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

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Abstract

Agricultural emissions have global consequences. When local enforcement is absent, governments have turned to indirect regulation, using tariffs or standards on agribusiness exporters at intermediary steps of the supply chain. Focusing on the Brazilian Amazon, I find that exporter-focused policies are ineffective for a surprising reason: the highest emissions are processed by small and informal domestic-only intermediaries. Exporters are relatively clean and more productive. I build a structural model to study how remoteness drives different entry decisions by exporters and non-exporters, then examine counterfactual policies. Shifting output away from small and informal firms can both reduce emissions and increase food production.

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1 Introduction:

Agriculture is a key driver of climate change, generating as much as one-fifth of global greenhouse gas emissions (IPCC, 2022). While their effects are felt worldwide, agricultural emissions sources are so numerous that direct regulation is often infeasible. New policies seek to overcome this challenge indirectly by imposing tariffs or standards on exporters[1]. But unlike a pigouvian tax, which directly targets the highest emitters, a tariff only affects the supply networks of exporters, regardless of their emissions intensity. Can exporter-focused policies change incentives for the highest emitters, even if indirectly?

This paper shows that exporter-focused policies fail when exporting firms are more productive and have relatively clean supply chains. Using rich data from the Amazon, I show that the most emissions-intensive production is processed by a fringe of small (often informal) agribusiness intermediary firms in remote regions. As a result, an environmental tax on exporters creates only small effects on emissions at the cost of high output reductions. This happens even with full international coordination (Hsiao, 2023; Dominguez-Iino, 2023). Using a structural model, I show how the distinct supply network of exporters relative to non-exporters drives my different findings, then simulate policies that are similarly indirect but more effective.

My analysis focuses on the cattle industry, a particularly important sector for the global climate. Beef cattle generates methane emissions and is also the leading driver of deforestation in the world (WRI, 2022). In the Brazilian Amazon, cattle drives 90% of deforestation, alone causing 1.7% of *global* (2017) greenhouse gas emissions. When cattle pasture replaces forest, carbon stocks in forest biomass are lost to fire and decomposition (Soto-Navarro et al., 2020). These emissions are the highest in remote parts of the Amazon, where forest naturally holds more carbon.

Small and informal meatpacking intermediaries dominate cattle sourcing in remote regions of the Amazon. Such small firms are often difficult to observe in developing countries (Macchiavello et al., 2022), but food safety regulations in the beef industry provide a unique

[1] A notable example is the recent EU regulation on deforestation-free products (EU, 2023). More broadly, carbon border-adjustment mechanisms and "climate clubs" have grown in popularity as policy proposals (Kortum and Weisbach, 2021; Nordhaus, 2015).

view of firms that are often missing in other data sources. Previous work on agricultural supply chains has relied on exporter (e.g. Dominguez-Iino (2023)) or tax (e.g. Zavala (2023)) data, but these tend to under-represent firms that only sell domestically or operate in the informal sector. Because beef can carry dangerous diseases, sanitary agencies in Brazil require comprehensive reporting of herd movements, even including farms and firms that operate without formal tax registration. With over 10 million records, I trace the journey of cattle from ranchers to meatpackers.

The structural model details how differences in meatpacker productivity and barriers to entry drive exporters and non-exporters to distinct regions. In each geographic market, a set of heterogeneous meatpackers make (static) entry decisions (Mazzeo, 2002; Toivanen and Waterson, 2005; Reiss, 1996), and then choose how much cattle they source in an oligopsony (Cournot) environment. I find that export-authorized meatpackers have high (revenue) productivity, but also high entry costs. These entry barriers keep exporters away from less profitable remote regions. In contrast, domestic-only meatpackers have low productivity, but their extremely low entry costs allow them to fill the gaps left in more remote regions.

Meatpacker sourcing strategies depend on the elasticities of cattle supply, which I estimate using a medium-run model of land use change. Atomistic landholders observe prices for cattle and other commodities and make land conversion decisions. The model incorporates switching costs, which are common in fully dynamic models (Hsiao, 2023; Araujo, Costa, and Sant'Anna, 2020; Scott, 2012), while retaining the tractability of static frameworks (Souza-Rodrigues, 2019). In my main specification, I focus on land use between 2015 and 2019. I estimate the model using high-resolution land use change data and a novel land tenure dataset.

The model helps explain a puzzling pattern - prices paid to cattle ranchers change little with remoteness, even though remote areas are isolated from high-earning exporters. This is due to differences in meatpacker monopsony power. Exporters are few and extract monopsony markdowns on the prices they pay to ranchers, but non-exporters are numerous and behave more competitively. Remoteness creates two countervailing forces - ranchers have less access to exporters but face a more competitive midstream market. This differs from Dominguez-Iino (2023), which uses exporter data and finds remote regions of Brazil and

Argentina to be less competitive. The regions studied are slightly different, I do not find sharp regional differences in supply elasticities, and the small firms I document drive more competition in remote places.

With the model estimates, I also use counterfactual exercises to compare policy interventions. First, I show that proposals to regulate only export-authorized meatpackers require large reductions in beef production to achieve small emissions reductions. This is because exporting meatpackers operate in lower-emitting regions, leaving high-emitting remote areas and small firms unregulated. But other supply chain policies can be effective. A subsidy to the lowest emitting regions can alleviate some of the distortions created by market power. Despite increasing production in targeted regions, the subsidy *decreases* aggregate emissions due to demand spillovers in higher-emitting places. Finally, I show that increasing barriers to entry for low-productivity domestic firms can reduce emissions dramatically while also *increasing* beef sales. The policy achieves this by reallocating output away from high-emitting regions, and towards lower-emitting places and more productive meatpackers.

This work provides two general lessons that apply well beyond the Amazon[2]. First, deforestation is most common and most impactful in remote regions of the world. I show that the firms which operate in these remote regions are fundamentally different from the more visible firms that operate in better-connected regions. In this sense, I add a supply chain perspective to a rich literature on deforestation (Assunção, Gandour, and Rocha, 2015; Moffette, Skidmore, and Gibbs, 2021; Burgess, Hansen, Olken, Potapov, and Sieber, 2012; 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; Balboni, Burgess, and Olken, 2021; Bragança and Dahis, 2022; Souza-Rodrigues, 2019; Araujo, Costa, and Sant'Anna, 2020; Araujo, 2023). Supply chain policies can be a promising avenue to overcome feasibility constraints to regulation, but only when they move output away from small and inefficient firms in remote regions.

The second, broader insight, relates to the abundance of small and informal firms in devel-

[2]Even as I emphasize general lessons, it is important to note the scale and relevance of this particular setting. The Brazilian Legal Amazon covers an area of almost 2 million square miles, about 2/3 that of the contiguous USA. My modeling exercise explores the economic differences over this large area, with implications for diverse ecosystems and the global climate.

oping countries (Dix-Carneiro, Goldberg, Meghir, and Ulyssea, 2021; Hsieh and Olken, 2014; Ponczek and Ulyssea, 2022), often a result of allocative inefficiencies (Hsieh and Klenow, 2009). Curbing the entry of informal firms can increase average productivity (Ulyssea, 2018; Meghir et al., 2015) - I also find that it can greatly reduce emissions. Similarly, a contemporaneous literature in macroeconomics finds that fossil fuel use is negatively correlated with firm revenue productivity (Klenow, Pastén, and Ruane, 2024; Kim, 2023). As Conte, Desmet, and Rossi-Hansberg (2024) show, decarbonization can be unilaterally optimal when it concentrates output in more productive regions. This could create a kind of "double dividend" (Goulder, 1995) without necessitating a revenue-neutral tax.

The policy exercises relate to a growing literature on trade and its environmental effects (Harstad, 2022; Shapiro, 2016, 2021; Copeland and Taylor, 1994; Antweiler, Copeland, and Taylor, 2001; Kortum and Weisbach, 2021; Nordhaus, 2015; Böhringer, Carbone, and Rutherford, 2016; Farrokhi and Lashkaripour, 2020; Farrokhi and Pellegrina, 2020; Hsiao, 2023; Dominguez-Iino, 2023). While previous work shows that environmental regulation through trade policy can be subject to leakage, I emphasize a different mechanism: policies focused on exporters burden the most productive firms and the lowest emitters. Trade policy can fail even without leakage.

Finally, this paper adds insight on how intermediated trade affects competition (Antras and Costinot, 2011; Grant and Startz, 2022). While I join a recent literature showing how agricultural markets face intermediary monopsony (Chatterjee, 2023; Zavala, 2023; Bergquist and Dinerstein, 2020; Rubens, 2023; Kochhar and Song, 2024), I also show how *competitive* some regions can be once I account for small and informal firms. From an environmental perspective market power can be beneficial: whereas market power is an *underproduction* problem, pollution externalities imply *overproduction* (Buchanan, 1969; Fowlie, Reguant, and Ryan, 2016; Preonas, 2023; Coulomb, Henriet, and Reitzmann, 2021). But my work shows that the environmental benefit of market power crucially depends on *where* each market failure operates. In my application, market power affects clean regions, but emissions-intensive remote areas are more competitive. Market power distorts the geography of price signals, ultimately increasing the average carbon intensity of production. Environmental policies must consider not only the presence of pre-existing distortions, but also their distribution

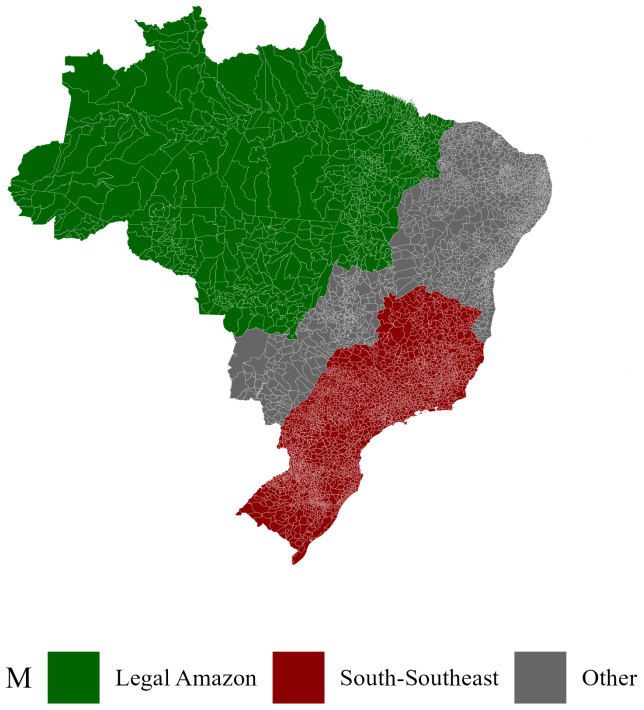
across space and firms.

In the next section, I describe the setting and data with some stylized facts. Those motivate a structural model, which I introduce in section 3. I discuss estimation in section 4, then present results and policy counterfactuals in sections 5 and 6.

2 Context and descriptive evidence

In the cattle industry, carbon emissions and supply chains both vary greatly across space. The variation I show in the stylized facts that follow plays out over a gradient of remoteness. Here, I define remoteness as the distance to São Paulo. It is Brazil's largest city, part of the country's South-Southeast region that houses more than half the country's population (Figure 1). Nearly all (99%) exports of beef coming from the Amazon go through ports in the South-Southeast.

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:

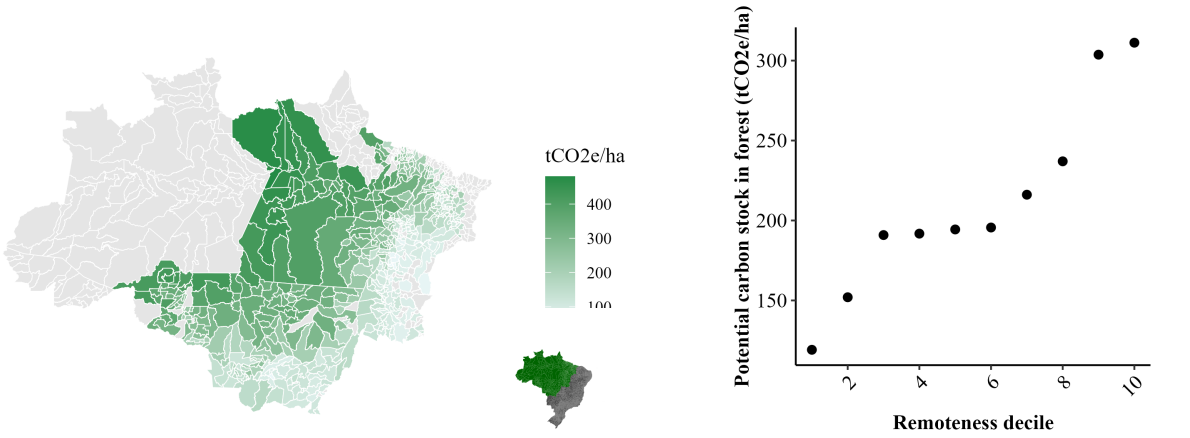
In the Amazon, agricultural emissions come primarily from the displacement of forests with pasture for cattle. Forests are a natural carbon capture technology. When trees perform photosynthesis, they pull carbon dioxide from the air and release oxygen. Through this process, they build up their biomass (wood, branches, and roots), which consists mostly of carbon. A standing forest thus comprises a carbon stock. When ranchers clear the forest to grow pasture, this carbon stock is quickly released through fire and decomposition. Pasture itself holds some carbon, but in most places less than a tenth of what forest can store. In the Amazon, pasture comprises 80% of agricultural land (roughly 20% of total land).

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, since humidity is much higher near the equator and tree species that inhabit it store more carbon. The sheer size of the region, roughly 2/3 that of the contiguous United States, naturally creates a great deal of spatial heterogeneity. As it moves south, the forest begins transitioning to the Cerrado, Brazil's savannah biome which holds much 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. It is important to emphasize that this is not because they are remote or untouched, since I am averaging only old-growth stocks[3].

[3]Rather, historically those regions *became* remote because they had such dense forest. The supplement (A.3) describes this historical context.

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 and the supplement (A.3) describes them in detail.

2.2 The geography of the beef cattle supply chain:

The cattle supply chain, like many other sectors, relies on intermediaries to process output and ship it to consumer markets. In this setting, cattle ranchers sell their output to meatpackers, which process the animals into beef products and sell them in Brazil and abroad. Meatpackers are distinguished by the type of consumer markets they can access. At lower levels of sanitary inspection (SIM and SIE), meatpackers can only sell within their states. Henceforth, I call these (and any meatpackers in the informal sector) **domestic-only** firms. Federally inspected (SIF) meatpackers can sell in all of Brazil, including outside the Amazon, and also internationally. I refer to them as **export-authorized** meatpackers.

Health regulations tied to beef allow me to observe sourcing at a uniquely rich level of detail. Meat products carry health risks, so strict phytosanitary regulations require traceability of cattle herds. To curb the spread of diseases, Brazilian ranchers are required to issue a record[4] of every cattle herd movement, including sales to meatpackers.

Export-authorized meatpackers source cattle in less remote regions, and domestic-only meatpackers operate in more remote regions (Figure 3, panel a)[5]. This geographic fragmentation in the supply chain arises from the costs and risks in transporting cattle. Rancher-to-meatpacker transactions occur over short distances, so meatpackers need to establish operations near their suppliers. Exporting meatpackers cluster near their main consumer markets and the ports that process 99% of beef exports. Where the export-authorized (SIF) meatpackers do not operate, domestic-only players fill the gaps. Although domestic-only meatpackers process 25% of all cattle[6], they can take up to 70% in more remote places.

This spatial distribution of meatpackers in the Amazon is robust across time and different datasets. The comprehensive GTA dataset I access is limited to years 2015-18. But alternative data sources confirm the patterns I find. Data on export-authorized meatpackers are more common[7], and with those I find the same patterns for years 2010-2020 (Figure 3): exporters are less likely to operate in remote regions.

The geographic clustering of firms by export status creates differences in concentration (Figure 4) in the midstream market. Export-authorized meatpackers are few and large, so regions dominated by them are highly concentrated. Domestic-only meatpackers are numerous and small, so remote regions are less concentrated.

As Figure 5 shows, both domestic and informal firms[8] are key drivers of differences in concentration across regions. Without them, remote regions would appear *more*, not less,

[4]Known in Portuguese as "*Guias de Trânsito Animal*" (GTA, roughly translated to "Records of animal transit"), GTAs contain information on the number of heads in the herd, the sex and age of the animals, and whether they are properly vaccinated. I include more information in the supplement (A.1).

[5]To provide some intuition for the variation in remoteness: straight-line distances to São Paulo vary in my sample from 588mi to 1783mi. The latter is roughly the distance between Boston and Denver, and slightly more than London to Istanbul.

[6]Export-authorized meatpackers lead both domestic and export sourcing. Only 20% of beef output from Brazil is exported, in line with global export shares in food production.

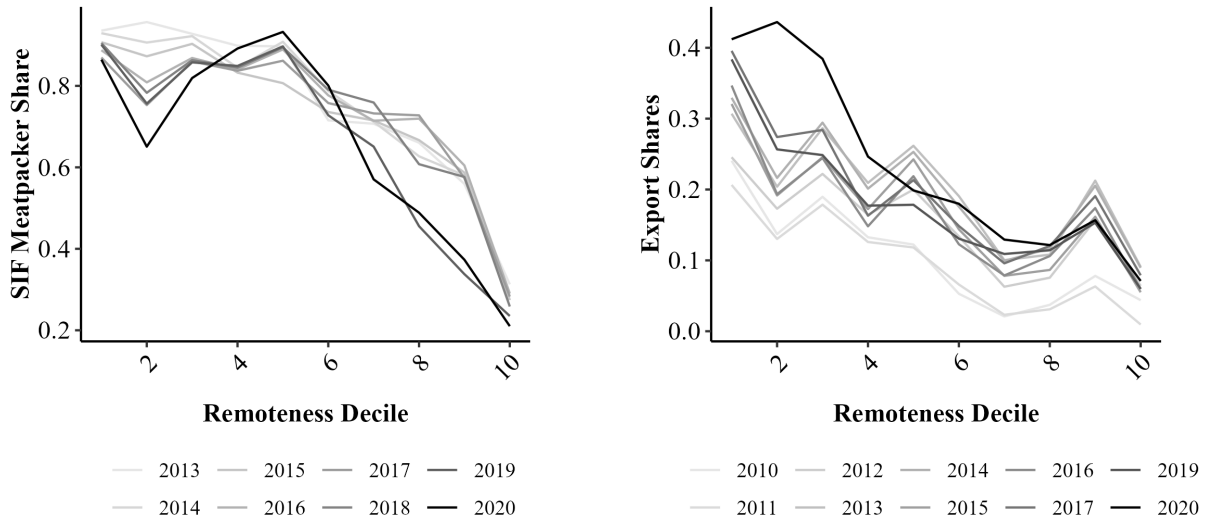
[7]The data supplement (A.2) describes the alternative data and their patterns at greater detail.

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

concentrated, suggesting an opposite pattern of market power.

The link between market concentration and market *power* depends on monopsonistic conduct, which I embed in the structural model below. In the supplement (B.1), I show empirical evidence consistent with monopsony through the effect of concentration on cattle prices and pass-through rates of demand shocks.

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

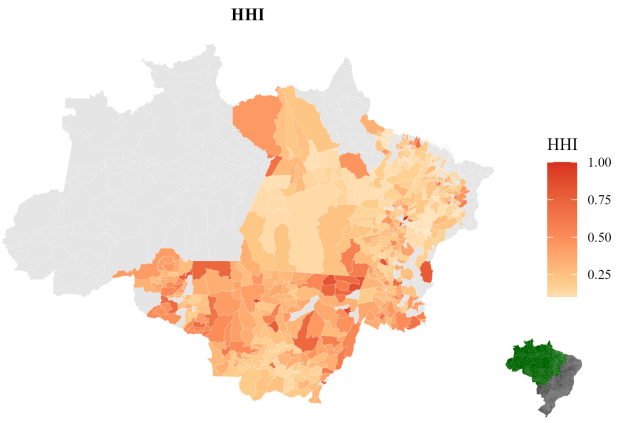


(a) Export-authorized (SIF) meatpacker shares in sourcing

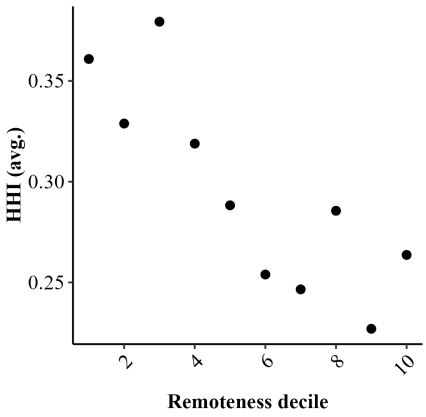
(b) Output share that is exported

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 supplement (A.2) describes them at greater detail.

Figure 4: Remote markets are less concentrated



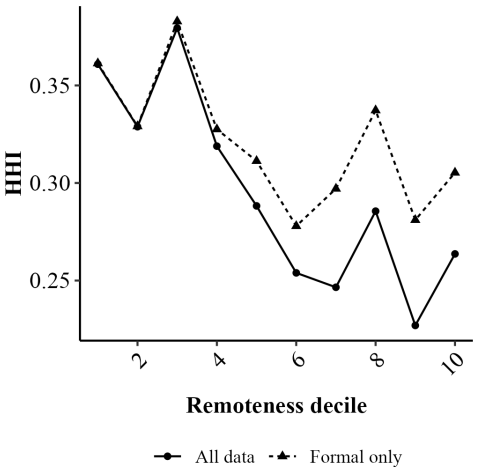
(a) Meatpacker sourcing HHI



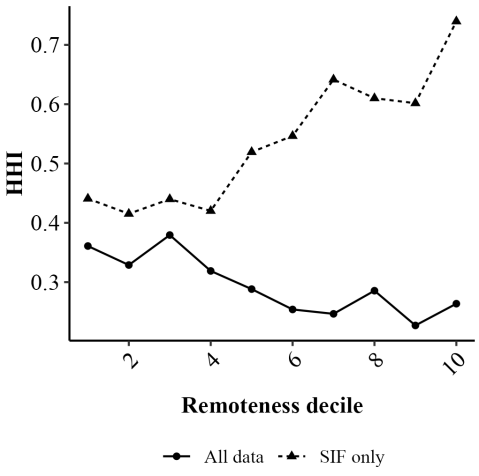
(b) HHI by decile of distance to São Paulo

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.

Figure 5: 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.

3 Structural Model

The stylized facts portray two types of cattle supply chain in the Amazon: one led by concentrated export-authorized meatpackers in lower-emitting regions, another led by many small domestic-only meatpackers in high-emitting remote areas. The goal of this model is to explain these patterns by analyzing the decisions of landholders, meatpacking firms, and consumers in equilibrium. Once estimated, the model can also deliver insight on how the supply chain responds to policy.

Land is segmented into geographic markets m (municipalities), each characterized by its remoteness - the distance to the large consumer markets and ports in Brazil's Southeast. Atomistic landholders make one-time land conversion decisions according to the commodity prices and conversion costs they face. Those that decide to produce cattle have to sell to meatpackers. Meatpackers make entry and sourcing quantity decisions, resulting in equilibrium cattle prices c_m. They then sell beef to "local" or "export" markets, depending on whether they are export authorized. Meatpackers are monopsonistic in sourcing but are price-takers in the downstream beef market.

3.1 Landholder problem

I model landholders[9] from a "medium-run" perspective: landholders observe commodity prices and make land use change decisions for a given time period. In the empirics, I focus on the 2015-2019 time frame. I choose this medium-run formulation of the model because it allows for switching costs, which are important in fully dynamic models (Scott, 2012), while retaining the tractability of static frameworks. In the supplement (C.1), I show that a fully dynamic version of the model does not overturn my main results and predicts similar supply elasticity patterns.

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

[9] I use the term "landholder" instead of "landowner" because property rights issues are common in the Amazon. Estimation is done separately for different land tenure classes.

different from j_0, to maximize:

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

where R_j is an observable measure of returns for land use j, $\xi_{j,j_0 m}$ 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 costs of transitioning from forest to pasture.

Agricultural returns are a function of output prices c_{jm} (for cattle or crops) and yields a_{jm}:

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

Since I do not observe prices for goods 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:

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

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

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

where $\rho_{j_0 m}$ denotes the land share of use j in the beginning of the period, and ρ_{jm} at the end. This expression is the bridge between the land use and meatpacker parts of the model – meatpacker consider cattle supply responses in making their quantity decisions.

3.2 Meatpacker Problem

Meatpackers i are the intermediaries in the industry - they buy cattle from ranchers in municipality m and sell to their different consumer markets. Meatpackers vary in terms of their productivity (z_{im}) and the type of consumers they serve. Domestic-only meatpackers ($i \in D$) sell beef at price P^D, whereas export-authorized meatpackers sell for P^E. Note that z_{im} varies by municipality (m), reflecting different transportation costs and quality for different regions. Meatpackers pay market-level cattle price c_m to ranchers for each unit of cattle they source, and they also incur a fixed entry cost (f_{im}^D or f_{im}^E). Putting this all together, meatpacker profits vary geographically and by meatpacker type:

$$\pi_{im} = (P^E z_{im} - c_m)\, q_{im} - f_{im}^E \qquad \forall i \in E \tag{5}$$

$$\pi_{im} = (P^D z_{im} - c_m)\, q_{im} - f_{im}^D \qquad \forall i \in D \tag{6}$$

Entry stage: The timing of the model is as follows. First, in each local cattle sourcing market m, $N_E + N_D$ potential entrants make entry decisions. Then, entrants choose cattle sourcing quantities simultaneously (Cournot), resulting in equilibrium cattle price c_m. In equilibrium, all meatpackers operating in market m make positive profits; and if others were to enter m, they would make negative profits. Formally, let I_m denote the set of meatpackers operating in m:

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

Quantity setting: In the second stage, meatpackers in each market simultaneously choose quantities q_{im} a la Cournot to maximize:

$$\max_{q_{im}} \{ \Big(P z_{im} - c_m(Q_m) \Big) * q_{im} \} \tag{7}$$

where P can be P^E or P^D depending on export authorization.

Solving the model: Beginning with the second stage - taking first-order conditions and solving for the equilibrium cattle price $c_m(Q_m)$:

$$c_m(Q_m) = Pz_{im}\Bigg(\underbrace{\frac{\partial c_m}{\partial Q_m}\frac{Q_m}{c_m}s_{im} + 1}_{\mu_{im}}\Bigg)^{-1} \tag{8}$$

where $s_{im} = \frac{q_{im}}{Q_m}$ is meatpacker i's market share in m. In words, the equilibrium price of cattle in m is a markdown μ_{im} over the meatpacker marginal revenue product. Markdowns are increasing (price decreasing) in the inverse elasticity of municipal cattle supply.

Moving back to the entry stage, I make an assumption of sequential moves to ensure a unique equilibrium. The player with the highest marginal revenue product (MRP) Pz_{im} for a given location m is first to decide whether to source from that location, then the second-highest Pz_{im}, and so on. Formally, the order is given by vector $B_m = (b_{tm}, ..., b_{Tm})$, where:

$$Pz_{b_{tm}} \geq Pz_{b_{t'm}} \quad \forall t \leq t'$$

This sequential assumption is common in the literature on entry under firm heterogeneity (Reiss, 1996; Mazzeo, 2002; Toivanen and Waterson, 2005). In my application, it ensures a unique equilibrium for the entry margin; that is, which meatpackers i operate in a given market m. When multiple equilibria are possible, this assumption favors the equilibrium that includes higher-ranked players. This mechanism of equilibrium selection reflects the notion that the largest meatpackers tend to be leaders in the industry and smaller players operate on the fringe. Although this assumption by definition affects the kind of equilibria I get, in the empirical supplement (B.2) I show that alternative orders yield similar equilibrium outcomes.

3.3 Demand:

Meatpackers sell to different consumers depending on whether they are export-authorized or sell to local markets. I model this as two separate sets of consumers, whose demand follows a simple isoelastic specification:

$$\log Y^D = \beta_0^D + \beta_{P^D} \log P^D \tag{9}$$

$$\log Y^E = \beta_0^E + \beta_{P^E} \log P^E \tag{10}$$

Crop sourcing is perfectly competitive and demand is perfectly elastic: Crops (e.g. soy) comprise less than 5% of land cover in my study region, so I simplify the supply chain and demand for crops. For crop land uses, I assume farmers sell directly to a perfectly competitive intermediary at $\bar{c}_m^{\text{crop}} = P^{\text{crop}}(\frac{z_m^{\text{crop}}}{\tau_m^{\text{crop}}})$. That is, they earn the international price for crops net of transportation costs. Assuming perfectly elastic demand (constant P^{crop}) is consistent with the fact that crop production takes a small share of land and is generally oriented for export.

3.4 Closing the model:

Market Clearing: Aggregate cattle supply from ranchers in the Amazon equals total demand by meatpackers. The resulting beef supply from meatpackers equals aggregate beef demand. Market clearing requires:

$$L_m \, a_{past,m} \sum_{j_0} \rho_{j_0 m} \, \rho_{\text{past},j_0 m} = \sum_i q_{im} \quad \forall m \tag{11}$$

$$\sum_{i \in D,\, m} q_{im} \, z_i \tau_m^{-1} = Y^D \tag{12}$$

$$\sum_{i \in E,\, m} q_{im} \, z_i \tau_m^{-1} = Y^E \tag{13}$$

where $Q_m = L_m \, a_{past,m} \sum_{j_0} \rho_{j_0 m} \, \rho_{\text{past},j_0 m}$ is the equilibrium cattle output in municipality m.

Equilibrium Given a set of land use parameters $\{\alpha\}$, slaughterhouse productivities, iceberg and fixed costs, and beef demand parameters β^D and β^E, an equilibrium is a vector of municipal cattle prices $\{c_m\}_m$ and beef prices P^E, P^D consistent with equations (3), (8), (9 - 10), and (11 - 13).

4 Estimation

Estimation brings the rich cattle movement records together with census prices and land use data to estimate the parameters of the land use and meatpacker models. I calibrate demand elasticities based on previous work. The appendix discusses my data sources.

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), we have the following regression:

$$\log\left(\frac{\rho_m(j, j_0)}{\rho_m(j', j_0)}\right) = \Delta\alpha_{0,j,j',j_0} + \alpha_R \Delta R_{j,j',m} + \Delta\xi_{j,j',j_0,m} \tag{14}$$

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. As is common in logit models, I do not separately identify each $\alpha_0(j, j_0)$, so I work with their relative values.

Identification Equation (14) is essentially a supply curve, which raises endogeneity concerns. For instance, unobserved supply shocks can affect local commodity prices or realized yields, so that $E[\Delta\xi_{j,j',j_0,m}|\Delta R_{j,j',m}] \neq 0$, thus biasing estimates of α_R.

To address endogeneity, I introduce two sets of instrumental variables. First, I use a 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:

$$SSIV_m = \sum_d g_{dt}\, s_{id}\, s_{im}$$

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 the model rationalizes those changes in demand conditions at destination countries as changes in firm productivity.

The key identifying assumption is that the country-level shocks are as good as randomly assigned. That is, $E\left[g_d \mid \bar{\xi}_d, s_d\right] = \mu$, demand shocks in destination countries have the same expected value (μ) 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. I address this by controlling for the share of each region's output that goes to exports (separately for soy and beef).

The second set of instruments consists of 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.

4.2 Meatpacker parameters:

Estimation for the meatpacking model proceeds in two stages, the first focusing on meatpacker productivity and how it is shaped by remoteness. I use meatpacker sourcing first order

conditions to invert their marginal revenue products (Pz_{im}, MRP henceforth). As Equation 8 shows, model-implied MRPs can be computed using local cattle prices and meatpacker market shares from the data, as well as local cattle supply elasticities implied from the estimated land model (Equation 4):

$$Pz_{im} = c_m\left(\left(\frac{\alpha_R\, R_{jm}}{\rho_{jm}}\sum_{j_0}\rho_{j_0 m}\,\rho_m(j,j_0)\,(1-\rho_m(j,j_0))\right)^{-1} s_{im} + 1\right) \tag{15}$$

Note that the productivity z_i is not separately identified from P without further assumptions, but I can identify how the MRP (Pz_{im}) varies across firms and space. Assuming constant returns to scale, it is the meatpacker's revenue productivity. I use OLS to estimate how MRPs vary by firm and across regions:

$$MRP_{im} = \alpha_i\,\text{Company}_i \;+\; \alpha_m \;+\; \epsilon_{im} \tag{16}$$

where Company_i is a set of meatpacker fixed effects, which separates domestic-only from export-authorized meatpackers, and also singles out key exporting meatpackers: JBS, Marfrig, and Minerva. α_m is a set of municipality fixed effects that captures geographic variation in meatpacker earnings. Deviations ϵ_{im} of predicted MRPs from the inverted values are seen from the lens of the model as measurement error.

Moving to the entry model, I use MRP values predicted from the regression as the productivity of potential entrants. Then I estimate fixed cost parameters to match the observed market structure. I parameterize fixed costs f_{im} as:

$$\log(f_{im}) = \sum \theta_{im}\mathrm{X}_{\mathbf{im}}$$

where X_{im} contains the following variables: the size of the municipality, whether the meatpacker is export-authorized (SIF), the share of municipal area in public land (interacted with SIF), log distance to São Paulo (interacted with SIF), and an indicator for being one of the top companies JBS, Marfrig, or Minerva. Each municipality has JBS, Marfrig, and

Minerva as potential entrants, plus N^E other SIF potential entrants, plus N^D domestic-only potential entrants. I choose N^E and N^D to be 2 more than the maximum number of entrants observed in each state.

Estimation algorithm: I take a set of parameters, solve the model (entry margin and Cournot game), and evaluate how closely it matches moments for market concentration and export-authorized shares. More formally, for a given guess of parameters $\tilde{\Theta}$:

1. Derive the $\log f_{im}(\tilde{\Theta})$ implied by the parameters.
2. Solve the model for each m.[10] Derive model-implied moments (more on this below).
3. Define objective function: $\hat{\Theta} = \arg\min_{\tilde{\Theta}} \left(m - \hat{m}(\tilde{\Theta})\right)' W \left(m - \hat{m}(\tilde{\Theta})\right)$
4. Iterate steps 1-3 over guesses $\tilde{\Theta}$ to find the $\hat{\Theta}$ which minimizes the objective function in step (3.)

I use a 2-stage nonlinear GMM estimator. In the first stage I use the identity matrix as W. Then, based on the results from the first stage, I compute the optimal weighting matrix $W^{opt} = \Omega^{-1}$ for the second stage, where Ω is the variance-covariance matrix of the moments. Estimation consists of 8 parameters with 20 moments, the first 10 being the average SIF (export-authorized) shares in cattle sourcing for each decile of remoteness (distance to São Paulo), and the remainder municipal cattle sourcing Herfindahl index (HHI) averaged over each remoteness decile.

4.3 Demand (calibration):

I calibrate the two demand parameters of the model. This allows the framework presented here to remain more tractable since the focus of this project is the supply side. For the demand elasticity on the local market, I use $\beta^D = \beta^E = -1.279$ from Coelho et al. (2010), which estimates demand elasticities for a variety of food items using Brazilian household expenditure data.

[10] See the empirical supplement (B.2) for more details on algorithm.

5 Estimation Results

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 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 change little with remoteness. 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. These two effects mostly cancel each other out along the remoteness gradient[11]. As a result, geographic differences in monopsony power are primarily driven by meatpacker concentration, not supply elasticities.

Table 1: Key land use estimation coefficients

	Parameter	Estimate	SE	Elasticity	F Stat
Land Use	$\alpha_{R(PublicDesignated)}$	1.80	(0.14)	0.33	35.56
	$\alpha_{R(PublicUndesignated)}$	1.21	(0.11)	0.14	32.14
	$\alpha_{R(PrivateUndisputed)}$	1.52	(0.09)	0.17	51.98
	$\alpha_{R(PrivateDisputed)}$	1.57	(0.10)	0.19	46.22

Note: Land use estimation includes state FE and policy covariates. (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 supplement (A.4) provides a discussion and summary statistics for different land tenure classes.

Meatpackers: Estimates from the meatpacker model help elucidate the relationship between market power and remoteness. Meatpacker marginal revenue products (MRPs) are lower in more remote places (Figure 6a). This is in part due to the costs created by distance and the shift to more domestic-only meatpackers in remote areas, which have have much

[11]Figure S11 in the supplement (C.1) shows spatial patterns of elasticity at greater detail. Dominguez-Iino (2023) finds that elasticities in South American agriculture sharply decrease with remoteness. 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 a new land tenure dataset. The models used are also distinct, and the state-dependence included in my model is known to lead to higher estimated elasticities (Scott, 2012).

lower estimated MRPs.

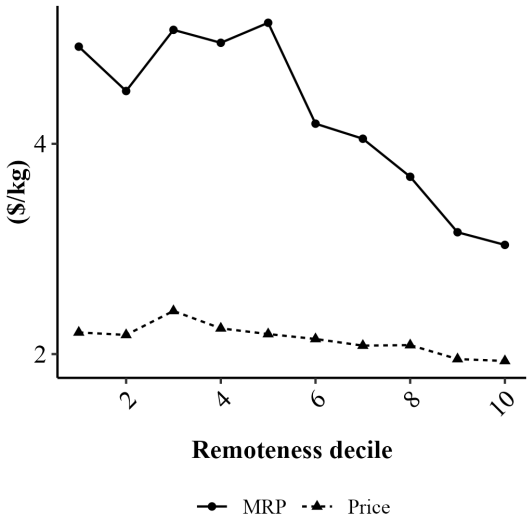
Regional differences in market power diminish price gaps across regions. Figure 6a shows the marginal revenue products (solid line) and the cattle price (dashed line) paid to ranchers. Meatpacker margins vary by firm, but the cattle price ranges from roughly 45% to 65% of the *average* meatpacker marginal revenue product, with remote ranchers earning a higher share of meatpacker earnings. The differences in meatpacker monopsony create a muted effect of remoteness on cattle prices. Meatpackers in the least remote decile earn 65% more (avg.) than those in the most remote decile. For cattle prices paid to ranchers, this regional gap is only 15%. These differences cushion the losses for ranchers due to remoteness, but as a result also incentivize cattle ranching in the places that emit the most.

Much of this pattern of market power is driven by entry costs. While export-authorized entry costs are much higher and grow with remoteness, domestic-only entry costs drop dramatically in more remote regions. This is consistent with the fact that state and regional governments set the phytosanitary standards for non-SIF meatpackers. More remote regions with weaker state presence can set lower barriers to entry, which opens the market to many domestic firms and drives up competition[12].

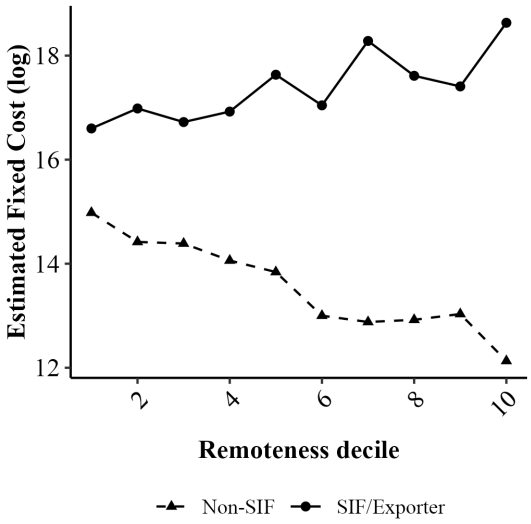
[12]Table 2 suggests a role for institutions in driving entry. Places where cattle pasture operates (often illegally) on public land tend to sell more to domestic-only players.

Figure 6: Estimation results - meatpacker marginal revenue products and fixed costs

(a) Estimated MRPs vs. cattle prices ($/kg)



(b) Estimated fixed costs



Note: Values are averaged by decile of distance to São Paulo. MRP values on panel (a) are averages of the estimated MRPs weighted by the share of export-authorized vs. domestic-only meatpackers. Those values are measured in terms of dollars per kilogram of carcass-weight equivalent.

Table 2: GMM Coefficient estimates for entry model

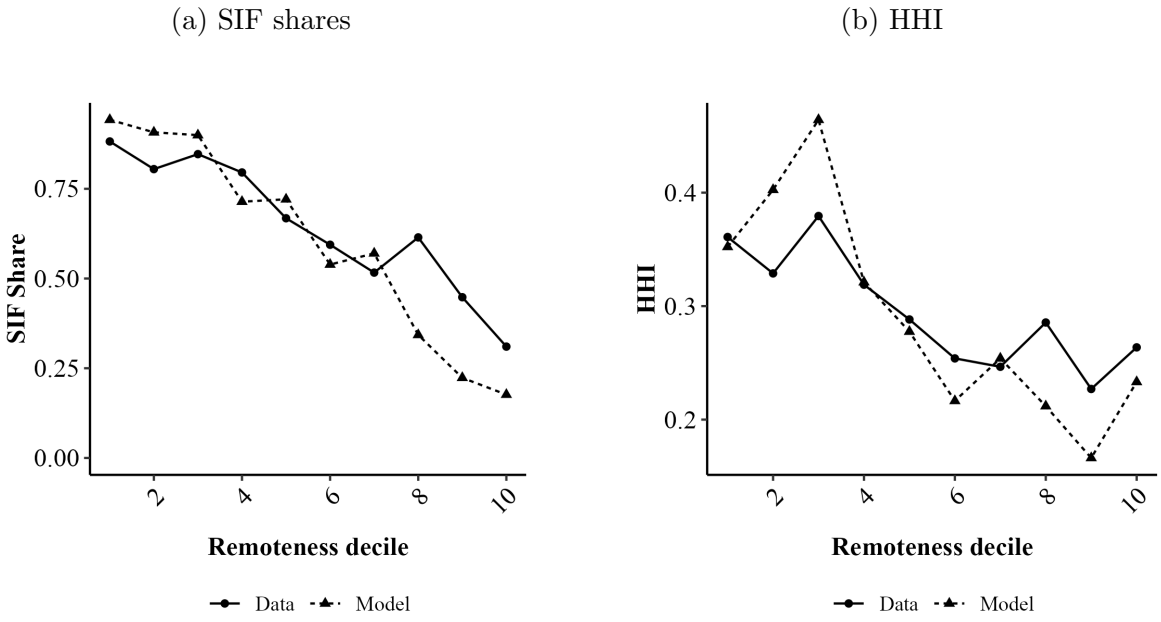
	Description	Coefficient	SE
1	Munic. size	1.04	(0.02)
2	Log SP dist. x SIF	0.20	(0.03)
3	Log SP dist. x non-SIF	-0.29	(0.07)
4	SIF	1.26	(0.20)
5	non-SIF	5.00	(0.39)
6	Top SIF	2.49	(1.11)
7	Public share x SIF	2.06	(1.00)
8	Public share x non-SIF	-4.78	(1.72)

Note: Standard errors come from 500 bootstrap runs. "SP dist" refers to the distance from the municipality to São Paulo as a measure of remoteness. "SIF" refers to export-authorized meatpackers. "Top SIF" refers to the three leading firms in the sector: JBS, Marfrig, Minerva. "Public Share" denotes the share of total land in the municipality that is public.

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 7 shows that

the model matches those patterns.

Figure 7: Model fit - export-authorized (SIF) meatpacker share and HHI



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

Caveats and extensions: The framework I estimate here assumes away any dynamics in the meatpacking industry[13]. However, the approach I use has the benefit of tractability and is tailored for explaining the geographic pattern of meatpacker market structure, which Figure 3 shows to be a long-run feature of the industry. The meatpacker model also abstracts away from the exact location decisions of meatpacking plants and their capacity constraints. The setting I study mitigates these concerns, in great part because of high cattle transportation costs. 75% of cattle sourcing happens within 250km from a meatpacking plant, so firm considerations like the proximity-concentration trade-off (Helpman et al., 2004) are confined to small geographies. Regarding capacity constraints, interviews I conducted with managers of meatpacking plants revealed that their key constraint was labor, not facility size or machinery. If they need to increase production, they can do so by hiring more workers or increasing the number of slaughter shifts in a day. Those margins can be adjusted in the medium run.

[13]For a discussion on the dynamics of land use, refer back to the model section or the supplement (C.1), which includes a dynamic extension.

6 Counterfactual Analysis

This section uses policy counterfactual simulations to show two things: (i) exporter-focused policies can be ineffective at reducing emissions and greatly distort production; (ii) other indirect policies focusing on the supply chain can be effective as long as they move output away from high-emitting regions and inefficient firms.

6.1 Policies that target only export-authorized meatpackers are less effective and burden already distorted markets:

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 has limited effectiveness. I do this by implementing a per-head cattle tax levied on different sets of players. The first scenario is a tax only on export-authorized meatpackers (all their output regardless of destination), the second on all meatpackers, and the last is targeted at only the highest emitting decile of regions. In all cases, I set the tax to be roughly 20% of the average cattle price. Then I assess the implied economic trade-offs by examining how sales fall in response to the tax.

When only export-authorized firms are included, there are small emissions reductions.

Table 3: Cattle tax counterfactuals

	Tax	Emissions Red.	Sales Red.	Sales/Emissions trade-off
SIFs only	∼20%	0.2%	5.9%	24.9
All meatpackers	∼20%	2.1%	9.9%	4.79
Top emitting regions	∼20%	3.3%	0.7%	0.22

Note: Tax percentages relative to average cattle price. Columns for "Emissions" and "Sales" inform percentage **reductions** relative to business-as-usual. SIFs are export-authorized meatpackers. Top emitting regions consist of the top decile of municipalities by their emissions intensity, which I calculate based on 2015-19 emissions divided by output.

Beef sales need to fall by 5.89% for a reduction of 0.24% in emissions, a ratio of 24.9 to 1. This trade-off is less than a fifth if all meatpackers are contemplated. If policy can target the highest-emitting regions, the trade-off is 0.22 - with the same tax rate reducing emissions by 3.3% while sacrificing only 0.7% of output. The supplement (B.3) includes versions of these exercises under different demand elasticities.

These differences are driven primarily by the fact that export-authorized meatpackers are located in less remote regions and are thus not the key sources of emissions[14]. A larger reduction in beef production would be necessary to reduce their emissions. On the other hand, the tax on top emitting regions is not only better targeted, but also faces higher rates of pass-through due to higher competition in remote regions.

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, my work suggests 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. Emissions from exporters are relatively low, and the low rates of pass-through due to exporter monopsony dampen the price signal from the policy.

[14]Exporter-focused policies only affect the high emitters indirectly, through demand spillovers. Impacts on regions that typically sell to exporters are partly offset by these regions selling more to domestic-only meatpackers. This drives down the beef price in the local market (P^D), which then drives minor emissions reductions in remote regions.

6.2 Targeted subsidies can increase output and reduce emissions:

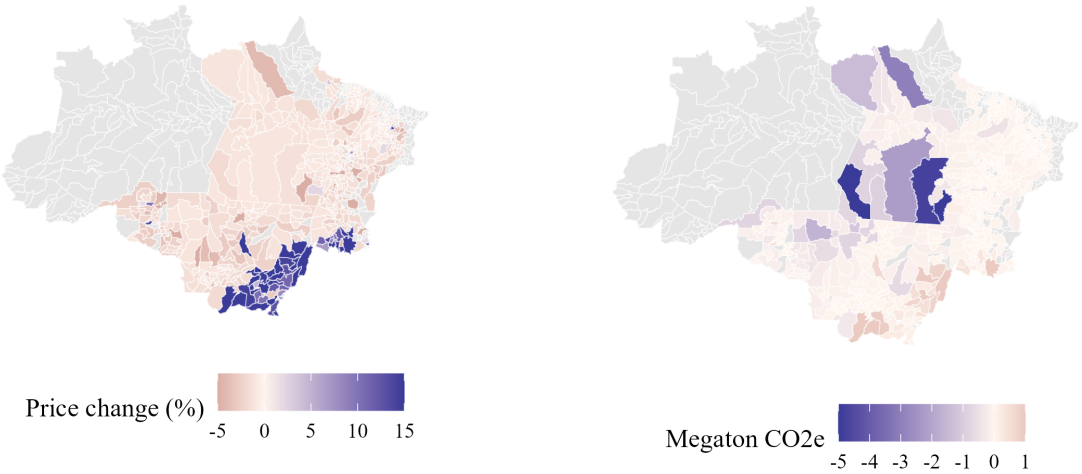
Subsidizing clean regions can actually *reduce* emissions. This result might seem counter-intuitive at first, but the skewed distribution of emissions along with geographic spillovers can create this effect. To show this, I simulate a counterfactual in which the least remote municipalities receive a subsidy of roughly 20% of the average cattle price in my sample. The targeted municipalities are chosen by taking the decile of municipalities in the Amazon nearest to São Paulo - the least remote places.

The subsidy affects a limited set of regions, so aggregate beef sales increase by 1.3%. Behind this number lie countervailing responses from different markets (Figure 8). Affected municipalities see their cattle prices increase, with varying rates depending on pass-through and changes in entry patterns induced by the policy. Higher cattle prices increase aggregate beef production, which then lowers beef prices on the consumer side. The reduction in consumer prices creates spillovers that reduce production in other regions. The regions affected through negative spillovers are higher emitters, so in aggregate the subsidy *reduces* emissions by 0.7%.

Figure 8: Targeted cattle subsidy - spatial effects on prices and emissions

(a) Cattle prices

(b) Emissions



Note: The cattle subsidy only applies to the decile of markets closest to Sao Paulo (panel a).

This policy exercise highlights the importance of geography in the relationship between market power and environmental externalities. The conventional model in Buchanan (1969), with a single region, predicts that any production subsidy to mitigate the effects of market power would necessarily increase emissions. But in a spatial economy with multiple regions, equilibrium interactions between places can lead to a richer set of responses. Here, the production subsidy alleviates the effects of market power in some of the places most affected by it, while the ensuing demand response reduces production in high-emitting places. In other words, this exercise shows that it is possible to both incentivize beef production in the Amazon while reducing emissions.

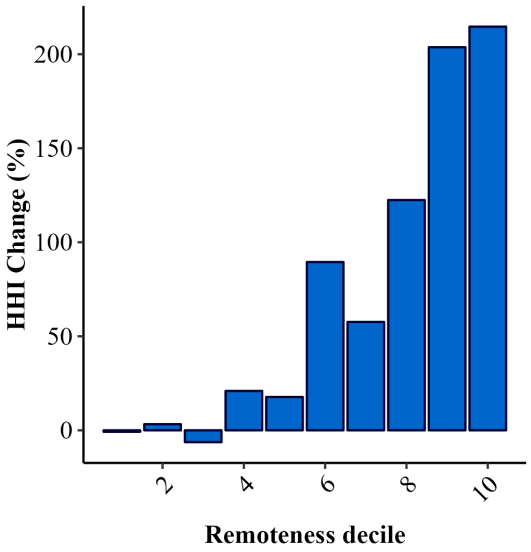
6.3 Increasing barriers to entry for non-SIF meatpackers can greatly reduce emissions while increasing beef sales:

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 meatpackers, and even smaller in remote regions. Here, I explore a scenario in which the entry costs for domestic-only meatpackers are as high as those for SIF (export-authorized) meatpackers.

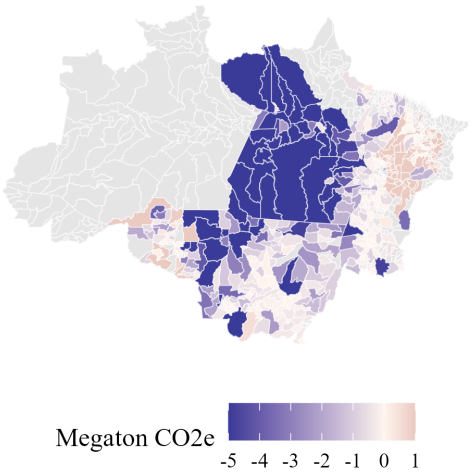
This anti-competitive policy reallocates output across regions and firms, resulting in emissions reductions of 21%. At the same time, beef sales would *increase* by 7.2%. This result is driven by several mechanisms. First, domestic-only meatpackers are much more likely to operate in remote regions. Restricting their entry makes HHI much higher in remote regions (Figure 9), leading to lower cattle prices. This reduces ranching in the regions with the highest emissions. Further, domestic-only meatpackers earn less because of lower (revenue) productivity. The policy substantially reallocates output to export-authorized (SIF) meatpackers, which have higher productivity.

Figure 9: Higher fixed costs - effects on HHI and emissions

(a) 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 more. For example, the entry cost counterfactual I just discussed, while increasing total sales, by design reduces the output of domestic-only meatpackers. However, beef is generally consumed by richer households (Car-

valho, 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[15]. In an economy largely driven by agriculture, they are the elite. Small farmers generally produce for subsistence[16], as do indigenous populations - often without cutting down the 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 20% of total land area, whereas in the most remote decile 70% 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)[17]. From this perspective, curbing emissions in remote regions could also protect the most vulnerable populations of the Amazon.

Instead of taking a stand on these various distributional issues, this work focuses exclusively 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

Environmental policies often try to address feasibility constraints by targeting intermediary firms or international trade. This paper shows that policies affecting exporters can distort the production of the most productive and cleanest firms. Much of this finding comes from detailed data that show how small firms can drive remarkable amounts of emissions. This insight is particularly relevant for the developing world, where small firms and informality

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

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

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

abound. Developing countries are today responsible for 63% of global carbon emissions (Busch, 2015) - environmental policies must contend with the pre-existing market structure in their industries.

Emissions from land use have global consequences. This has gathered global attention, but the problem is local - 75% of world food production serves domestic markets (D'odorico et al., 2014; Li et al., 2022; Geyik et al., 2021). In the region that hosts the world's largest rainforest, policies that focus only on exporters fail to regulate the most emissions-intensive places. Effective policies will shift production away from where agriculture threatens high-carbon forests, and towards places with low emissions. My work considers supply chain policies that can create that effect - whether through entry barriers in high-emitting regions, or by subsidizing cleaner production.

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)[18]. 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[19]. 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)[20] dataset. 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: Emissions in agriculture come from a variety of sources and vary in intensity across space. To account for this, I rely on SEEG [21], a civil society project in Brazil that pro-

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

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

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

[21] https://seeg.eco.br/#

vides an inventory of the country's carbon emissions. It uses a variety of sources to estimate the emissions intensity of various activities, including deforestation (and how it varies regionally), enteric fermentation, soil correction, fertilizer, among others. All emissions figures in this paper rely on intensity estimates from SEEG's methodological notes (Alencar et al., 2020) - 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. The data supplement (A.3) discusses this further.

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Supplemental information for: "Where is the Beef? Supply Chains and Carbon Emissions in the Amazon"

Supplement A Data

A.1 Cattle movement records:

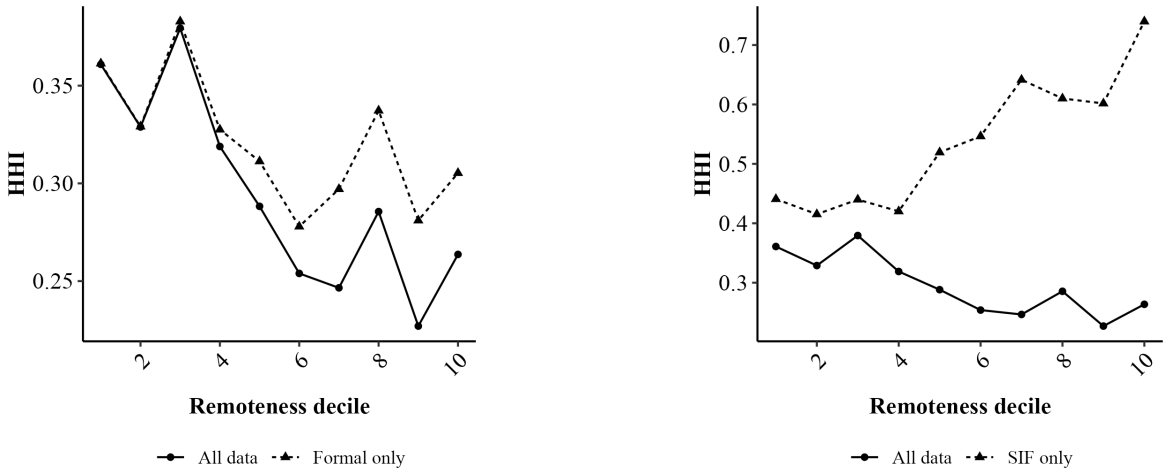
In Brazil, under federal law 12.097 and Decree 7.623, all movements of animals must be registered to sanitation agencies. Known as Guias de Transito Animal (GTA), these records include information on sales of beef cattle to meatpackers. A typical GTA includes the number of animals moved, the age and 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 under-reporting. 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.



(a) Formal meatpackers

(b) Export-authorized (SIF) meatpackers

Figure S1: HHI values differ if data are restricted to just export-authorized or formal meatpackers

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[22].

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:

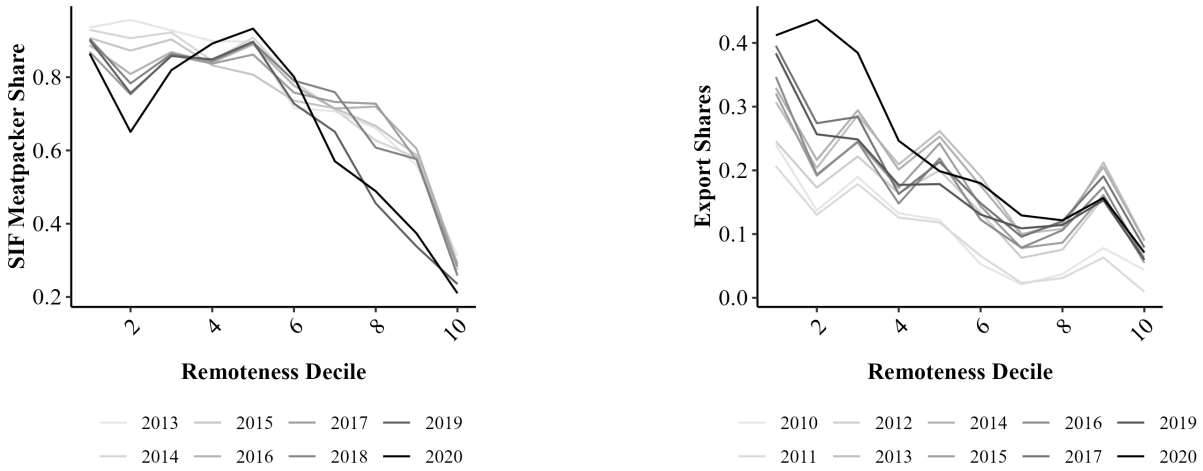
1. The share of cattle sourcing by large (SIF) meatpackers by municipality for 2013-2020.

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

[22]Figures available upon request.

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.



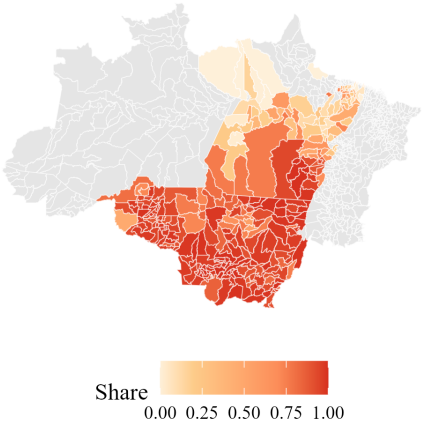
(a) Large meatpacker (SIF) shares in sourcing

(b) Output share that is exported

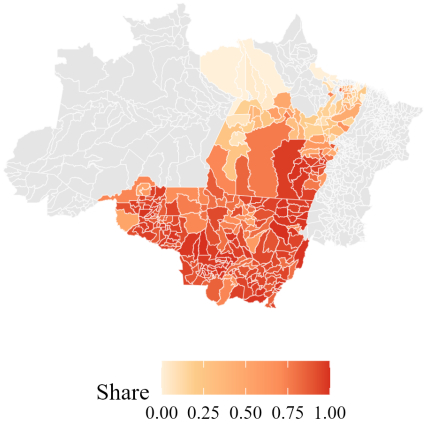
Figure S2: Large meatpacker (SIF) shares and export shares decrease with remoteness

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.

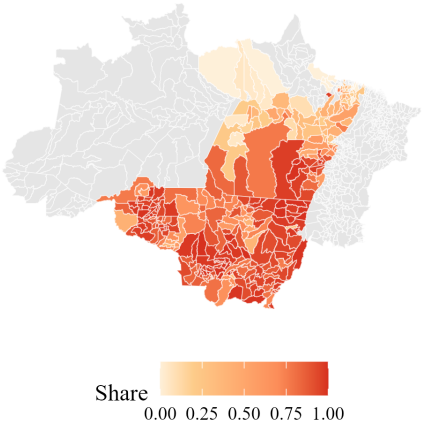
Figure S3: Spatial distribution of export-authorized meatpacker (SIF) shares



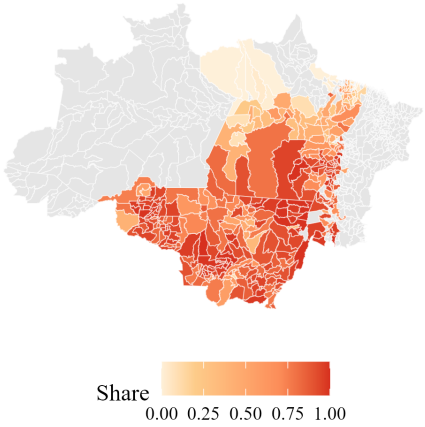
(a) 2013



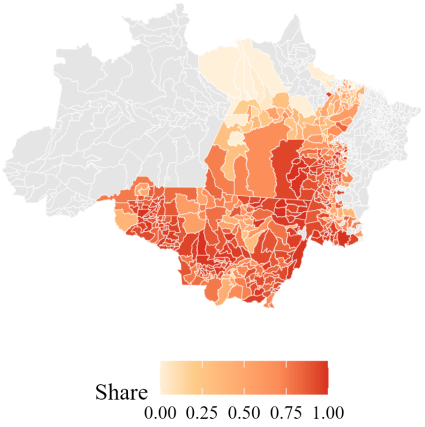
(b) 2014



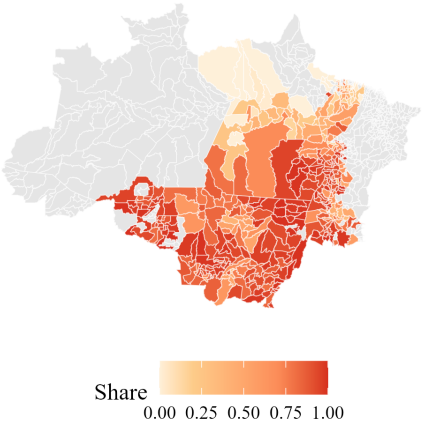
(c) 2015



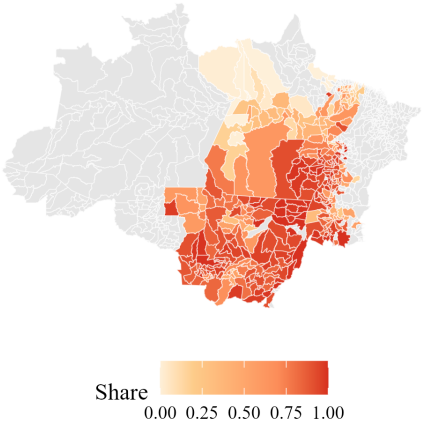
(d) 2016



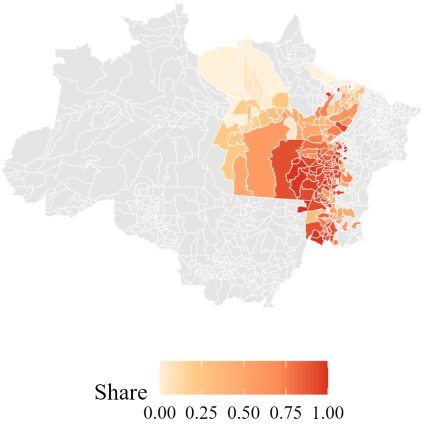
(e) 2017



(f) 2018

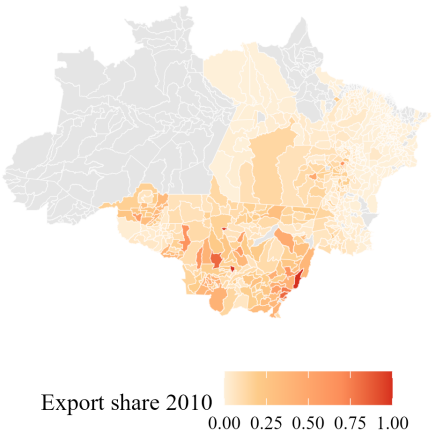


(g) 2019

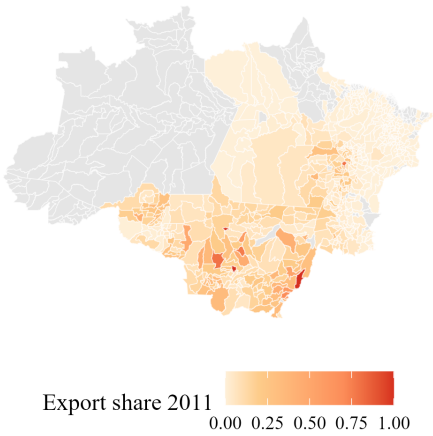


(h) 2020

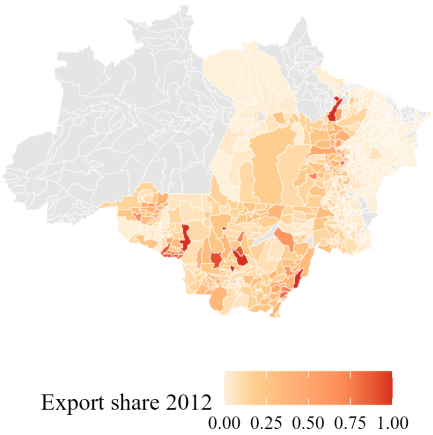
Figure S4: Spatial distribution of export shares



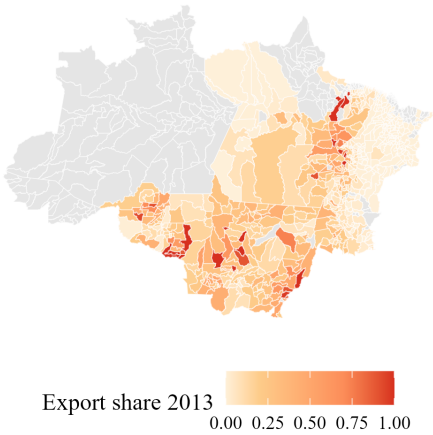
(a) 2010



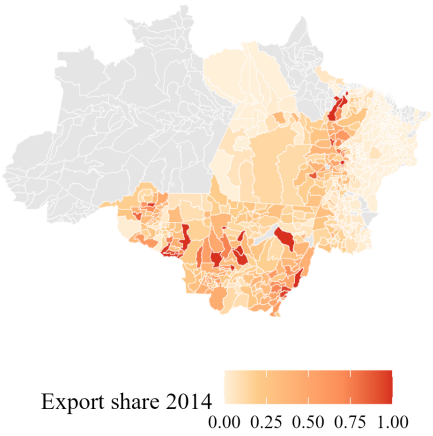
(b) 2011



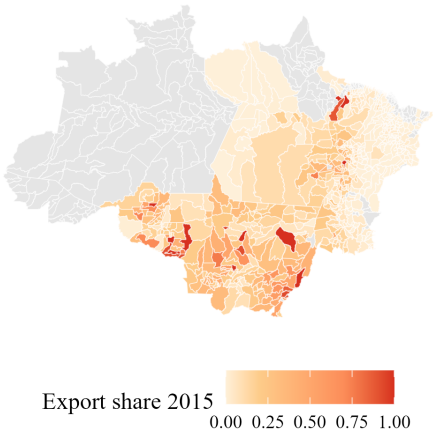
(c) 2012



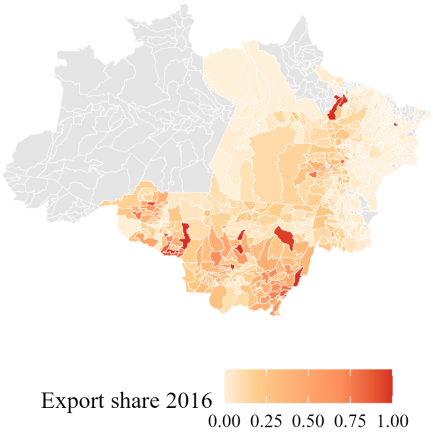
(d) 2013



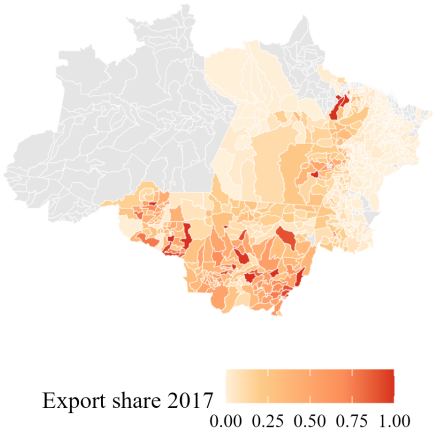
(e) 2014



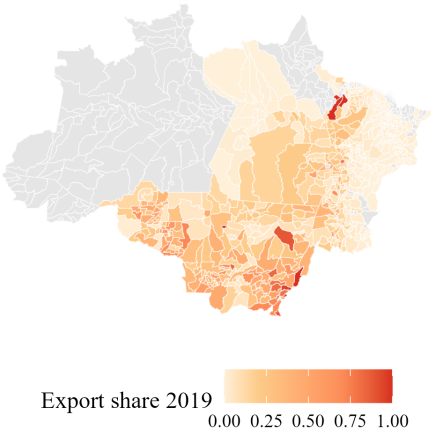
(f) 2015



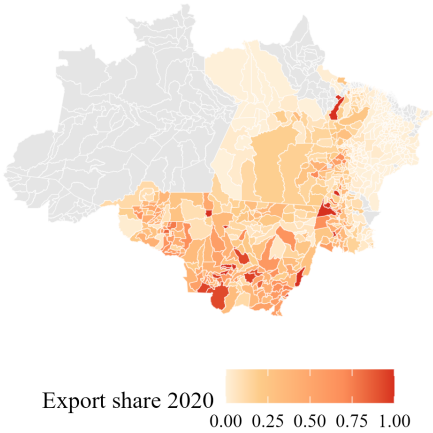
(g) 2016



(h) 2017


Export share 2019
0.00 0.25 0.50 0.75 1.00

(i) 2019


Export share 2020
0.00 0.25 0.50 0.75 1.00

(j) 2020

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.

My analysis of carbon emissions relies primarily on two sources: carbon stocks from Spawn et al. (2020), and all other emissions sources from SEEG[23]. 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 [24]. 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 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

[23] https://seeg.eco.br/

[24] 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.

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[25] dollar terms, damages would range from $3,375 to $7,175. Even with a relatively low discount factor, emissions from deforestation are mostly greater than accumulated agricultural emissions, especially in remote regions with high-carbon forests.

[25]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.

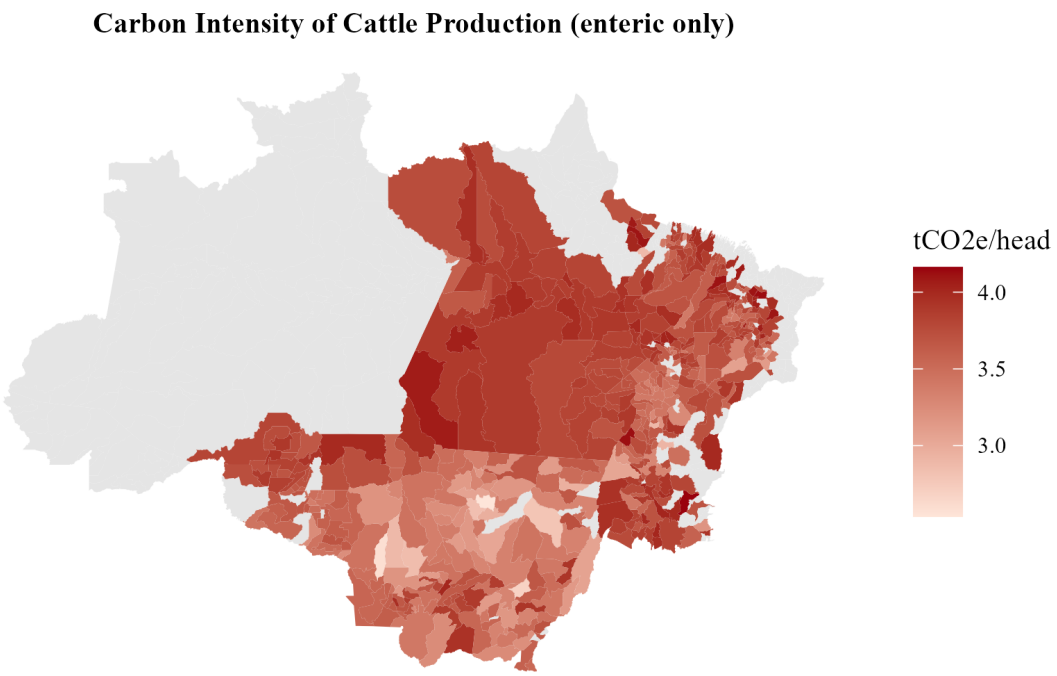
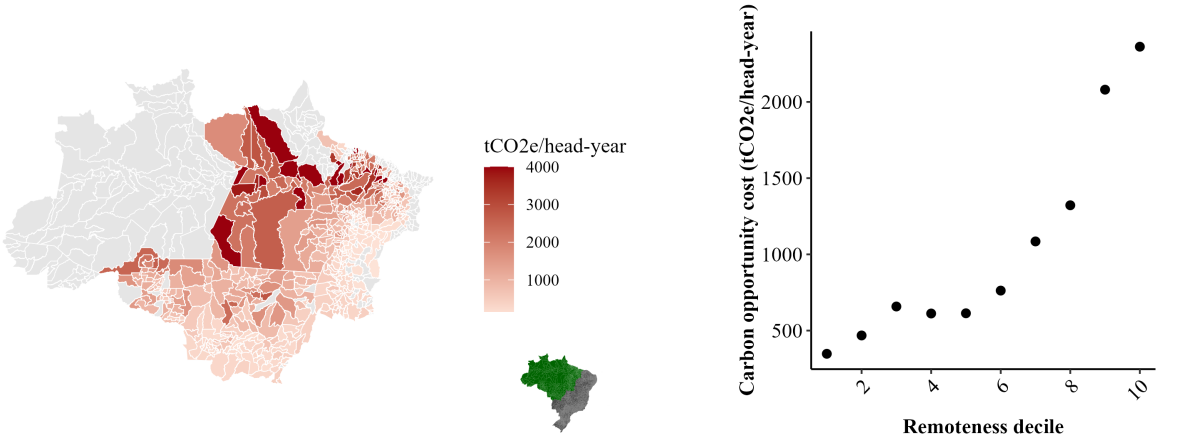


Figure S5: Enteric emissions (per head) are higher in remote regions

Figure S6: 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. As European colonization took place in Brazil, settlers had difficulty penetrating the densest parts of the Amazon. 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 to 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. In general, denser forests discourage certain types of human settlement, thus becoming more remote[26]. This implicitly protects the highest-carbon forests from agriculture.

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 S7 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 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.

[26]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).

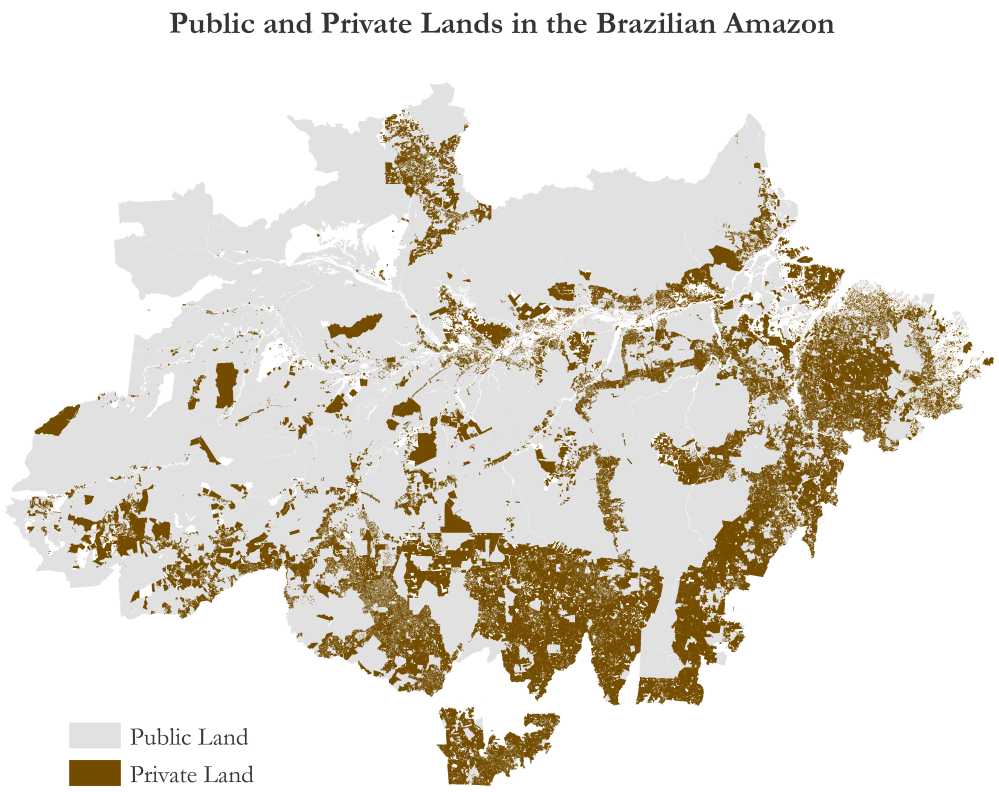


Figure S7: Public and private land in the Brazilian Amazon

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%

Supplement B Empirics

B.1 Evidence of market power in cattle sourcing:

Market concentration hints at the existence of market power in the cattle supply chain. But to establish that it is indeed present one needs to show that firms are behaving in a way consistent with oligopsony conduct. In the main text, I show that prices paid to ranchers vary little with remoteness, even though less remote regions have access to much higher-earning exporters. That is at least suggestive of market power. In this section I present further evidence - more concentrated regions display lower prices, and that pass-through of demand shocks to cattle prices varies with 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 shows exactly that - 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)
SIF 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 8 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[27] and substituting terms:

$$d \ln c_m = d \ln \bar{\varphi}_m \left(1 - \frac{1}{N\varepsilon_m + 1} \frac{\partial \ln \varepsilon_m}{\partial \ln c_m} \right)^{-1} \tag{17}$$

Equation 17 shows that whenever $\frac{\partial \ln \varepsilon_m}{\partial \ln c_m} < 0$ [28], pass-through is incomplete. Further, the

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

[28] 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:

$$\frac{\partial \ln \epsilon_m}{\partial \ln c_m} = \left(\frac{\alpha_R \, \rho_{jm} - \alpha_R \, c_m \, \rho'_{jm}}{(\rho_{jm})^2} \, \rho'_{jm} + \frac{\alpha_R \, c_m}{\rho_{jm}} \left(\rho'_{jm} \, \rho_{j_{t-1}m} \; - 2 \, \rho'_{jm} \, \rho_{j_{t-1}m} \, \rho_m(j, j_{t-1}) \right) \right) \frac{c_m}{\epsilon_m} \tag{18}$$

where $\rho'_{jm} = \sum_{j_{t-1}} \rho_m(j, j_{t-1}) \, \rho_{j_{t-1}m}(1 - \rho_m(j, j_{t-1}))$. The sign of the expression above depends on model parameter values - the estimated model delivers elasticities that decrease in prices (Figure S8).

For an alternative model, think of a region of farmers that processes in-house and sells at the market 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 17, I estimate the following regression:

$$\Delta \ln c_{mt} = \alpha_0 + \alpha_1 Shock_{mt} + \alpha_2 Shock_{mt} \, * \, HHI_{mt} + \epsilon_{mt} \tag{19}$$

where $Shock_{mt}$ is a shift-share like the one used as an instrument in land-use estimation. I use demand shocks[29] at destination countries d over two-year intervals (2015-2017, 2017-2019). The shocks are interacted with each meatpacker i's exposure to that destination in the initial period, as well as the market share of that meatpacker in each m. HHI_{mt} is the Herfindahl index of market concentration among meatpackers sourcing in m at the beginning of each period.

I only have prices for all municipalities in the Amazon for one year (2017). However, for one of the states in my sample (Mato Grosso) I have yearly data from 2008. Those come from the Instituto Mato-grossense de Economia Agropecuaria (IMEA), an agricultural think-tank. Limitations in the supply chain data only allow me to run the regression over the 2015-17 and 2017-19 intervals for that subset of municipalities. The sample is thus small,

[29]This is defined as changes in country d demand from all countries excluding Brazil.

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

Shock	0.018^{***}	0.030^{***}	0.034^{**}
	(0.004)	(0.006)	(0.011)
Shock x HHI		-0.021^{*}	-0.014
		(0.010)	(0.018)
HHI		0.010^{**}	0.020^{*}
		(0.004)	(0.008)
Export Share	0.004^{*}	-0.003	-0.011
	(0.002)	(0.003)	(0.007)
Intercept	-0.045^{***}	-0.044^{***}	-0.051^{***}
	(0.001)	(0.001)	(0.006)
Year FE	X	X	X
Munic FE			X
R^2	0.993	0.993	0.997
Num. obs.	251	251	251

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

but sufficient to show suggestive evidence of market power.

Table S4 shows the regression results. As predicted, the pass-through of export demand shocks to prices is lower in more concentrated regions. Municipality fixed effects absorb a lot of the variation in a limited time panel, so the interaction coefficient loses significance in the last specification - but it remains negative.

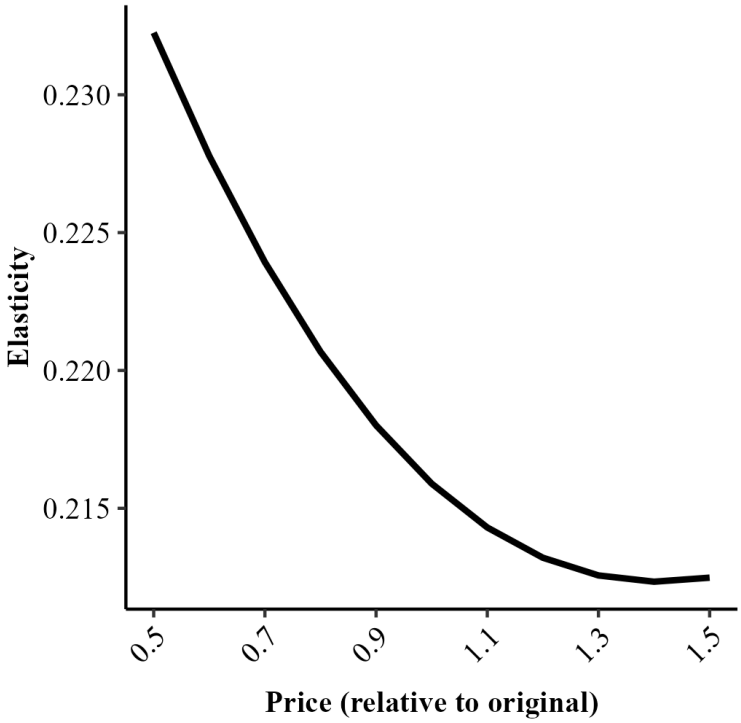


Figure S8: Cattle supply elasticity by price (averaged across municipalities and tenure classes)

B.2 Entry model algorithm:

This section provides more detail on how I implement the sequential entry algorithm in my estimation procedure. I also show robustness checks to alternative entry sequences.

A meatpacker i in municipality market m is defined by its marginal revenue product $P\,z_{im}$ and the fixed entry cost f_{im} it faces. I rank all potential entrants by their marginal revenue products, which in the data implies export-authorized meatpackers move first.

To solve for an equilibrium on the entry margin, I first begin with the top ranked player as a monopsonist and solve for the equilibrium. Then I repeat the following steps until convergence:

1. For each of the meatpackers i currently outside the market, solve for a counterfactual equilibrium including current entrants plus that i.

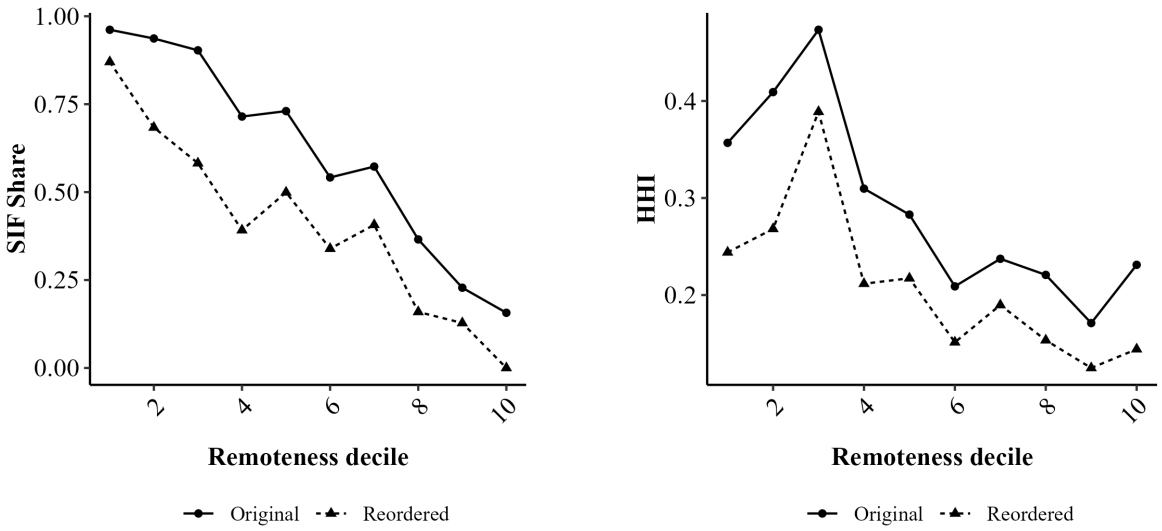
2. If there is any profitable i in these scenarios, add the highest-ranked meatpacker that is both profitable and not yet in the market.

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

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

This process continues until there are no changes to the market. Adding the highest ranked player and removing the lowest ranked player in each round selects equilibria that favor more productive meatpackers, but this does not exclude equilibria with low-ranked players in lieu of higher ranked ones. Indeed, in markets where entry costs are low for domestic-only meatpackers, many of these small players enter and bid cattle prices up to an extent that makes some export-authorized meatpackers unprofitable.

The sequential assumption is not testable, but I can show predictions that would result from alternative orderings. In Figure S9, I flip the order of sequential entry, with the least productive meatpackers moving first. This affects the equilibrium outcomes slightly, creating lower SIF shares and lower HHIs (more competition), but the magnitudes are not large and the spatial patterns are the same.



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

(b) HHI

Figure S9: Robustness checks - entry model inverting sequential order

B.3 Different demand elasticities

Brazilian beef production, even from export-authorized meatpackers, is 80% for domestic markets. Whether this is close to the average domestic share of food production, other agricultural settings might feature goods that have higher export rates. They would likely face more elastic demand. A small country that sells a globally-traded commodity might face perfectly elastic demand. In this robustness check, I double the calibrated demand elasticities (to -2.558) and re-run the counterfactuals shown on Table 3 in the main text. I also show a version where demand is perfectly elastic. The key logic remains - policies focused on exporters burden production more for the same amount of emissions reductions. Because demand is more elastic, the tax falls more on the supply side, which explains the higher emissions/output reductions.

Table S5: Robustness: Cattle tax counterfactuals (elasticity=-2.558)

	Tax	Emissions Red.	Sales Red.	Sales/Emissions Trade-off
SIFs only	∼20%	2%	7%	3.45
All meatpackers	∼20%	6.5%	11.2%	1.72
Top emitting regions	∼20%	3.3%	0.8%	0.24

Note: Tax percentages relative to average cattle price. Columns for "Emissions" and "Sales" inform percentage **reductions** relative to business-as-usual. SIFs are export-authorized meatpackers. Top emitting regions consist of the top decile of municipalities by their emissions intensity, which I calculate based on 2015-19 emissions divided by output.

Table S6: Robustness: Cattle tax counterfactuals (perfectly elastic demand)

	Tax	Emissions Red.	Sales Red.	Sales/Emissions Trade-off
SIFs only	∼20%	3.6%	10.2%	2.84
All meatpackers	∼20%	11.7%	11.2%	0.96
Top emitting regions	∼20%	3.9%	0.7%	0.18

Note: Tax percentages relative to average cattle price. Columns for "Emissions" and "Sales" inform percentage **reductions** relative to business-as-usual. SIFs are export-authorized meatpackers. Top emitting regions consist of the top decile of municipalities by their emissions intensity, which I calculate based on 2015-19 emissions divided by output.

Supplement C Model Extensions

C.1 Land use dynamics:

Land use change has dynamic features. Actions such as deforestation carry sunk costs[30] and involve irreversibilities - forest takes decades to regrow once lost. In the paper, I rely on a "medium term" model of land use change - agents consider returns over a span of 5 years (4 transitions). This allows me to capture important aspects of land use emissions while keeping the model simple enough to focus on its supply chain aspects.

Here, I present a dynamic extension to the main land use model and show that it yields similar elasticities for the timeframes I study. The model is very similar to 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 that can be used for estimation. While it does incorporate the state of the art in land use dynamics, there are important dynamic incentives faced by landholders in the Amazon which are not necessarily covered here - such

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

as expectations over future environmental enforcement, property rights issues, among others. Those are interesting avenues for future work.

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:

$$\pi(j, j_{t-1}, \omega_t, \nu_{it}) = \alpha_0(j, j_{t-1}) + \alpha_R R_j(\omega_t) + \xi_{jj_{t-1}}(\omega_t) + \nu_{jit} \tag{20}$$

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:

$$V\left(k_{it}, \omega_t, \nu_{it}\right) \equiv \max_{j^*} E\left(\sum_{s \geq t}^{\infty} \beta^{s-t} \pi\left(j^*\left(j_{is-1}, \omega_s, \nu_{is}\right), j_{is-1}, \omega_s, \nu_{is}\right) \mid k_{it}, \omega_t, \nu_{it}\right) \tag{21}$$

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:

$$\bar{V}_t(j_{t-1}) \equiv \int \dots \int V_t\left(j_{t-1}, (\nu_1, \dots, \nu_J)\right) dF\left(\nu_1\right) \dots dF\left(\nu_J\right) \tag{22}$$

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:

$$v_t(j, j_{t-1}) \equiv \bar{\pi}_t(j, j_{t-1}) + \beta E_t\left[\bar{V}_{t+1}\left(j\right)\right] \tag{23}$$

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:

$$p_t(j, j_{t-1}) = \frac{\exp\left(v_t(j, j_{t-1})\right)}{\sum_{j' \in J} \exp\left(v_t\left(j', j_{t-1}\right)\right)} \tag{24}$$

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

$$\bar{V}_t(j_{t-1}) \equiv \ln\left(\sum_{j \in J} \exp\left(v_t(j, j_{t-1})\right)\right) + \gamma \tag{25}$$

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:

$$\ln\left(\frac{p_t(j,j_{t-1})}{p_t(j',j_{t-1})}\right) = v_t(j,j_{t-1}) - v_t(j',j_{t-1}). \tag{26}$$

Using the definition from (23), this becomes:

$$\bar{\pi}_t(j,j_{t-1}) - \bar{\pi}_t\left(j',j_{t-1}\right) - \ln\left(\frac{p_t(j,j_{t-1})}{p_t\left(j',j_{t-1}\right)}\right) = \beta E_t\left[\bar{V}_{t+1}\left(j'\right)\right] - \beta E_t\left[\bar{V}_{t+1}\left(j\right)\right] \tag{27}$$

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:

$$\begin{aligned}\bar{\pi}_t(j,j_{t-1}) - \bar{\pi}_t\left(j',j_{t-1}\right) - \ln\left(\frac{p_t(j,j_{t-1})}{p_t\left(j',j_{t-1}\right)}\right) = \beta\left(\bar{V}_{t+1}\left(j'\right) - \bar{V}_{t+1}(j)\right) \\ +\varepsilon_t^V\left(j'\right) - \varepsilon_t^V(j)\end{aligned} \tag{28}$$

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:

$$\forall j : \bar{V}(j_{t-1}) = v_t(j,j_{t-1}) - \ln\left(p_t(j,j_{t-1})\right) + \gamma \tag{29}$$

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:

$$\begin{aligned}\bar{\pi}_t(j, j_{t-1}) - \bar{\pi}_t(j', j_{t-1}) - \ln\left(\frac{p_t(j, j_{t-1})}{p_t(j', j_{t-1})}\right) =& \beta\left(v_{t+1}(j, j') - v_{t+1}(j, j)\right) \\ &- \beta\left(\ln\left(\frac{p_{t+1}(j, j')}{p_{t+1}(j, j)}\right)\right) \\ &+ \varepsilon_t^V(j', j_{t-1}) - \varepsilon_t^V(j, j_{t-1}).\end{aligned} \tag{30}$$

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

$$v_{t+1}(j, j') - v_{t+1}(j, j) = \bar{\pi}_{t+1}(j, j') - \bar{\pi}_{t+1}(j, j) \tag{31}$$

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:

$$\begin{aligned}\bar{\pi}_t(j, j_{t-1}) - \bar{\pi}_t(j', j_{t-1}) - \ln\left(\frac{p_t(j, j_{t-1})}{p_t(j', j_{t-1})}\right) =& \beta\left(\bar{\pi}_{t+1}(j, j') - \bar{\pi}_{t+1}(j, j)\right) \\ &- \beta \ln\left(\frac{p_{t+1}(j, j')}{p_{t+1}(j, j))}\right) \\ &+ \varepsilon_t^V(j', j_{t-1}) - \varepsilon_t^V(j, j_{t-1})\end{aligned} \tag{32}$$

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 (29), I can express that in terms of period $t+1$ profits and choice probabilities. Thus the right hand side of (32) 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:

$$Y_{tj_{t-1}} = \tilde{\Delta}\alpha_{0j_{t-1}} + \alpha_R \Delta R_t + \tilde{\Delta}\xi_{tj_{t-1}} + \Delta\varepsilon^V_{tj_{t-1}} \tag{33}$$

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:

$$Y_{mtj_{t-1}} = \tilde{\Delta}\alpha_{0j_{t-1}} + \alpha_R R_{mt} + \tilde{\Delta}\xi_{mtj_{t-1}} + \Delta\varepsilon^V_{mtj_{t-1}} \tag{34}$$

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 S7 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

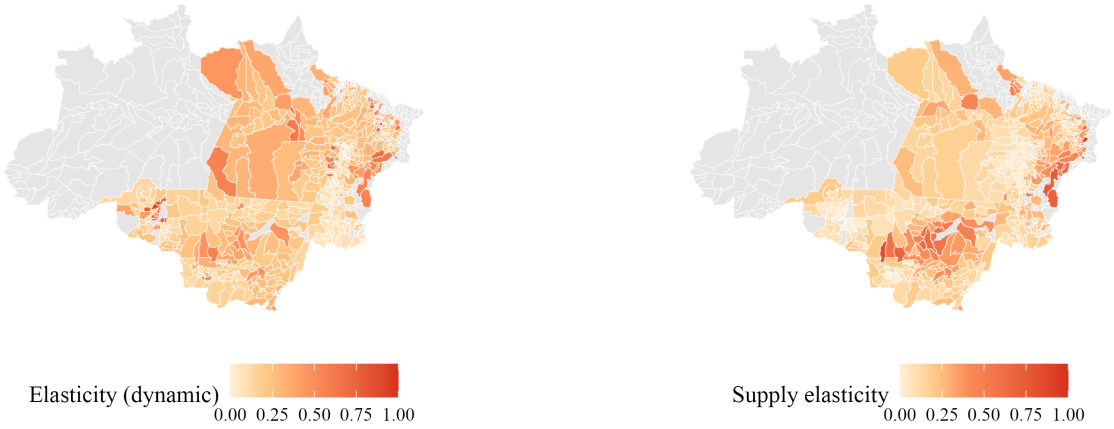
transitions in the scenario with the perturbation versus business-as-usual.

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 S10). Remote regions end up slightly more elastic (Figure S11), 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 S7: Dynamic Estimates of α_R

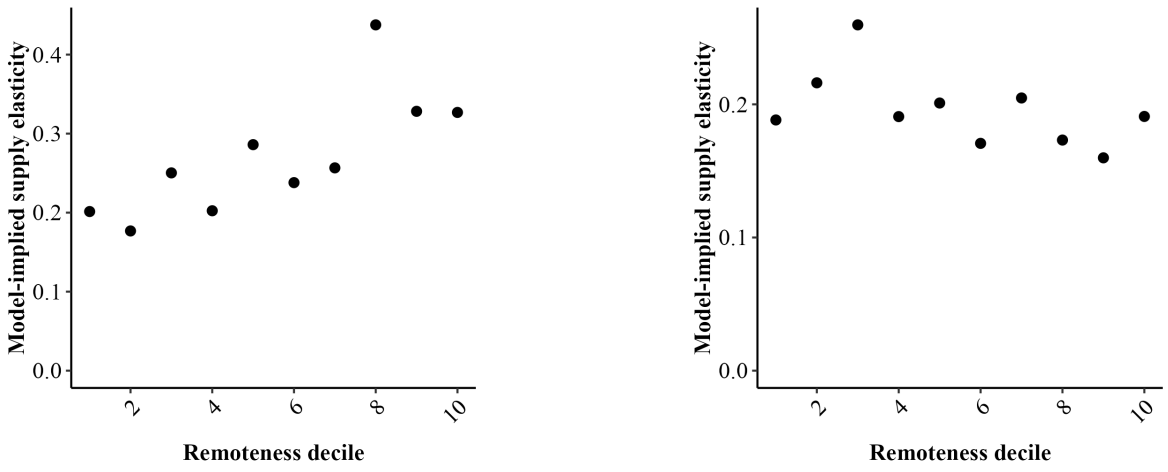
	OLS	IV
Public Designated	0.13^{***}	0.72^{***}
	(0.03)	(0.10)
Public Undesignated	0.24^{***}	0.57^{***}
	(0.03)	(0.10)
Private Undisputed	0.26^{***}	0.56^{***}
	(0.24)	(0.08)
Private Disputed	0.21^{***}	0.89^{***}
	(0.03)	(0.09)

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 S10: Cattle supply elasticities - dynamics vs. main model



(a) Dynamic (b) Main model

Figure S11: Supply elasticities by remoteness - dynamics vs. main model