*

H.3 Cattle prices

I derive local cattle prices from sales and revenue data obtained in the 2006 and 2017 administrations of *Agricultural Census*. These represent the cattle price per animal sold for slaughter in each municipality. To project prices for the subsequent year, I adjust them using variations in a national cattle price index. This variation is computed by comparing the average index in the census year with the average for the 12 months following the census.

The cattle price index, sourced from the *Center for Advanced Studies in Applied Economics* (CEPEA, 2024), measures the average price of 15 kg of carcass weight at slaughter for finished bull sales in São Paulo State. São Paulo prices are industry benchmarks; less productive regions typically have lower prices but exhibit similar trends. All prices are deflated to December 2022 values using the Extended National Consumer Price Index (IPCA).

H.4 International trade

To address endogeneity concerns in price determination, I use exogenous demand shocks derived from trends in Chinese agricultural imports as instrumental variables. These shocks represent external demand variations that are independent of local supply conditions. Specifically, I construct a shift-share instrumental variable that allocates aggregate demand shocks from China to Brazilian municipalities in proportion to their respective market shares. This approach allows me to isolate exogenous variation in local prices that stems from global market conditions.

The trade data for constructing this instrument come from the *CEPII BACI - International Trade Database at the Product-Level* (Gaulier; Zignago, 2010). The BACI dataset provides detailed bilateral trade flows between more than 200 countries and covers approximately 5,000 products classified using the Harmonized System (6-digit codes). The dataset spans the period 1995 – 2022, and I align my analysis with the broader China-shock literature by using 2000 as the base year, reflecting China's accession to the World Trade Organization (WTO) in 2001.

H.5 Aboveground carbon biomass

In the model, the returns to maintaining fields as natural vegetation depend on their aboveground carbon biomass. For this, I rely on high-resolution (30-meter) spatial data of Aboveground Live Woody Biomass (AGB), measured in megagrams per hectare for the year 2000. This data was developed by Harris et al. (2021), based on the methodology developed by Baccini et al. (2012). The authors integrate ground-based biomass measurements from over 700,000 sample locations with satellite imagery from Landsat, processed through a machine-learning predictive model.

Finally, I convert the biomass weight provided in the dataset to the potential of CO2 release, accounting for the molecular weight of carbon dioxide, following Araujo, Costa, and Sant'Anna (2020). To convert aboveground biomass to potential CO2 release, I first divide the weight by 2 to estimate the carbon content, as biomass is roughly 50% carbon. Then, I multiply this carbon content by the ratio of the molecular weights of CO2 (44) to carbon (12), which converts the carbon content into the equivalent amount of carbon dioxide. This conversion enables direct comparison with international estimations of the social cost of carbon.

H.6 Weather controls

For weather controls, I utilize data from the *TerraClimate* dataset, which offers global high-resolution monthly climate and water balance data (Abatzoglou et al., 2018). TerraClimate integrates climatological normals with time-varying data to produce comprehensive monthly estimates. I include data on minimum, mean, and maximum temperatures, as well as the Palmer Drought Severity Index (PDSI), a standardized measure of long-term moisture availability that accounts for precipitation, evapotranspiration, and soil water balance. The PDSI is particularly relevant for its impact on pasture quality, as it reflects the availability of water for plant growth, with drought conditions leading to reduced forage productivity and quality.

H.7 Transportation cost and market access

To control for the effects of transportation infrastructure on deforestation, I use quality-adjusted transportation cost estimates and a measure of market access to other regions (Araujo; Assunção; Bragança, 2023; Araujo; Costa; Sant'Anna, 2024). These metrics are based on detailed geographical data on roads, waterways, railways, and ports. They estimate the cost of transporting goods to international markets and quantify a municipality's connectivity to other regions. The market access measure is derived from an inter-regional trade model that incorporates population distribution and trade elasticity.

H.8 Pasture suitability

To account for biophysical factors influencing agricultural productivity, I use a pasture suitability index developed by the *Food and Agriculture Organizations (FAO) Global Agro-Ecological Zones project* (Velthuizen et al., 2007). This index integrates multiple dimensions of climate, soil, and terrain characteristics to estimate attainable productivity for pasture, providing a score from 0 to 10000. The climate factors include thermal conditions, the length of the growing period, climate variability, and limitations such as cold temperatures or insufficient moisture. Soil characteristics, such as depth, type, and quality, are also considered, along with terrain features like slope. With it, I can control for several environmental determinants of pasture productivity at once.