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

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Abstract

This paper studies environmental policy in settings where small and informal firms are prevalent, showing how policy shapes entry decisions and the resulting productivity distribution. I focus on the Brazilian Amazon's cattle industry, the world's leading driver of deforestation. Using rich data, I show that a large number of processing firms operate informally or only sell domestically, with notable spatial clustering by firm type. Using a quantitative model, I show that policies targeting only prominent (formal and exporting) firms can have adverse effects, reallocating production toward less efficient firms and high-emitting upstream suppliers. Ignoring this margin of firm heterogeneity overestimates emissions reductions and underestimates output losses more than two-fold. Alternative policies that better account for small and informal firms greatly reduce abatement costs.

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1 Introduction:

Future global greenhouse gas emissions will be concentrated in developing countries, generating an urgent need for environmental policies that work where state capacity is limited (Besley and Persson, 2013). In these settings, a large proportion of firms remain small, so as to operate under informality and avoid government regulations (La Porta and Shleifer, 2014; Ulyssea, 2018).[1] As a result, some of these firms may remain outside the reach of environmental enforcement (Greenstone and Jack, 2015; Burgess, Costa, and Olken, 2023). Despite rich work on environmental policies in developing countries, we still lack a better understanding of how informality and firm size should shape these policies.

This paper argues that informality changes what environmental policy does in equilibrium. Small and informal firms are typically less productive (Hsieh and Olken, 2014), so an economy served only by formal firms could allocate inputs more efficiently (Hsieh and Klenow, 2009; Restuccia and Rogerson, 2008). But small firms may also face lower entry barriers and can therefore enter markets that larger firms do not serve, especially in remote areas. Environmental regulation reshapes this trade-off by changing which firms enter, how inputs are allocated, and where production occurs. I develop a framework to quantify these entry and reallocation margins, and I use it to compare policies that ignore the left tail of the firm size distribution to designs that explicitly account for it.

The empirical setting is the cattle supply chain in the Brazilian Amazon and its effects on deforestation, which generates up to 20 percent of global greenhouse gas emissions (Asner, 2009).[2] Ranchers clear forest to raise cattle and sell to nearby meatpackers, which process cattle into beef for domestic consumption and export. To study this setting, I bring in rich data on meatpacking firms, including whether they are formally registered and have export permits. Then I develop a structural framework to assess how environmental regulation centered on meatpackers reshapes their organization through entry and reallocation.

My analysis begins with stylized facts that show the coexistence of small and informal meatpackers with large exporting meatpackers in the cattle supply chain. For this, I rely on

[1] The informal sector accounts for 40% of GDP in Brazil, 41.9% in Colombia, and 31.9% in Mexico (Ulyssea, 2018).

[2] In addition, deforestation threatens biodiversity (Ferreira et al., 2018) and disrupts rainfall patterns (Araujo et al., 2023). Cattle ranching also produces methane emissions through animal enteric fermentation.

rich phytosanitary records. Because health risks in beef production require strict monitoring of herd movements, these records provide unusually comprehensive coverage even for farms and processors without formal tax registration. The data reveal two main types of meatpackers, which I label as *export-authorized* and *domestic-informal* firms. Transportation costs for cattle are high, requiring meatpackers to run processing operations near their rancher suppliers. Export-authorized meatpackers are larger and cluster near major ports and population centers, generating concentrated (and monopsonistic) cattle procurement markets.[3] By contrast, domestic-informal meatpackers occupy remote areas in high numbers. For instance, in the most remote decile of regions about nine-tenths of meatpackers are domestic-only, and 64% are informal.

The structural model centers on how heterogeneous productivity and entry costs shape meatpacker entry and cattle sourcing decisions, leading to the observed patterns as equilibrium outcomes. In each geographic market, meatpackers are allowed to differ by type (export-authorized or domestic-informal), which determines their entry costs and the ex-ante distribution of their productivity. Conditional on entry, firms draw productivity and compete for cattle in an oligopsonistic (Cournot) environment. Meatpacker sourcing decisions depend on local cattle supply, which I estimate using a land-use model of atomistic landholders making land conversion decisions in response to prices.

Estimates from the model show how fundamental differences in productivity and entry barriers result in a spatial segmentation of the supply chain by firm type. Export-authorized firms have generally higher productivity draws, but also face higher estimated entry costs. As a result, only a few export-authorized firms enter. In remote areas, transportation costs reduce exporter earnings, so they cannot cover their entry costs. Domestic-informal firms are less productive but can enter at lower cost, so they fill the gaps left by exporters in remote regions, creating low-concentration markets with many small firms. Thus, ex-ante differences in productivity and entry cost result in equilibrium differences in firm size and location. This informs an efficiency trade-off implied by small and informal firms. Monopsony markdowns are not mere distortions, they are necessary to cover meatpacker entry costs;

[3] I also show reduced-form evidence consistent with monopsony power: demand shocks to meatpackers pass through differently to ranchers depending on market concentration. See Online Appendix B.1.

small and informal firms require *lower markdowns* to cover their fixed costs, but they are also *less productive*. Small firms soften the "curse of remoteness" by increasing competition for cattle in isolated regions, partially compensating ranchers' limited access to exporters. This same mechanism, however, reallocates production toward less efficient meatpackers. Because remote regions also have more carbon-dense forests, increased production in these areas shifts activity toward higher-emission zones.

Environmental policy can generate unintended consequences when small and informal firms remain outside the regulatory net. New environmental policy can induce entry, exit, and reallocation, shifting the balance of trade-offs implied by small firms. I use counterfactual simulations to compare different policy designs, focusing on export-authorized meatpackers, which have been the target of many recent proposals. The appeal of regulating exporters is feasibility: direct regulation of deforestation emissions is difficult over a territory as vast and remote as the Amazon, whereas meatpackers are fewer and more prominent. I study a cattle tax and a market-exclusion standard similar to the recently approved EU Deforestation Regulation (EUDR).[4]

Across these policies, a common pattern emerges. Once domestic-informal firms are accounted for, regulation focused on exporters is substantially less effective. Under the exporter tax, entry by export-authorized firms falls by 27.4%. Domestic-informal firms expand in response, reallocating production toward less productive firms and remote regions where emissions are higher due to greater forest carbon density. In an alternative model without firm heterogeneity and endogenous entry, emissions reductions are overstated by a factor of 2 and output effects are understated by a factor of 3.

The EUDR-inspired standard also has high abatement costs, but they come from different reallocation margins. Under the standard, export-authorized meatpackers are prohibited from sourcing cattle from ranchers with recent deforestation,[5] leaving non-compliant ranchers with only domestic-informal firms as potential buyers. This segmentation bifurcates local cattle markets, creating a highly concentrated submarket for non-compliant producers and

[4]These policies impose requirements on the inputs procured by intermediaries to compensate for the difficulty of regulating upstream producers directly. Related examples include the Roundtable on Sustainable Palm Oil, and the Soy Moratorium in Brazil (Heilmayr et al., 2020; Klingler et al., 2018).

[5]The cutoff year is chosen to be 2008 to match similar policies, such as the Soy Moratorium, and existing provisions in Brazil's Forest Code.

lowering equilibrium cattle prices in that segment. As a result, the primary effect of the policy is a redistribution of surplus away from ranchers and toward domestic-informal meatpackers. Environmental benefits are muted even under perfect enforcement, because emissions are concentrated in remote regions already dominated by small and informal processors.

Alternatively, I find evidence that curbing small and informal firms can lead to improvements in both productivity and environmental outcomes. I study a policy that raises entry barriers for domestic-informal meatpackers, equalizing them with those faced by export-authorized firms. The policy directly targets the margin that sustains small and informal firms – it increases concentration in remote regions, and reallocates production toward more productive firms and locations with lower carbon intensity. This increased productivity outweighs the higher expenditure on fixed costs, and thus generates allocative gains in addition to the emissions reductions. As a result, abatement costs are near zero, which suggests that increasing productivity and curbing emissions can be complementary approaches.

Literature This paper shows that small and informal firms are central to the effects of environmental policy. Informal firms are prominent in the developing world and have been shown to shape the effects of policy interventions, including trade liberalization, labor market regulation, and urbanization (De Paula and Scheinkman, 2011; Ulyssea, 2018; Dix-Carneiro, Goldberg, Meghir, and Ulyssea, 2025; Imbert and Ulyssea, 2025). While environmental policy in developing countries has been studied extensively, there is still very limited evidence on how small and informal firms shape its equilibrium effects.[6] In my setting, informality affects not only compliance, but also firm entry and the reallocation of production across firms. I also show that geography is central to these margins: although they coexist within the same industry, different types of firms locate their supply networks differently.[7] Finally, whereas most empirical work on informality has focused on manufacturing and services, this paper provides new evidence from agriculture, a sector that is central to developing countries but often missing from the literature.[8]

[6]Notably, Bento et al. (2018) use theory to discuss the role of informality in the effects of energy taxes.

[7]In this sense, my results are similar to theoretical work in Coşar and Fajgelbaum (2016), which shows separate regional specialization of exporting and non-exporting firms.

[8]The literature on agri-food value chains also highlights an important dearth of data on informal midstream operators (Macchiavello, Reardon, and Richards, 2022; Barrett, Reardon, Swinnen, and Zilberman,

This paper also contributes a firm-level perspective to a growing literature on the economics of deforestation, recently reviewed by Costa, Hsiao, Pellegrina, and Souza-Rodrigues (2025). Dominguez-Iino (2025) also examines supply chains, but focuses on how commodity exporter monopsony can drive incomplete pass-through of environmental tariffs, dampening the responses to policy. My framework moves beyond exporting firms, showing the importance of domestic-informal traders, which are pervasive in the developing world and matter especially in the key emissions hotspots of the Amazon. By doing so, my analysis also reveals new mechanisms shaping environmental policies.[9] My findings also complement Hsiao (2025), which shows that environmental tariffs can be ineffective without international coordination. I show that, even under perfect coordination, policy can remain ineffective when informality and endogenous entry responses are central features of the supply chain. More broadly, this paper contributes to the structural work in this literature (Souza-Rodrigues, 2019; Sant'Anna, 2024; Araujo, Costa, and Sant'Anna, 2025; Araujo, 2023; Farrokhi, Kang, Pellegrina, and Sotelo, 2025; Restrepo and Mariante, 2024; Akerman, 2024; Scott, Souza-Rodrigues, Rosenbaum, and Goel, 2025) by analyzing endogenous supply chain responses to policy. In addition, whereas much of the existing policy analysis focuses on taxes, my framework allows the evaluation of non-price instruments such as sourcing standards (Alfaro-Ureña, Faber, Gaubert, Manelici, and Vasquez, 2022), which are important where state capacity is limited.

Finally, this paper relates to work on environmental regulation under imperfect competition. Classic insights show that market power can partially offset environmental externalities by reducing output (Buchanan, 1969). In my setting, however, this countervailing force is limited because the largest distortions arise among the most productive firms and the cleanest suppliers.[10] My results also add nuance to recent evidence of substantial monopsony power in agricultural markets (Chatterjee, 2023; Zavala, 2023; Rubens, 2023; Kochhar and Song, 2024). Small and informal firms can mitigate intermediary monopsony by expanding

2022).

[9]The inclusion of small and informal firms also implies different patterns of intermediary monopsony and the pass-through of policies. Once small firms are accounted for, remote regions are shown to be *more* competitive in cattle procurement markets.

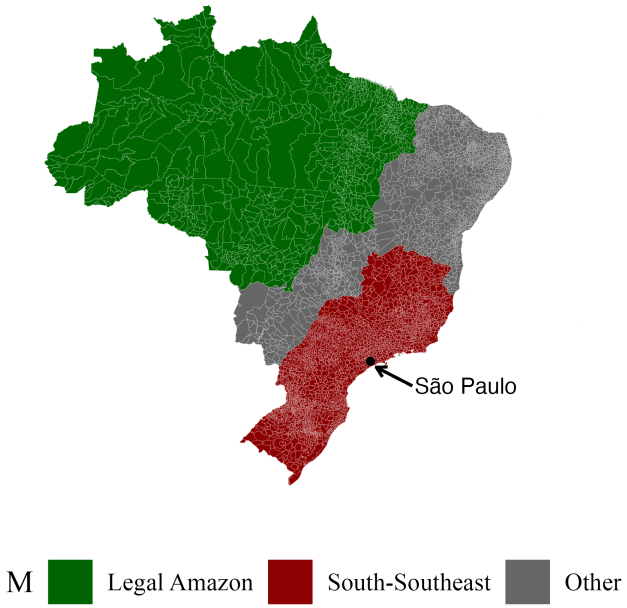
[10]Asker, Collard-Wexler, De Canniere, De Loecker, and Knittel (2024) document a similar compositional effect in oil extraction, where market power reduces aggregate output but shifts production toward higher-emission varieties.

buyer options for ranchers,[11] but this same mechanism reallocates production toward less efficient firms and higher-emissions locations. Conversely, policies that explicitly account for small and informal firms can reduce both emissions and allocative inefficiencies.

2 Stylized facts

The cattle industry is responsible for roughly 80% of agricultural land use in the Amazon. The Brazilian Amazon covers an area larger than the European Union, and as a result there is a great deal of variability both in the types of firms that operate supply chains there, and also the carbon intensity of land use in different regions. In the stylized facts that follow, I discuss geographic variation in terms of remoteness defined as the distance to São Paulo (Figure 1). São Paulo is the key economic hub of Brazil's South-Southeast, the region which concentrates Brazil's largest cities and port infrastructure. Nearly all (99%) exports of beef coming from the Amazon go through ports in the South-Southeast.

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



[11] This analogous to findings in labor markets where informality and self-employment weaken employer monopsony (Amodio, Medina, and Morlacco, 2025).

2.1 The geography of the beef cattle supply chain:

Cattle ranchers depend on intermediaries, meatpackers, to process output into beef and distribute it to consumer markets in Brazil and abroad. Meatpackers vary by official inspection levels. The highest category of firms are those federally inspected (SIF), which grants them the highest quality grade and allows them to export.[12] For clarity, I henceforth refer to them as **export-authorized** meatpackers. Firms with lower inspection grade, including those in the informal sector, will be referred to as **domestic-informal** meatpackers.

Brazil's stringent phytosanitary regulations provide remarkably detailed data on cattle sourcing. Ranchers are required to file a record for every herd movement, including sales to meatpackers.[13] The crucial aspect of these data is that they serve health-related purposes, such as tracking animal vaccinations and the spread of disease. There are high stakes involved – contaminated meat can lead to death, and an outbreak of mad cow or foot-and-mouth disease can lead to immediate sales bans for entire regions. This creates incentives for local authorities to enforce this regulation for all suppliers regardless of size. Furthermore, there are no environmental policies tied to these records that could drive systematic underreporting. Ranchers and meatpackers can issue these records regardless of whether they are environmentally compliant or operate in the formal sector. As a result, this dataset provides a uniquely rich view of agricultural supply chains, including information on firms often missing in typically used datasets, like tax or customs records. The data are available for the subset of states in the Amazon shown in Figure 3: together, those comprise 94.1% of Amazonian cattle production.[14]

Meatpacking firms of different inspection type vary in size and geographic location. Export-authorized meatpackers are larger: although only a fifth of Brazilian beef is exported, they also dominate domestic markets, processing three quarters of all cattle. They

[12] Although they are authorized to export, not all of them do, as 80% of beef output stays in Brazil.

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

[14] Source: 2017 Agricultural Census (head sold to slaughter). Other states, despite their size, have too little agriculture so their data are not available.

also tend to source cattle from less remote parts of the Amazon (Figure 2, panel a), clustering their processing near consumer hubs and the ports that handle 99% of beef exports.[15] In contrast, where exporters are absent, domestic-informal firms fill the gap. Although they process only a quarter of all cattle, domestic-informal meatpackers account for well over half of sourcing in the most remote decile of regions, and about nine-tenths of the number of firms.

This geographic pattern is consistent over time and across data sources. While the comprehensive GTA data I use are limited, other datasets confirm the same trends. For export-authorized meatpackers, data are more widely available,[16] and reveal similar patterns from 2010 to 2020 (Figure 2): exporters are less common in remote regions.

Informality is widespread in this industry, especially in remote regions. I use a *legalistic* definition of informality (Ulyssea, 2020). Informal meatpackers are those that operate without a formal firm tax identification (CNPJ), instead reporting GTAs with their personal tax identification number (CPF). Among meatpackers, 3% are informal in the least remote decile, but 64% are informal in the most remote decile of regions. Because informal meatpackers cannot export and exhibit similar sourcing patterns and geographic location as formal domestic-only meatpackers, I consider domestic-informal meatpackers as a joint category in most of my analysis.

Transporting cattle is especially risky and costly, which results in highly geographically concentrated cattle procurement markets. About 75% of rancher-to-meatpacker transactions occur within 250 km, limiting ranchers' options to nearby buyers. This, combined with the geographic sorting of firms by export status, generates differences in market concentration (Figure 3). Export-authorized firms are few and large, creating high concentration where they dominate. Domestic-informal firms are numerous and small, so remote areas are *less* concentrated.

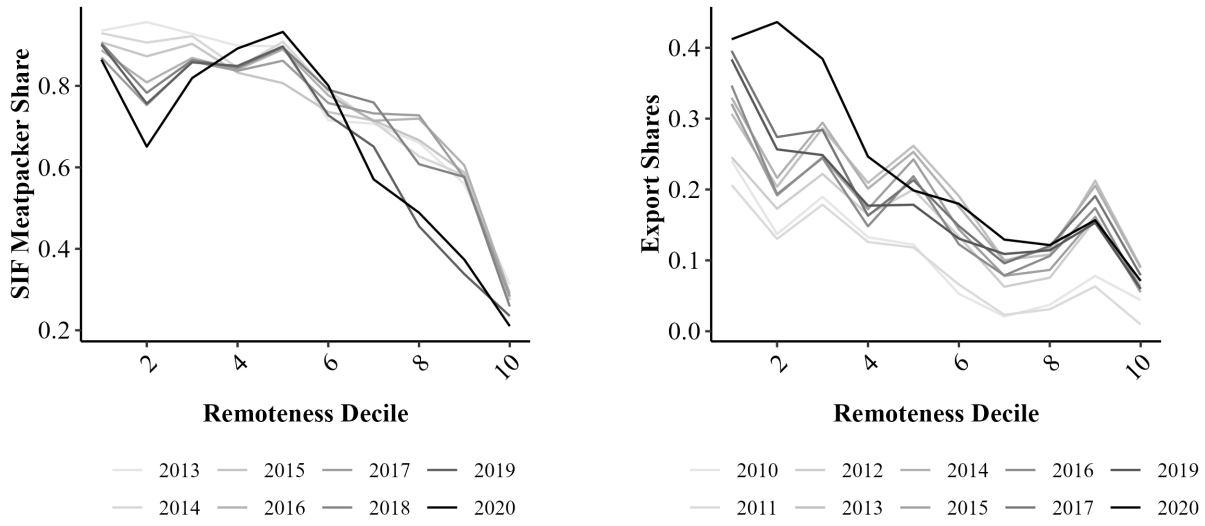
While concentration suggests potential market power, where meatpackers pay ranchers below competitive prices, quantifying monopsony markdowns depends on a particular conduct, which I describe in the next section. In Online Appendix B.1, I also use richer

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

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

price data available for one state to show reduced-form evidence consistent with monopsony,[17] including the relationship between concentration, cattle prices, and the pass-through of demand shocks. My setting aligns with a growing literature on intermediary monopsony in agriculture (Chatterjee, 2023; Zavala, 2023; Rubens, 2023; Dominguez-Iino, 2025). The key distinction is that the rich GTA data reveal how *competitive* remote regions can be once domestic-informal meatpackers are included. In Online Appendix A.1, I show that excluding these firms would substantially overstate concentration in remote areas.

Figure 2: Export-authorized (SIF) and export shares decrease with remoteness



(a) Export-authorized meatpacker shares

(b) Output share that is exported

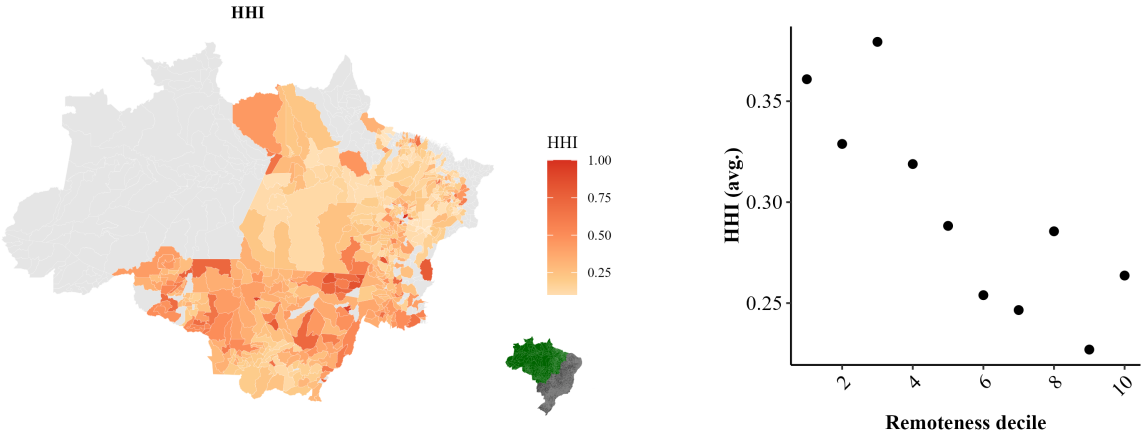
Note: Panel (a) shows the share of cattle that is sourced by export-authorized meatpackers for each decile of distance to São Paulo. Not all cattle sourced by export-authorized firms is exported, some of it goes to Brazil's largest cities. Panel (b) shows the share of output sourced by meatpackers that is actually exported. See Online Appendix (A.2) for more detail on the data sources.

2.2 The geography of carbon in the Amazon:

In the Amazon, agricultural emissions come primarily from the displacement of forests with pasture for cattle. Forests are a natural carbon capture technology. Trees perform pho-

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

Figure 3: Remote markets are less concentrated



(a) Meatpacker sourcing HHI

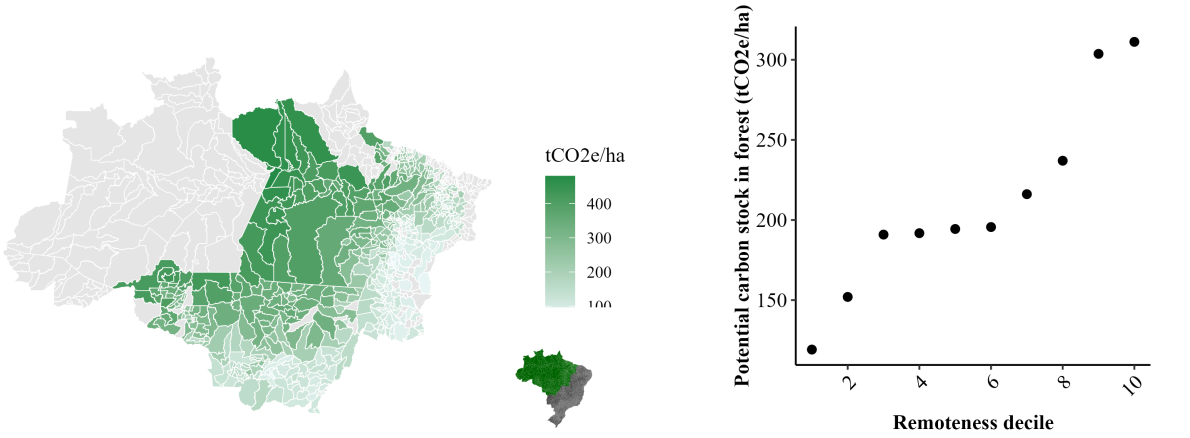
(b) HHI by distance to São Paulo

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. On panel (b), HHI values are averaged by decile of distance to Sao Paulo.

tosynthesis and build up their biomass (wood, branches, and roots), which contains large amounts of carbon. When ranchers clear the forest to grow pasture, these carbon stocks are quickly released through fire and decomposition. Pasture itself holds some carbon, but in most places less than a tenth of what natural forest can store.

As Figure (4) shows, forest in the Amazon varies greatly in its potential carbon stocks. This is due to natural factors, with higher humidity near the equator driving different species and tree density. The sheer size of the region naturally creates a great deal of spatial heterogeneity. As it moves south, the forest begins transitioning to the Cerrado, Brazil's savannah biome whose natural vegetation holds less carbon. Figure 4 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 4 shows.

Figure 4: 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.[18]

Beyond its strictly environmental impacts, the expansion of agriculture in the Amazon also threatens the traditional ways of life of indigenous populations and other subsistence communities. To better illustrate this,[19] I collect various sources of land tenure information to build a dataset that distinguishes private from public land. These more vulnerable populations live on public land, which is generally in more remote areas: 68% of land is public in the most remote decile, compared to 10% in the least remote. Although I focus on the carbon emissions aspect, this suggests social costs from the expansion of commodity production in more remote areas beyond carbon (e.g. conflict).

[18]The appendix describes the sources I use for carbon emissions calculations.

[19]I cannot fully account for the welfare of subsistence and indigenous communities in my empirical framework, but the data I collect on land tenure allow me to predict the impacts of policy on land use in different regions and tenure classes. The counterfactual exercises account for how different tenure classes are affected by policy, and online appendix A.3 discusses the land tenure data in more detail.

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

The structural model in the next section seeks to explain the firm decisions that result in the patterns shown here. As such, it is important to clarify which components will be modeled endogenously and which are exogenous. Meatpacker entry and sourcing decisions along the remoteness gradient are modeled endogenously, with heterogeneous entry costs and productivity as the key driving primitives. Based on those, the model generates predictions for the geographic and firm-level variation in entry, cattle sourcing, meatpacker size, and monopsony markdowns. In contrast, the remoteness gradient itself, shaped by the geographic distribution of Brazil's major cities inherited from the colonial period,[20] is treated as exogenous, and so is the naturally-determined carbon density of primary forest.

3 Structural Model

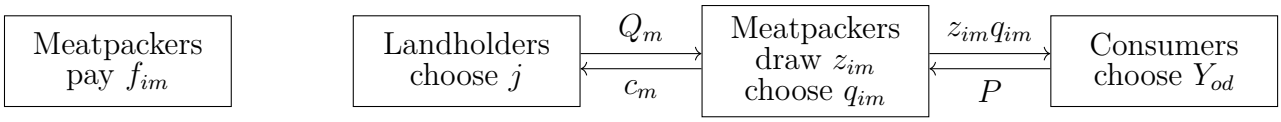
This section outlines the empirical framework I use. The most important part of the model centers on meatpackers, taking entry costs and productivity as key model primitives, resulting in equilibrium entry and sourcing decisions across space. Upstream from meatpackers are landholders,[21] from which I microfound supply-side and emissions responses. Meatpackers exert monopsony power in cattle sourcing, but they are price-takers in the downstream beef market.[22] Downstream demand outlines aggregate consumer responses, which can drive spatial spillovers.

[20]Brazil's history of agricultural colonization initially avoided the dense forests of the Amazon, instead centering on regions suitable for plantation agriculture. Coffee, its key export product of the 19th century, was the key factor for population to concentrate in the Southeast.

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

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

Figure 5: Model overview



Stage 1: Meatpacker entry

Stage 2: Quantity setting

3.1 Landholder problem

I begin the model with landholders, which observe commodity prices and make one-time land use (change) decisions for a given time window. This formulation preserves the tractability of a static model but allows for land conversion costs, which are important in my setting.[23] In the empirics, I focus on the 2015-2019 time frame.

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

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

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. The constant $\alpha_0(j, j_0)$ depends on j_0 and can capture, for example, the ("switching") costs of transitioning from forest to pasture.

[23] This one-time transition formulation accommodates the limitation of having only a single cross-section of prices for this period. It takes advantage of the rich land use data by allowing for switching costs, which are important in fully dynamic models (Scott, 2012), while retaining the one-time nature of static approaches. Other work (Araujo et al., 2025) deals with this limitation by constructing a panel of market returns that take time-series prices at ports and adjust them with transportation costs. This approach assumes no intermediation or requires a perfectly competitive intermediary, which is not the case in my model. In Online Appendix (C.1), I explore alternative modeling approaches and find similar supply elasticity patterns.

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

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

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

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

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

Equation 3 relates observed land use change decisions (from any starting use j_0 to j) to the observed yield-adjusted returns to using the land for j. The parameter governing this relationship (α_R) and the preference shifters (α_0) will be estimated. Output (for cattle or crops) in municipality m is equal to the total acreage in use j times the yield:[24]

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

where L_m is the total area of m and $\rho_{j_0 m}$ is the share of that area initially in use j_0.

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

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

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

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

3.2 Meatpacker Problem

Meatpackers i are intermediaries in the industry, purchasing cattle from ranchers in municipality m and selling beef to consumer markets in Brazil and abroad. The model proceeds in two stages. In the first stage, potential entrants in each municipality decide whether to enter and source cattle from m,[25] subject to a fixed entry cost. In the second stage, firms draw productivities *after* entering and play a static Cournot oligopsony game,[26] strategically choosing quantities. This second stage occurs simultaneously with land-use decisions and final demand.

Meatpacker profits, for a given realization of productivity, are given by

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

where P denotes the price of Brazilian beef, z_{im} is firm i's productivity in municipality m, and $c_m(Q_m)$ is the inverse cattle supply curve implied by land-use decisions, with $Q_m = \sum_i q_{im}$ denoting total cattle sourced in m.

3.2.1 First stage – entry

Each municipality m has a set of potential entrants M_m.[27] Prior to entry, firms differ by type $F \in \{E, D\}$, where E denotes export-authorized meatpackers and D denotes domestic-informal meatpackers. Let M_m^F denote the set of potential entrants of type F in municipality m. Within each type, firms face a common fixed entry cost f_m^F and draw productivity i.i.d. from a distribution $G_m^F(z)$ after entry.

[25] Market definition at the municipality level reflects the highly localized nature of cattle procurement in the Amazon: 75% of cattle sourcing occurs within 250 km of the destination meatpacking plant. I also abstract from rancher specialization in specific steps of the cattle cycle (breeding, rearing, fattening). Upstream rancher-to-rancher trade is even more localized (91% within 150 km), which supports treating cattle supply as locally aggregated. See Scott, Souza-Rodrigues, Rosenbaum, and Goel (2025) for work that models herd dynamics while relying on region-level representative agents.

[26] It is common to assume a particular structure when conduct, in this case Cournot, cannot be directly tested. Reassuringly, evidence from the setting is consistent with this assumption – rancher sales are confined to a geographic region by transportation costs (see previous footnote), but within a region any given rancher does not sell exclusively to a particular meatpacker (Skidmore et al., 2024).

[27] In the model, decisions are independent across municipalities. Although in reality firms may control multiple meatpacking operations, each facility only serves a small catchment area due to the high transportation costs for cattle.

This structure implies three layers of heterogeneity. First, firms differ *ex-ante* by type through entry costs and productivity distributions. Second, productivity distributions are allowed to vary across municipalities, reflecting geographic differences such as transportation costs or quality. Finally, conditional on entry, firms draw productivities, generating *ex-post* heterogeneity within markets.

Entry decisions are made based on expected profits, as productivity draws are only realized after entry. Let $I_m = \{N_m^E, N_m^D\}$ denote the realized entry configuration in municipality m. An entry equilibrium satisfies the conditions

$$\begin{aligned} E[\pi_{im}(I_m)] &\geq 0 \quad \forall i \in I_m, \\ E[\pi_{i'm}(I_m \cup \{i'\})] &< 0 \quad \forall i' \notin I_m, \end{aligned}$$

so that all entrants earn non-negative expected profits and any additional entrant would earn negative expected profits.

Uniqueness The above conditions characterize the set of Nash equilibria of the entry game, but they do not guarantee uniqueness. As is well known in empirical entry models (De Paula, 2013; Bresnahan and Reiss, 1991), multiple equilibria may arise when firms are heterogeneous. In my case, this issue arises because there are two types of potential entrants, with different ex-ante productivity distributions.

To select a unique equilibrium, I impose a sequential entry structure. Export-authorized firms ($F = E$) make entry decisions first. Conditional on the number of exporters that enter, domestic-informal firms ($F = D$) then decide whether to enter. This assumption builds on the sequential-move frameworks of Berry (1992), Mazzeo (2002), and Toivanen and Waterson (2005). An important distinction is that I allow firms to vary by both productivity and entry costs, which means the ranking of profitability by firm type is not invariant to the set of entrants. Online Appendix B.3 shows in detail the algorithm I develop to solve the model under both margins of heterogeneity. There, I also show that the selected equilibrium maximizes the number of exporters among the set of possible equilibria, favoring one type of firm as in Jia (2008) albeit with a different structure. While the sequential entry

assumption is not directly testable, it reflects salient features of the industry, where federally inspected meatpackers (e.g. JBS) exert greater influence. The resulting structure preserves computational tractability, which is essential given that supply, entry, and demand must be solved jointly in policy counterfactuals. Finally, and most importantly, in robustness checks I also re-estimate the model under alternative entry orderings and find very similar results on policy counterfactuals.[28] Therefore, the sequential asssumption does not affect the key conclusions of this paper.

3.2.2 Second stage – Cournot

In the second stage, firms draw productivities z_{im} after entering. Observing their own productivity and those of their competitors, firms simultaneously choose quantities q_{im} to maximize

$$\max_{q_{im}} \left(P z_{im} - c_m(Q_m)\right) q_{im}, \tag{6}$$

taking as given the inverse cattle supply curve $c_m(Q_m)$ implied by land-use decisions.

Using the inverse supply curve, the first-order condition for firm i can be written as

$$c_m = P z_{im} \left(1 + \frac{\partial c_m}{\partial Q_m} \frac{Q_m}{c_m} s_{im}\right)^{-1}, \tag{7}$$

where $s_{im} = q_{im}/Q_m$ denotes firm i's market share in municipality m.

Equation (7) shows that the cattle price reflects a markdown relative to the marginal revenue product of cattle. Markdowns create the margins that allow meatpackers to cover their entry costs. They increase with firms' market shares and with the inverse elasticity of municipal cattle supply, linking monopsony power directly to land-use responses.

3.3 Demand:

Meatpackers sell beef in Brazil and abroad. Demand serves to link sourcing decisions across space by clearing a common beef market, so that changes in production in one location affect equilibrium prices faced elsewhere. Thus, the key purpose of this part of the model is to

[28] See Online Appendix B.6.

provide a basis for potential spillovers across regions in policy counterfactuals. Consider a world economy comprised of countries $d \in \mathcal{D}$. In each country, a representative agent has quasilinear preferences across beef products and a freely-traded outside good:

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

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

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

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

$$Y_{od} = \beta_d \frac{\beta_{od} \left(P_o T_{od}\right)^{-\sigma}}{\sum_{o' \in \mathcal{D}} \beta_{o'd} \left(P_{o'} T_{o'd}\right)^{1-\sigma}} \tag{8}$$

where T_{od} is the (iceberg) trade cost of delivering beef from origin o to d.[29]

This specification implies a single origin-level price P_o for all beef sold from Brazil. As a result, shocks that change aggregate sourcing from one region affect equilibrium beef prices and propagate to other regions through demand.

3.4 Closing the model:

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

$$Q_m = L_m \, a_{jm} \sum_{j_0} \rho_{j_0 m} \, \rho_m(j, j_0) = \sum_i q_{im} \quad \forall m \tag{9}$$

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

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

$$Y = \sum_{i,m} q_{im}\, z_{im} \tag{10}$$

where the subscript $o =$ Brazil is implied.

4 Estimation

Table 1 shows the key parameters to be estimated. In this section, I describe the parameterization and the estimation procedure for each of the three parts of the model.

Table 1: Parameters to be estimated

Land use	
α_R	Sensitivity of land use choices to yield-adjusted returns.
$\alpha_0(j, j_0)$	Parameters governing state-dependence for transitions from j_0 to j (identified up to normalization).
Meatpackers	
$(\alpha_F^z,\ \nu_F^2)$	Mean and variance of log productivity for meatpackers of type $F \in \{E, D\}$, as in $\log z_{im} \sim \mathcal{N}(X_m'\alpha_F^z, \nu_F^2)$.
α^f	Parameters governing fixed entry costs by firm type and municipality.
Demand	
σ	Elasticity of substitution across origin countries in Equation (8).

4.1 Land use parameters:

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

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

$$\log\left(\frac{\rho_m(j, j_0)}{\rho_m(j', j_0)}\right) = \Delta\alpha_{0,j,j',j_0} + \alpha_R \Delta R_{j,j',m} + \Delta\xi_{j,j',j_0,m} \tag{11}$$

where Δ denotes a difference, e.g. $\Delta R_{j,j',m} = R_{jm} - R_{j'm}$. $\Delta\xi_{j,j',j_0,m} = \xi_{j,j_0,m} - \xi_{j',j_0,m}$ is an

error term. I do not separately identify each $\alpha_0(j, j_0)$, so I work with their relative values.

Identification The regression equation (11) raises concerns related to the endogeneity of market returns $R_{j,j',m}$. For instance, unobserved supply shocks can affect local commodity prices or realized yields, so that $E[\Delta\xi_{j,j',j_0,m}|\Delta R_{j,j',m}] \neq 0$, biasing estimates of α_R.

To address endogeneity, I introduce two sets of instrumental variables. The first set of instruments consists of yield shifters using agroclimactic suitability indices from the FAO-GAEZ dataset for pasture and soy. Actual yields vary due to different agricultural practices and input usage, but the suitability indices serve as a good exogenous predictor of differences in yields across space.

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

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

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

From the lens of the model, this instrument can be interpreted as shocks to the efficiency z_{im} of intermediaries. In this interpretation, the stochastic element of z_{im} draws includes particularities in the meatpacker-retailer match that may change a meatpacker's earnings ex-post.

The key identifying assumption is that the country-level shocks are as good as randomly assigned. That is, $E\left[g_d \mid \bar{\xi}_d, s_d\right] = \gamma$, demand shocks in destination countries have the same expected value (γ) regardless of the average exposure shares they face (s_d) or the average supply shocks in the regions most exposed to it ($\bar{\xi}_d$) (Borusyak et al., 2018). Not all beef is

exported, which leads to an "incomplete shares" problem.[30] I address this by controlling for the (lagged) share of each region's output that goes to exports (separately for soy and beef), following the recommendations in Borusyak et al. (2024). Online appendix B.2 also shows that estimates are robust to a version of the instrument in the spirit of Borusyak and Hull (2023), where the instruments are "de-meaned" by their meso-region average.

4.2 Meatpacker parameters

Estimation for the meatpacking model proceeds in two stages. In the first stage, I recover firm-level revenue productivity implied by observed prices and quantities and use these to estimate the parameters governing productivity distributions. In the second stage, I estimate fixed entry costs by matching observed entry patterns to those implied by the model using simulation.

4.2.1 Meatpacker productivity

By rearranging the first-order condition of the Cournot oligopsony game (Equation 7), the model delivers an expression for firm-level revenue productivity as a function of observed prices, market shares, and supply elasticities:

$$Pz_{im,\text{inv}} = c_m \left(1 + \frac{s_{im}}{\hat{\varepsilon}_m}\right), \tag{12}$$

where c_m is the municipal cattle price, s_{im} is firm i's market share in municipality m, and $\hat{\varepsilon}_m$ is the estimated elasticity of cattle supply implied by the land-use model (Equation 4) evaluated at the estimated land-use parameters.[31]

It is worth noting, for estimation purposes, that model productivity draws occur *after* firms make entry decisions. Entry is therefore based on expected profits that integrate over the productivity distribution, but do not condition on realized productivity. Conditional on entry, observed productivity realizations can thus be treated as draws from the distribution

[30] That is, domestic shocks are mechanically 0, creating a different expected value of the shock for places more exposed to the domestic market. Online appendix B.2 maps the distribution of these trade shares.

[31] The inversion recovers revenue productivity Pz_{im} rather than physical productivity z_{im}. Separating the two is not necessary for estimation. In counterfactuals, the beef price P adjusts endogenously in equilibrium.

$G_m^F(z)$ (without truncation).

I assume that productivity is lognormally distributed. Equivalently, $\log z_{im}$ follows a normal distribution with type-specific mean and variance.[32] Under this assumption, productivity draws satisfy

$$\log z_{im} \sim \mathcal{N}\left(X'_{Fm}\alpha_F^z,\ \nu_F^2\right),$$

where the mean depends on observable municipality characteristics and firm type. The parameters governing the mean and dispersion of productivity draws can therefore be estimated from a linear projection of log revenue productivity on observables.

I estimate the parameters separately for export-authorized and domestic-informal meatpackers. The regressor vector X_m includes state fixed effects and a measure of remoteness (log distance to São Paulo), capturing fundamental differences in transportation costs and access to consumer markets. The variance ν_F^2 is assumed to be the same within a meatpacker type (but can differ between types E, D), determining the dispersion of productivity draws used in the simulation-based estimation of entry.

4.2.2 Meatpacker entry costs

To estimate the parameters governing entry costs, I match model-implied entry patterns to those in the data. Fixed entry costs are parameterized as

$$\log f_m^F = X_m^{F\prime}\alpha^f, \tag{13}$$

where X_m^F consists of indicators for firm type and a regional shifter (more on this below).[33]

Estimation relies on the Simulated Method of Moments (Gourieroux et al., 1993). The estimation procedure uses the model as a data generating process that simulates a set of decisions by agents in the model. I compute meatpacker expected profits using 100 simulations of the 517 municipalities in the data. Draws for firm productivity are taken given the

[32] Online Appendix B.5 shows that the lognormal distribution is a good approximation for the actual inverted values.

[33] Fixed costs are deterministic functions of observables and parameters. Unlike productivity, there are no private shocks to entry costs in the model, heterogeneity in ex-ante entry decisions is captured by firm type F.

parameters for $G_m^F(z)$ estimated in the previous step. Expected profits determine equilibrium entry decisions (as in Section 3.2.1) for a given candidate parameter vector $\tilde{\alpha}^f$. These endogenous choices are translated into moments, and the estimator searches over values of $\tilde{\alpha}^f$ to minimize the distance between the moments in the data to those simulated by the model.

Estimation uses three parameters and four moments. The parameters are: (i) a baseline fixed cost for export-authorized meatpackers, (ii) a baseline fixed cost for domestic-informal meatpackers, and (iii) an additional fixed-cost shifter for domestic-informal firms in the states of Pará and Maranhão.[34] The four moments are the average number of exporters and domestic-informal entrants (averaged across the municipalities), and these counts interacted with distance to São Paulo (see Table 2).

Table 2: Entry cost parameters and moments

	Notation	Description
Parameters	α_E^f	Entry cost for export-authorized meatpackers.
	α_D^f	Entry cost for domestic-informal meatpackers.
	$\alpha_{D,\text{PA/MA}}^f$	Entry cost shifter for domestic-informal meatpackers in Pará and Maranhão.
Moments	$\frac{1}{\mathcal{M}}\sum_{m=1}^{\mathcal{M}} N_m^E$	Avg. number of export-authorized meatpackers.
	$\frac{1}{\mathcal{M}}\sum_{m=1}^{\mathcal{M}} N_m^D$	Avg. number of domestic-informal meatpackers.
	$\frac{1}{\mathcal{M}}\sum_{m=1}^{\mathcal{M}} N_m^E \cdot \log \text{dist}_m$	Exporter entry × remoteness (log distance to São Paulo).
	$\frac{1}{\mathcal{M}}\sum_{m=1}^{\mathcal{M}} N_m^D \cdot \log \text{dist}_m.$	Domestic-informal entry × remoteness.

Entry equilibrium and algorithm For a given parameter vector $\tilde{\alpha}^f$, I solve for the entry equilibrium in each municipality using the sequential entry structure described in the model. Candidate entrants are considered in the order implied by the sequential game, and expected profits are computed using simulated productivity draws. Entry continues until no additional firm can earn non-negative expected profits. Additional details on the equilibrium algorithm and its implementation are provided in Online Appendix B.3.

Let g denote the vector of empirical moments and let $\hat{g}(\tilde{\alpha}^f)$ denote the corresponding

[34]Inspection standards for domestic-informal meatpackers are set at the state level. That extra parameter helps with model fit and reflects the relative ease of setting up a slaughterhouse in those states relative to Rondônia, Mato Grosso, and Tocantins, the other states in the sample. See Online Appendix B.4 for a further discussion on how moments drive parameter estimates.

moments implied by the model at parameter vector $\tilde{\alpha}^f$. Parameters are estimated by minimizing the simulated method of moments objective

$$Q(\tilde{\alpha}^f) = \big(g - \hat{g}(\tilde{\alpha}^f)\big)' W \big(g - \hat{g}(\tilde{\alpha}^f)\big). \tag{14}$$

Estimation proceeds in two steps. In the first step, I use the identity matrix for W. I then construct the optimal weighting matrix $W^{opt} = \Omega^{-1}$, where Ω is the variance-covariance matrix of the moments, and re-estimate parameters using W^{opt}. Standard errors for the entry cost parameters are computed following Gourieroux et al. (1993).

In principle, all parameters are jointly estimated to match the moments, but some moments are more informative than others for particular parameters. In Online Appendix B.4, I discuss this more formally using the sensitivity exercises proposed by Andrews, Gentzkow, and Shapiro (2017) and Honore, Jørgensen, and de Paula (2020). To briefly summarize, N_m^E is most important for α_E^f, while α_D^f and $\alpha_{D,\text{PA/MA}}^f$ are jointly pinned down by N_D and $N_m^D \cdot \log \text{dist}_m$. While transportation costs (in z_{im}, thus outside the entry model) inform much of the entry patterns for exporters, entry for domestic-informal firms is also governed by different barriers to entry driven by local policies, as states have the prerogative to set standards for non-exporting meatpackers, and enforcement against informal slaughter also varies locally.

4.3 Demand:

Here I estimate σ, the elasticity of substitution for beef across different country origins. Taking the log of Equation (8) divided by $Y_d = \sum_o Y_{od}$ yields the following equation:

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

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

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

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

5 Estimation Results

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

Land Use: Table 3 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. To aid interpretation, I also computed the average elasticity of cattle supply implied by the estimates. Estimates range from 0.14 to 0.33.

Supply elasticities matter for the responsiveness of land use to prices and for the strategic sourcing decisions of meatpackers. Based on my estimates, two types of places tend to have higher elasticities: (i) remote places with high shares of public land, and (ii) less remote places suitable for soy, which serves as a substitute for cattle ranching. Considering the remoteness gradient, these two effects mostly cancel each other out, as Figure 6 shows.[35] As a result, the key drivers of differences in monopsony power across space are the type and number of meatpackers operating, as I show next.

[35] Dominguez-Iino (2025) 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. (2025)) alongside the land tenure dataset I assembled. Public land plays an important role in driving higher elasticities. The models used are also distinct, and the state-dependence included in my model is known to lead to higher estimated elasticities (Scott, 2012).

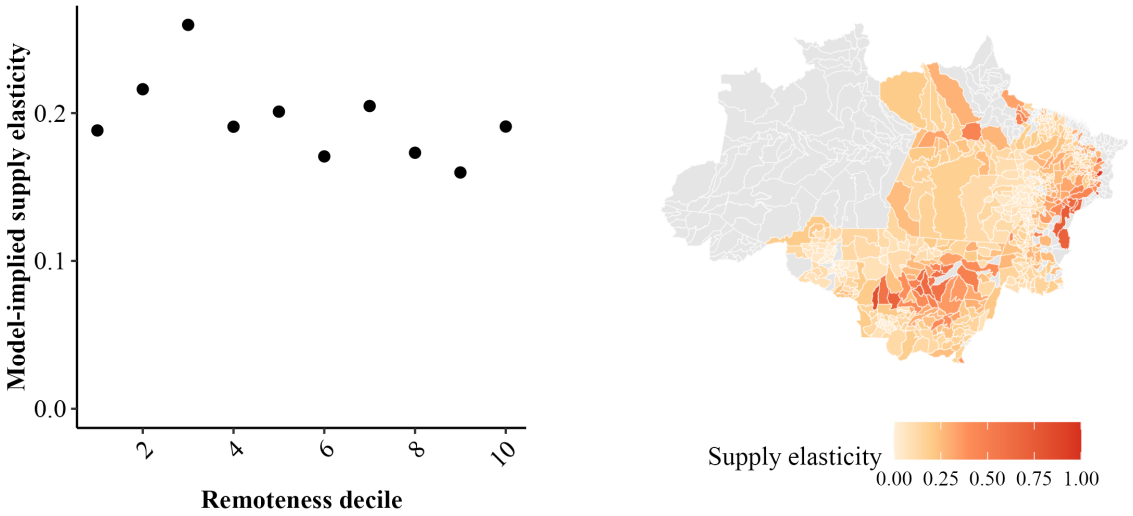
Table 3: Key coefficient estimates

	Parameter	Estimate	SE	Elasticity	F Stat
Land Use	$\alpha_{R(PublicDesignated)}$	1.80	(0.23)	0.33	31.9
	$\alpha_{R(PublicUndesignated)}$	1.21	(0.36)	0.14	28.8
	$\alpha_{R(PrivateUndisputed)}$	1.52	(0.29)	0.17	46.7
	$\alpha_{R(PrivateDisputed)}$	1.57	(0.31)	0.19	41.5
Demand	σ	4.44	(0.33)	–	34.8
Meatpackers	ν_E^2	0.270	(0.005)	–	–
	ν_D^2	0.070	(0.003)	–	–
	α_E^f	3.971	(0.037)	–	–
	α_D^f	2.274	(0.070)	–	–
	$\alpha_{D,\text{PA/MA}}^f$	-1.105	(0.068)	–	–

Notes: Land use estimation includes state fixed effects and policy covariates. Conley standard errors (250km cutoff) are reported in parentheses for the land use model. Elasticities are computed by simulating the land-use model following a small increase in cattle prices and resolving for equilibrium pasture area by tenure class. The parameters ν_F^2 govern the dispersion of productivity draws for export-authorized ($F = E$) and domestic-only ($F = D$) meatpackers. Their standard errors are computed via a clustered bootstrap at the municipality level ($N = 500$), where each iteration resamples municipalities with replacement and re-estimates the productivity distribution parameters. Standard errors for meatpacker entry parameters are computed using the asymptotic formula in Gourieroux et al. (1993) .

Figure 6: Estimation results - cattle supply elasticities and remoteness

(a) By remoteness decile (b) Map



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

Meatpackers: Estimates from the meatpacker model show how productivity and entry costs shape geographic differences in market structure. Export-authorized meatpackers are more productive: their lognormal productivity draws have both a higher mean and a higher variance, and the average exporter draw is 65% higher than that of domestic-informal firms. But exporters also face substantially higher entry costs (Table 3). In regions closer to major consumer markets and ports, these more productive firms can profitably enter and dominate cattle procurement. In more remote regions, transportation costs reduce meatpacker earnings, so fewer exporters can cover their higher fixed costs.

Domestic-informal firms instead face lower estimated entry costs.[36] This allows more of them to source cattle in remote regions, increasing competition in cattle procurement there. Ranchers receive on average 50.8% of the meatpacker marginal revenue product in the more exporter-dominated decile of regions, corresponding to a markdown μ_m of 1.97, and as much as 69% in some more remote deciles (61% in the most remote).[37]

From an efficiency standpoint, this geographic segmentation has ambiguous implications. On one hand, smaller firms serve ranchers in regions where larger meatpackers cannot recover their higher fixed costs. This attenuates the "curse of remoteness". On the other hand, this shifts procurement toward less productive intermediaries. As a result, the least distorted procurement markets are also those with the lowest average meatpacker productivity. In my setting, this pattern is especially consequential because the areas served by these firms also tend to have more emissions-intensive land-use change. The result is that the smallest, least productive, and least distorted firms operate the most emissions-intensive supply networks.

Model fit: The model fits the targeted moments closely, in addition to non-targeted moments I discuss in Online Appendix B.5. Figure 7 plots entry of both firm types by decile of distance to São Paulo. The model with only 3 parameters on the entry costs replicates well the patterns of entry across space. This is also true of moments that are not explicitly tar-

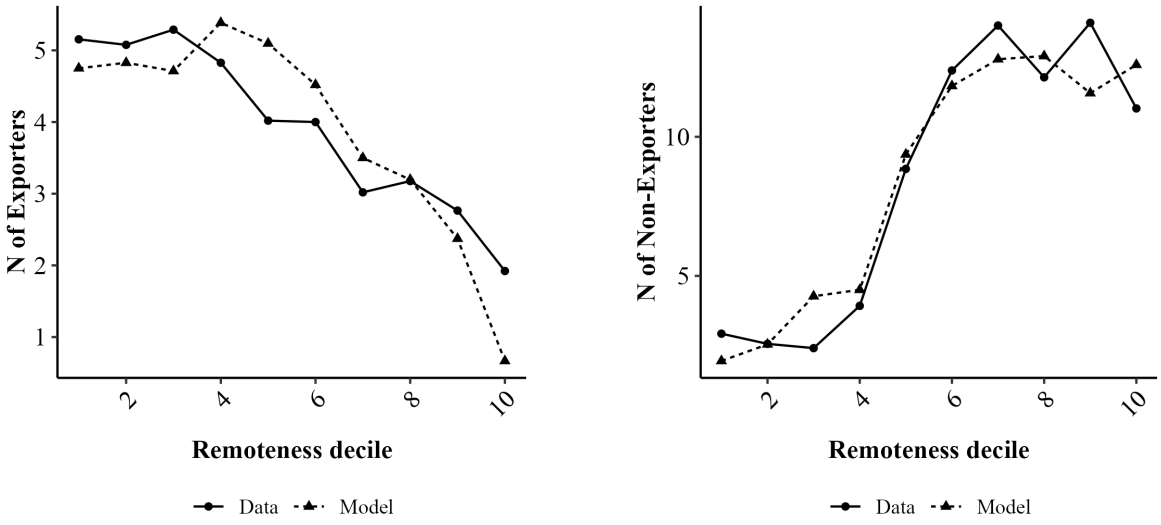
[36] This is even more so in the states of Pará and Maranhão. These lower entry barriers reflect local policy and do not have a clear relationship with remoteness. Both states have municipalities in various deciles of remoteness.

[37] A municipality-level average markdown μ_m can be derived by summing the firm first-order conditions in Eq. 7: $c_m = \frac{\sum Pz_{im}}{N_m} \underbrace{\left(\frac{1}{\varepsilon_m N_m} + 1 \right)}_{\mu_m}^{-1}$.

geted in the model. Both export-authorized shares and the Herfindahl index (concentration) are lower in more remote regions as shown in the stylized facts, and Figure S4 in the Online Appendix shows that the model matches those patterns well. I see those as a joint test of model specification and fit across the productivity distribution and entry. The entry model is estimated to match the number of entrants, but not whether their market shares are evenly distributed. Concentration and exporter shares depend jointly on entry, the Cournot structure, and the assumed productivity distribution. With the lognormal productivity draws and the estimated entry costs, the model is able to match well those non-targeted patterns of shares and concentration.

Figure 7: Model Fit - Targeted Moments - Entry

(a) Export-authorized (b) Domestic-informal



Note: Figures show the average number of meatpackers sourcing cattle from municipalities in the different deciles of distance to São Paulo. Panel (a) shows export-authorized meatpackers, panel (b) shows domestic-informal meatpackers.

6 Policy Analysis

The estimated model shows how firm decisions drive geographic segmentation of export-authorized and domestic-informal firms into separate markets – this section now considers how firms respond endogenously to policy, and the implications this has for strategies to

reduce emissions in the Amazon. For this, I run model simulations of several policy scenarios, conveniently summarized on Table 4.

Across the policies, I consider their effects on cattle ranchers, consumer surplus, and meatpacker profits. Those figures are reported on Table 5. To derive abatement cost values, I rely on the following welfare definition in the model:[38]

$$W = \underbrace{\left(\sum_m L_m \left(\sum_{j_0} \frac{\rho_{j_0}}{\alpha_R} \ln\left(\sum_j \exp(V_{mj;j_0})\right)\right) + K\right)}_{\text{Landholder Surplus}} + \underbrace{\left(\sum_m \sum_i (P z_{im} - c_m) q_{im} - f_{im}\right)}_{\text{Meatpacker Profits}} + \underbrace{\sum_d \mathcal{W}_d + \beta_d \ln \mathcal{Y}_d - \mathcal{P}_d \mathcal{Y}_d}_{\text{Consumer Surplus}}. \tag{16}$$

In general, two main mechanisms drive the welfare cost of policies. First, there is the marginal abatement cost of policy:[39] it is increasing in the (weighted) average productivity of meatpackers sourcing in a region, and decreasing in the emissions intensity of local cattle production. Second, policy can induce entry and exit of firms. Changing the identity of firms sourcing cattle in a market shifts average productivity and affects the trade-off between costly entry and the increased production with more competition.[40] In the analysis that follows, I describe how those mechanisms shape each policy.

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

[39]Differentiating Equation (16) with respect to c_m and collecting terms, the model yields the following expression for *marginal* abatement costs: $\frac{\partial W}{\partial \bar{E}_m} = \frac{1}{b'_m(Q_m)}(\sum_i P z_{im} s_{im})$. The first term is the emissions intensity of cattle production in m, the second is the revenue productivity of meatpackers operating there, weighted by their market shares.

[40]There is a business-stealing externality (Mankiw and Whinston, 1986) operating here: as firms make costly entry decisions, they consider their own potential profits, but not the reduction in the profits of other firms. As a result, entry can be inefficiently high.

Table 4: Policy Counterfactuals - Taxonomy

Policy	Description
Exporter tax	Ad-valorem tax (20%) on cattle sourced by export-authorized meatpackers.
Exporter tax†	Same tax applied in a model without entry or firm heterogeneity.
Market exclusion	Export-authorized meatpackers do not source from land deforested after 2008, segmenting cattle markets by compliance status. Inspired by EU Deforestation Regulation.
Tax on all	Ad-valorem tax (20%) on cattle sourced by *all* meatpackers, regardless of export status.
Higher entry cost	Raise the entry costs of domestic-informal meatpackers to match those of exporters.

6.1 Taxes and standards on beef production:

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

To illustrate how policies targeting exporters affect the supply chain, I run counterfactual simulations under price and quantity-based mechanisms. The price mechanism is a tax on cattle sourced by export-authorized meatpackers. Note that this tax is on *all* the sourcing by exporting firms regardless of destination (including Brazil). I later compare it to a tax on all meatpackers, both export-authorized and domestic-informal.

The quantity-based policy is a standard similar to the EU Deforestation Regulation (EUDR).[41] It works through market exclusion – my exercise assumes that all export-authorized firms are required to *not* purchase cattle from any land that was deforested after 2008 (Figure 8). This bifurcates the cattle procurement market in each municipality. Compliant ranchers can sell to all meatpackers, whereas non-compliant ranchers can only sell to domestic-informal meatpackers. The limited set of buyers creates a more concentrated market for

[41]The EUDR 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". In addition to the EUDR, 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).

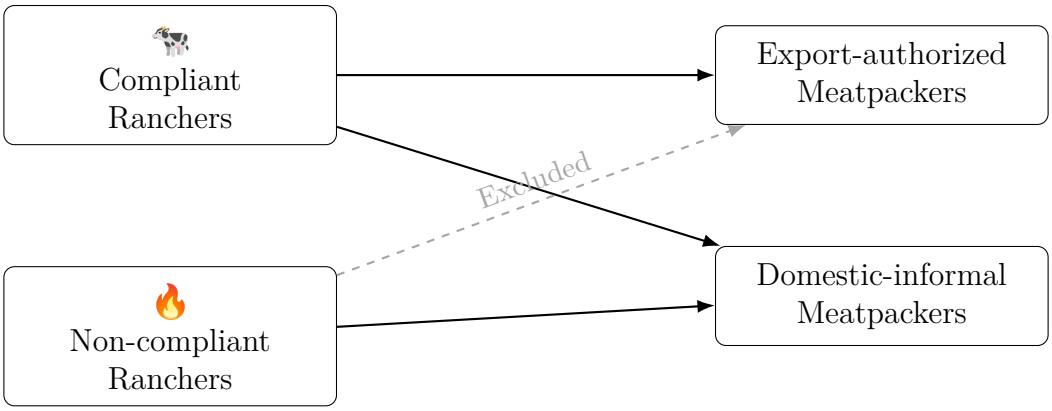


Figure 8: Cattle supply chain under the market exclusion mechanism.

non-compliant ranchers, lowering the cattle price they earn in equilibrium. This lower equilibrium price acts as the disincentive for deforestation. Unlike the tax, this instrument does not generate revenue. Since my focus is on changes to entry and sourcing by meatpackers, I assume perfect enforcement on exporters (but not domestic-informal firms).[42]

Tax results As Table 5 shows, the tax targeted on exporters implies abatement costs more than three times higher than the general tax. The exporter tax reduces emissions less, but reduces production more. There are several reasons for this. First, it is mistargeted, both geographically and across firms, reflecting the different marginal abatement costs. Exporters operate in relatively clean regions, generally away from the high upstream emissions of remote places. These exporting firms also have the highest estimated productivity, which further adds to the welfare cost of abatement.

There are also important second-order impacts as the supply chain reorganizes across space and firms. Reducing output in regions dominated by exporters raises beef prices, which creates demand spillovers that increase production in more remote places (Figure 9), partly offsetting the emissions reductions. Furthermore, the tax reallocates output between firms: from more productive exporters to less productive and informal firms. The combined effect of these distortions can create meaningful welfare effects in a country that is already low income: \$49.36 per ton of CO2-equivalent abated, or \$75.36 without considering revenue. This is still smaller than recent estimates of the social cost of carbon (Moore et al., 2024), but towers in comparison to much more effective and less distortionary policies.

[42]Studying strategic behavior by ranchers to circumvent these regulations is an interesting avenue for future work.

Table 5: Policy counterfactuals - results summary

Policy	Emissions	Beef	Average Abatement Cost ($/ton CO2e) Total	No revenue	CS	Profits	Landholders
Exporter tax	-3.24%	-14.14%	49.36	75.36	23.34	32.89	19.14
Exporter tax†	-7.37%	-3.86%	28.26	37.02	2.07	18.73	16.21
Market Exclusion	-4.64%	-19.14%	32.42	32.42	22.63	-2.99	12.78
Tax on all	-12.38%	-10.07%	14.57	21.39	4.27	5.95	11.16
Higher entry cost	-7.83%	+4.40%	-0.40	0.02	-2.77	-7.22	10.01

Note: "Exporter tax†" refers to the counterfactual using a model without entry or firm heterogeneity. Column "No revenue" specifies average abatement cost without considering tax revenue. The subsequent columns consider impacts on consumer welfare, meatpacker profits, and landholder welfare, respectively. Ad-valorem tax is set to 20%. "Higher entry cost" refers to the counterfactual where entry costs for domestic-informal firms are set to those of exporters. The Online Appendix (B.6) includes versions of these exercises under different tax rates and alternative formulations of the model.

The breakdown of different welfare impacts can shed further light on the distortionary effects of exporter-focused policies. For the comprehensive tax, welfare impacts are driven by losses for landholders. With a second-best tax on production, the only way to reduce emissions is by reducing cattle production, so the burden on ranchers is unavoidable. However, the exporter tax creates other kinds of distortions that greatly increase its welfare cost. Consumers lose as a result of sharp reductions in beef production. And so do firms - the policy punishes the most efficient firms while leaving domestic-informal firms unregulated. Entry rates provide an easy way to see this: they decrease by 27.4% for exporters and increase by 48.6% for non-exporters, shifting output to less productive firms on both the intensive and extensive margins. Online Appendix B.6 shows the robustness of these results under different tax rates and assumptions on entry ordering.

The importance of entry and heterogeneity On Table 5 under "Exporter tax†", I quantify the importance of the model mechanisms by showing the same tax counterfactual in a simplified model without firm heterogeneity and entry. To do so, I assume all firms draw productivity from a common distribution, and hold the number of entrants constant to its original level. This scenario overstates the effectiveness of the policy, and understates its negative effect on beef production, more than two-fold. By assuming firms are (ex-ante) homogeneous, this stylized model does not account for the cross-region reallocations

and, most importantly, for the adverse reallocations across firms that drive down average productivity. When it comes to welfare, there is a slightly narrower gap, which reflects the higher entry cost burden in this alternative scenario. When entry is held fixed, firms are "forced" to remain in the market even if their profits go below zero. This creates a countervailing effect and is reflected under profits – the rigidity prevents some gains from lowering the total expenditure on entry costs. In the original counterfactual, the reallocation to domestic-informal firms economizes on entry costs despite lowering productivity. This again illustrates the trade-off implied by small and informal meatpackers: with imperfect enforcement output moves to less efficient firms, but they are able to operate with lower setup costs.

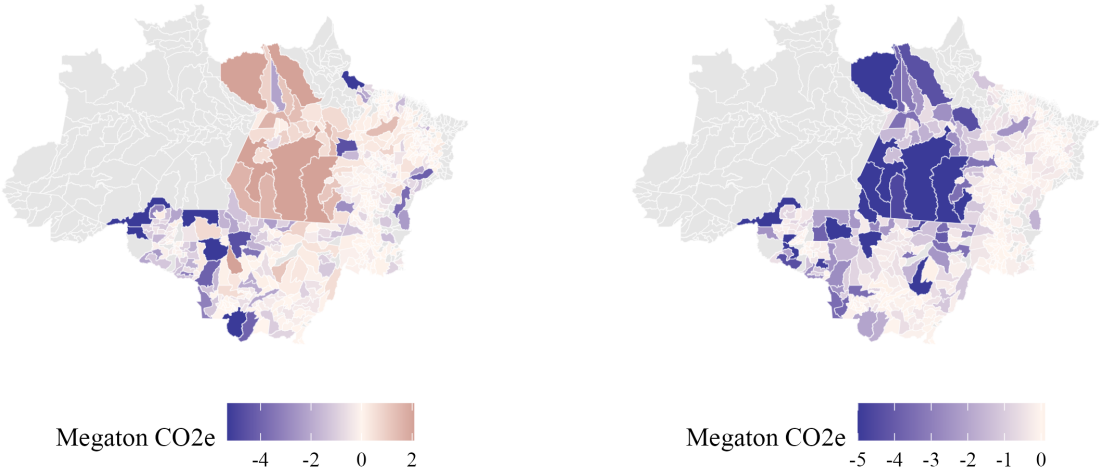
Market exclusion standard The market exclusion (EUDR-inspired) policy also has high abatement costs, but mechanisms differ in interesting ways. Like the exporter tax, it reduces exporter market shares and induces a reallocation across regions through demand spillovers. But market exclusion has an additional mechanism: it incentivizes entry of domestic-informal firms by granting them a less competitive cattle procurement segment where they earn high markdowns. Those higher markdowns allow more of them to cover their entry costs, which then shifts inputs towards lower productivity firms even in the compliant markets. By creating high-concentration segments, much of the welfare effect of this policy is a transfer from non-compliant ranchers to unregulated domestic-informal meatpackers, whose profits increase.

Together, the results of the simulated exporter tax and the market exclusion mechanism call into question approaches that center regulation only on the largest, most prominent firms. Note that the tax and standard on exporters regulate *all* their production, not just exports. Export-authorized meatpackers also lead sales in Brazil. Even in an optimistic scenario of full international coordination that includes domestic output from exporting firms, these regulations will have only modest effects. In the Amazon, domestic-informal firms have a remarkable ability to fill gaps left by incomplete regulation. The adverse effects of those policies are compounded by geography – as small meatpackers operate in remote, high emitting regions – and misallocation effects, as policies can shift production to lower-

productivity firms on the intensive and extensive margins.

Figure 9: Cattle taxes - effects on emissions

(a) Tax on exporters (b) Tax on all



6.2 Changing barriers to entry for intermediaries:

In estimation, I find that the presence of domestic-informal firms in the Amazon, despite their lower productivity, is due to their lower entry costs. By operating in informality or under lower inspection grades, those firms can save on overhead costs, taxation, and face less stringent food safety standards. What if those entry barriers were not so low?

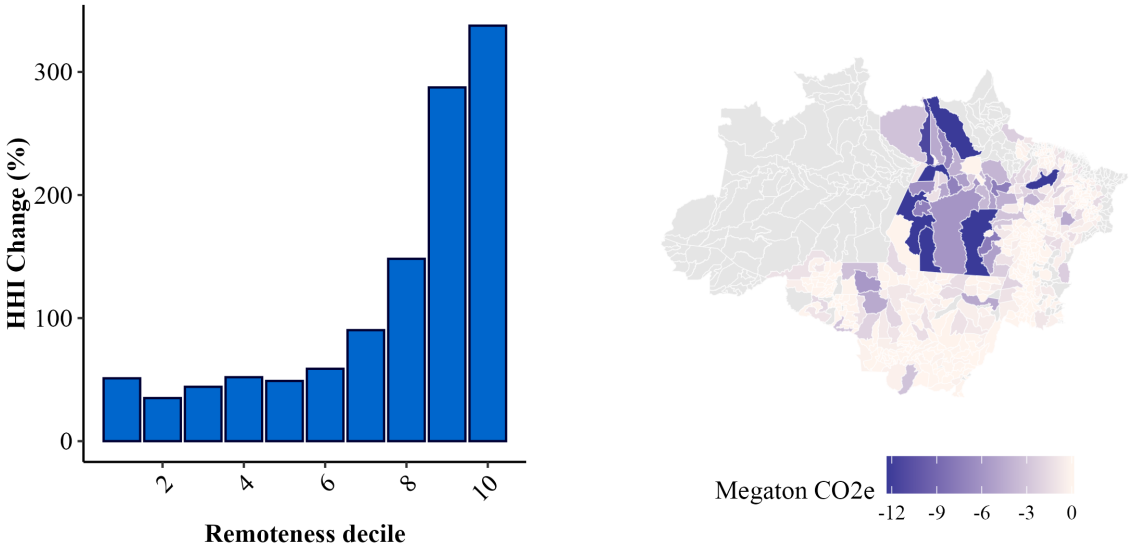
In this section, I simulate scenarios in which the entry costs for domestic-informal meatpackers are *the same* as those for export-authorized meatpackers. This policy is anti-competitive, shifting rents from ranchers to meatpackers, but it also reallocates output across regions and firms, resulting in emissions reductions of 7.83%. At the same time, total beef sales *increase* by 4.4%.

This result is driven by several mechanisms. First, domestic-informal meatpackers are much more likely to operate in remote regions. Restricting their entry makes concentration much higher in remote regions (Figure 10), leading to lower cattle prices. This reduces ranching in the regions with the highest emissions. The increase in beef production is driven

by the reallocation of output to export-authorized meatpackers, which increase entry by 10%. Although cattle ranchers are adversely affected, the improvements in allocative efficiency drive the average abatement cost of the policy to near zero. This suggests that a reduced reliance on small and informal firms on this supply chain could generate environmental and productivity gains that remediate the distortions it would generate to cattle production.

Figure 10: Higher entry costs - effects on meatpacker concentration and emissions

(a) Concentration (HHI) change (%) (b) Emissions



Feasibility and distributional considerations: There are a few costs and benefits to policies that cannot be fully accounted for in the model, so it is worthwhile to consider how they might affect my analysis. First, I do not consider the administrative costs of monitoring and enforcing different policies. Taxes and standards would require animal-level traceability, which currently is not in place – only herds are tracked, not individual animals. Entry barrier policies may be less costly because they can be embedded in already-existing phytosanitary regulations, and incumbent firms could be incentivized to contribute to monitoring as a mechanism for entry deterrence (Glaeser and Shleifer, 2001). Second, I do not account for food safety risks: changing the share of domestic-informal firms may affect the incidence of food-borne diseases.

Policies have different distributional consequences, but none of the mechanisms I study

here is unambiguously progressive or regressive. Cattle ranchers are generally the most negatively affected constituency among the policies I explore, which could drive local backlash. However, effects on ranchers are heterogeneous, with some incumbents potentially gaining from reduced aggregate supply. Furthermore, cattle ranching in the Amazon often involves conflict and land theft from indigenous reservations (CPT, 2005). It is also notorious for its cases of modern slavery (Siqueira, 2018). From this perspective, curbing emissions could also protect the most vulnerable populations of the Amazon.

7 Conclusion

This paper develops an empirical framework for studying environmental policy in settings with many small and informal firms. Focusing on supply chains in developing countries, the structural model shows how differences in firm productivity and entry costs can generate geographic segmentation in equilibrium. Large, more productive firms concentrate in regions with better access to consumers and ports, creating highly concentrated procurement markets. Smaller and less productive firms instead cluster in remote regions. This segmentation has important environmental consequences. In my setting—the world's largest rainforest – those consequences are especially stark because of the exogenous geographic distribution of carbon storage potential. As a result, the smallest and least productive firms, operating in the most competitive procurement markets, are located precisely where land-use change is most emissions-intensive.

These findings carry clear implications for environmental policy in the Amazon. Small firms often remain small to avoid regulation, while many recently proposed policies focus on prominent exporting firms. I find that such policies can adversely reallocate activity within the supply chain, shifting production toward less productive firms with higher-emitting suppliers and substantially increasing abatement costs. More broadly, the results call into question the effectiveness of unilateral tariffs or standards imposed on exporters. Even under perfect international coordination, such policies may have limited effects when small and informal firms in developing countries can fill the gaps left by incomplete regulation. A more promising approach may involve cooperative arrangements in which importing coun-

tries reward exporters for achieving verifiable environmental outcomes. This logic echoes the framework in Harstad (2022), and existing efforts such as the Amazon Fund, financed by Norway and Germany, move in a similar direction.

More broadly, the evidence in this paper points to the importance of measuring and accounting for small and informal firms in analyses of environmental policy. The issues I analyze extend well beyond agriculture, since many industries in developing countries are comprised of small and informal producers. As the framework I develop here shows, policy conclusions will be context-dependent. In my setting, enforcement that curbs the activity of small and informal firms can both drive productivity improvements and reduce the most emissions-intensive production. But in other contexts, small firms may be an important buffer against some of the distortions that result from policy-induced exit.

Appendix

Other data sources

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

Land Use: Land use data come from Mapbiomas (Souza et al., 2020).[43] It is the result of a collaboration between researchers to classify land uses in Brazil using Landsat imagery. 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.[44] I use the transition rasters between 2015-2019 to create land transition matrices by municipality and land tenure class.

Suitability Index: Farm yields can vary across space, which affects land use decisions. Yields are greatly influenced by the agroclimactic conditions of the land in a given region. Since actual yields may be endogenous, as an instrument I use agroclimactic suitability indices from the FAO-GAEZ (Fischer et al., 2021) dataset.[45] 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: To go from land use decisions in the structural model to emissions, I need data on the emissions intensities of production. In the cattle sector, that is a non-trivial task

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

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

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

because there are several different (direct and indirect) sources of emissions, all of which also vary geographically.

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

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

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

My analysis of carbon emissions relies primarily on two sources: carbon stocks from Spawn et al. (2020), and all other emissions sources from SEEG.[46] For the carbon stocks, I infer the *potential* carbon stocks of forest by subsetting the data from Spawn et al. (2020) to only pixels that have been forest since the beginning of the Mapbiomas dataset (1985), which is as far back as one can determine old-growth forests. To derive emissions in counterfactual land use change, I also use information on the age distribution of forests that are cut down.

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

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

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

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

SEEG provides data on two kinds of agricultural emissions. First, there are emissions related to land (e.g. fertilizer, soil emissions), which average 0.14 tCO2e per hectare-year. Slightly more impactful are animal emissions. Cows emit methane through their digestive tract, and total emissions depend on how long the animal lives before slaughter. Some regions employ more intensive practices and slaughter the animals at a younger age, creating a range of 2.1-4.2 tCO2e/head.[47] 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.

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

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

Online Appendix A Data

A.1 Cattle movement records:

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

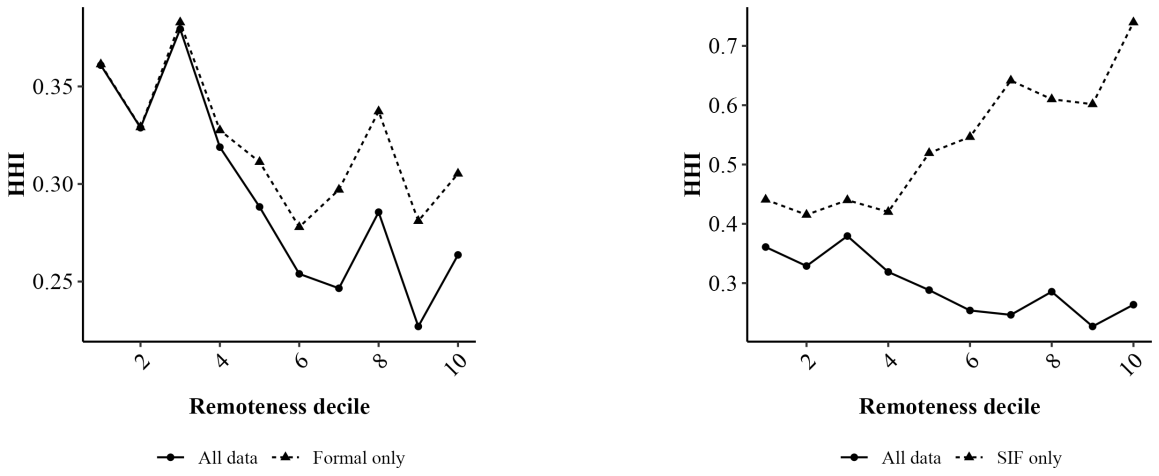
Through a data use agreement with a partner organization, I access GTA records for the Legal Amazon states of Pará, Mato Grosso, Rondônia, Tocantins, and Maranhão. These states account for 92% of the Brazilian Amazon's pasture area and 94.1% of cattle production. The data are available for some of the 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-informal meatpackers operate disproportionately in remote regions, without including them those regions would appear much more concentrated than they actually are.

Figure S1: HHI pattern would change with limited data



(a) Formal meatpackers only

(b) Export-authorized (SIF) only

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

Table S1: Road and Euclidean distance are highly correlated.

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

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

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

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

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

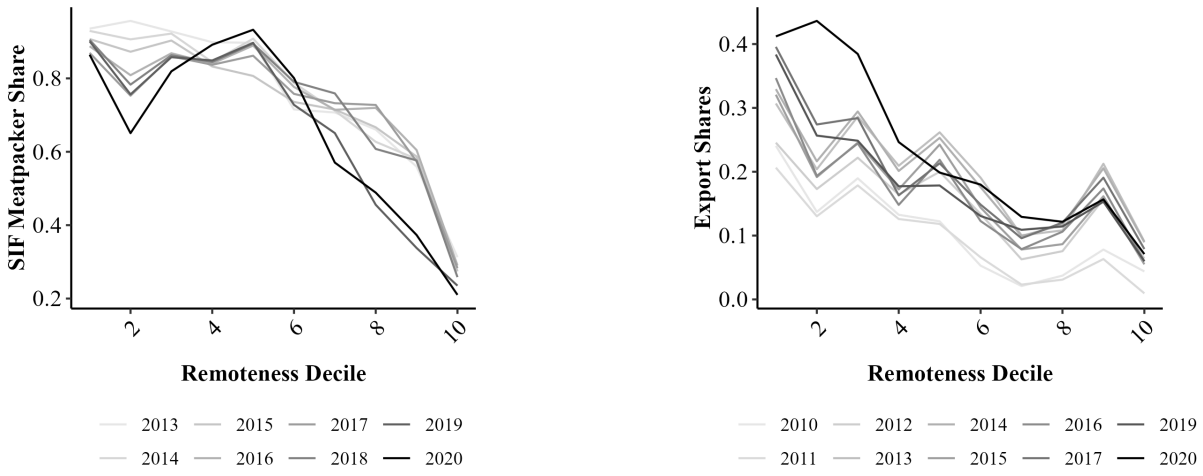
The key message of this paper rests on the geographic distribution of meatpackers - with few export-authorized firms in the "core" and a fringe of many domestic-informal buyers in remote areas. The rich data I have shows *all* meatpackers (large and small), but are limited to a few years (2015-18). With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

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

2. The share of municipal output that goes to exports for 2010-2020.

Dataset (1) was generously shared by Gibbs Land Use Lab. SIF (export-authorized) meatpackers are those that face the strictest (federal) level of inspection, which allows them to access markets in all of Brazil and to obtain licenses for export. I construct (2) 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-informal meatpackers that elude regulation.

A.3 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. Within public land, there is designated public land (national and state parks, indigenous reservations, protected areas)

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%

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 that identifies intersecting claims. Even after removing anything resembling a duplicate, there were places with over 10 intersecting claims. 7% of all land area (15% of private land) in my sample has more than one intersecting claim.

Online Appendix B Empirics

B.1 Evidence of market power in cattle sourcing:

In this section, I develop a simple model of cattle procurement that yields an estimating equation to test for monopsony power in cattle through the pass-through of demand shocks faced by meatpackers. The model is more general than Cournot (it nests it as a sub-case), and relies on a simplified specification of supply. This is not meant to replace the structural model, but serves as a reduced-form exercise that motivates oligopsony model I use.

Consider a local procurement market indexed by m and time t. Ranchers supply quantity

Q_{mt} to intermediaries at farmgate price c_{mt}. Inverse supply is

$$c_{mt} = s(Q_{mt}, A_{mt}), \qquad s_Q(\cdot) > 0,$$

where A_{mt} is a supply shifter.

Intermediaries sell beef downstream and face a marginal value of procurement φ_{mt} in market m at time t. This is comparable to Pz_{im} in the structural model. Rather than specifying a particular market structure, conduct is summarized by a parameter $\theta_{mt} \geq 0$ capturing how much intermediaries internalize the effect of their purchases on the farmgate price:

$$\varphi_{mt} - c_{mt} = \theta_{mt}\, Q_{mt}\, \frac{\partial c_{mt}}{\partial Q_{mt}}. \tag{17}$$

Perfect competition corresponds to $\theta_{mt} = 0$. Larger values represent stronger oligopsonistic conduct (Cournot, collusion, etc.).

Define the local supply elasticity at the equilibrium as

$$\varepsilon_{mt} \equiv \frac{\partial \ln Q_{mt}}{\partial \ln c_{mt}} = \left(\frac{Q_{mt}}{c_{mt}} \frac{\partial c_{mt}}{\partial Q_{mt}} \right)^{-1}.$$

Using $Q_{mt}\, \partial c_{mt}/\partial Q_{mt} = c_{mt}/\varepsilon_{mt}$, equation (17) implies the markdown formula

$$\varphi_{mt} = c_{mt} \left(1 + \frac{\theta_{mt}}{\varepsilon_{mt}} \right), \qquad c_{mt} = \lambda_{mt}\, \varphi_{mt}, \qquad \lambda_{mt} \equiv \left(1 + \frac{\theta_{mt}}{\varepsilon_{mt}} \right)^{-1} \in (0, 1]. \tag{18}$$

The coefficient λ_{mt} is the *pass-through* from downstream marginal revenue product φ_{mt} to the farmgate price c_{mt}. It is strictly below one whenever $\theta_{mt} > 0$. This yields the following comparative statics:

$$\frac{\partial \lambda_{mt}}{\partial \theta_{mt}} < 0, \qquad \frac{\partial \lambda_{mt}}{\partial \varepsilon_{mt}} > 0.$$

Thus, for a given downstream shock $d\varphi_{mt}$, price responses are smaller in markets with stronger oligopsonistic conduct (higher θ_{mt}) and in markets where rancher supply is less elastic (lower ε_{mt}).

Export-demand shocks, realized export prices, and shifters of φ_{mt} The empirical exercise uses export demand changes as a shock from which I can estimate how pass-through rates vary with concentration. The first is a *realized* export-price shock faced by the set of exporters purchasing cattle from municipality m, constructed from observed export unit values. Interpreting an increase in exporters' average unit earnings as raising the marginal value of procurement implies that this realized shock loads into φ_{mt}. I define Δp_{mt}^{exp} as the change in the municipality-level export price faced by exporters sourcing from m (in $\$/ton$) over a two-year window.

Changes in export demand may be endogenous to other contemporaneous shocks facing that procurement market. As an instrument, I use an *export-demand shifter* constructed as a shift-share based on destination-level changes in import demand excluding Brazil and baseline supply-chain exposure. This shifter is used as an instrument for Δp_{mt}^{exp}, isolating variation in export prices driven by foreign demand conditions rather than contemporaneous Brazilian supply shifts or other shocks correlated with cattle prices.

Using (18), and taking a first-order approximation around the equilibrium, yields

$$\Delta c_{mt} \approx \lambda_{mt} \, \Delta \varphi_{mt} \tag{19}$$

To connect this expression to concentration, let HHI_{mt} proxy for the strength of oligopsonistic conduct. A linear approximation of λ_{mt} in HHI_{mt} gives

$$\lambda_{mt} \approx \beta_0 + \beta_1 HHI_{mt}, \qquad \beta_1 < 0,$$

so that (19) motivates a pass-through regression in which the export-price shock is interacted with concentration.

Constructing the instrument: a shift-share excluding Brazil Let Δp_{dt} denote a destination-level level shifter capturing the change in import demand in destination d over the relevant two-year window, measured using imports *excluding Brazil* (the change in import value constructed from third-country imports). Define s_{id} as exporter i's baseline share of exports shipped to destination d, and s_{im} as exporter i's baseline sourcing share from mu-

nicipality m (both measured in a pre-period). The municipality-level shift-share instrument is

$$Z^{\$}_{mt} = \sum_{d,i} \Delta p_{dt}\, s_{id}\, s_{im}. \tag{20}$$

This instrument varies across municipalities because they differ in baseline exposure to exporters that are themselves differentially exposed to destinations with changing import demand.

Guided by (19)–(20), I estimate a two-stage least squares regression where the endogenous regressor is the realized export-price shock. The first stage is

$$\Delta p^{exp}_{mt} = \pi_0 + \pi_1\, Z^{\$}_{mt} + \pi_2\, (Z^{\$}_{mt} \times HHI_{mt}) + X'_{mt}\Pi + \mu_m + \tau_t + \nu_{mt}, \tag{21}$$

and the second stage is

$$\Delta c_{mt} = \alpha_0 + \alpha_1\, \widehat{\Delta p^{exp}_{mt}} + \alpha_2\, (\widehat{\Delta p^{exp}_{mt}} \times HHI_{mt}) + X'_{mt}\Gamma + \mu_m + \tau_t + \varepsilon_{mt}. \tag{22}$$

Here Δc_{mt} is the change in the farmgate cattle price in market m between the start and end of each two-year period, HHI_{mt} is the Herfindahl index of meatpacker concentration in market m measured at the beginning of the period, and X_{mt} includes time-varying controls (including the share of trade captured by the matched exporter network). Municipality fixed effects μ_m absorb time-invariant differences across markets, while period fixed effects τ_t absorb common shocks.

As I discuss in the main text, data on cattle prices for the entire Amazon are limited to one cross-section in 2017 from the agricultural census.[48] Since this side-analysis involves *changes* to cattle prices, I need to use different datasets, which are available for more years, but more limited geographically. Namely, the Instituto Mato-grossense de Economia Agropecuaria (IMEA), an agricultural think-tank, has collected panel data on cattle prices for municipalities in the state of Mato Grosso. I match those with data from Trase for municipality-level

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

Table S3: Pass-through evidence of meatpacker monopsony

Shock	0.025***	0.049***	0.112***
	(0.007)	(0.012)	(0.025)
Shock x HHI		−0.037*	−0.073*
		(0.017)	(0.032)
HHI		0.059	0.155*
		(0.041)	(0.076)
Exporter Share	0.047*	0.001	−0.048
	(0.018)	(0.033)	(0.059)
Year FE	X	X	X
Munic FE			X
R^2	0.992	0.992	0.996
Adj. R^2	0.991	0.992	0.992
Num. obs.	251	251	251

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

exposure to trade with different countries.

Table S3 shows the regression results. As predicted, the pass-through of export demand shocks to prices is lower in more concentrated regions.

B.2 Shift-share instrument

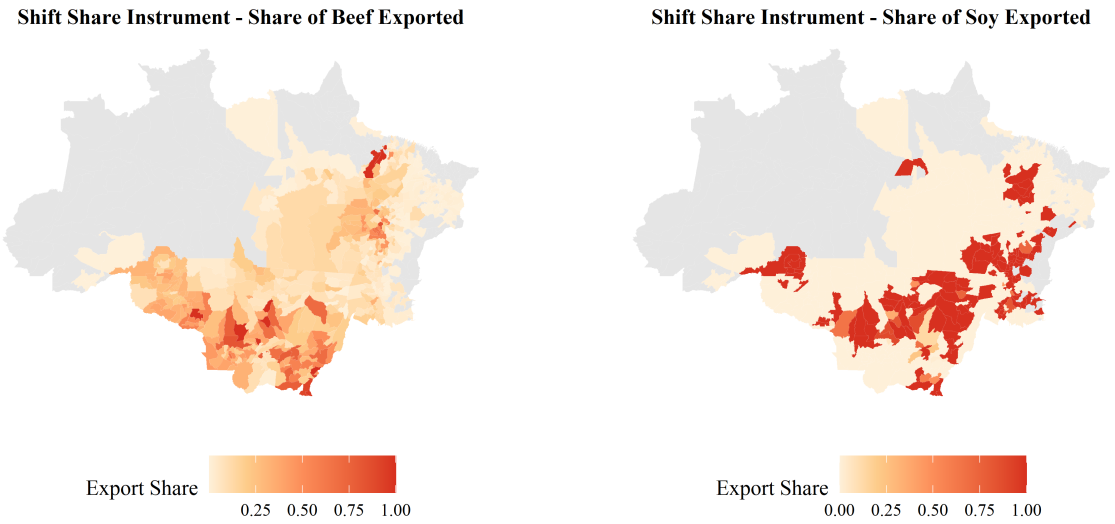
The land use model uses a set of shift-share demand shocks for beef and soy as instruments. I rely on exogenous changes in import demand g_{dt} interacted with regional exposure shares through the supply chain. Using the cattle supply chain as an example, ranchers in different regions are exposed to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

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

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

The exposure shares are "incomplete" (Borusyak et al., 2018), in the sense that not all

output is exported outside of Brazil. In the main text, I address this by controlling for the (lagged) trade share, as suggested in Borusyak et al. (2024). Here, I show maps of the export shares of beef and soy output, and also display coefficient estimates of the land use model using a "re-centered" instrument (in the spirit of Borusyak and Hull (2023)) which subtracts the meso-region mean of the instrument from its original value. Meso-regions are Brazil's third lowest administrative unit (municipality and micro-region being the first two).



(a) Beef (b) Soy

Figure S3: Export shares of Brazilian beef and soy output

Table S4: Key land use estimation coefficients - Re-centered SSIV

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

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

B.3 Entry model algorithm:

The entry game I outline in the main text does not guarantee a unique equilibrium without further assumptions. This issue is not unique to my model: when firms are heterogeneous,

there are often multiple possible arrangements of different firms that constitute an equilibrium. In my application, I rely on an assumption of sequential entry as a mechanism of equilibrium selection, ensuring a unique equilibrium. This is similar to the approach Berry (1992) (and also Mazzeo (2002); Toivanen and Waterson (2005)) take, but with a key added challenge - meatpackers differ in *both* productivity and entry costs. As a result, there is no stable ranking of profitability that is invariant to entry arrangements. I make a small methodological innovation to accommodate this heterogeneity along two dimensions.

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

$$\min\{t \in I_m^* \setminus I_m'\} < \min\{t \in I_m' \setminus I_m^*\} \tag{23}$$

In the main text, this rank order sets export-authorized firms as first movers, followed by domestic-informal firms. Since productivity draws are realized post-entry, firms are ex-ante homogeneous *within* a type, so their within-group order also does not matter in terms of outcomes. In that case, the condition in (23) can be reinterpreted to mean that, among possible equilibria, I select the one that maximizes the number of exporters N_E. This echoes Jia (2008) in the sense that it favors one type of firm, although our frameworks differ.

This equilibrium selection is consistent with the industry context, where large export-authorized firms are leaders in the market and possess strong political connections. The nuance in (23) is that, while higher-ranked players are favored, an equilibrium with several lower-ranked players is possible when these have lower entry costs. All that (23) requires is that, for any pair of possible equilibria, the top ranked player that is not in both equilibria be a firm that is in the selected equilibrium.

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

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

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

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

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

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

Step 3 is key for identifying situations in which less productive players may be in the equilibrium if they have lower entry costs. The algorithm allows for the possibility that a low-productivity player can enter and "push out" a higher-ranked player, but this only happens if the lower-ranked player can be profitable in the presence of the higher-ranked player, but the converse is not true: entry of the lower-ranked player renders the higher-ranked player unprofitable. Below, I prove that the algorithm recovers the (unique) equilibrium described by Equation (23) for my application. A more general proof is an interesting avenue for future work.

My setting is characterized by two conditions:

1. Entry costs can take two values within a municipality: f_E for export-authorized meatpackers $i \in E$, and f_D for domestic-informal meatpackers ($i \in D$).

2. Meatpacker productivity is drawn i.i.d. from two possible distributions within a municipality (but can vary across municipalities): $G_m^E(z)$ for export-authorized players and $G_m^D(z)$ for domestic-informal players.

- Since productivity draws are realized post-entry, firms are ex-ante homogeneous *within* a type. For any entrant set I we can write $I = \{N^E, N^D\}$, and expected profits as $E[\pi^F(N^E, N^D)]$ for $F \in \{E, D\}$.
- Within each type, the rank order t is therefore just a tie-breaking priority rule; the algorithm always selects the lowest-t firm among profitable candidates.
- Cournot-stage comparative statics imply that cattle procurement prices are weakly increasing in (N^E, N^D), and therefore $E[\pi^F(N^E, N^D)]$ is weakly decreasing in both N^E and N^D for each F.

Proof. I proceed by contradiction. Let I^* denote the entrant set returned by the algorithm. Suppose there exists an equilibrium $\tilde{I} \neq I^*$ such that

$$\min\{t \in \tilde{I} \setminus I^*\} \leq \min\{t \in I^* \setminus \tilde{I}\}.$$

Because the within-type order is only a tie-breaker and the across-type order puts all E-types ahead of all D-types, the inequality above implies that $\tilde{I}$ must have either (i) strictly more exporters than I^*, or (ii) the same number of exporters but strictly more domestic-informal entrants. Formally, letting (N_E^*, N_D^*) and $(\tilde{N}_E, \tilde{N}_D)$ denote the corresponding type counts,

$$\text{either } \tilde{N}_E > N_E^* \quad \text{or} \quad \tilde{N}_E = N_E^* \text{ and } \tilde{N}_D > N_D^*.$$

Case 1: $\tilde{N}_E > N_E^*$**.** Since $\tilde{I}$ is an equilibrium, exporters must be profitable given $(\tilde{N}_E, \tilde{N}_D)$:

$$E[\pi^E(\tilde{N}_E, \tilde{N}_D)] \geq 0.$$

By monotonicity of expected profits in N_D, this implies

$$E[\pi^E(\tilde{N}_E, 0)] \geq E[\pi^E(\tilde{N}_E, \tilde{N}_D)] \geq 0.$$

Therefore, starting from $(1, 0)$ and adding the highest-ranked profitable outside firm each iteration, the algorithm must eventually reach a state with at least $\tilde{N}_E$ exporters before any domestic-informal firm can be selected (since exporters are ranked ahead of domestics and

are profitable at $(\tilde{N}_E, 0)$).

Yet the algorithm converges to $N_E^* < \tilde{N}_E$, so along its path at least one exporter beyond rank N_E^* is ultimately *removed* at some iteration. Consider the first iteration at which, holding $N_E = \tilde{N}_E$, the algorithm adds a domestic-informal entrant and then removes an exporter due to unprofitability. This implies the existence of an integer threshold $N_D^{CRIT}(\tilde{N}_E) \geq 1$ such that

$$\begin{aligned} E[\pi^E(\tilde{N}_E, N_D^{CRIT}(\tilde{N}_E) - 1)] &\geq 0, \\ E[\pi^E(\tilde{N}_E, N_D^{CRIT}(\tilde{N}_E))] &< 0, \\ E[\pi^D(\tilde{N}_E, N_D^{CRIT}(\tilde{N}_E))] &\geq 0. \end{aligned}$$

These inequalities are exactly the add-then-remove step: a domestic firm is profitable at $(\tilde{N}_E, N_D^{CRIT})$, but its entry makes at least one exporter unprofitable, triggering removal of the lowest-priority exporter.

Now check whether $(\tilde{N}_E, \tilde{N}_D)$ can be an equilibrium.

If $\tilde{N}_D \geq N_D^{CRIT}(\tilde{N}_E)$, then by monotonicity of exporter profits in N_D,

$$E[\pi^E(\tilde{N}_E, \tilde{N}_D)] \leq E[\pi^E(\tilde{N}_E, N_D^{CRIT}(\tilde{N}_E))] < 0,$$

contradicting that all exporters in an equilibrium must be profitable.

If instead $\tilde{N}_D < N_D^{CRIT}(\tilde{N}_E)$, then by monotonicity of domestic-informal profits in N_D,

$$E[\pi^D(\tilde{N}_E, \tilde{N}_D + 1)] \geq E[\pi^D(\tilde{N}_E, N_D^{CRIT}(\tilde{N}_E))] \geq 0,$$

so an additional domestic-informal entrant would be profitable at $(\tilde{N}_E, \tilde{N}_D)$, contradicting that $\tilde{I}$ is an equilibrium.

Thus no equilibrium can satisfy $\tilde{N}_E > N_E^*$.

Case 2: $\tilde{N}_E = N_E^*$ and $\tilde{N}_D > N_D^*$. At convergence, the algorithm has no profitable outside entrants. In particular, it must be that the next domestic-informal entrant is not profitable:

$$E[\pi^D(N_E^*, N_D^* + 1)] < 0.$$

By monotonicity of domestic-informal profits in N_D,

$$E[\pi^D(N_E^*, \tilde{N}_D)] \leq E[\pi^D(N_E^*, N_D^* + 1)] < 0,$$

so a market with $(N_E^*, \tilde{N}_D)$ cannot be an equilibrium because the marginal domestic-informal entrant would be unprofitable. This contradicts that $\tilde{I}$ is an equilibrium.

Since both cases yield contradictions, no equilibrium $\tilde{I}$ can violate the complement-minimum condition in (23). Therefore the algorithm recovers the unique equilibrium selected by the sequential rule. □

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

Other approaches: My approach has both advantages and limitations. On the benefits side, it allows me to incorporate a large number of heterogeneous firms across many regions while remaining tractable, even when accounting for demand spillovers and land use responses. However, the sequential entry assumption is fundamentally untestable. Nevertheless, this assumption aligns with the industry context, where large, more productive meatpackers exert significant influence and maintain strong political connections. Furthermore, a different ordering would not affect the policy conclusions from my policy simulations (see Online Appendix B.6).

Other work in the literature takes different approaches. One class of models accounts for multiple equilibria, generally employing partial identification in estimation (e.g. Ciliberto and Tamer (2009)). Another set of solutions relies on private information shocks, where firms form expectations over other firms' profitability shocks, leading to a unique equilibrium (e.g., Seim (2006)). I do not adopt these approaches for two reasons. First, methods robust to multiple equilibria are computationally prohibitive in my setting. They require verifying

equilibrium conditions across 2^M potential entry scenarios, where M represents the number of potential entrants. Given that M can be higher than 40 in my application, the number of equilibria to compute would be infeasibly large. This challenge is compounded by the need to solve for equilibrium in all three compenents of the model.[49] Second, models with incomplete information are highly sensitive to assumptions on the number of potential entrants, and perfectly private information models have been found to not fit the data well (Grieco, 2014; Magnolfi and Roncoroni, 2023).

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

B.4 Estimation - Sensitivity checks:

In this section, I check the sensitivity of estimated entry cost parameters to estimation moments (Table S5). This exercise clarifies which moments are most informative for each parameter. Panel $M1$ corresponds to the Λ matrix of Andrews, Gentzkow, and Shapiro (2017) and reports local sensitivity of parameter estimates to small moment misspecification. Consistent with intuition, α_E^f is primarily pinned down by the exporter-count moment N_E. The geographic pattern of non-exporter entry pins α_D^f and $\alpha_{D,\text{PA/MA}}^f$ in opposite directions, as the opposite signs on N_D and $N_D \times \ln(\text{dist})$ show, indicating a level-composition tradeoff in non-exporter entry across space. The values under $N_E \times \ln(\text{dist})$ are generally lower because to a great degree the spatial pattern of exporter entry is determined by transportation costs; as one moves to more remote areas, meatpacker variable earnings decrease. Entry costs for exporters are set nationally through a federal inspection system. On the other hand, for domestic-informal firms there is substantial state-level variation in inspection stringency, so there is some state-level variation in entry costs beyond what is driven by the distribution

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

of (ex-ante) productivity.

The other panels in Table S5 follow Honore et al. (2020). $\mathcal{E}_2$ measures the local loss of precision if a moment becomes noisier, while $\mathcal{E}_4$ measures the relative increase in asymptotic variance when a moment is excluded.[50] Since there are four moments for three parameters, dropping one moment leaves the system just-identified.[51] Both $\mathcal{E}_2$ and $\mathcal{E}_4$ confirm that N_D and $N_D \times \ln(\text{dist})$ are the key moments for identifying α_D^f and $\alpha_{D,\text{PA/MA}}^f$.

Table S5: Sensitivity Measures, Entry Model

	Moment			
	N_E	N_D	$N_E \times \ln(\text{dist})$	$N_D \times \ln(\text{dist})$
M1				
α_E^f	1.028	0.448	-0.138	-0.338
α_D^f	-0.037	5.632	0.737	-5.234
$\alpha_{D,\text{PA/MA}}^f$	0.644	-5.791	-0.832	6.158
$\mathcal{E}_2$				
α_E^f	1.349	0.334	0.030	0.179
α_D^f	4.76e-04	14.320	0.233	11.669
$\alpha_{D,\text{PA/MA}}^f$	0.157	16.459	0.323	17.561
$\mathcal{E}_4$				
α_E^f	0.181	0.271	0.003	0.143
α_D^f	6.40e-05	11.611	0.026	9.324
$\alpha_{D,\text{PA/MA}}^f$	0.021	13.345	0.037	14.031

Notes: Rows correspond to α_E^f, α_D^f, and $\alpha_{D,\text{PA/MA}}^f$. $M1$ is AGS sensitivity (Λ). $\mathcal{E}_2$ is the elasticity of estimator variance with respect to moment variance. $\mathcal{E}_4$ is the relative increase in estimator variance when a moment is excluded.

B.5 Model Fit - Non-targeted moments:

The main text shows that the model closely matches the targeted entry moments. Here I report additional moments that are not explicitly targeted in estimation (Figure S4). I view these as a joint test of the model's entry structure and its within-market heterogeneity. Exporter shares and the Herfindahl index depend on how quantities are allocated across entrants, which in the model is governed by the Cournot oligopsony mapping from productivity draws into equilibrium quantities, together with the dispersion of productivity within each firm type and the local supply elasticity.

Figure S4 shows that both exporter market shares and HHI decline with remoteness in

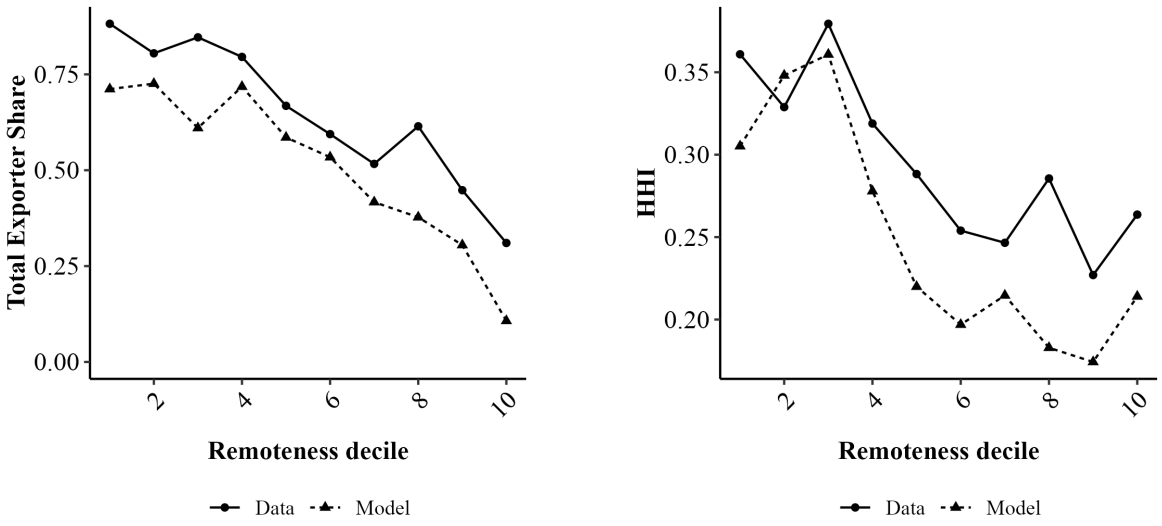
[50] I also computed $\mathcal{E}_3$ and $\mathcal{E}_5$, which coincide with $\mathcal{E}_2$ and $\mathcal{E}_4$, respectively, in this application.

[51] In this application, $G'\tilde{W}_k G$ remained full rank for all k.

the data, and that the model reproduces these patterns well. The exporter-share gradient reflects lower expected exporter profitability in remote markets, which reduces exporter participation and, conditional on entry, their equilibrium sourcing shares. The HHI gradient highlights that concentration is shaped not only by the number of entrants, but also by the *dispersion* of productivity draws across entrants, which determines whether sourcing is spread evenly or concentrated among a few high-productivity firms. The model's ability to match these untargeted features of market structure supports the assumed interaction between endogenous entry and within-market productivity heterogeneity.

Figure S4: Model Fit - Nontargeted Moments - Exporter share and HHI

(a) Exporter share (b) HHI

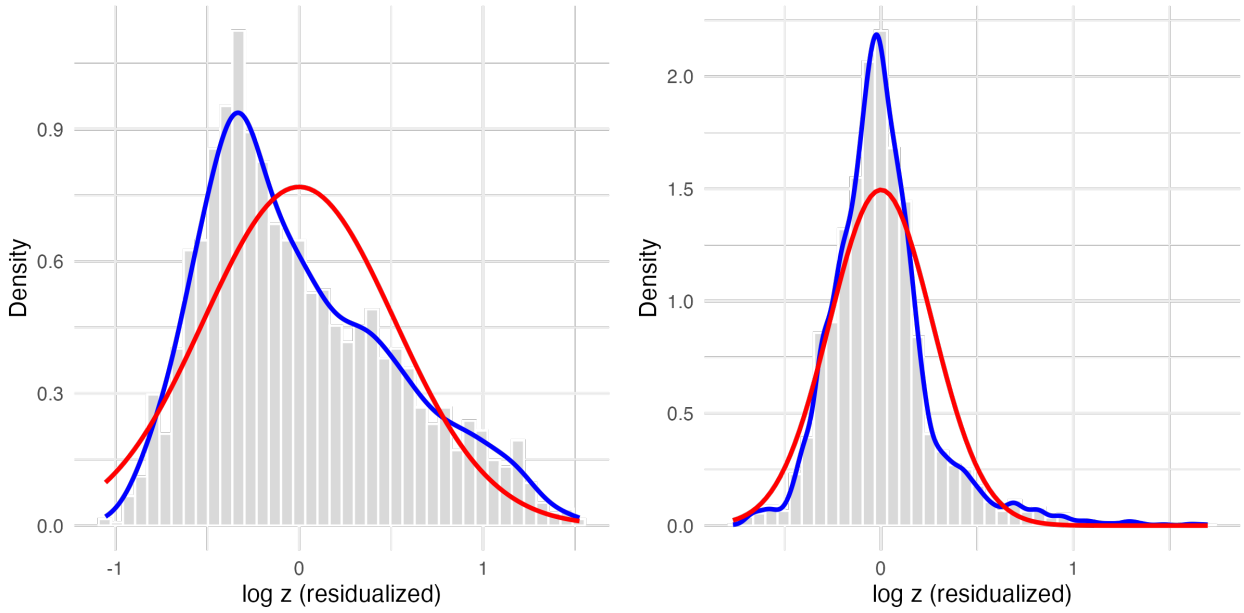


Note: Values are averaged by decile of distance to São Paulo.

A complementary diagnostic comes from the implied distribution of firm-level productivities. Using the Cournot first-order condition and estimated supply elasticities, I invert revenue productivity for each observed firm–municipality pair. Figure S5 compares the empirical distribution of inverted log revenue productivity (after netting out observables) to the distribution implied by the estimated lognormal productivity model. The close alignment again indicates that the assumption of Cournot competition with lognormal productivities provides a good approximation of the actual market structure and productivity distribution.

Figure S5: Model Fit - inverted productivities (blue) and estimated lognormal (red)

(a) Export-authorized (b) Domestic-informal



B.6 Counterfactual exercises - Robustness checks

Here, I run two exercises that show the robustness of my counterfactual exercises. First, and more simple, I just run the tax counterfactuals under a different tax rate (Table S6) – 10% instead of 20% in the main text. Although the magnitudes of effects naturally vary, it is reassuring to see that the abatement cost values are similar and consistent with the policy conclusions and discussion in the main text.

I then show robustness to different assumptions on entry orderings. As I discuss in the main text, I rely on an assumption of sequential entry to guarantee uniqueness given that firms vary both in productivity and entry costs. My main analysis has entry favoring exporters. I re-run estimation and counterfactuals with an entry game where domestic-informal meatpackers get to move first. Table S6 panel B shows results for all policy counterfactuals. Again, results are similar and lead to the same qualitative conclusions.

Table S6: Policy counterfactuals - Robustness

Panel A: 10% ad valorem

Policy	Emissions	Beef	Average Abatement Cost ($/ton) Total	No revenue	CS	Profits	Landholders
Exporter tax	-2.92%	-6.37%	31.21	42.98	11.25	17.62	14.10
Exporter tax†	-2.68%	-1.06%	25.95	34.42	2.08	18.95	13.39
Tax on all	-6.43%	-5.13%	14.15	20.96	4.09	5.71	11.15

Panel B: Inverted entry order

Policy	Emissions	Beef	Average Abatement Cost ($/ton) Total	No revenue	CS	Profits	Landholders
Exporter tax	-4.10%	-22.01%	51.66	61.31	28.35	14.33	18.63
Exporter tax†	-8.07%	-3.92%	24.63	32.33	1.73	15.76	14.83
Market Exclusion	-20.98%	-47.31%	16.01	16.01	13.78	-12.27	14.49
Tax on all	-13.19%	-12.09%	14.13	20.07	4.61	3.99	11.48
Higher entry cost	-9.40%	+9.11%	-5.30	-0.25	-4.45	-2.06	6.26

Note: "Exporter tax†" refers to the counterfactual using a model without entry or firm heterogeneity. Column "No revenue" specifies average abatement cost without considering tax revenue. The subsequent columns consider impacts on consumer welfare, meatpacker profits, and landholder welfare, respectively. Ad-valorem cattle tax is set to 20%. "Higher entry cost" refers to the counterfactual where entry costs for domestic-informal firms are set to those of exporters.

Online Appendix C Model Extensions

C.1 Land use dynamics:

Land use change has dynamic features. Actions such as deforestation carry sunk costs[52] and involve irreversibilities - forest takes decades to regrow once lost. In the paper, I adopt a long-difference model of land use change, where agents evaluate returns over a span of 5 years (4 transitions). As I discussed in the main text, this choice is primarily driven by data limitations on prices for cattle and crops.

In this appendix, I introduce a dynamic extension of the land use model and demonstrate that it produces similar elasticities for the timeframes I study. The approach follows the structure of Araujo et al. (2025) and Scott (2012), relying on rational expectations over the path of future returns to derive a discrete analog of an Euler equation for estimation. The primary limitation of this extension is that it relies on a single cross-section of prices for

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

estimation, reflecting the data limitations in my setting and preventing the inclusion of fixed effects used in standard applications. Despite this constraint, the exercise provides a useful robustness check, illustrating that my main findings are not highly sensitive to the specific modeling assumptions regarding the decision horizon.

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:

$$\pi(j, j_{t-1}, \omega_t, \nu_{it}) = \alpha_0(j, j_{t-1}) + \alpha_R R_j(\omega_t) + \xi_{jj_{t-1}}(\omega_t) + \nu_{jit} \tag{24}$$

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:

$$V\left(k_{it}, \omega_t, \nu_{it}\right) \equiv \max_{j^*} E\left(\sum_{s \geq t}^{\infty} \beta^{s-t} \pi\left(j^*\left(j_{is-1}, \omega_s, \nu_{is}\right), j_{is-1}, \omega_s, \nu_{is}\right) \mid k_{it}, \omega_t, \nu_{it}\right) \tag{25}$$

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:

$$\bar{V}_t(j_{t-1}) \equiv \int \dots \int V_t\left(j_{t-1}, (\nu_1, \dots, \nu_J)\right) dF\left(\nu_1\right) \dots dF\left(\nu_J\right) \tag{26}$$

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:

$$v_t(j, j_{t-1}) \equiv \bar{\pi}_t(j, j_{t-1}) + \beta E_t\left[\bar{V}_{t+1}\left(j\right)\right] \tag{27}$$

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:

$$p_t(j, j_{t-1}) = \frac{\exp\left(v_t(j, j_{t-1})\right)}{\sum_{j' \in J} \exp\left(v_t\left(j', j_{t-1}\right)\right)} \tag{28}$$

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

$$\bar{V}_t(j_{t-1}) \equiv \ln\left(\sum_{j \in J} \exp\left(v_t(j, j_{t-1})\right)\right) + \gamma \tag{29}$$

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:

$$\ln\left(\frac{p_t(j,j_{t-1})}{p_t(j',j_{t-1})}\right) = v_t(j,j_{t-1}) - v_t(j',j_{t-1}). \tag{30}$$

Using the definition from (27), this becomes:

$$\bar{\pi}_t(j,j_{t-1}) - \bar{\pi}_t\left(j',j_{t-1}\right) - \ln\left(\frac{p_t(j,j_{t-1})}{p_t\left(j',j_{t-1}\right)}\right) = \beta E_t\left[\bar{V}_{t+1}\left(j'\right)\right] - \beta E_t\left[\bar{V}_{t+1}\left(j\right)\right] \tag{31}$$

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:

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

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:

$$\forall j : \bar{V}(j_{t-1}) = v_t(j,j_{t-1}) - \ln\left(p_t(j,j_{t-1})\right) + \gamma \tag{33}$$

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:

$$\begin{aligned}\bar{\pi}_t(j, j_{t-1}) - \bar{\pi}_t(j', j_{t-1}) - \ln\left(\frac{p_t(j, j_{t-1})}{p_t(j', j_{t-1})}\right) =& \beta\left(v_{t+1}(j, j') - v_{t+1}(j, j)\right) \\ &- \beta\left(\ln\left(\frac{p_{t+1}(j, j')}{p_{t+1}(j, j)}\right)\right) \\ &+ \varepsilon_t^V(j', j_{t-1}) - \varepsilon_t^V(j, j_{t-1}).\end{aligned} \tag{34}$$

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

$$v_{t+1}(j, j') - v_{t+1}(j, j) = \bar{\pi}_{t+1}(j, j') - \bar{\pi}_{t+1}(j, j) \tag{35}$$

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:

$$\begin{aligned}\bar{\pi}_t(j, j_{t-1}) - \bar{\pi}_t(j', j_{t-1}) - \ln\left(\frac{p_t(j, j_{t-1})}{p_t(j', j_{t-1})}\right) =& \beta\left(\bar{\pi}_{t+1}(j, j') - \bar{\pi}_{t+1}(j, j)\right) \\ &- \beta \ln\left(\frac{p_{t+1}(j, j')}{p_{t+1}(j, j))}\right) \\ &+ \varepsilon_t^V(j', j_{t-1}) - \varepsilon_t^V(j, j_{t-1})\end{aligned} \tag{36}$$

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 (33), I can express that in terms of period $t+1$ profits and choice probabilities. Thus the right hand side of (36) 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:

$$Y_{tj_{t-1}} = \tilde{\Delta}\alpha_{0j_{t-1}} + \alpha_R \Delta R_t + \tilde{\Delta}\xi_{tj_{t-1}} + \Delta\varepsilon^V_{tj_{t-1}} \tag{37}$$

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:

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

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

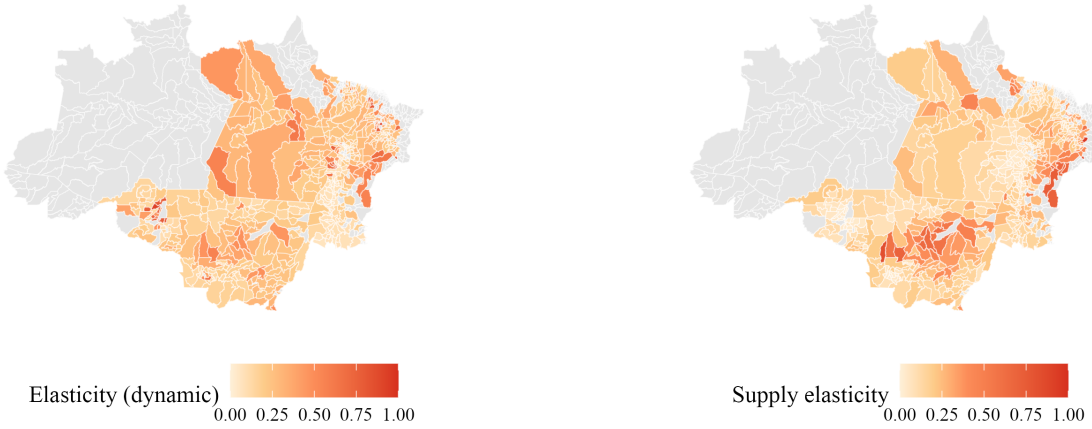
transitions in the scenario with the perturbation versus business-as-usual.

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 S6). Remote regions end up slightly more elastic (Figure S7), 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

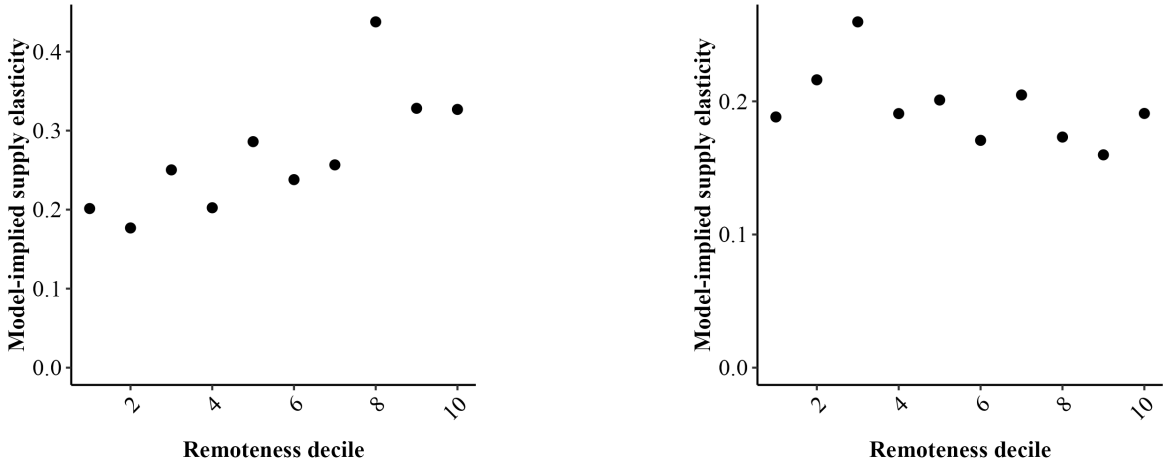
	OLS	IV
Public Designated	0.13^{***}	0.72^{***}
	(0.03)	(0.10)
Public Undesignated	0.24^{***}	0.57^{***}
	(0.03)	(0.10)
Private Undisputed	0.26^{***}	0.56^{***}
	(0.24)	(0.08)
Private Disputed	0.21^{***}	0.89^{***}
	(0.03)	(0.09)

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 S6: Cattle supply elasticities - dynamics vs. main model



(a) Dynamic (b) Main model

Figure S7: Supply elasticities by remoteness - dynamics vs. main model