Efficiency and Redistribution in Environmental Policy: An Equilibrium Analysis of Agricultural Supply Chains

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Abstract

This paper provides an equilibrium framework to evaluate environmental policy in trade-exposed industries with imperfectly competitive supply chains. The empirical setting is the South American agricultural sector, a global agricultural powerhouse with a major environmental impact. On the supply side, I address key margins determining emissions: how much land farmers choose to deforest, which commodity they choose to produce, and the geographic location where deforestation and production take place. On the demand side, I allow for market power along the supply chain: farmers’ access to consumers is intermediated by a monopolistic agribusiness sector. Given the infeasibility of a first-best carbon tax, I use my framework to evaluate feasible alternatives, such as environmental tariffs on imports from South America. Unless all trading partners regulate their imports, emissions reductions achieved by regulated markets are mostly offset by increased trade flows to non-regulated markets. Apart from being ineffective, unilateral tariffs have regressive distributional effects across space, as farmers in the poorest regions, where supply is most inelastic, disproportionately bear the burden of regulation through lower farm-gate prices. Finally, agribusiness market power exacerbates the ineffectiveness and regressivity of the policy. Thus, policies aimed at correcting a single externality can interact with other market distortions—affecting their performance not only in efficiency terms, but also in how they skew the distribution of the remaining surplus.

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1 Introduction

Many of the major industries contributing to climate-change produce goods that are tradable and are subject to distortions beyond the environmental externality, market power being a case in point. How can we regulate such industries efficiently, and what are the distributional consequences of regulation? This paper provides an equilibrium framework to evaluate environmental policy in trade-exposed industries with imperfectly competitive supply chains. The empirical setting is the South American agricultural sector, a global agricultural powerhouse with a major environmental impact, whose trade flows are intermediated by a concentrated agribusiness sector. On the supply side, I address key margins determining emissions: how much land farmers choose to deforest, which commodity they choose to produce, and the geographic location where deforestation and production take place. On the demand side, I allow for market power along the supply chain: farmers’ access to consumers is intermediated by a monopsonistic agribusiness sector. I combine both sides to evaluate the equilibrium effects of environmental policy in agricultural supply chains, taking into account efficiency and distributional implications.

In the agricultural sector, first-best carbon taxes on farmers are largely absent, in large part due to their political infeasibility. Given this constraint, I consider alternatives that have been realistically discussed, such as environmental tariffs on agricultural imports from South America. Such regulations perform poorly on efficiency grounds if only a subset of trading partners regulate their imports, because emissions reductions achieved by this subset are offset by increased trade flows to non-regulated markets in equilibrium. In terms of redistribution, I find such a policy has regressive effects across space, as farmers in the poorest regions, where supply is most inelastic, disproportionately bear the burden of environmental regulation through lower farm-gate prices. Furthermore, market structure plays a role: agribusiness market power exacerbates the ineffectiveness and regressivity of the policy. First, due to incomplete pass-through, quantities drop less, and so do emissions. Second, farm-gate prices drop less nominally under imperfect competition, but their initial pre-tariff level is also lower, leading to a higher implied tax rate on farmer income. Thus, policies aimed at correcting a single externality can interact with other market distortions— affecting their performance not only in efficiency terms, but also in how they skew the distribution of the remaining surplus.

Agricultural greenhouse gases account for 26% of world emissions (Poore and Nemecek, 2018). Despite being a crucial item on the sustainable-development agenda, environmental policy in agriculture is constrained for several reasons. First, the distributional effects of an agricultural carbon tax are regressive on both demand and supply: poor households spend a larger share of their income on food, and farmers often lie at the bottom of the income distribution. Second, agricultural commodities are traded in highly integrated global markets, resulting in substantial “leakage” risk: if one country unilaterally regulates its imports from a polluting exporter, the goods are diverted to non-regulated markets and the environmental externality remains uncorrected. Third, agricultural supply chains in developing countries are often unintegrated, typically consisting of
atomistic farmers selling their output to a concentrated intermediary sector (Bergquist and Dienerstein, 2020; Chatterjee, 2019; Rubens, 2019; Dhingra and Tenreyro, 2020). Monopsony power of intermediaries over farmers, especially in remote agricultural regions, introduces an additional market imperfection on top of the environmental externality. To evaluate environmental policy in this setting, I develop an equilibrium model of agriculture with the following features: a supply side with rich spatial heterogeneity that incorporates the key margins driving agricultural emissions, international trade to capture leakage effects, and market power of agribusiness firms over farmers. I now proceed to describe each feature in detail.

First, I present a model of land use incorporating two crucial margins driving the environmental impact of agriculture: an extensive margin of converting natural forested land into new agricultural land, and the choice of which specific agricultural commodity is produced on existing agricultural land. Disentangling the two is critical to evaluate policies operating through one margin but not the other, for example, commodity-blind deforestation fines versus commodity-specific subsidies. However, existing work typically focuses on a single margin at a time. On the one hand, a recent trade literature uses the Ricardian framework of Eaton and Kortum (2002) to study the determinants of the spatial distribution of agricultural activity, but abstracts from the extensive margin since environmental consequences, such as those arising from deforestation, are not their object of study (Costinot, Donaldson and Smith, 2016; Pellegrina, 2019; Sotelo, 2020). On the other hand, a recent applied microeconomics literature on land-use change addresses the extensive margin, but abstracts from the mechanisms by which specific agricultural commodities are allocated to the cleared land (Scott, 2013; Souza-Rodrigues, 2019). I simultaneously incorporate both margins by modeling farmers’ land use decisions as a nested choice problem, with a natural land use nest and an agricultural land use nest. Within the agricultural nest, the model collapses to the Ricardian framework and the substitution patterns between commodities map to trade elasticities, while substitution patterns across nests map to land-use change elasticities. Thus, my land use model incorporates two crucial margins driving agricultural emissions within a unified framework—how much land is cleared and what gets produced on the cleared land—while delivering empirical results consistent with existing work estimating each margin separately.

Second, I allow for market power on the demand side by having farmers’ access to consumers intermediated by a monopsonistic agribusiness sector. The farm-gate prices farmers receive are therefore marked down from the marginal revenue they generate for the agribusiness firm, with the size of the markdown depending on the supply elasticity of farmers. Because carbon tax proposals in this sector typically suggest levying the tax at the downstream stage of the supply chain on the agribusiness firms, rather than on the farmers, market structure matters to quantify the extent to which such taxes are passed through to the upstream farmers who ultimately make the environmentally-relevant decisions. Finally, consumers at the end of the supply chain are located in domestic as well as foreign markets, which opens the door for emissions leakage from incomplete regulation. Leakage arises when an incomplete coalition of trading partners regulates emissions-intensive imports with environmental tariffs. In equilibrium, prices drop and the
goods are diverted to the non-participating trading partners, or simply back to the domestic South American market, with emissions levels and deforestation rates mostly unaffected.

Apart from understanding how market power reduces the effectiveness of such policies due to incomplete pass-through, I focus especially on how it affects the distributional effects on farmers. This stands in contrast to previous studies of environmental policy under imperfect competition, where market power is exercised by firms on downstream consumers and the question is how different regulations rank along efficiency grounds (Ryan, 2012; Fowlie, Reguant and Ryan, 2016). Instead, I focus on how firms exercise market power on upstream farmers, opening a distributional channel on the supply side that stands in contrast to most work on carbon tax incidence on demand (Bento, 2013). Understanding supply-side distributional effects is first order in this setting because agricultural policy is often designed with redistribution toward farmers as an explicit goal, thus posing a major constraint in advancing environmental regulation.

Finally, I exploit the spatial structure of my model to highlight the unique challenges agriculture presents when it comes to emissions regulation and the implications for choosing between market-based and command-and-control policy tools. In agriculture, direct regulation at the externality’s source is logistically difficult because of how dispersed the sources of the emissions are across millions of farmers, in contrast to the manufacturing or power generation sectors, where emissions from the burning of fossil fuels are typically concentrated among a few large firms. Hence, market-based tools such as carbon taxes are especially attractive in agriculture because they avoid the high implementation and enforcement costs of command-and-control policies, but they are not typically levied on the farmers whose incentives they aim to correct. Instead, existing proposals suggest implementing the corrective tax where the supply chain becomes more concentrated—downstream on the agribusiness firms at the port of export—because enforcement is easier and it can be implemented at low administrative cost as an export tax. Market structure therefore matters for how such taxes are passed through to the upstream farmers who ultimately make the environmentally-relevant decisions. Furthermore, such taxes can be blunt due to their lack of spatial targeting. Because of difficulties in tracing the origin of the commodities once they arrive at the port, a national average emissions footprint is typically assumed to determine the size of the corrective tax, regardless of whether the commodities were produced on land with high or low carbon density. Therefore, the extent to which such a market-based policy is spatially mis-targeted is increasing in the degree of spatial heterogeneity of carbon density. Through counterfactuals, I show targeted command-and-control policies that are restricted to a subset of high-carbon locations can dominate market-based policies when such heterogeneity is wide enough.

Related literature. First, I link a trade literature that studies how comparative advantage shapes the spatial distribution of agriculture (Costinot et al., 2016; Pellegrina, 2019; Sotelo, 2020) to a recent land-use change literature in agricultural economics and empirical IO (Berry and Schlenker, 2011; Roberts and Schlenker, 2013; Scott, 2013; Souza-Rodrigues, 2019). The trade literature studies how different commodities are allocated across existing agricultural land, but abstracts from the extensive margin of land conversion. By contrast, the land-use change studies, in particular
the ones relying on structural methods, typically model the land-use change margin as binary—
land is either left in its natural forested state, or used for agriculture broadly defined—but ab-
stracts from which specific commodities are produced. The trade literature’s implied land-use
change elasticities are significantly higher than those from the land use studies, in part because
they are estimated from substitution patterns across commodities on already cleared land, where
switching costs might be lower than along the extensive margin. I incorporate both margins by
modeling farmers’ decisions as a nested choice problem, and I show how this can reconcile the rel-
atively high substitution elasticities between commodities estimated by the trade literature with
the relatively low land-use change elasticities from the land-use change studies.

Second, this paper relates to a large literature at the intersection of trade and climate change. I
use similar quantitative trade methods as a strand of this work studying adaptation mechanisms
to climate change (Costinot et al., 2016; Balboni, 2019; Conte, 2020; Nath, 2020; Alvarez and Rossi-
Hansberg, 2021). However, I focus on how trade policies can be used to curb a specific sector’s
climate change impact, rather than how the damages from climate change can be mitigated by
trade. In this regard, this paper relates to an extensive body of work on the use of trade policy
as environmental regulation (Copeland and Taylor, 1994; Antweiler, Copeland and Taylor, 2001;
Nordhaus, 2015; Kortum and Weisbach, 2017; Harstad, 2012; Farrokhi and Lashkaripour, 2021;
Hsiao, 2021), but departs in two specific ways. The first is the within-country analysis, which
stems from markets being defined at a sub-national level. This allows for rich spatial heterogene-
ity in the effectiveness and incidence of environmental policy, which is crucial in my agricultural
setting because geography is a key dimension along which agricultural productivity and the en-
vironmental externality vary. By contrast, most studies define markets at a global level between
countries, limiting the analysis of a policy’s effectiveness and incidence at a sub-national level.
Within-country incidence is especially important for understanding the internal political econ-
omy constraints governments face when choosing to implement domestic environmental regu-
lations. The second departure is the imperfectly competitive setting, and in particular having
market power on the demand side. I incorporate this in my model in a way that nests the per-
fectedly competitive case in order to alternate between conduct assumptions, and thus evaluate how
market structure alters the effects of market-based environmental policy.

Third, this paper contributes to a literature at the intersection of industrial organization and en-
vironmental economics going back at least to Buchanan (1969), with empirical research appearing
fairly recently (Fowlie, 2009; Ryan, 2012; Fowlie et al., 2016). In such studies, firms exercise market
close|downstream on consumers, and the question is how to design environmental policy along
efficiency criteria. I contribute to this literature by considering the case where firms exercise mar-
ket power upstream on their suppliers: the farmers. In doing so, I open a distributional channel on
the supply-side, whereas most work on environmental policy incidence focuses on downstream
effects across consumers (Bento, Goulder, Jacobsen and Von Haefen, 2009; Fabra and Reguant,
2014; Reguant, 2019). Furthermore, the imperfectly competitive setting of the paper relates to a re-
cent literature on intermediaries and market power in the developing world, much of which takes
place in agricultural markets (Antras and Costinot, 2011; Atkin and Donaldson, 2015; Bergquist and Dinerstein, 2020; Chatterjee, 2019; Méndez-Chacón and Van Patten, 2019; Rubens, 2019; Dhingra and Tenreyro, 2020; Zavala, 2021). Similar to these recent studies, this paper is concerned with how market power affects not only efficiency, but also the division of surplus. However, to the best of my knowledge, none of this work studies how market power in developing world agriculture matters for environmental regulation.

2 Data

I construct a county-level panel of agricultural supply and demand from 1995-2017 by combining multiple data sources from Argentina and Brazil. The supply side consists of a county-level panel of land use, agricultural output, agronomic productivity, and farm-gate prices for the most environmentally relevant commodities: beef, soybeans, maize, wheat, rice, sunflower, and sugarcane. These commodities account for over 85% of all agricultural land in Argentina and Brazil. For the demand side, I connect each county’s production to its country-level destination markets using trade flow data. Summaries for each data source are listed below.

**Geographic unit of analysis.** The smallest administrative unit at which the data is available for Argentina is a department (“partido”), while for Brazil it is a municipality (“município”). Brazilian municipalities and their borders have changed over time, so comparing municipality-level outcomes across different periods requires the use of time-consistent spatial units. I follow the procedure from Ehrl (2017) to construct such units, known as “Áreas Mínimas Comparáveis” (AMC). Throughout the paper, the use of the term “counties” corresponds to Argentine departments and Brazilian AMCs.

**Agronomic productivity.** Data on agricultural productivity for the world’s major crops is available from the Food and Agriculture Organization’s Global Agro-Ecological Zones project (FAO-GAEZ) at 5 arc-minute resolution (approximately a $10 \times 10$ km grid cell) for over one million grid cells around the globe (IIASA/FAO, 2012). Agricultural productivity is measured as potential yields predicted by an agronomic model based on agro-climatic fundamentals. The model’s parameters are estimated from field and lab experiments in the agronomic literature, and its specific inputs are: soil characteristics, land gradient, elevation, temperature, rainfall, and sun exposure.

**Land-use.** County-level data on forested area, agricultural area, and pasture area are from the agricultural censuses of Argentina and Brazil. For Argentina, the source is the National Statistical Institute (INDEC) and for Brazil it is the Brazilian Institute of Geography and Statistics (IBGE). The Brazilian census also reports acreage allocated to individual crops. For Argentina, I obtain individual crop acreage from the Ministry of Agriculture’s “Datos Agroindustriales” database (DA-MAGYP).

**Agricultural output.** County-level crop and livestock production for Argentina is from the agricultural census, DA-MAGYP, and the registry of livestock producers at the National Food Safety
Agency (SENASA). For Brazil I use the agricultural census, which I complement with higher-frequency municipal survey data from Produção Agrícola Municipal (PAM) and Pesquisa da Pecuária Municipal (PPM).

**Trade flows.** International trade flows of agricultural commodities at the country-to-country level are obtained from FAOSTAT. To determine sourcing within Argentina and Brazil I use supply chain data from TRASE. This data is constructed from customs records and maps trade flows (in physical quantities and port of export FOB values) from source counties to destination markets, as well as to the agribusiness firms intermediating the transactions.

**Prices.** Farm-gate prices of crops and cattle are obtained from production quantity and value data. For Brazil, the sources are PAM and the agricultural census. For Argentina, I use cattle transaction microdata from DA-MAGYP that directly reports transaction prices. Destination prices are obtained from the TRASE data on quantities and values.

**Emissions.** I compute land-use change emissions from biomass data at 300m spatial resolution from the Global Aboveground and Belowground Biomass Carbon Density Maps compiled by Spawn and Gibbs (2020) and available at NASA Earthdata. To compute emissions footprints across commodities I use data from Poore and Nemecek (2018) and Clark, Domingo, Colgan, Thakrar, Tilman, Lynch, Azevedo and Hill (2020).

**Weather shocks.** Data on extreme temperatures at the country level are from FAOSTAT. I construct local county-level weather data from the National Centers for Environmental Prediction’s Climate Forecast System Reanalysis (CFSR) database.

### 3 Stylized facts

First, I introduce the environmental science facts that indicate which economic decision margins are most relevant for determining agricultural emissions. Second, I introduce the main economic and institutional features of the markets I study—the agricultural sectors of Argentina and Brazil. Third, I describe how both environmental and economic facts are incorporated into my model.

**Fact 1: Agricultural emissions are determined along three key margins**

Agriculture is responsible for 26% of anthropogenic emissions (Poore and Nemecek, 2018). This paper addresses three crucial margins driving the sector’s emissions:

i. *How much land is cleared.* Over 80% of agricultural emissions are generated before the commodities leave the farm-gate, mostly due to land-use change and on-farm input use (Figure 1). This contrasts with other high-emissions sectors of the economy, where the main emissions source is the burning of fossil fuels for energy use.

ii. *Which commodity is produced on the cleared land.* Emissions footprints vary widely across agricultural commodities, even after taking into account differing land requirements (Figure 1).
For example, beef contains 25 times more CO$_2$e/kg of protein than plant-based high-protein alternatives. Substantial variation exists even among plant-based commodities, with rice generating twice as much CO$_2$e/kcal than wheat and three times as much as maize.

iii. Where the clearing and producing takes place. Emissions footprints vary widely across space, as reflected by the uneven geographic distribution of carbon stocks that would be potentially released into the atmosphere from land clearing (Figure 2).

For South America specifically, agricultural emissions have fluctuated around 2 billion metric tons (BMT) annually since 1990, representing approximately 20% of the world’s annual agricultural emissions (FAOSTAT). To place this in perspective, such magnitudes exceed those of any major sector of the US economy in 2018 (EPA): industry (1.5 BMT), electricity (1.8 BMT), or transportation (1.9 BMT). South American agricultural emissions are therefore comparable to those of fossil-fuel intensive sectors typically targeted by environmental agencies in industrialized economies.

Figure 1: Emissions footprints and sources for different food products.

Notes: Figures are constructed using data on food emissions footprints from Poore and Nemecek (2018).
Fact 2: International demand is a major driver of South American land use trends

In Argentina and Brazil, the agricultural sector’s most salient feature over the past half-century has been the dramatic expansion of soybean production. Before 1980, soybean acreage was the lowest of any major crop, yet by 2005 it exceeded all other major crops combined (Figure 3). Growing international demand, especially from Asia, has been a major driver behind such trends: over 70% of soybean output is exported, with over 50% of exports going to Asia (FAOSTAT).

Notes: Figures are constructed using data on carbon densities from Spawn and Gibbs (2020).

Notes: By 2017, 91% of all planted land in Argentina was concentrated among four crops: soybeans (46%), maize (24%), wheat (16%), and sunflower (5%). By 2017, 85% of all planted land in Brazil was concentrated among four crops: soybeans (44%), maize (21%), sugarcane (11%), beans (4%), wheat (3%), and rice (2%). Sources: DA-MAGYP (Argentina) and CONAB (Brazil).
Figure 4: Changes in land allocated to soybeans, pasture, and forest (1995-2017).

**Brazilian counties**
- Soybean expansion $\not\Rightarrow$ deforestation
- Soybean expansion $\Rightarrow$ displaced pasture
- Displaced pasture $\Rightarrow$ deforestation

**Argentine counties**
- Soybean expansion $\not\Rightarrow$ deforestation
- Soybean expansion $\Rightarrow$ displaced pasture
- Displaced pasture $\Rightarrow$ deforestation
Fact 3: Agricultural activities compete with each other in local land markets

Over the past three decades, soybean expansion has increased competition for land. Cattle grazing has shifted from the most soybean-suitable areas (central-south Brazil and mid-east Argentina) to cheaper land markets in frontier agricultural regions (north Brazil and Argentina), which is where the forests lie. Hence, although soybean expansion may not directly lead to deforestation, it may do so indirectly by displacing land-intensive cattle grazing to the agricultural frontier (Figure 4). Accounting for interactions between agricultural commodities is therefore crucial for understanding deforestation in the South American context.¹

Fact 4: Atomistic farmers face a concentrated sector of agribusiness buyers

Farmers do not access consumer markets directly. Instead, they sell their output to intermediating agribusiness firms. In the case of the Brazilian beef market, 2.4 million upstream ranching establishments raise cattle, which they sell downstream to a concentrated agribusiness sector. In the median county, the top three agribusiness firms account for 95% of sourced beef, with the top firm accounting for over 60% (Table 1). JBS, the industry leader, was responsible for 36% of purchases nationwide, sourcing from 46% of all counties with a median local market share of 28% (Table 2).

Table 1: Agribusiness concentration measures (2017).

<table>
<thead>
<tr>
<th>Brazil</th>
<th>Argentina</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Beef</td>
</tr>
<tr>
<td>Number of agricultural establishments (sellers)</td>
<td>2457512</td>
</tr>
<tr>
<td>Number of agribusiness firms (buyers)</td>
<td>118</td>
</tr>
<tr>
<td>Number of source counties</td>
<td>2803</td>
</tr>
<tr>
<td>Number of destination countries</td>
<td>130</td>
</tr>
<tr>
<td>CR-1 (national market)</td>
<td>0.36</td>
</tr>
<tr>
<td>CR-3 (national market)</td>
<td>0.69</td>
</tr>
<tr>
<td>CR-1 (local market, median)</td>
<td>0.63</td>
</tr>
<tr>
<td>CR-3 (local market, median)</td>
<td>0.95</td>
</tr>
<tr>
<td>Share of source counties with 1 agribusiness firm</td>
<td>0.13</td>
</tr>
</tbody>
</table>

Sources: 2017-2018 agricultural censuses and TRASE. Local markets are defined at the county-level.

Figure 5 shows how agribusiness concentration varies across space and how it correlates with a proxy measure of a markdown—the ratio of the farm-gate price received by the farmer with respect to the price the agribusiness firm receives at the port. The stylized fact is that farm-gate prices are subject to wider markdowns in locations with higher concentration. It is worth stressing this finding should not be interpreted as a causal relationship from market concentration to market outcomes. Concentration is itself a market outcome, and just like prices and markdowns it

¹The extent to which interactions between different commodities matter for deforestation is context-specific. For example, in the Indonesian context, deforestation is driven almost entirely and directly by a single commodity (palm oil), so abstracting from such interactions would seem reasonable (Hsiao, 2021).
Table 2: Major agribusiness firms (2017).

<table>
<thead>
<tr>
<th>Country</th>
<th>Commodity</th>
<th>Firm</th>
<th>Market share of firm</th>
<th>Counties sourced by firm</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td>National</td>
<td>Local*</td>
</tr>
<tr>
<td>Brazil</td>
<td>Beef</td>
<td>Jbs</td>
<td>0.36</td>
<td>0.28</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Marfrig</td>
<td>0.18</td>
<td>0.30</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Minerva</td>
<td>0.15</td>
<td>0.19</td>
</tr>
<tr>
<td>Maize</td>
<td>Cargill</td>
<td>0.18</td>
<td>0.47</td>
<td>50</td>
</tr>
<tr>
<td></td>
<td>Bunge</td>
<td>0.16</td>
<td>0.32</td>
<td>45</td>
</tr>
<tr>
<td></td>
<td>Amaggi</td>
<td>0.12</td>
<td>0.32</td>
<td>34</td>
</tr>
<tr>
<td>Soybean</td>
<td>Bunge</td>
<td>0.16</td>
<td>1.00</td>
<td>176</td>
</tr>
<tr>
<td></td>
<td>Cargill</td>
<td>0.14</td>
<td>1.00</td>
<td>194</td>
</tr>
<tr>
<td></td>
<td>Adm</td>
<td>0.13</td>
<td>0.93</td>
<td>100</td>
</tr>
<tr>
<td>Argentina</td>
<td>Soybean</td>
<td>Vicentin</td>
<td>0.13</td>
<td>0.13</td>
</tr>
<tr>
<td></td>
<td>Cargill</td>
<td>0.12</td>
<td>0.09</td>
<td>190</td>
</tr>
<tr>
<td></td>
<td>Bunge</td>
<td>0.12</td>
<td>0.11</td>
<td>182</td>
</tr>
</tbody>
</table>

*The reported local market share is the firm’s median share across all the counties it sources from.

is determined by supply and demand primitives (Bresnahan, 1989). Moreover, the correlation between concentration and markups can be positive or negative depending on how such primitives are chosen (Syverson, 2019).

Figure 5: Agribusiness concentration (beef, Brazil, 2017).

Modeling implications

Fact 1 suggests deforestation, commodity choice, and the geographic location of production are crucial margins determining agricultural emissions. Therefore, I propose a model where farmers

2Higher concentration is associated with higher profit margins in models with a fixed number of firms, such as the standard Cournot model. However, if we allow entry the relationship can be reversed: markets with low profit margins can be highly concentrated because the gains for potential entrants are too small to justify entry.
make decisions along two separate margins: first, they decide how much of their land to clear, and second, they decide which specific commodity to produce on the cleared land. Furthermore, the model has internal geography in order to incorporate spatial heterogeneity in agriculture’s productivity and its environmental cost. Fact 2 suggests international demand shocks are an important driver of farmers’ land use decisions, and hence trade policy can serve as environmental policy. I therefore allow for output to be purchased by both domestic and international consumers, which opens the door for carbon leakage from incomplete regulation. Fact 3 suggests different commodities interact with each other by competing for land—in particular, they compete in local land markets because land is non-tradable. Thus, positive demand shocks for a specific commodity increase land prices in locations suitable for the commodity, displacing production of other commodities to locations with cheaper land. I incorporate this by allowing farmers to choose among different commodities, as mentioned previously, and also by having commodity markets clear locally at the county-level. Fact 4 suggests agribusiness firms might plausibly hold buyer market power over farmers, and the extent of such market power may vary across space. Therefore, I model agribusiness firms as oligopsonists in local upstream markets. I do so in a way that nests the perfectly competitive case in order to alternate between conduct assumptions, and thus evaluate how market structure alters the effects of environmental policy.

4 Model

On the supply side, atomistic farmers choose between leaving their land in its natural forested state or converting it to agriculture and producing a specific commodity. Final demand consists of consumers distributed across domestic and foreign markets. However, farmers do not access consumer markets directly, they instead sell their output to intermediating agribusiness firms.

4.1 Supply side: Farmers

Land use decision. Each county \( i \) contains a continuum of fields indexed \( \omega \). Each field \( \omega \) is owned by a farmer, who chooses a land use from a discrete choice set consisting of a natural-use option \( \mathcal{N} \) and a nest of agricultural commodities \( \mathcal{C} \). Field \( \omega \)'s output of commodity \( c \in \mathcal{C} \) is,

\[
Q_c^\omega = A_c^\omega L_c^\omega \quad \text{with} \quad A_c^\omega = A_c^\omega \exp(\varepsilon_c^\omega(\omega)),
\]

where \( A_c^\omega(\omega) \) is the field’s productivity in commodity \( c \) and \( L_c^\omega(\omega) \) is its size. A field’s productivity is decomposed into a county-level mean \( A_c^\omega \) and a field-level idiosyncratic shock \( \varepsilon_c^\omega(\omega) \). If \( p_c \) is the commodity’s farm-gate price, then the payoff per unit of land allocated to commodity \( c \) is \( p_c^\omega A_c^\omega(\omega) \). Let \( A_c^N(\omega) \) denote the payoff per unit of land left in its natural state, which is also decomposed into a county-level mean \( A_c^N \) and a field-level idiosyncratic shock \( \varepsilon_c^N(\omega) \).

Payoff from natural use. The payoff from allocating land to a commodity \( c \) is market-based and observable from data: it is a dollar-value constructed from market prices and yields. This differs
from the payoff to natural use because farmers are generally not paid to keep their land forested, and even in cases in which they are, we typically don’t have comprehensive data on such payments. Therefore, the interpretation of $A_N^{i*}(\omega)$ is that it captures the dollar-value of any incentives to preserve forests that are unobserved to the econometrician. Such incentives may be pecuniary or non-pecuniary, and static or dynamic. Examples of static incentives are: the aesthetic value of trees to landowners, unobserved forestation payments, or non-pecuniary benefits (e.g., prevention of soil erosion), as in Souza-Rodrigues (2019). An example of a dynamic incentive is the option value of deforesting in the future, as in Scott (2013).

**Nesting assumption.** The key nesting assumption is that the field-level idiosyncratic shocks are correlated between agricultural commodities, but not between a commodity and the natural-use option. There are two crucial parameters to keep track of: $\theta$ governs the dispersion of shocks across fields, while $\lambda \in (0, 1)$ governs the correlation of shocks between commodities. Higher values of $\theta$ correspond to lower dispersion across fields, and higher values of $\lambda$ correspond to lower correlation between commodities.\(^3\) Under these distributional assumptions, the probability commodity $c$ is chosen, conditional on the farmer choosing the agricultural nest $C$, is given by,

$$\pi_{i}^{c|C} = \frac{(p_{i}^{c} A_{i}^{c})^{\frac{\theta}{\lambda}}}{\sum_{c' \in C} (p_{i}^{c'} A_{i}^{c'})^{\frac{\theta}{\lambda}}} \tag{2}$$

while the choice probability of the agricultural nest $C$ is,

$$\pi_{i}^{C} = \frac{(PC_{i})^{\lambda}}{(A_{i}^{N})^{\theta} + (PC_{i})^{\lambda}} \quad \text{with} \quad PC_{i} \equiv \sum_{c' \in C} (p_{i}^{c'} A_{i}^{c'})^{\frac{\theta}{\lambda}}. \tag{3}$$

$PC_{i}$ is defined as the payoff of the agricultural nest as a whole, since it is an index comprising the returns of all the nest’s commodities—technically, $\ln PC_{i}$ is the nest’s inclusive value in the nested logit model. The share allocated to natural use is $\pi_{i}^{N} = 1 - \pi_{i}^{C}$. The nested structure implies the unconditional choice probabilities, which map to land shares in the data, can be written as $\pi_{i}^{c} = \pi_{i}^{c|C} \pi_{i}^{C}$. If the county’s total surface is $\bar{L}_{i}$, then the county’s total acreage of commodity $c$ is

\(^3\)Formally, we have a nested logit model of land-use with the following log returns per hectare of land,

$$r_{i}^{k}(\omega) = \begin{cases} \theta \ln (p_{i}^{c} A_{i}^{c}) + \epsilon_{i}^{c}(\omega)^* & \text{if } k = c \in C \\ \theta \ln (A_{i}^{N}) + \epsilon_{i}^{N}(\omega)^* & \text{if } k = N. \end{cases}$$

$\epsilon_{i}^{c}(\omega)$ is distributed type I EV with location parameter 0 and standard deviation $\sigma \frac{\pi}{\sqrt{6}}$, which is equivalent to having $A_{i}^{c}(\omega)$ distributed type II EV (Fréchet) with location parameter 0, scale parameter $\Gamma (1 - \sigma^{-1}) A_{i}^{c}$ and shape parameter $\theta \equiv \sigma^{-1}$. Either case implies $E[A_{i}^{c}(\omega)] = A_{i}^{c}$. The type I EV formulation conveniently casts the nested choice problem as a nested logit model. Notice that we have rescaled payoffs by $\sigma^{-1}$, so that $\epsilon_{i}^{c}(\omega)^*$ is a standardized type I EV error: its location parameter is 0 and its standard deviation is $\frac{\pi}{\sqrt{6}}$. \[13\]
\[ L_i^c = \pi_i^c \bar{L}_i. \]

Finally, we have a closed form expression for the county-level supply of commodity \( c \),

\[ Q_i^c = \int_\omega Q_i^c(\omega) d\omega = A_i^c \left( \pi_i^{c|c} \right) \frac{\theta}{\lambda} L_i^c. \] (4)

Notice that as \( \lambda \to 1 \), correlation between commodities goes to zero and the nested model collapses to a multinomial model, a common specification in Ricardian models of agricultural trade (Costinot et al., 2016; Sotelo, 2020). The nested structure is important for my setting, because a multinomial model would restrict substitution between commodities to be just as easy as substitution between natural and agricultural use.\(^4\) First, such restrictions are unrealistic if we expect land clearing to be costlier than switching between commodities on existing agricultural land. Second, disentangling the two margins allows for evaluation of policies operating through one margin but not the other. For example, the substitution margin within the agricultural nest matters for evaluating commodity-specific policies, such as maize-ethanol subsidies. By contrast, the impact of deforestation fines, which are commodity-blind because they disincentivize agriculture as a whole, are determined by the across-nest substitution margin.

**Key supply-side elasticities.** From (4) we can derive the price-elasticity of output,

\[ \frac{\partial \ln Q_i^c}{\partial \ln p_i^c} = \left( \frac{\theta}{\lambda} - 1 \right) \left( 1 - \pi_i^{c|c} \right) + \theta \pi_i^{c|c} \left( 1 - \pi_i^c \right). \] (5)

Notice supply becomes more elastic when \( \theta \to \infty \) or \( \lambda \to 0 \). To understand why, recall \( \theta \) governs the dispersion of productivity across fields: as \( \theta \to \infty \), marginal fields become identical to inframarginal fields, so county-level supply curves become flat. On the other hand, \( \lambda \) governs the correlation of productivity between commodities: as \( \lambda \to 0 \) correlation becomes perfect, implying all fields order their commodity choices in the same way (although the levels of payoffs may differ across fields). Because all fields make the same commodity choice, heterogeneity across fields disappears, and we obtain a flat supply curve at the county-level. Therefore, a highly elastic supply curve can be explained by low dispersion of productivity across fields (high \( \theta \)) or high correlation of productivity between commodities (low \( \lambda \)).

To separate the role of \( \theta \) from \( \lambda \) it is useful to consider the odds ratios within- and across-nests,

\[ \ln \left( \frac{\pi_i^{c|c}}{\pi_i} \right) = \frac{\theta}{\lambda} \ln \left( \frac{p_i^c A_i^c}{p_i^{c'} A_i^{c'}} \right) \quad \text{and} \quad \ln \left( \frac{\pi_i^c}{\pi_i} \right) = \lambda \ln \left( \sum_{c \in C} \left( \frac{p_i^c A_i^c}{A_i^N} \right) \frac{\theta}{\lambda} \right). \] (6)

The elasticity of substitution within-nest, \( \frac{\theta}{\lambda} \), can be high because of low dispersion across fields (high \( \theta \)) or high correlation of productivity between commodities (low \( \lambda \)) for the reasons mentioned in the preced-
The elasticity of substitution across nests, which we interpret as the deforestation elasticity, is equal to $\lambda$. What is the intuition for why $\lambda$, the correlation of productivity between commodities, is connected to the deforestation elasticity? As $\lambda \to 0$ the correlation across commodities increases, hence the within-nest heterogeneity falls relative to the across-nest heterogeneity. As fields become relatively more heterogeneous along the across-nest margin, county-level supply curves (of agriculture as a whole) become less elastic, i.e., the deforestation elasticity falls. To conclude, consider the deforestation elasticity in terms of levels rather than shares, i.e., how the amount of land allocated to the agricultural nest, $L^C_i$, responds to the payoff of agriculture as a whole, rather than to the payoff of any individual commodity. To do so, we use $P^C_i$ from equation 3 as the “price” of the agricultural nest, and then derive the “price”-elasticity of agricultural land,

$$\frac{\partial \ln L^C_i}{\partial \ln P^C_i} = \lambda(1 - \pi^C_i).$$ (7)

Since increases in $L^C_i$ necessarily reduce natural land use, 7 can be interpreted as a deforestation elasticity. As mentioned before, the parameter governing this across-nest adjustment margin is $\lambda$.

4.2 Demand side: Agribusiness intermediaries and consumers

The demand side consists of two stages along the supply chain. First, agribusiness intermediaries buy commodities from upstream farmers in sources indexed $i \in I$. Second, intermediaries sell the commodity to downstream consumers in destinations indexed $j \in J$. Intermediaries hold market power as buyers in the upstream market, but take prices as given in the downstream market. I abstract from market power of intermediaries as sellers because my data is not rich enough on the downstream market side.

**Agribusiness intermediaries.** There are $N^C_i$ identical intermediary firms purchasing $q^C_i$ units of commodity $c$ from source $i$. Farmers do not perceive the firms as differentiated buyers, hence all firms buy the commodity at the same farm-gate price $p^C_i$. Apart from transporting the commodities from source to destination, we allow firms to add value by transforming the commodity into a processed version (e.g., soybeans into soybean oil) by using a technology $f_c(q^C_i)$. Firms then sell the processed version at the closest port to $i$, obtaining a free-on-board price $\bar{p}^C_i$. Hence, the transport cost from the port to the final destination is paid by final consumers: a destination $j$ consumer pays $p^C_{ij} = \bar{p}^C_i \tau_{ij}^c$, where $\tau_{ij}^c$ is an iceberg trade cost. We can now pose each firm’s maximization problem, taking demand of the other firms as given,

$$\max_{q^C_i} p^C_i f_c(q^C_i) - \bar{p}^C_i (Q_i^C) q^C_i,$$
where \( q^c_i \) is an individual firm’s demand, \( Q^c_i \) is total demand from source \( i \), and \( p^c_i (Q^c_i) \) is source \( i \)’s inverse supply equation. From the first order conditions we obtain the farm-gate price is a fraction \( \mu^c_i \) of the marginal revenue it generates for the intermediary,

\[
\frac{p^c_i}{p^c_i f^c_i(q^c_i)} = \left(1 + \frac{1}{e^c_i N^c_i} \right)^{-1} \quad \text{where} \quad \frac{1}{e^c_i} \equiv \frac{\partial \ln p^c_i}{\partial \ln Q^c_i}.
\]

A farmer from source \( i \) obtains \( \mu^c_i \) cents for every dollar the intermediary makes from the commodity. I define \( \mu^c_i \), the ratio of the input’s price to its marginal revenue, as the “markdown-wedge”. Throughout the rest of the paper, when using the term “markdown” I am referring to this “markdown-wedge”. Intuitively, markdowns follow an inverse-elasticity rule: sources with less elastic supply (higher \( \frac{1}{e^c_i} \)) are subject to larger markdowns (lower \( \mu^c_i \)). Markdowns are also larger in sources with few competing firms (low \( N^c_i \)).

The setup of the intermediary problem is purposefully simple—firms are identical and there is no entry—the goal being to obtain the smallest departure from the perfectly competitive setting typically assumed by the agricultural trade literature as well as to parsimoniously nest it. Perfect competition is obtained by imposing \( \mu^c_i = 1 \), and trade of unprocessed commodities by imposing \( f^c_i(q^c_i) = q^c_i \). In these limiting cases, the farm-gate price is equal to the free-on-board price, and the destination market price is therefore simply the farm-gate price adjusted by trade costs, i.e., \( p^c_{ij} = p^c_i \tau^c_{ij} \). I discuss how the model can be adjusted to admit firm heterogeneity and exit/entry, and the implications of doing so, in Appendix C.2.

**Consumers.** To interpret what destination market “consumers” are in the model, it is worth emphasizing how we measure them in the data. The demand-side data measures how much of a commodity arrives at the destination port, and not how much is purchased by final consumers at the final retail stage. Therefore, “consumers” in this model should be interpreted as the agents in the first stage of the destination market’s supply chain, which are mostly food processing companies that transform the commodity into retail food products.

I model consumers with a three-level CES demand system. In the upper level, they substitute between commodities (e.g., maize vs. wheat). In the middle level, they substitute between source countries of a given commodity (e.g., Brazilian maize vs. US maize). In the lower level, they substitute between counties within a country (e.g., maize from Northern Brazil vs. maize from Southern Brazil). The lower level is necessary to obtain demand at the county-level.

Given our interpretation of what a “consumer” is, the different levels of the CES system should therefore not be interpreted as the degree to which final retail consumers literally differentiate as a matter of taste—indeed, it is unlikely final retail consumers perceive significant quality differences between maize from one county versus another. Instead, the different levels should be interpreted as the degree to which a food processor substitutes inputs across different sources. Hence, the lower-level reflects the degree to which food processors perceive the process of sourcing from one county versus another as differentiated, even if the underlying product being sourced from both
counties is identical. Concretely, I assume each destination \( j \) has a representative consumer with the following three-level CES utility function,

\[
U_j = \left( \frac{\sum_c (a^c_j)^{\frac{1}{\eta_u}} (C_j^c)^{\frac{\eta_m}{\eta_u - 1}})}{\sum_n (a^{n, c}_j)^{\frac{1}{\eta_u}} (C^{n, c}_j)^{\frac{\eta_m}{\eta_u - 1}}} \right)^{\frac{\eta_u}{\eta_u - 1}}, \text{ where } C_j^c = \left( \sum_n (a^{n, c}_j)^{\frac{1}{\eta_u}} (C^{n, c}_j)^{\frac{\eta_m}{\eta_u - 1}} \right)^{\frac{\eta_m}{\eta_u - 1}} \text{ and } C^{n, c}_j = \left( \sum_i (C^i_j)^{\frac{\eta_m - 1}{\eta_m}} \right)^{\frac{\eta_m}{\eta_u - 1}}.
\]

\( C_j^c \) is consumption of good \( c \) aggregated across source countries indexed \( n \). \( C^{n, c}_j \) is consumption of good \( c \) aggregated across source counties indexed \( i \) belonging to country \( n \). \( \eta_u \) is the upper elasticity of substitution between goods, \( \eta_m \) is the middle elasticity of substitution between source countries, and \( \eta_l \) is the lower elasticity of substitution between counties within a country. The \( a \)'s are preference shifters across goods and sources. These preferences deliver the following county-level demand equation,

\[
C^c_{ij} = \left( \frac{p^c_{ij}}{P^c_{nj}} \right)^{\frac{1}{\eta_u}} a^{c, n, j}_i \left( \frac{p^c_{nj}}{P^c_{nj}} \right)^{\frac{1}{\eta_u}} a^c_j \left( \frac{p^c_j}{P_j} \right)^{\frac{1}{\eta_u}} X_j \forall i \in n,
\]

where \( X_j \) is destination \( j \) income, and price indices for each level are defined as follows,

\[
p^c_{nj} \equiv \left( \sum_{i \in n} (p^c_{ij})^{1-\eta_u} \right)^{\frac{1}{1-\eta_u}}, \quad P^c_{nj} \equiv \left( \sum_n a^{c, n, j}_i (P^c_{nj})^{1-\eta_u} \right)^{\frac{1}{1-\eta_u}}, \quad P_j \equiv \left( \sum_c a^c_j (P_j)^{1-\eta_u} \right)^{\frac{1}{1-\eta_u}}.
\]

### 4.3 Equilibrium

An equilibrium is a set of farm-gate prices \( \{p^c_i\}_{i,c} \) such that supply in each county is equal to the total demand from that county, and this holds for every commodity,

\[
Q^c_i(p^c_i) = \sum_j C^c_{ij}(p^c_{ij}) \tau_{ij} \forall i, c, \text{ where } p^c_{ij} = \frac{p^c_{ij}}{\mu^c_j} f^c_j(q^c_{ij}^\mu).
\]

It is worth stressing that market clearing occurs county-by-county, i.e., at a sub-national level. This is key to allow for within-country spatial heterogeneity in the effectiveness and incidence of environmental policy, which is important to take into account for two reasons. First, the carbon tariffs often proposed on imports from South America are uniform—they do not take into account the within-country source of the commodity—and as a result they are spatially mis-targeted because of the wide geographic heterogeneity in carbon footprints within South America. Quantifying the extent to which they are mis-targeted requires understanding how quantities differentially respond to policy across sub-national markets. Second, it is also important to understand how farm-gate prices respond differentially across sub-national markets because it reflects the internal political costs South American governments face when considering self-regulation.

The within-country analysis contrasts with most work in the environmental trade literature, where markets typically clear at the country-level, thus placing a limit on the kind of sub-national
analysis that can be carried out. Even in the subset of studies where supply is modeled at a sub-national level, the equilibrium is not defined at such level. Instead, it is often defined as the set of country-level prices such that each country’s supply aggregated across all its sub-national units equates the international demand for the country as a whole. Hence, the equilibrium prices are country-level prices, limiting a full understanding of the internal distributional effects of policy.  

5 Estimation

In section 4, the model is presented for expositional purposes without time subscripts because it is static. In this section, I explicitly introduce time subscripts because I will combine cross-sectional and temporal variation for estimation. A time period is a decade because that is the frequency of the census data. The observed outcomes across time are therefore interpreted through the lens of the model as a sequence of static equilibria separated by a substantial time lag. The static model is therefore used as a first approximation for studying decisions with relatively long time lags, in part because dynamic considerations such as switching costs become less relevant the longer the temporal horizon is. Examples of recent studies taking such an approach—estimating static discrete choice models using temporal variation at decadal frequency—are Diamond (2016) and Donaldson (2018).

5.1 Supply elasticities

To understand the variation in the data that is used to estimate the supply-side parameters, it is useful to consider the odds ratio between two commodities $c$ and $c'$ within the agricultural nest,

$$\ln \left( \frac{\pi^c_{it}}{\pi^{c'}_{it}} \right) = \frac{\theta}{\lambda} \ln \left( \frac{p^c_{it} A^c_i}{p^{c'}_{it} A^{c'}_i} \right) + u^{cc'}_{it}, \quad (10)$$

where $\pi^c_{it}$ is county $i$’s land share in commodity $c$ at time $t$, $p^c_{it}$ is the farm-gate price, $A^c_i$ is the county’s mean productivity, and $u^{cc'}_{it}$ is an unobservable error term. In particular, because 10 is a supply equation of commodity $c$ relative to $c'$, we interpret $u^{cc'}_{it}$ as an unobservable supply shifter of $c$ relative to $c'$. The ratio of parameters $\frac{\theta}{\lambda}$ is the elasticity of substitution between commodities, i.e., within the agricultural nest. A useful interpretation of $\frac{\theta}{\lambda}$ is as a supply elasticity of $c$ relative to $c'$. This elasticity is large when productivity dispersion across fields goes to zero ($\theta \to \infty$) because marginal fields in a county become identical to the infra-marginal fields, and as a result, the supply curve becomes flat. This elasticity can also be large when productivity is perfectly 

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6In such models, the prices the producers from different regions within a country receive are the country-level prices adjusted by a transport cost. In this sense, there are no local market mechanisms (such as market power in this paper) determining such producer prices beyond the mechanical transport cost adjustment.

7Such an interpretation is common in the spatial economics literature, where having rich spatial heterogeneity is the main priority when choosing a dataset, but which often comes at the cost of lacking the temporal features required for estimating a fully dynamic model. For example, this is typical of census data, which has rich cross-sectional heterogeneity but individual decision makers cannot be linked across time and the frequency of the data is too low to incorporate full dynamics.
correlated across commodities \((\lambda \to 0)\). Thus, knowing this supply elasticity is not enough to separately identify \(\theta\) from \(\lambda\). The additional restriction needed for identification exploits variation across nests: it is the odds ratio between nest \(\mathcal{C}\) and natural use \(\mathcal{N}\),

\[
\ln \left( \frac{\tau_{it}^C}{\tau_{it}^N} \right) = \lambda \ln \left( P_i^C \right) - \theta \ln \left( A_i^N \right) + u_{it}^{C,N} \quad \text{with} \quad P_i^C = \sum_{cc} (p_{iit}^c A_i^c)^{\frac{\varrho}{\lambda}},
\]

where \(\ln P_i^C\) is the inclusive value of the agricultural nest in county \(i\) at time \(t\), \(\theta \ln \left( A_i^N \right)\) is unobservable and time-invariant so it is estimated as a county fixed effect, and \(u_{it}^{C,N}\) is an unobservable supply shifter of agricultural relative to forested land. The parameter \(\lambda\) is the substitution elasticity across nests, i.e., the deforestation elasticity. Given the composite parameter \(\varrho / \lambda\) estimated from 10, we can construct the inclusive value term in 11, and then \(\lambda\) is identified.

**Instruments.** OLS estimates will be biased towards zero due to simultaneity bias, specifically because the unobservable supply shocks \(u_{it}^{cc'}\) will be correlated with relative land shares and relative returns. For example, if the unobservable local productivity of commodity \(c\) increases relative to \(c'\), its relative land share would increase and its relative price would drop, biasing the estimate of \(\varrho / \lambda\) downwards. Since we are estimating a supply equation, an appropriate instrument is a demand shifter varying at the county-year \(it\) and commodity-pair \(cc'\) level. I construct such an instrument from the export network data as follows,

\[
s_{ij}^{cc'} = \sum_j s_{ij}^{cc'} d_{ij}^{cc'} \quad \text{with} \quad s_{ij}^{cc'} = s_{ij}^c, \quad d_{ij}^{cc'} = d_{ij}^c,
\]

where \(s_{ij}^c\) is the share of commodity \(c\) output produced in county \(i\) that historically goes to destination \(j\), and \(d_{ij}^c\) is a time-varying measure of demand conditions for commodity \(c\) in destination \(j\). Intuitively, if demand conditions for crop \(c\) relative to \(c'\) increase in destination \(j\), counties that historically supplied \(j\) are more exposed and receive larger demand shocks. I use destination \(j\)'s imports from every country except Argentina and Brazil as the demand measure \(d_{ij}^c\), thus purging away supply-side effects in Argentina and Brazil that could directly affect the imports of \(j\). Under this research design, the identifying assumption is that the cross-sectional exposure measure \(s_{ij}^{cc'}\) is uncorrelated with changes in the error term \(\Delta u_{it}^{cc'}\), whereas correlation with levels \(u_{it}^{cc'}\) is allowed (Goldsmith-Pinkham, Sorkin and Swift, 2020).\(^9\)

We also need an instrument for equation 11 for the same reasons as for equation 10: if unobserved agricultural productivity increases overall for all commodities, then the agricultural nest’s

\(^8\)Zero field dispersion means all fields in a county are identical; that is, any two fields \(\omega\) and \(\omega'\) satisfy \(A_i^c(\omega') = A_i^c(\omega) \forall c\). Perfect correlation across commodities is a weaker restriction because it allows any two fields \(\omega\) and \(\omega'\) to be different in the sense that \(A_i^c(\omega) \neq A_i^c(\omega') \forall c\), but it restricts every field to have the same ordering over commodities. Because ordering is all that matters in discrete choice problems, all fields choose the same commodity, and within-county heterogeneity in choices disappears.

\(^9\)The assumption allows for counties with high unobservable productivity of \(c\) relative to \(c'\) to selectively export to specific destinations. It also allows counties that historically exported to specific destinations to experience faster growth in their overall unobservable productivity, but not in their relative productivity of commodity \(c\) relative to \(c'\).
share would increase and its price index $P_i^C$ would decrease, biasing the estimate of $\lambda$ towards zero. We now need a shifter of demand for agriculture overall. We construct it similarly to 12, but now summing across all commodities,

$$z_{it}^C = \sum_j \sum_{c \in C} s_{ij}^c d_{jt}$$  \hspace{1cm} (13)

**Results.** OLS and IV estimates of $\theta \lambda$, the substitution elasticity between commodities, are shown in columns 1 and 2 of Table 3. The values are comparable to trade elasticity estimates from Ricardian models of agriculture, which are estimated from variation across commodities within the agricultural nest and abstract from deforestation, typically ranging between 1.5-4 (Costinot et al., 2016; Sotelo, 2020; Pellegrina, 2019). Columns 3 and 4 add interactions with a frontier region indicator to allow for spatial heterogeneity. The negative sign of the interaction coefficients imply substitution across commodities is costlier for farmers in frontier regions.

Table 3: Nested model - substitution elasticity between commodities (within-nest).

<table>
<thead>
<tr>
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<th>OLS</th>
<th>IV</th>
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<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
<td>(4)</td>
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<tr>
<td>$\theta \lambda$</td>
<td>1.043</td>
<td>2.116</td>
<td>1.040</td>
<td>2.083</td>
</tr>
<tr>
<td></td>
<td>*(0.038)</td>
<td>*(0.190)</td>
<td>*(0.038)</td>
<td>*(0.182)</td>
</tr>
<tr>
<td>$\theta \lambda \times$ frontier region</td>
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<td>-0.842</td>
<td>*(0.356)</td>
<td>*(0.382)</td>
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<tr>
<td>Year FE</td>
<td>X</td>
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<td>X</td>
</tr>
<tr>
<td>County FE</td>
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<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>Observations</td>
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<td>9,547</td>
<td>9,547</td>
<td>9,547</td>
</tr>
<tr>
<td>Adjusted R²</td>
<td>0.320</td>
<td>0.199</td>
<td>0.320</td>
<td>0.208</td>
</tr>
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</table>

*Note:* First stage F-statistic = 264.4. *p<0.1; **p<0.05; ***p<0.01.

Table 4: Nested model - deforestation elasticity (substitution elasticity across-nests).

<table>
<thead>
<tr>
<th></th>
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<th>OLS</th>
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<tr>
<td></td>
<td>(1)</td>
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<tr>
<td>$\lambda$</td>
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<td>0.120</td>
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<td></td>
<td>*(0.013)</td>
<td>*(0.180)</td>
<td>*(0.013)</td>
<td>*(0.165)</td>
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<tr>
<td>$\lambda \times$ frontier region</td>
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<td>-0.217</td>
<td>*(0.061)</td>
<td>*(0.153)</td>
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<tr>
<td>Year FE</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
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</table>

*Note:* First stage F-statistic = 577.9. *p<0.1; **p<0.05; ***p<0.01.
Table 4 shows estimates of $\lambda$, the deforestation elasticity. The estimates are consistent with the agricultural and empirical IO literature. Berry and Schlenker (2011) and Roberts and Schlenker (2013) both estimate land-use change elasticities for Brazil between 0.2-0.4. Within Brazil and focusing exclusively on the Amazon biome, Souza-Rodrigues (2019) estimates land-use change elasticities near zero. Although I don’t find such small values, my estimates for frontier regions such as the Amazon are half the size of those from core agricultural regions.\footnote{All of these findings are from static models, which may underestimate long-run land-use change elasticities if estimated on annual panel data. For example, Scott (2013) estimates a dynamic discrete choice model from annual panel data for the US, finding land-use change elasticities estimated from his dynamic version are 10 times larger than in his static version. Souza-Rodrigues (2019) uses cross-sectional data, so his static framework is appropriate to estimate long-run elasticities. In my case I use panel data, but the frequency is 10 years because I use decadal censuses. Given the relatively long time horizon, I interpret the results as long-run elasticities.}

**Role of the nesting structure.** How important is the nesting structure? Estimating a (non-nested) multinomial model amounts to imposing $\lambda = 1$ and estimating a single parameter $\theta$ from variation between commodities and natural use simultaneously. Table 5 shows the results for such a model.

Table 5: Multinomial model - single substitution elasticity between all land uses.

<table>
<thead>
<tr>
<th></th>
<th>OLS</th>
<th>IV</th>
<th>OLS</th>
<th>IV</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
<td>(4)</td>
</tr>
<tr>
<td>$\theta$</td>
<td>0.242***</td>
<td>0.167***</td>
<td>0.252***</td>
<td>0.174***</td>
</tr>
<tr>
<td>($0.007$)</td>
<td>($0.008$)</td>
<td>($0.007$)</td>
<td>($0.008$)</td>
<td></td>
</tr>
<tr>
<td>$\theta \times$ frontier region</td>
<td></td>
<td></td>
<td>-0.209***</td>
<td>-0.131***</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>($0.027$)</td>
<td>($0.028$)</td>
</tr>
<tr>
<td>Year FE</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>County FE</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>Observations</td>
<td>14,278</td>
<td>14,278</td>
<td>14,278</td>
<td>14,278</td>
</tr>
<tr>
<td>Adjusted $R^2$</td>
<td>0.206</td>
<td>0.197</td>
<td>0.209</td>
<td>0.200</td>
</tr>
</tbody>
</table>

**Note:** First stage F-statistic = 35.07. *p<0.1; **p<0.05; ***p<0.01.

The multinomial model mixes variation within and across nests to deliver a single elasticity: notice the multinomial OLS estimates are sandwiched between the nested model’s within- and across-nest elasticities. In this case, the land-use change elasticity is restricted to equal the substitution elasticity between commodities,

$$
\frac{d \ln \pi^c_i}{d \ln p^c_i} = \theta (1 - \pi^c_i).
$$

Because estimates of $\theta$ are well above 1 in the trade literature, the estimates from the multinomial model are hard to reconcile with land-use change elasticities that are found to be well below 1 in the agricultural and empirical IO literature. The trade elasticities are estimated from substitution between commodities on existing agricultural land, ignoring the extensive margin of switching from non-agricultural to agricultural land. By contrast, the agricultural and empirical IO literature
often ignores substitution between commodities within agriculture in order to focus on the binary extensive margin (Scott, 2013; Souza-Rodrigues, 2019). One would expect the extensive-margin elasticities to be smaller if switching from forest to cropland is costlier than switching between crops on already cleared land. The nested model’s objective is to allow changes in a commodity’s acreage to be decomposed into both margins:

\[
\frac{d \ln \pi^c_i}{d \ln p^c_i} = \frac{d \ln \pi^{c|c}_i}{d \ln p^c_i} + \frac{d \ln \pi^C_i}{d \ln p^C_i}.
\]

commodity substitution: \( \frac{\theta}{\pi} (1 - \pi^{c|c}_i) \)  
land conversion: \( \frac{\theta}{\pi} \pi^{c|c}_i \times \lambda (1 - \pi^C_i) \)

The first term is identical to the land-use change elasticity implied by Ricardian models and indicates how crop \( c \) acreage increases by stealing land shares from other crops. The second term tells us how crop \( c \) land use increases by stealing land shares from natural land. Total agricultural land responds to overall agricultural returns, measured as the price index \( P^C_i \), as follows:

\[
\frac{d \ln \pi^C_i}{d \ln P^C_i} = \lambda (1 - \pi^C_i),
\]

By separating the two margins, the model can reconcile relatively high substitution elasticities identified from variation within the agricultural nest (high \( \frac{\theta}{\pi} \)) with relatively low land-use change elasticities identified from variation across nests (low \( \lambda \)). Finally, Figures 6-7 display the fit of the nested and multinomial models, in terms of the land shares they predict from the observed prices, and how such predictions compare to observed land shares.

Figure 6: Model fit, agricultural share of total land \( \ln (\pi^c_i) \).

Nested model.  
Multinomial model.

Notes: Bubble sizes are proportional to total acreage.

The nested model’s fit, as measured by R-squared, is twice as good as the multinomial model.
The multinomial model is especially poor at predicting how agricultural land is divided between commodities. Because the multinomial model’s single parameter $\theta$ is significantly lower than the nested model’s within-nest parameter $\theta_\lambda$ (and these parameters determine how farmers substitute across commodities) it predicts little variation in land shares across commodities.

### 5.2 Trade costs

Trade costs are never fully observed by researchers, and therefore need to be inferred. I build on Donaldson (2018)’s approach, inferring trade costs from price gaps between an origin location $i$ and a destination location $j$. Implementing such a strategy requires data on origin producer prices and destination consumer prices for the goods shipped from that specific origin. I use county-level farm-gate prices from agricultural censuses as origin producer prices $p_{ic}$. The agribusiness sourcing data allows me to obtain origin-destination prices $p_{ijc}$, which are often the more stringent data requirement of the two. In perfectly competitive settings such as Donaldson (2018), the price gap between origin $i$ and destination $j$ identifies bilateral trade costs,

$$\frac{p_{ijc}}{p_{ic}} = \tau_{ijc}.$$  
(14)

However, if intermediaries hold market power, the price gap identifies a combination of trade costs and markdowns (Atkin and Donaldson, 2015). Furthermore, if intermediaries are processing
the commodity rather than trading it raw, we need to account for value added by \( f_c(q^c_i) \),

\[
\frac{p^c_{ij}}{\bar{p}^c_i} = \frac{\tau^c_{ij}}{\mu^c_i f'_c(q^c_i)}.
\] (15)

Without further assumptions, trade costs, markdowns, and marginal products cannot be separately identified from price gaps. The conduct assumption serves as an identifying restriction: it pins down \( \mu_i \) as a function of supply elasticities and number of firms. By imposing 15 only on trade flows of raw commodities (e.g., unprocessed soybeans and maize) we can impose \( f'_c(q^c_i) = 1 \) and trade costs are identified.\(^{11}\) Notice different conduct assumptions will imply different trade costs through \( \mu_i \). Hence, conduct assumptions can be inferred by how reasonable their implied trade costs are, in the same spirit as the “menu approach” from the empirical IO literature, which infers conduct by how reasonable the implied marginal costs are (Nevo, 2001).

**Results.** Figure 8 shows the distribution of \( \mu_i \), the ratio of the input’s price to its marginal revenue. The results suggest agribusiness market power is more significant in the beef sector. The markdown estimates \( \mu_i \) have implications for measuring trade costs, since they are combined with origin and destination prices to back out trade costs using equation 15. Figure 9 shows the distribution of trade costs implied by the estimated markdowns, and compares it to that implied by a perfect competition assumption. Ignoring market power leads to an upward bias: trade costs are on average 15% higher if perfect competition is assumed. Furthermore, this bias varies across space. Because counties in frontier agricultural regions face larger markdowns due to their relatively inelastic supply, the upward bias in trade costs is larger in such regions.

Figure 8: Distribution of input price to marginal revenue product \( \mu_i \).

\(^{11}\) Alternatively, we would need to estimate or calibrate \( f_c(q^c_i) \) if dealing with trade flows of processed commodities, such as soybean oil.
5.3 Demand parameters

The lower-level substitution elasticity $\rho$ is identified from expenditure variation across source counties $i$ within a source country $n$:

$$\ln \left( \frac{X_{ijt}^c}{X_{njt}^c} \right) = (1 - \eta_l) \ln \left( \frac{p_{ijt}^c}{p_{njt}^c} \right) + \lambda_{njt}^c + \varepsilon_{ijt}^c \quad \forall i \in n,$$

(16)

where $X_{ijt}^c$ is destination $j$’s expenditure on good $c$ from county $i$ and $X_{njt}^c = \sum_{i \in n} X_{ijt}^c$. Because (16) is a demand equation, I instrument for price with a supply shifter, which I construct using weather shocks at the origin $W_{it}$ interacted with the destination’s historic import share from county $i$, $s_{ijt}^c$:

$$Z_{ijt}^c \equiv \ln \left( s_{ijt}^c W_{it} \right).$$

(17)

The relevance condition of the instrument is straightforward: given a negative supply shock caused by adverse weather in source county $i$, the effective size of the supply shock faced by the destination market $j$ depends on how exposed it is to county $i$ through the supply chain network. The exclusion restriction is that these origin-destination specific supply shocks are uncorrelated with origin-destination specific demand shocks.\(^\text{13}\) The middle-level elasticity $\eta_m$ is identified from expenditure variation across countries:

$$\ln \left( \frac{X_{njt}^c}{X_{njt}^c} \right) = (1 - \eta_m) \ln \left( \frac{p_{njt}^c}{p_{njt}^c} \right) + \lambda_{njt}^c + \varepsilon_{njt}^c,$$

(18)

12Here, $\lambda_{njt}^c \equiv - \ln \left( \sum_{i \in n} p_{ijt}^c \right)^{1 - \eta_l}$ is treated as a good-source-destination-time fixed effect.

13More specifically, a destination market’s exposure measure is not predictive of future supply shocks.
where $X_{jt}^c$ is destination $j$’s total expenditure on good $c$ across all source countries.\footnote{The term $\lambda_{jt}^c \equiv - \ln \left( \sum_{c'} a_{jt}^c \left( P_{jt}^c \right)^{1-\eta_m} \right)$ and $\epsilon_{jt}^c \equiv \ln \left( a_{jt}^c \right)$.} Since 18 is a demand equation, I again instrument for price by constructing a supply shifter as in equation 17, however at the country rather than county level. Finally, the upper-level elasticity $\eta_u$ is identified from expenditure variation across goods,

$$\ln \left( \frac{X_{jt}^c}{X_{jt}} \right) = (1 - \eta_u) \ln \left( P_{jt}^c \right) + \lambda_{jt} + \epsilon_{jt}^c. \quad (19)$$

where $X_{jt}$ is destination $j$’s total expenditure on all imports.\footnote{To construct the price indices required for the upper-level estimation I use the residuals from the middle-level equation 18. That is, $P_{jt}^c \equiv \left( \sum_c a_{jt}^c \left( P_{jt}^c \right)^{1-\eta_m} \right)^{\frac{1}{1-\eta_m}}$, where $\hat{a}_{jt}^c = \exp \left( \hat{\epsilon}_{jt}^c \right)$. Furthermore, $\lambda_{jt} \equiv - \ln \left( \sum_c a_{jt}^c \left( P_{jt}^c \right)^{1-\eta_m} \right)$ is treated as a destination-time fixed effect and $a_{jt}^c = \exp \left( \epsilon_{jt}^c \right)$.} The required instrument is now a supply shifter varying across goods. Therefore, I construct good-specific supply shocks at destination, by interacting destination weather $W_{jt}$ with the destination’s potential yield for $A_{jt}^c$,

$$Z_{jt}^c = \ln \left( A_{jt}^c W_{jt} \right). \quad (20)$$

**Results.** Table 6 shows substitution elasticity estimates for each level of the demand system. IV estimates are larger than OLS estimates, in line with simultaneity bias, and the results indicate stronger substitutability across product sources than across products. Furthermore, substitutability across counties is substantially higher than across countries, as would be expected. At the country and good levels, the implied CES parameter values are $\eta_m = 6.52$ and $\epsilon_u = 1.88$. These results are similar to those in the related literature. For example, Costinot et al. (2016) estimate demand substitution across countries and goods, finding values of $\eta_m = 5.40$ and $\eta_u = 2.82$.

<table>
<thead>
<tr>
<th>Dependent variable: ln expenditure share</th>
<th>Lower level (across counties)</th>
<th>Middle level (across countries)</th>
<th>Upper level (across goods)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>OLS</td>
<td>IV</td>
<td>OLS</td>
</tr>
<tr>
<td>ln price</td>
<td>0.647***</td>
<td>-14.398***</td>
<td>-0.541***</td>
</tr>
<tr>
<td></td>
<td>(0.026)</td>
<td>(1.476)</td>
<td>(0.066)</td>
</tr>
<tr>
<td>Observations</td>
<td>203,365</td>
<td>203,365</td>
<td>59,734</td>
</tr>
<tr>
<td>1st stage F-stat</td>
<td>-</td>
<td>4345.23</td>
<td>-</td>
</tr>
</tbody>
</table>

Note: *p<0.1; **p<0.05; ***p<0.01.
6 Policy counterfactuals

6.1 Environmental tariffs: Efficiency and distributional impacts

Given the political infeasibility of a first-best carbon tax levied by developing country governments on their own agricultural sectors, foreign trading partners may intervene with environmental tariffs. A recent example is the EU’s proposal to veto its potential free trade agreement with the South American trade bloc, with the stated goal of reducing deforestation and emissions. Motivated by this proposal, I simulate an EU tariff on South American beef exports, which is levied as a carbon tax at the port, based on the average emissions content of South American beef and using a social cost of carbon of 30 USD/tonne.

**Efficiency: unilateral efforts to reduce emissions are undermined by leakage.** Figure 10 shows the equilibrium effect of an EU-only environmental tariff on South American beef. Since regulation is incomplete, the drop in exports to the EU is offset in equilibrium by increased exports to non-EU markets. The tariff’s corrective potential is hence substantially limited by this “leakage” effect: over 80% of emissions reductions achieved by the drop in EU consumption are offset by increased trade flows to non-EU markets (Figure 11).

Figure 10: Effect of an EU environmental tariff on beef imports from South America.
An alternative way of quantifying leakage is to compare the total emissions reductions from unilateral EU regulation to a full regulation counterfactual, i.e., when every market, including the domestic market, imposes the carbon tax on beef consumption. Unilateral regulation by a single actor is relatively efficient if the share of the full regulation emissions reductions it can attain is large compared to the actor’s market share. I find that while EU consumption is 10% of South American beef production in the model, a EU unilateral tariff attains less than 4% of the emissions reductions possible from full regulation.

**Redistribution: farmers from poorer regions bear a larger regulatory burden.** Beyond the limited effectiveness of the EU tariff, what are the distributional effects on farmers? Figure 12 shows the policy’s effect on farm-gate beef prices across production locations in South America. The left panel shows the percentage drop in farm-gate prices, which reflects the effective rate at which farmer income is taxed. The right panel shows how the regulatory burden is shared between producers and consumers: how much farm-gate prices drop relative to the how much consumer prices rise. In the frontier agricultural regions where supply is least elastic—and which also happen to be the poorest regions—farmer income is effectively taxed at a higher rate and farmers bear a larger burden of the regulation. Hence, apart from increasing food prices for consumers, the policy is regressive on the supply side, and in particular it is regressive across space: farmers in poor regions are taxed at a higher rate than farmers in rich regions.

**Role of market structure.** To isolate the role of market power, I repeat the counterfactual policy under a perfectly competitive setting, and compare it to the baseline imperfectly competitive
model. First, the nominal reduction in quantities is smaller when intermediaries have market power because pass-through of the tax is incomplete. Quantitatively, the drop in emissions is roughly 0.8 of what it is under the perfectly competitive case. Thus, the presence of intermediary market power reduces the effectiveness of the policy. Second, when intermediaries hold market power, farm-gate prices drop less in nominal terms due to incomplete pass-through. However, for the purposes of defining regressivity, what we care about isn’t the nominal drop in farmer income, but the rate at which farmer income drops relative to its pre-tariff level—i.e., the implied tax rate on farmer income. Because the pre-tariff prices are lower under imperfect competition due to markdowns, the rate at which farm-gate prices drop can be higher under imperfect competition, and this is what Figure 13 shows. In this sense, the regressive effects of the policy on the supply side are exacerbated by market power.

\[ \Delta% \text{ farm-gate price} \]

\[ \Delta P_{farmers} / \Delta P_{consumers} \]
6.2 Targeting emissions margins: Deforestation choices vs. Commodity choices

We now move on to consider the case of domestic regulation, assuming South American governments are willing to self-regulate. The supply model’s nested structure allows us to evaluate domestic environmental policies targeting different emissions margins: anti-deforestation policies targeting the extensive margin of land clearing, and commodity-specific policies targeting particular agricultural activities. For example, consider a commodity-blind policy versus a commodity-specific policy: a deforestation tax on all agricultural land vs. a livestock-specific tax. Figure 14 compares the effects of these two policies on land shares.

A deforestation tax does not target specific commodities, so both crop and livestock land shares fall, and total agricultural land declines. The size of this extensive-margin effect depends on the nested model’s across-nest elasticity $\lambda$. By contrast, a livestock tax substantially changes agriculture’s composition—grazing land decreases and cropland increases—while overall agricultural land declines significantly less than under the deforestation tax. The size of this substitution effect on the composition of agriculture depends on the within-nest substitution elasticity $\theta / \lambda$. Each policy targets a different emissions source: deforestation taxes aim to reduce emissions from land conversion, whereas the livestock tax aims to reduce emissions through substitution towards less emissions-intensive commodities. The role of the nested structure is to disentangle the two mar-
gins, and thus allow for the evaluation of targeted policies.

Figure 14: Effect of a deforestation tax (left) compared with a livestock tax (right) on land use.

Consider two polar-opposite scenarios delivering different policy implications. In the first case, substitution across nests is low ($\lambda \to 0$) and within-nests is high ($\theta \lambda \to \infty$). If the goal is to reduce emissions regardless of their source, a deforestation tax on all agricultural activities will be ineffective because farmers don’t respond much along the extensive margin. Furthermore, because the policy does not change relative commodity prices, no response occurs along the commodity-choice margin either. Instead, a commodity-specific tax targets the more responsive commodity choice margin, reducing emissions by changing the composition of existing agricultural land. In the second case, substitution across nests is high ($\lambda \to 1$) and within-nests is low ($\theta \lambda \to 1$). In this case, the extensive margin is the responsive one, so a deforestation tax will be more effective.

Anti-deforestation policies have been implemented with mixed success, mostly due to the logistical difficulty of enforcement across thousands of small farmers making deforestation decisions. Alternatively, policies aiming to change the composition of agriculture, for example through dietary change, have been gaining traction recently. A rationale behind such policies is that absent such dietary changes, sustainability targets cannot be realistically met in a world with population
peaking at 10 billion by 2050. The nested framework is therefore especially suitable to evaluate these types of policies.

6.3 Market-based vs. Command-and-Control policy in agricultural supply chains

The funnel-like structure of agricultural supply chains, with millions of atomistic farmers upstream and a few large agribusiness firms downstream, has implications for which kind of policy tool is most effective at reducing emissions. Because agricultural emissions are mostly generated upstream before the commodities leave the farm-gate, their sources are spread out across millions of farmers, making direct “command-and-control” regulation challenging in terms of implementation and enforcement costs. This contrasts with the manufacturing or power generation sectors, where emissions from the burning of fossil fuels are typically concentrated across a few large firms, making it easier to regulate directly through a combination of audits and a fine system.

Market-based policy instruments such as carbon taxes, which operate by changing incentives through the price mechanism and avoid the enforcement costs of command-and-control regulation, are therefore especially attractive in the agricultural context. However, these taxes are typically not levied on the farmers who are making the environmentally relevant decisions. Instead, existing proposals suggest implementing the carbon tax where the supply chain becomes more concentrated—downstream on the agribusiness firms at the port—because the implementation costs are lower and enforcement is easier. The argument is that at the port stage there is already a system in place to levy and enforce export duties, so simply adding a carbon adjustment tax is straightforward. The limitation of such a policy is that the tax would have to be levied uniformly on a given commodity regardless of which specific region it comes from (e.g., a flat tax per ton of beef based on a national average emissions intensity). This is due to how fragmented supply chains are in the South American context and how difficult it is to trace a commodity’s specific origin, especially for the case of the beef supply chain, which is significantly less vertically integrated than crops. Therefore, a flat tax at the port is blunt due to its lack of spatial targeting; high-carbon beef from the Amazon biome would be taxed at the same rate as low-carbon beef from Southern Brazil. How blunt the market-based policy is will depend on how much spatial heterogeneity there is in carbon intensities across producing regions: in a limit with no heterogeneity at all, the flat tax at the port would be perfectly targeted. Finally, given this is a market-based policy and as such operates through the market mechanism, how blunt it is will also depend on market structure—how downstream intermediaries pass-through the carbon tax to upstream farmers.

In contrast to the market-based policy, a command-and-control policy in our context would take the form of a conservation zone in a high-carbon density area, where the quantity of deforestation is explicitly set and enforced through an audit and fine system at a given administrative cost. The appeal of the command-and-control policy is that it is perfectly targeted, although only to a specific geographic area due to its high implementation and enforcement cost. Hence, choosing between a market-based policy (flat tax at the port) and a command-and-control policy (conservation zone in a high-carbon density region) involves a trade-off between targeting and en-
forcement costs. This section’s counterfactual shows that this trade-off depends on the degree of spatial heterogeneity in carbon intensities across producing regions. Concretely, the market-based policy dominates the command-and-control policy in terms of emissions abatement only if spatial heterogeneity is low enough. The counterfactual involves the following four steps:

1. Market-based counterfactual: I simulate an equilibrium where every commodity is taxed at the port with a carbon tax of 30 USD/tonne of CO\(_2\)-eq. The CO\(_2\)-eq content per tonne of a given commodity’s output is calculated as a national average. For example, this means that the tax per tonne of beef sourced from the Amazon is the same as it is for beef from Southern Brazil, and is therefore spatially mis-targeted.

2. Command-and-control counterfactual: I simulate an equilibrium where the forest share in the Amazon biome is forced to be at its socially efficient level.

3. I compute the emissions abated by 1. and 2. relative to the laissez-faire, and denote the emissions abated (in tonnes) by each policy as \(A_{MB}\) and \(A_{CC}\), respectively.

4. I repeat steps 1-3 under an alternative spatial distribution of carbon density which is mean-preserving. The baseline distribution of carbon density (i.e., CO\(_2\)-eq/ha) is the one observed in the data and displayed in Figure 2, with a mean we denote as \(\mu\) and a standard deviation denoted \(\sigma\). Hence, the alternative distribution also has mean \(\mu\), but an alternative standard deviation denoted \(\tilde{\sigma}\). At the end of this step I obtain \(A_{MB}(\tilde{\sigma})\) and \(A_{CC}(\tilde{\sigma})\). I repeat this for various values of \(\tilde{\sigma}\).

Given the abatement potentials of each policy, \(A_{MB}(\sigma)\) and \(A_{CC}(\sigma)\), we now consider a policymaker choosing between these two options in order to minimize emissions. Denote \(C\) as the enforcement cost of the command-and-control policy. If the policymaker’s objective is to minimize emissions net of enforcement costs, she will choose the command-and-control policy over the market-based one under the following condition,

\[
SCC \times A_{CC}(\sigma) - C > SCC \times A_{MB}(\sigma) \iff C < \frac{SCC \times (A_{CC}(\sigma) - A_{MB}(\sigma))}{\overline{C}(\sigma)},
\]

where SCC is the social cost of carbon. Hence, the abatement premium of the command-and-control policy over the market-based policy, which we denote \(\overline{C}(\sigma)\), places an upper bound on the socially acceptable enforcement costs \(C\) that would justify implementing a command-and-control policy. As enforcement costs \(C\) decline, for example due to improvements in satellite image technology, command-and-control policies become more desirable. Finally, the command-and-control premium is increasing in \(\sigma\): the more spatial heterogeneity there is, the more mis-targeted the market-based policy is and the more valuable command-and-control becomes (Figure 15).
7 Conclusion

This paper provides an equilibrium framework to evaluate environmental policy in trade-exposed industries with imperfectly competitive supply chains. The empirical setting is the South American agricultural sector, a global agricultural powerhouse with a major environmental impact, whose trade flows are intermediated by a concentrated agribusiness sector.

First, I incorporate two crucial supply-side margins determining agriculture’s environmental impact: the choice of which commodity to produce on existing agricultural land, and an extensive margin of converting natural land into new agricultural land. I show how modeling farmers’ decisions as a nested choice problem allows for substitution patterns that reconcile relatively high land-use change elasticities implied by the trade literature with relatively low values found by recent work in agricultural economics and empirical IO. Through counterfactuals, I show how each margin responds to different policy tools, and the implications of ignoring these separate margins. Second, I document concentration among agribusiness firms and incorporate buyer market power into my model with a demand side consisting of monopsonistic intermediaries. Market power of intermediaries over farmers opens a distributional channel on the supply side, in contrast to most work studying carbon-tax incidence on demand. Supply-side distributional effects are especially
salient in agriculture, where policy is often designed with redistribution towards farmers as an explicit goal, hence posing a major barrier to advancing environmental regulation.

Given the infeasibility of a first-best carbon tax, I use my framework to evaluate often-debated alternatives, such as environmental tariffs on imports from South America. I find the potential emissions reductions of such policies are mostly undone by leakage from trade. Apart from being ineffective, the policy’s distributional effects are regressive because farmers in the poorest regions, where supply is most inelastic, disproportionately bear the burden of regulation. Agribusiness monopsony power exacerbates the ineffectiveness and regressivity of the policy. First, due to incomplete pass-through, quantities drop less, and so do emissions. Second, although farm-gate prices drop less nominally, they drop more relative to their pre-tariff level, resulting in an implied tax rate on farmer income that is higher under imperfect competition. Thus, policies aimed at correcting a single externality can interact with other market distortions—affecting their performance not only in efficiency terms, but also in how they skew the distribution of the remaining surplus. Finally, I exploit the spatial structure of my model to show how a policymaker’s preferred choice between a market-based policy such as a carbon-tax on output and a command-and-control policy such as a conservation zone depends on the spatial heterogeneity of environmental costs, as measured by the carbon density of land.

To conclude, agriculture presents unique challenges when it comes to emissions regulation. Direct regulation at the externality’s source is logistically hard because of how dispersed the sources of the emissions are. Hence, market-based tools such as carbon taxes are attractive because they avoid the implementation and enforcement costs of command-and-control policies, but they are not typically levied on the farmers whose incentives they aim to correct. Instead, they are implemented where the supply chain becomes more concentrated: downstream on the agribusiness firms. Market structure therefore matters for how such taxes are passed through to the upstream farmers who ultimately make the environmentally-relevant decisions. How blunt such market-based policies are due to their lack of spatial targeting depends on both market structure and the degree of spatial heterogeneity in environmental costs, and they can even be dominated by command-and-control policies when such heterogeneity is wide enough.

References


IIASA/FAO (2012). *Global Agro-ecological Zones (GAEZ v. 3.0)*. IIASA, Laxenburg, Austria and FAO, Rome, Italy.


### Appendix A. Tables

#### Table 7: Main land use categories

<table>
<thead>
<tr>
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<th></th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Acreage (million ha)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
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<td></td>
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<tr>
<td>Total surface area</td>
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<td>277.84</td>
<td>850.28</td>
<td>850.28</td>
<td>850.28</td>
<td>508.90</td>
<td>508.90</td>
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Note: The Amazon biome contains the states of Amazonas, Pará, Roraima, Acre, Amapá, Rondonia, and sections of Mato Grosso, Maranhão, and Tocantins. In this table, Mato Grosso, Maranhão, and Tocantins are counted as part of the Amazon biome. “Other” land use corresponds to unusable land, trails, buildings.
### Table 8: Summary statistics (Argentina, livestock sector)

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### Table 9: Summary statistics (Brazil, livestock sector)

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Appendix B. Figures

Figure 16: Share of global emissions for selected sources. “Transportation” corresponds to “tailpipe” emissions from road, rail, air, and marine transport. “Livestock” corresponds to all emissions along the livestock supply chain. Source: EPA and Gerber et al. (2013).

Figure 17: Share of emissions for each stage of the livestock supply chain. “Direct” land-use change corresponds to pasture expansion, while “indirect” refers to feed crop expansion. “Postfarm” corresponds to processing and transportation up to the retail point. Source: Gerber et al. (2013).
Figure 18: Geographic units for Argentina and Brazil.
Appendix C. Theory

C.1 Derivations of the nested logit model

Field productivity for a land use \( k \) is decomposed into a common component \( A_k^i(\omega) \) and a field-idiosyncratic deviation \( \epsilon_k^i(\omega) \) distributed type I EV with location parameter 0 and standard deviation \( \sigma \sqrt{\pi} \).

\[
A_k^i(\omega) = A_k^i \exp(\epsilon_k^i(\omega)) \quad \forall k \in N \cup C
\]

Let \( R_k^i(\omega) \) denote field \( i \)'s return per unit of land from choice \( k \),

\[
R_k^i(\omega) = \begin{cases} 
p_c^i A_c^i(\omega) & \text{if } k = c \in C \\
A_N^i(\omega) & \text{if } k = N
\end{cases}
\]

where \( p_c^i \) is the price of good \( c \). Since returns are linear in land it is optimal to allocate the entire field to a single use.

Taking logs of \( R_k^i(\omega) \) and denoting logged variables in lower-case,

\[
r_k^i(\omega) = \begin{cases} 
\ln(p_c^i A_c^i) + \epsilon_c^i(\omega) & \text{if } k = c \in C \\
\ln(A_N^i) + \epsilon_N^i(\omega) & \text{if } k = N
\end{cases}
\]

Since the scale of \( r_k^i(\omega) \) is irrelevant for the farmer’s decision, I follow common practice in re-scaling by \( \sigma^{-1} \), which is equivalent to setting the standard deviation of the re-scaled type I EV error to \( \frac{\pi}{\sqrt{6}} \) (Train, 2009). To make the notation comparable to the trade literature, I define the scaling factor \( \theta \) as the inverse of the dispersion of farmer unobservables \( \theta \equiv \frac{\sigma^{-1}}{\pi} \), where

\[
r_k^i(\omega)^* = \begin{cases} 
\theta \ln(p_c^i A_c^i) + \epsilon_c^i(\omega)^* & \text{if } k = c \in C \\
\theta \ln(A_N^i) + \epsilon_N^i(\omega)^* & \text{if } k = N
\end{cases}
\]

Under these distributional assumptions, the probability commodity \( c \) is chosen, conditional on the farmer choosing the agricultural nest, is given by,

\[
\pi_c^i = \frac{(p_c^i A_c^i)^{\frac{\theta}{2}}}{\sum_{c' \in C} (p_c' A_c')^{\frac{\theta}{2}}}, \quad \text{(CCP)}
\]

and the choice probabilities of the two nests are,

\[
\pi_C^i = \frac{\left[ \sum_{c' \in C} (p_c' A_c')^{\frac{\theta}{2}} \right]^{\lambda}}{(A_N^i)^{\theta} + \left[ \sum_{c' \in C} (p_c' A_c')^{\frac{\theta}{2}} \right]^{\lambda}} \quad \text{and} \quad \pi_N^i = \frac{(A_N^i)^{\theta}}{(A_N^i)^{\theta} + \left[ \sum_{c' \in C} (p_c' A_c')^{\frac{\theta}{2}} \right]^{\lambda}}. \quad \text{(NCP)}
\]

C.2 Firm heterogeneity and entry/exit

Entry with homogenous firms. Consider an extension of the intermediary model that allows for entry, but maintains the firm homogeneity assumption. We assume that in each market \( i \) there is a fixed entry cost \( \phi_i^e \). Potential entrants
enter until the incumbent profits equal the entry cost,

\[ \bar{p}_i f_i(q_i^e) - \bar{p}_i f_i'(q_i^e) \mu_i(q_i^e, N_i^e) q_i^e = \phi_i^e. \]

In the case of linear technology \( f_i(q_i^e) = \alpha_i q_i^e \) we have,

\[ \bar{p}_i \alpha_i q_i^e [1 - \mu_i(q_i^e, N_i^e)] = \phi_i^e. \]

The role of allowing for entry, while keeping firms identical, is to let the relationship between market concentration and markdowns be more flexible. With no entry we have the Cournot result: concentrated markets necessarily have large markdowns. With entry, markets with large markdowns (for example due to less elastic supply) will induce a lot of entry and will be less concentrated. Hence, the correlation between concentration and the firm’s profit margins can go in any direction.

The key empirical challenge is obtaining estimates of \( \phi_i^e \). We can use the number of firms at one point in time to back out values for \( \phi_i^e \), and in counterfactuals assume \( \phi_i^e \) is fixed. These assumptions are also quite strong, and it is not obvious this approach is more credible than the baseline model’s assumption of keeping the number of firms fixed, especially since there isn’t much observed entry or exit in the data to begin with. For this reason, I use the baseline model presented in the main text, which is upfront about the difficulty of dealing with entry.

**Entry with heterogenous firms.** If one combines firm heterogeneity with entry then we can have selection of highly productive firms into the market, and thus obtain the typical extensive-margin efficiency gains emphasized by the long-standing firm heterogeneity literature (Melitz, 2003). To the extent our main goal is to allow for a relationship between market concentration and profit margins that is more flexible than imposed by the baseline model—and this can be obtained with the entry extension alone—firm heterogeneity is not crucial for the paper’s qualitative results.

### Appendix D. Institutional background

**D.1 Scale of Argentina and Brazil’s agricultural sector**

The agricultural sectors of Argentina and Brazil account for 50% of the world’s soybean production and 20% of its cattle stock. Within South America, Argentina and Brazil jointly hold over 75% of the continent’s cattle herd and beef production, and over 90% of soybean and maize output. Growing international demand, in particular from Asia, has been one of the major drivers behind soybean expansion: over 70% of soybean output in both countries is exported, with over 50% of exports going to Asia.\(^{17}\)

**D.2 Agricultural land ownership**

According to Argentina’s agricultural census, there are 250,881 farming establishments nationwide, 50% of which are less than 100 ha, and 57% in which the producer is the landowner.\(^{18}\) According to Brazil’s agricultural census, there

\(^{17}\)Sources: FAOSTAT and TRASE. Following Argentina and Brazil, the US is the next major producer with a 35% share. Regarding exports, Argentina and Brazil account for over 50% of global soybean exports while the US holds a 35% share (these values holds for raw soybeans as well as processed soybeans in cake or oil format). Soybeans can be exported raw or in processed form (soybean cake, meal, oil). All reported values correspond to exports in raw soybean-equivalent units and are calculated using the TRASE export data. Following Asia, the next major export destination for South American soybeans is Europe, with a 20% share.

\(^{18}\)An establishment is defined as a contiguous land area where agricultural production takes place, which may be interrupted by streams, rivers, roads, or railways and whose management is carried out by a single agricultural producer. An agricultural producer is defined as a natural or legal person responsible for the technical and economic management of the establishment. The producer does not necessarily own the land he/she/it manages. Source: CNA 2018.
are 5.1 million agricultural farming establishments nationwide. 89% of establishments are less than 100 ha, and in 81% of them the agricultural producer is also the landowner. Furthermore, 77% of establishments are classified as family farms.\(^{19}\) As of 2006, agriculture’s share of employment was 15.7% in Brazil and 1.05% in Argentina.\(^{20}\)

**D.3 Growing and breeding seasons**

In South America, planting of major annual crops such as soybeans and maize takes place in spring (September-November) and harvest is in the fall (March-May). Double-cropping and fitting a second-harvest within the same growing season is feasible in certain regions for certain crop combinations, i.e., the harvest of a primary crop can be followed by the planting of a secondary crop on the same land within the same year. Conditional on double-cropping, the wheat-soybean sequence is common in Argentina: primary winter wheat is harvested in December, which is followed by a late planting of second-harvest soybeans. In Brazil, the soybean-maize sequence is common: an early soybean harvest takes place in February, followed by planting of second-harvest maize, which is harvested in winter, known as *safrinha*. Crop combinations are chosen to avoid loss of soil nutrients. Cereal crops such as maize, wheat, and rice are nitrogen-depleting, and thus should be followed by the planting of nitrogen-fixing crops such as legumes.

As for the livestock sector, cattle are polyestrous so they come into heat many times over a year, with gestation periods of 9 months. Breeders strategically time pregnancies so that calving occurs in the spring, when grass is most abundant.

**D.4 Soybean supply chain**

In Argentina, there are roughly 60,000 soybean producers of heterogenous size. 80% of producers are relatively small, with a planted area less than 260 ha.\(^{21}\) Raw soybeans are purchased from farmers by agribusiness firms such as Cargill, Louis Dreyfus, and ADM, either for direct export in raw format, or for processing into soybean oil and meal. A quarter of total soybean production is exported raw, while the remainder is processed, with 70-80% of the processed products exported. As of 2012, there are a total of 50 soybean crushing plants, corresponding to 37 firms. The top 8 firms account for 80% of national processing capacity and over 90% of exports (Pierrri, Wesz Junior et al., 2017). These firms typically hold state of the art storage and processing facilities (grain elevators, silos, etc.) as well as their own port terminals along the Paraná river. High entry costs exist in the form of large investments in physical infrastructure and the development of a logistical/marketing network. The industry structure is very similar in Brazil, the main difference being that export of raw soybeans is more common than in processed form (Burgos, Mattos and Medina, 2014). As of 2017 there are 236,245 soybean farms—of which 84% are less than 200 ha and 70% are family farms—and 96 crushing facilities in Brazil.\(^{22}\)

Both countries underwent similar liberalization and privatization processes in the 1990s that spurred agricultural commodity exports and the expansion of multinational agribusiness firms. First, price support programs were either eliminated or scaled down in both countries. For example, Argentina dismantled its *Junta Nacional de Granos* in 1991, whose purpose was to purchase grain crops at a guaranteed minimum price. Second, exports duties on agricultural commodities were either eliminated or significantly reduced, raising the international competitiveness of local producers. For example, the 1996 Kandir Law in Brazil exempted export goods from paying domestic circulation duties. Third, the management of port authorities was decentralized to subnational/local governments, establishing the legal framework for large multinationals to build their own processing facilities within private port terminals. In Argentina this was enabled with the approval of Law 24,093 in 1992, and in Brazil with Law 8,630 in 1993.

\(^{19}\)Source: IBGE Table 6710 and Table 6770. Classification of establishments as “family farms” is for the purposes of agricultural support programs. The definition of a family farm is based on presidential decree 9,064, and essentially requires the producer to live on or near the establishment.


\(^{21}\)Source: MAGYP.

\(^{22}\)Source: IBGE Table 6957, Table 6959, and TRASE.
D.5  Beef supply chain

Commercial cattle rearing consists of three stages: breeding, backgrounding, and finishing. In the breeding stage, calves are kept with their mothers, feeding exclusively on milk and grass. Backgrounding follows, which consists of developing the calf’s frame at a moderate pace so that it resists the rapid weight gains it will be subject to in the final finishing stage. Breeding takes place on pasture, whereas diets in the backgrounding and finishing stage can consist of pasture, feed, or both. Historically, a single operator would have been responsible for the whole rearing process: breeding, backgrounding, and finishing. However, single operators are becoming less common with the appearance of feedlots. Although instances of vertical integration between slaughterhouses and feedlots exist, integration further upstream with ranchers at the breeding stage is rare, resulting in a fragmented supply chain.

Cattle move through the supply chain by changing ownership in live cattle markets, which according to cattle transaction microdata tend to be fairly local. Two different types of transactions in these markets are worth distinguishing. First, in transactions between two rearing establishments, cattle is sold as an intermediate capital good: the animal will continue to be fattened by the buyer, or used for breeding. Second, in transactions between a rearing establishment and a slaughterhouse, cattle is sold as a final consumption good because it will be immediately slaughtered. When cattle is sold as an intermediate good, 80% of the transactions take place between establishments within the same province, and 50% within the same county. When sold as a final good, transactions are significantly less likely to stay within county borders: over 80% of them involve a rearing establishment and a slaughterhouse from different counties. Based on interviews with industry participants, the main reason for the local nature of live cattle markets is the cost of transporting live cattle over extended distances. Thus, conditional on being transported over long distances, cattle are likely being sent to slaughter rather than to continue to be fattened elsewhere.

Note that over 70% of beef output in both countries is consumed domestically. This is in contrast to cash crops such as soybeans, which are almost entirely exported. Argentina and Brazil together hold approximately 20% of the world’s cattle stock, produce 20% of the world’s beef, and account for 30% of world beef exports.

In Argentina, the beef supply chain begins with a primary sector consisting of approximately 130,000 breeding and finishing establishments, of which 52% hold less than 100 head of cattle. Live cattle are purchased from these

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23 As of 2018, 38% of Argentina’s cattle stock was held by full-cycle breeders. Source: 2018 Agricultural Census, Table 5.3.
24 Vertical integration between ranchers and packers is less common in beef than in other livestock sectors such as poultry for structural reasons. Commercial poultry farming involves high start-up infrastructure costs to build chicken houses, and requires a steady supply of grain-based feed and antibiotics to prevent disease outbreaks. In a typical vertical arrangement, downstream processors provide the initial capital to build the infrastructure, and may also finance the inputs, in exchange for a share of the farmer’s output. By contrast, cattle require grazing on extensive pasture land in the early stages of their life, therefore infrastructure and feed costs are not critical constraints, and they take at least two years to reach slaughter weight. Both of these factors result in limited scale economies from integration (Crespi and Saitone, 2018). Vertical integration is substantial in sectors such as fresh fruits and vegetables because of the wide variation in quality and their high perishability: integration allows processors to control quality and minimize lags between harvest and processing (Otsuka, Nakano and Takahashi, 2016). By contrast, the gains from vertical integration in crops such as soybeans are smaller due to their storability and relatively homogenous quality.
25 Risk of injury and death are major concerns, both during the on-loading and off-loading of animals onto the transport vehicle, as well as during the crowded voyage. Distances exceeding a day’s travel require the logistical challenge of finding overnight accommodation for the animals because they can’t be left indefinitely on cargo trucks. Furthermore, extended trips result in weight loss, not just during the trip but also after, due to the induced stress. These losses can be significant, considering a typical fattening plan requires animals to put on at least two pounds of weight per day.
26 Of the beef that is exported, over half goes to Asia, and 20-30% to Europe. Jointly, Argentina and Brazilian beef exports account for nearly 30% of world beef exports. By itself, Brazil’s share is 20%, making it the world’s single largest beef-exporting country. Source: FAOSTAT.
27 The other major countries with large cattle stocks are India (12% of the world cattle stock), China (7%), and the United States (6%). The next major producers after Argentina and Brazil are the United States (18% of world production) and China (9%). The next major exporters after Argentina and Brazil are the United States, Australia, and India, with world export shares between 10-15% each. Source: FAOSTAT.
28 Source: SENASA.
establishments by slaughterhouses, of which there are approximately 400. Vertical integration between breeders and slaughterhouses is limited compared to other animal agriculture sectors such as poultry.29 Around half of cattle transactions take place directly between the breeding establishment and the slaughterhouse, a quarter is intermediated by a broker, and the remaining quarter takes place in local spot markets/auctions (Bisang, Santagelo, Annillo and Campi, 2007). In Brazil, as of 2017 there are 2.55 million cattle ranching establishments, 73% of which are less than 50 ha, 79% of which hold less than 50 head of cattle, and 76% of which are family farms.30 As in Argentina, the supply chain is vertically unintegrated and divided into three parts: breeders, finishers, and slaughterhouses.

D.6 Major agricultural policies in Argentina and Brazil

The major difference between agricultural policy in developed and developing countries is the former heavily subsidize agriculture while the latter provide limited support, in some cases even taxing agriculture (OECD, 2019). Argentina’s agricultural policy consists mainly of taxing commodity exports with the goal of raising fiscal revenue. For example, during the 15 years following the macroeconomic crisis of 2001 export taxes were increased, fluctuating between 20-35% across major commodities, and export quotas were periodically implemented on certain products such as beef to keep prices low for domestic consumers (Lema, Gallacher, Yerovi and De Salvo, 2018). Soybeans, the country’s most important crop, have been taxed at an ad valorem rate fluctuating around 35% during this period.

Brazil provides limited support to its agricultural sector. While price supports exist and vary by region, prices received by Brazilian producers are mostly determined by the market. The major support policy is agricultural credit for small farmers in disadvantaged regions. Another important policy area is biofuels. Brazil is one of the world’s largest ethanol producers, using sugarcane as feedstock. The government has mandated its use in vehicle fuels since the 1970s with fuel-security goals in mind, with the current fuel blend requirement around 25%. While the net environmental benefit of biofuels has been questioned due to accelerated land-use change, in the Brazilian context this is attenuated by the fact that sugarcane suitable regions are not located in the Amazon biome.

D.7 Current regulation of agricultural greenhouse gas emissions

Economists widely support a carbon tax as the most efficient solution to climate-change, yet in practice less than 20% of world emissions are covered by a carbon pricing agreement.31 Policy action has been especially limited in the specific case of agricultural emissions, even though designing abatement strategies that are compatible with food security are becoming an urgent item on the sustainable-development agenda (Searchinger, Waite, Hanson, Ranganathan, Dumas and Matthews, 2019; Clark et al., 2020).32

Demand-side measures such as beef-consumption taxes have only been seriously discussed in a few developed countries, and are mostly absent elsewhere due to the regressivity of raising food prices.33 Regulation through trade policy, mainly tariffs from developed countries on imports from developing countries linked to deforestation, are often discussed, but exporters argue these policies are protectionism masked as environmentalism.34 Furthermore, the

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29Vertical integration between breeders and slaughterhouses is less common in beef than in other livestock sectors such as poultry for structural reasons. While poultry can be raised exclusively on grain within a few months, cattle require grazing on extensive pasture land at least in the early stages of their life, and take at least 2 years to reach slaughter weight. Both of these factors result in limited scale economies from integration (Crespi and Saitone, 2018).

30Sources: IBGE Table 6783 and Table 6910 and Table 6783.

31Source: Klenert, Mattauch, Combet, Edlenhofer, Hepburn, Rafaty and Stern (2018). The largest public statement in the history of the economics profession, spanning 3,500 research economists and 27 Nobel laureates, was issued in 2019 supporting a carbon tax as the most efficient solution to climate-change. Source: Climate Leadership Council.

32World population is projected to peak at 10 billion by 2050, and global meat consumption to increase 88%, with most growth coming from the developing world. Even if agricultural productivity continues to grow at historic rates, the additional land required to meet 2050 food demand is roughly twice the size of India (Searchinger et al., 2019).

33Germany, Sweden, and Denmark. Source: vox.com.

34For example, European boycotts on South American beef (source: BBC).
effectiveness of such policies is limited due to leakage risk—exports are diverted to the non-regulated trading partners or back to the domestic market. Supply-side measures taxing farmers are practically absent due to their political infeasibility. Indeed, many countries design agricultural policy with redistribution towards farmers as an explicit goal. Policies aiming to reduce emissions by increasing the sector’s productivity are more promising due to their political feasibility and the inevitable growth in global beef demand (Herrero, Thornton, Notenbaert, Wood, Msangi, Freeman, Bossio, Dixon, Peters, van de Steeg et al., 2010; Herrero, Havlík, Valin, Notenbaert, Rufino, Thornton, Blümmel, Weiss, Grace and Obersteiner, 2013; Springmann, Clark, Mason-D’Croz, Wiebe, Bodirsky, Lassaletta, de Vries, Vermeulen, Herrero, Carlson et al., 2018). Gerber et al. (2013) point out the wide variation in productivity at the local level suggests important abatement potential: a 30% reduction in livestock emissions is possible if producers in a given system, region, and climate adopted the technologies and practices currently used by the 10% of producers with the lowest emission intensity. For example, supplementing pasture diets with high-quality grain feed can achieve important reductions in enteric methane: daily methane emitted per cow is reduced by improved digestibility, and lifetime methane is reduced by shortening the time required for animals to reach slaughter weight.35

D.8 South American agricultural emissions

South American agricultural emissions have fluctuated around 2 billion metric tons annually since 1990, representing 20% of the world’s annual agricultural emissions.36 To place this in perspective, such magnitudes exceed emissions from any major sector in the US economy in 2018: industry (1.5 billion metric tons), electricity generation (1.8 billion metric tons), or transportation (1.9 billion metric tons).37 South American agricultural emissions are therefore comparable to those of the fossil-fuel intensive sectors that are typically targeted by environmental agencies.

Appendix E. Environmental science background

E.1 Basic climate-change science and emissions accounting

Global warming is caused by the accumulation of greenhouse gases (GHG) in the atmosphere. As the Earth absorbs visible and ultraviolet light from the sun, it generates infrared radiation which needs to be released back into space for temperatures to remain stable. GHG do not absorb visible and ultraviolet sunlight, so the incoming radiation from the sun is not affected. However, since GHGs absorb infrared radiation, the outgoing radiation is blocked, thus increasing the net inflow of radiant energy and destabilizing global temperatures (Hsiang and Kopp, 2018). A GHG’s effectiveness at trapping heat is measured in units of “radiative forcing”, typically reported in watts per m². Since GHG differ in their radiative forcing, climate scientists calculate a “global warming potential” (GWP) for each gas, which measures how much energy the emissions of 1 tonne of the gas absorbs over a given time period, relative to the emissions of 1 tonne of CO₂. Thus, the GWP of CO₂ is 1 by definition. For example, methane (CH₄) is over 80 times as effective at trapping heat as CO₂ over a period of 20 years (i.e., GWP₂₀ ≈ 80). In order to add up different GHGs into a single emissions inventory, GWPs are used to convert non-CO₂ gases into CO₂-equivalent (CO₂-eq) units. Under this aggregation method, CO₂ represents 75% of all GHG emissions, while CH₄ stands at 16%, making it the second most important GHG in the atmosphere (IPCC, 2014).

The other major dimension along which GHGs differ is their persistence in the atmosphere, which is the reason why GWP measures are reported conditional on a time horizon. While the exact atmospheric lifetime of CO₂ is notoriously

For example, feedlot subsidies (sources: Reuters UK, Reuters). Other promising avenues are improving veterinary care and increasing weaning rates, which would shrink the herd overhead (the unproductive part of the herd required for breeding). Improved pasture management would maximize the carbon sequestration potential of grasslands. The major mitigation potential lies in ruminant systems operating at low productivity (South Asia, South America, and Africa).

Source: FAOSTAT. This includes emissions from land-use change. Approximately 63% of South American agricultural emissions are generated in Argentina and Brazil.

Source: EPA.
difficult to pin down, it is typically reported to be in the order of centuries to millennia (Inman, 2008). Specifically, about 50% of CO\textsubscript{2} that is released into the atmosphere is removed within 30 years by cycling into the biosphere and the oceans. A further 30% is removed over the next few centuries, while the remaining 20% may linger in the atmosphere for thousands of years (Menon, Denman, Brasseur, Chidthaisong, Ciais, Cox, Dickinson, Hauglustaine, Heinze, Holland et al., 2007). By contrast, the atmospheric lifetime of CH\textsubscript{4} is approximately 12 years, after which it breaks down into CO\textsubscript{2} and water.

### E.2 Key differences between agricultural emissions and fossil fuel emissions

The burning of fossil fuels adds “new” CO\textsubscript{2} to the atmosphere because it releases CO\textsubscript{2} which had made its way deep underground over millions of years. Because of this and the long atmospheric lifetime of CO\textsubscript{2}, reductions in fossil fuel use are inevitable to curb global warming and are at the core of all long-run climate-change policies. Nevertheless, the abatement of potent but short-lived GHGs such as CH\textsubscript{4} offers an opportunity to reduce radiative forcing quickly, in a way CO\textsubscript{2} reductions cannot. Avoiding peak forcing is especially important considering the non-linear damages climate scientists predict due to feedback effects from the melting of ice sheets and ocean acidification. By complementing CO\textsubscript{2} abatement strategies with CH\textsubscript{4} abatement, the probability of the climate irreversibly entering tipping point scenarios in the near future can be reduced (Montzka, Dlugokencky and Butler, 2011). Given the largest source of global anthropogenic CH\textsubscript{4} emissions is the livestock industry, abatement strategies in this sector can mitigate climate-change damages in a substantial way (Ripple, Smith, Haberl, Montzka, McAlpine and Boucher, 2013).

### E.3 Emissions pricing

Conceptually, calculating the social cost of carbon consists of evaluating the present value of the future damages from releasing one tonne of CO\textsubscript{2} today. These calculations are therefore highly sensitive to how future damages are discounted. The Stern Review (Stern, 2007) is the most cited work on the social cost of carbon since it was the first study of its kind. It proposes a relatively high carbon price of 85 USD per tonne of CO\textsubscript{2}, which has been criticized due to its use of a near-zero discount rate that is inconsistent with discount rates estimated from market-based returns (Nordhaus, 2007). While the literature is still far from a consensus on what the social cost of carbon is, most estimates typically range between 20-40 USD.

Less than 20% of world emissions are currently covered by a pricing agreement (Klenert et al., 2018). In existing agreements, rather than setting a carbon price the approach has been to set a cap on emissions and then allow the carbon price to be determined as a market outcome. The European Union’s Emissions Trading System (EU ETS) is the world’s largest greenhouse gas emissions scheme, covering roughly 40% of the EU’s emissions, and uses such a cap-and-trade system. As of February 2020, the EU ETS carbon price is 25 USD per tonne of CO\textsubscript{2}.

### E.4 Emissions footprint of food products

The environmental impact of food products is measured using life cycle assessment (LCA) methods, which evaluate the full environmental impacts of a product throughout its life cycle. The method typically takes into account emissions generated from the production of inputs, infrastructure construction, direct emissions generated by the production of the good itself, as well as the post farm-gate emissions from transport and distribution of goods to consumers. For example, in the case of beef, the emissions impact would include emissions from land clearing, feed production, enteric methane, and distribution.

Agricultural products present wide variation in their greenhouse gas intensity. Poore and Nemecek (2018) provide one of the most comprehensive LCA assessments to date, taking into account land use, on-farm and post farm-gate emissions. They conduct a meta-analysis of 570 studies with a median reference year of 2010, covering over 38,000 commercially viable farms in 119 countries and 40 products representing 90% of global protein and calorie consumption. Emissions per calorie or per gram of protein of animal products are orders of magnitude above those of plant
products, and especially so for ruminant beef. In terms of emissions sources, on-farm emissions exceed those of emissions from land-use change for beef and nearly every product. In the case of beef, there is significant variation across and within-countries in the diets animals are fed, and the amount of time they spend in each production stage, both of which result in heterogeneity in methane emissions intensities.

Tilman and Clark (2014) present a meta-analysis of over 120 publications of life cycle assessments for a total of 82 food products. In contrast to Poore and Nemecek (2018), emissions from land-use change and post-farm activities are not taken into account. Even without taking into account land use, animal-based foods have substantially higher GHG emissions intensities than plant-based foods. Within animal products, aquaculture, poultry and pork all have much lower emissions per gram of protein than ruminant meats. The reasons behind ruminant’s high emissions intensity are: low feed conversion rates, long reproductive and growth cycles, and enteric methane emissions which are unique to ruminants’ digestive systems.

E.5 Livestock sector emissions

Agriculture uses 43% of the world’s ice- and desert-free land and is responsible for 26% of anthropogenic emissions. Within the agricultural sector, livestock production is especially resource-intensive among agricultural activities, occupying 77% of the world’s agricultural land yet producing 18% of its calories and 37% of its protein (Poore and Nemecek, 2018). Apart from its resource intensity, the livestock sector is a major source of greenhouse gases, accounting for 14.5% of world emissions. Beef’s notoriously high emissions intensity stems from cattle’s unique digestive system, which produces methane as a byproduct of digestion in a process known as enteric fermentation. Nearly half of the livestock industry’s emissions are due to enteric fermentation, significantly more than any other component of the supply chain (Gerber et al., 2013). Enteric methane alone represents 6% of world emissions, which is comparable to the carbon footprint of the global cement industry. In South America, emissions intensities are especially high due to extensive grazing practices. Animals are typically bred and fattened on pasture, requiring copious land as well as substantial time for animals to reach slaughter weight. Thus, beyond intensifying land use, shortening the animal life cycle can reduce overall emissions by reducing lifetime methane (Gonda, Feldkamp, Jaurena, Ferrer, Arroquy and Garcia, 2017). The increased use of grain-based animal feed and the growth of the feedlot sector are fairly recent trends, and can play a role in reducing emissions intensities by alleviating land requirements and shortening time to slaughter.

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38 In order to calculate the land clearing component of a product’s emissions footprint, land use change emissions are amortized over 20 years from conversion according to the supplementary materials from Poore and Nemecek (2018).

39 In the United States weaning typically takes place between 6 and 10 months of age, backgrounding lasts 4-6 months, and finishing on grain takes 4-6 months. Finishing on grass may last up to 10 months. Thus, a US animal is typically ready for slaughter at 18 months of age, although this can range between 14 months and 26 months. In the case of developing countries such as Argentina, variability is higher and mainly due to a longer right tail: slaughter age ranges from 14 to 31 months depending on the region and feed type used. This right tail is even longer in Brazil, where animals may take up to 47 months to reach slaughter weight under traditional pasture methods (Vale, Gibbs, Vale, Christie, Florence, Munger and Sabaini, 2019).

40 Between 2010 and 2017, average kg of CO₂-eq emissions per kg of beef output was 34 in Brazil and 30 in Argentina, compared with 11 in the US. Source: FAOSTAT.