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How Do Climate Adaptation Policies Affect Production and Environmental Outcomes? Evidence from a Water Policy

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Where is the Beef? Supply Chains and Carbon Emissions in the Amazon

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Abstract

Deforestation emissions have global consequences. I develop an empirical framework to study the supply chains driving those emissions, with a focus on how heterogeneous agricultural processing firms organize their production across space. Focusing on the Amazon's beef industry, I show that intermediary monopsony creates substantial misallocation, diverting production away from the most productive firms and the lowest-emitting regions. Exporter-targeted policies can exacerbate these distortions by shifting output toward less productive, informal firms operating in high-emission areas. Alternative policies that better account for equilibrium responses in firm entry and sourcing can reduce abatement costs by an order of magnitude.

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1 Introduction:

Deforestation is a major global policy concern. In addition to threatening biodiversity (Ferreira et al., 2018) and disrupting rainfall patterns (Araujo et al., 2023), it generates up to 20% of global greenhouse gas emissions (Asner, 2009). But regulating those emissions directly is difficult, as approaches like carbon taxes or direct enforcement require monitoring vast remote territories (Burgess et al., 2019). Since the majority of deforestation is embedded in commodity supply chains, recent policy proposals shift regulation towards the firms that buy from polluting farmers. These indirect approaches could overcome feasibility concerns by targeting the relatively few exporters (e.g. tariffs) or agricultural processing firms (e.g. sustainability standards).[1] Can supply-chain approaches efficiently reduce emissions?

This paper examines how firm heterogeneity and market power in agricultural supply chains shape the welfare effects of environmental policy. I develop a quantitative spatial model, estimated for the cattle supply chain in the Brazilian Amazon, to analyze how policy interventions reshape supply chains by altering the entry and sourcing decisions of agricultural intermediaries. I focus on how equilibrium responses to policy can interact with pre-existing distortions like market power, and potentially drive misallocation as inputs shift across firms of varying productivity.

The cattle industry is central to the global climate challenge: pasture expansion is the leading driver of deforestation worldwide (WRI, 2022), responsible for 90% of recent forest loss in the Brazilian Amazon. As forests are cleared, the carbon stored in biomass is released through fire and decomposition (Soto-Navarro et al., 2020). My study region—larger than the European Union and nearly two-thirds the size of the contiguous United States—features substantial variation in forest carbon stocks. This spatial heterogeneity means the carbon intensity of cattle production differs sharply across municipalities, with the highest emissions coming from remote areas where forests are naturally denser.

To study how emissions are shaped by supply chains, I use a detailed phytosanitary

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[1] Notable examples include the recent European Union regulation on deforestation-free products (EUDR), the Roundtable on Sustainable Palm Oil, the Soy Moratorium and Cattle Agreements in Brazil (Heilmayr et al., 2020; Alix-Garcia and Gibbs, 2017; Klingler et al., 2018). A similar logic applies to other polluting industries like oil and gas, where emissions occur at upstream stages of production but regulation can be more feasible midstream (Metcalf and Weisbach, 2009).

dataset that traces cattle flows from ranchers to meatpacking intermediaries. I focus on two key forms of heterogeneity: export status and sourcing location. Export-authorized meatpackers are larger and tend to cluster near major ports and population centers, creating cattle markets that are concentrated and dominated by a few large players. By contrast, remote areas are served by many small meatpackers, often operating in the informal sector. This spatial variation in market structure affects the degree of intermediary monopsony: meatpackers can extract markdowns on cattle prices depending on local competition. I use the structural model to estimate these markdowns.[2] My setting contributes to a growing literature on monopsony in agriculture (Chatterjee, 2023; Bergquist and Dinerstein, 2020; Rubens, 2023; Kochhar and Song, 2024), but drawing attention to an important nuance: remote regions are *more* competitive. This is due to the presence of small domestic and informal firms, which are often omitted in administrative datasets such as tax (e.g., Zavala (2023)) or customs records (e.g., Dominguez-Iino (2023)).[3]

The structural model captures how meatpackers choose where to operate and source cattle, leading to spatial clustering by export status. I build on recent models of monopsony in agriculture, extending them to incorporate heterogeneous firms and endogenous entry. In each geographic market, meatpackers decide whether to enter and how much cattle to source, competing in an oligopsonistic (Cournot) environment. Entry here resembles the sequential frameworks in Bresnahan and Reiss (1991) and Berry (1992) that guarantee equilibrium uniqueness, with the key distinction that my model allows firms to differ in *both* productivity and entry costs.[4] Meatpacker sourcing decisions also depend on the responsiveness of local cattle supply, which I estimate through a land-use model. In this framework, atomistic landholders observe commodity prices and decide how to allocate land. The model includes switching costs to reflect frictions in land conversion, drawing on features common in fully

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[2] Reduced-form evidence also supports the presence of monopsony power: demand shocks to meatpackers pass through differently to ranchers depending on market concentration.

[3] Dominguez-Iino (2023) analyzes monopsony and environmental policy using export data, which omits domestic and informal firms. My more focused regional scope and access to rich data allow me to capture these firms, which make remote regions *less* concentrated. This leads me to estimate a different geographic pattern of agricultural monopsony, with divergent policy implications. Unlike their setting, I also find no strong regional differences in supply elasticities.

[4] Heterogeneity along two dimensions makes it such that the ranking of firms by profitability is not invariant to the set of entrants in a market. This raises challenges for equilibrium selection and how one can recover it in an empirical application. See Section 3.2.2 of the paper and online appendix B.3.

dynamic frameworks (Hsiao, 2023; Araujo, Costa, and Sant'Anna, 2020; Scott, 2012), while retaining the tractability of a static structure (Souza-Rodrigues, 2019) that accommodates limited price data for Brazil. The main estimation focuses on the period from 2015 to 2019, using high-resolution land use data and newly assembled records on land tenure.

Estimates from the model allow me to quantify how monopsony power varies across space, as well as its impacts on allocative efficiency and emissions. More productive firms typically possess greater market power (Melitz and Ottaviano, 2008; De Loecker and Warzynski, 2012), and in my setting, spatial clustering augments this relationship. Export-authorized firms are more productive but face higher entry costs. In contrast, domestic-only firms are less productive but can enter more easily, allowing them to populate remote areas in high numbers. This leads to a tradeoff: while greater competition benefits ranchers in remote areas, it increases misallocation by shifting production to the least efficient meatpackers. Furthermore, because remote regions have more carbon-dense forests, increased competition shifts production toward higher-emission zones. This effect is substantial, raising emissions by 11.6% relative to a benchmark scenario with spatially homogeneous monopsony markdowns. In short, competition in remote areas alleviates spatial frictions due to remoteness, but creates distortions by reallocating production to the most emission-intensive parts of the Amazon and the least efficient firms.

Environmental policy can generate unintended consequences—here, by exacerbating distortions already present in the spatial distribution of meatpacker monopsony. I use counterfactual simulations to compare different policy designs, focusing in particular on export-authorized firms, which are the target of many recent proposals. In one scenario, I impose a tax on all output produced by export-authorized meatpackers, regardless of its final destination. I compare this to a comprehensive tax applied to all firms. Although exporters account for three-quarters of total output, the exporter-only tax achieves less than one-fifth of the emissions reductions produced by the comprehensive tax, while reducing beef production by 48% more. Abatement costs are over ten times higher, largely due to shifts in entry and sourcing across space. Entry by export-authorized firms falls by 27.5%, reducing average productivity by 8.6%. As a result, small and informal firms expand, partly reallocating production toward remote regions where emissions are higher due to the greater carbon content of forest biomass.

As an alternative, I examine a policy that raises entry barriers for domestic-only and informal meatpackers. This intervention increases market concentration in remote regions, reallocating production toward higher-productivity firms and areas with lower carbon intensity. On account of this reallocation, the policy raises welfare even before considering environmental benefits. It increases both beef output and firm profits, while reducing emissions by 14%.

My analysis implies an even starker result than the recent literature, which finds that international pressure to reduce land use emissions is undermined without coordination across countries (Hsiao, 2023; Dominguez-Iino, 2023). Even fully-coordinated policies – even those that include domestic output from export-authorized firms – can be ineffective and distortionary because of how the supply chain reorganizes. This adds a supply chain perspective to a growing literature on deforestation, which has primarily studied the successes and failures of different enforcement policies using reduced-form tools (Assunção, Gandour, and Rocha, 2015; Moffette, Skidmore, and Gibbs, 2021; Burgess, Costa, and Olken, 2019; Pfaff, 1999; Assunção, Gandour, and Rocha, 2013; Assunção, Gandour, Rocha, and Rocha, 2020; Skidmore, Moffette, Rausch, Christie, Munger, and Gibbs, 2021; Bragança and Dahis, 2022). Other work has used structural approaches (Souza-Rodrigues, 2019; Araujo et al., 2020; Araujo, 2023; Hsiao, 2023), but mostly abstracting away from supply chains, with Dominguez-Iino (2023) as a notable exception. The key distinction of my approach is the inclusion of firm heterogeneity and endogenous entry, which are crucial for my policy conclusions. In the same way that openness to trade drives welfare gains through reallocations across firms (Melitz, 2003; Melitz and Redding, 2015), exclusively burdening exporting firms can have the opposite effect, substantially raising abatement costs. Indirect regulation through supply chains can be effective, but only when it contemplates small and informal firms. This rules out broad tools like tariffs, but creates a role for international incentives for more targeted domestic policies (see e.g. Harstad (2022)).

More broadly, the framework I develop helps understand industry responses to environmental regulation when firms are heterogeneous and competition is imperfect (Fowlie, Reguant, and Ryan, 2016; Preonas, 2023; Asker, Collard-Wexler, De Canniere, De Loecker, and Knittel, 2024). Policy that ignores these features can be distortionary not just because of the presence of market power (e.g. Buchanan (1969)), but because of its *differences* across markets and firms. In my setting, meatpacker monopsony is most severe for the most productive firms in the cleanest regions,[5] and some policies can add to those distortions. Conversely, targeted environmental policies can also help address allocative inefficiencies, adding to their welfare benefits. In this sense, this paper echoes contemporaneous work in macroeconomics that finds a negative correlation between firm revenue productivity and fossil fuel use (Klenow, Pastén, and Ruane, 2024; Kim, 2023), suggesting a role for unilateral decarbonization as a means to improve allocative efficiency.

2 Stylized facts

There is a great deal of geographic variability in Brazil's Legal Amazon both in terms of (i) the carbon intensity of land use and (ii) the meatpacking firms operating cattle supply chains. Indeed, the interaction between the geography of cattle production and the geography of carbon emissions is an essential element of the analysis that follows. Thus, I first describe the basic geographic set-up of carbon emissions and cattle production. Specifically, I discuss this variation in terms of remoteness defined as the distance to São Paulo. São Paulo is the key economic hub of Brazil's South-Southeast, the region which concentrates Brazil's largest cities and port infrastructure. Nearly all (99%) exports of beef coming from the Amazon go through ports in the South-Southeast.

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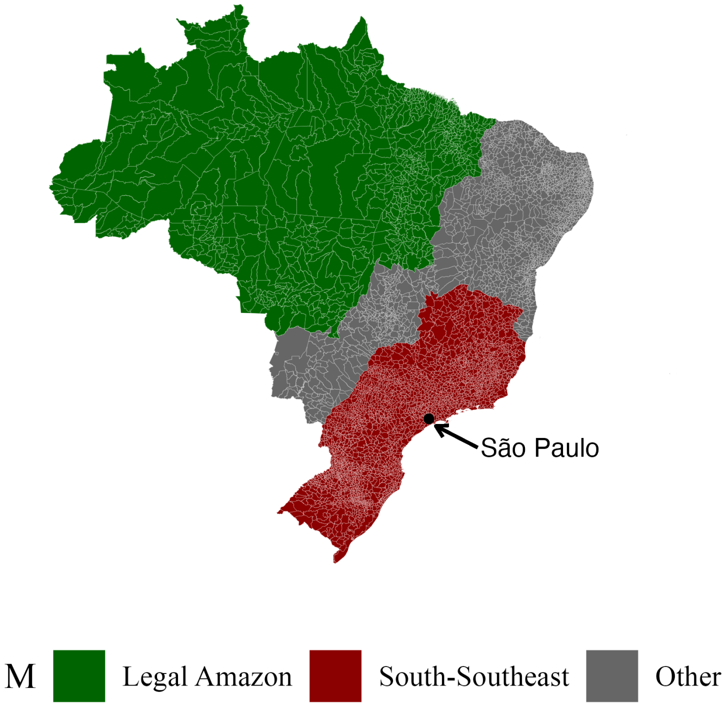
[5] Asker, Collard-Wexler, De Canniere, De Loecker, and Knittel (2024) show a similar pattern in oil extraction. OPEC market power drives environmental benefits through reduced production (volume-effect), but shifts the composition of oil extracted towards higher-cost and higher-emission varieties. Relative to this setting, my work also shows how some environmental policies can aggravate the adverse compositional effects of market power.

Figure 1: Brazil - High-carbon forests in the North, consumer markets and ports in South-Southeast

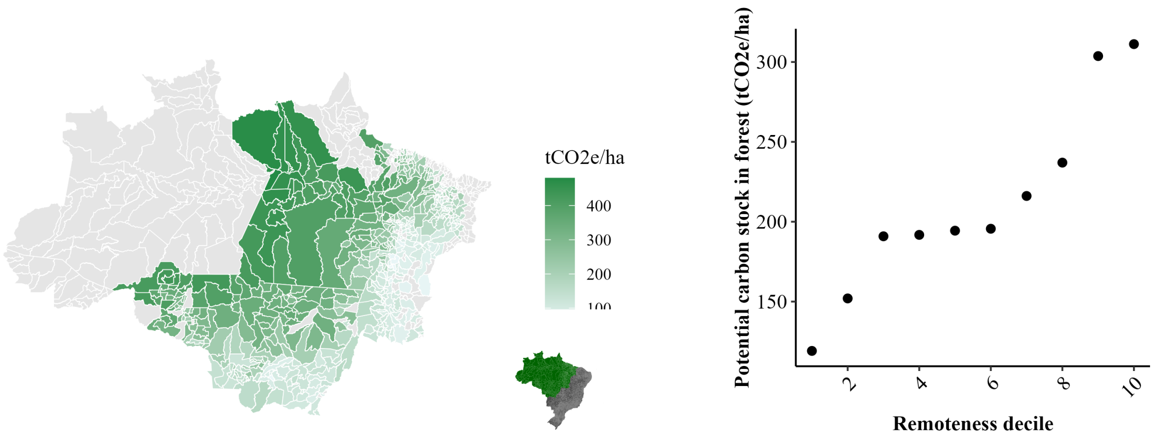


2.1 The geography of carbon in the Amazon:

In the Amazon, agricultural emissions come primarily from the displacement of forests with pasture for cattle. Forests are a natural carbon capture technology. Trees perform photosynthesis and build up their biomass (wood, branches, and roots), which contains large amounts of carbon. When ranchers clear the forest to grow pasture, these carbon stocks are quickly released through fire and decomposition. Pasture itself holds some carbon, but in most places less than a tenth of what natural forest can store.

As Figure (2) shows, forest in the Amazon is not homogeneous and varies greatly in its potential carbon stocks. This is due to natural factors, with higher humidity near the equator driving different tree species and tree density. The sheer size of the region, larger than the European Union, naturally creates a great deal of spatial heterogeneity. As it moves south, the forest begins transitioning to the Cerrado, Brazil's savannah biome whose natural vegetation holds less carbon. Figure 2 shows averages of carbon stocks in primary (old-growth) forests by municipality. Forest carbon stocks (averaged by municipality) range from 28.5 to 480.5 tCO2e/ha in my sample. Forests in remote regions (those far from São Paulo) have a much greater carbon storage potential, as panel (b) of Figure 2 shows.

Figure 2: Remote forests have greater carbon storage potential



(a) Carbon stocks in old-growth forests (tCO2e/ha)

(b) Stocks by deciles of distance to São Paulo

Other emissions sources (e.g. animal methane) also play a role, but are quantitatively overwhelmed by forest loss. Still, they all follow a similar remoteness gradient, only compounding the environmental impact of cattle ranching in more remote regions. Remote regions emit more animal methane in the animal lifecycle. Remote regions have lower yields in terms of heads per hectare, so cattle ranching both emits more and leads to lower economic returns (per-hectare). In my quantitative exercises, I track all relevant sources of emissions.[6]

Beyond its strictly environmental impacts, the expansion of agriculture in the Amazon also threatens the traditional ways of life of indigenous populations and other subsistence communities. To better illustrate this,[7] I collect various sources of land tenure information

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[6] The appendix describes the sources I use for carbon emissions calculations, and the online appendix (A.3) discusses different emissions sources further.

[7] I cannot fully account for the welfare of subsistence and indigenous communities in my empirical framework, but the data I collect on land tenure allow me to predict the impacts of policy on land use in different regions and tenure classes. The counterfactual exercises account for how different tenure classes are affected by policy, and online appendix A.4 discusses the land tenure data in more detail.

to build a dataset that distinguishes private from public land. These more vulnerable populations live on public land, which is generally in more remote areas: 68% of land is public in the most remote decile, compared to 10% in the least remote. Although I focus on the carbon emissions aspect, this suggests social costs from the expansion of commodity production in more remote areas beyond carbon (e.g. conflict).

2.2 The geography of the beef cattle supply chain:

Like many sectors, the cattle supply chain depends on intermediaries to process output and distribute it to consumer markets. In Brazil, ranchers sell cattle to meatpackers, which process the animals into beef products for domestic and international sale. Meatpackers differ in the markets they can access, with the largest being federally inspected (SIF) firms, which I henceforth refer to as **export-authorized** meatpackers. Other firms, including those in the informal sector, will be referred to as **domestic-only** meatpackers.

Brazil's stringent phytosanitary regulations provide remarkably detailed data on cattle sourcing. Ranchers are required to file a record for every herd movement, including sales to meatpackers.[8] The crucial aspect of these data is that they serve health-related purposes, such as tracking animal vaccinations and the spread of disease. There are high stakes involved – contaminated meat can lead to death, and an outbreak of mad cow or foot-and-mouth disease can lead to immediate sales bans for entire regions. This creates incentives for local authorities to enforce this regulation for all suppliers regardless of size. Furthermore, there are no environmental policies tied to these records that could drive systematic underreporting. Ranchers and meatpackers can issue these records regardless of whether they are environmentally compliant or operate in the formal sector. As a result, this dataset provides a uniquely rich view of agricultural supply chains, including information on firms often missing in typically used datasets, like tax or customs records.

Export-authorized meatpackers tend to source cattle from less remote parts of the Ama-

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[8] Known as "*Guias de Trânsito Animal*" (GTA), these documents include herd size, animal characteristics, and vaccination status. GTA data are generally regarded as reliable sources of information on cattle movements (Klingler et al., 2018; West et al., 2022). In 2017 alone, they track the movement of over 10 million animals to slaughter. The GTA data have been used in other fields (Zu Ermgassen et al., 2020; Skidmore et al., 2021), and recently began to appear in economics (Skidmore, 2023). See online appendix A.1 for more details.

zon, while domestic-only firms operate in more isolated regions (Figure 3, panel a).[9] This spatial divide reflects the costs and risks of transporting cattle. Because most rancher-to-meatpacker transactions occur over short distances, meatpackers locate near their suppliers. Exporters cluster near consumer hubs and the ports that handle 99% of beef exports. Where exporters are absent, domestic-only firms fill the gap. Although they process only 25% of all cattle,[10] domestic-only meatpackers can account for up to 70% of sourcing in remote areas.

This geographic pattern is consistent over time and across data sources. While the comprehensive GTA data I use cover only 2015–2018, other datasets confirm the same trends. For export-authorized meatpackers, data are more widely available,[11] and reveal similar patterns from 2010 to 2020 (Figure 3): exporters are less common in remote regions.

Informality is widespread in this industry, especially in remote areas. In my data, 99% of ranchers operate without formal firm identification. Among meatpackers, 3% are informal in the least remote decile,[12] but 64% are informal in the most remote decile of regions.

High cattle transportation costs lead to localized markets and geographic segmentation. About 75% of rancher-to-meatpacker transactions occur within 250 km, limiting ranchers' options to nearby buyers. This, combined with the geographic sorting of firms by export status, generates differences in market concentration (Figure 4). Export-authorized firms are few and large, creating high concentration where they dominate. Domestic-only firms are numerous and small, so remote areas are *less* concentrated.

While concentration suggests potential market power—where meatpackers pay ranchers below competitive prices—quantifying monopsony markdowns requires a structural model, which I describe in the next section. In Online Appendix B.1, I also use richer price data available for one state to show reduced-form evidence consistent with monopsony,[13] includ-

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[9] To illustrate variation in remoteness: straight-line distances to São Paulo in my sample range from 588 to 1,783 miles—the latter roughly the distance from Boston to Denver or from London to Istanbul.

[10] Export-authorized firms dominate both domestic and export channels. Only 20% of Brazilian beef production is exported, consistent with global food export shares.

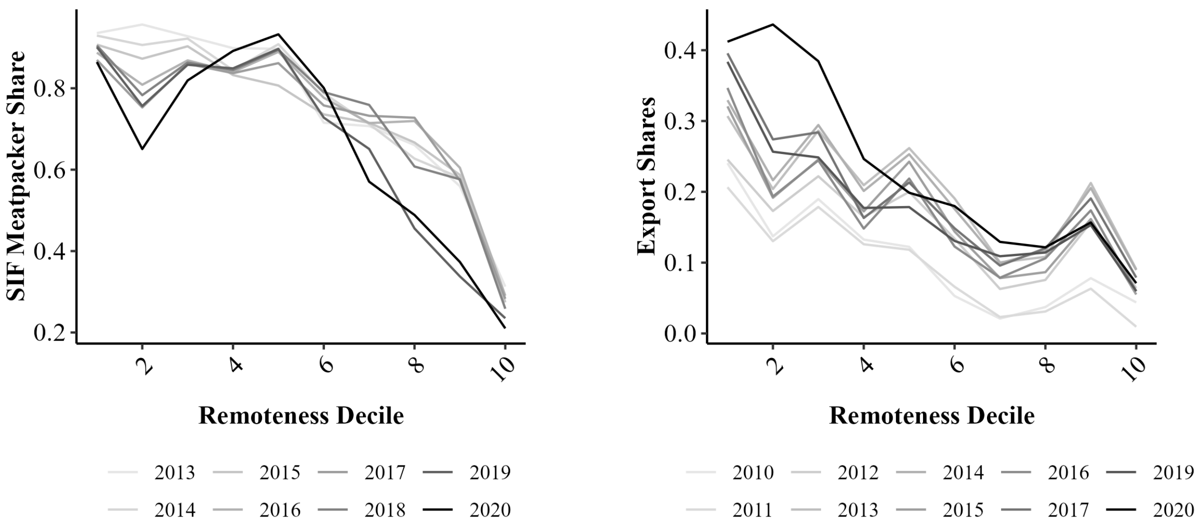
[11] See Online Appendix A.2 for more detail on alternative sources.

[12] I define informal meatpackers as those which operate with a personal tax identification number (CPF) instead of a formal firm tax identification (CNPJ).

[13] A pass-through analysis requires a panel on cattle prices, which is not available for the entire Amazon. For that, in the Online Appendix I describe data different from what are used in the main analysis that provide a full panel for one state. With those, I show how demand shocks face different pass-through rates depending on concentration.

ing the relationship between concentration, cattle prices, and the pass-through of demand shocks. My setting aligns with a growing literature on intermediary monopsony in agriculture (Chatterjee, 2023; Zavala, 2023; Bergquist and Dinerstein, 2020; Rubens, 2023; Kochhar and Song, 2024). The key distinction is that the rich GTA data reveal how *competitive* remote regions can be once informal and small-scale meatpackers are included. In Online Appendix A.1, I show that excluding these firms would substantially overstate concentration in remote areas—highlighting the value of this detailed dataset and potentially explaining divergences from findings in Dominguez-Iino (2023), though our study regions differ.

Figure 3: Export-authorized (SIF) and export shares decrease with remoteness

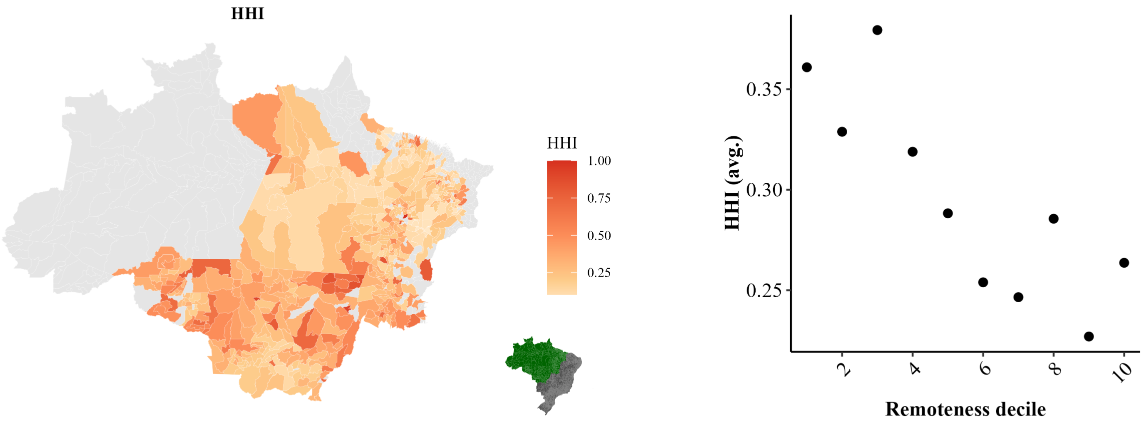


(a) Export-authorized (SIF) meatpacker shares in sourcing

(b) Output share that is exported

Note: Panel (a) shows the share of cattle that is sourced by export-authorized meatpackers for each decile of distance to São Paulo. Not all cattle sourced by export-authorized firms is exported, some of it goes to Brazil's largest cities. Panel (b) shows the share of output sourced by meatpackers that is actually exported. This figure uses datasets different from those I employ for my main analysis. They serve as robustness, and the data online appendix (A.2) describes them at greater detail.

Figure 4: Remote markets are less concentrated



(a) Meatpacker sourcing HHI

(b) HHI by decile of distance to São Paulo

Note: Markets are defined as municipalities, Brazil's lowest administrative unit. HHI is the Herfindahl-Hirschman index, defined by $\sum s_{im}^2$, where s_{im} is the market share of meatpacker i in market m. For reference, a market with 3 players with equal shares would have an HHI of 0.33. On panel (b), HHI values are averaged by decile of distance to Sao Paulo.

Together, these stylized facts point to a correlation between emissions intensity and the spatial organization of the supply chain. The highest-emitting parts of the Amazon are also where the smallest firms operate, in the least concentrated cattle markets. In contrast, large exporters tend to operate in relatively low-emission areas — regions where output is already depressed by meatpacker monopsony, as I show next.

Modelling implications: As the analysis turns to the structural model, it is important to clarify which components of the observed patterns are modeled endogenously and which are taken as given. Meatpacker entry and sourcing decisions along the remoteness gradient are modeled endogenously, shaped by entry barriers and transportation costs. The model also generates predictions for the markdowns charged by different firms and how firm behavior responds to policy. In contrast, the remoteness gradient itself — shaped by the geographic distribution of Brazil's major cities — is treated as exogenous. This makes the analysis specific to the Amazon, a region that is especially relevant due to its size and importance for global climate change. Still, there is reason to believe that the observed relationship between remoteness and carbon density may apply more broadly. In Brazil, dense forest areas historically deterred large-scale agriculture and discouraged colonization, effectively making these high-carbon areas more remote.[14] Similar geographic patterns may be relevant in other tropical forest regions, such as parts of equatorial Africa and Southeast Asia.

A final note before turning to the model concerns data availability. While data on land use and cattle movements are rich and detailed, other key variables are less well-documented. In particular, regional cattle prices are available only as a single cross-section from the 2017 Agricultural Census. The model is therefore designed to leverage the granular movement and land use data to the fullest extent, while remaining estimable with less abundant price information.

3 Structural Model

This model develops an empirical framework to study the variation in production, intermediary monopsony power, and emissions in the Amazon. Three factors are essential for shaping this variation and will be the key objects for estimation: the productivity of different meatpackers, the entry costs these meatpackers face, and the supply elasticities of ranchers which shape monopsony markdowns in equilibrium.[15] Although meatpackers exert monopsony power in cattle sourcing, they are price-takers in the downstream beef market.[16]

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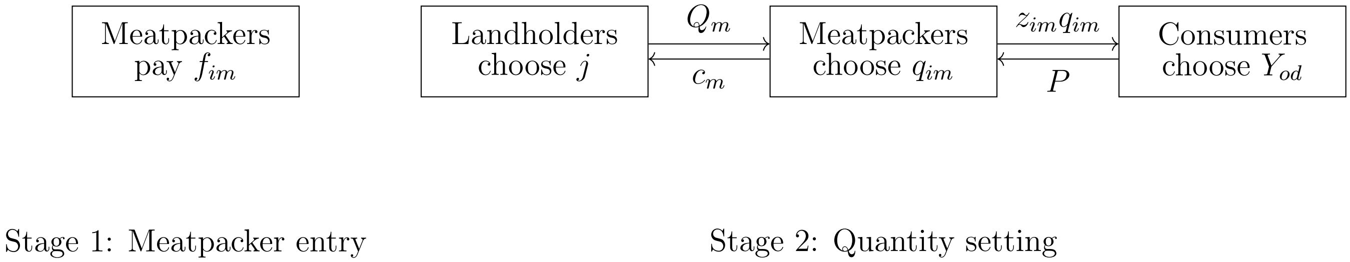
[14] I discuss the region's history in more detail in Online Appendix A.3

[15] The approach I take relies on specifying rancher supply to compute markdowns. There are other approaches, namely through production function estimation (De Loecker and Warzynski, 2012; Rubens, 2023), which can estimate markups/markdowns while making fewer assumptions on the particular game played by firms, although they impose structure on their production technology. I do not rely on such approaches because my analysis focuses on policy counterfactuals, so estimating rancher supply is essential.

[16] Transporting cattle is costlier and riskier than transporting beef. Three quarters of cattle transactions occur within 250 km of a meatpacking plant, while beef is sold nationwide and abroad. Meatpackers face few competitors as buyers but many as sellers.

Figure 5: Model overview



3.1 Landholder problem

I model landholders from a "medium-run" perspective:[17] landholders observe commodity prices and make land use change decisions for a given time period.[18] In the empirics, I focus on the 2015-2019 time frame.

Each municipality m consists of a set of atomistic landholders f, which begin in a land use j_0. They choose a land use $j \in \{\text{Pasture, Crops, Forest}\}$ for the period, which can be different from j_0, to maximize:

$$\pi_{fm}(j, j_0, \nu_{fj}) = \alpha_0(j, j_0) + \alpha_R R_{jm} + \xi_{j,j_0m} + \nu_{fjm} \tag{1}$$

where R_j is an observable measure of returns for land use j, ξ_{j,j_0m} is a market-level unobservable return, ν_{fjm} an idiosyncratic preference shifter. State-dependence comes from $\alpha_0(j, j_0)$, which depends on j_0 and can capture, for example, the ("switching") costs of transitioning from forest to pasture.

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[17] I use "landholder" rather than "landowner" to reflect the prevalence of property rights issues in the Amazon. Estimation is done separately for different land tenure classes.

[18] This one-time transition formulation accommodates the limitation of having only a single cross-section of prices for this period. It takes advantage of the rich land use data by allowing for switching costs, which are important in fully dynamic models (Scott, 2012), while retaining the one-time nature of static approaches. Other work (Araujo et al., 2020) deals with this limitation by constructing a panel of market returns that take time-series prices at ports and adjust them with transportation costs. This approach assumes no intermediation or requires a perfectly competitive intermediary, which is not the case in my model. In the online appendix (C.1), I explore alternative modeling approaches and find similar supply elasticity patterns.

Agricultural returns are a function of output prices c_{jm} and yields a_{jm}:

$$R_{jm} = \begin{cases} 0 & \text{if } j = \text{ forest} \\ a_{jm}\, c_{jm} & \text{for cattle or crops.} \end{cases} \tag{2}$$

Since I do not observe prices for goods (if any) resulting from forest activities, I set those to 0. As a result, the private costs and benefits of holding forest are absorbed by term $\alpha_0(j, j_0)$.

I assume that idiosyncratic shock ν_{fj} follows a Type-1 (Gumbel) extreme value distribution, which yields a closed-form solution for conditional choice probabilities:

$$\rho_m(j, j_0) = \frac{\exp\left(\alpha_0(j, j_0) + \alpha_R R_{jm} + \xi_{j,j_0m}\right)}{\sum_{j' \in J} \exp\left(\alpha_0(j', j_0) + \alpha_R R_{j'm} + \xi_{j'j_0m}\right)} \tag{3}$$

Equation 3 relates observed land use change decisions (from any starting use j_0 to j) to the observed yield-adjusted returns to using the land for j. The parameter governing this relationship (α_R) and the preference shifters (α_0) will be estimated. Output (for cattle or crops) in municipality m is equal to the total acreage in use j times the yield:[19]

$$Q_{jm} = a_{jm}\, L_m \sum_{j_0} \rho_{j_0m}\, \rho_m(j, j_0)$$

where L_m is the total area of m and ρ_{j_0m} is the share of that area initially in use j_0.

Another useful property of this model is the elasticity of supply with respect to prices:

$$\frac{\partial Q_{jm}}{\partial c_{jm}} \frac{c_{jm}}{Q_{jm}} = \alpha_R \sum_{j_0} \rho_m(j, j_0)\, \rho_{j_0m}(1 - \rho_m(j, j_0)) \frac{R_{jm}}{\rho_{jm}} \tag{4}$$

where ρ_{j_0m} denotes the land share of use j in the beginning of the period, and ρ_{jm} at the end, both of which are observable. This expression is the bridge between the land use and meatpacker parts of the model – meatpackers consider cattle supply responses in making their quantity decisions.

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[19] For cattle, it is how much cattle carcass weight-equivalent output is created per unit of pastureland times the total pasture acreage.

3.2 Meatpacker Problem

Meatpackers i are the intermediaries in the industry, purchasing cattle from ranchers in municipality m and selling beef to different consumer markets. The model proceeds in two stages. First, potential entrants in each municipality decide whether to enter and source cattle in m. In the second stage, entrants play a static Cournot oligopsony game, strategically choosing their quantity (q_{im}). This stage occurs simultaneously with the other parts (land use and demand) of the model.

Meatpackers are heterogeneous in their **productivity** (z_{im}) and **entry costs** (f_{im}) they face. Productivity z_{im} captures both a quantity dimension (how efficiently a meatpacker converts cattle into beef) and a quality dimension (higher-quality beef being effectively valued as more beef). Regional variation in z_{im} reflects different transportation costs and quality.[20]

Meatpacker profits are given by:

$$\pi_{im} = (Pz_{im} - c_m)\, q_{im} - f_{im} \tag{5}$$

where P denotes the (output) price meatpackers receive per unit of beef, and c_m is the (input) price they pay ranchers for a unit of cattle.

3.2.1 Second stage - Cournot:

For expositional clarity, I begin by discussing the second stage of the game. Conditional on entering a market, meatpackers make simultaneous quantity choices q_{im} to maximize:

$$\max_{q_{im}} \{ \Bigg(Pz_{im} - c_m \Bigg) * q_{im} \} \tag{6}$$

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[20] This is isomorphic to a specification where $z_{im} = z_i \tau_m^{-1}$, with an "iceberg" transportation cost reflecting the costs of transporting beef to consumer markets in refrigerated trucks. As discussed in the next section, estimation will flexibly account for differences in z across space.

Taking first-order conditions and solving for the equilibrium cattle price c_m yields:

$$c_m = P z_{im} \Bigg(\underbrace{\frac{\partial c_m}{\partial Q_m} \frac{Q_m}{c_m} s_{im} + 1}_{\mu_{im}} \Bigg)^{-1} \tag{7}$$

where $s_{im} = \frac{q_{im}}{Q_m}$ is meatpacker i's market share in m. In equilibrium, the cattle price in m reflects a **markdown** μ_{im} on the meatpacker's earnings per unit of cattle. These markdowns increase (and prices decrease) with the inverse elasticity of municipal cattle supply.

3.2.2 Entry stage:

Each municipality m has a set of potential entrants M_m. Meatpackers make independent entry decisions based on complete information—they observe each other's productivity and entry costs. The equilibrium set of entrants I_m satisfies two conditions: (1) no active firm earns negative profits, and (2) no inactive firm could profitably deviate by entering. Formally, equilibrium entry satisfies:

$$\begin{aligned} \pi_{im}(c_m(I_m)) &\geq 0 \qquad \forall i \in I_m \\ \pi_{i'm}(c_m(I_m \cup \{i'\})) &< 0 \qquad \forall i' \notin I_m. \end{aligned}$$

The revealed-preference conditions described above identify a set of equilibria in which no profitable deviations occur, but they do not guarantee uniqueness. This is a well-known challenge in the empirical analysis of entry games with complete information (Bresnahan and Reiss, 1991). When firms are homogeneous, one can abstract away from firm identity and focus on the number of entrants; however, firm heterogeneity—as in my setting—makes equilibrium selection non-trivial.

To address this, I introduce a sequential entry structure that ensures uniqueness. Specifically, I assume that firms make entry decisions one at a time, in a fixed order determined by productivity (z_{im}). The most productive firm in a given municipality decides first whether to enter, taking into account the profits it would earn if it were to do so alone. If it enters, the second-most productive firm then evaluates whether it wants to enter, given the first firm's decision, and so on.

Formally, firms are ranked by $t \in \{1, ..., M_m\}$, such that:

$$z_{tm} \geq z_{t'm} \quad \forall t < t'$$

This approach builds on the sequential-move frameworks of Berry (1992), Mazzeo (2002), and Toivanen and Waterson (2005). However, there is a key difference in my setting: firms differ not only in productivity but also in fixed entry costs, which may vary across regions and by firm type. As a result, the ranking by profitability does not necessarily align with the ranking by productivity. A less productive firm may choose to enter instead of a more productive one if its entry costs are sufficiently lower.

This has implications for how I solve and estimate the model. Sequential entry here favors higher-productivity firms, but does not necessarily preclude lower-productivity firms if their entry costs are low. Formally, my sequential mechanism selects the equilibrium set of entrants I_m^* which, for any distinct possible equilibrium set I_m', the following is true about their relative complements:

$$\min\{t \in I_m^* \setminus I_m'\} < \min\{t \in I_m' \setminus I_m^*\} \tag{8}$$

The condition outlined in (8) poses that if we are comparing distinct equilibria, the highest-ranked firm in I_m^* but not in I_m' must be of a higher rank (lower t) than the highest-ranked firm in I_m' that is not in I_m^*. It ensures that, if multiple equilibria are possible, it picks the equilibrium with the highest-ranked firm that is not in both sets. To provide further intuition, consider a simple example with only two types of firms in a market: exporters (type E) and domestic-only (type D). Within a type, all firms have the same productivity and entry costs, and exporting firms are more productive ($z^E > z^D$). In online appendix B.3, I show that under these conditions the selection mechanism maximizes the number of exporters N^E that enter the market among possible equilibria. In this sense, it is similar to Jia (2008), favoring one type of firm.

The estimation section describes the algorithm I use to implement the equilibrium selection rule defined by (8), including extensions to accommodate heterogeneity among exporters. While the sequential entry assumption is inherently untestable, it reflects salient features of the industry: larger, more productive meatpackers have substantial influence, often reinforced by political connections. The algorithm also allows for alternative orderings as robustness checks, which yield similar spatial patterns of entry.[21]

The main advantage of this approach is computational tractability. My full model includes supply, cattle sourcing, and demand, all of which must be solved jointly. Especially in policy counterfactuals, this becomes computationally demanding. Methods that allow for multiple equilibria—such as through partial identification (e.g., Ciliberto and Tamer (2009)) – or those that achieve uniqueness through private information (e.g., Seim (2006)) would be infeasible given the number of potential entrants (up to 44 per market).[22] The sequential structure offers a middle ground: it accommodates firm heterogeneity in both productivity and entry costs, while preserving the feasibility of solving the full equilibrium and conducting counterfactual analysis. This tractability is important for making predictions about how market structure, prices, and emissions respond to policy interventions.

3.3 Demand:

Meatpackers sell beef in Brazil and abroad. Consider a world economy comprised of countries $d \in \mathcal{D}$. In each country, a representative agent has quasilinear preferences across beef products and a freely-traded outside good:

$$\mathcal{U}_d = \mathcal{Y}_d^0 + \beta_d \ln \mathcal{Y}_d$$

The beef consumption aggregate depends on beef consumption from each origin country

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[21] See online appendix B.3 for the robustness check, and also a discussion of alternative approaches in more detail.

[22] Private information approaches are also highly sensitive to the assumed number of potential entrants (Grieco, 2014).

o.[23]

$$\mathcal{Y}_d = \left[\sum_{o \in \mathcal{O}} \left(\beta_{od}\right)^{1/\sigma} \left(Y_{od}\right)^{(\sigma-1)/\sigma} \right]^{\sigma/(\sigma-1)}$$

In equilibrium, utility maximization delivers d's demand for beef from origin o:

$$Y_{od} = \beta_d \frac{\beta_{od} \left(P_o T_{od}\right)^{-\sigma}}{\sum_{o' \in \mathcal{D}} \beta_{o'd} \left(P_{o'} T_{o'd}\right)^{1-\sigma}} \tag{9}$$

where T_{od} is the (iceberg) trade cost of delivering beef from origin o to d.[24]

This specification assumes one price P_o for all the beef sold from Brazil, regardless of which firm sells it. This could be an issue if exporters only sold abroad, but in fact export-authorized meatpackers also provide the majority of beef sold domestically. As a robustness check, in Online Appendix B.4 I also present my policy analysis treating Brazilian beef as two separate varieties, one from exporters and the other from domestic-only firms, and find similar results.

3.4 Closing the model:

Market Clearing in the Amazon: Market clearing requires that all cattle sourced by meatpackers (q_{im}) be equal to municipal output Q_m:

$$Q_m = L_m \, a_{jm} \sum_{j_0} \rho_{j_0 m} \, \rho_m(j, j_0) = \sum_i q_{im} \quad \forall m \tag{10}$$

for $j =$ pasture. And once cattle is turned into beef, total beef output by meatpackers is equal to what is consumed:

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[23] This abstracts away from different preferences for different beef within a country. This simplification follows data limitations on domestic beef consumption across different regions of Brazil (and elsewhere) that make estimation of a more detailed model infeasible. To my knowledge, there are no data on beef prices and quantities sold at a disaggregated level within Brazil for the period I study.

[24] The focus on the cattle sector in Brazil requires a simplification on the supply-side in different countries and in the crop sector. In policy counterfactuals, I hold beef prices from other countries constant. Crops (e.g. soy) comprise less than 5% of land cover in my study region, so I simplify their supply chain and demand. For crop land uses, I assume farmers sell directly to a perfectly competitive intermediary at $\bar{c}_m^{\text{crop}} = P^{\text{crop}}(\frac{z_m^{\text{crop}}}{\tau_m^{\text{crop}}}))$. Although Brazil as a whole is an important player in the global market for soy, only a small amount of Amazonian land is devoted to crops, generally soy for export markets. Thus, it is feasible to conceive of the Amazon as wielding little influence on crop markets worldwide.

$$Y = \sum_{i,m} q_{im} \, z_{im} \tag{11}$$

where the subscript $o =$ Brazil is implied.

Equilibrium Given a set of land use parameters α, meatpacker productivities and fixed costs, and beef demand elasticity of substitution σ, an equilibrium is a vector of municipal cattle prices $\mathbf{c_m}$ and beef prices $\mathbf{P_o}$ consistent with equations (3), (7), (9), (10), and (11).

4 Estimation

4.1 Land use parameters:

Remotely-sensed data from Mapbiomas provide land use transitions by municipality $\rho_m(j, j_0)$. Regional prices c_{jm} and yields a_{jm} for both commodities (cattle and crops) come from Brazil's 2017 agricultural census.

Taking log odds-ratios between j and j' pairs from equation (3) generates the following regression:

$$\log\left(\frac{\rho_m(j, j_0)}{\rho_m(j', j_0)}\right) = \Delta\alpha_{0,j,j',j_0} + \alpha_R \Delta R_{j,j',m} + \Delta\xi_{j,j',j_0,m} \tag{12}$$

where Δ denotes a difference, e.g. $\Delta R_{j,j',m} = R_{jm} - R_{j'm}$. $\Delta\xi_{j,j',j_0,m} = \xi_{j,j_0,m} - \xi_{j',j_0,m}$ is an error term. I do not separately identify each $\alpha_0(j, j_0)$, so I work with their relative values.

Identification The regression equation (12) raises concerns related to the endogeneity of market returns $R_{j,j',m}$. For instance, unobserved supply shocks can affect local commodity prices or realized yields, so that $E[\Delta\xi_{j,j',j_0,m} | \Delta R_{j,j',m}] \neq 0$, biasing estimates of α_R.

To address endogeneity, I introduce two sets of instrumental variables. The first set of instruments consists of yield shifters using agroclimactic suitability indices from the FAO-

GAEZ dataset for pasture and soy. Actual yields vary due to different agricultural practices and input usage, but the suitability indices serve as a good exogenous predictor of differences in yields across space.

Second, I use demand shifters. I rely on exogenous changes in import demand g_{dt} in partner countries (excluding Brazil) to build two shift-share instrumental variables (SSIV), one for beef and another for soy. Using the cattle supply chain as an example, ranchers in different regions are exposed to different meatpackers (s_{im}), which in turn export to different countries (s_{id}). Each shift-share instrument is defined as follows:

$$SSIV_m = \sum_{d,i} g_{dt}\, s_{id}\, s_{im}$$

where s_{id} is the share of intermediary i's output which goes to d, s_{im} is i's market share sourcing from m. s_{id} is constructed from customs data, and s_{im} is constructed from data on the production networks of beef and soy. Both share variables are for 2015, the start of the study period.

From the lens of the model, the instruments can be interpreted as shocks to the efficiency z_{im} of intermediaries. In meatpacking, for example, after attaining export authorization in the SIF system, each meatpacker needs country-specific export permits. This creates variation in import partners for each meatpacker, and from the lens of the model those changes at destination countries are shocks to firm productivity z_{im}.

The key identifying assumption is that the country-level shocks are as good as randomly assigned. That is, $E\left[g_d \mid \bar{\xi}_d, s_d\right] = \gamma$, demand shocks in destination countries have the same expected value (γ) regardless of the average exposure shares they face (s_d) or the average supply shocks in the regions most exposed to it ($\bar{\xi}_d$) (Borusyak et al., 2018). Not all beef is exported, which leads to an "incomplete shares" problem.[25] I address this by controlling for the (lagged) share of each region's output that goes to exports (separately for soy and beef), following the recommendations in Borusyak et al. (2024).

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[25] That is, domestic shocks are mechanically 0, creating a different expected value of the shock for places more exposed to the domestic market. Online appendix B.2 maps the distribution of these trade shares and shows that estimates are robust to a version of the instrument in the spirit of Borusyak and Hull (2023), where the instruments are "de-meaned" by their meso-region average.

4.2 Meatpacker parameters:

Estimation for the meatpacking model proceeds in two stages. In the first stage, I invert model-implied meatpacker (revenue) productivities using variation in market shares and municipal cattle prices. These inverted values are then used to estimate the productivities of potential entrants.

4.2.1 Meatpacker productivity:

Rearranging the first order conditions in the model (Equation 7), I invert model-implied Pz_{im} using data on municipal cattle prices,[26] meatpacker market shares, and municipal cattle supply elasticities implied from the estimated land use model (Equation 4):

$$Pz_{im,\text{inv}} = c_m \left(\left(\frac{\alpha_R \, R_{jm}}{\rho_{jm}} \sum_{j_0} \rho_{j_0 m} \, \rho_m(j, j_0) \, (1 - \rho_m(j, j_0)) \right)^{-1} s_{im} + 1 \right) \tag{13}$$

To use these inverted values for estimating the productivity of *potential* entrants, I project them onto municipality and firm characteristics:

$$Pz_{im,\text{inv}} = \mathbf{X'_{im}} \, \alpha \, + \, \xi^z_{im} \tag{14}$$

where X_{im} is a set of firm/location characteristics, including municipality fixed effects, indicators for export-authorization, and a measure of remoteness (log distance to São Paulo) interacted with export status, reflecting the costs these meatpackers face transporting beef to Brazil's largest population centers and ports. I also include an indicator for JBS (interacted with state), the top firm in the industry, to capture their different (higher) productivity. The error term (ξ^z_{im}) captures unobserved sources of meatpacker heterogeneity.[27]

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[26] Note that I identify Pz_{im} jointly. With additional assumptions, it is possible to separate the two, but this is not necessary for estimation. In counterfactual analysis, P adjusts in equilibrium in response to policy.

[27] Here, deviations ξ^z_{im} reflect optimization or measurement error rather than fundamental heterogeneity. One could extend the model by incorporating productivity shocks that meatpackers face post-entry, allowing estimation to include parameters governing the distribution of these shocks. However, doing so would significantly increase computational complexity: counterfactuals would require simulating multiple realizations of these shocks, making computation infeasible given the already high costs of solving for a single equilibrium

4.2.2 Meatpacker entry costs

The second stage of estimation uses the fitted values from (14) as the productivity of potential entrants to then estimate the parameters governing entry costs. Here, entry costs vary according to the export authorization of the firm, denoted by F. Variation in entry decisions for meatpackers of different export status and in different regions is used to reveal the magnitude and variation of fixed entry costs. I parameterize f_m^F as:

$$\log(f_m^F) = \mathbf{X_m'^F}\,\theta + \xi_m^{Ff}$$

where X_m^F is a vector of the following meatpacker-municipality characteristics: the size of the municipality, whether the meatpacker is export-authorized (SIF), log distance to São Paulo (interacted with export status). ξ_{im}^f captures unobserved (to the researcher) factors that shape fixed costs, and is assumed to be orthogonal to X_m^F.[28] I set JBS (the leading firm) as a potential entrant, plus a number M_m^E of export authorized and M_m^D domestic-only potential entrants. M_m^E and M_m^D are chosen to be 2 more than the maximum number of entrants of each kind observed in the state where m is located.[29]

Solution Algorithm For each set of parameters being tested, estimation requires solving the entry margin equilibrium in each municipality. I use the following algorithm.[30] I first begin with the top ranked player as a monopsonist. Then I repeat the following steps until convergence:

1. For each of the meatpackers i currently outside the market, solve for a counterfactual

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that jointly accounts for land use, meatpacking, and demand. That said, the model already incorporates substantial heterogeneity. Exporters (and JBS separately) and non-exporters are allowed to differ systematically across 517 distinct markets. While adding post-entry productivity shocks would introduce additional flexibility, the current structure already allows for differences across firms and locations.

[28] This assumes away potentially interesting correlations in unobservables for the sake of tractability. One possible departure would be allowing for spatially correlated shocks within the same company, potentially reflecting scale economies in setting up a sourcing network across neighboring municipalities. However, a key feature of this market helps mitigate concerns about such interdependencies: meatpackers primarily source cattle from nearby suppliers, with 75% of sourcing occurring within 250 km of the plant. These interdependencies would thus be limited in their geographic scope, but they present an interesting avenue for future work.

[29] M^E ranges between 10-17, M^D ranges between 7-44.

[30] Online Appendix B.4 shows that this algorithm recovers the sequential equilibrium described in the model.

Cournot stage including current entrants plus that i.

2. If there is any profitable i in these scenarios, add the highest-ranked (lowest t) meatpacker that would be profitable and is not in the market.

3. Solve profits for all entrants in this new scenario.

4. If there are any unprofitable i in this scenario, remove the lowest-ranked (highest t) meatpacker that is in the market and is not profitable.

This process continues until there are no changes to the market. Estimation then searches over values of θ to match moments for entry patterns in different regions.

Estimation For a given guess of parameters $\tilde{\theta}$:

1. Derive the entry costs $f_m^F(\tilde{\theta})$ implied by the parameters.

2. Solve the Cournot and entry games. Derive model-implied moments $\hat{g}(\tilde{\theta})$.

3. Define the objective function: $Q(\tilde{\theta}) = \big(g - \hat{g}(\tilde{\theta})\big)' W \big(g - \hat{g}(\tilde{\theta})\big)$.

4. Iterate steps 1–3 over parameter guesses $\tilde{\theta}$, minimizing $Q(\tilde{\theta})$ to obtain the estimate $\hat{\theta}$.

Estimation proceeds in two stages. In the first stage, I use the identity matrix as my set of weights. I then compute the optimal weighting matrix, $W^{opt} = \Omega^{-1}$, where Ω is the variance-covariance matrix of the moments. The second stage uses W^{opt} for estimation. The model is over-identified, with six parameters and 20 moments: the first 10 correspond to the average share of SIF (export-authorized) meatpackers in cattle sourcing for each decile of remoteness (distance to São Paulo), while the remaining 10 correspond to the municipal cattle sourcing Herfindahl index (HHI), also averaged over each remoteness decile.

4.3 Demand:

Here I estimate σ, the elasticity of substitution for beef across different country origins. Taking the log of equation (9) divided by $Y_d = \sum_o Y_{od}$ yields the following equation:

$$\log \frac{Y_{od}}{Y_d} = -\log \sum_{o' \in \mathcal{D}} \beta_{o'd} \left(P_{o'} T_{o'd}\right)^{-\sigma} - \sigma \log P_o T_{od} + \log \beta_{od}$$

Collecting the first term into a destination fixed effect leads to the following regression:

$$\log \frac{Y_{od}}{Y_d} = \alpha_d - \sigma \log P_o T_{od} + \xi_{od}^{\text{Demand}} \tag{15}$$

For Y_{od} I use trade flows in beef products from FAOSTAT. Prices are implied from quantities in dollars over weight. To address potential endogeneity, I supply shifters as instruments, namely rainfall and temperature deviations from the (1960-2000) mean during the pasture growing season in origin countries.

5 Estimation Results

I first discuss coefficient estimates for each part of the model. Then, I connect these different estimates to show how they drive the geographic patterns of entry, productivity, and cattle prices.

Land Use: Table 1 shows estimated coefficients for α_R, the parameter that governs responses to yield-adjusted cattle and crop prices. I run estimation separately for different land tenure categories to account for differences in property rights regimes. To aid interpretation, I also computed the average elasticity of cattle supply implied by the estimates. Elasticity estimates range from 0.14 to 0.33, slightly higher than those of static models for the Amazon (Souza-Rodrigues, 2019; Dominguez-Iino, 2023).

Supply elasticities matter for the responsiveness of land use to prices and for the strategic sourcing decisions of meatpackers. Based on my estimates, two types of places tend to have higher elasticities: (i) remote places with high shares of public land, and (ii) less remote places suitable for soy, which serves as a substitute for cattle ranching. Considering the remoteness gradient, these two effects mostly cancel each other out, as Figure 6 shows.[31] As

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[31] Dominguez-Iino (2023) finds that elasticities in South American agriculture sharply decrease with re-

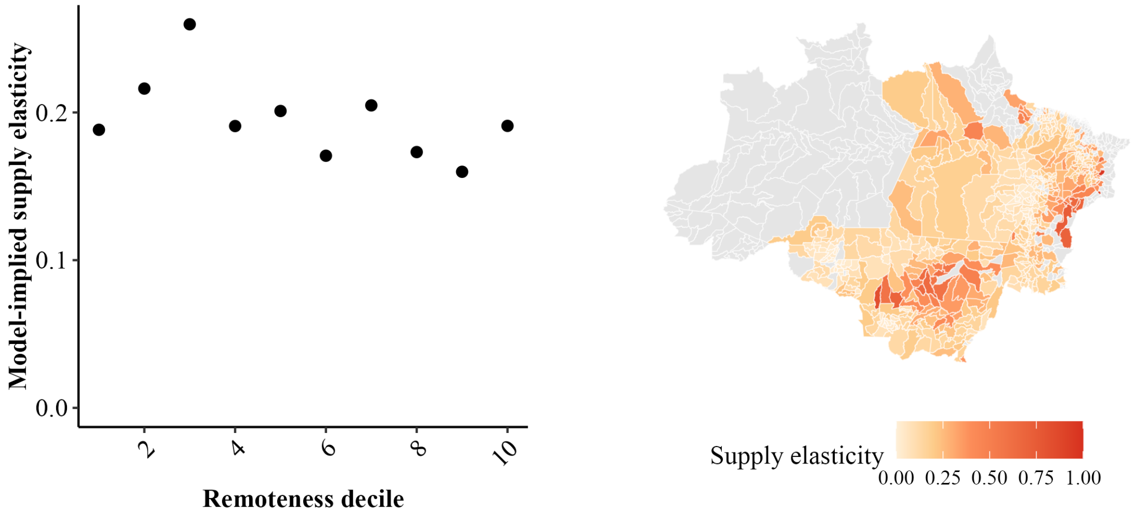
a result, the key drivers of differences in monopsony power across space are the type and number of meatpackers operating, as I show next.

Table 1: Key land use and demand estimation coefficients

	Parameter	Estimate	SE	Elasticity	F Stat
Land Use	$\alpha_{R(PublicDesignated)}$	1.80	(0.23)	0.33	31.9
	$\alpha_{R(PublicUndesignated)}$	1.21	(0.36)	0.14	28.8
	$\alpha_{R(PrivateUndisputed)}$	1.52	(0.29)	0.17	46.7
	$\alpha_{R(PrivateDisputed)}$	1.57	(0.31)	0.19	41.5
Demand	σ	4.44	(0.33)	-	34.8

Note: Land use estimation includes state FE and policy covariates. Conley standard errors reported in parentheses for the land use model. (Arc) Elasticities are computed by simulating the land model with a small increase in cattle prices, then solving for the aggregate increase in pasture area for each tenure category. The online appendix (A.4) provides a discussion and summary statistics for different land tenure classes.

Figure 6: Estimation results - cattle supply elasticities and remoteness



(a) By remoteness decile

(b) Map

Note: Values on the left panel averaged by decile of distance to São Paulo.

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moteness. The differences could be due to the different regions analyzed, or the different datasets used. Ibid. (and Souza-Rodrigues (2019)) uses self-reported census data, whereas I use remotely-sensed land use data (like Araujo et al. (2020)) alongside the land tenure dataset I assembled. Public land plays an important role in driving higher elasticities. The models used are also distinct, and the state-dependence included in my model is known to lead to higher estimated elasticities (Scott, 2012).

Meatpackers: Before turning to the coefficient estimates, it's useful to revisit the structure of the model to clarify how they influence cattle prices and ultimately affect emissions. Summing the firm-level first-order conditions (Eq. 7) across all meatpackers in each m yields:

$$c_m = \frac{\sum Pz_{im}}{N_m} \left(\underbrace{\frac{\partial c_m}{\partial Q_m} \frac{Q_m}{c_m} \frac{1}{N_m} + 1}_{\mu_m} \right)^{-1} \tag{16}$$

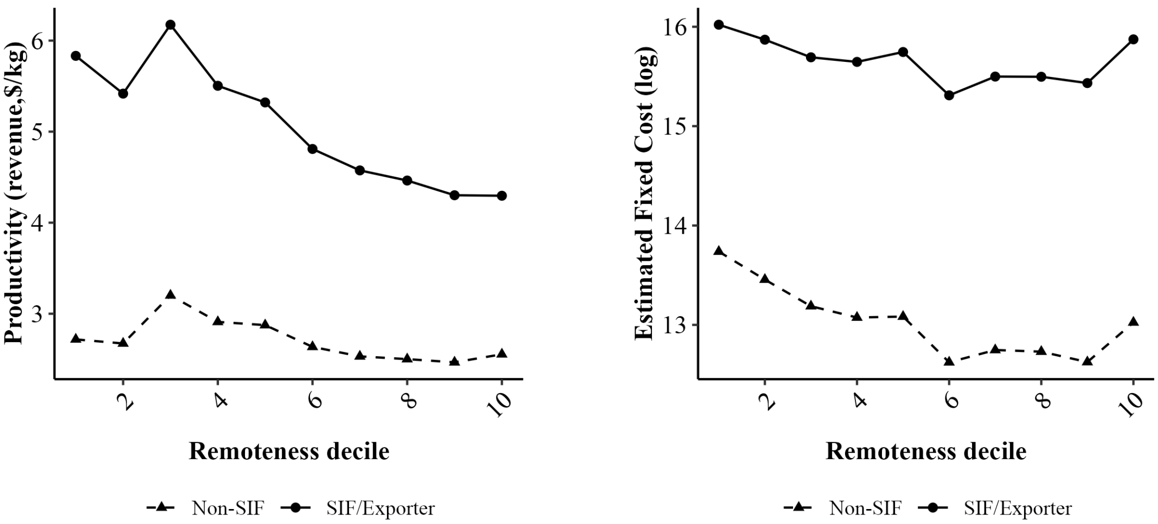
Equation 16 makes clear that the local price of cattle is shaped by three forces: the average marginal revenue product (MRP) of meatpackers ($\frac{\sum Pz_{im}}{N_m}$), the degree of competition (number of entrants N_m), and the supply elasticity of cattle (embedded in the markdown term μ_m). Each of these elements links back to the model's structural parameters: the MRPs are estimated from observed firm-level sourcing decisions, the number of firms N_m comes from entry patterns, and the supply elasticity is informed by the land use model.

Table 2: Coefficient estimates for entry model

	Description	Coefficient	SE
1	Munic. size	1.02	(0.02)
2	SP dist. x Exporter	-0.72	(0.14)
3	SP dist. x Non-exporter	-1.52	(0.55)
4	Exporter	3.96	(0.19)
5	Non-exporter	1.82	(0.24)

Note: "SP dist" refers to the (log of) distance from the municipality to São Paulo as a measure of remoteness. Standard errors (in parentheses) are block-bootstrapped by resampling a new set of municipalities (with replacement), repeated 500 times.

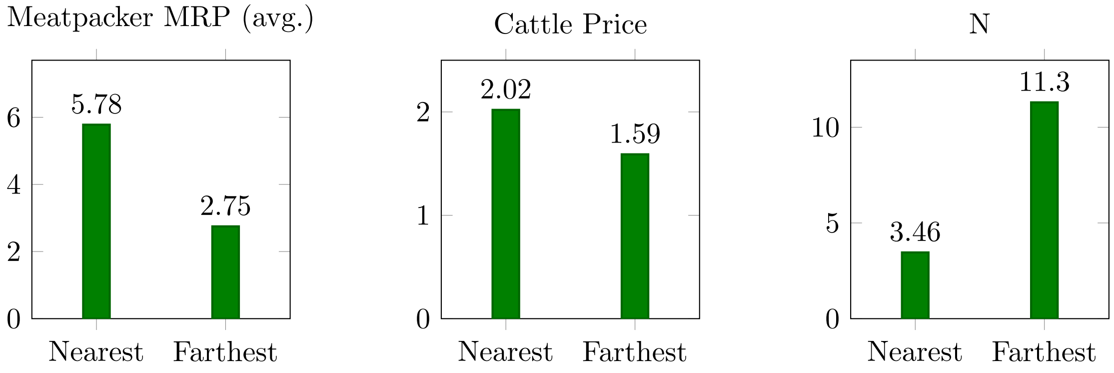
Figure 7: Estimation results - meatpacker marginal revenue products and fixed costs


(a) Estimated MRPs

(b) Estimated fixed costs

Note: Values are averaged by decile of distance to São Paulo. Those values are measured in terms of dollars per kilogram of carcass-weight equivalent.

Figure 8: Key drivers of cattle prices - comparison across remoteness deciles



Note: Values are averaged across municipalities for the nearest and farthest deciles of distance to São Paulo. “Meatpacker MRP” denotes the weighted average revenue productivity of meatpackers (in $/kg CWE), “N” denotes the average number of meatpacker entrants into sourcing in municipalities for a given decile.

Figure 8 breaks down the key sources of variation as implied by the estimates. Meatpackers on average earn 52% less in the most remote decile relative to the least remote. This difference is driven by a combination of two factors. First, remoteness drives down the earnings of exporting meatpackers, with a reduction of 26% across nearest and farthest deciles as shown on the left panel of Figure (7). Second, remote regions sell predominantly to domestic-only meatpackers, which on average earn 41% less than exporters in the most remote decile.

The estimated entry costs shed further light on the geographic segmentation of the supply chain. Entry costs are higher for exporters,[32] which means fewer exporters find it profitable to enter in more distant places as remoteness reduces their margins. Furthermore, fixed costs are lower for non-exporters, and decreasing in remote regions. This opens the market for smaller and less efficient meatpackers to drive high entry rates in remote places.

As a result, whereas average meatpacker MRPs ($\frac{\sum Pz_{im}}{N_m}$) decline with remoteness, entry (N_m) increases. In equilibrium, these two forces push in opposite directions in the cattle price equation. On the one hand, lower MRPs reduce cattle prices. On the other, higher entry partially offsets this by compressing markdowns μ_m. Quantitatively, the decline in meatpacker productivity dominates. As a result, cattle prices fall by 22% between the nearest and farthest deciles. This wedge is substantial for rancher incentives, but notably smaller than the MRP gap.

These spatial patterns in market structure have adverse efficiency and environmental implications. In particular, productivity is lowest—and competition highest—in precisely the places where forest carbon stocks are highest. I quantify this misallocation by simulating a counterfactual scenario that equalizes markdowns μ_m across municipalities, holding aggregate beef output fixed. Relative to the spatially homogeneous markdown benchmark, the observed spatial distribution of monopsony leads to 3.4% lower average productivity and 11.6% higher emissions.[33] In short, the same market frictions that distort production also dampen the price signals that would otherwise steer deforestation toward less carbon-rich

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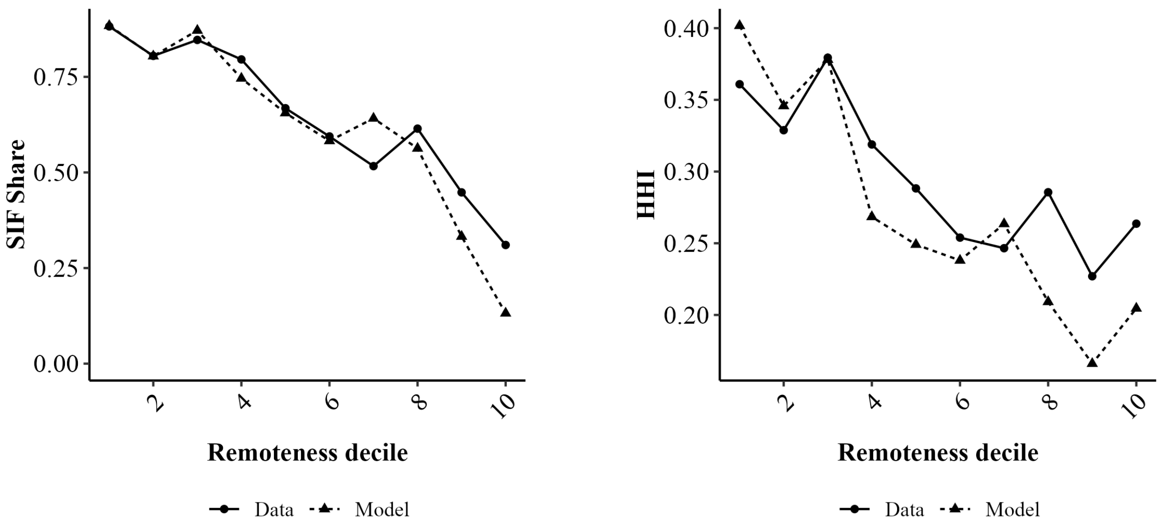
[32] Possible reasons for higher costs for export-authorized meatpackers include the fact that export-driven slaughter operations require trained labor, which is more scarce in remote regions. While I do not model labor in the production function explicitly, labor costs would be absorbed into these fixed costs. In addition, many remote regions face occasional embargoes due to the spread of animal illnesses like foot-and-mouth disease (Bowman, 2016). As for domestic-only meatpackers, individual states and municipalities have the prerogative to set different phytosanitary standards. Remote regions with weaker state presence may have fewer regulatory barriers to entry, which opens the market to many domestic firms and drives up competition.

[33] Note that this exercise changes markdowns only across regions, leaving the set of firms that comprise $\frac{\sum Pz_{im}}{N_m}$ constant. It does not address potential misallocation between firms in the same municipality. The next section fully solves for entry adjustments in response to policy.

regions.

Model fit: The model fits the targeted moments closely. Both export-authorized (SIF) shares and the Herfindahl index are lower in more remote regions, and Figure 9 shows that the model matches those patterns.

Figure 9: Model fit - export-authorized (SIF) meatpacker share and HHI



(a) SIF shares

(b) HHI

Note: Values are averaged by decile of distance to São Paulo.

6 Policy Analysis

This section assesses the welfare effects of several policies to reduce emissions in Amazonian cattle. First I define welfare according to my model and briefly discuss economic mechanisms that shape abatement costs in the theory. Then, using my estimated model I simulate different policies and compare their effects on emissions, beef production, average meatpacker productivity, and welfare.

6.1 From theory to policy:

Welfare in this model (excluding externalities) is given by:[34]

$$W = \underbrace{\left(\sum_m L_m \left(\sum_{j_0} \frac{\rho_{j_0}}{\alpha_R} \ln \left(\sum_j \exp(V_{mj;j_0})\right)\right) + K\right)}_{\text{Landholder Surplus}} + \underbrace{\left(\sum_m \sum_i (Pz_{im} - c_m) q_{im} - f_{im}\right)}_{\text{Meatpacker Profits}} + \underbrace{\sum_d \mathcal{W}_d + \beta_d \ln \mathcal{Y}_d - \mathcal{P}_d \mathcal{Y}_d}_{\text{Consumer Surplus}} \tag{17}$$

Carbon emissions E_m come from many different sources, reflecting all margins for land use change and agricultural activity, with great heterogeneity in emissions intensity for each. This paper considers policies when regulating all these different sources directly is infeasible. Instead, the regulator changes emissions indirectly by changing the *quantity* of cattle produced in different regions. The policymaker observes some function $\tilde{E}_m = b_m(Q_m)$, and shifts emissions indirectly through policies that affect cattle prices in equilibrium and thus change cattle production Q_m for different regions.

Changing cattle production has welfare impacts that vary across regions. Differentiating equation (17) with respect to c_m and collecting terms, the model yields the following expression for **marginal** abatement costs:

$$\frac{\partial W}{\partial \tilde{E}_m} = \frac{1}{b'_m(Q_m)} \left(\sum_i P z_{im} s_{im}\right) \tag{18}$$

Equation 18 is a function of two simple terms: the emissions intensity of cattle production in m ($b'_m(Q_m)$) and the revenue productivity of meatpackers operating there, weighted by their market shares. This suggests the most effective policies shift production *away* from the

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[34] Note that $V_{fmj;j_0} = \alpha_0(j, j_0) + \alpha_R R_{jm}$. Landholder surplus is defined up to a constant, as is common in discrete choice models (Train, 2009). This constant is differenced out in comparing two policy scenarios. On the demand side, quasilinear utility rules out income effects from changes in beef prices, so my measure of consumer welfare corresponds to both equivalent and compensating variation. $\mathcal{W}_d$ represents the total consumer budget in d and $\mathcal{P}_d = (\sum_o \beta_{od} P_{od}^{1-\sigma})^{\frac{1}{1-\sigma}}$ is a beef price index in destination d.

most emissions-intensive places and the least productive meatpackers.

Second-order effects become particularly important when considering sizable changes to the policy environment. Among these, a key channel is the effect of policy on meatpacker entry, which has an ex-ante ambiguous impact on welfare. Although more entry increases production and cattle prices, markets may have "too many" firms due to business-stealing externalities (Mankiw and Whinston, 1986). In addition, changes to the entry margin reallocate inputs (cattle) across firms, with their efficiency implications depending on the productivity of the firms entering and exiting. In short, supply chain responses drive a wedge between the marginal and the average abatement costs of large policies, depending on the location and productivity of the firms affected.

6.2 Taxes on beef production:

Many policy proposals to reduce emissions in the Amazon's cattle supply chain have focused on the largest firms. Export-authorized meatpackers command a large share of beef production and, because they sell in Brazil's largest consumer markets and also abroad, they naturally face more public scrutiny.

Examples of such policies include the EU's new regulation on deforestation-free products, which was approved in 2023 but has yet to be enforced (EU, 2023). This regulation seeks to "avoid that the listed products Europeans buy, use and consume contribute to deforestation and forest degradation in the EU and globally". Some civil society efforts have placed pressures on large meatpackers to monitor their sourcing for deforestation and other illegal activities. But the programs that have so far been implemented have been shown to have no effect due to design flaws and loopholes (Alix-Garcia and Gibbs, 2017; Skidmore et al., 2024). Beyond the cattle sector, the "soy moratorium" has been a notable example of commitments by large companies to reduce deforestation (Heilmayr et al., 2020).

Instead of focusing on a particular policy design, for this counterfactual exercise I focus on broadly displaying how targeting exporters yields different costs and benefits relative to other approaches. I do this by implementing an ad-valorem tax on beef, in two separate scenarios - one affecting only *export-authorized* meatpackers, the other affecting *all* meatpackers. Then I assess the implied economic trade-offs by examining changes in emissions, beef output, and the welfare costs implied by each policy.

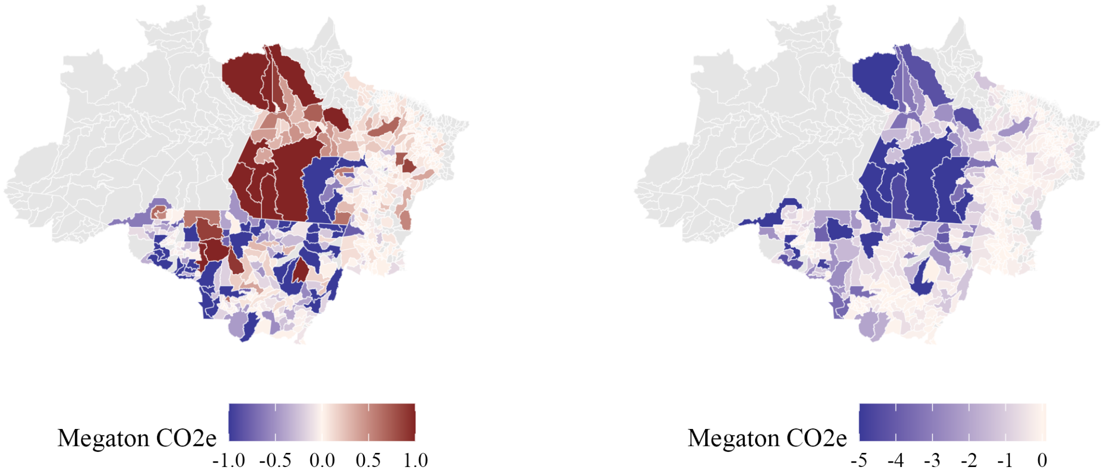
As Table 3 shows, the tax targeted on exporters implies abatement costs more than ten times higher than the general tax. The exporter tax reduces emissions the least (1.34%), but reduces production the most (9.54%). There are several reasons for this. First, it is mistargeted, both geographically and across firms, reflecting the first-order effects from Equation (18). Exporters operate in relatively clean regions, generally away from the high upstream emissions of remote places. These exporting firms also have the highest estimated productivity, which further adds to the welfare cost of abatement.

There are also important second-order impacts as the supply chain reorganizes across space and firms. Reducing output in regions dominated by exporters raises beef prices, which creates demand spillovers that increase production in more remote places (Figure 10), partly offsetting the emissions reductions. Furthermore, the tax reallocates output between firms: from more productive exporters to less productive informal firms. The combined effect of these distortions can create meaningful welfare effects in a country that is already low income - if the regulation is implemented without tax revenue (simply restricting quantities), the abatement cost can be as high as $104.61 per ton of CO2-equivalent abated. This is still smaller than recent estimates of the social cost of carbon (Moore et al., 2024), but towers in comparison to much more effective and less distortionary policies.

The breakdown of different welfare impacts can shed further light on the distortionary effects of exporter-focused policies. For the comprehensive tax, negative welfare impacts are driven by landholder earnings. With a second-best tax on production, the only way to reduce emissions is by reducing cattle production, so the burden on ranchers is unavoidable. However, the exporter tax creates other kinds of distortions that even exceed the effect on ranchers. Consumers lose the most, with sharp reductions in beef production. And so do firms - the policy punishes the most efficient firms while leaving a fringe of unproductive firms unregulated. Entry rates provide an easy way to see this: they decrease by 27.5% for exporters and increase 50% for non-exporters. As a result, average meatpacker productivity drops by 8.6%. Online appendix B.4 shows the robustness of these results under different tax rates and a different assumption on demand that splits beef into two separate varieties (export vs. domestic-grade). Although the exact numbers differ, their policy conclusions are the same.

Note that the tax on export-authorized meatpackers includes *all* their production, not just exports. Export-authorized meatpackers also lead sales in Brazil. Previous work has discussed tariffs from importing countries as a mechanism to address deforestation in the tropics (Hsiao, 2023; Dominguez-Iino, 2023). They find that tariffs are only effective when there is coordination across multiple large countries and long-term commitment to maintaining the policy. In the world's largest rainforest, these exercises suggest an even starker result. Even in a best-case, full-coordination scenario that includes domestic output from exporting firms, a tax on exporters will have only modest effects. The policy creates reallocations across space that drive up emissions elsewhere, while also distorting firm entry and sourcing decisions.

Figure 10: Cattle taxes - effects on emissions


(a) Tax on exporters

(b) Tax on all

6.3 Changing barriers to entry for intermediaries:

Entry costs are, in great part, the result of policy choices. In food production, health-related concerns motivate various regulations on intermediaries and processors that affect firm entry patterns. In estimation, I find that these barriers to entry are much smaller for domestic-only

Table 3: Policy counterfactuals - results summary

			Average Abatement Cost ($/ton)				
Policy	Emissions	Beef	Total	No revenue	CS	Profits	Landholders
Exporter tax	-1.34%	-9.53%	25.11	104.61	30.68	47.80	26.12
Tax on all	-7.52%	-6.43%	1.62	20.35	3.63	5.29	11.43
Higher entry cost	-14.33%	+6.77%	-0.64	-0.64	-1.90	-6.60	7.86

Note: Column "No revenue" specifies average abatement cost without considering tax revenue. The subsequent columns consider impacts on consumer welfare, meatpacker profits, and landholder welfare, respectively. Ad-valorem beef tax is set to 10%. "Higher entry cost" refers to the counterfactual where entry costs for domestic-only firms are set to those of exporters. A negative abatement cost implies the policy is welfare-improving even without considering its effect on emissions. The online appendix (B.4) includes versions of these exercises under different tax rates and demand assumptions.

meatpackers, and even smaller in remote regions. This is one of the factors that drives the least productive firms to the highest-emitting parts of the Amazon.

In this section, I solve an equilibrium in which the entry costs for domestic-only meatpackers are set as high as those for export-authorized meatpackers everywhere in business-as-usual. This anti-competitive policy reallocates output across regions and firms, resulting in emissions reductions of 14.33%. At the same time, beef sales would *increase* by 6.77%. This result is driven by several mechanisms. First, domestic-only meatpackers are much more likely to operate in remote regions. Restricting their entry makes concentration much higher in remote regions (Figure 11), leading to lower cattle prices. This reduces ranching in the regions with the highest emissions. The increase in beef production is driven by the reallocation of output to export-authorized meatpackers, for which entry increases by 33%.

This policy creates winners and losers, but as a whole it is welfare-improving even *without* considering its beneficial impact on the environment. Although cattle ranchers are adversely affected, the improvements in allocative efficiency and increased beef production drive a net improvement. This creates a type of "double-dividend",[35] where the environmental policy is justified purely on economic grounds.

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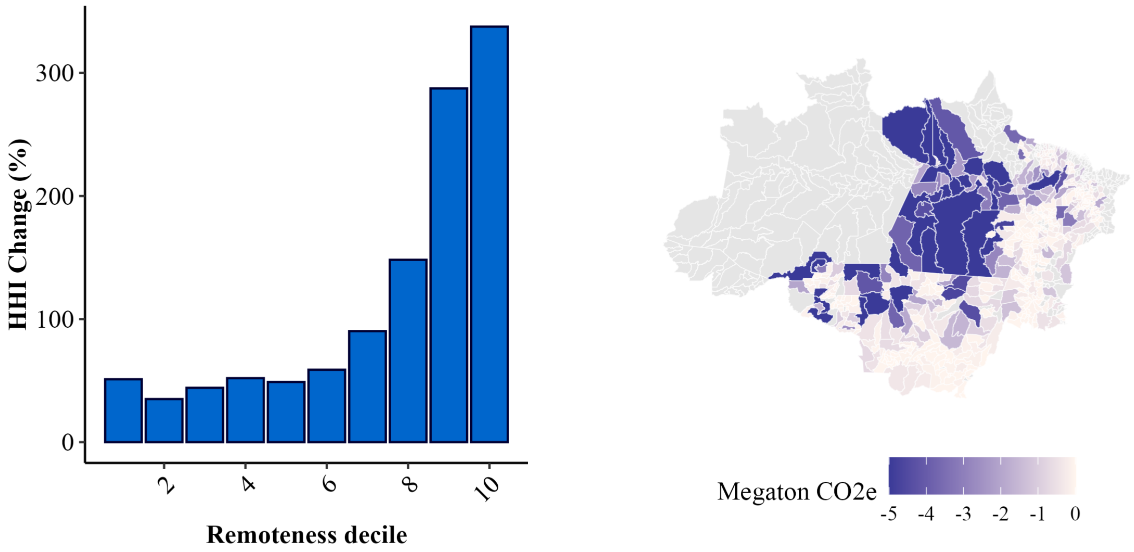
[35] To be clear, this double-dividend is different from the one proposed by Goulder (1995), where an environmental tax is met with a countervailing reduction in distortionary taxes.

Figure 11: Higher fixed costs - effects on meatpacker concentration and emissions



(a) Concentration (HHI) change (%)

(b) Emissions

This policy does effectively what exporter-focused policies set out to do: overcome feasibility constraints through indirect regulation. It can take advantage of already existing (phytosanitary) regulatory structures, and even simplify them by reducing the number of regulated firms. A more extreme version of this policy could assign one "regulated monopsonist" for the whole market, and set rules to meet both food security and environmental goals. More generally, this exercise shows that barriers to entry can have important environmental implications through their effects on concentration and the distribution of firm productivity.

Distributional considerations: The methodology I develop in this paper is tailored for studying questions of efficiency. Issues around distribution are multidimensional in this setting. I briefly discuss them here.

Considering first the demand side, policies that address emissions in remote parts of the Amazon will invariably affect local beef consumption. However, beef is generally consumed by richer households (Carvalho, 2007), and the Amazon has abundant sources of freshwater fish, which are especially consumed in more remote areas.

On the supply side, environmental policy that targets emissions in the Amazon will likely reduce cattle rancher incomes in remote regions, as Dominguez-Iino (2023) shows for South American commodities. Nevertheless, cattle producers in the Amazon tend to operate medium to large-sized estates.[36] In an economy largely driven by agriculture, they are the elite.

Small landholders generally produce for subsistence,[37] as do indigenous populations - often depending on standing forest. These groups occupy collective land and tend to be more common in remote regions. For example, in the least remote decile of municipalities public land takes less than 10% of total land area, whereas in the most remote decile 68% of land is public. As a result, pressures to expand commodity production create conflicts between cattle ranchers and incumbent small subsistence communities (CPT, 2005). The cattle sector in the Amazon is also notorious for its cases of modern slavery (Siqueira, 2018).[38] From this perspective, curbing emissions in remote regions could also protect the most vulnerable populations of the Amazon. Indeed, 71% of avoided deforestation in the entry cost counterfactual occurs on public land.

Instead of taking a stand on these various distributional issues, this work focuses on carbon emissions. Future work can build on this analysis by studying effects of environmental policy across the farm size distribution, or looking closely at food consumption and substitution patterns away from beef.

7 Conclusion

This paper provides a framework for understanding industry responses to regulation when firms are heterogeneous. Exporting firms, by virtue of their size and productivity, often charge higher markups or markdowns. Regulation that focuses on the largest firms can deepen the distortions already present due their higher market power. Focusing on the Amazon, I add a spatial perspective to this insight. Similar meatpacking firms tend to

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[36] Costa (2021) provides a rich discussion of farm size distributions and land grabs in the Amazon.

[37] Souza-Rodrigues (2019) shows that small farmers respond less to price signals in environmental policy, likely because they operate for subsistence.

[38] And despite increases in acreage in recent years, employment in Amazonian agriculture fell by 16% between 2012-2019 (Gonzaga et al., 2021).

cluster in similar regions, creating a large dispersion in monopsony markdowns. This is further aggravated by the fact that the least productive meatpackers cluster in the highest-emitting regions and behave most competitively.

The framework I develop captures how supply chain firms adjust their entry and sourcing decisions in response to policy. In the Amazon, many proposed policies center on prominent exporting firms. I find that these policies adversely reshape the supply chain, worsening the misallocation caused by spatial differences in market power and driving up abatement costs by an order of magnitude. On the international stage, these findings call into question the effectiveness of unilateral tariffs or standards imposed on exporters. A more promising approach may involve cooperative policies in which importing countries reward exporting countries for achieving verifiable environmental outcomes. This echoes the theoretical framework in Harstad (2022), and existing efforts like the Amazon Fund funded by Norway and Germany go in a similar direction.

More broadly, the methodology developed here can offer tools for various settings. As in the Amazon, firms that export may operate differently from firms that only sell domestically, and 75% of world food production serves domestic markets (D'odorico et al., 2014; Li et al., 2022; Geyik et al., 2021). Beyond agriculture, fossil-fuel emissions also originate in upstream stages of production and percolate through imperfectly competitive industries with heterogeneous firms. Understanding how these firms respond at both the intensive and extensive margins is paramount for assessing the welfare costs of reducing emissions.

Appendix

Other data sources

In addition to the cattle movement records, I use other data sources which I summarize here.

Land Use: Land use data come from Mapbiomas (Souza et al., 2020).[39] It is the result of a collaboration between researchers to classify land uses in Brazil using Landsat imagery between 1985-2019. The resulting data comprise a set of raster layers at a 30x30m resolution. Each pixel reports land use categories, such as native forest, pasture, crops, and many others. The Mapbiomas platform also offers a set of rasters documenting transitions between land use states for each pixel.[40] I use the transition rasters between 2015-2019 to create land transition matrices by municipality and land tenure class.

Suitability Index: Farm yields can vary across space, which affects land use decisions. Yields are greatly influenced by the agroclimactic conditions of the land in a given region. Since actual yields may be endogenous, as an instrument I use agroclimactic suitability indices from the FAO-GAEZ (Fischer et al., 2021) dataset.[41] FAO researchers use land, humidity, altitude and solar exposure information to model suitability for a variety of crops and pasture. This dataset has been widely used in economics (e.g. (Costinot et al., 2016; Nunn and Qian, 2011)).

Agricultural Census: Through Brazil's Agricultural Census of 2017 (IBGE, 2017), I observe average sales prices of cattle at the municipality level, as well as average prices for different crops. I use mainly the price of cattle and soy.

Carbon: The structural model I estimate here shows how different incentives and market structure can change deforestation and cattle production decisions. To go from these production decisions to emissions, I need data on the emissions intensities of production. In

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[39] `https://mapbiomas.org/en?cama_set_language=en`

[40] Methodology is described in detail here: `https://mapbiomas.org/en/download-dos-atbds?cama_set_language=en`

[41] `https://iiasa.ac.at/web/home/research/researchPrograms/water/GAEZ_v.4_Data_Portal.html`

the cattle sector, that is a non-trivial task because there are several different (direct and indirect) sources of emissions, all of which also vary geographically.

Emissions come from a variety of land use activities and with intensities that vary geographically:

$$E_m = L_m \sum_j \left(\rho_j \, e^{\text{direct}}_{jm} + \sum_{j_o} \rho_{j_o} \rho_m(j, j_o) \, e^{\text{indirect}}_{j,j_o,m} \right)$$

where e^{direct}_{jm} pertains to “direct” emissions, such as those from animal methane and soil correction. Standing forest sequesters carbon, creating negative emissions. $e^{\text{indirect}}_{j,j_o,m}$ refers to emissions resulting from land use change, such as the carbon released in deforestation or sequestered when pasture is abandoned. When computing policy counterfactuals, I consider how changes to each of these margins ($\rho_m(j, j_o)$) alters the emissions in a municipality. I do this by inferring the intensities e from remote-sensing work and an emissions accounting project.

My analysis of carbon emissions relies primarily on two sources: carbon stocks from Spawn et al. (2020), and all other emissions sources from SEEG.[42] For the carbon stocks, I infer the *potential* carbon stocks of forest by subsetting the data from Spawn et al. (2020) to only pixels that have been forest since the beginning of the Mapbiomas dataset, which is as far back as one can determine old-growth forests. To derive emissions in counterfactual land use change, I also use information on the age distribution of forests that are cut down.

Potential forest stocks vary by a factor of 10 in the Amazon, from 43 tCO2e/ha to 480 tCO2e/ha, depending on the region. The average municipality has the potential of storing 297tCO2e per hectare. In addition to carrying those large stocks of carbon, forests also sequester a yearly amount of CO2 through photosynthesis. Estimates for this flow of sequestration vary, and in this paper I rely on estimates from SEEG, a Brazilian research platform that systematically tracks emissions in all sectors, from agribusiness to energy. They estimate 1.76tCO2e/ha per year for the Amazon biome and 0.73tCO2e/ha-year for the transitional edges of the Cerrado biome that lie within the Legal Amazon.

For other agricultural emissions sources, I also rely on SEEG. Their data report emissions

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[42] `https://seeg.eco.br/`

levels per sector and year. To use this in the context of my model and counterfactuals, I go through their documentation (Alencar et al., 2020) and follow their methodology to infer the emissions intensities of various activities. All figures and assumptions are available on their website. Using their methodology for each activity allows me to estimate emissions under counterfactual scenarios, including environmental policies.

SEEG provides data on two kinds of agricultural emissions. First, there are emissions related to land (e.g. fertilizer, soil emissions), which average 0.14 tCO2e per hectare-year. Slightly more impactful are animal emissions. Cows emit methane through their digestive tract, and total emissions depend on how long the animal lives before slaughter. Some regions employ more intensive practices and slaughter the animals at a younger age, creating a range of 2.1-4.2 tCO2e/head.[43] Assuming the average yearly per-hectare output of 0.23 head/ha, animal emissions range 0.48-0.97 tCO2e/ha per year. These animal emissions also follow the remoteness pattern I discuss in this paper, with animals in remote regions taking longer to fatten and therefore emitting more. Total agricultural emissions, including land and animal-related, thus range roughly between 0.62-1.11 tCO2e/ha per year.

The online appendix (A.3) describes carbon emissions further, including a discussion on stocks versus flows of carbon and their implications for the magnitudes of environmental impacts across different time horizons.

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[43] I take data on age at slaughter from the GTA cattle movement records. Methane has different greenhouse effects compared to CO2. Here I rely on the conventional conversion factor of 25 ton of CO2-equivalent (CO2e) per ton of CH4.

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Online appendix for: “Where is the Beef? Supply Chains and Carbon Emissions in the Amazon”

Online Appendix A Data

A.1 Cattle movement records:

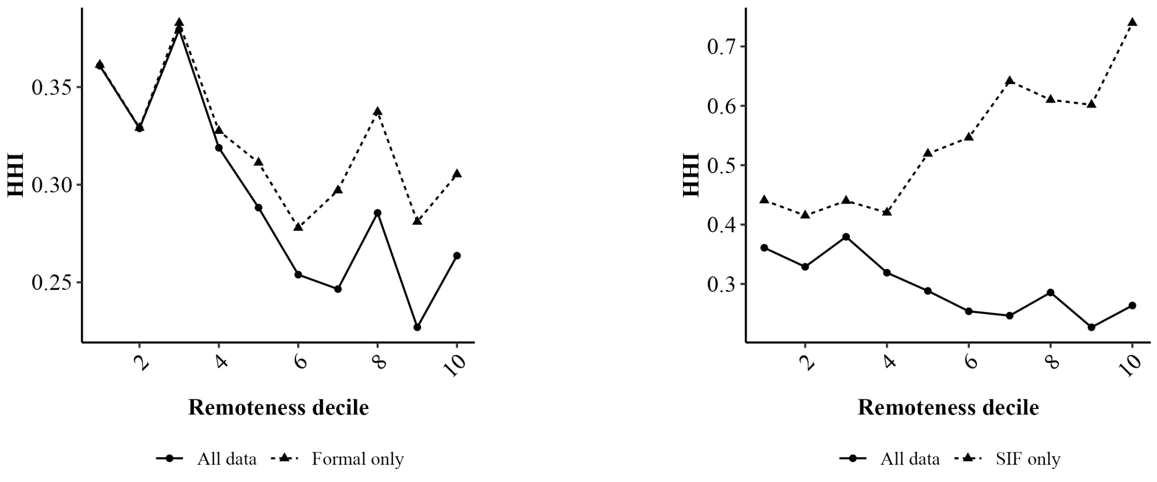
In Brazil, under federal law 12.097 and Decree 7.623, all movements of animals must be registered to sanitation agencies. Known as Guias de Transito Animal (GTA), these records include information on sales of beef cattle to meatpackers. A typical GTA includes the number of animals moved, the age and sex distribution of the animals, identifiers for the origin and destination entities, as well as the municipalities where they are located, and the purpose of the movement. I use records which have a stated purpose of slaughter.

Through a data use agreement with a partner organization, I access GTA records for the Legal Amazon states of Pará, Mato Grosso, Rondônia, Tocantins, and Maranhão. These states account for 92% of the Brazilian Amazon’s pasture area. The data are available for some of the states through years 2015-18, but only 2017 is represented in all state datasets. Fortunately, this matches the year of the latest agricultural census, which contains municipality level price information. The GTA data provide disaggregated data for quantities sold between ranchers and meatpackers, but do not inform individual transaction prices. As a result, I rely on municipality-level price averages in the structural model.

GTA data are generally regarded as reliable sources of information on cattle movements (Klingler et al., 2018; West et al., 2022). In 2017 alone, they track the movement of over 10 million animals to slaughter. The GTA data have been used in other fields (Zu Ermgassen et al., 2020; Skidmore et al., 2021), and recently began to appear in economics (Skidmore, 2023). The crucial aspect of these data is that they serve health-related purposes, such as tracking animal vaccinations and the spread of disease. There are high stakes involved – contaminated meat can lead to death, and an outbreak of mad cow or foot-and-mouth disease can lead to immediate sales bans for entire regions. This creates incentives for local authorities to enforce this regulation for all suppliers regardless of size. Furthermore, there are no environmental policies tied to these records that could drive systematic underreporting. Ranchers and meatpackers can issue these records regardless of whether they are environmentally compliant, or whether they operate in the formal sector. Indeed, only 1% of ranchers in the data operate with a formal firm identification number (CNPJ), the remainder issue GTAs with their personal identification number (CPF). On the meatpacker side, there is important geographic heterogeneity. Considering deciles of distance to São Paulo, in the least remote decile 97% of meatpackers are formal, whereas in the most remote decile only 36% are formal.

The ability to observe domestic and informal meatpackers is essential for the results of this work. As Figure S1 shows, the relationship between HHI and remoteness would be almost flat if I did not consider informal meatpackers. And if I only observed export-authorized meatpackers, the relationship would dramatically reverse. Again, because small, domestic-only, and informal meatpackers operate disproportionately in remote regions, without including them those regions would appear much more concentrated than they actually are.

Figure S1: HHI pattern would change with limited data



(a) Formal meatpackers only

(b) Export-authorized (SIF) only

Note: For these figures, I restrict the GTA cattle movements to only formal (panel a) or SIF meatpackers (panel b). Then I calculate market shares based on the restricted data. HHI here also calculated as $\sum s_{im}^2$, where s_{im} is the market share of meatpacker i in market m.

Table S1: Road and Euclidean distance are highly correlated.

	Road Distance
(Intercept)	-115.71^{***}
	(33.19)
Euclidean Distance	1.29^{***}
	(0.02)
R^2	0.91
Num. obs.	515

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Note: Distances (in km) routed using the Open Source Routing Machine (https://project-osrm.org). Two observations are missing because the algorithm cannot find a land route for such remote places.

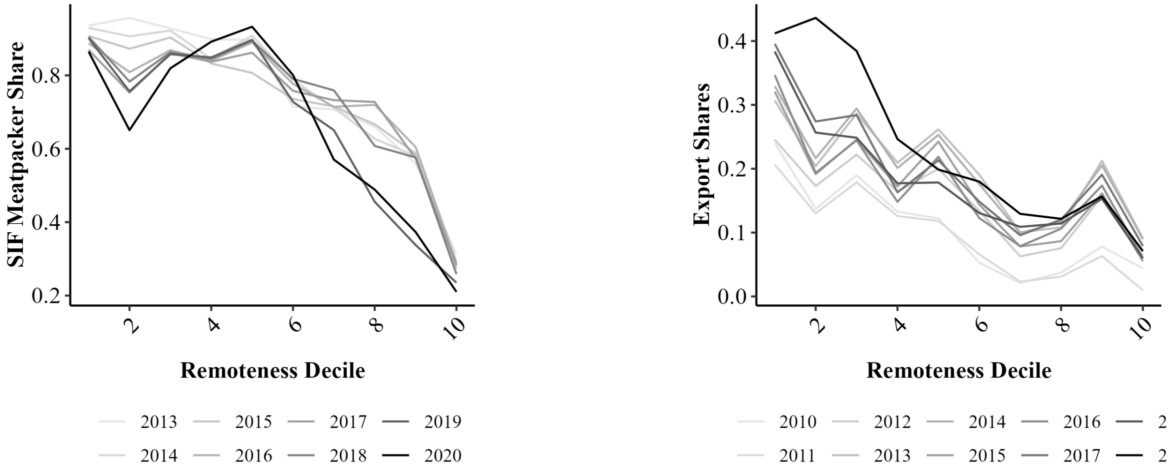
Meatpackers and remoteness: Throughout the paper, I define remoteness as the *euclidean* distance to São Paulo, Brazil's largest city. All the descriptive work and estimation follow this definition. It is possible to use other definitions, such as the distance along an optimal road path. I focus on euclidean distance to encompass all the dimensions of remoteness, not just road transportation costs. Still, road and euclidean distances are very highly correlated (Table (S1)), and all the descriptive relationships shown in the paper also hold with a road distance definition of remoteness.

A.2 Meatpacker market structure over time (2010-2020):

The key message of this paper rests on the geographic distribution of meatpackers - with export-authorized monopsonists in the "core" and a fringe of many domestic buyers in remote areas. The rich data I have shows *all* meatpackers (large and small), but are limited to a few years (2015-18). With two other data sources, I show that the spatial patterns I document are robust over time and space. This exercise relies on the following datasets:

1. The share of cattle sourcing by large (SIF) meatpackers by municipality for 2013-2020.
2. The share of municipal output that goes to exports for 2010-2020.

Dataset (1) was generously shared by Gibbs Land Use Lab. SIF (export-authorized) meatpackers are those that face the strictest (federal) level of inspection, which allows them to access markets in all of Brazil and to obtain licenses for export. (2) I construct using a mix of Trase export data, the 2017 Agricultural Census, and the *Pesquisa Pecuária Municipal*, all of which are available online. SIF meatpackers sell both domestically and abroad, which means that exported beef is a subset of SIF output.



(a) Large meatpacker (SIF) shares in sourcing

(b) Output share that is exported

Figure S2: Large meatpacker (SIF) shares and export shares decrease with remoteness

Figure S2 summarizes the patterns for both data sources, and year-specific maps are below. Large meatpackers operate and exports come from core regions closer to Brazil's major urban centers. The pattern is remarkably stable over an entire decade. Remote regions have, if anything, become more frontier-like in recent years, with shrinking large meatpacker and export shares. Where those large players do not operate, I show in the main text that the gap is filled by many domestic "fringe" meatpackers that elude environmental regulation.

A.3 Carbon stocks and carbon emissions:

The structural model I estimate here shows how different incentives and market structure can change deforestation and cattle production decisions. To go from these production decisions to emissions, I need data on the emissions intensities of production. In the cattle sector, that is a non-trivial task because there are several different (direct and indirect) sources of emissions, all of which also vary geographically.

Emissions come from a variety of land use activities and with intensities that vary geographically:

$$E_m = L_m \sum_j \left(\rho_j \, e^{\text{direct}}_{jm} + \sum_{j_o} \rho_{j_o} \rho_m(j, j_o) \, e^{\text{indirect}}_{j,j_o,m} \right)$$

where e^{direct}_{jm} pertains to "direct" emissions, such as those from animal methane and soil correction. Standing forest sequesters carbon, creating negative emissions. $e^{\text{indirect}}_{j,j_o,m}$ refers to emissions resulting from land use change, such as the carbon released in deforestation or sequestered when pasture is abandoned. When computing policy counterfactuals, I consider how changes to each of these margins $(\rho_m(j, j_o))$ alters the emissions in a municipality. I do this by inferring the intensities e from an emissions accounting project along with some of my own calculations.

My analysis of carbon emissions relies primarily on two sources: carbon stocks from Spawn et al. (2020), and all other emissions sources from SEEG.[44] SEEG is a Brazilian research platform that systematically tracks emissions in all sectors, from agribusiness to energy. Their data report emissions levels per sector and year. To use this in the context of my model and counterfactuals, I go through their documentation and follow their methodology to infer the emissions intensities of various related activities.

SEEG provides data on two kinds of agricultural emissions. First, there are emissions related to land (e.g. fertilizer, soil emissions), which average 0.14 tCO2e per hectare-year. Slightly more impactful are animal emissions. Cows emit methane through their digestive tract, and total emissions depend on how long the animal lives before slaughter. Some regions employ more intensive practices and slaughter the animals at a younger age, creating a range of 2.1-4.2 tCO2e/head.[45] Assuming the average yearly per-hectare output of 0.23 head/ha, animal emissions range 0.48-0.97 tCO2e/ha per year. These animal emissions also follow the remoteness pattern I discuss in this paper, with animals in remote regions taking longer to fatten and therefore emitting more. Total agricultural emissions, including land and

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[44] `https://seeg.eco.br/`

[45] I take data on age at slaughter from the GTA cattle movement records. Methane has different greenhouse effects compared to CO2. Here I rely on the conventional assumption of 25 ton of CO2-equivalent (CO2e) per ton of CH4.

animal-related, thus range roughly between 0.62-1.11 tCO2e/ha per year.

The emissions which I emphasize in this paper come from the clearing of forest to grow pasture. Plants absorb CO2 from the atmosphere and store it in forest biomass. With deforestation, these stocks are lost. Because of natural variation in climate and biome characteristics, potential forest stocks vary by a factor of 10 in the Amazon, from 43 tCO2e/ha to 480 tCO2e/ha, depending on the region. The average municipality has the potential of storing 297tCO2e per hectare. In addition to carrying those large stocks of carbon, forests also sequester a yearly amount of CO2 through photosynthesis. Estimates for this flow of sequestration vary, and in this paper I rely on estimates from SEEG of 1.76tCO2e/ha per year for the Amazon biome and 0.73 for the transitional edges of the Cerrado biome that lie within the Legal Amazon.

Stocks and flows of carbon are different processes, but with some assumptions one can compare their impacts. In the structural model I present here, land use change occurs in a 2015-2019 window. So for the policy analysis I add up all emissions that occur during that period, both in real or counterfactual scenarios. This means that I add emissions from deforestation, sequestration from abandoned pasture, and cattle production emissions all within the 2015-2019 window.

A slightly different exercise would be to estimate *total* expected discounted damages from indirect (deforestation) versus direct sources. Assume, for example, a social cost of carbon (SCC) of \$50 and a discount rate of 2%. Suppose a rancher cuts down one hectare of forest to grow pasture. This implies an immediate release of forest carbon stocks, creating damages to the order of \$2,150-\$24,000 from deforestation alone. It also yields yearly emissions from agriculture and suppresses the yearly carbon sequestration from the forest. Altogether, those will be in the 1.35-2.87 tCO2e range per year. In present dollar terms,[46] damages would range from \$3,375 to \$7,175. Even with a relatively low discount factor, damages from deforestation are mostly greater than those from all other agricultural emissions combined, especially in remote regions with high-carbon forests.

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[46] Discounting here can be thought of as a pure rate of time preference, or come from assumptions about diminishing marginal utilities. The prospect of future climate adaptation or carbon removal can also justify this discounting. Finally, every year about 0.075% of pasture is abandoned. This limits the total direct emissions cattle production can generate.

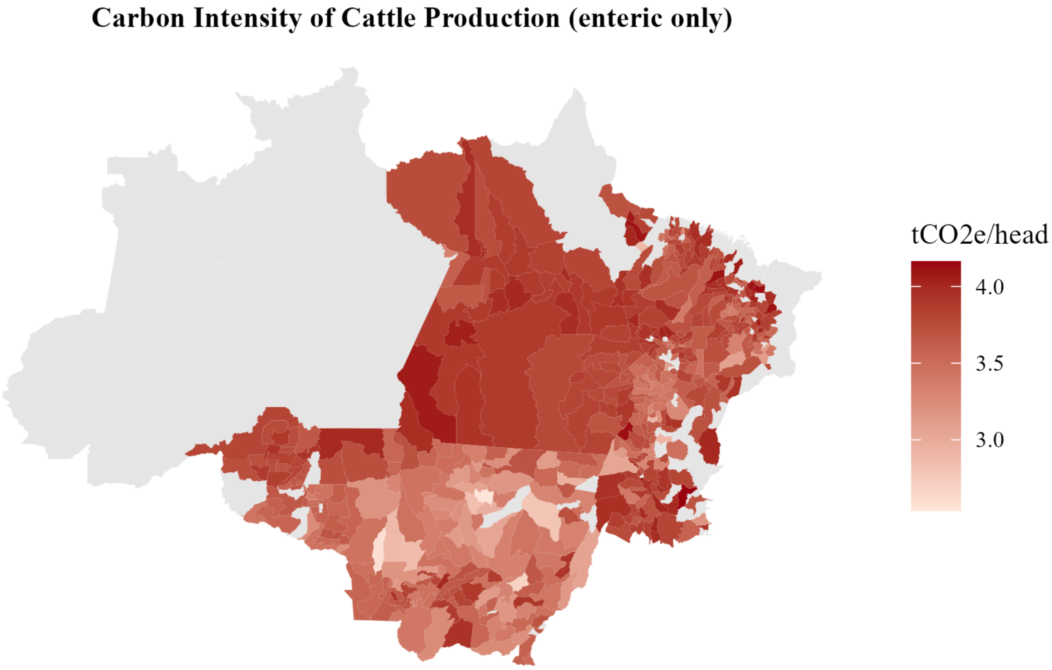
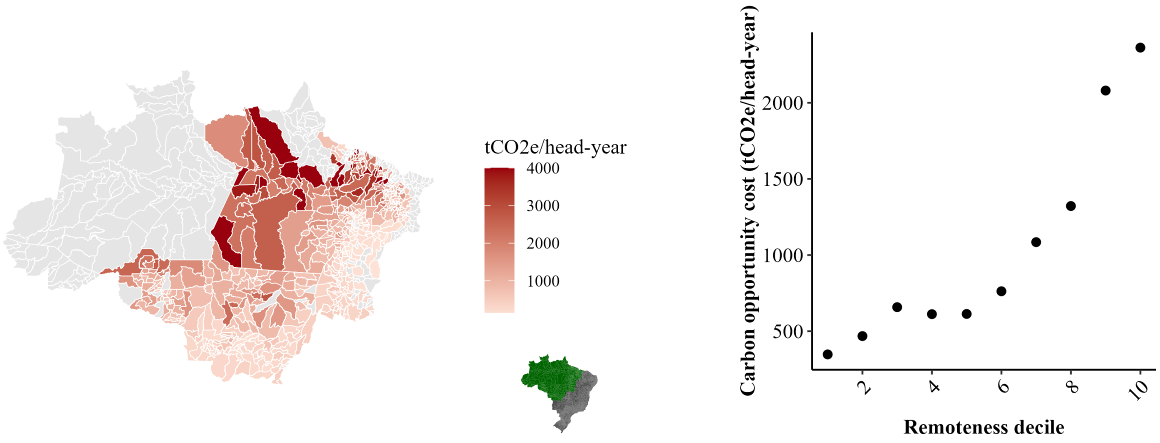


Figure S3: Enteric emissions (per head) are higher in remote regions

Figure S4: Greater environmental opportunity cost of ranching on remote lands



(a) Carbon opportunity cost of ranching (tCO2e/head)

(b) Opportunity cost by deciles of distance to São Paulo

Note: Opportunity cost calculated for each municipality by taking the ratio of carbon stocks per hectare (net loss from forest to pasture) and ranching output per hectare in a year. Figure informs the one-time environmental cost (in tons of CO2e) of clearing land to allow for the yearly production of one head of cattle. On the right panel, I average the municipal values by São Paulo distance decile.

Historical Considerations: The paper shows how remote regions emit the most carbon because remote forests have the highest carbon stocks. One might be concerned that those stocks are high *because* those places are remote in a long-run dynamic processs of change. It is important to note that those are their *potential* stocks, not the result human action.

Rather, historically those regions *became* remote because they had such dense forest. European colonization began early in all parts of Brazil. There are records of colonial presence in the Amazon dating back to the 16th century. But the region proved incompatible to the monoculture-focused style of agriculture attempted by the Portuguese, largely due to the costs of clearing forest, the nutrient-poor soils of the Amazon, its climate and diseases. In the centuries that followed, populations in the Amazon remained largely focused on subsistence activities (Costa, 2018). Portuguese plantation agriculture was more successful first in the Northeast, and then in the South-Southeastern parts of the country, where the land and climate were more suitable for monoculture. As a result, by 1900 55% of Brazil's population lived in the South-Southeast. Today, that fraction is even slightly higher, with 56%

living in that region. The historical process that concentrated Brazilian populations in the South-Southeast implicitly left the most carbon-rich parts of the Amazon more isolated.

In general, denser forests discourage certain types of human settlement, which may cause them to become remote relative to large population centers.[47] Although this paper does not cover other important regions like central Africa and Southeast Asia, one may expect that similar forces shaped the human geography of those regions. This means that the patterns studied here can provide lessons for other settings: remote regions are crucial for conservation, and the firms that operate there may be different from the more prominent commodity trading firms that export and face more environmental scrutiny.

A.4 Land tenure:

Land property rights regimes vary across space in the Amazon. While that is not the focus of this work, I estimate the land use model for different land use categories in order to account for their different patterns of land use change.

To do this, I rely on various administrative data sources to create a novel land tenure dataset. It divides land in the Amazon into two categories, each with two subcategories. I used the Imaflora Atlas to separate public from private land, as Figure S5 shows. Within public land, there is designated public land (national and state parks, indigenous reservations, protected areas) and undesignated public land (not private but also not set for a particular purpose).

Within private land, I create two subcategories: disputed and undisputed. To do this, I pull land claims from Brazil's Cadastro Ambiental Rural (CAR). CAR is an effort from the Brazilian federal government to centralize information on land ownership. Land property rights have been the subject of disputes since the colonial period, and before the introduction of CAR in 2012 there was no centralized collection of claims. With CAR, each landholder submits a record (using mapping software) to the land which they claim to own. A CAR record is a requirement for access to subsidized farm loans. The problem is that there are

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[47] It is worth clarifying that this is specific to the European/Old World approach to agriculture. Recent archaeological evidence points to large pre-colonial populations in the Amazon that thrived in lower-density cultivation within the forest (Neves, 2022).

vast areas where multiple people claim to own the same land. I extracted all CAR records and created a dataset which maps where there are intersecting claims. Even after removing anything resembling a duplicate, there were places with over 10 intersecting claims. 7% of all land (15% of private land) in my sample has more than one intersecting claim.

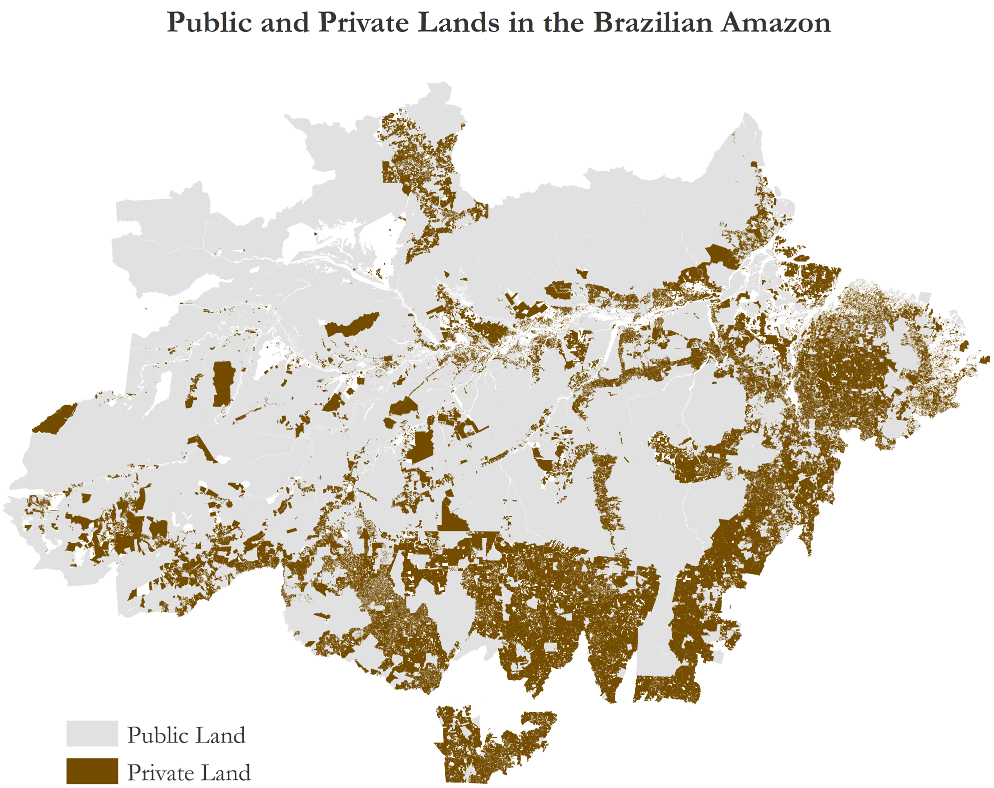

Figure S5: Public and private land in the Brazilian Amazon

Table S2: Land tenure summary statistics

	Private		Public	
	Undisputed	**Disputed**	**Designated**	**Undesignated**
Land Share	42%	7%	42%	11%
Deforestation	4%	5%	2%	7%
Reforestation	5%	6%	8%	10%

Online Appendix B Empirics

B.1 Evidence of market power in cattle sourcing:

Market concentration suggests potential monopsony power in the cattle supply chain, and the structural model embeds a Cournot structure to estimate monopsony markdowns. In this section, I provide some further evidence consistent with monopsonistic conduct by meatpacking firms. Regions with a more concentrated set of meatpackers display lower cattle prices, and pass-through of demand shocks to cattle prices is decreasing in market concentration.

The first piece of evidence is more intuitive. Meatpacker monopsony power should lead to cattle prices that are lower than they would be under perfect competition. Table S3 is consistent with that model - more concentrated regions (as measured by the Herfindahl index) face lower cattle prices.

Table S3: Concentration is associated with lower prices

HHI	-0.110^{**}	-0.092^{*}
	(0.041)	(0.040)
Exporter share	0.254^{***}	0.182^{***}
	(0.026)	(0.046)
Distance to Highway	-0.003	-0.009
	(0.006)	(0.006)
Intercept	1.861^{***}	1.946^{***}
	(0.060)	(0.070)
State FE		X
R^2	0.134	0.208
Num. obs.	613	613

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

The specification has log cattle prices as the outcome variable.

Pass-through is another useful tool for studying market power (Weyl and Fabinger, 2013; Pless and van Benthem, 2019). I show that, consistent with market power, demand shocks face lower rates of pass-through to cattle prices in more concentrated markets. To establish a connection between the model and this empirical exercise, I first take equation 7 and sum it over all meatpackers:

$$c_m = \bar{\varphi}_m \left(\frac{1}{\varepsilon_m} \frac{1}{N_m} + 1 \right)^{-1}$$

where $\bar{\varphi}_m = \frac{\sum_i P z_i}{N_m}$ is the average marginal revenue product across all meatpackers sourcing in m, ϵ_m denotes the elasticity of cattle supply from ranchers, and N_m is the number of meatpackers sourcing in m. Taking the total differential around the equilibrium and substituting terms:[48]

$$d \ln c_m = d \ln \bar{\varphi}_m \left(1 - \frac{1}{N\varepsilon_m + 1} \frac{\partial \ln \varepsilon_m}{\partial \ln c_m} \right)^{-1} \tag{19}$$

Equation 19 shows that whenever $\frac{\partial \ln \varepsilon_m}{\partial \ln c_m} < 0$,[49] pass-through is incomplete. Further, the

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[48] And holding fixed the entry margin of meatpacker sourcing.

[49] That is, ranchers are less elastic at higher levels of c_m

pass-through rate is lower for lower values of N_m and ϵ_m. Using equation 4 from the land use model:

$$\frac{\partial \ln \epsilon_m}{\partial \ln c_m} = \left(\frac{\alpha_R \, \rho_{jm} - \alpha_R \, c_m \, \rho'_{jm}}{(\rho_{jm})^2} \, \rho'_{jm} + \frac{\alpha_R \, c_m}{\rho_{jm}} \left(\rho'_{jm} \, \rho_{j_0 m} \, - 2 \, \rho'_{jm} \, \rho_{j_0 m} \, \rho_m(j, j_0) \right) \right) \frac{c_m}{\epsilon_m} \tag{20}$$

where $\rho'_{jm} = \sum_{j_0} \rho_m(j, j_0) \, \rho_{j_0 m}(1 - \rho_m(j, j_0))$. The sign of the expression above depends on model parameter values - the estimated model delivers elasticities that decrease in prices (Figure S6).

For an alternative model, think of a region of ranchers that processes in-house and sells at the national price of beef. Since each region is small relative to the whole market, we can say each region faces perfectly elastic demand. A shift in the demand curve would necessarily yield full pass-through.

Guided by equation 19, I estimate the following regression:

$$\Delta \ln c_{mt} = \alpha_0 + \alpha_1 Shock_{mt} + \alpha_2 Shock_{mt} \, * \, HHI_{mt} + \epsilon_{mt} \tag{21}$$

where $Shock_{mt}$ is a shift-share like the one used as an instrument in land-use estimation.

$$Shock_{mt} = \sum_{d,i} g_{dt} \, s_{id} \, s_{im}$$

where s_{id} is the share of intermediary i's output which goes to d, s_{im} is i's market share sourcing from m. The shocks are log-changes in import demand at d for beef (excluding Brazil), defined over two-year periods, consistent with the lifecycles of cattle sold for export. HHI_{mt} is the Herfindahl index of market concentration among meatpackers sourcing in m at the beginning of each period.

As I discuss in the main text, data on cattle prices for the entire Amazon are limited to one cross-section in 2017 from the agricultural census.[50] Since this side-analysis involves *changes*

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[50] The occurs roughly every 10 years; the previous one (2006) could presumably be used but I do not have supply-chain data for that period.

to cattle prices, I need to use different datasets, which are available for more years, but more limited geographically. Namely, the Instituto Mato-grossense de Economia Agropecuaria (IMEA), an agricultural think-tank, has collected panel data on cattle prices for municipalities in the state of Mato Grosso. I match those with data from Trase for municipality-level exposure to trade with different countries.

Table S4 shows the regression results. As predicted, the pass-through of export demand shocks to prices is lower in more concentrated regions.

Table S4: Incomplete Pass-through of export demand shocks to cattle prices

Shock	0.011	0.011^{*}
	(0.01)	(0.005)
Shock x HHI	-0.023	-0.020^{***}
	(0.016)	(0.005)
HHI	0.005	-0.01^{*}
	(0.005)	(0.005)
Exporter Share	-0.004^{*}	-0.001
	(0.005)	(0.005)
Year FE	X	X
Munic FE		X
R^2	0.997	0.997
Num. obs.	705	705

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

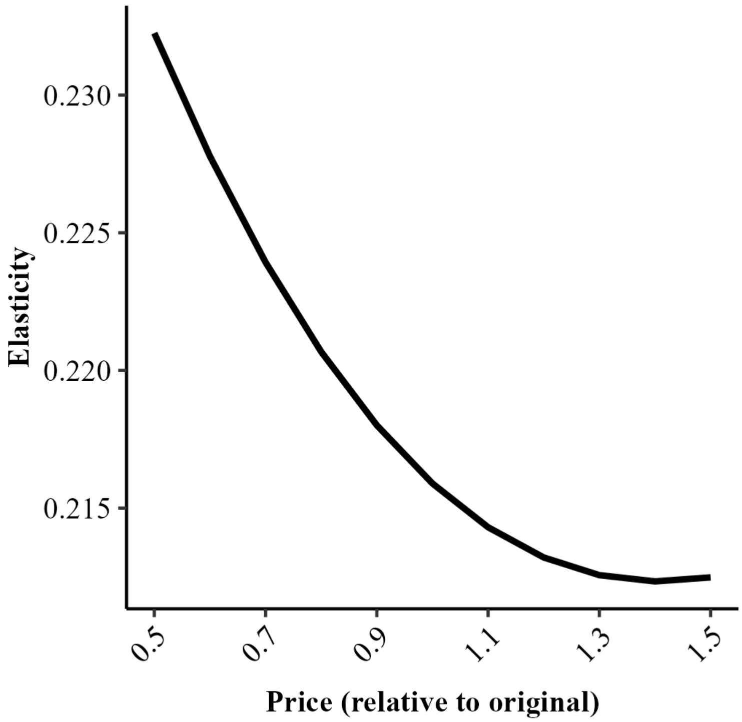


Figure S6: Cattle supply elasticity by price (averaged across municipalities and tenure classes)

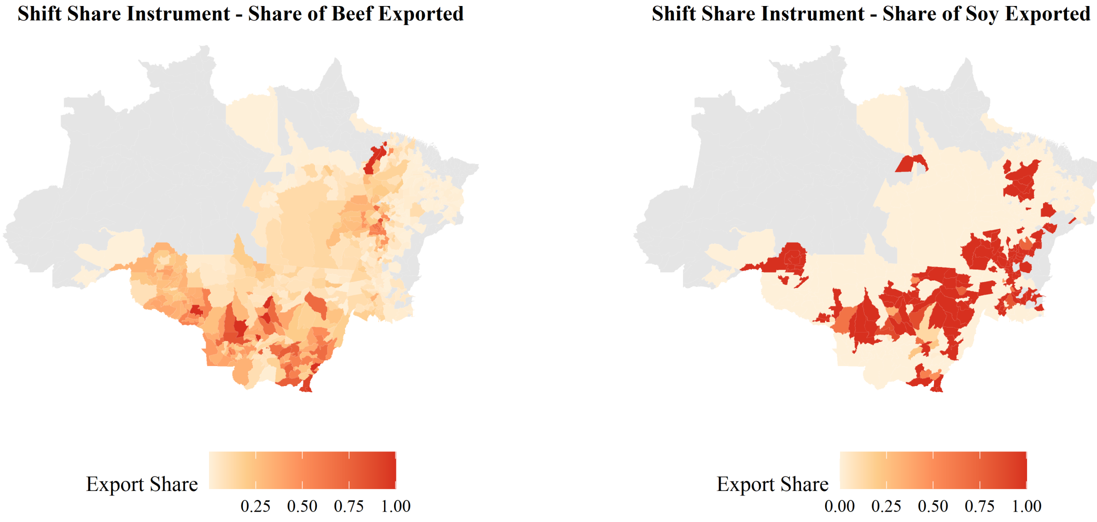
B.2 Shift-share instrument

The land use model uses a set of shift-share demand shocks for beef and soy as instruments. I rely on exogenous changes in import demand g_{dt} interacted with regional exposure shares through the supply chain. Using the cattle supply chain as an example, ranchers in different regions are exposed to different meatpackers (s_{im}), which in turn export to different countries (s_{id}). Each shift-share instrument is defined as follows:

$$SSIV_m = \sum_d g_d \, s_{id} \, s_{im}$$

where s_{id} is the share of intermediary i's output which goes to d, s_{im} is i's market share sourcing from m. s_{id} is constructed from customs data, and s_{im} is constructed from data on the production networks of beef and soy. Both share variables are for 2015, the start of the study period.

The exposure shares are "incomplete" (Borusyak et al., 2018), in the sense that not all output is exported outside of Brazil. In the main text, I address this by controlling for the (lagged) trade share, as suggested in Borusyak et al. (2024). Here, I show maps of the export shares of beef and soy output, and also display coefficient estimates of the land use model using a "re-centered" instrument (in the spirit of Borusyak and Hull (2023)) which subtracts the meso-region mean of the instrument from its original value. Meso-regions are Brazil's third lowest administrative unit (municipality and micro-region being the first two).



(a) Beef

(b) Soy

Figure S7: Export shares of Brazilian beef and soy output

Table S5: Key land use estimation coefficients - Re-centered SSIV

	Parameter	Estimate	SE	F Stat
Land Use	$\alpha_{R(PublicDesignated)}$	1.86	(0.22)	20.4
	$\alpha_{R(PublicUndesignated)}$	1.16	(0.34)	22.2
	$\alpha_{R(PrivateUndisputed)}$	1.50	(0.34)	25.8
	$\alpha_{R(PrivateDisputed)}$	1.64	(0.36)	22.7

Note: Land use estimation includes state FE and policy covariates.

B.3 Entry model algorithm:

The entry game I outline in the main text does not guarantee a unique equilibrium without further assumptions. This issue is not unique to my model: when firms are heterogeneous, there are often multiple possible arrangements of different firms that constitute an equilibrium. In my application, I rely on an assumption of sequential entry as a mechanism of equilibrium selection, ensuring a unique equilibrium. This is similar to the approach Berry (1992) (and also Mazzeo (2002); Toivanen and Waterson (2005)) take, but with a key added challenge - meatpackers differ in *both* productivity and entry costs. As a result, there is no stable ranking of profitability that is invariant to entry arrangements. I make a small methodological innovation to accommodate this heterogeneity along two dimensions.

To illustrate the issue, consider a stylized example with two potential entrants. Firm 1 is more productive ($z = 1.1$) than Firm 2 ($z = 1$). If only Firm 1 enters, cattle supply is $Q = 100$ and the cattle price is $c = 0.5$. If only Firm 2 enters, $Q = 80$ and $c = 0.4$. If both enter, $Q = 120$, $c = 0.6$, and market shares are split 60/40: $s_1 = 0.6$, $s_2 = 0.4$.

Figure S8 shows the resulting payoffs assuming zero entry costs. The unique equilibrium is for both firms to enter ($I = (1, 1)$). In all outcomes where Firm 1 enters, it earns higher profits than Firm 2 because it is more productive.

However, equilibrium need not be unique. Introducing equal fixed costs of 40 for both firms makes the market unable to sustain two entrants. As shown in Figure S9, there are now two equilibria: either Firm 1 enters alone ($I = (1, 0)$), or Firm 2 does ($I = (0, 1)$). This multiplicity is a core empirical challenge.

Allowing fixed costs to differ further complicates the picture. In Figure S10, Firm 1 faces a higher fixed cost (40) than Firm 2 (10). Firm 2 now earns positive profits when both enter ($I = (1, 1)$), while Firm 1 does not. This rules out $(1, 0)$ as an equilibrium and leaves $(0, 1)$ as the unique solution.

In summary, the entry game poses two key challenges. First, equilibria may not be unique. Second, when firms differ in both productivity and entry costs, their profitability rankings may not follow the ranking of productivity. This undermines simple selection rules and complicates empirical implementation. In small games, such as the 2-by-2 example above, one can solve for every entry combination and check if equilibrium conditions are met. But with more than 40 potential entrants in my empirical application, brute-force enumeration becomes infeasible. I therefore develop and implement an algorithmic selection mechanism, described below.

Figure S8: Example - Two-firm entry, no fixed costs

		Firm 2 (Low prod.)	
		Enter (1)	**Not enter (0)**
Firm 1 (High prod.)	**Enter (1)**	36, 19.2	60, 0
	Not enter (0)	0, 48	0, 0

Figure S9: Example - Two-firm entry, common fixed costs (40)

		Firm 2 (Low prod.)	
		Enter (1)	**Not enter (0)**
Firm 1 (High prod.)	**Enter (1)**	-4, -20.8	20, 0
	Not enter (0)	0, 8	0, 0

Figure S10: Example - Two-firm entry, heterogeneous fixed costs (40 vs. 10)

		Firm 2 (Low prod.)	
		Enter (1)	**Not enter (0)**
Firm 1 (High prod.)	**Enter (1)**	-4, 9.2	20, 0
	Not enter (0)	0, 38	0, 0

Sequential entry A potential meatpacker entrant i in municipality market m is defined by its productivity z_{im} and the fixed entry cost f_{im} it faces. To ensure a unique equilibrium, I assume meatpackers make entry decisions sequentially. Formally, entry follows some vector T_m, where each meatpacker in that market is indexed by its place in the entry order t. The sequential mechanism selects the equilibrium set of entrants I_m^* which, for any distinct possible equilibrium set I_m', the following is true about their relative complements:

$$\min\{t \in I_m^* \setminus I_m'\} < \min\{t \in I_m' \setminus I_m^*\} \tag{22}$$

In the main text, this rank order follows productivity, such that

$$z_{tm} \geq z_{t'm} \quad \forall t < t'$$

Empirically, this means that export-authorized meatpackers move first. This is consistent with the industry context, where large export-authorized firms are leaders in the market and possess strong political connections. The nuance in (22) is that, while higher-ranked players are favored, equilibria with several lower-ranked players are possible when these have lower entry costs. All that (22) requires is that, for any pair of possible equilibria, the top ranked player that is not in both equilibria be a firm that is in the selected equilibrium.

Algorithm Each municipality market is solved separately, so henceforth I omit m subscripts. In the empirical implementation, to solve for an equilibrium on the entry margin, I first begin with the top ranked player as a monopsonist. Then I repeat the following steps until convergence:

1. For each of the meatpackers i currently outside the market, solve for a counterfactual Cournot stage including current entrants plus that i.
2. If there is any profitable i in these scenarios, add the highest-ranked (lowest t) meatpacker that is both profitable and not in the market.
3. Solve profits for all entrants in this new scenario.
4. If there are any unprofitable i in this scenario, remove the lowest-ranked (highest t) meatpacker that is in the market and is not profitable.

This process continues until there are no changes to the market.

Step 3 is key for identifying situations in which less productive players may be in the equilibrium if they have lower entry costs. The algorithm allows for the possibility that a low-productivity player can enter and "push out" a higher-ranked player, but this only happens if the lower-ranked player can be profitable in the presence of the higher-ranked player, but the converse is not true: entry of the lower-ranked player renders the higher-ranked player unprofitable. Below, I prove that the algorithm recovers the (unique) equilibrium described by (22) for my application. A more general proof is an interesting avenue for future work. My setting is characterized by two conditions:

1. Entry costs can take two values within a municipality: f_E for export-authorized meatpackers $i \in E$, and f_D for domestic-only ($i \in D$).
    - This implies a stable ranking of profits *within* each meatpacker type regardless of equilibrium: for $t, t' \in F$ if $t \leq t'$, then $\pi_t \geq \pi_{t'}$. This may not be stable comparing different types - a less productive meatpacker could be more profitable in some equilibria if its entry costs are lower.
2. Meatpacker productivity can take three possible values *within* a municipality (but can further vary across municipalities): z_E^{JBS}, representing leading firm JBS, z_E for other exporting meatpackers, and z_D for domestic only firms.

- This is such that any set of entrants I can be characterized by $I = \{I^{JBS} \in \{0,1\}, N^E, N^D\}$, where N^E denotes the number of export-authorized entrants other than JBS, and N^D the number of (identical) domestic-only entrants.

Proof. I proceed by contradiction. Suppose there exists an equilibrium $\tilde{I}$, such that $\min\{t \in \tilde{I} \setminus I^*\} \leq \min\{t \in I^* \setminus \tilde{I}\}$.

If $\tilde{I}$ is an equilibrium, then one of the following has to be true about it:

1. $I^{JBS} = 1$ in $\tilde{I}$. Here, it follows that either $I^{JBS} = 0$ in I^*, or JBS is in both but $\tilde{N}_E > N_E^*$.
2. $I^{JBS} = 0$ in $\tilde{I}$ and I^*. And therefore also $\tilde{N}_E > N_E^*$.

For case (1), there are two sub-cases. In the first, the extra exporters ($t \geq N_E^* + 1$) are never added by the algorithm. This implies that $\pi_E(1, \tilde{N}_E, 0) < 0$. That is, those exporters are not profitable if there are $\tilde{N}_E$ exporters in the market even without any non-exporters, so $\tilde{I}$ cannot be an equilibrium.

The more interesting sub-case is one in which $\tilde{N}_E$ exporters or more are added into the market by the algorithm, but later are removed from I^* as D-types enter. In this sub-case, for every firm ranked $N_E^* + 1$ or lower (higher t), there exists a number of domestic entrants $N_D^{CRIT}(N_E)$ such that:

$$\begin{aligned}
\pi_E(1, N_E, N_D^{CRIT}(N_E) - 1) \geq 0,\\
\pi_E(1, N_E, N_D^{CRIT}(N_E)) < 0,\\
\pi_D(1, N_E, N_D^{CRIT}(N_E)) \geq 0,
\end{aligned}$$

The inequalities above describe steps in the algorithm in which exporters are removed. In other words, there is a step in the algorithm where a domestic-only firm is added, but this addition causes an E-type firm to be rendered unprofitable. At this point, one E-type firm is removed, with $N_D^{CRIT}(N_E)$ representing the critical number of domestic-only firms at which this removal happens.

Considering that prices are monotonically increasing with more entry in Cournot, we can say the following about the equilibrium cattle prices at these critical points:

$$\begin{aligned} c(1, \tilde{N}_E, N_D^{CRIT}(\tilde{N}_E)) &> c(1, \tilde{N}_E, \tilde{N}_D) \\ c(1, \tilde{N}_E, N_D^{CRIT}(\tilde{N}_E)) &< c(1, \tilde{N}_E, \tilde{N}_D + 1) \end{aligned}$$

The first inequality is true because E-types are not profitable in the $(1, \tilde{N}_E, N_D^{CRIT}(\tilde{N}_E))$ allocation, but have to be profitable in $\tilde{I} = (1, \tilde{N}_E, \tilde{N}_D)$ for it to be an equilibrium. The second inequality follows from the fact that D-types are profitable in $c(1, \tilde{N}_E, N_D^{CRIT}(\tilde{N}_E))$ but cannot be profitable in $(1, \tilde{N}_E, \tilde{N}_D + 1)$ in order for $\tilde{I}$ to be an equilibrium.

Contrasting the two inequalities, the first inequality implies that $N_D^{CRIT}(\tilde{N}_E) > \tilde{N}_D$. Because of integer constraints in entry, the second inequality implies $N_D^{CRIT}(\tilde{N}_E) \leq \tilde{N}_D$, which is a contradiction.

This subcase also shows that, in the case where there is no JBS option and there are only two types of firms (exporters and non-exporters), then the sequential algorithm selects the equilibrium that maximizes the number of exporters. In this sense it is similar to Jia (2008), favoring one type of firm, albeit with a different model and setting.

Note that this subcase also nests a situation in which $\tilde{N}_E = 0$, which would imply that JBS is in $\tilde{I}$ but not I^*. Here, there would be an N_D^{CRIT} at which the JBS entrant is removed in the algorithm:

$$\begin{aligned} \pi_E^{JBS}(1, 0, N_D^{CRIT}(JBS) - 1) &\geq 0, \\ \pi_E^{JBS}(1, 0, N_D^{CRIT}(JBS)) &< 0, \\ \pi_D(1, 0, N_D^{CRIT}(JBS)) &\geq 0, \end{aligned}$$

with $N_D^{CRIT}(JBS) \leq N_D^*$. Here, if $\tilde{N}_D \geq N_D^{CRIT}(JBS)$, then $\tilde{I}$ cannot be an equilibrium because JBS would not be profitable. If $\tilde{N}_D < N_D^{CRIT}(JBS)$, $\tilde{I}$ cannot be an equilibrium because there would be more D-types which could profitably enter.

Now I turn to the second case, where $I^{JBS} = 0$ in $\tilde{I}$ and I^* and $\tilde{N}_E > N_E^*$. If the algorithm sets $I^{JBS} = 0$, then its ordering also implies $N_E^* = 0$. If JBS was removed by the algorithm, there exists some $N_D^{CRIT}(JBS) \leq N_D^*$ such that $\pi_E^{JBS}(1, 0, N_D^{CRIT}(JBS)) < 0$ and $\pi_D(1, 0, N_D^{CRIT}(JBS)) \geq 0$. This also implies that $\pi_E(0, 1, N_D^{CRIT}(JBS)) < 0$ and $\pi_D(0, 1, N_D^{CRIT}(JBS)) \geq 0$, which means that $\tilde{N}_D \geq N_D^{CRIT}(JBS)$, and rules out any allocation with $\tilde{N}_E > 0$ as a possible equilibrium.

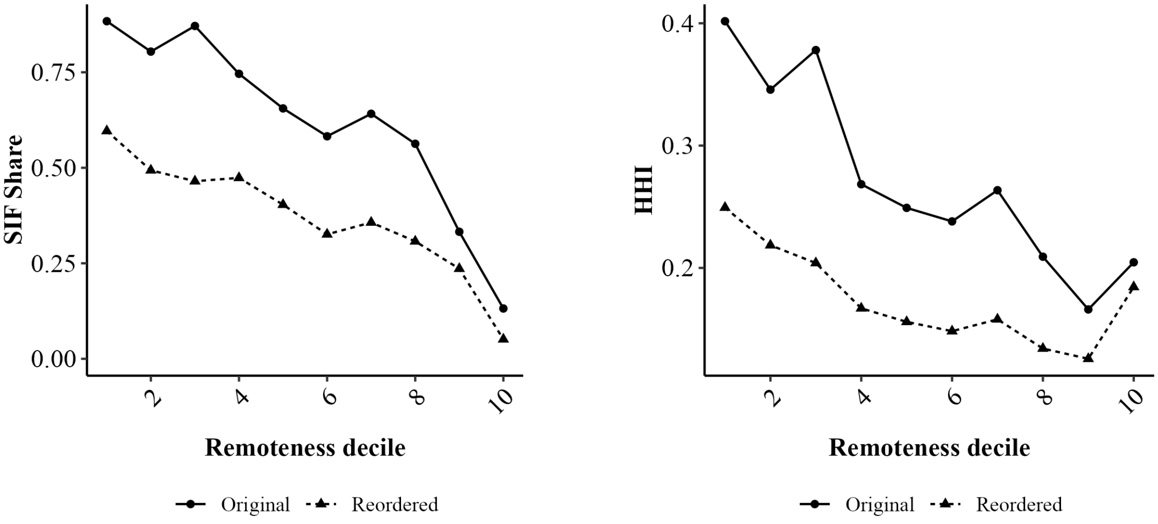
□

I showed above that the selection mechanism I apply favors the equilibrium with higher-ranked players, but it is important to clarify that this does not necessarily exclude low-ranked players. Lower-productivity firms can appear in a market if their entry costs are low. In my application, entry costs are low for domestic-only meatpackers, so many of these small players enter and bid cattle prices up to an extent that makes some export-authorized meatpackers unprofitable. The algorithm I use accommodates this possibility.

Other approaches: My approach has both advantages and limitations. On the benefits side, it allows me to incorporate a large number of heterogeneous firms across many regions while remaining tractable, even when accounting for demand spillovers and land use responses. However, it also imposes restrictions on the types of unobservables the model can accommodate, and the sequential entry assumption is fundamentally untestable. Nevertheless, this assumption aligns with the industry context, where large, more productive meatpackers exert significant influence and maintain strong political connections. In addition, as a robustness check I can show predictions that would result from alternative orderings. In Figure S11, I flip the order of sequential entry, with the least productive meatpackers moving first. This affects the equilibrium outcomes slightly, creating lower export-authorized shares and lower HHIs (less concentration), but the spatial trends are the same.

Other work in the literature takes different approaches. One class of models accounts for multiple equilibria, generally employing partial identification in estimation (e.g. Ciliberto and Tamer (2009)). Another set of solutions relies on private information shocks, where firms form expectations over other firms' profitability shocks, leading to a unique equilibrium (e.g., Seim (2006)). I do not adopt these approaches for two reasons. First, methods robust to multiple equilibria are computationally prohibitive in my setting. They require verifying equilibrium conditions across 2^M potential entry scenarios, where M represents the number of potential entrants. Given that M can be higher than 40 in my application, the number of equilibria to compute would be infeasibly large. This challenge is compounded by the need to solve for equilibrium in all three compenents of the model.[51] Second, models with incomplete information are highly sensitive to assumptions on the number of potential entrants, and perfectly private information models have been found to not fit the data well (Grieco, 2014; Magnolfi and Roncoroni, 2023).

The approach I take strikes a balance between allowing for firm heterogeneity in productivity and entry costs while maintaining tractability in solving the three-part equilibrium. This tractability is crucial for conducting counterfactual exercises that generate specific predictions about how market structure, prices, and emissions respond to policy changes.



(a) Export-authorized (SIF) meatpacker shares in sourcing

(b) HHI

Figure S11: Robustness checks - entry model inverting sequential order

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[51] This complexity is particularly severe in policy counterfactuals, where equilibrium must be solved for land use, cattle sourcing, and demand simultaneously. Meatpackers internalize rancher supply elasticities, which vary at each price point and must be computed across multiple market structures within the solution algorithm. Additionally, the demand side introduces spatial spillovers, such that shocks in one municipality influence demand conditions in others.

B.4 Counterfactual exercises

In this section, I discuss some implementation aspects in counterfactual exercises, then present robustness checks.

B.4.1 Implementation

My model differs from many in the discrete games literature in that the firm profit function is fully specified. This allows for a broader set of policy exercises, but it introduces computational challenges. These arise primarily because, under a policy change, (i) land use conditions adjust, affecting cattle supply elasticities adjust at every price point; and (ii) demand conditions shift, requiring beef prices to adjust to clear the market. The process involves finding a fixed point across many equations for land use, meatpacker first-order conditions, demand, as well as finding entry patterns consistent with meatpacker profit inequality conditions. A few comments on implementation:

1. For stage (1) of the entry algorithm above, I need to solve counterfactual prices conditional on the current entrants plus a given i entrant. The supply elasticity ϵ_m that meatpackers internalize in solving their optimal quantity decisions needs to be consistent with the elasticity at the equilibrium price. For each counterfactual price, I run the following sequence to reach a fixed-point:

   $$c_m \leftarrow \frac{\sum_{i \in I_m} P z_{im}}{N_m} \Big(\epsilon_m(c_m) + 1 \Big)^{-1} \tag{23}$$

   for the given set of entrants I_m considered in that counterfactual. The equilibrium price for the next step in the sequence is given by the set of entrants I_m considered in that counterfactual and the elasticity implied by the price in the previous step. This converges relatively quickly and is done for roughly 18000 potential entrants across all the municipalities in each step of the entry algorithm.

2. Step (2) of the entry algorithm requires checking if a given meatpacker would be profitable if they were added. This is not trivial, since meatpacker profitability depends on both their productivity and their fixed costs. The fastest way to do this is to

compute that meatpacker's critical price c_{im}^{crit} below which it makes positive profits. Rearranging terms in the profit function:

$$c_{im}^{crit} = \frac{-\sqrt{f_{im}}\sqrt{4Pz_{im}\epsilon_m Q_m + f_{im}} + f_{im} + 2\epsilon_m Q_m P z_{im}}{2\epsilon_m Q_m} \tag{24}$$

Note again that both the elasticity ϵ_m and cattle output Q_m depend on c_{im}^{crit}, so I employ a nested fixed point approach like the one I describe above. This c_{im}^{crit} changes at every value of P or with the presence of a tax. The approach I take has the advantage that I only need to compute it once per round of the entry algorithm, given values of P, z_{im}, f_{im}.

3. Meatpackers sell beef to a common beef market. This means that changes in one region can affect aggregate supply and thus drive spillover effects to other regions as demand adjusts. To account for this, I search for equilibrium values of P such that aggregate beef demand equals aggregate beef supply (Equation 9).[52] Each iteration of this search requires solving the entire supply side, as changes in consumer prices affect meatpacker returns, affecting their entry and sourcing decisions. I implement this using standard non-linear optimization packages. Given the need to repeatedly solve the supply side to equilibrate it with demand, this process is computationally intensive.

B.4.2 Robustness check - Different tax rates:

Below is an alternative version of my counterfactual exercises with a 20% ad-valorem tax. The conclusions are the same as in the main text, just with a stronger effect. With a higher tax rate, the distortionary effects of targeting only exporters are even starker, raising the abatement costs substantially.

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[52] Or P^E,P^D in the robustness check with separate varieties

Table S6: Policy counterfactuals - 20% ad-valorem tax

			Average Abatement Cost ($/ton)				
Policy	Emissions	Beef	Total	No revenue	CS	Profits	Landholders
Exporter tax	-0.52%	-21.89%	212.39	489.22	193.49	213.30	82.42
Tax on all	-14.61%	-12.54%	2.30	20.79	3.75	5.72	11.32

Note: Column "No revenue" specifies average abatement cost without considering tax revenue. The subsequent columns consider impacts on consumer welfare, meatpacker profits, and landholder welfare, respectively. Ad-valorem tax set at 20%.

B.4.3 Robustness check - Different demand assumptions:

In the demand model, consumers choose beef varieties from different countries. This approach allows me to use customs data to estimate beef demand elasticities of substitution. With this specification, different pieces of beef from the same country are treated as perfect substitutes. As a result, although domestic-only meatpackers are estimated to be less productive, any beef they produce is a perfect substitute to beef from export-authorized firms. Although they can export, export-authorized meatpackers still sell the majority of their output to Brazilian consumers. Due to data limitations on domestic beef consumption and prices, I am not able to estimate the degree of substitutability of beef from different firm types. But I am able to run my policy analysis under different assumptions on demand. Below, I solve all counterfactual exercises again but treating beef sold by domestic-only and export-authorized firms as entirely different varieties, therefore imperfect substitutes. This is likely a lower bound on substitutability because it assumes these two varieties to be as different as if they were from different countries.

Table S7 shows that the qualitative results still hold under this extreme assumption of separate varieties. Exporter taxes have lower effectiveness and impose a greater burden on welfare than any other policy. The difference is smaller because this scenario constrains the ability of small and informal firms to fill the gaps left by export-authorized firms. Taxing the entry of domestic-only firms is still welfare-improving (without considering emissions reductions), but this "double-dividend" only appears if the added entry cost is revenue-generating. Otherwise the welfare impact is nearly zero - before considering the environmental benefits. Taken together, these results suggest that more complex patterns of substitution that account

Table S7: Policy counterfactuals - separate varieties for domestic versus “export-grade” beef

			Average Abatement Cost ($/ton)				
Policy	Emissions	Beef	Total	No revenue	CS	Profits	Landholders
Exporter tax	-3.05%	-4.41%	18.85	61.65	41.49	8.36	11.89
Tax on all	-6.24%	-2.83%	5.61	30.24	16.82	2.95	10.47
Higher entry cost	-9.65%	+6.86%	-0.52	0.91	1.88	-9.08	8.12

Note: Column “No revenue” specifies average abatement cost without considering tax revenue. The subsequent columns consider impacts on consumer welfare, meatpacker profits, and landholder welfare, respectively. Ad-valorem tax set at 10%. “Higher entry cost” refers to the counterfactual where entry costs for domestic-only firms are set to those of exporters. A negative abatement cost implies the policy is welfare-improving even without considering its effect on emissions.

for within-country differences would not greatly change the conclusions from the paper.

Online Appendix C Model Extensions

C.1 Land use dynamics:

Land use change has dynamic features. Actions such as deforestation carry sunk costs[53] and involve irreversibilities - forest takes decades to regrow once lost. In the paper, I adopt a “medium term” model of land use change, where agents evaluate returns over a span of 5 years (4 transitions). As I discussed in the main text, this choice is primarily driven by data limitations on prices for cattle and crops.

In this appendix, I introduce a dynamic extension of the land use model and demonstrate that it produces similar elasticities for the timeframes I study. The approach follows the structure of Araujo et al. (2020) and Scott (2012), relying on rational expectations over the path of future returns to derive a discrete analog of an Euler equation for estimation. The primary limitation of this extension is that it relies on a single cross-section of prices for estimation, reflecting the data limitations in my setting and preventing the inclusion of fixed effects used in standard applications. Despite this constraint, the exercise provides a useful robustness check, illustrating that my main findings are not highly sensitive to the specific modeling assumptions regarding the decision horizon.

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[53] Such as using tractors and metal chains to break large trees, burning vegetation, etc.

A dynamic model of land use change: A set of small fields i clustered in municipalities m make independent land use choices to maximize expected discounted profits. During each period, field holders decide on land use, whether it is pasture for cattle, crops or forest.

Landholders choose land use to maximize their payoffs, which depend on the land choice, market conditions ω_t and the current state of the field. For simplicity, field state here depends only of the previous period's state j_{it-1}, such that payoffs are:

$$\pi(j, j_{t-1}, \omega_t, \nu_{it}) = \alpha_0(j, j_{t-1}) + \alpha_R R_j(\omega_t) + \xi_{jj_{t-1}}(\omega_t) + \nu_{jit} \tag{25}$$

where $\xi_{jk}(\omega_t)$ is a market level shock to returns and ν_{jit} is a field-level idiosyncratic shock. $R_j(\omega_t)$ is an observable component of returns.

Dynamic incentives come from term $\alpha_0(j, j_{t-1})$, which depends on field state j_{t-1}. This can rationalize, for example, switching costs between forest and agriculture.

The key assumption which will allow for estimation is one of *small fields.* That is such that a change in land use in one field will not affect market conditions or create externalities for other fields. Formally, I assume the market state evolves according to a Markov process which satisfies $G(\omega_{t+1}|\omega_t, j_{it} = j) = G(\omega_{t+1}|\omega_t)$.

Let β represent a common discount factor. A field owner i's value function is defined as follows:

$$V\left(k_{it}, \omega_t, \nu_{it}\right) \equiv \max_{j^*} E\left(\sum_{s \geq t}^{\infty} \beta^{s-t} \pi\left(j^*\left(j_{is-1}, \omega_s, \nu_{is}\right), j_{is-1}, \omega_s, \nu_{is}\right) \mid k_{it}, \omega_t, \nu_{it}\right) \tag{26}$$

I assume that shocks ν_{ijt} are distributed EV1 with variance normalized (WLOG) to $\frac{\pi^2}{6}$. This assumption will deliver closed-form solutions for conditional choice probabilities (CCP). To see that, I first need a few definitions. First the ex ante value function is defined as:

$$\bar{V}_t(j_{t-1}) \equiv \int \ldots \int V_t\left(j_{t-1}, (\nu_1, \ldots, \nu_J)\right) dF\left(\nu_1\right) \ldots dF\left(\nu_J\right) \tag{27}$$

which can be interpreted as the expectation of the value function before the realization of the idiosyncratic shocks. And the conditional value function, which represents expected returns *conditional* on an action, is defined as:

$$v_t(j, j_{t-1}) \equiv \bar{\pi}_t(j, j_{t-1}) + \beta E_t \left[\bar{V}_{t+1}(j)\right] \tag{28}$$

where $\bar{\pi}_t(j,k)$ represents period payoffs before the realization of idiosyncratic shocks. Using the definitions above, I can define the CCPs based on the EV1 assumption:

$$p_t(j, j_{t-1}) = \frac{\exp\left(v_t(j, j_{t-1})\right)}{\sum_{j' \in J} \exp\left(v_t\left(j', j_{t-1}\right)\right)} \tag{29}$$

It also implies a convenient expression for the ex ante value function, which will soon be useful:

$$\bar{V}_t(j_{t-1}) \equiv \ln\left(\sum_{j \in J} \exp\left(v_t(j, j_{t-1})\right)\right) + \gamma \tag{30}$$

From this theoretical basis I can derive a linear regression that can be used to estimate model parameters. This consists of deriving a discrete analog of an Euler equation: I set up short-term perturbations while holding long term decisions fixed such that continuation values difference out.

This derivation starts with the Hotz-Miller inversion, a rearrangement of the CCPs which provides information on differences in conditional value functions between two choices:

$$\ln\left(\frac{p_t(j, j_{t-1})}{p_t(j', j_{t-1})}\right) = v_t(j, j_{t-1}) - v_t(j', j_{t-1}). \tag{31}$$

Using the definition from (28), this becomes:

$$\bar{\pi}_t(j, j_{t-1}) - \bar{\pi}_t\left(j', j_{t-1}\right) - \ln\left(\frac{p_t(j, j_{t-1})}{p_t\left(j', j_{t-1}\right)}\right) = \beta E_t\left[\bar{V}_{t+1}\left(j'\right)\right] - \beta E_t\left[\bar{V}_{t+1}\left(j\right)\right] \tag{32}$$

If j represents pasture and j' forest, then $\ln\left(\frac{p_t(j,j_{t-1})}{p_t(j',j_{t-1})}\right)$ can be interpreted as the cutoff value for the difference in idiosyncratic shocks $(\nu_{ijt} - \nu_{ij't})$ above which field i chooses pasture.

Now I replace the expected difference in continuation values with its realization and errors:

$$\begin{aligned} \bar{\pi}_t(j, j_{t-1}) - \bar{\pi}_t\left(j', j_{t-1}\right) - \ln\left(\frac{p_t(j, j_{t-1})}{p_t\left(j', j_{t-1}\right)}\right) &= \beta\left(\bar{V}_{t+1}\left(j'\right) - \bar{V}_{t+1}(j)\right) \\ &+ \varepsilon_t^V\left(j'\right) - \varepsilon_t^V(j) \end{aligned} \tag{33}$$

where

$$\varepsilon_t^V(j) \equiv \beta\left(E_t\left[\bar{V}_{t+1}(j)\right] - \bar{V}_{t+1}(j)\right)$$

Finally, Lemma 1 in Arcidiacono and Miller (2011) provides a useful relationship between ex-ante $(\bar{V}_{t+1})$ and conditional $(v_t(j, k))$ value functions:

$$\forall j : \bar{V}(j_{t-1}) = v_t(j, j_{t-1}) - \ln\left(p_t(j, j_{t-1})\right) + \gamma \tag{34}$$

Note that this relationship applies for all j: take any given choice, its choice probability and conditional value function will inform the ex-ante value. Since this relationship holds for any choice, substituting the right-hand side above with the same choice allows me to cancel out terms:

$$\begin{aligned}\bar{\pi}_t(j, j_{t-1}) - \bar{\pi}_t\left(j', j_{t-1}\right) - \ln\left(\frac{p_t(j, j_{t-1})}{p_t\left(j', j_{t-1}\right)}\right) =& \beta\left(v_{t+1}\left(j, j'\right) - v_{t+1}\left(j, j\right)\right) \\ & - \beta\left(\ln\left(\frac{p_{t+1}\left(j, j'\right)}{p_{t+1}\left(j, j\right)}\right)\right) \\ & + \varepsilon_t^V\left(j', j_{t-1}\right) - \varepsilon_t^V(j, j_{t-1}).\end{aligned} \tag{35}$$

Because the state variable only changes according to the previous period's decision, continuation values cancel out:

$$v_{t+1}\left(j, j'\right) - v_{t+1}\left(j, j\right) = \bar{\pi}_{t+1}\left(j, j'\right) - \bar{\pi}_{t+1}\left(j, j\right) \tag{36}$$

This is an example of *finite dependence*: because returns on a choice depend only on the previous period's state, once i makes the same choice in period $t+1$ the continuation values are the same in $t+2$ regardless of the decisions in t or before. This result also holds when longer lag periods also affect payoffs, as long as there is some "renewal action" after which payoffs don't differ (Scott, 2012). Thus I can cancel out the continuation values, which then imply the Euler equation below:

$$\begin{aligned}\bar{\pi}_t(j, j_{t-1}) - \bar{\pi}_t\left(j', j_{t-1}\right) - \ln\left(\frac{p_t(j, j_{t-1})}{p_t\left(j', j_{t-1}\right)}\right) =& \beta\left(\bar{\pi}_{t+1}\left(j, j'\right) - \bar{\pi}_{t+1}\left(j, j\right)\right) \\ & - \beta\ln\left(\frac{p_{t+1}\left(j, j'\right)}{p_{t+1}\left(j, j\right))}\right) \\ & + \varepsilon_t^V\left(j', j_{t-1}\right) - \varepsilon_t^V(j, j_{t-1})\end{aligned} \tag{37}$$

The left side of the equation can be interpreted as the minimum difference in period t profits necessary to justify a choice of j at t instead of j'. The right side denotes the loss in continuation values which result from choosing j and not j'. Because of equation (34), I can express that in terms of period $t+1$ profits and choice probabilities. Thus the right hand side of (37) can be interpreted as the (discounted) difference in profits in $t+1$ resulting from an action which compensates for the impact of period t land use plus a term which corrects for the fact that this action is not always optimal.

Using the definition of period profits and using combinations of the 3 land choices as j and j', I can derive the regression equation below:

$$Y_{tj_{t-1}} = \tilde{\Delta}\alpha_{0j_{t-1}} + \alpha_R \Delta R_t + \tilde{\Delta}\xi_{tj_{t-1}} + \Delta\varepsilon^V_{tj_{t-1}} \tag{38}$$

where:

$$\begin{aligned}
Y_{tj_{t-1}} \equiv& \ln\left(\frac{p_t(\text{ j }, j_{t-1})}{p_t(j', j_{t-1})}\right) + \beta \ln\left(\frac{p_{t+1}(\text{ j }, j)}{p_{t+1}\,(\text{ j }, j'))}\right) \\
\tilde{\Delta}\alpha_{0j_{t-1}} \equiv& \alpha_0(\text{ j }, j_{t-1}) - \alpha_0(j', j_{t-1}) \\
& + \beta\left(\alpha_0(\text{ j }, j) - \alpha_0\,(\text{ j }, j'))\right) \\
\Delta R_t \equiv& R_{\text{j },t} - R_{j',t} \\
\tilde{\Delta}\xi_{tj_{t-1}} \equiv& \xi_{\text{j },j_{t-1},t} - \xi_{j',j_{t-1},t} + \beta\left(\xi_{\text{j },0,t+1} - \xi_{\text{j },1,t+1}\right) \\
\Delta\varepsilon^V_{tj_{t-1}} \equiv& \varepsilon^V_t(\text{ j }, j_{t-1}) - \varepsilon^V_t(j', j_{t-1})
\end{aligned}$$

I run the following regression at the municipal level:

$$Y_{mtj_{t-1}} = \tilde{\Delta}\alpha_{0j_{t-1}} + \alpha_R R_{mt} + \tilde{\Delta}\xi_{mtj_{t-1}} + \Delta\varepsilon^V_{mtj_{t-1}} \tag{39}$$

where R_{mt} denotes yield-adjusted prices and returns to forest are set to 0. The outcome variable uses land use transition matrices for years 17-18 and 18-19. The usual identification concerns from estimating supply using prices apply. To address this, I use the same demand instrument as in the main model.

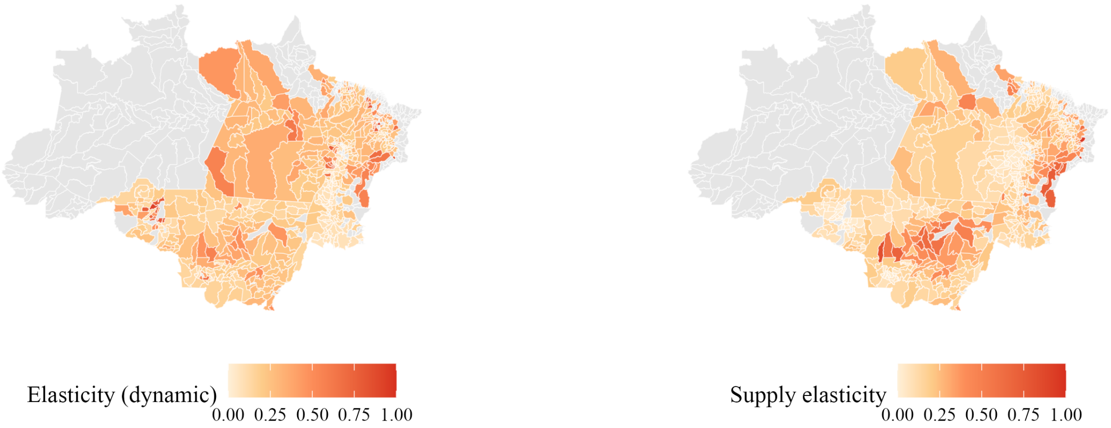
Results: Table S8 shows the key estimate on the ΔR_{mt} coefficient. More importantly, I use the estimated model to compute the average elasticity of pasture acreage with respect to cattle prices. To provide a useful comparison with the main model, I forward-simulate the model for 4 one-year transitions given a temporary 1% perturbation to prices over the same period. I then estimate the arc-elasticity by comparing pasture acreage after the 4 transitions in the scenario with the perturbation versus business-as-usual.

Elasticity estimates are remarkably similar. In my main "medium-term" model, I estimate an average elasticity of 0.216, whereas the dynamic model predicts an elasticity of 0.235. The higher estimates from the dynamic model predict more competitive markets, but by a very small margin. Geographically, the dynamic model also features the pattern of higher elasticities in less remote soy-growing places, and also remote places with high shares of public land (Figure S12). Remote regions end up slightly more elastic (Figure S13), which would only augment my main results of higher competition in remote regions. This shows that my main results, despite abstracting from dynamics, are not overturned by the addition of a dynamic model of land use.

Table S8: Dynamic Estimates of α_R

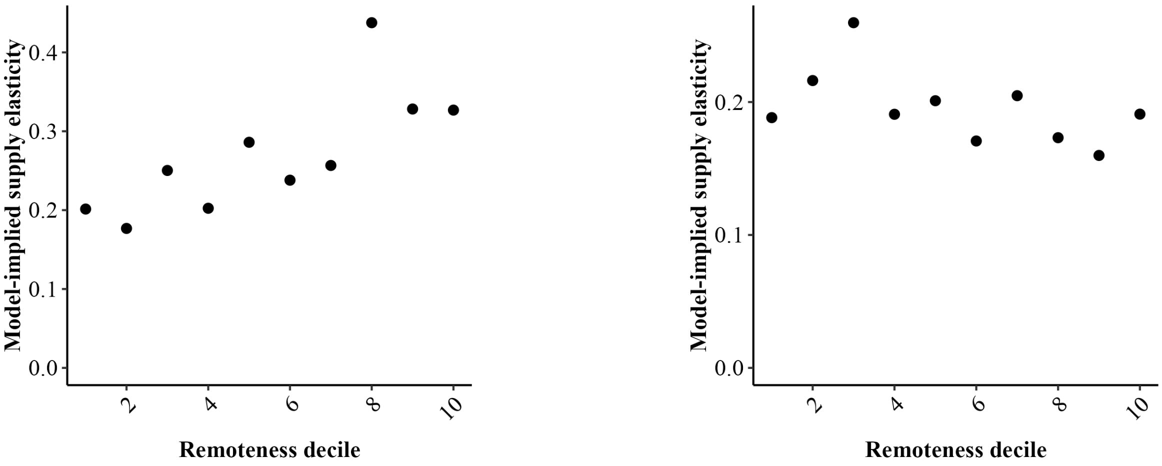
	OLS	IV
Public Designated	0.13^{***}	0.72^{***}
	(0.03)	(0.10)
Public Undesignated	0.24^{***}	0.57^{***}
	(0.03)	(0.10)
Private Undisputed	0.26^{***}	0.56^{***}
	(0.24)	(0.08)
Private Disputed	0.21^{***}	0.89^{***}
	(0.03)	(0.09)

Regressions include state fixed effects and control for enforcement priority municipalities. $^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$



(a) Dynamic (b) Main model

Figure S12: Cattle supply elasticities - dynamics vs. main model



(a) Dynamic (b) Main model

Figure S13: Supply elasticities by remoteness - dynamics vs. main model