Cattle Supply Chains and Deforestation in Brazil

Abstract

Tropical forests are crucial to the global environment, serving as biodiversity hubs and storing carbon, yet they face severe threats from agricultural expansion. Recognizing their role in deforestation, countries like the UK and EU have implemented trade policies to curb deforestation by requiring proof that the production of a set of agricultural commodities is deforestation-free. A key question is whether these policies will encourage farmers to adopt sustainable practices or instead push them toward less regulated buyers.

In this paper, we adopt a structural approach to evaluate the effectiveness and potential leakages of sustainable supply-chain policies in the context of Brazil's cattle sector. First, we leverage a unique dataset on animal transport, matched with property boundaries, to document key empirical patterns of deforestation and the supply network of cattle at the farm level in the state of Pará, Brazil. Second, we build a structural model of farm-level land use decisions with an endogenous supply-chain network. Third, guided by model-derived gravity equations, we estimate the role of existing domestic supply-chain zero-deforestation commitments (ZDC) in shaping the trade of cattle. Our results indicate that a 10% increase in deforestation by a farm is associated with a 14% decrease in its probability of being chosen as the supplier by a ZDC slaughterhouse. Finally, we use the model to conduct a counterfactual exercise that removes zero-deforestation penalties while holding land use fixed, in order to isolate the role of supply-chain restrictions in shaping market access and equilibrium outcomes.

1 Introduction

Tropical deforestation is advancing at a high rate, threatening our capacity to reduce greenhouse gas emissions and to preserve ecosystems. Agriculture is a major driver of this deforestation, representing up to 90% of deforestation (Pendrill et al., 2022). Acknowledging the limitations of public forest conservation policies at curbing deforestation, there has been a recent surge in strategies to reduce deforestation through supply chain policies. Supply chain policies place responsibility on large sourcing firms to purchase deforestation-free commodities, potentially excluding suppliers who fail to meet environmental standards, such as avoiding deforestation. Some of these have taken the form of private voluntary standards (e.g. the G4 in Brazil or RSPO in Indonesia) or government-led certification schemes. Such supply chain policies will soon become mandatory for exporters to the European Union (EU) with the new deforestation regulation (EUDR) coming into effect at the end of 2025. The EUDR will prohibit the importation of commodities like coffee, cattle, cocoa, palm oil, and soy unless companies can prove their production is not associated with deforestation. In this paper, we analyze the potential effectiveness of supply-chain policies in the cattle sector in the state of Pará in Brazil.

Despite their increasing popularity, the efficacy of supply chain policies has remained an open question in the literature. Several studies point out the many possibilities of evading such policies, be it by shifting production to non-targeted regions, by shifting sales towards buyers without restrictions, or by shifting deforestation upstream in the supply chain (Alix-Garcia and Gibbs, 2017; Levy et al., 2023; Gollnow et al., 2022). Cattle *laundering*, whereby illegally raised cattle enter deforestation-free supply chains, has been a pervasive concern due to the difficulty for companies to monitor producers beyond their first direct suppliers. This situation is likely to change rapidly with the EUDR, which mandates companies to monitor their entire supply chain. Whether this is going to effectively incentivize suppliers to reduce their deforestation or instead shift their production toward less restrictive importers remains a challenging yet important question to address. Most current land use models are not well-suited to understand these phenomena, as they tend to abstract away from the supply-chain organization of agriculture. Two recent papers are the exception, Domiguez-Iino (2024) and Barrozo (2024). They highlight the importance of slaughterhouse market power in mediating the impact of existing anti-deforestation policies. We contribute to this growing literature by looking at the multi-tiered nature of the cattle market. We consider farm-to-farm as well as farm-to-slaughterhouse transactions and model how farms endogenously decide whether to be direct or indirect suppliers.

We leverage a granular transaction-level dataset for the cattle sector in Pará, Brazil, combining animal transport records that link farm-to-farm and farm-to-slaughterhouse transactions (2016–2020) with georeferenced property boundaries and remotely sensed land use, which we use to track each farm's land use history over the period 2004–2020. Three stylized facts emerge from these data. First, upstream trade is quantitatively important: a large share of cattle transactions occur between farms rather than directly with slaughterhouses, implying that farms' exposure to zero-deforestation commitments (ZDCs) is mediated by endogenous supply-chain relationships. Second, churn rates are high. Overall buyer-seller relationships seem to exhibit a low level of fidelity. This is especially true for upstream (between farms) sales, as shown in Skidmore et al. (2024). Third, buyer composition is systematically related to land-use history: farms that have deforested more since 2009 sell a lower share of their output to ZDC slaughterhouses, even within narrowly defined locations and years, while no comparable pattern is observed for sales to non-ZDC buyers or other farms. These patterns indicate that market access responds endogenously to deforestation and that ZDCs operate through differential screening of suppliers rather than through farm-level treatment.

Motivated by these stylized facts, we develop a spatial quantitative model of cattle trade in which ZDCs enter as buyer-type–specific trade costs that increase in a supplier's cumulative deforestation since 2009. The model delivers closed-form expressions for sourcing probabilities that can be directly matched to observed trade shares, allowing us to estimate bilateral trade frictions and deforestation-related trade penalties. Empirically, we estimate a gravity elasticity of trade with respect to distance of approximately -2.2, implying that a 10% increase in distance reduces expected trade volumes by about 19%. We further estimate that a 10 percentage point increase in the share of a farm's 2009 forest that has been deforested lowers its probability of supplying a ZDC slaughterhouse relative by roughly 5% compared to its probability of selling to non-ZDC buyers. Using the model's equilibrium conditions, we then recover spatial variation in baseline pasture rental rates. These rental rates should be interpreted as an equilibrium summary of farms' market access through the supply chain, and a measure of how appealing it is for a landowner to deforest an extra hectare. Then, we are able to characterize how eliminating the ZDC penalty would reallocate sourcing patterns and rents when land use is held fixed.

Endogenous deforestation responses and welfare impacts are the subject of ongoing work. In particular, the next step is to combine the estimated market-access channel with a land-use component to quantify how counterfactual changes in ZDC coverage and enforcement affect deforestation and its leakage through endogenous re-routing in the cattle network. This would require estimating a farm-level deforestation cost function.

We contribute to three broad branches of literature. First, we contribute to a large literature analyzing the impacts and scope of zero-deforestation commitments in supply chains such as cattle in Brazil (Alix-Garcia and Gibbs, 2017; Levy et al., 2023; Skidmore et al., 2021; Gibbs et al., 2016; Villoria et al., 2022), soy in Brazil (Gollnow et al., 2022; Heilmayr et al., 2020b), timber in Chile (Heilmayr and Lambin, 2016), and palm oil in Indonesia (Carlson et al., 2018; Heilmayr et al., 2020a; Lee et al., 2020). While this literature has provided valuable insights into the effectiveness of supply chain commitments, a key limitation is its reliance on reduced-form estimates that assume the supply chain is fixed and exogenous. Our main contribution is the development of a structural framework that jointly models land use and supply chain decisions, enabling counterfactual analyses of supply chain policies while accounting for strategic reallocation within the supply chain. Second, we contribute to a growing literature employing structural models to analyze deforestation (Hsiao, 2024; Domiguez-Iino, 2024; Farrokhi et al., 2024). These models have made substantial contributions to the understanding of deforestation as a dynamic process, and to the importance of the equilibrium consequences of policies via leakage and changes in comparative advantage in agriculture. Our main departure from these models is to consider farms, instead of pixels, as the unit of analysis. In our framework, decisions about how much to deforest, how to produce, and whom to sell to, are made at the level of the property, rather than at the level of the pixel. This enables us to better explain the observed heterogeneity in land use and sales. Third, we contribute to a growing literature on the role of production networks (Antras and Chor, 2022; Bernard and Moxnes, 2018; Caliendo and Parro, 2014; Eaton et al., 2022). The closest papers to our setting are Bernard et al. (2019), Arkolakis et al. (2023), and Panigrahi (2022) which consider spatial frictions in the context of firm-to-firm trade and allow for firm heterogeneity in productivity. The majority of models in this literature assume that trade flows can be represented by a dense trade matrix —-an assumption that contradicts the cattle flows observed in our dataset, where a typical farm sells cattle to only a handful of other farms. To address this, we follow closely the setup in Panigrahi (2022) as it deals with the sparsity of the production network as discussed in Bernard and Zi (2022), and delivers predictions for the probability of trade with firm-level granularity.

2 Data and Context

Our granular dataset of farm-level deforestation and supply chain decisions comes from three distinct sources, 1) the animal transport dataset (GTA) for the state of Para, 2) the property boundary dataset (CAR) and 3) deforestation maps from MapBiomas. The GTA was matched to the CAR dataset using fuzzy matching, as in Levy (2022). This results in a dataset of 20 years of land use and deforestation decisions (2001-2020), five years of animal transactions (2016-2020) and property size information. Analysis of this dataset reveals key facts on the nature of the cattle supply network.

Table 1: Descriptive statistics of the sample

Variable	Value
Number of farms	51,915
Area property (km2), median	0.93
Share of pasture (%), median	75.11
Share of farms with cropland >5% (%)	1.06
Number of buyers, mean	2.98
Number of sellers, mean	2.55
Number of cows sold, mean	207.19
Share sold to slaughterhouse (%)	20.38

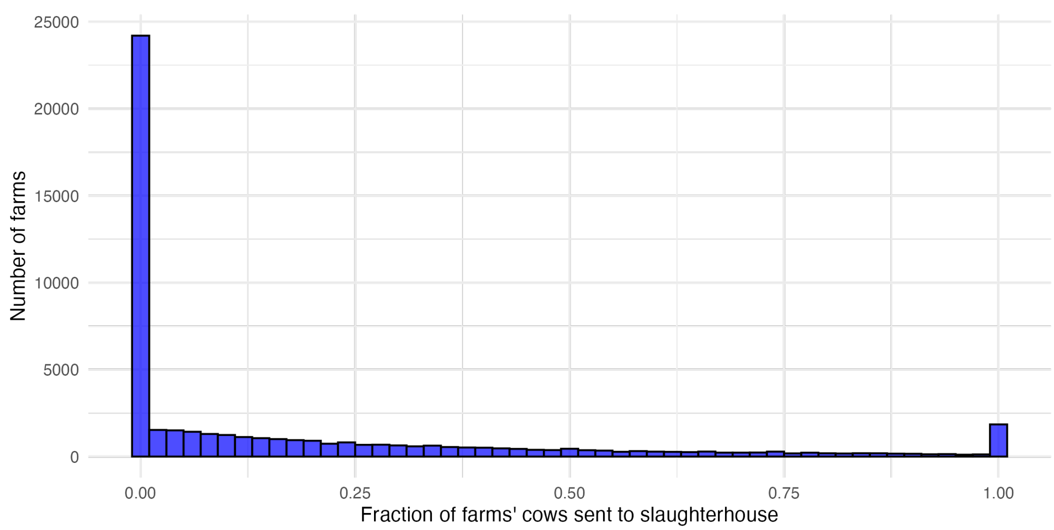
Table 1 shows descriptive statistics about our final sample. The sample comprises 51,915 farms across the state of Para, with a median size of 0.9 km^2. At the beginning of the sample, these farms have a large share of pasture, with a median value of 75%, and very few farms have any crops. Farms trade on average with only a few buyers (2.98) and sellers (2.55) annually and 20% of the cattle sales are sent for slaughter.

3 Stylized Facts

Fact 1: Farm-to-farm trade is very important and few farms are fully direct. In 2017, 77% of all recorded transactions were farm-to-farm, and they accounted for 63% of cows sold. Even farms that sell some cows to slaughterhouses often choose to sell a large fraction of their cows to other farms. Figure 1 is a histogram of the share of a farm's cattle sent to a slaughterhouse, aggregated over the five years of data. It shows that a considerable fraction of the farms, 41.7%, sell all of their cows to other farms, and thus are fully ‘‘indirect’’. It also shows that out of the farms that sell to slaughterhouses, very few are fully ‘‘direct’’ suppliers, i.e. sell exclusively to slaughterhouses, only 3.7%. Instead, most farms do a mix of both farm-to-farm and farm-to-slaughterhouse sales, and sending a large fraction of one's cow sales for slaughter is rare.

This distribution of share sold for slaughter has two important implications for our analysis. First, it seems like from the perspective of the farm as a seller of cattle, other farms can be a substitute, albeit imperfect, for slaughterhouses. In particular, deforesting farms that sell for slaughter and want to avoid ZDC regulations may be redirecting their sales to farms and not just to non-ZDC slaughterhouses. It seems unlikely that ZDCs can achieve full supply chain exclusion of any farm. Second, there are many (42%) farms that are purely indirect within our sample period. We interpret this as evidence of the fact that some farms specialize in breeding calves and selling to farms that will rear and fatten for slaughter. This will play a role when deciding whether to let a farm's production costs be the same for cows for slaughter and for cows for rearing. In our preferred specification, we allow for these two costs to be different, but the same between ZDC and non-ZDC slaughterhouses, and potentially infinite for the farms that do not sell any cows for slaughter.

Figure 1: Distribution of the share of cows sent to a slaughterhouse across farms



Fact 2: Churn rates are high. There does not seem to be a high level of persistence among trade partners, a finding consistent with the existing literature (Reis et al., 2020, 2023; Skidmore et al., 2024). Out of 146,888 active buyer-supplier pairs in 2015, 83% are not active in 2016, and 75% are not active ever again in our sample. This is similar when we look at other years. The numbers are not much lower if we restrict attention only to those links in which the supplier appears in all five years of our data --79% of links disappear in the following year and 68% disappear for the following four years. This indicates that sellers

break buyer-seller links and form new ones easily. In 2019, our last year of transactions data, 70% of the buyer-seller pairs were new, that is, they had not happened since 2015. The number goes down to 64% when restricting attention to suppliers that appear in our data every year since 2015.

Fact 3: Probability of becoming a direct supplier of ZDC slaughterhouses differs by deforestation behavior. To illustrate how deforestation relates to buyer composition, we examine how farms' sales shares across buyer types vary with cumulative deforestation. We regress the share of cattle sold by a farm to each buyer type on binned measures of the fraction of its 2009 forest area that has been deforested, controlling for origin-by-year fixed effects at the 20 km $\times$ 20 km level and farm characteristics. The results, shown in Figure 2, indicate that farms with higher cumulative deforestation shares sell a smaller share of their output directly to slaughterhouses, with the decline being much starker when looking at slaughterhouses subject to zero-deforestation commitments.

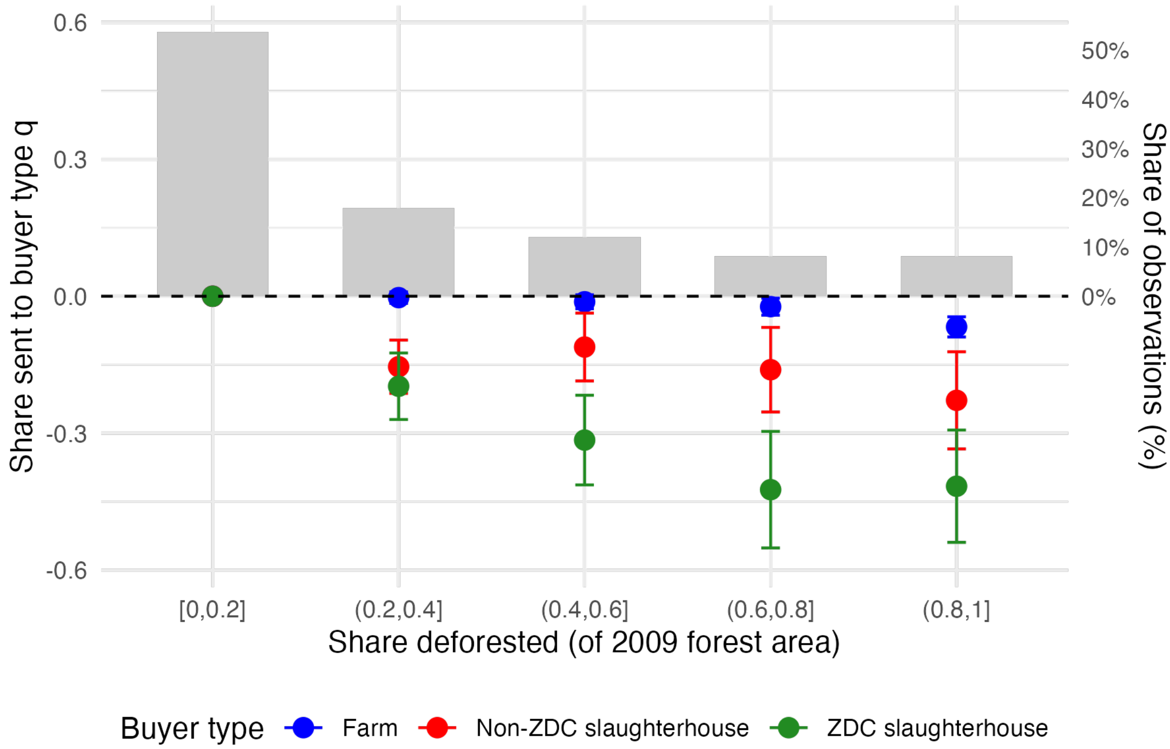
4 Model

We develop a spatial structural model of the cattle market with endogenous deforestation and supply network formation. The model incorporates three main elements. First, it incorporates a round-about production structure in the spirit of (Caliendo and Parro, 2014), where cattle is both an input and an output in all farms' production function. Each farm buys cattle which then it combines with pasture in order to produce more cattle weight via fattening and reproduction to eventually sell as cattle ready for slaughter to the slaughterhouse. Second, farm-level deforestation histories affect buyers' choice of suppliers. In particular, ZDC slaughterhouses have higher trade costs from farms with higher levels of deforestation, all else equal. Accounting for equilibrium re-sorting, all farms will be affected by a farm's deforestation choices. Third, landowners' returns to deforestation are driven by the returns to pasture land, an equilibrium outcome which increases with farms' market access to buyers. This is affected by their location but also by their individual deforestation histories. This makes it such that, although we can coarsen the spatial dimension of the problem, the farm-level granularity does not fully go away.

Our stylized facts suggest that both phenomena are likely to be at play. On one hand, we know that farms that currently sell to ZDC slaughterhouses have reduced their levels of deforestation since the onset of the policy in 2009. On the other hand, we see that farms change who they sell to after deforesting, and in particular they sell less to ZDC slaughterhouses. Since there is no pre-ZDC regulation supply-network data, a model is needed to provide evidence on the relative strength of supply-network reshuffling versus actual deforestation reductions. Equipped with this model, we will be able to simulate different counterfactual scenarios. For example, one in which there are no zero-deforestation commitments, or one in which more slaughterhouses become ZDC. We could also use the model to get a sense of what would make for an efficient spatial targeting of such a regulation.

The model features three types of agents: landowners, cattle farmers, and slaughterhouses.

Figure 2: Share of cows sent to different buyer types vs. share of 2009 forests deforested



Notes: This figure reports estimates from regressions of the share of cattle sold by farm s in year t from origin cell o to buyer type q on binned measures of cumulative deforestation since 2009. The dependent variable is Cows Sold to Buyer Type q_{sot}/Total Cows Sold$_{sot}$, where buyer types are $q \in \{$farms, non-ZDC slaughterhouses, ZDC slaughterhouses$\}$. The key regressors are indicators for bins of the share of the farm's 2009 forest area that has been deforested up to year $t \in \{2016, 2017, 2018, 2019\}$. All specifications include origin-by-year fixed effects at the 20 km × 20 km level and control for (log) total farm area, (log) area in pasture, and (log) area in forest. Coefficients are reported with 95% confidence intervals.

Each landowner owns a farm, chooses how much to deforest within it, and rents it out to cattle farmers.[1] When choosing how much to deforest, the landowner internalizes how deforesting will reduce the farmers' ability to sell to a ZDC slaughterhouse, thus reducing their willingness to pay for that land. This is especially true if the main demand in their region comes from this type of slaughterhouse. Farmers produce cows for sale by mixing the pasture land that they rent and cows that are bought from other farms. The total value of these bought cows is increased when they are fed pasture. In practice this is reflected by higher weight of the cows or by an increased number of cows, since they can be reproduced in

[1]The device of distinguishing the landowner from the farmer follows common practice in the deforestation literature (Domiguez-Iino, 2024; Farrokhi et al., 2024; Sotelo, 2020). It is not needed that farmers and landowners are different people. It is employed as a way of separating the two decisions and simplifying the model by considering deforestation and trade sequentially.

the farm. The fattened or reproduced cows are then sold to other farms or slaughterhouses, which can be ZDC or non ZDC. Cows are thus an intermediate output. For simplicity, we let each slaughterhouse's expenditure in cattle be exogenous.

4.1 Deforestation

The set of all farms is $\mathcal{S}$ with size S. Each landowner owns a farm $s \in \mathcal{S}$ with total amount of land $\bar{l}(s)$, and an amount of already deforested land, that is the area in pastures, $l^0(s)$. The amount they choose to deforest, $l^{\text{defor}}(s)$, bounded above by $\bar{l}(s) - l(s)$ dictates the amount of pasture land that they will have available to rent[2],

$$l(s) = l^0(s) + l^{\text{defor}}(s).$$

Deforestation, even in the absence of slaughterhouse regulations, is a costly activity. These costs are partly due to the physical effort and resources required to fell down trees and partly due to the potential risk of being directly caught by environmental authorities and fined, as the vast majority of deforestation in the Amazon is illegal. We assume that the cost of deforestation, $\phi(l^{\text{defor}}(s))$, is increasing and convex in the amount of land deforested.

Optimal deforestation decision. The landowner with farm s of size $\bar{l}(s)$, of which $\underline{l}(s) \leq \bar{l}(s)$ is pasture in the initial period (2009), is choosing how much of the remaining forested land to clear, $l^{\text{defor}}(s) \leq \bar{l}(s) - \underline{l}(s)$ to have additional pasture area.[3] The resulting pasture area, $l(s) = \underline{l}(s) + l^{\text{defor}}(s)$ gets rented out to cattle farmers at an endogenous rental rate $r(s)$. In equilibrium, the rental rate will depend on the total area in pasture of farm s and on how much of that pasture has been deforested since 2009. Considering this static framework in which the decision to deforest gets made once and it determines the rental rate $r(s, l(s), l^{\text{defor}}(s))$ for the foreseeable future, the landowner solves the following maximization problem

$$\max_{l^{\text{defor}}(s)} \left\{ \frac{1}{1-\rho} r(s, l(s), l^{\text{defor}}(s)) \times l(s) - \phi(s, l^{\text{defor}}(s)) \right\} \tag{1}$$

In this framework, slaughterhouses' ZDC regulations influence the landowners' deforestation decision by making the rental rate of the land more sensitive to deforestation. As the area of deforested land in farm s goes up, the demand for cattle raised in s goes down, and thus cattle farmers have less demand for that landowner's land, lowering the equilibrium rental rate $r(s)$. In mathematical terms, more stringent or more widespread ZDC regulations further decrease $\partial r / \partial l^{\text{defor}(s)} < 0$. This is substantially different from the effect on deforestation of command-and-control policies that affects landowners' direct costs of deforestation, as highlighted in Alix-Garcia and Gibbs (2017). Those types of regulations can be seen as decreasing the marginal costs of deforestation, $\partial \phi / \partial l^{\text{defor}} > 0$.

[2]We abstract away from forest regeneration, pasture degradation, and the planting of other crops for the time being.

[3]The choice to reforest or abandon pasture is currently ruled out of the model.

A key feature of ZDC regulations as an anti-deforestation policy is that the precise way in which it affects a farm's deforestation decisions depends on how much it depends on the demand from ZDC slaughterhouses. This is difficult to understand without a model, as it depends on many factors that interact. First, the level of competition from other farms that do not deforest. Second, paradoxically, having a lot of non-deforesting farms nearby can also enable a farm's deforestation because it means there are farms with high demand for cows as input. Third, on how much demand from non-ZDC slaughterhouses there is. In general, all of these factors are heavily mediated by geography since cattle trade is particularly sensitive to distance, as shown in stylized fact 3.

4.2 Cattle farming technology

Given a farm's amount of pasture land and its intrinsic productivity, the farm chooses how to participate in the cattle supply network, that is, how many cows to buy and sell, who to buy them from, and who to sell them to. Slaughterhouses buy mature cattle and produce beef they sell to domestic and international consumers. Farms and slaughterhouses differ in their location and productivity.

Cows are produced with a Cobb-Douglas production function that combines a bundle of cows from other farms $m(s)$ and land $l(s)$ with a constant returns to scale (CRS) technology and Hicks-neutral productivity $z(s)$,

$$y(s) = z(s)\left(\frac{l(s)}{\beta}\right)^{\beta}\left(\frac{m(s)}{1-\beta}\right)^{1-\beta}$$

for a share of land in production $0 < \beta < 1$ and a current amount of land in pastures $l(s)$. The bundle of cows bought as intermediate inputs is an aggregate of a finite number of purchases K from other farms[4]

$$m(s) = \prod_{k=1}^{K} m(s,k)^{1/K}.$$

Farmers choose the amount of land they rent and the amount of cows they buy and whom to buy cows from in order to minimize their unit costs of production. The rental rate of land and the price at which suppliers sell them cows will dictate the costs of production, which in turn dictates the price at which they sell to their buyers, leading to a recursive formula for production costs.

4.3 Slaughterhouse demand

Slaughterhouses buy cows for slaughter and produce beef that is sold to consumers. We assume that a slaughterhouse b of type $q \in \{\text{non ZDC s.h., ZDC s.h.}\}$ in location d has a fixed

[4]The assumption of complementarities between purchases is made to ensure tractability. In practice, it can be thought of as coming from the fact that cows reproduce and in that sense augment each other's productivity. Moreover, genetic diversity is desirable.

expenditure in cows $X_d^q(b)$. This can be rationalized by (s) consumers with an exogenously fixed income and Cobb-Douglas preferences, (ii) no substitution between beef from different slaughterhouses, and (iii) Cobb-Douglas production of beef. The second assumption is harder to justify as an accurate depiction of the real world, but it is helpful in order to quantify the channels of main interest to us. Our primary goal is to understand how the impact of a slaughterhouse having stricter environmental regulation can be mitigated by laundering and avoidance, even if that slaughterhouse continues to spend the same amount on cattle. It is straightforward to extend the model to allow for substitution between slaughterhouses but for now we avoid doing so in order to isolate the role of the upstream margin of the supply chain of beef.

4.4 Production network formation in space

The choice of who to supply from is done by choosing the least cost supplier for each of the finite number, K, of transactions that a buyer makes. First, a few words on notation. We index buyers (farms or slaughterhouses) by b and sellers (farms) by s. The *type* of the buyer, which can be either *farm*, *non ZDC slaughterhouse*, or *ZDC slaughterhouse*, is indexed by q. The location of the seller, also referred to as the origin, is indexed by o, and the location of the buyer, or destination, is indexed by d. Although we have the precise location of all farms and slaughterhouses, we coarsen geography to a grid of 10 km wide squares[5]. This helps computationally by greatly reducing the dimensionality of the trade cost matrix to be estimated.

Sourcing decisions. For each purchase k that a buyer b of type q at destination d makes, it sources from the supplier farm s from origin o that offers the lowest price out of those that are visible to b. Out of all the farms in the economy, buyer b sees only a subset, $\mathcal{S}(b) \subseteq \mathcal{S}$ such that each supplier belongs to that subset with probability $\frac{\lambda}{S}$ via independent Bernoulli trials. Thus the chosen supplier for purchase k by buyer b equals,

$$s^*(b,k) = \arg \min_{s \in \mathcal{S}(b)} p_{od}(s,b,k).$$

where the price $p_{od}(s,b,k)$ offered by suppliers in turn depends on geography, supply chain anti-deforestation policy, production costs, and other idiosyncratic shocks. Formally,

$$p_{od}(s,b,k) = \frac{\overline{m}_{od}(s,b,k)c_o(s)\kappa^q(s)\tau_{od}^q}{a_{od}(s,b,k)}$$

where $\mathcal{S}(b)$ is the set of suppliers visible to b, each visible with iid probability λ, $c_o(s)$ is the marginal cost of production of supplier farm s in origin o, $\kappa^q(s)$ is the deforestation penalty, τ_{od}^q is the iceberg trade cost between o and d, $a_{od}(s,b,k)$ is a random transaction-pair productivity shock, and $\overline{m}_{od}(s,b,k)$ is the mark-up charged. Since only a finite number of potential suppliers are visible, the lowest cost supplier can sell at the price charged by the

[5] As a robustness exercise we try bigger grid cells.

second cheapest, leading to markups. We assume that $a_{od}(s,b,k)$ are i.i.d. and follow a Pareto distribution with shape parameter ζ and scale parameter a_0,

$$a_{od}(s,b,k)\; i.i.d. \sim F_a(a) = 1 - (a/a_0)^{-\zeta}.$$

The Deforestation Penalty. Our main departure from production network models in the literature is to add a seller-buyer type-specific trade cost, the deforestation penalty $\kappa^q(l^{\text{defor}}(s))$. The deforestation penalty operates as an iceberg trade cost between sellers and buyers.

We assume that $\kappa^q(0) = 1$ and will show that it is increasing in l^{defor} and that

$$\kappa^{\text{farm}}(x) < \kappa^{\text{non ZDC s.h.}}(x) < \kappa^{\text{ZDC s.h.}}(x).$$

We estimate how deforesting will persistently reduce a farm's ability to trade with different types of buyers. In particular, we can see how deforesting more, but keeping all else equal, lowers the likelihood of selling to ZDC slaughterhouses. After closing the model, we will estimate how the deforestation penalty will reduce landowners' incentives to deforest in equilibrium.

Recursive formulation of costs. This functional form for suppliers' prices leads to a recursive formula for farms' production costs where the production cost of each farm b, $c_d(b)$, depends on the rental rate of land r_d and the prices charged by its suppliers for inputs, which in turn depend on their costs,

$$c_d(b) = \frac{r_d^{\beta}}{z_d(b)} \times \prod_{k=1}^{K} \min_{s \in \mathcal{S}_d(b)} \left\{ \frac{\overline{m}_{od}(s,b,k)\tau_{od}^{\text{farm}}}{a_{od}(s,b,k)} \times c_o(s)\kappa_o^{\text{farm}}(s) \right\}^{\frac{1-\beta}{K}}.$$

From Panigrahi (2022)'s Proposition 1, it follows that, before the idiosyncratic match-specific productivities $a_{od}(s,b,k)$ are realized, b supplies any task k from s with probability

$$\mathbb{E}[\pi_{od}^q(s,b)] = \frac{(c_o(s)\kappa_o^q(s)\tau_{od}^q)^{-\zeta}}{\sum_{s'}(c_{o'}(s))\kappa_o^q(s')\tau_{o'd}^q)^{-\zeta}}. \tag{2}$$

This equation summarizes how trade probabilities between a buyer and a supplier depend on distance, on deforestation histories, and on farm-level productivities. The multiplicative nature of the relationship allows for its decomposition into components that vary at different levels of aggregation of the transaction data. As we will see in the next section, this is the main equation that we will rely on to estimate the (i) deforestation penalty $\kappa_o^q(s)$, (ii) trade frictions τ_{od}^q and how they depend on distance, and, eventually, (iii) back out the productivity of each farm.

4.5 Closing the model

In equilibrium, the land rent payments of farmers s towards their landlord, $r(s)l(s)$, amount to a fraction β, --the Cobb-Douglas cost share of land-- of their expected total costs of cattle farming, which are equal to the expected revenues divided by the markup which is, in expectation, equal to $\frac{\zeta+1}{\zeta} > 1$. The expected revenues received by a farmer, or seller, s, in location o, amount to the sum of all payments that s received from other farms and slaughterhouses. The payments from a buyer of type q in a location d can be calculated as their expenditures in cows, $X_d^q(b)$, times their expected share sourced from s, $\mathbb{E}(\pi_{od}^q(s,-))$. For slaughterhouses, expenditures are taken to be exogenous and fixed. For farms, this is equal to $\frac{1-\beta}{\beta}$ times the rental rate payments that those buying farms make, $r_d(b)l_d(b)$. Therefore,

$$
\begin{aligned}
r_o(s)l_o(s) &= \frac{\zeta}{1+\zeta}\beta\Big(\mathbb{E}Y^{\text{farm}}(s) + \mathbb{E}Y^{\text{non ZDC s.h.}}(s) + \mathbb{E}Y^{\text{ZDC s.h.}}(s)\Big) \\
&= \frac{\beta\zeta}{\zeta+1}\sum_d \mathbb{E}(\pi_{od}^{\text{farm}}(s,-)) \underbrace{\sum_{b\in\mathcal{B}_d^{\text{farm}}} \frac{1-\beta}{\beta} r_d(b)l_d(b)}_{X_d^{\text{farm}}} \\
&+ \frac{\beta\zeta}{\zeta+1}\sum_d \mathbb{E}(\pi_{od}^{\text{non ZDC SH}}(s,-))X_d^{\text{non ZDC s.h.}} \\
&+ \frac{\beta\zeta}{\zeta+1}\sum_d \mathbb{E}(\pi_{od}^{\text{ZDC SH}}(s,-))X_d^{\text{ZDC s.h.}}
\end{aligned} \tag{3}
$$

The market clearing equation above serves three main purposes. First, it can be used to invert the model and solve for the rental rates $r(s)$ of each farm in the baseline equilibrium, in which ZDC policies are in place. Notice that it is a system of S equations with S unknowns, where S is the number of farms and $\{r_o(s)\}_{s\in\mathcal{S}}$ are the unknowns. This requires data on: (i) the land in pastures of each farm, $l_o(s)$, which we observe, (ii) the expected trade shares of each type of buyer in each destination for each seller, $\mathbb{E}(\pi_{od}^q(s,-))$, which we can estimate using the structure of the model and data on observed trade shares $\pi_{od}^q(s,b)$, and (iii) the aggregate expenditures of slaughterhouses in each destination on cows, $X_d^{\text{non ZDC s.h.}}$ and $X_d^{\text{ZDC s.h.}}$. This is done in the next section, where we take the model to data.

Second, equation (3) can be used to model how we expect the land rents from farm s to vary with deforestation, and how that depends on ZDC regulation in partial equilibrium. We can rewrite the landowners' optimal deforestation decision laid out in (1) using (3) to understand the dependence of the land rents from a farm, $r_o(s)l_o(s)$, on its level of deforestation, $l_o^{\text{defor}}(s)$. There are two main competing channels: (i) deforestation increases revenues by increasing the amount of pasture land available to rent out to cattle farmers, $l_o(s) = \underline{l_o}(s) + l_o^{\text{defor}}(s)$, albeit with decreasing marginal returns since $r_o(s)$ is decreasing in $l_o(s)$, and (ii) deforestation reduces the rental rates of land $r_o(s)$ by lowering the ability of farmers to sell cows to ZDC slaughterhouses. The second channel is less prevalent for farms that expect to sell relatively less to ZDC slaughterhouses, either because they specialize in calving, and hence to no direct sales to slaughterhouses, because they are far from ZDC slaughterhouses relative to other types of buyers, or because they have already deforested a large area since 2009.

Third, having the rental rates in the baseline equilibrium and a model for how landowners make optimal deforestation decisions while taking ZDC regulation into account, we can simulate how deforestation decisions would have been different in an alternative market equilibrium without such policies.

4.6 Deforestation in equilibrium

In equilibrium, the landowner is deciding how much to deforest, $l_o^{\text{defor}}(s)$, in order to maximize their profits as outlined in maximization problem (1), while accounting for the following three channels. First, that more land in pastures means receiving more rents, $\frac{\partial r_o(s) l_o(s)}{\partial l_o(s)} = r_o(s)$. Second, that more land in pastures lowers rental rates per hectare, $\frac{\partial r_o(s)}{\partial l_o(s)} l_o(s) = -\frac{1}{1+\beta\zeta} r_o(s)$. And third, that deforestation lowers rental rates per hectare due to ZDC regulation. If only ZDC slaughterhouses penalize deforesting farms, i.e. $\kappa^{\text{farm}}(s) = \kappa^{\text{non ZDC sh}}(s) = 1$, then this channel can be quantified as follows,

$$\frac{\partial r_o(s) l_o(s)}{\partial l^{\text{defor}}(s)} = \frac{\beta\zeta}{1+\zeta} \frac{1}{\kappa_o^{\text{ZDC}}(s)} \frac{\partial \kappa_o^{\text{ZDC}}(s)}{\partial l_o^{\text{defor}}(s)} \mathbb{E} Y_o^{\text{ZDC}}(s),$$

where $\mathbb{E} Y^{\text{ZDC}}(s)$ are the sales of farm s to ZDC slaughterhouses in expectation.

Assuming that $\kappa_o^{\text{ZDC}}(s) = \exp(\alpha \cdot (l^{\text{defor}}(s)/l^{\text{forest}}(s)))$, then, as shown in appendix section A.3,

$$\begin{aligned} \frac{d\text{Landowner Rent}_o(s)}{dl_o^{\text{defor}}(s)} &= \frac{\partial r_o(s) l_o(s)}{\partial l_o(s)} + \frac{\partial r_o(s)}{\partial l_o(s)} l_o(s) + \frac{\partial r_o(s)}{\partial l^{\text{defor}}(s)} l_o(s) \\ &\approx \frac{\beta\zeta}{1+\beta\zeta} \left(r_o(s) - \frac{\alpha\zeta}{1+\zeta} \frac{1}{l_o^{\text{forest}}(s)} \mathbb{E} Y_o^{\text{ZDC}}(s) \right). \end{aligned} \tag{4}$$

Equation (4) shows that, from the perspective of the landowner, the marginal benefits from deforesting an extra hectare increase linearly with the current rental rate and decrease with the farms' current expected sales to ZDC slaughterhouses divided by the initial forest cover in 2009. This implies that farms that sell a lot to ZDC slaughterhouses have a lot more to lose from increasing their deforestation levels and also that farms with initially (in 2009) low forest cover are more penalized for deforestation. This is a feature of the deforestation penalty's functional form. When taking the model to data we justify empirically our choice of functional form (Section 5.2).

5 Taking the model to data

We rely on five years of trade flows between farms and slaughterhouses, their geographical locations, and the land use history of each farm, to take the model to data as follows. In an initial step, we decompose the model-derived expected trade shares to understand what the main determinants of trade between a buyer and a seller are. We then estimate key parameters of the supply-network formation model. The main two are: (i) the deforestation penalty $\kappa_o^q(s)$ (see 5.2), and (ii) the distance-elasticity of trade costs τ_{od}, estimated through a gravity equation (see 5.3). Second, we invert the model to back out farm-level rental rates at baseline. In a third step, these rental rates are used to back out the implied marginal costs of deforestation. This is a function of deforestation that rationalizes observed deforestation rates given the estimated profitability of cattle production coming from the supply-network model.

5.1 Expected Trade Probabilities: Who trades with whom and why?

Using structural equation (2), we can use data on observed trade flows to parse out the role of characteristics of the seller, the origin location, the buyer, the destination location, and the origin-destination pair. We re-write (2) to show this more explicitly,

$$\mathbb{E}[\pi_{od}^q(s,b)] = \underbrace{(c_o^q(s)\kappa_o^q(s))^{-\zeta}}_{\text{Supplier-Buyer Type}} \times \underbrace{(\tau_{od}^q)^{-\zeta}}_{\text{Origin-Destination-Buyer Type}} \times \underbrace{\frac{1}{\sum_{s'}(c_{o'}(s')\kappa_o^q(s')\tau_{o'd}^q)^{-\zeta}}}_{\text{Destination-Buyer Type}}. \quad (5)$$

The structural determinants of expected trade probabilities are of three types. First, the characteristics of the supplier that vary by buyer type, thus including the costs of production of cows and the deforestation penalty. This carries the implicit assumption that all buyers of the same type are on average equally strict on their rules towards buyers that deforest. Second, the role of geography, varying at the origin and destination location pair, which we will assume follow a specific increasing function of distance. And third, the role of demand from a certain type of buyer at each destination, which varies at the destination and buyer type level.

5.2 Estimating the Deforestation Penalty

The deforestation penalty $\kappa_o^q(s)$ governs the degree to which a farm's deforestation history lowers its attractiveness to each of the three types q of buyers: farms, non-ZDC slaughterhouses, and ZDC slaughterhouses differentially. As motivation, we showed that the share of cows that a farm sells to each type of seller varies as a result of the amount of deforestation it does (see fact 3, page 6). This is true even when we control for farm fixed effects using the panel of transactions for years 2015-2019. In this section, we take a structural approach to estimate a parametric form for the deforestation penalty as a function of the area deforested since 2009. We assume the following functional form for the deforestation penalty,

$$\kappa_o^q(s) = \kappa_o\Big(l^{\text{defor}}(s)\Big) = \exp\left(\alpha^q \cdot \Big(l^{\text{defor since 2009}}(s)/l^{\text{forest in 2009}}(s)\Big)\right),$$

where the deforestation penalty parameter α^q captures how much farms are penalized for each additional increase in deforestation in selling to buyers of type q. It approximates an elasticity, so that a 1% increase in deforestation should reflect an α^q% increase in (iceberg) costs of trading with buyers of type q. We also make the normalization assumption that $\kappa_o^{\text{farm}}(s) = 1$, that is $\alpha^{\text{farm}} = 0$.

For this estimation we focus on the variation in transaction volumes that comes from the supplier-buyer type combination. First, we decompose the farm unit production costs into location and farm components

$$c_o^q(s) = \underbrace{\tilde{c}_o^q(s)}_{\text{Supplier level}} \times \underbrace{c_o^q}_{\text{Origin level}},$$

where the term $\tilde{c}_o^q(s)$ is normalized such that $\sum_{s\in o}(\tilde{c}_o^q(s))^{-\zeta} = 1$[6]. Second, we do a similar decomposition of the deforestation penalty,

$$\kappa^q(s) = \underbrace{\tilde{\kappa}^q(s)}_{\text{Supplier-Buyer type level}} \times \underbrace{\kappa_o^q}_{\text{Origin-Buyer type level}},$$

where the term $\tilde{\kappa}^q(s)$ is normalized such that $\sum_{s\in o}(\tilde{c}_o^q(s)\tilde{\kappa}_o^q(s))^{-\zeta} = 1$[7]. Then, relying on the same logic as Proposition 2 from Panigrahi (2022), we can show that the closed-form formula for the seller-buyer type-year fixed effect estimator is

$$\left(\tilde{c}_o^q(s)^{-\zeta}\tilde{\kappa}_o^q(s)^{-\zeta}\right)^* = \frac{\sum_b \pi_{od}^q(s,b)}{\sum_{s'\in o}\sum_{b'} \pi_{od}^q(s',b')} \equiv \frac{\text{intensity of use}^q(s)}{\sum_{s'\in o}\text{intensity of use}^q(s')}. \tag{6}$$

In order to estimate α^q, we rely on the estimator of the farm-specific fixed effects $\left(\tilde{c}_o^q(s)^{-\zeta}\tilde{\kappa}_o^q(s)^{-\zeta}\right)^*$ given above. This estimator captures the characteristics of a farm that make it a more attractive supplier to buyers of type q relative to other farms in the same origin o, since it is normalized. This includes both the farm's (relative) productivity as well as the deforestation penalty. In order to estimate α^q we would like to know how these fixed effects vary with the level of deforestation of the farm, all else equal. Our preferred identification strategy uses the 2015-2019 panel data on transactions to document how changes in cumulative deforestation from 2009 leads to changes in the farm-specific fixed effects for each type of buyer. Specifically, we run the following PPML regressions of the

[6] Define $c_o \equiv \left(\sum_{s\in o}\left(c_o(s)\right)^{-\zeta}\right)^{-1/\zeta}$ and let $\tilde{c}_o(s) \equiv c_o(s)/c_o$.

[7] Define $\kappa_o^q \equiv \left(\sum_{s\in o}\left(\tilde{c}_o(s)\kappa_o^q(s)\right)^{-\zeta}\right)^{-1/\zeta}$ and let $\tilde{\kappa}_o(s) \equiv \kappa_o^q(s)/\kappa_o^q$.

fixed effect estimator on the share of deforestation since 2009 with different sets of controls and fixed effects,

$$\left(\tilde{c}_{ot}^{q}(s)^{-\zeta}\tilde{\kappa}_{ot}^{q}(s)^{-\zeta}\right)^{*} = \exp\left(\beta^{q}\cdot \text{ShareDefor}_{ot}(s) + \delta^{q} Z_t(s) + (\gamma_s) + \eta_{ot}^{q}\right) + \epsilon_{ot}^{q}(s). \quad (7)$$

The results from different specifications of that equation are shown in table 2. The relationship between the regression coefficients β^q and our object of interest, the deforestation penalty, α^q, depends on the identifying assumptions we make about underlying distributions and about the structure of the model. For instance, if we were to assume that deforestation shares are uncorrelated with other factors affecting the costs of production of a farm, we would get that the estimated coefficients equal $-\zeta\alpha^q$. This can of course be relaxed to be a conditional exogeneity assumption when we introduce more controls. We can also, at the cost of losing observations that do not deforest in the period 2016-2020, include farm-specific fixed effects γ_s. This, however, does not deal with the fact that deforestation may be correlated with time-varying factors affecting $\tilde{c}_{ot}^{q}(s)$ rather than $\tilde{\kappa}_{ot}^{q}(s)$. It could be that there are productivity shocks to the farm (due to changes in labor or input markets, for example) that lead farms to both deforest more and sell more cattle. To deal with this, our preferred assumptions are

- A1 Production costs can differ between cattle for slaughter and cattle for sale to farms, that is $c_{ot}^{\text{sh}}(s) = c_{ot}^{\text{non-ZDC}}(s) = c_{ot}^{\text{ZDC}}(s)$, but is not necessarily equal to $c_{ot}^{\text{farm}}(s)$.
- A2 The only buyer with a deforestation penalty are ZDC slaughterhouses. That is, $\kappa_{ot}^{\text{farm}}(s) = \kappa_{ot}^{\text{non-ZDC}}(s) = 1$, that is $\alpha^{\text{farm}} = \alpha^{\text{non-ZDC}} = 0$

Under these assumptions, β^{farm} gives us the semi-elasticity of production costs for the upstream market with respect to the share deforested, $\beta^{\text{non-ZDC}}$ gives us the semi-elasticity of production costs for the downstream market (slaughter) with respect to the share deforested, and β^{ZDC} gives us the sum of the semi-elasticities of production costs for the downstream market (slaughter) plus the semi-elasticity of the deforestation penalty with respect to the share deforested. Therefore, we can estimate α^{ZDC} as

$$\widehat{\alpha}^{\text{ZDC}} = \frac{\widehat{\beta}^{\text{ZDC}} - \widehat{\beta}^{\text{non-ZDC}}}{\zeta}$$

All columns include origin-year-buyer type fixed effects in order to control for the characteristics of the farm that vary by location and year such as climate and weather, access to markets, and economic shocks that may be differently relevant for different types of buyer. For instance, there may be years in which ZDC slaughterhouses have more demand in certain locations. It is also well documented that certain years have much more demand for cow slaughter than others, in which most transactions happen between farms, this is often referred to as the cattle cycle. Columns (1)-(2) rely on cross-sectional comparisons of farms within the same 20 km wide grid cell, whereas columns (3) and (4) include farm-level fixed effects. Column (1) has no other controls, and shows that farms that deforest more area sell more

	Dep. Var: $\tilde{c}^q(s)^{-\zeta}\kappa^q(s)^{-\zeta}$			
	(1)	(2)	(3)	(4)
Defor. Frac. since 2009 x To Farm	-0.27^{***}	-0.17^{***}	0.40^{***}	0.38^{***}
	(0.04)	(0.04)	(0.10)	(0.10)
Defor. Frac. since 2009 x To non ZDC sh	-0.47^{***}	-0.40^{***}	0.34	0.37
	(0.08)	(0.10)	(0.34)	(0.34)
Defor. Frac. since 2009 x To ZDC sh	-1.23^{***}	-1.03^{***}	-0.04	-0.07
	(0.11)	(0.13)	(0.36)	(0.36)
Defor. Frac. 2003-2009 x To Farm		0.16^{*}		
		(0.07)		
Defor. Frac. 2003-2009 x To non ZDC sh		0.31		
		(0.17)		
Defor. Frac. 2003-2009 x To ZDC sh		0.03		
		(0.24)		
Origin cell x Buyer Type x Year FE	X	X	X	X
Land Use Controls x Buyer Type FE		X		X
Seller x Buyer Type FE			X	X
Num. Obs	513610	423651	291631	289452
Num. Origin cell x Buyer Type x Year	12524	12209	12524	12375
Num. Seller x Buyer Type			62035	61628

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

Table 2: Fixed Effects Poisson Regression, D=20 km

cows, but less so for ZDC sales. Column (2) controls for the size of the farm, and the share of its property area that was deforested 2003-2009, as a ''placebo'' test, to show that there is something special about post-2009 deforestation. Since larger farms sell more cows to all farms, and in particular to ZDC slaughterhouses, and also deforest lower shares of their 2009 forests, this lowers the magnitude of the deforestation penalty. Columns (3) and (4) exploit within-farm variation. That is, we look at how farms that deforested in the period 2016-2020 changed in how attractive they were to different types of buyers. Column (4) controls for changes in land use, which is important to avoid confounding increases in area deforested since 2009 with increases in area in pasture[8].

Column (4) is perhaps the most credible specification, but the object of interest for estimation, $\widehat{\beta}^{\text{ZDC}} - \widehat{\beta}^{\text{non-ZDC}}$, is not statistically different from zero. All columns, however, seem to consistently suggest a deforestation penalty parameter (multiplied by ζ), $\zeta\alpha^{\text{ZDC}}$, between 0.38 and 0.76. We take a round value in this range, $\zeta\alpha^{\text{ZDC}} = 0.5$, for our baseline calibration, and set $\zeta = 5$ following Panigrahi (2022). This number, if we take the causal interpretation seriously, implies that a 10 pp increase the share of the 2009 forests that is deforested leads to 5% increase in the likelihood that a ZDC buyer chooses him as supplier on any particular purchase that they do.

5.3 Structural Gravity Equation

In order to estimate the distance-elasticity of trade costs τ_{od}, we rely on the closed-form expression for the estimator of the (o, d, t)-specific term in 5, which equals[9]

$$\left(\frac{(c_o \kappa_o^q \tau_{od}^q)^{-\zeta}}{\sum_{o'} (c_{o'} \kappa_{o'}^q \tau_{o'd}^q)^{-\zeta}} \right)^* = \frac{1}{B_d^q} \sum_{b \in d} \sum_{s \in o} \pi_{od}^q(s, b) = \text{Average Sourcing Intensity}_{od}^q.$$

This allows running a structurally-derived gravity equation with the average sourcing intensity as the dependent variable on origin-year fixed effects ν_{ot} and destination-year fixed effects η_{dt}, so that the remaining variation is due to origin-destination-year variation, namely trade costs. Trade costs will depend on distance but their exact value will also depend on the quality of roads, traffic, and the availability of vehicles to transport the cattle. We run a simple gravity equation on log of distance[10]. We run this equation pooling all types of buyers q and also separately for different buyer types, as the trade costs for different types of buyers may be different,

$$\text{Average Sourcing Intensity}_{odt}^q = \exp\left(\nu_{ot}^q + \eta_{dt}^q + \beta^q \cdot \log\left(\text{Distance}_{od}\right)\right) + u_{odt}$$

[8] These two are not collinear because of the choice of functional forms. Since we are taking logarithms, a 1% increase in deforestation is not necessarily a 1% increase in pasture area, it would depend on the baseline pasture area.

[9] This is also shown in Proposition 2 in Panigrahi (2022).

[10] The distance for two establishments within the same square is taken to be the average distance between two random points in a square of width D, which equals approximately $4.276 \times D$, and for all other point is equals the distance between their centroids plus approximately $5.79 \times D$. Therefore it is always greater than zero and so we can take logarithms.

	Dep. Var: Sourcing Intensity (oqt)	
	(1)	(2)
log(Distance)	-2.17^{***}	
	(0.01)	
log(Distance) x To Farm		-2.17^{***}
		(0.01)
log(Distance) x To non ZDC sh		-2.03^{***}
		(0.10)
log(Distance) x To ZDC sh		-2.22^{***}
		(0.29)
Num. Obs	8381294	8381294
Num. Origin cell x Buyer Type x Year	12524	12524
Num. Destination cell x Buyer Type x Year	6468	6468

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

Table 3: Fixed Effects Poisson Regression, D=20 km

The gravity equation results, shown in table 3, show that cattle trade steeply decreases with distance. This elasticity is high relative to what is usually found in the trade literature for all traded goods. This makes sense since cattle needs to be fed and hydrated during transport, making each additional increase in travel distance more salient.

5.4 Baseline Rental Rate Estimation

The next step in this quantification exercise is to back out the rental rates $r_o(s)$ of all farms at baseline. The estimation procedure is described in detail in appendix section A.4. It consists of four steps. First, we calculate the expected sourcing intensities, $\pi^{q*}_{od}(\bullet, -) = \sum_{s \in \mathcal{S}_o} \pi^{q*}_{od}(s, b)$, or expected aggregate trade shares. These represent the expected probability that a buyer in a destination d chooses to source from a buyer in an origin o. In order to approximate these, we use the fitted values from cross-sectional gravity equations that pool together transactions from all years of data. Second, we aggregate the market clearing equation at the level of the grid-cell location so that the only unknowns are the aggregate rental payments to all landowners in each location, $R_o \equiv \sum_{s \in o} r_o(s) l_o(s)$. Then, using as data (i) the expected trade shares, and (ii) the aggregate expenditure of slaughterhouses in cows, we can solve the linear system of N unknown where N is the number of locations or grid-cells, and estimate R_o for all $o = 1, 2, \dots, N$. In the third step, we use transactions data to estimate the seller-buyer type fixed effects, $FE^q_o(s) = (\tilde{c}_o(s)\kappa^q_o(s))^{-\zeta}$. In the fourth and final step, we return to the disaggregated market clearing equation, and, relying on the estimated farm-level expected trade shares and the aggregate rental payments, we can calculate farm-level rents $r_o(s) l_o(s)$.

Estimating farm-level fixed effects

The most significant step is the estimation of the farm-level fixed effects, $FE^q_o(s)$. They capture the attractiveness of a farm s as a supplier relative to neighboring farms. The fixed effect captures both how productive the farm is and how suitable it is for each type of buyer. One way of estimating them is taking farms' relative intensity of use as in equation (6). This is described in step 3A of appendix section A.4. The weakness of this strategy is that if a farm did not sell to a ZDC slaughterhouse in the data, it will not sell to a ZDC in any counterfactual simulation either, as this would only be rationalized by an infinite penalty. Alternatively, we can impose the following functional form on the deforestation penalty, let it be $\kappa^q(s) = \exp\left(\alpha^q \cdot (l^{\text{defor}}(s)/l^{\text{forest}}(s))\right)$. Using this functional form and the fact that unit costs of production are the same for cows sold to slaughterhouses as for cows sold to farms, the fixed effects can be re-estimated as shown in Step 3B in the appendix section A.4. This estimation strategy has the opposite weakness of the first one, though. It implies that in expectation all farms would sell some cows to farms and some cows to slaughterhouses, whereas in reality we see specialization. In our preferred specification, described in Step 3C of appendix section A.4, we rely on the empirical observation that farms tend to partially specialize in stages of the cows' life-cycle. Farms seem to be either purely indirect, that is, they sell only to other farms, or a mix of direct and indirect, in which case they sell to slaughterhouses and farms. With this in mind, we let farms have two productivities, a productivity to produce cows to sell to other farms $z^{\text{farm}}(s)$ and a productivity to produce cows to sell to slaughterhouses $z^{\text{sh}}(s)$. As a result, the unit costs for each type of production differ, $c^{\text{farm}}(s)$ and $c^{\text{sh}}(s)$. Thus, we can estimate the fixed effects separately for farms and for slaughterhouses as

$$FE^{\text{farm}*}_o(s) \equiv (\tilde{c}^{\text{farm}}_o(s)^{-\zeta}\tilde{\kappa}^{\text{farm}}(s)^{-\zeta})^* = \frac{\text{Intensity of use}^{\text{farm}}(s)}{\sum_{s'\in o}\text{Intensity of use}^{\text{farm}}(s')}$$

and

$$\text{FE}^{q*}_o(s) \equiv (\tilde{c}^{\text{sh}}_o(s)^{-\zeta})^*(\tilde{\kappa}^q_o(s)^{-\zeta})^* = \frac{(\tilde{c}^{\text{sh}}_o(s)^{-\zeta})^* \cdot \exp\left(-\zeta\alpha^{q*}\cdot(l^{\text{defor}}(s)/l^{\text{forest}}(s))\right)}{\sum_{s'\in o}(\tilde{c}^{\text{sh}}_o(s')^{-\zeta})^* \cdot \exp\left(-\zeta\alpha^{q*}\cdot(l^{\text{defor}}(s')/l^{\text{forest}}(s'))\right)},$$

where the estimated relative costs of production for cows for slaughter is given by pooling together the intensity of use of cows for slaughter net of deforestation cost,

$$(\tilde{c}^{\text{sh}}_o(s)^{-\zeta})^* = \sum_{q \text{ is sh}} \frac{\text{Intensity of use}^q(s)}{\exp\left(-\zeta\alpha^{q*}\cdot(l^{\text{defor}}(s)/l^{\text{forest}}(s))\right)} \Bigg/ \sum_{q \text{ is sh}}\sum_{s'\in o}\frac{\text{Intensity of use}^q(s')}{\exp\left(-\zeta\alpha^{q*}\cdot(l^{\text{defor}}(s')/l^{\text{forest}}(s'))\right)}.$$

for $q \in \{\text{non ZDC s.h.}, \text{ZDC s.h.}\}$.

5.5 Model fit

This section evaluates the in-sample fit of the model under our preferred specification, which allows farms that sell to slaughterhouses to reallocate sales between ZDC and non-ZDC buyers, while preserving the observed extensive-margin selection into slaughterhouse markets. We assess model fit along three dimensions: (i) farm-level ZDC sourcing shares, (ii) the relationship between ZDC sourcing and deforestation histories, and (iii) the spatial distribution of equilibrium baseline rental rates implied by the model.

Farm-level fit for ZDC sourcing shares. Figure 3 compares observed and predicted ZDC sourcing shares at the farm level. Each dot reports the mean observed ZDC share within bins of the *predicted* ZDC share across farms. The solid line shows a linear fit at the farm level, the dashed line indicates the 45-degree benchmark, and the shaded bars display the distribution of observed ZDC sourcing shares. The model reproduces substantial cross-sectional heterogeneity in ZDC exposure across farms, with predicted sourcing closely tracking observed outcomes over the region of the distribution with the highest mass. The fit is even better when we take locations to be given by the 50 km by 50 km grid-cells.

Fit by deforestation deciles. A key empirical pattern documented in the data is that farms with more cumulative deforestation have systematically lower access to ZDC slaughterhouses. Figure 4 assesses whether the model reproduces this relationship. Farms are grouped into deciles based on the share of their 2009 forest area that has been deforested since 2009, and we plot the average observed and predicted ZDC sourcing shares within each decile. The model matches the monotonic decline in ZDC sourcing with deforestation, indicating that the estimated deforestation penalty embedded in buyer-type–specific trade costs is quantitatively consistent with the observed gradient.

Spatial patterns in baseline rental rates. Beyond matching trade shares, the model implies equilibrium baseline rental rates for pasture, which summarize each location's market access through the endogenous supply network. Figure 5 maps the spatial distribution of farm-level log rental rates under this specification. Higher rental rates reflect proximity to high-demand slaughterhouses, lower effective trade frictions (including deforestation penalties), and higher exogenous productivity. These rental rates are the key object linking supply-chain policies to land-use incentives in the model.

Finally, Figure 6 relates baseline rental rates to deforestation histories, highlighting the empirical relevance of the rental-rate object for understanding land-use incentives. Locations with higher equilibrium returns to pasture exhibit systematically different deforestation outcomes, consistent with the mechanism through which supply-chain access affects land-use decisions. Perhaps unexpectedly, higher rental rates are associated with a lower fraction of farms being deforested. This could, however, be the result of the supply-side of land. That is, those places where it is cheaper to deforest are also less productive or have lower market access as suppliers of cattle, i.e. they are further from other farms and slaughterhouses.

Taken together, these diagnostics show that our modeling framework is able to jointly match heterogeneity in farms' exposure to ZDC buyers, the systematic relationship between deforestation and buyer composition, and economically interpretable spatial patterns in baseline rents. In the next section, we use the fitted model to recover land-use incentives and to quantify counterfactual reallocations under alternative ZDC scenarios.

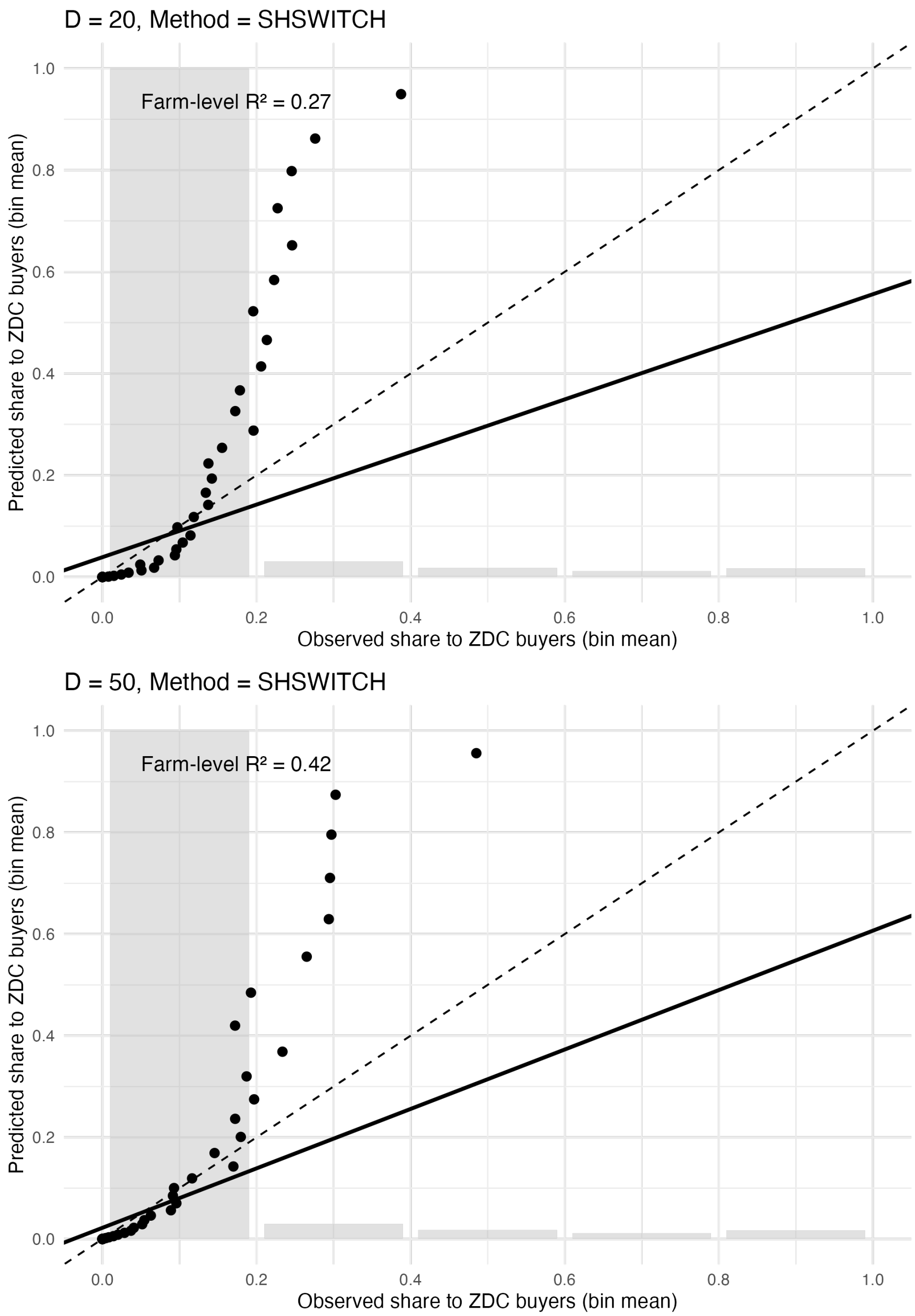


Figure 3: Observed vs. predicted ZDC sourcing shares at the farm level (SHSWITCH).

6 Counterfactual: Removing the deforestation penalty

We consider a counterfactual equilibrium in which the deforestation penalty faced by ZDC slaughterhouses is removed. Formally, we set the deforestation-penalty parameter to zero, $\alpha = 0$, so that $\kappa_o^{\mathrm{ZDC}}(s) = 1$ for all farms and locations. Importantly, we hold farms'

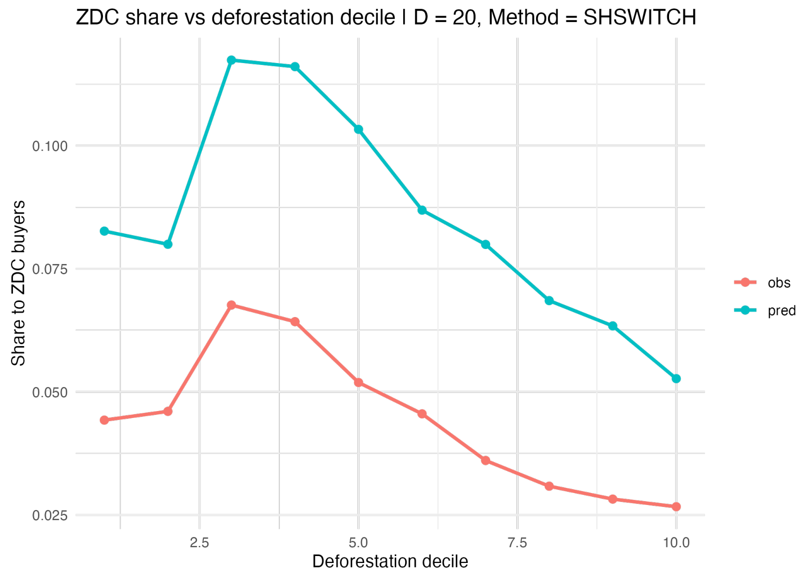


Figure 4: Observed and predicted ZDC sourcing by deforestation decile (SHSWITCH).

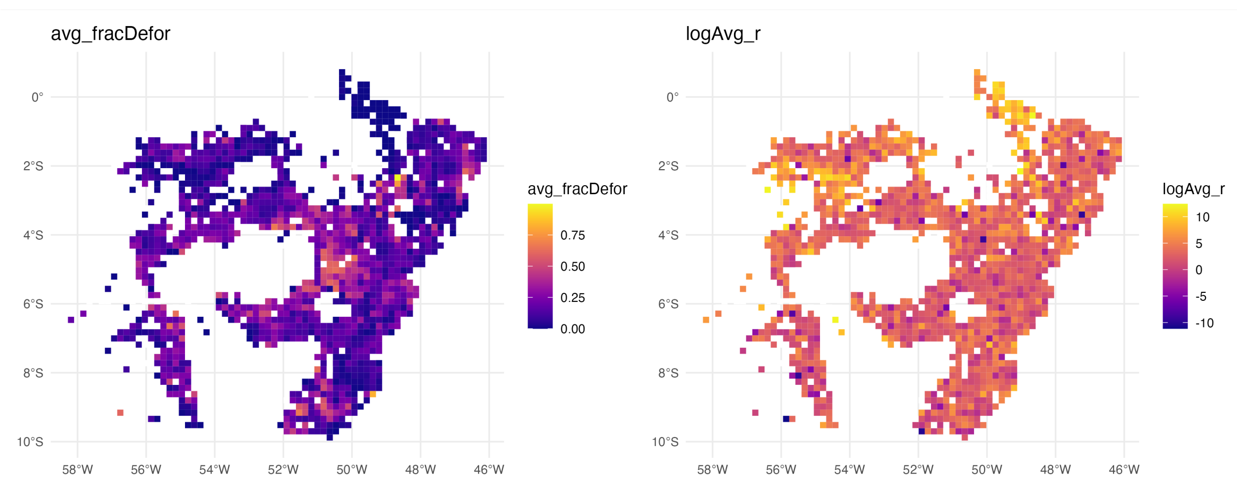


Figure 5: Spatial distribution of baseline farm-level rental rates (log).

deforestation histories fixed at their observed levels and recompute the full equilibrium of the model, allowing trade shares, market access, and rental rates to adjust endogenously. This counterfactual should be interpreted as a sudden removal of the ZDC penalty in an economy where deforestation has already occurred, rather than as a scenario in which the penalty had never existed.

The counterfactual is implemented by recomputing equilibrium sourcing probabilities and land rental rates under the new trade-cost structure implied by $\alpha = 0$, taking the supply network and demand structure as given. The full derivation of the counterfactual equilibrium,

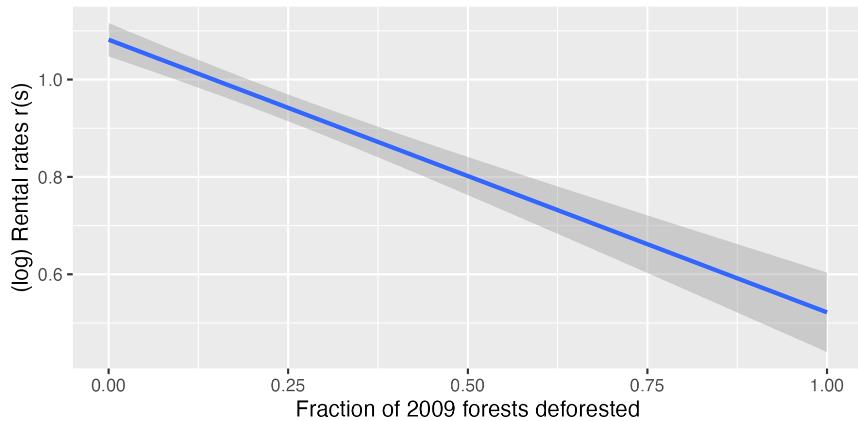


Figure 6: Baseline rental rates and deforestation histories.

including the system of equations governing changes in market access and rental rates, is provided in Appendix A.5.

6.1 Effects on ZDC sourcing

Figure 7 summarizes how the removal of the deforestation penalty affects farms' exposure to ZDC slaughterhouses. The figure reports binned averages of the percentage change in the fraction of cattle sold to ZDC slaughterhouses as a function of average cumulative deforestation since 2009. Farms with higher deforestation histories experience larger increases in ZDC sourcing when the penalty is removed, reflecting the elimination of buyer-type–specific trade costs that previously restricted their access to ZDC buyers.

6.2 General-equilibrium effects of removing the deforestation penalty

Removing the deforestation penalty faced by ZDC slaughterhouses has a direct and an indirect effect on farms' outcomes. The direct effect, discussed above, is that all farms face lower effective trade costs when selling to ZDC buyers. As a result, farms reallocate sales toward ZDC slaughterhouses, with particularly large increases among farms with higher deforestation histories.

Less obvious, however, is an indirect general-equilibrium effect operating through the upstream cattle market. As farms sell a larger share of their output directly for slaughter, fewer cows remain available as intermediate inputs for other farms. This reduction in the effective supply of feeder cattle raises the equilibrium price of cows as intermediate inputs, tightening upstream market access for some producers.

Figure 8 illustrates this mechanism spatially. The right-hand panel maps the percentage change in market access to intermediate cattle following the removal of the deforestation penalty. Despite the relaxation of downstream trade frictions, many locations experience a decline in market access to suppliers, reflecting increased competition for intermediate inputs

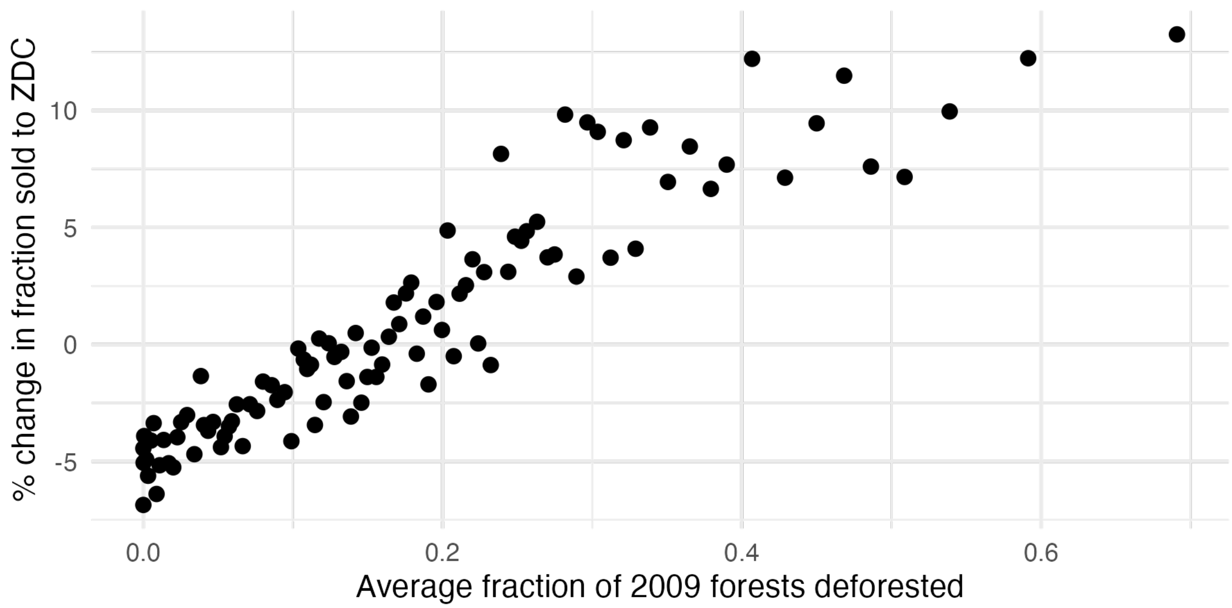


Figure 7: Percentage change in the fraction of cattle sold to ZDC slaughterhouses following the removal of the deforestation penalty ($\alpha = 0$), by deforestation history.

as more cattle are diverted toward slaughterhouse sales. These effects are geographically diffuse and not confined to areas with high deforestation, highlighting their general-equilibrium nature.

The implications of this upstream channel for farm revenues are summarized in Figure 9. The figure plots binned averages of percentage changes in farm-level rental rates as a function of cumulative deforestation since 2009. Farms with higher deforestation histories tend to experience increases in rental rates, reflecting the strong direct effect of improved access to ZDC buyers. In contrast, farms with little or no deforestation often experience smaller gains or even declines in rental rates. These farms benefit less from the direct relaxation of ZDC trade costs, while still facing higher prices for intermediate cattle due to increased competition upstream.

Taken together, these results show that removing deforestation penalties generates heterogeneous effects through general-equilibrium adjustments in the supply chain. While all farms face improved access to ZDC buyers, increased demand for intermediate cattle raises input prices and can reduce revenues per hectare for farms that do not strongly benefit from the downstream effect.

7 Conclusion

The cattle sector plays a central role in deforestation in the Amazon. A growing number of public and private initiatives seek to reduce deforestation through supply-chain zero-deforestation commitments (ZDCs). These policies shift the monitoring of individual farms

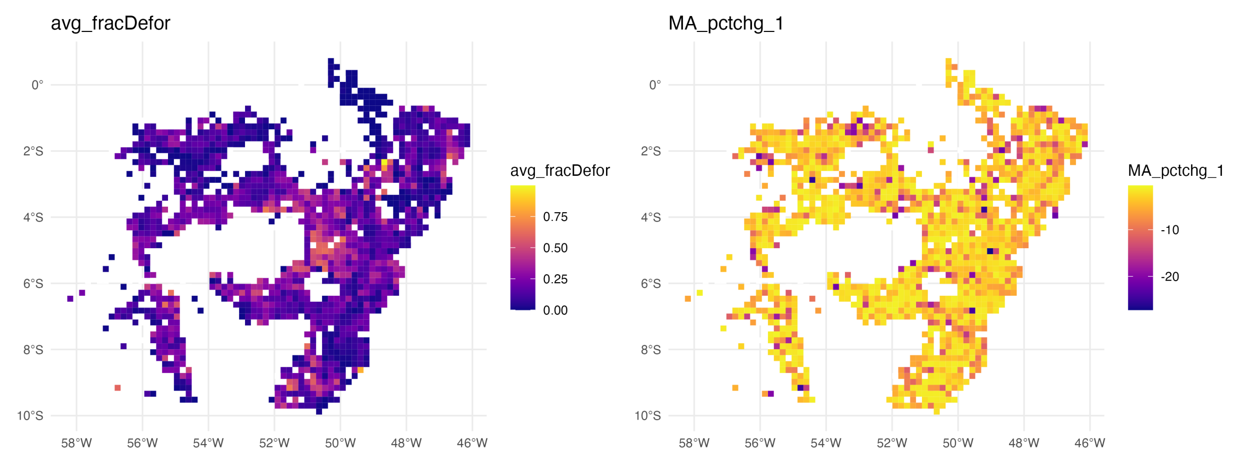


Figure 8: Spatial distribution of percentage changes in market access to intermediate cattle following the removal of the deforestation penalty ($\alpha = 0$).

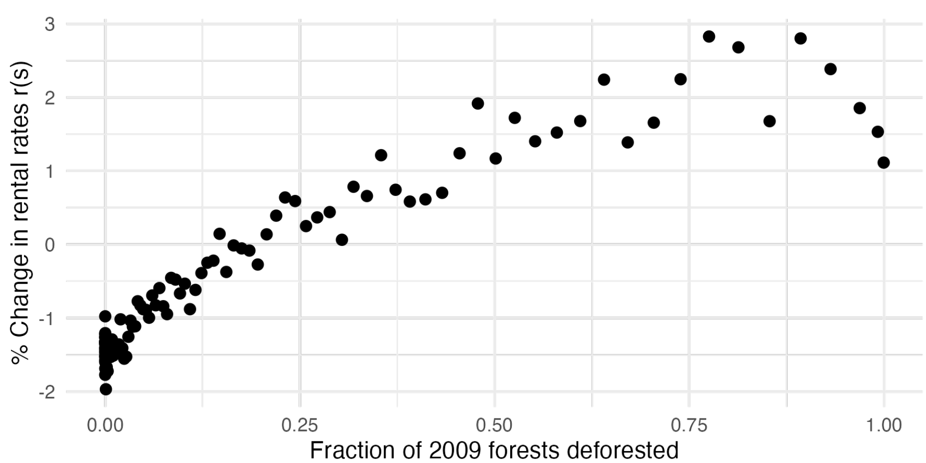


Figure 9: Percentage change in farm-level rental rates following the removal of the deforestation penalty ($\alpha = 0$), by deforestation history.

from public enforcement agencies to slaughterhouses, leveraging the high degree of market concentration at this stage of the supply chain. They operate by making slaughterhouses responsible for enforcing zero-deforestation requirements among their suppliers, effectively restricting sourcing to non-deforesting farms. These policies introduce frictions in a farm's ability to sell to a segment of the market, regulated slaughterhouses, thus lowering the potential profits from deforestation.

However, the effectiveness of these supply-chain policies can be undermined by leakage, as suppliers may avoid regulation by selling to slaughterhouses without zero-deforestation commitments or by re-routing production upstream to mask deforestation at the point of origin. These two forms of leakage pose serious concerns about the effectiveness of supply-chain policies, and threats to the causal identification of the overall effect of supply-chain policies. To date, most of the literature evaluating the effect of ZDCs on deforestation reduction has taken the supply chain as exogenous, despite the fact that slaughterhouses select their suppliers based on past deforestation.

We fill this gap by developing a model of the beef supply chain that takes cattle farms as the unit of analysis and considers both farm-to-farm as well as farm-to-slaughterhouse transactions. We adapt a state-of-the-art model of firm-to-firm trade with endogenous network formation and trade frictions to our setting. Our key contribution is to extend production network models by incorporating a land-use decision component, in which deforestation operates as a trade friction that reduces a farm's probability of being selected by large, formal slaughterhouses. In this framework, each period consists of two stages: a land-use and a supply-chain decision. First, deforestation decisions are made. Then, with all land use and deforestation histories taken as given, production and trade happen between farms and slaughterhouses.

Leveraging a unique dataset of farm-to-farm and farm-to-slaughterhouses sales matched with geo-localized farm deforestation, our results show that trade is heavily shaped by farms' deforestation histories. In particular, farms in the same 10km wide square, with the same property size, and the same area in pasture and forest, are significantly less likely to trade with slaughterhouses, and especially ZDC slaughterhouses, if they have deforested. Moreover, the amount of deforestation matters: more deforestation leads to less trade with ZDC slaughterhouses. We model this as stemming from an iceberg trade cost that depends on farms' deforestation since the policy's starting period (2009), and refer to it as the deforestation penalty. Our results indicate that ZDC regulation changes the consequences of deforestation for farms. These effects are robust to different specifications, statistically significant, and large. We estimate that a farm that deforests is 16% less likely to be chosen as a ZDC slaughterhouse supplier, and each additional 10% increase in deforestation is associated with an 8.3% decrease in trade probability with ZDC slaughterhouses.

Finally, we use the estimated model to conduct a counterfactual exercise in which the deforestation penalty imposed by zero-deforestation commitments is removed, while farms' land-use decisions are held fixed. The purpose of this first counterfactual exercise is not to quantify deforestation responses, but to isolate how supply-chain restrictions shape market access, prices, and reallocation within the cattle network in equilibrium. By abstracting from endogenous land-use adjustments, this counterfactual provides a transparent benchmark that clarifies the mechanisms through which supply-chain policies operate, as well as the channels through which leakage and re-routing can arise in a multi-tiered production network. This benchmark serves as a foundation for ongoing work that endogenizes deforestation decisions, allowing us to quantify counterfactual deforestation responses and to evaluate alternative policy scenarios in which the regulatory penalty is strengthened rather than eliminated.

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A Mathematical Appendix

A.1 Continuum Approximation for Large Network Economies

The following definition formalizes the notion of the limiting economy in the context of this paper. RE-DO with my notation

Definition. Consider a sequence of finite economies $\{\mathcal{E}_t : t \in \mathbb{N}\}$ where $\mathcal{E}_t \equiv \{\mathcal{S}_t, \mathcal{L}_t, \mathcal{J}_t\}$ is such that the t^{th} economy has the form $\mathcal{M}_t = \{m_1, \cdots, m_{M_t}\} \subset [0,1], \mathcal{L}_t = \{\ell_1, \cdots, \ell_{L_t}\} \subset [0,1]$ and $\mathcal{J}_t = \mathcal{J}$. The uniform distribution on $\mathcal{M}_t$ is given by $\mathcal{U}_t^M\left(\mathcal{M}_t^0\right) = \frac{M_t^0}{M_t}$ for all $\mathcal{M}_t^0 \subset \mathcal{M}_t$. Similarly, the uniform distribution on $\mathcal{L}_t$ is given by $\mathcal{U}_t^L\left(\mathcal{L}_t^0\right) = \frac{L_t^0}{L_t}$ for all $\mathcal{L}_t^0 \subset \mathcal{L}_t$. Then, $\{\mathcal{E}_t : t \in \mathbb{N}\}$ is a discretizing sequence of economies if it satisfies:

(1) $\mathcal{M}_t \subset \mathcal{M}_{t+1}$ and $\mathcal{L}_t \subset \mathcal{L}_{t+1}$ for all t,

(2) $\lim_{t\to\infty} \mathcal{U}_t^M\left(\mathcal{M}_t \cap [a_l, a_h]\right) = \mathcal{U}\left([a_l, a_h]\right)$,

(3) $\lim_{t\to\infty} \mathcal{U}_t^L\left(\mathcal{L}_t \cap [a_l, a_h]\right) = \mathcal{U}\left([a_l, a_h]\right)$,

where $\mathcal{U}(\bullet)$ denotes the uniform distribution with support over $[0,1]$ and $[a_l, a_h] \subset [0,1]$.

Assumption 2. The discretizing sequence of economies $\{\mathcal{E}_t : t \in \mathbb{N}\}$ satisfies the following conditions: [11]

(1) $\{\lambda_t, a_{0,t} : t \in \mathbb{N}\}$ is such that $\lambda_t = o\left(M_t\right)$ and $\lambda_t a_{0,t}^{\zeta} = \Theta(1)$

(2) $\left\{M_{d,t}, L_{d,t} : d \in \mathcal{J}, t \in \mathbb{N}\right\}$ is such that $M_{d,t} = \Theta\left(M_t\right)$ and $L_{d,t} = \Theta\left(L_t\right)$ for all $d \in \mathcal{J}$

A.2 Deriving Market Clearing Equation

Joint Distribution of the Lowest and the Second Lowest Effective Costs. We begin by characterizing the joint distribution of the lowest and second lowest effective cost available to buyer b of type q located at d,

$$\widetilde{F}_{p_d^q}\left(p^{(1)}, p^{(2)}\right) = \mathbb{P}\left(p_d^{q*}(b,k) \leq p^{(1)}, p_d^q(b,k) \geq p^{(2)}\right).$$

To do so, we evaluate the probability with which b receives exactly one offer with an effective cost no greater than $p^{(1)}$ and no other offers less than $p^{(2)}\left(> p^{(1)}\right)$. The lowest cost offer $p^{(1)}$ can be from any one of the locations. We evaluate the probability with which this offer is from any given location o and sum it across all locations. The probability with which

[11] For any two functions $f(n)$ and $g(n)$, $f(n) = o(g(n)) \implies \lim_{n\to\infty} \frac{f(n)}{g(n)} = 0$ and $f(n) = \Theta(g(n)) \implies \limsup_{n\to\infty} \frac{|f(n)|}{g(n)} < \infty$ and $\limsup_{n\to\infty} \left|\frac{f(n)}{g(n)}\right| > 0$.

b receives one offer with an effective cost no greater than $p^{(1)}$ from o and no other offers less than $p^{(2)}$ across all locations is given by:

$$\begin{cases} \binom{S_o}{1}\frac{\lambda}{S}\mathbb{P}\left(\frac{c_o^q(s)\kappa_o^q(s)\tau_{od}^q}{a_{od}(s,b,k)} \leq p^{(1)}\right) & \text{if } o \neq d \\ \times\left(1-\frac{\lambda}{S}\mathbb{P}\left(\frac{c_o^q(s)\kappa_o^q(s)\tau_{od}^q}{a_{od}(s,b,k)} \leq p^{(2)}\right)\right)^{S_o-1} & \\ \times\left(1-\frac{\lambda}{S}\mathbb{P}\left(\frac{c_d(s)\kappa_o^q(s)\tau_{dd}^q}{a_{dd}(s,b,k)} \leq p^{(2)}\right)\right)^{S_d-1} & \\ \times\prod_{o'\notin\{o,d\}}\left(1-\frac{\lambda}{M}\mathbb{P}\left(\frac{c_{o'}^q(s)\tau_{o'd}^q}{a_{o'd}(s,b,k)} \leq p^{(2)}\right)\right)^{M_{o'}} & \\ & \\ \binom{S_o-1}{1}\frac{\lambda}{S}\mathbb{P}\left(\frac{c_o^q(s)\kappa_o^q(s)\tau_{od}^q}{a_{od}(s,b,k)} \leq p^{(1)}\right) & \text{if } o = d \\ \times\left(1-\frac{\lambda}{S}\mathbb{P}\left(\frac{c_o^q(s)\kappa_o^q(s)\tau_{od}^q}{a_{od}(s,b,k)} \leq p^{(2)}\right)\right)^{S_o-2} & \\ \times\prod_{o'\neq o}\left(1-\frac{\lambda}{S}\mathbb{P}\left(\frac{c_{o'}^q(s)\kappa_o^q(s)\tau_{o'd}^q}{a_{o'd}(s,b,k)} \leq p^{(2)}\right)\right)^{S_{o'}} & \end{cases}$$

Under Assumption 2, the probability with which b encounters exactly one supplier who can deliver at a cost no greater than $p^{(1)}$ and encounters no other suppliers with offers less than $p^{(2)}$ across all locations is given by:

$$\widetilde{F}_{p_d^q}\left(p^{(1)},p^{(2)}\right) = \sum_o \lambda\mu_o\mathbb{P}\left(\frac{c_o^q(s)\kappa_o^q(s)\tau_{od}^q}{a_{od}(s,b,k)} \leq p^{(1)}\right)\exp\left(-\sum_{o'}\lambda\mu_{o'}\mathbb{P}\left(\frac{c_{o'}^q(s)\kappa_o^q(s)\tau_{o'd}^q}{a_{o'd}(s,b,k)} \leq p^{(2)}\right)\right)$$

Using the limit $\lim_{t\to\infty}\lambda_t a_{0,t}^{\zeta} \to 1$, this can be further simplified as $A_d^q\left(p^{(1)}\right)^{\zeta}\exp\left(-A_d^q\left(p^{(2)}\right)^{\zeta}\right)$ where $A_d^q = \sum_o \mu_o(\tau_{od}^q)^{-\zeta}\mathbb{E}\left[(c_o^q(\cdot)\kappa_o^q(\cdot))^{-\zeta}\right]$ is obtained as follows:

$$\begin{aligned} A_d^q p^{\zeta} &= \sum_o \lambda\mu_o\mathbb{P}\left(\frac{c_o^q(s)\kappa_o^q(s)\tau_{od}^q}{a_{od}(s,b,k)} \leq p\right) \\ &= \sum_o \lambda\mu_o\mathbb{E}_{\{c_o^q\}}\left[1-F_a\left(\frac{c_o^q(s)\kappa_o^q(s)\tau_{od}^q}{p}\right)\right] \\ &= \left(\sum_o \mu_o(\tau_{od}^q)^{-\zeta}\mathbb{E}\left[(c_o^q(\cdot)\kappa_o^q(\cdot))^{-\zeta}\right]\right)p^{\zeta} \\ \Longrightarrow A_d^q &= \sum_o \mu_o(\tau_{od}^q)^{-\zeta}\mathbb{E}\left[(c_o^q(\cdot)\kappa_o^q(\cdot))^{-\zeta}\right] \end{aligned} \tag{8}$$

The density function is then obtained by the negative cross-derivative of $\widetilde{F}_{p_d^q}\left(p^{(1)},p^{(2)}\right)$ as follows:

$$
\begin{aligned}
\widetilde{F}'_{p_d^q}\left(p^{(1)},p^{(2)}\right) &= -\frac{\partial^2 F_{p_d^q}\left(p^{(1)},p^{(2)}\right)}{\partial p^{(1)}\partial p^{(2)}} \\
&= -\frac{\partial\left(A_d^q\left(p^{(1)}\right)^{\zeta}\right)}{\partial p^{(1)}}\frac{\partial\left(\exp\left(-A_d^q\left(p^{(2)}\right)^{\zeta}\right)\right)}{\partial p^{(2)}} \\
&= \zeta^2(A_d^q)^2\left(p^{(1)}p^{(2)}\right)^{\zeta-1}e^{-A_d^q\left(p^{(2)}\right)^{\zeta}}
\end{aligned}
$$

Distribution of Effective Prices. We derive an expression for $F_{p_d^q}(p)$, that is, the probability with which any firm b of type q located in d faces an effective price no greater than p for one of its tasks k. Firm b faces an effective price no greater than p if the second-lowest cost available to it is no less than p. This is obtained as:

$$
\begin{aligned}
F_{p_d^q}(p) &= \int_0^p\left(\int_0^{p^{(2)}}F'_{p_d}\left(p^{(1)},p^{(2)}\right)dp^{(1)}\right)dp^{(2)} \\
&= 1-A_d^q p^{\zeta}\exp\left(-A_d^q p^{\zeta}\right)-\exp\left(-A_d^q p^{\zeta}\right)
\end{aligned}
$$

Derivation of Market Access. Given supplier's rental rate $r_o(s)$, the cost of production is given by

$$
c_o^q(s) = \frac{1}{z_o^q(s)}r_o(s)^{\beta}\left(\prod_{k=1}^{K}p_o^{\text{farm}}(s,k)^{1/K}\right)^{1-\beta} \tag{9}
$$

$$
\begin{aligned}
\implies \mathbb{E}\left[c_o^q(\cdot)^{-\zeta}\kappa_o^q(\cdot)^{-\zeta}\right] &= \mathbb{E}\left[\left(\frac{r_o(\cdot)^{\beta}\left(\prod_{k=1}^{K}p_o^{\text{farm}}(\cdot,k)^{1/K}\right)^{1-\beta}}{z_o^q(\cdot)}\right)^{-\zeta}\kappa_o^q(\cdot)^{-\zeta}\right] \\
&= \mathbb{E}\left[\prod_{k=1}^{K}p_o^{\text{farm}}(\cdot,k)^{-(1-\beta)\zeta/K}\right]\mathbb{E}\left[r_o(\cdot)^{-\zeta\beta}z_o^q(\cdot)^{\zeta}\kappa_o^q(\cdot)^{-\zeta}\right] \\
&= \prod_{k=1}^{K}\mathbb{E}\left[p_o^{\text{farm}}(\cdot,k)^{-(1-\beta)\zeta/K}\right]\mathbb{E}\left[r_o(\cdot)^{-\zeta\beta}z_o^q(\cdot)^{\zeta}\kappa_o^q(\cdot)^{-\zeta}\right] \\
&= \mathbb{E}\Big[r_o(\cdot)^{-\zeta\beta}z_o^q(\cdot)^{\zeta}\kappa_o^q(\cdot)^{-\zeta}\Big]\Gamma\left(2-\frac{1-\beta}{K}\right)^{K}(A_o^{\text{farm}})^{1-\beta}
\end{aligned}
$$

This is because, using the distribution of effective prices derived above, the probability density function equals

$$
f_{p_d^q}(p) = (A_d^q)^2 p^{2\zeta-1}\exp\left(-A_d^q p^{\zeta}\right),
$$

so that

$$\mathbb{E}\left[p_o^q(\cdot,k)^{-(1-\beta)\zeta/K}\right] = \int_0^\infty p^{\zeta(2-(1-\beta)/K)-1}(A_d^q)^2 \exp\left(-A_d^q p^\zeta\right) dp$$
$$= (A_d^q)^{\frac{1-\beta}{K}}\Gamma\Big(2-\frac{1-\beta}{K}\Big)$$

This implies that the market access of each location for farms $\left\{A_d^{\text{farm}}\right\}_d$ solves the following fixed point problem:

$$A_d^{\text{farm}} = \sum_o \mu_o \mathbb{E}\Big[r_o(\cdot)^{-\zeta\beta} z_o^{\text{farm}}(\cdot)^\zeta \kappa_o^{\text{farm}}(\cdot)^{-\zeta}\Big]\Gamma\left(2-\frac{1-\beta}{K}\right)^K (\tau_{od}^{\text{farm}})^{-\zeta}(A_o^{\text{farm}})^{1-\beta} \tag{10}$$

and the market access terms for slaughterhouses equal

$$A_d^q = \sum_o \mu_o \mathbb{E}\Big[r_o(\cdot)^{-\zeta\beta} z_o^q(\cdot)^\zeta \kappa_o^q(\cdot)^{-\zeta}\Big]\Gamma\left(2-\frac{1-\beta}{K}\right)^K (\tau_{od}^q)^{-\zeta}(A_o^{\text{farm}})^{1-\beta} \tag{11}$$

Sourcing probabilities (origin-destination). For any realization of farm-level productivities, deforestation levels, and trade costs, the probability with which any firm at d of type q sources from firms at o for any of its tasks is given by

$$\begin{aligned}
\pi_{od}^{q0}(\bullet,-) &= \left(\lim_{t\to\infty}\frac{S_o}{S}\right)\left(\lim_{t\to\infty}\frac{1}{S_o}\sum_{s\in\mathcal{S}_o}\pi_{od}^{q0}(s,-)\right)\\
&= \left(\lim_{t\to\infty}\frac{S_o}{S}\right)\left(\lim_{t\to\infty}\frac{1}{S_o}\sum_{s\in\mathcal{S}_o}\frac{c_o(s)^{-\zeta}\kappa_o^q(s)^{-\zeta}(\tau_{od}^q)^{-\zeta}}{A_d^q}\right)\\
&= \frac{\mu_o\mathbb{E}\left[c_o(\cdot)^{-\zeta}\kappa_o^q(\cdot)^{-\zeta}\right](\tau_{od}^q)^{-\zeta}}{A_d^q}\\
&= \frac{\mu_o\mathbb{E}\Big[r_o(\cdot)^{-\zeta\beta}z_o^q(\cdot)^\zeta\kappa_o^q(\cdot)^{-\zeta}\Big]\Gamma\left(2-\frac{1-\beta}{K}\right)^K(\tau_{od}^q)^{-\zeta}(A_o^{\text{farm}})^{1-\beta}}{A_d^q}
\end{aligned} \tag{12}$$

The law of large numbers implies that in the limiting economy

$$\frac{1}{B_d^q}\sum_{b\in\mathcal{B}_d^q}\pi^q(\bullet,b) \xrightarrow{t\to\infty} \pi^{q0}(\bullet,-).$$

Thus we can close the model to characterize the rental rates of land in equilibrium in the limiting economy.

Sourcing probabilities (supplier-destination). For any realization of farm-level productivities, deforestation levels, and trade costs, the probability with which any firm at d of type q sources from firms at o for any of its tasks is given by

$$\begin{aligned}\pi_{od}^{q0}(s,-) &= \widetilde{c}_o^q(s)^{-\zeta}\widetilde{\kappa}_o^q(s)^{-\zeta}\pi_{od}^{q0}(\bullet,-)\\ &= \widetilde{c}_o^q(s)^{-\zeta}\widetilde{\kappa}_o^q(s)^{-\zeta}\frac{\mu_o\mathbb{E}\left[r_o(\cdot)^{-\zeta\beta}z_o^q(\cdot)^{\zeta}\kappa_o^q(\cdot)^{-\zeta}\right]\Gamma\left(2-\frac{1-\beta}{K}\right)^K(\tau_{od}^q)^{-\zeta}(A_o^{\text{farm}})^{1-\beta}}{A_d^q}\end{aligned}$$

Closing the model. For any realization of σ, land demand by farm b at d can be expressed as:

$$r_d(b)l_d(b) = \beta c_d^{\text{farm}}(b)y_d(b)$$

Where $l_d(b)$ is data. Goods market clearing condition for firm s located at o can be simplified as:

$$y_o(s) = \sum_d\sum_q\sum_{b\in\mathcal{B}_d^q}\sum_{k=1}^{K}\frac{\tau_{od}^q(s)\kappa^q(s)m_{od}^q(s,b,k)}{a_{od}(s,b,k)}$$

$$\begin{aligned}\implies c_o^{\text{farm}}(s)y_o(s) &= \sum_d(1-\beta)\sum_{b\in\mathcal{S}_d}\left(\frac{1}{K}\sum_{k=1}^{K}\frac{\mathbf{1}\left\{s=s_d^*(b,k)\right\}}{\bar{m}_d(b,k)}\right)c_d(b)y_d(b)\\ &+\sum_d\sum_{q\in\{SH,ZDC\}}\sum_{b\in\mathcal{B}_d^q}\left(\frac{1}{K}\sum_{k=1}^{K}\frac{\mathbf{1}\left\{s=s_d^*(b,k)\right\}}{\bar{m}_d(b,k)}\right)X^q(b)\end{aligned}$$

We can simplify the LHS by making use of the land market clearing condition as:

$$\text{Supply}(s) = c_o^{\text{farm}}(s)y_o(s) = \frac{r_o(s)l_o(s)}{\beta}$$

We can the demand for cattle from farms as follows

Farm cattle demand (s)

$$= \sum_d (1-\beta) \sum_{b \in \mathcal{B}_d^{\text{farm}}} \left(\frac{1}{K} \sum_{k \in \mathcal{K}} \frac{\mathbf{1}\{s_d^*(b,k) = s\}}{\bar{m}_d(b,k)} \right) c_d(b) y_d(b)$$

$$\sum_d (1-\beta) \frac{\overbrace{\frac{1}{B_d^{\text{farm}}} \sum_{b \in \mathcal{B}_d^{\text{farm}}} \left(\frac{1}{K} \sum_{k=1}^{K} \frac{\mathbf{1}\{s_d^*(b,k) = s\}}{\bar{m}_d(b,k)} \right) c_d(b) y_d(b)}^{(A)}}{\underbrace{\frac{1}{B_d^{\text{farm}}} \sum_{b \in \mathcal{B}_d^{\text{farm}}} c_d(b) y_d(b)}_{(B)}} \times \sum_{b \in \mathcal{B}_d^{\text{farm}}} c_d(b) y_d(b)$$

Term (A) can be simplified as follows:

$$\begin{aligned}
(A) &= \frac{1}{\mathcal{B}_d^{\text{farm}}} \sum_{b \in \mathcal{B}_d^{\text{farm}}} \left(\frac{1}{K} \sum_{k \in \mathcal{K}} \frac{\mathbf{1}\{s_d^*(b,k) = s\}}{\bar{m}_d(b,k)} \right) c_d(b) y_d(b) \\
&\xrightarrow{t \to \infty} \mathbb{E}\left[\left(\frac{1}{K} \sum_{k \in \mathcal{K}} \frac{\mathbf{1}\{s_d^*(\cdot,k) = s\}}{\bar{m}_d(\cdot,k)} \right) c_d(\cdot) y_d(\cdot) \right] \\
&= \mathbb{E}\left[\left(\frac{1}{K} \sum_{k \in \mathcal{K}} \frac{\mathbf{1}\{s_d^*(\cdot,k) = s\}}{\bar{m}_d(\cdot,k)} \right) \right] \mathbb{E}\left[c_d(\cdot) y_d(\cdot) \right] \\
&= \mathbb{E}\left[\left(\frac{1}{K} \sum_{k \in \mathcal{K}} \frac{\mathbf{1}\{s_d^*(\cdot,k) = s\}}{\bar{m}_d(\cdot,k)} \right) \right] \mathbb{E}\left[c_d(\cdot) y_d(\cdot) \right] \\
&= \frac{1}{K} \sum_{k \in \mathcal{K}} \mathbb{E}\left[\frac{\mathbf{1}\{s_d^*(\cdot,k) = s\}}{\bar{m}_d(\cdot,k)} \right] \mathbb{E}\left[c_d(\cdot) y_d(\cdot) \right] \\
&= \mathbb{E}\left[\frac{\mathbf{1}\{s_d^*(\cdot,\cdot) = s\}}{\bar{m}_d(\cdot,\cdot)} \right] \mathbb{E}\left[c_d(\cdot) y_d(\cdot) \right] \\
&= \mathbb{E}\left[\frac{1}{\bar{m}_d(\cdot,\cdot)} \right] \mathbb{E}\left[\mathbf{1}\{s_d^*(\cdot,\cdot) = s\} \right] \mathbb{E}\left[c_d(\cdot) y_d(\cdot) \right] \\
&= \frac{\zeta}{\zeta+1} \mathbb{E}(\pi_{od}^{\text{farm}}(s,-)) \mathbb{E}\left[c_d(\cdot) y_d(\cdot) \right]
\end{aligned}$$

Term (B) can be simplified as follows:

$$\begin{aligned}
(B) &= \frac{1}{B_d^{\text{farm}}} \sum_{b \in \mathcal{B}_d^{\text{farm}}} c_d(b) y_d(b) \\
&\xrightarrow{t \to \infty} \mathbb{E}\left[c_d(\cdot) y_d(\cdot) \right]
\end{aligned}$$

Substituting (A) and (B) back in the Farm Input Demand, we obtain:

$$\text{Farm Input Demand (s)} = \sum_d \frac{1-\beta}{\beta}\frac{\zeta}{\zeta+1}\mathbb{E}(\pi_{od}^{\text{farm}}(s,-)) \sum_{b\in\mathcal{B}_d^{\text{farm}}} r_d(b)l_d(b)$$

We can simplify term Slaughterhouses' demand as

$$\begin{aligned}
&\text{Slaughterhouse of Type q Demand (s)} \\
&= \sum_d \sum_{b\in\mathcal{B}_d^q} \left(\frac{1}{K}\sum_{k=1}^{K} \frac{\mathbf{1}\{s_d^*(b,k)=s\}}{\bar{m}_d(b,k_1)}\right) X_d^q(b) \\
&\xrightarrow{t\to\infty} \sum_d \mathbb{E}\left[\frac{\mathbf{1}\{s_d^*(\cdot,k)=s\}}{\bar{m}_d(\cdot,k)}\right] \sum_{b\in\mathcal{B}_d^q} X_d^q(b) \\
&= \sum_d \mathbb{E}\left[\frac{1}{\bar{m}_d(\cdot,\cdot)}\right] \mathbb{E}\left[\mathbf{1}\{s_d^*(\cdot,\cdot)=s\}\right] X_d^q \\
&= \sum_d \frac{\zeta}{\zeta+1}\mathbb{E}(\pi_{od}^q(s,-))X_d^q
\end{aligned}$$

Market clearing equation. Putting these together we can further simplify the cattle market clearing condition. If supplier s charges an average markup of $\frac{\zeta+1}{\zeta} > 1$, then, after multiplying both sides of the market clearing equation by β and substituting in the Farm and Slaughterhouse inpt demand formulas,

$$\begin{aligned}
r_o(s)l_o(s) = &\frac{\zeta}{\zeta+1}(1-\beta)\sum_d \mathbb{E}(\pi_{od}^{\text{farm}}(s,-)) \sum_{b\in\mathcal{B}_d^{\text{farm}}} r_d(b)l_d(b) \\
&+ \frac{\beta\zeta}{\zeta+1}\sum_d \mathbb{E}(\pi_{od}^{\text{non ZDC SH}}(s,-))X_d^{\text{non ZDC s.h.}} \\
&+ \frac{\beta\zeta}{\zeta+1}\sum_d \mathbb{E}(\pi_{od}^{\text{ZDC SH}}(s,-))X_d^{\text{ZDC s.h.}}
\end{aligned}$$

The first term in the RHS equal the total payments from farms who buy the cows from s as intermediate inputs, divided by the markup and multiplied by the share that goes towards input costs. This is because the payments farm b makes towards cow inputs equal $\frac{1-\beta}{\beta}$ times the payments it makes towards land rental rates. Out of those, in expectation, a fraction $\pi_{od}^{\text{farm}}(s,-)$ goes towards s. As the number of buyers in d increases, by the law of large numbers, the income from sales to farms in d approaches its expected value. The second and third terms are the total amount of payments the non ZDC and ZDC slaughterhouses make, collectively, towards cows from s.

This can also be written in a simplified form that makes the dependence on $r_o(s)$ more explicit,

$$r_o(s)^{1+\beta\zeta}l_o(s) = G_o(s)$$

where

$$G_o(s) \equiv \frac{\zeta}{\zeta+1}\,(p_o)^{-\zeta(1-\beta)} \left((1-\beta) \sum_d \frac{\tau_{od}^{-\zeta} z_o^{\text{farm}}(s)^\zeta}{\sum_{o'} (c_{o'}^{\text{farm}} \tau_{o'd})^{-\zeta}} \sum_{b \in \mathcal{B}_d^{\text{farm}}} r_d(b) l_d(b) \right.$$
$$+ \beta \sum_d \frac{\tau_{od}^{-\zeta} z_o^{\text{sh}}(s)^\zeta}{\sum_{o'} (c_{o'}^{\text{sh}} \tau_{o'd})^{-\zeta}} X_d^{\text{non ZDC s.h.}}$$
$$\left. + \beta \sum_d \frac{\tau_{od}^{-\zeta} z_o^{\text{sh}}(s)^\zeta \kappa_o^{\text{ZDC}}(s)^{-\zeta}}{\sum_{o'} (c_{o'}^{\text{sh}} \kappa_{o'}^{\text{ZDC}} \tau_{o'd})^{-\zeta}} X_d^{\text{ZDC s.h.}} \right)$$

A.3 Optimal level of deforestation

The level of deforestation in equilibrium is assumed be optimal, that is to maximize the long term profits of the landowner, who receives land rents and pays the direct costs of cutting down the trees. Thus, we need to (i) understand how land owner rents vary with the amount of pasture land in a farm, and (ii) the deforestation cost function.

First let us calculate how the land rents of a landowner change with changing levels of area in pasture, $l_o(s)$. There will be a mechanical increase as there is more land to produce in, but also a decrease in the rental rate of land as more land of that quality and in that farm is being made available. In what follows we describe how the equilibrium land rents change with $l_o(s)$.

$$\text{Landowner Rent}_o(s) \equiv r_o(s) l_o(s),$$

so that the profits of a landowner equal

$$\text{Landowner Profits}_o(s) \equiv \frac{1}{1-\rho} r_o(s) l_o(s) - \phi(l_o(s) - \underline{l_o}(s))$$

where $\phi(\cdot)$ is the deforestation cost function, $\underline{l_o}(s)$ is the amount of already deforested land so that $l_o^{\text{defor}} = l_o(s) - \underline{l_o}(s)$, and ρ is a time discount factor to account for the fact that rent increases are perceived over a lifetime.

First order conditions of Landowner. If there is an interior solution (the landowner deforests a positive amount but not the entire farm, then the marginal

$$\frac{1}{1-\rho} \frac{d\text{Landowner Rent}(s)}{dl_o^{\text{defor}}(s)} = \phi'(l_o^{\text{defor}}(s))$$

We then employ the structure of our model to estimate how landowner rents depend on the amount of land deforested.

Case 1. No ZDC policy. Without deforestation penalties for any buyer, in equilibrium,

$$\frac{d\text{Landowner Rent}(s)}{dl_o^{\text{defor}}(s)} = \frac{\partial r_o(s)}{\partial l_o(s)} l_o(s) + r_o(s) \approx r_o(s)\Big(- \frac{1}{1+\beta\zeta} + 1\Big) = \frac{\beta\zeta}{1+\beta\zeta} r_o(s).$$

Elasticity interpretation. A 1% increase in pasture land leads to a $\frac{\beta\zeta}{1+\beta\zeta}$% increase in land rents received by the owner.

Case 2. ZDC policy. If we also consider deforestation penalties for ZDC buyers, then

$$\begin{aligned}\frac{d\text{Landowner Rent}(s)}{dl_o^{\text{defor}}(s)} \approx& \frac{\beta\zeta}{1+\beta\zeta} r_o(s) + \frac{\partial r_o(s) l_o(s)}{\partial l_o^{\text{defor}}(s)} \\ \approx& \frac{\beta\zeta}{1+\beta\zeta} r_o(s) \\ &- \frac{\beta\zeta^2}{1+\zeta} \frac{1}{\kappa_o^{\text{ZDC}}(s)} \underbrace{\frac{\partial \kappa_o^{\text{ZDC}}(s)}{\partial l_o^{\text{defor}}(s)}}_{>0} Y^{\text{ZDC}*}(s).\end{aligned}$$

where $Y^{\text{ZDC}}(s)$ is the total amount of sales of farm s to ZDC buyers (endogenous)

Assuming that $\kappa_o^{ZDC}(s)$ equals $\kappa_o^{\text{ZDC}}(s) = \exp(\alpha \cdot (l_o^{\text{defor}}(s)/l_o^{\text{forest}}(s))$, which asymptotically approximates $\kappa l_o^{\text{defor}}(s)^\alpha$, we get that

$$\frac{1}{\kappa_o^{\text{ZDC}}(s)} \frac{\partial \kappa_o^{\text{ZDC}}(s)}{\partial l_o^{\text{defor}}(s)} = \alpha \frac{1}{l_o^{\text{defor}}(s)},$$

and hence,

$$\frac{d\text{Landowner Rent}(s)}{dl_o^{\text{defor}}(s)} \approx \frac{\beta\zeta}{1+\beta\zeta} \left(r_o(s) - \frac{\alpha\zeta}{1+\zeta} \frac{1}{l_o^{\text{defor}}(s)} Y^{\text{ZDC}*}(s) \right).$$

Then the first order condition, in the general case which allows for a deforestation penalty,

$$\frac{d\phi(l_o^{\text{defor}}(s))}{dl_o^{\text{defor}}(s))} = \frac{\beta\zeta}{(1-\rho)(1+\beta\zeta)} \left(r_o(s) - \frac{\alpha\zeta}{1+\zeta} \frac{1}{l_o^{\text{defor}}(s)} Y^{\text{ZDC}*}(s) \right)$$

Approximation needed to estimate $\frac{\partial r_o(s)}{\partial l_o(s)} l_o(s)$. In order to estimate $\frac{\partial r_o(s)}{\partial l_o(s)} l_o(s)$ we rely on an approximation. Let's write the market clearing equation as

$$r_o(s)^{1+\beta\zeta} l_o(s) = G_o(s).$$

Notice that $G_o(s)$ comes from writing explicitly the dependence of the trade shares on the rental rate and decomposing it.

$$\mathbb{E}[\pi_{od}^q(s,b)] = \frac{(c_o(s)\tau_{od}\kappa_o^q(s))^{-\zeta}}{\sum_{s'}(c_{o'}(s')\tau_{o'd}\kappa_o^q(s'))^{-\zeta}} = r_o(s)^{-\beta\zeta} \frac{\left(\frac{1}{z_o(s)}(p_o^*)^{1-\beta}\tau_{od}\kappa_o^q(s)\right)^{-\zeta}}{\sum_{s'}(c_{o'}(s')\tau_{o'd}\kappa_o^q(s'))^{-\zeta}}$$

By doing this, we are taking into account how the numerator changes with $r_o(s)$, via $c_o(s)$, but not how the denominator does, since s is on of the terms added in the denominator. More over, $r_o(s)$ could also cause changes in p^* in equilibrium. As such, the full formula for how rental rates change with land in pasture, calculated using the simplified market clearing equation, solving for $l_o(s)$ and using the formula for the derivative of an inverse function, and multiplying by $l_o(s)$, equals

$$\frac{\partial r_o(s)}{\partial l_o(s)} l_o(s) = \frac{r_o(s)}{-(1+\beta\zeta) + \frac{dG_o(s)}{dr_o(s)} \frac{r_o(s)}{G_o(s)}} \approx -\frac{r_o(s)}{1+\beta\zeta}$$

The assumption required for this approximation is that

$$\left| \frac{\partial G_o(s)}{\partial r_o(s)} \frac{r_o(s)}{G_o(s)} \right| \ll 1 + \beta\zeta.$$

That is, that the elasticity of $G_o(s)$ with respect to $r_o(s)$ is sufficiently small. Intuitively, it means that farms are small players and do not perceive for their effects on equilibrium prices.

A.4 Model inversion

Step 1: Compute the expected aggregate trade shares $\pi_{od}^{q*}(\bullet, -)$.

Rather than using the observed aggregate trade shares, which are often zero, we use the fitted shares from the gravity regressions

$$\pi_{od}^{q}(\bullet, -) = \exp\left(\nu_{ot}^{q} + \eta_{dt}^{q} + \beta^{q} \cdot \log\left(\text{Distance}_{od}\right)\right) + u_{odt}$$

where the left hand side is defined as

$$\pi_{od}^{q}(\bullet, -) = \text{Average Sourcing Intensity}_{od}^{q} = \frac{1}{N_d^q} \sum_{b \in d} \sum_{s \in o} \pi_{od}^{q}(s, b).$$

Step 2: Compute aggregate rental rate payments in initial state.

In the initial state, the vector of rental rates $(r_o(s) l_o(s) : s \in \mathcal{S})$ is the solution to the following system of equations:

$$\begin{aligned} \frac{r_o(s) l_o(s)}{\beta} &= \frac{\zeta}{\zeta+1} \frac{1-\beta}{\beta} \sum_d \pi_{od}^{\text{farm}*}(s, -) \sum_{b \in \mathcal{B}_d^{\text{farm}}} r_d(b) l_d(b) \\ &+ \frac{\zeta}{\zeta+1} \sum_d \pi_{od}^{\text{nonZDCs.h.}*}(s, -)\, X_d^{\text{nonZDCs.h.}} \\ &+ \frac{\zeta}{\zeta+1} \sum_d \pi_{od}^{\text{ZDCs.h.}*}(s, -)\, X_d^{\text{ZDCs.h.}} \end{aligned}$$

Solving this linear system of size 60,000 would be computationally challenging. Fortunately, this is not necessary, as the RHS only has the region-level aggregate land rents. Define region-level land rents,

$$R_d \equiv \sum_{b \in \mathcal{B}_d} r_d(b) l_d(b).$$

Then, adding up over all farms s in location o who are buyers, and denoting the total expected expenditure of slaughterhouses on cows from origin o by $Y_o^{\text{s.h.}*}$,[12] we get the following aggregate market clearing equation,

$$R_o = \frac{\zeta}{\zeta+1}(1-\beta)\sum_d \pi_{od}^{\text{farm}*}\left(\bullet,-\right) R_d + \frac{\zeta}{\zeta+1}\beta Y_o^{\text{s.h.}*}$$

since, by construction, the farm fixed effects within a location add up to 1.
Let $\mathbf{\Pi}^{\text{farm}*}$ be the matrix with entries $\pi_{od}^{\text{farm}*}\left(\cdot,-\right)$, the fitted values from the gravity equations, then aggregate land rents are the solution to the matrix equation

$$\vec{R} = \frac{\zeta}{1+\zeta}(1-\beta)\mathbf{\Pi}^{\text{farm}*}\vec{R} + \frac{\zeta}{1+\zeta}\beta\vec{Y}^{\text{s.h.}*}$$

$$\implies \vec{R} = \left(\frac{1+\zeta}{\zeta}\mathbf{I} - (1-\beta)\mathbf{\Pi}^{\text{farm}*}\right)^{-1}\beta\vec{Y}^{\text{s.h.}*}$$

So if there are N regions, we need to invert an $N \times N$ matrix.

Step 3A: Estimate farm-buyer type level fixed effects with buyer-specific unit costs

Using this strategy, farm level unit costs $\tilde{c}_o^q(s)$ vary by buyer type and are estimated so that they exactly match the farm fixed effect by buyer type. Thus, whatever the level of deforestation does not explain, is a fixed characteristic of the farm that differentially affects its ability to sell to a type of buyer,

$$\text{FE}_o^{q*}(s) \equiv (\tilde{c}_o^q(s)^{-\zeta}\tilde{\kappa}_o^q(s)^{-\zeta})^* = \frac{\text{Intensity of use}^q(s)}{\sum_{s' \in o}\text{Intensity of use}^q(s')}.$$

Therefore, using the deforestation penalty as with the assumed functional form and the estimated parameters α^{q*},

$$(\kappa_o^q(s)^{-\zeta})^* = \exp\Big(-\zeta\alpha^{q*}\cdot(l^{\text{defor}}(s)/l^{\text{forest}}(s))\Big).$$

The normalized penalty equals, by definition,

$$(\tilde{\kappa}_o^q(s)^{-\zeta})^* = \frac{(\kappa_o^q(s)^{-\zeta})^*}{((\kappa_o^q)^{-\zeta})^*} = \frac{\exp\Big(-\zeta\alpha^{q*}\cdot(l^{\text{defor}}(s)/l^{\text{forest}}(s))\Big)}{\sum_{s' \in \mathcal{S}_o}(\tilde{c}_o^q(s')^{-\zeta}\tilde{\kappa}_o^q(s')^{-\zeta})^*}.$$

[12] This differs from actual expenditures because we use expected rather than observed trade shares.

And the normalized unit costs equal

$$(\widetilde{c}_o^q(s)^{-\zeta})^* = \frac{(\widetilde{c}_o^q(s)^{-\zeta}\widetilde{\kappa}_o^q(s)^{-\zeta})^*}{(\widetilde{\kappa}_o^q(s)^{-\zeta})^*}.$$

In this case, costs of producing for a type q will be estimated to be infinite, or $(\widetilde{c}_o(s)^{-\zeta})^* = 0$, if s does not sell to type q buyers. This has very important implications for counterfactual scenarios, as no extensive-margin switching of buyers will be allowed.

Step 3B: Estimate farm-level fixed effects with equal unit costs across buyers

An alternative strategy is to attribute all differences in a farm's ability to sell to different types of buyers to its deforestation penalty. In this case, we force unit costs to be the same across all buyer types. For that, we use a ‘‘net-of-deforestation-penalty'' intensity of use measure to get the unit costs,

$$\text{Net-of-defor Intensity of use}^q(s) = \frac{\text{Intensity of use}^q(s)}{(\widetilde{\kappa}_o^q(s)^{-\zeta})^*}.$$

And using this, we can aggregate to get a total (across all types of buyers) intensity of use of farm s net of deforestation. This can be thought of as the intensity of use that s would get if it did not deforest and everything else stayed constant

$$\text{Net-of-defor Intensity of use}(s) = \sum_q \frac{\text{Intensity of use}^q(s)}{(\widetilde{\kappa}_o^q(s)^{-\zeta})^*}.$$

Then we use the net-of-deforestation-penalty intensity of use measures to estimate farm-level unit costs,

$$(\widetilde{c}_o(s)^{-\zeta})^* = \frac{\text{Net-of-defor Intensity of use}(s)}{\sum_{s' \in \mathcal{S}_o} \text{Net-of-defor Intensity of use}(s')}$$

If the estimated deforestation penalty is assumed to be $(\kappa_o^q(s)^{-\zeta})^* = \exp\Big(-\zeta\alpha^{q*} \cdot (l^{\text{defor}}(s)/l^{\text{forest}}(s))\Big)$, then the normalized deforestation penalty, $(\widetilde{\kappa}_o^q(s)^{-\zeta})^* = (\kappa_o^q)^\zeta \cdot \exp\Big(-\zeta\alpha^{q*} \cdot (l^{\text{defor}}(s)/l^{\text{forest}}(s))\Big)$. Thus,

$$(\widetilde{c}_o(s)^{-\zeta})^* = \sum_q \frac{\text{Intensity of use}^q(s)}{\exp\Big(-\zeta\alpha^{q*} \cdot (l^{\text{defor}}(s)/l^{\text{forest}}(s))\Big)} \Bigg/ \sum_q \sum_{s' \in o} \frac{\text{Intensity of use}^q(s')}{\exp\Big(-\zeta\alpha^{q*} \cdot (l^{\text{defor}}(s')/l^{\text{forest}}(s'))\Big)}.$$

To calculate the normalized deforestation penalty, notice

$$(\widetilde{\kappa}_o^q(s)^{-\zeta})^* = \frac{(\kappa_o^q(s)^{-\zeta})^*}{((\kappa_o^q)^{-\zeta})^*} = \frac{(\kappa_o^q(s)^{-\zeta})^*}{\sum_{s' \in o}(\widetilde{c}_o(s')^{-\zeta})^*(\kappa_o^q(s')^{-\zeta})^*}.$$

Thus the farm-buyer type fixed effect needed to get the farm-buyer type level expected trade shares equal

$$\text{FE}_o^{q*}(s) \equiv (\widetilde{c}_o(s)^{-\zeta})^*(\widetilde{\kappa}_o^q(s)^{-\zeta})^* = \frac{(\widetilde{c}_o(s)^{-\zeta})^* \cdot \exp\Big(-\zeta\alpha^{q*} \cdot (l^{\text{defor}}(s)/l^{\text{forest}}(s))\Big)}{\sum_{s' \in o}(\widetilde{c}_o(s')^{-\zeta})^* \cdot \exp\Big(-\zeta\alpha^{q*} \cdot (l^{\text{defor}}(s')/l^{\text{forest}}(s'))\Big)}.$$

In this case, all farms are able to sell to different types of buyers, and all that influences their relative ability to sell to one versus the other (holding geographical distances fixed) is their level of deforestation.

Step 3C: Estimate farm-buyer type level fixed effects with productivity for sale to slaughterhouses and farms

In this case, there are two marginal costs: the marginal cost of producing cows for slaughter, $c^{\text{sh}}(s)$, and the marginal cost of producing cows for rearing/fattening, $c^{\text{farm}}(s)$, i.e. to sell to other farms. Then we estimate the fixed effect relating to sales to farms as in the no-switching case,

$$FE_o^{\text{farm}*}(s) \equiv (\tilde{c}_o^{\text{farm}}(s)^{-\zeta}\tilde{\kappa}^{\text{farm}}(s)^{-\zeta})^* = \frac{\text{Intensity of use}^{\text{farm}}(s)}{\sum_{s'\in o}\text{Intensity of use}^{\text{farm}}(s')}$$

And for the sales to slaughterhouses, the marginal cost is multiplied by the deforestation penalty, $(\kappa_o^q(s)^{-\zeta})^* = \Delta_o^q \cdot \exp\big(-\zeta\alpha^{q*}\cdot(l^{\text{defor}}(s)/l^{\text{forest}}(s))\big)$, estimated up to an unknown origin-buyer type level constant Δ_o^q, so that the normalized deforestation penalty equals $(\tilde{\kappa}_o^q(s)^{-\zeta})^* = \tilde{\Delta}_o^q \exp\big(-\zeta\alpha^{q*}\cdot(l^{\text{defor}}(s)/l^{\text{forest}}(s))\big)$. Thus the normalised costs of production of cows for slaughter equals

$$(\tilde{c}_o^{\text{sh}}(s)^{-\zeta})^* = \sum_{q\text{ is sh}} \frac{\text{Intensity of use}^q(s)}{\exp\big(-\zeta\alpha^{q*}\cdot(l^{\text{defor}}(s)/l^{\text{forest}}(s))\big)} \Big/ \sum_{q\text{ is sh}}\sum_{s'\in o}\frac{\text{Intensity of use}^q(s')}{\exp\big(-\zeta\alpha^{q*}\cdot(l^{\text{defor}}(s')/l^{\text{forest}}(s'))\big)}.$$

To calculate the normalized deforestation penalty, notice

$$(\tilde{\kappa}_o^q(s)^{-\zeta})^* = \frac{(\kappa_o^q(s)^{-\zeta})^*}{((\kappa_o^q)^{-\zeta})^*} = \frac{(\kappa_o^q(s)^{-\zeta})^*}{\sum_{s'\in o}(\tilde{c}_o(s')^{-\zeta})^*(\kappa_o^q(s')^{-\zeta})^*}.$$

Thus the farm-slaughterhouse-type fixed effect needed to get the farm-slaughterhouse-type level expected trade shares equal, for $q \in \{\text{non ZDC s.h.}, \text{ZDC s.h.}\}$,

$$\text{FE}_o^{q*}(s) \equiv (\tilde{c}_o^{\text{sh}}(s)^{-\zeta})^*(\tilde{\kappa}_o^q(s)^{-\zeta})^* = \frac{(\tilde{c}_o^{\text{sh}}(s)^{-\zeta})^*\cdot\exp\big(-\zeta\alpha^{q*}\cdot(l^{\text{defor}}(s)/l^{\text{forest}}(s))\big)}{\sum_{s'\in o}(\tilde{c}_o^{\text{sh}}(s')^{-\zeta})^*\cdot\exp\big(-\zeta\alpha^{q*}\cdot(l^{\text{defor}}(s')/l^{\text{forest}}(s'))\big)}.$$

Step 4: Compute farm-level values equilibrium rental rates in the initial state.

Having the baseline values of aggregate land rents, we can plug them into the RHS (demand side) of the disaggregated equation, so that we solve for $r_o(s)$,

$$\begin{aligned} r_o(s) = \frac{\zeta}{\zeta+1}\frac{1}{l_o(s)}\Bigg(& (1-\beta)\sum_d \pi_{od}^{\text{farm}*}(s,-)\,R_d \\ & + \beta\sum_d \pi_{od}^{\text{nonZDCs.h.}*}(s,-)\,X_d^{\text{nonZDCs.h.}} \\ & + \beta\sum_d \pi_{od}^{\text{ZDCs.h.}*}(s,-)\,X_d^{\text{ZDCs.h.}}\Bigg) \end{aligned}$$

which can be re-written as

$$r_o(s) = \frac{\zeta}{\zeta+1}\frac{1}{l_o(s)}\Bigg((1-\beta)\cdot \mathrm{FE}_o^{\mathrm{farm}*}(s)\cdot\sum_d \pi_{od}^{\mathrm{farm}*}(\bullet,-)\,R_d \\ + \beta\cdot \mathrm{FE}_o^{\mathrm{nonZDCs.h.}*}(s)\cdot Y_o^{\mathrm{nonZDCs.h.}*} \\ + \beta\cdot \mathrm{FE}_o^{\mathrm{ZDCs.h.}*}(s)\cdot Y_o^{\mathrm{ZDCs.h.}*}\Bigg)$$

where the expected purchases of cows from in origin o by ZDC slaughterhouses, Y_o^{q*}, equal

$$Y_o^{q*} \equiv \sum_d \pi_{od}^{q*}(\bullet,-)\,X_d^{\mathrm{ZDCs.h.}}$$

Step 5: Estimate marginal deforestation costs.

If the optimal level of deforestation is a local maximum, we can rely on the first order conditions of the deforestation problem to notice that, if the deforestation decision problem had an interior solution, it satisfies:

$$\frac{d\phi(l_o^{\mathrm{defor}}(s))}{dl_o^{\mathrm{defor}}(s))} = \frac{\beta\zeta}{(1-\rho)(1+\beta\zeta)}\left(r_o(s) - \frac{\alpha\zeta}{1+\zeta}\frac{1}{l_o^{\mathrm{defor}}(s)}Y^{\mathrm{ZDC}*}(s)\right)$$

Since everything in the left hand side we either already have from the calibration, is data, or we have assumed outside of the model, we know the marginal costs of deforestation $\frac{d\phi(l_o^{\mathrm{defor}}(s))}{dl_o^{\mathrm{defor}}(s))}$ for each farm at the baseline equilibrium.

Step 6: Estimate farm-level productivities.

Short summary: Get $(c_o^q\kappa_o^q)^*$ from gravity equation, multiply by $(\tilde{c}_o^q(s)\tilde{\kappa}^q(s))^*$ and divide by $\kappa_o^q(s)^*$. Get market access of farms at origins to cows from gravity equation to get expected input prices. Then rely on the unit cost equation (9) and on the estimated rental rates to back out farm-level productivity $z_o^q(s)$.

A.5 Counterfactual estimation

A.6 No ZDC policy counterfactuals, i.e. $\alpha = 0$

Step 1: Derive change in rental rates of land from FOC

Assuming locally linear deforestation costs, that is that the marginal cost of deforestation is the same at baseline as in the counterfactual, we can estimate the change in rental rates of land in each farm for a counterfactual scenario in which the deforestation penalty is removed, i.e. $\alpha = 0$ and $\kappa_o^q(s) = 1$ for all. Denoting the new equilibrium prices and quantities with primes, and the changes with hats, if both the old and new equilibria have interior solutions for the optimal amount of deforestation,

$$\begin{aligned}\frac{d\phi(l_o^{\text{defor}}(s))}{dl_o^{\text{defor}}(s))} &= \frac{\beta\zeta}{(1-\rho)(1+\beta\zeta)}\left(r_o(s) - \frac{\alpha\zeta}{1+\zeta}\frac{1}{l_o^{\text{defor}}(s)}\mathbb{E}Y_o^{\text{ZDC}}(s)\right)\\ \approx \frac{d\phi(l_o^{\text{defor}}(s)')}{dl_o^{\text{defor}}(s))} &= \frac{\beta\zeta}{(1-\rho)(1+\beta\zeta)}\left(r_o(s)'\right).\end{aligned} \tag{13}$$

Therefore, the change in rental rates $\widehat{r_o}(s)$ is given by:

$$\widehat{r_o}(s) \approx 1 - \frac{1}{r_o(s)}\frac{\alpha\zeta}{1+\zeta}\frac{1}{l_o^{\text{defor}}(s)}\mathbb{E}Y_o^{\text{ZDC}}(s)$$

Step 2: Define and compute policy shifters

First define policy shifters, both farm specific and aggregated at the region level, as follows:

$$\widehat{\delta_o^q}(s) \equiv \widehat{r_o}(s)^{-\beta\zeta}\widehat{\kappa}_o^q(s)^{-\zeta}, \quad \text{and}$$

$$\widehat{\delta_o^q} = \sum_{s\in\mathcal{S}_o}\omega_o^q(s)\widehat{\delta_o}^q(s)$$

where

$$\omega_o^q(s) \equiv \frac{z_o^q(s)^\zeta r_o(s)^{-\beta\zeta}\kappa_o^q(s)^{-\zeta}}{\sum_{s\in\mathcal{S}_o} z_o^q(s)^\zeta r_o(s)^{-\zeta}\kappa_o^q(s)^{-\beta\zeta}}.$$

The change in rental rates, $\widehat{r_o}(s)$, comes from the previous step, and the change in deforestation penalty $\widehat{\kappa}_o^q(s)$ can be directly computed without needing to know the counterfactual deforestation rate. In this case, the deforestation penalty for farms and non ZDC slaughterhouses stays null, so there is no change, i.e. $\widehat{\kappa_o^q}(s) = 1$ if $q \in \{\text{farm}, \text{non ZDC s.h.}\}$. For ZDC slaughterhouses, the penalty goes away, so all we need is to know the current rate of deforestation and not the counterfactual one to compute the change,

$$\widehat{\kappa_o^{\text{ZDC}}}(s) = (\kappa_o^{\text{ZDC}}(s))^{-1} = \exp\Big(-\alpha\cdot(l^{\text{defor}}(s)/l^{\text{forest}}(s))\Big).$$

In order to get the aggregate policy shifters by locations, we need to weight individual changes by farms' productivities.

Step 3: Get changes in aggregate sourcing probabilities

To solve for the changes in sourcing probabilities, we make use of the market access term defined in equation (8), A_d^q, which captured the access of buyers of type q to low cost suppliers.

The relationship between sourcing probabilities and market access is summarized by equation (12), which shows how expected sourcing probabilities from o to d from buyers of type q change with (i) origin characteristics such as the TFP of cattle ranching, the deforestation penalty towards buyers of type q, and the rental rate of land, (ii) the trade costs between o and d, (iii) the access of farms in o to cheap cows, and (iv) the availability of competing suppliers from other origins, given by A_d^q. From equations (10) and (11), we can derive an expression for how changes in market access terms as well as in land rates of land and deforestation, as captured by the policy shifters in the previous step, will lead to a change in sourcing probabilities,

$$\mathbb{E}\pi_{od}^q(\bullet,-)' = \mathbb{E}\pi_{od}^q(\bullet,-)\frac{\widehat{\delta_o^q}(\widehat{A}_o^{\text{farm}})^{1-\beta}}{\widehat{A}_d^q}$$

Adding up over all origins equals 1 by definition, that is, $\sum_o \mathbb{E}\pi_{od}^q(\bullet,-)' = 1$. Doing this in the market for cows in particular, we get that $\widehat{A}_d^{\text{farm}}$ solves the following non-linear system of equations

$$\widehat{A}_d^{\text{farm}} = \sum_o \mathbb{E}\pi_{od}^{\text{farm}}(\bullet,-)\widehat{\delta_o^{\text{farm}}}(\widehat{A}_o^{\text{farm}})^{1-\beta}$$

where $\mathbb{E}\pi_{od}^q(\bullet,-)$ are the baseline sourcing intensities as predicted by the gravity equations. Then the market access changes for slaughterhouses of type q can be computed as follows once we know $\widehat{A}_d^{\text{farm}}$,

$$\widehat{A}_d^q = \sum_o \mathbb{E}\pi_{od}^q(\bullet,-)\widehat{\delta_o^q}(\widehat{A}_o^{\text{farm}})^{1-\beta}.$$

Having solved for changes in market access, we can back out the counterfactual sourcing probabilities.

Step 4: Back out new landlord rents $r_o(s)l_o(s)$

Using the farm-level shifters, we can compute the counterfactual farm-level fixed effects,

$$\text{FE}_o^q(s)' \equiv \left(\widetilde{c}_o^q(s)'\widetilde{\kappa}_o^q(s)'\right)^{-\zeta} = \frac{\text{FE}_o^q(s)\widehat{\delta_o^q}(s)}{\sum_{s'\in\mathcal{S}_o}\text{FE}_o^q(s')\widehat{\delta_o^q}(s')}.$$

Making use of these and the counterfactual aggregate sourcing probabilities, $\mathbb{E}\pi_{od}^q(\bullet,-)'$, we can repeat the procedure used in the model inversion to back out $r_o(s)'l_o(s)'$, and since we had the counterfactual rental rates $r_o(s)'$, from step 1, this means we can also back out the amount of land $l_o(s)'$, and counterfactual level of deforestation!

B Structural estimation

B.1 Model fit: NOSWITCH specification

This section evaluates the in-sample fit of the model under the NOSWITCH specification, which restricts farms to sell only to buyer types they are observed to transact with in the data. In particular, farms that never sell to slaughterhouses in the baseline are assumed to face prohibitively high costs of accessing slaughterhouse markets, ruling out reallocation across buyer types on the extensive margin. This specification preserves the observed buyer-type composition at the farm level and therefore represents a conservative benchmark with limited reoptimization. We assess model fit along the same three dimensions as in the main specification.

Farm-level fit for ZDC sourcing shares. Figure 10 compares observed and predicted ZDC sourcing shares at the farm level. As in the main specification, each dot reports the mean observed ZDC share within bins of the predicted ZDC share, the solid line shows a linear fit, the dashed line indicates the 45-degree benchmark, and shaded bars report the distribution of observed ZDC shares. The NOSWITCH model captures variation in ZDC exposure among farms that already participate in slaughterhouse markets, but mechanically assigns zero predicted ZDC sourcing to farms without baseline slaughterhouse links. As a result, the fit is concentrated among farms with existing slaughterhouse relationships, and overall dispersion in predicted ZDC exposure is more limited than in specifications allowing reallocation.

Fit by deforestation deciles. Figure 11 evaluates whether the model reproduces the negative relationship between deforestation and ZDC access observed in the data. While the NOSWITCH specification matches the qualitative decline in ZDC sourcing across deforestation deciles among farms with slaughterhouse access, it understates the magnitude of the gradient. This reflects the restriction that farms cannot adjust buyer types in response to deforestation penalties, limiting the role of endogenous trade reallocation in generating the observed pattern.

Spatial patterns in baseline rental rates. Figure 12 maps the spatial distribution of baseline farm-level rental rates implied by the NOSWITCH specification. Because sourcing patterns are tightly constrained by observed buyer-type links, spatial variation in rental rates is driven primarily by geography and baseline productivity rather than by endogenous reallocation across buyer types. As a result, rental-rate dispersion is more muted relative to specifications allowing switching, particularly in areas where farms are close to slaughterhouses but do not transact with them in the data.

Overall, the NOSWITCH specification fits observed outcomes well within the subset of farms with existing slaughterhouse relationships but, by construction, limits the model's ability to capture reallocation of trade in response to deforestation penalties. We therefore view it as a lower bound on the importance of endogenous supply-chain adjustment.

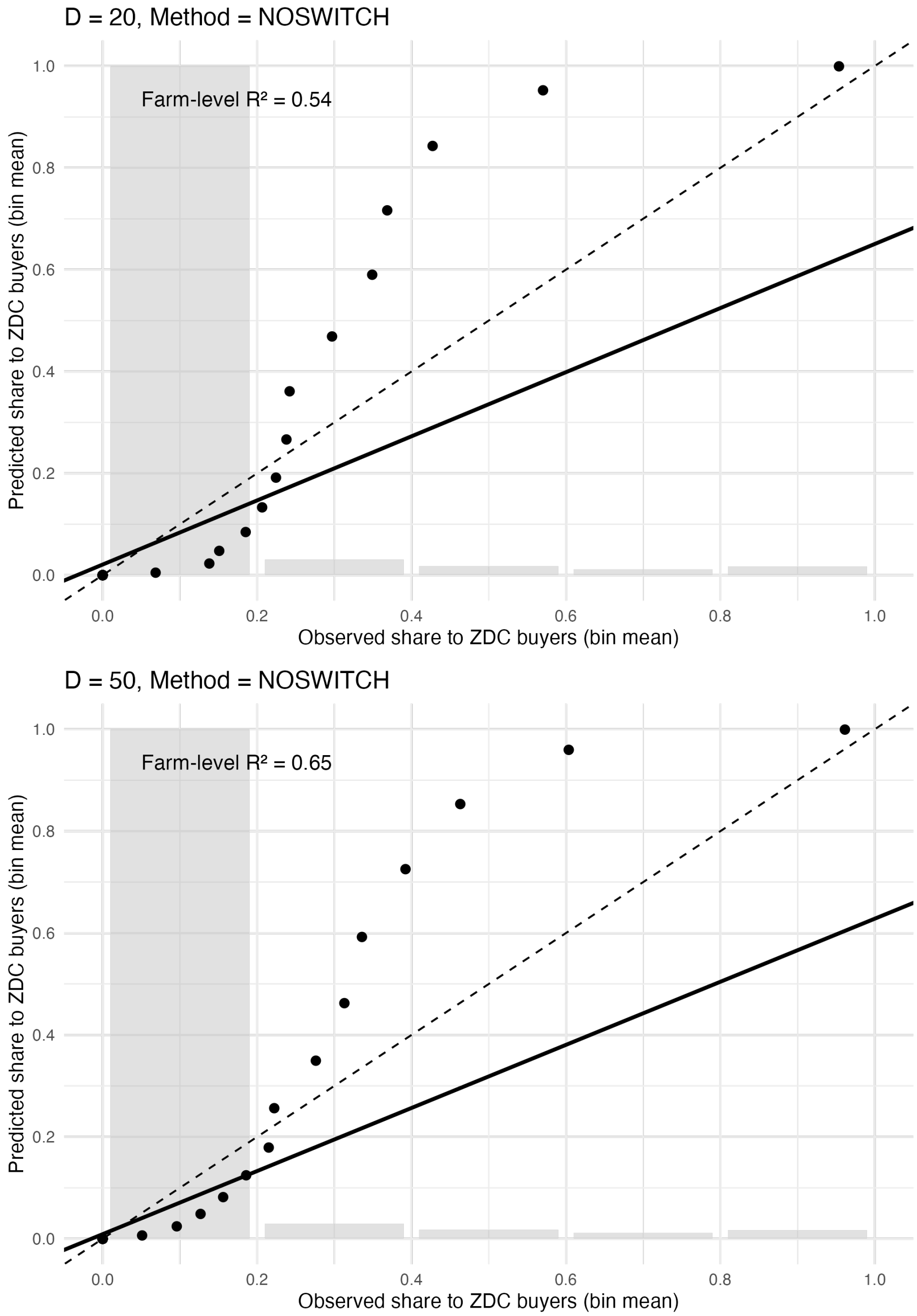

Figure 10: Observed vs. predicted ZDC sourcing shares at the farm level (NOSWITCH).

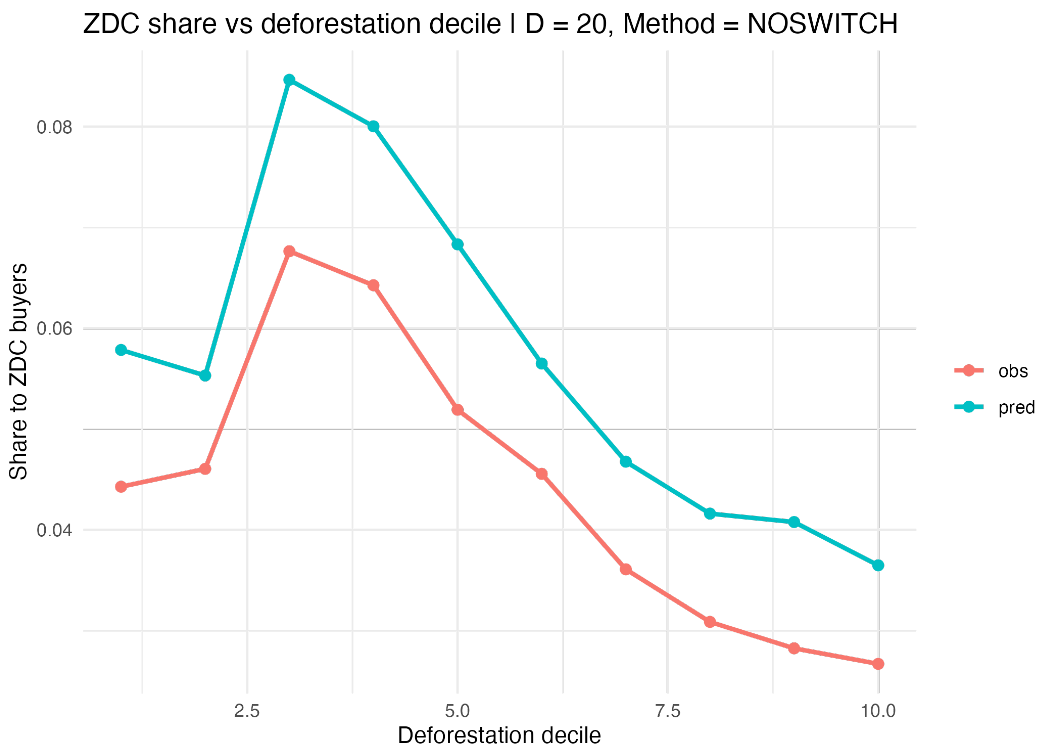

Figure 11: Observed and predicted ZDC sourcing by deforestation decile (NOSWITCH).

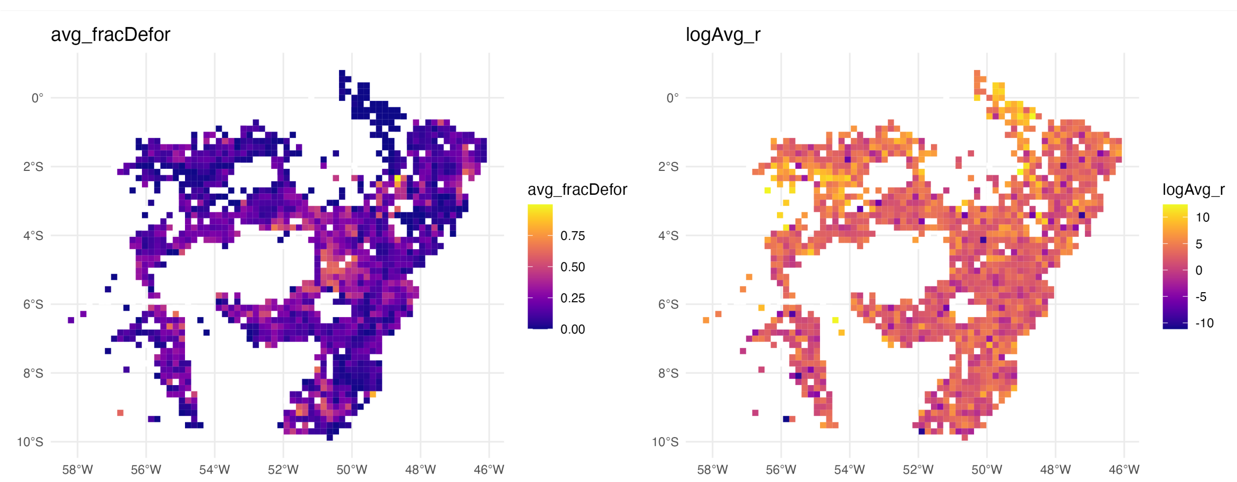

Figure 12: Spatial distribution of baseline farm-level rental rates (log), NOSWITCH.

B.2 Model fit: SWITCH specification

This section evaluates the in-sample fit of the model under the SWITCH specification, which allows all farms to reallocate sales freely across buyer types, regardless of their observed baseline transactions. In this specification, unit production costs are assumed to be identical across buyer types, implying that any farm can costlessly switch between selling to farms, non-ZDC slaughterhouses, and ZDC slaughterhouses. This represents a polar benchmark with maximal reoptimization and strong general-equilibrium responses.

Farm-level fit for ZDC sourcing shares. Figure 13 compares observed and predicted ZDC sourcing shares at the farm level. The model generates substantial dispersion in predicted ZDC exposure, reflecting unrestricted reallocation toward buyers offering higher net returns. This specification overpredicts ZDC participation among farms that never sell to slaughterhouses in the baseline, leading to a weaker alignment along the 45-degree line relative to more restrictive specifications.

Fit by deforestation deciles. Figure 14 reports observed and predicted ZDC sourcing shares by deforestation decile. The SWITCH specification reproduces a steep decline in ZDC sourcing with deforestation, often exceeding the magnitude observed in the data. This reflects the fact that, with unrestricted switching, deforestation penalties translate directly into large reallocations away from ZDC buyers, amplifying the role of buyer-type–specific trade costs.

Spatial patterns in baseline rental rates. Figure 15 shows the spatial distribution of baseline farm-level rental rates under the SWITCH specification. Because all farms can access slaughterhouse markets, spatial differences in rental rates are driven primarily by distance to demand centers and by equilibrium competition for intermediate cattle. Compared to the preferred SHSWITCH specification, rental rates are more compressed spatially, reflecting stronger arbitrage across buyer types.

In sum, the SWITCH specification provides an upper bound on the degree of trade reallocation and the strength of deforestation penalties in shaping sourcing patterns. While useful as a benchmark, its unrestricted nature leads to counterfactual patterns of slaughterhouse participation that are less consistent with observed extensive-margin behavior.

C Additional Empirical Results

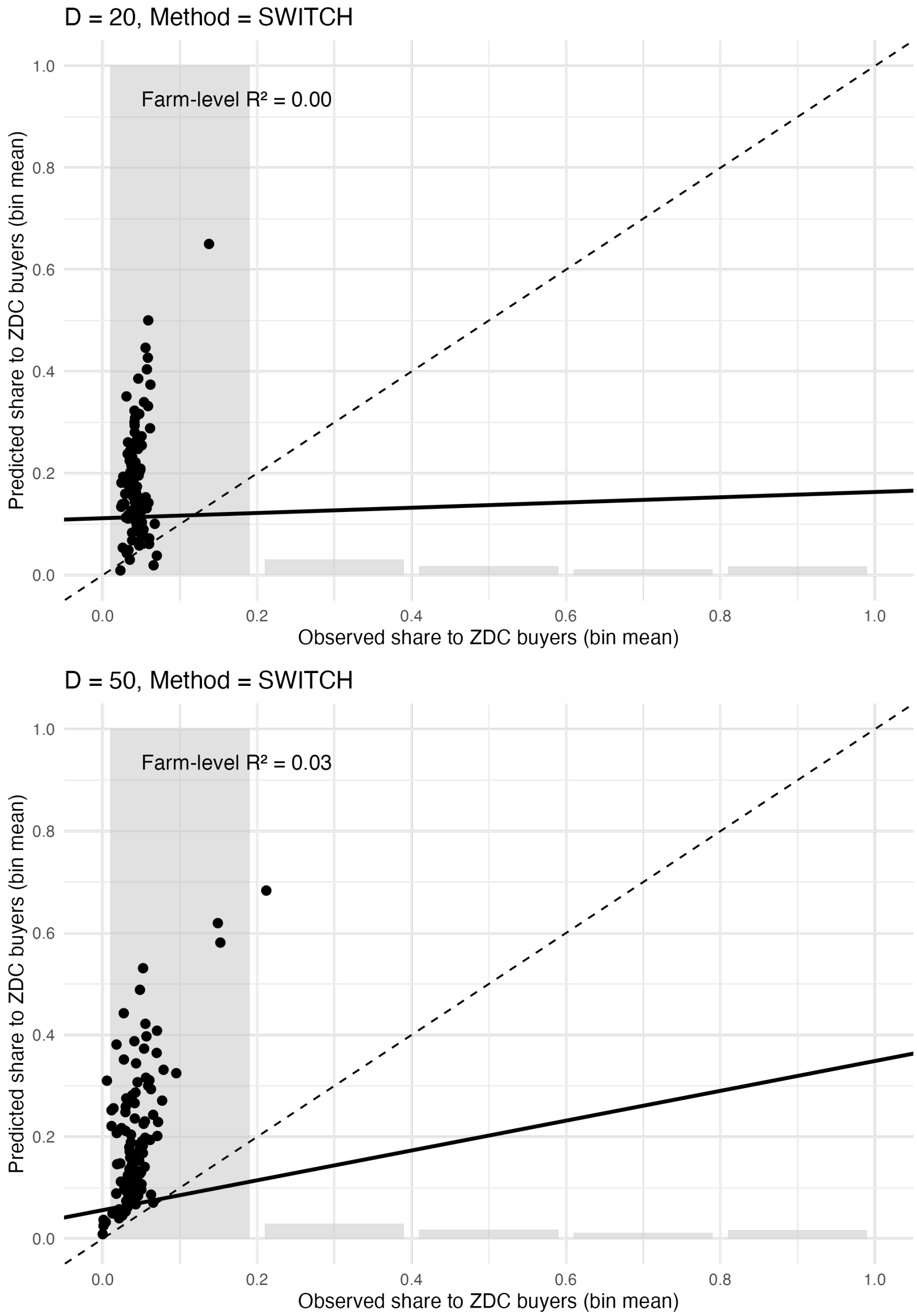

Figure 13: Observed vs. predicted ZDC sourcing shares at the farm level (SWITCH).

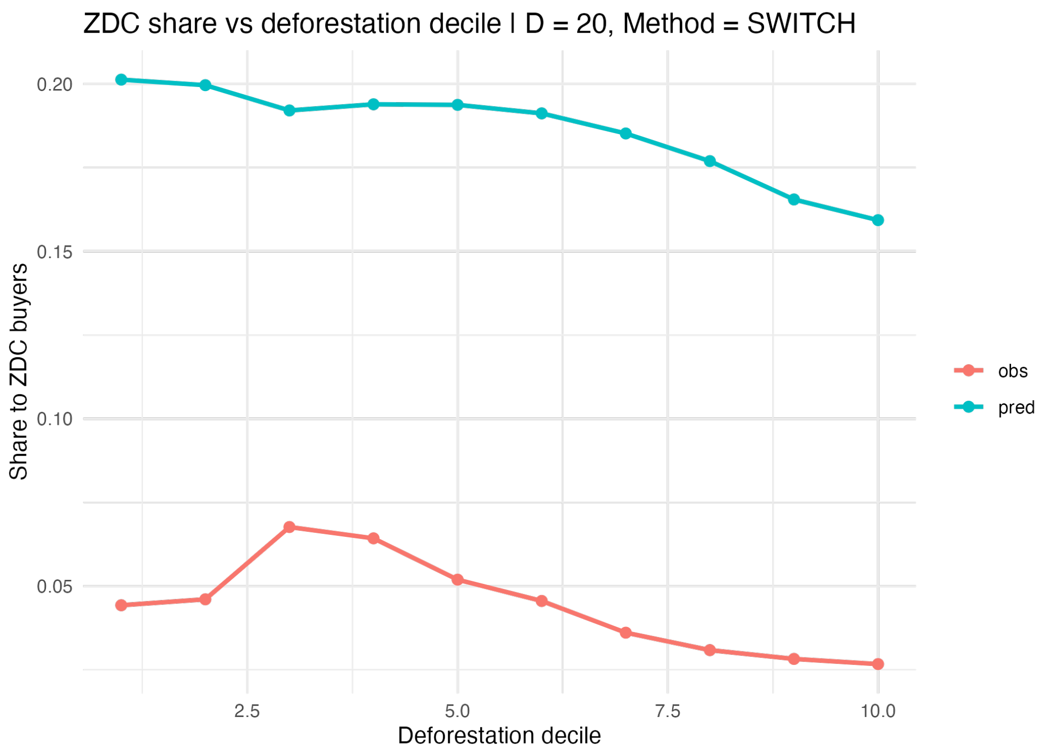

Figure 14: Observed and predicted ZDC sourcing by deforestation decile (SWITCH).

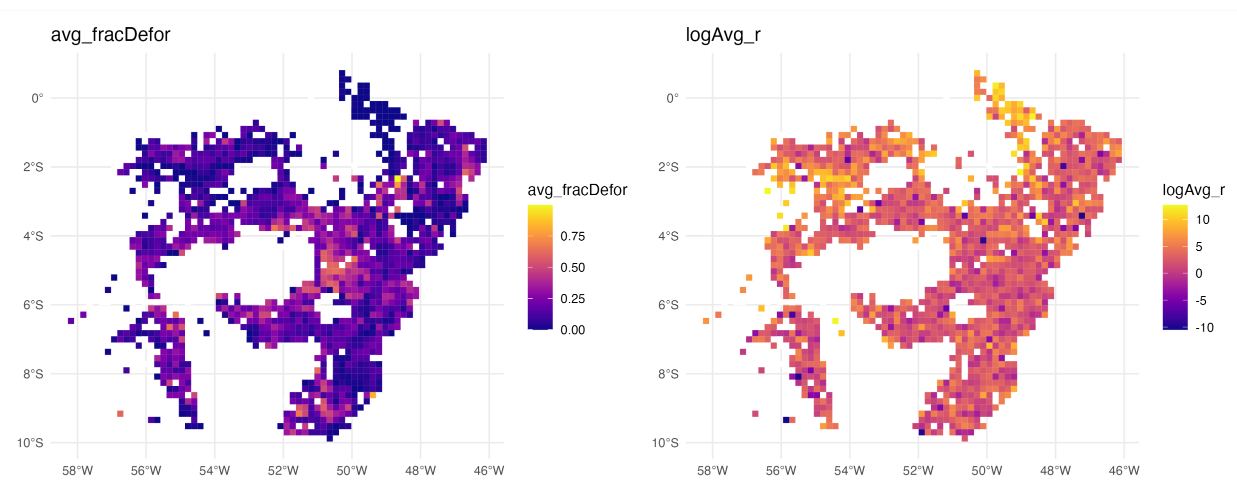

Figure 15: Spatial distribution of baseline farm-level rental rates (log), SWITCH.

	Dep. Var: Share sold to each buyer type			
	(1)	(2)	(3)	(4)
Defor. Frac. since 2009 x To Farm	-0.05^{***}	-0.06^{***}	0.16^{***}	0.15^{***}
	(0.01)	(0.01)	(0.03)	(0.03)
Defor. Frac. since 2009 x To non ZDC sh	-0.17^{***}	-0.32^{***}	0.34	0.33
	(0.05)	(0.06)	(0.18)	(0.18)
Defor. Frac. since 2009 x To ZDC sh	-0.68^{***}	-0.60^{***}	-0.01	-0.02
	(0.07)	(0.09)	(0.22)	(0.22)
Defor. Frac. 2003-2009 x To Farm		0.09^{***}		
		(0.02)		
Defor. Frac. 2003-2009 x To non ZDC sh		0.10		
		(0.12)		
Defor. Frac. 2003-2009 x To ZDC sh		-0.23		
		(0.15)		
Origin cell x Buyer Type x Year FE	X	X	X	X
Land Use Controls x Buyer Type FE		X		X
Seller x Buyer Type FE			X	X
Num. Obs	513610	423651	291631	289452
Num. Origin cell x Buyer Type x Year	12524	12209	12524	12375
Num. Seller x Buyer Type			62035	61628

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

Table 4: Fixed Effects Poisson Regression, D=20 km

	Dep. Var: Any sales to Buyer Type			
	(1)	(2)	(3)	(4)
Defor. Frac. since 2009 x To Farm	-0.07^{***}	-0.09^{***}	0.15^{***}	0.14^{***}
	(0.01)	(0.01)	(0.03)	(0.03)
Defor. Frac. since 2009 x To non ZDC sh	-0.24^{***}	-0.36^{***}	0.28^{*}	0.27
	(0.04)	(0.05)	(0.14)	(0.14)
Defor. Frac. since 2009 x To ZDC sh	-0.72^{***}	-0.66^{***}	-0.07	-0.08
	(0.07)	(0.07)	(0.17)	(0.17)
Defor. Frac. 2003-2009 x To Farm		0.09^{***}		
		(0.02)		
Defor. Frac. 2003-2009 x To non ZDC sh		0.21^{*}		
		(0.10)		
Defor. Frac. 2003-2009 x To ZDC sh		-0.07		
		(0.13)		
Origin cell x Buyer Type x Year FE	X	X	X	X
Land Use Controls x Buyer Type FE		X		X
Seller x Buyer Type FE			X	X
Num. Obs	513610	423651	291631	289452
Num. Origin cell x Buyer Type x Year	12524	12209	12524	12375
Num. Seller x Buyer Type			62035	61628

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

Table 5: Fixed Effects Poisson Regression, D=20 km

	Dep. Var: Number of buyers of each type			
	(1)	(2)	(3)	(4)
Defor. Frac. since 2009 x To Farm	-0.17^{***}	-0.16^{***}	0.14^{***}	0.14^{***}
	(0.02)	(0.03)	(0.04)	(0.04)
Defor. Frac. since 2009 x To non ZDC sh	-0.27^{***}	-0.39^{***}	0.31^{*}	0.30^{*}
	(0.05)	(0.06)	(0.14)	(0.14)
Defor. Frac. since 2009 x To ZDC sh	-0.77^{***}	-0.72^{***}	-0.02	-0.03
	(0.07)	(0.07)	(0.17)	(0.17)
Defor. Frac. 2003-2009 x To Farm		0.12^{**}		
		(0.04)		
Defor. Frac. 2003-2009 x To non ZDC sh		0.21		
		(0.11)		
Defor. Frac. 2003-2009 x To ZDC sh		-0.08		
		(0.15)		
Origin cell x Buyer Type x Year FE	X	X	X	X
Land Use Controls x Buyer Type FE		X		X
Seller x Buyer Type FE			X	X
Num. Obs	513610	423651	291631	289452
Num. Origin cell x Buyer Type x Year	12524	12209	12524	12375
Num. Seller x Buyer Type			62035	61628

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

Table 6: Fixed Effects Poisson Regression, D=20 km