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, whose trade flows are intermediated by a concentrated agribusiness sector. On the supply side, I innovate by introducing three key margins driving emissions in the agricultural sector: deforestation, commodity choice, and input substitution in livestock production. On the demand side, I innovate by introducing market power along the supply chain, requiring atomistic farmers to sell their output to monopsonistic intermediaries in order to access consumer markets. 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 environmental regulation through lower farm-gate prices. Agribusiness monopsony power exacerbates these effects, as farm-gate prices drop more relative to their pre-regulation level. Thus, policies aimed at correcting a single externality can exacerbate other market distortions—not only in efficiency terms, but also in skewing 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.¹

On the supply side, I innovate by introducing three key margins driving emissions in the agricultural sector: deforestation, commodity choice, and input substitution in livestock production. On the demand side, I innovate by introducing market power along the supply chain, requiring atomistic farmers to sell their output to monopsonistic intermediaries in order to access consumer markets. I combine both sides to evaluate the equilibrium effects of environmental policy in agricultural markets, taking into account its efficiency as well as 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.² 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 for both the efficiency and distributional implications of regulation. In particular, when intermediaries hold monopsony power, farm-gate prices drop more relative to their pre-regulation level. Thus, policies targeting a single externality can interact with and exacerbate other market distortions—not only in efficiency terms, but also in skewing

¹For drivers of deforestation in the Amazon and policy responses see Assunção and Bragança (2015), Assunção et al. (2015), Vale et al. (2019), and Gibbs et al. (2019). For the emissions impact of the livestock industry, a major component of South American agricultural emissions, see Gerber et al. (2013).

²For example, tariffs on South American beef with the goal of slowing down deforestation have been recently proposed by the European Union (sources: BBC, Deutsche Welle).
the distribution of the remaining surplus.

Although agricultural greenhouse gases account for 26% of world emissions and are 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 (Lagakos and Waugh, 2013; Gollin et al., 2014). 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 Dinerstein, 2019; 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: the choice of which specific agricultural activity is conducted on existing agricultural land, and an extensive margin of converting natural land into new agricultural land. Disentangling the two is critical to evaluate policies operating through one margin but not the other, for example, crop-blind deforestation fines versus crop-specific subsidies. However, existing work typically focuses on a single margin at a time. On the one hand, a recent trade literature uses the modern Ricardian framework of Eaton and Kortum (2002) to study the spatial distribution of agricultural activity, but abstracts from the extensive margin (Costinot et al., 2016; Pellegrina, 2019; Sotelo, 2020). On the other hand, a recent land-use change literature in agricul-

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3Source: Poore and Nemecek (2018)
4The choice of specific agricultural activity matters because commodities vary widely in their emissions footprint. For example, beef’s footprint (CO$_2$e per kg of protein) is 25 times higher than high-protein plant-based alternatives (Poore and Nemecek, 2018).
tural economics and empirical IO addresses the extensive margin, but abstracts from which specific agricultural activities are conducted on the cleared land (Berry and Schlenker, 2011; Roberts and Schlenker, 2013; Scott, 2013; Souza-Rodrigues, 2019). I simultaneously incorporate both margins by modeling farmers’ 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 activities map to trade elasticities, which I estimate to be consistent with the related trade literature. Substitution patterns across nests map to land-use change elasticities, which I find to be in line with the agricultural and empirical IO literature. 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, emissions intensities are also determined by the choice of inputs used in production. I address this margin through a model of livestock production, given livestock emissions are largely driven by the factor intensity of land relative to non-land inputs, such as animal feed. Quantifying how ranchers substitute between these inputs is key to evaluate input-specific subsidies and their emissions abatement potential. To this end, I estimate the livestock industry’s production function, using South American data covering 20% of the world’s cattle stock. I use the South American soybean boom as a shifter of land prices to identify the livestock sector’s substitution elasticity between pasture land and non-land inputs. I show the implications of my estimates by evaluating a counterfactual feed subsidy whose goal is to curb deforestation by having ranchers switch from pasture- to feed-intensive production. Whereas the feed subsidy reduces the land intensity of production by inducing substitution away from pasture, the scale of production rises if consumer demand is sufficiently elastic. In such a case, scale effects dominate substitution effects and the policy backfires: overall input use and emissions levels increase.

Third, I close the model with a demand side consisting of domestic and foreign consumers, opening 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, 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.\(^5\) My focus is on the incidence of such policies on farmers, and how they are exacerbated by market power along the supply chain. 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 et al., 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.

The remainder of the paper is organized as follows. Section 2 discusses how this paper contributes to the related literature at the intersection of industrial organization, trade, and environmental economics. Section 3 provides an overview of the South American agricultural sector and its environmental impact. Section 4 describes the various data sources I assemble for the empirical exercise. Section 5 summarizes the stylized facts from the data that motivate the model’s main features. Section 6 lays out the theoretical model. Section 7 describes how the model is estimated and presents the empirical results. Section 8 evaluates policy counterfactuals.

\(^5\)Leakage back to the domestic market is highly relevant for beef, given 70%-80% of production in Argentina and Brazil is consumed domestically.
2 Related literature

First, this paper contributes to a literature at the intersection of trade and IO studying environmental policy in second-best settings—specifically, when incomplete regulation leads to emissions leakage through trade and/or the environmental externality coexists with other market distortions.\(^6\) Emissions leakage has been studied by a long-standing trade literature, however, mostly in competitive settings and from an applied-theory perspective (Copeland and Taylor, 1994; Antweiler et al., 2001; Nordhaus, 2015; Kortum and Weisbach, 2017). The study of environmental policy under imperfect competition goes back at least to Buchanan (1969), with empirical research on this topic appearing relatively recently (Fowlie, 2009; Ryan, 2012; Fowlie et al., 2016). In such studies, firms exercise market power 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 market 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 et al., 2009; Fabra and Reguant, 2014; Reguant, 2019).

Second, the upstream analysis relates to an agricultural economics literature on imperfect competition surveyed in Sexton and Lavoie (2001) and Sexton and Xia (2018), as well as a growing literature on intermediaries and market power in developing world agriculture (Antras and Costinot, 2011; Atkin and Donaldson, 2015; Bergquist and Dinerstein, 2019; Chatterjee, 2019; Méndez-Chacón and Van Patten, 2019; Rubens, 2019; Dhingra and Tenreyro, 2020; Grant and Startz, 2020). 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.

Third, I link a trade literature that studies how comparative advantage shapes the spatial distribution of agricultural activity (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; Sandmo, 1975; Bovenberg and Goulder, 1994; Barrage, 2020).

\(^6\)Other important second-best settings apart from incomplete regulation and imperfect competition include information asymmetries between regulators and polluters (Weitzman, 1974; Baron and Myerson, 1982; Cicala et al., 2019) and regulators who use Pigouvian taxes to simultaneously correct an externality and meet a fiscal revenue target (Sandmo, 1975; Bovenberg and Goulder, 1994; Barrage, 2020).
Roberts and Schlenker, 2013; Scott, 2013; Souza-Rodrigues, 2019). The trade literature studies how different commodities are allocated across existing agricultural land, while abstracting from the extensive margin of land conversion. By contrast, the agricultural and empirical IO literature models the land-use change margin as binary—land is either left in its natural state, or used for agriculture broadly defined—but abstracts from which specific agricultural activities are conducted on the cleared land. The trade literature’s implied land-use change elasticities are significantly higher than those from the land use literature, 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. To reconcile these findings, I incorporate both margins by modeling farmers’ decisions as a choice problem with two nests: natural land use and agricultural use. Within the agricultural nest, the model collapses to the standard Ricardian framework, and I estimate substitution patterns between commodities that align with those found in the trade literature. Substitution patterns across nests map to land-use change elasticities, which I estimate to be in line with the findings from the agricultural and empirical IO literature.

Finally, this paper relates to a literature on climate-change adaptation, which initially consisted of quantifying the impact of extreme climate on agriculture (Mendelsohn et al., 1994; Deschênes and Greenstone, 2007; Hornbeck, 2012). More recent work leverages the quantitative trade framework to study adaptation in an equilibrium setting, where climate-change alters the spatial pattern of absolute and comparative advantage (Desmet and Rossi-Hansberg, 2015; Costinot et al., 2016; Dingel et al., 2019; Balboni, 2019). My model’s structure is closer to this latter literature, however, I focus on equilibrium responses to environmental policy (e.g., leakage) rather than equilibrium responses to long-term climate-change (e.g., migration to temperate regions).
3 Industry background

Throughout this paper, the analysis is restricted to Argentina and Brazil, which account for over 75% of South America’s cattle herd and beef production, and produce over 90% of its soybeans and maize. Globally, the two countries account for half of world soybean production and approximately 20% of the world’s cattle stock.

3.1 Role of export markets

Agriculture has played a major role in the early economic development of both countries through export-driven growth: beef and wheat in the case of Argentina, and sugar and coffee in the case of Brazil. However, over the past half-century, the sector’s most salient feature has been the dramatic expansion of soybean production in both countries. Figure 1 shows the time series of acreage allocated to the region’s traditionally most important crops. Before 1980, soybean acreage was the least of these crops, and by 2005, it had exceeded all the other major crops combined.

Figure 1: Agricultural area allocated to major crops in Argentina (top), Brazil (middle), and both countries combined (bottom). As of 2017, 91% of all planted land in Argentina was concentrated among four crops: soybeans (46%), maize (24%), wheat (16%), and sunflower (5%). As of 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%). Source: Datos Agroindustriales (Argentina) and CONAB (Brazil).

Source: FAOSTAT.

7Source: FAOSTAT.
Argentina and Brazil account for nearly 50% of soybean production worldwide, followed by the United States with roughly a 35% share. Over 70% of soybeans produced in both countries are exported, and over 50% of these exports go to Asia. Rising incomes in emerging Asian economies have therefore been a major demand-side driver of the soybean boom. Currently, Argentina and Brazil combined account for over 50% of world soybean exports.

3.2 The cattle 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.

Finally, 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.
3.3 Sources of agricultural greenhouse gas emissions

Agriculture uses 43% of the world’s ice- and desert-free land and is responsible for 26% of anthropogenic emissions (Poore and Nemecek, 2018). The bulk of agricultural emissions are generated before products leave the farm-gate, mostly due to land-use change and on-farm input use (e.g., fertilizer use for crops, enteric methane from cattle). Figure 2 shows the wide heterogeneity in carbon footprints across food products, which remains substantial even after abstracting from land-use change. Beef’s footprint, measured as CO$_2$e per kg of protein, is 25 times larger than high-protein plant-based foods, whereas alternative meats such as chicken or pork have substantially smaller footprints. $^{17}$ These orders of magnitude also hold for footprints calculated on a per kcal basis (see Appendix section G). Substantial variation also exists within the plant-based category, with rice’s footprint being over three times larger than wheat’s.

![Figure 2: Average emissions footprint and sources. Land-use change emissions are amortized over 20 years from conversion. Source: OWID and Poore and Nemecek (2018).](image)

Livestock 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

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$^{17}$Beef’s unusually high emissions intensity is due to cattle’s four-chambered stomach, which produces methane as a byproduct of digestion. As grass enters the first stomach, the rumen, microbes break down cellulose and generate methane, which is then belched by the animal. This process, known as enteric fermentation, is repeated hundreds of times daily, resulting in a constant release of methane into the atmosphere.
gases, accounting for 14.5% of world emissions. 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.

Significant variation exists 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 wide heterogeneity in livestock emissions intensities. South American emissions intensities are especially high due to extensive grazing practices and the implied emissions cost of land-use change. Animals are typically bred and fattened on pasture, requiring copious amounts of land and substantial time for animals to reach slaughter weight. Recent work has indicated shortening the animal life cycle presents an important opportunity for emissions abatement through a reduction in lifetime methane (Gonda et al., 2017). The use of grain-based animal feed and the appearance of feedlots is a relatively recent phenomenon, and can play a role in reducing emissions intensities by alleviating land requirements and shortening time to slaughter.

South American agricultural emissions have fluctuated around 2 billion metric tons annually since 1990, which corresponds to 20% of the world’s annual agricultural emissions. Such a magnitude exceeds 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). To conclude, the environmental impact of agriculture is substantial by any measure, and three crucial margins determine the sector’s emissions: how much land is cleared, which specific commodity is produced, and the input combinations used in production (in the livestock sector the choice of grain-based or pasture-based methods is crucial).

To quantify the emissions cost of agricultural production along each margin, I use data on

18 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 et al., 2019).

19 Between 2010 and 2017, average kg of CO₂e emissions per kg of beef output was 34 in Brazil and 30 in Argentina, compared with 11 in the US. Source: FAOSTAT.

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

21 Source: EPA.

22 Appendix section A provides a detailed account of the scientific basis for agricultural emissions abatement as a complementary tool to fossil fuel emissions abatement for curbing global warming.
emissions footprints across commodities as well as across space. First, I use the datasets from Poore and Nemecek (2018) and Clark et al. (2020) to compute CO2e per ton of output for major commodities. Second, to quantify emissions from land use change, I use biomass data at high spatial resolution from the Global Aboveground and Belowground Biomass Carbon Density Maps (Spawn and Gibbs, 2020). Figure 3 shows the resulting spatial distribution of carbon stocks (tonnes of CO2 per ha) for Argentina and Brazil.

Figure 3: Spatial distribution of below- and above-ground carbon stocks (tonnes of carbon per ha)
3.4 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.\(^\text{23}\) 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 et al., 2019; Clark et al., 2020).\(^\text{24}\)

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.\(^\text{25}\) 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.\(^\text{26}\) Furthermore, the 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 et al., 2010, 2013; Springmann 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

\(^{23}\)Source: Klenert et al. (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.

\(^{24}\)World 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).

\(^{25}\)Germany, Sweden, and Denmark. Source: vox.com.

\(^{26}\)For example, European boycotts on South American beef (source: BBC).
weight.\textsuperscript{27}

\textsuperscript{27}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).
4 Data

This section summarizes the various data sources I combine to construct a county-level panel of agricultural supply and demand data for the period 1995-2017. For the supply side, I construct a county-level panel for Argentina and Brazil of agricultural production (land use, output, prices, agronomic measures of productivity, cattle stocks) for commodities that are relevant from an environmental standpoint: 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 construct a panel of trade flows between South American counties and destination markets for these commodities. Further details on each data source are in Appendix section E.1.

Agronomic data

Data on agricultural productivity for the world’s major crops are available from the Food and Agriculture Organization’s Global Agro-Ecological Zones project (FAO-GAEZ) at 5 arc-minute resolution for over one million grid cells around the globe (IIASA/FAO, 2012). The key feature of the FAO-GAEZ data is that agricultural productivity is measured as potential yields predicted by an agronomic model based on agro-climatic fundamentals, rather than with realized yields. The distinction is important because realized yields deliver upward-biased productivity measures because locations select into producing the crops they are especially productive in. By removing this selection effect, potential yields provide a quasi-exogenous measure of productivity that has been exploited in recent applied work (Nunn and Qian, 2011; Bustos et al., 2016; Costinot et al., 2016).

Agricultural output, input, and value data

Data for Argentina are from agricultural censuses at the National Statistical Institute (INDEC), the registry of livestock producers at the National Food Safety Agency (SENASA), and the agroindustrial database at the Ministry of Agriculture (MAGYP). I use the agricultural censuses to measure

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28 A 5 arc-minute grid cell is approximately a $10 \times 10$ km grid cell near the equator and becomes smaller as one moves toward the poles.

29 The agronomic model’s parameters are based on estimates from field and lab experiments in the agronomic literature, and its specific inputs are: soil characteristics, land gradient, elevation, average temperature, rainfall, and sun exposure.
long-run outcomes on agricultural output and cattle stocks. Data for Brazil are from the Brazilian Institute of Geography and Statistics (IBGE). I use the agricultural censuses to measure long-run outcomes on agricultural output, value, and cattle stocks. I complement these data with municipal survey data from the Pesquisa da Pecuária Municipal (PPM) and the Produção Agrícola Municipal (PAM) to obtain higher frequency data.

Land-use data

Land-use data on forest cover, agricultural area, and acreage allocated to specific commodities are from the agricultural censuses of Argentina and Brazil, which are available at decadal frequency. Higher-frequency land-use data on specific crops are from the Datos Agroindustriales database (DA) for Argentina, and from the Produção Agrícola Municipal database (PAM) for Brazil.

Trade flows and supply chain data

Data on international trade flows of agricultural products are from FAOSTAT. To link demand to individual counties I use supply chain data from TRASE, which is available for major commodities such as beef and soybeans. This dataset is constructed from customs data and maps trade flows, in physical quantities and value, from individual counties to firms, and to destination markets.

Weather data

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.

Emissions data

Land-use change emissions are computed 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 products I use the datasets from Poore and Nemecek (2018) and Clark et al. (2020).
5 Stylized facts

Fact 1: Agronomic fundamentals shape the spatial distribution of agriculture

Exogenous agro-climatic conditions such as average precipitation, natural soil quality, and terrain ruggedness determine productivity to a first order in agriculture. As a result, natural comparative advantage is an important driver of the spatial distribution of agricultural activity. This is consistent with the spatial impact of the South American soybean boom I described in section 3.1. Between 1995 and 2006, the share of cropland allocated to soybeans for the median county grew from 14% to 54% in Argentina, and from 19% to 43% in Brazil. Figure 4 shows growth was highest in areas with higher fundamental suitability for soybeans, as measured by FAO-GAEZ potential yields.

Figure 4: FAO-GAEZ potential soybean yield (left) and change in the soybean share of land (right).
Furthermore, other agricultural activities compete with soybeans in local land markets. Areas with stronger soybean growth had larger declines in land allocated to cattle grazing as well as in the number of cattle establishments, consistent with a displacement effect of soybean activity on cattle activity (see Figure 5). A 0.10 increase in the soybean share of land is associated with a 0.05 decline in the grazing share of land and a reduction of 38 cattle establishments. The results are economically and statistically significant given the median county initially had a grazing share of land of 0.76 and 176 cattle establishments.

Figure 5: Cross-county correlations between cattle industry variables and changes in the soybean share of land. Bubble sizes are proportional to initial values of land allocated to grazing.

Figure 6 shows how the previous facts play out over space. The most suitable areas for soybean production are located in central and southern Brazil and mideastern Argentina. Extensive cattle grazing has been displaced from these areas to frontier agricultural regions in northern Brazil and Argentina. In the Amazon’s case, this expansion of the agricultural frontier is visibly linked to deforestation. As a mirror image, the decline in grazing land in core agricultural regions coincides with intensification of the livestock activity that remains, which brings us to the next stylized fact.

30Results are in Appendix table 11.
Figure 6: Effects of the soybean boom over space. The “displacement effect” consists of extensive, low-productivity cattle grazing moving inland towards the agricultural frontier: northern Argentina and Brazil. This coincides with land conversion from forest into agriculture, especially in the Amazon region. The “intensification effect” shows up through an increase in cattle stocks per hectare almost everywhere, but especially in the core agricultural regions: mid-eastern Argentina and southern Brazil. In several frontier regions, a reverse “extensification effect” is visible.
Fact 2: Agricultural intensification takes place where land is scarce

Agricultural intensification is the increased use of non-land inputs relative to land (fertilizer or machinery in the case of crops, cattle in the case of livestock production). In my setting, cattle production in areas exposed to high soybean growth have intensified the most, as measured by growth in cattle head per establishment and per hectare. A 0.10 increase in the soybean share of land is associated with increases of 0.04 cattle head per ha and 8 cattle head per establishment. The results are economically and statistically significant given the median county initially had 1.08 cattle head per ha and 93 cattle head per establishment.

Fact 3: Atomistic farmers face a concentrated agribusiness sector

Table 1 summarizes concentration measures for commodity export markets in Argentina and Brazil. In Brazil, over 2.5 million upstream establishments are raising cattle and over 236,000 are growing soybeans, facing a downstream agribusiness sector that is substantially concentrated. In 2016, 72% of Brazilian beef exports were exported by only three agribusiness firms. In the median county, the top three firms account for 97% of the beef that is sourced, with the top firm accounting for over 67%.

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<th>Table 1: Agribusiness concentration measures</th>
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<tr>
<td>Brazil</td>
</tr>
<tr>
<td>Beef</td>
</tr>
<tr>
<td>Number of agribusiness firms</td>
</tr>
<tr>
<td>Number of upstream agricultural establishments</td>
</tr>
<tr>
<td>CR-1 (nationwide)</td>
</tr>
<tr>
<td>CR-3 (nationwide)</td>
</tr>
<tr>
<td>CR-1 (median across counties)</td>
</tr>
<tr>
<td>CR-3 (median across counties)</td>
</tr>
<tr>
<td>Share of source counties with 1 agribusiness firm</td>
</tr>
<tr>
<td>Number of source counties</td>
</tr>
<tr>
<td>Number of destination countries</td>
</tr>
</tbody>
</table>

*Values are constructed from TRASE and agricultural census data between 2016-2018.

Table 2 reports concentration measures for individual agribusiness firms. JBS, the world’s
largest meatpacker and industry leader, was responsible for 39% of exports nationwide and sourced its beef from 48% of all exporting counties. Similar patterns hold for the soybean sector. Fifty-five percent of Brazilian source counties have only one active trader, and in both countries, the top five traders account for over 50% of exports nationwide.

Table 2: Major agribusiness firms

<table>
<thead>
<tr>
<th>Country</th>
<th>Exporter</th>
<th>Commodity</th>
<th>National market share</th>
<th>Local market share*</th>
<th>Share of all counties exporter sources from**</th>
</tr>
</thead>
<tbody>
<tr>
<td>Brazil</td>
<td>JBS</td>
<td>Beef</td>
<td>0.39</td>
<td>0.36</td>
<td>0.48 (1296)</td>
</tr>
<tr>
<td></td>
<td>Marfrig Global</td>
<td>Beef</td>
<td>0.17</td>
<td>0.17</td>
<td>0.36 (973)</td>
</tr>
<tr>
<td></td>
<td>Minerva</td>
<td>Beef</td>
<td>0.16</td>
<td>0.25</td>
<td>0.46 (1222)</td>
</tr>
<tr>
<td></td>
<td>Bunge</td>
<td>Soybeans</td>
<td>0.17</td>
<td>0.47</td>
<td>0.18 (342)</td>
</tr>
<tr>
<td></td>
<td>Cargill</td>
<td>Soybeans</td>
<td>0.14</td>
<td>0.59</td>
<td>0.15 (290)</td>
</tr>
<tr>
<td></td>
<td>ADM</td>
<td>Soybeans</td>
<td>0.08</td>
<td>0.43</td>
<td>0.14 (258)</td>
</tr>
<tr>
<td></td>
<td>Amaggi</td>
<td>Soybeans</td>
<td>0.07</td>
<td>0.32</td>
<td>0.1 (192)</td>
</tr>
<tr>
<td></td>
<td>Louis Dreyfus</td>
<td>Soybeans</td>
<td>0.06</td>
<td>1.00</td>
<td>0.07 (126)</td>
</tr>
<tr>
<td>Argentina</td>
<td>Vicentin</td>
<td>Soybeans</td>
<td>0.13</td>
<td>0.15</td>
<td>0.67 (137)</td>
</tr>
<tr>
<td></td>
<td>COFCO</td>
<td>Soybeans</td>
<td>0.13</td>
<td>0.12</td>
<td>0.9 (184)</td>
</tr>
<tr>
<td></td>
<td>Bunge</td>
<td>Soybeans</td>
<td>0.12</td>
<td>0.11</td>
<td>0.9 (185)</td>
</tr>
<tr>
<td></td>
<td>AG Deheza</td>
<td>Soybeans</td>
<td>0.12</td>
<td>0.13</td>
<td>0.66 (136)</td>
</tr>
<tr>
<td></td>
<td>Cargill</td>
<td>Soybeans</td>
<td>0.11</td>
<td>0.11</td>
<td>0.91 (187)</td>
</tr>
</tbody>
</table>

*Local markets are defined at the county level. The reported share is the median share the exporter holds across the counties it sources from. All market shares in this table are calculated for the year 2016.

**Values in parentheses are the number of counties the exporter sources from. The reported share is this number divided by all counties exporting the commodity nationwide. A total of 2,683 Brazilian counties export beef, and 1,883 export soybeans. A total of 205 Argentine counties export soybeans.

Figure 7 shows how agribusiness concentration, farm-gate prices, and a proxy measure of agribusiness profit margins correlate with each other. Figure 8 shows how these variables vary across space for the case of Brazilian cattle. Concentration is positively correlated with the agribusiness price spread (the ratio of the price the firm receives at the port relative to the price paid to the farmer) and negatively with the farm-gate prices farmers receive. Cattle farm-gate prices in southern states are over 30% higher than in the state of Amazonas, for example. Part of this could be due to differences in quality, however even for relatively homogenous commodities such as soybeans there is substantial variation. It is also important to take into account that the agribusiness price spread reflects a combination of trade costs as well as potential markdowns, which a
priori cannot be disentangled. I revisit this point when estimating trade costs in section 7.3.

Figure 7: Reported values are median values across all counties in each state in 2017. Bubble sizes are proportional to total state output for each commodity.

Moving beyond concentration measures and descriptive correlations, one straightforward approach to measure buyer market power is to estimate the residual supply curve each agribusiness firm faces. To be clear, while upward sloping residual supply indicates the existence of buyer
Figure 8: Reported values are median values across all counties in each state in 2017. The agribusiness price spread is the ratio of the price the firm receives at the port relative to the price paid to the farmer.

market power, this does not imply firms choose to exploit it, which is a matter of conduct.\textsuperscript{31} I implement this “supply-side” approach to measuring buyer market power by using the agribusiness network data (see Appendix section H.1). The residual supply elasticities I find are similar in magnitude to those from recent studies of monopsonistic labor markets, which also employ a similar “supply-side” approach (Azar et al., 2019; Goolsbee and Syverson, 2019).\textsuperscript{32} Under a monopsony conduct assumption, my estimates would imply farmers receive 0.86 of the agribusiness firm’s marginal revenue product.

**Modeling implications**

Fact 1 suggests agronomic fundamentals are an important determinant of the spatial distribution of agriculture. Therefore, I model agricultural productivity by adapting the Eaton and Kortum (2002) framework to my setting, where Ricardian comparative advantage dictates what gets produced where. Fact 2 suggests livestock producers adjust their factor intensities—which determine

\textsuperscript{31}Identification of oligopoly conduct cannot be attained by a shift in demand, but rather by a rotation (Bresnahan, 1982, 1989). The mirror image of this result is that identification of the oligopsony conduct parameter can be attained by a rotation in supply. This exact intuition has been applied as early as Just and Chern (1980) to identify buyer conduct in agricultural markets, where market power is often suspect on the buyer side—for example, large food processors facing atomistic farmers. Given conduct assumptions, one can then use the supply elasticity estimates to infer the markdowns implied by the model’s equilibrium conditions.

\textsuperscript{32}More closely related to my agricultural setting, Rubens (2019) estimates both markups on cigarette prices and markdowns on tobacco leaf prices set by Chinese cigarette manufacturers. Separate identification of markups and markdowns is achieved by using the production function approach to estimate markups, and a model of farmers’ tobacco leaf supply to infer markdowns.
emissions footprints to a first order—in response to changes in relative factor prices. Therefore, I model livestock production with a technology that allows for substitution between land and non-land inputs such as animal feed. Because the degree of input substitution has critical implications for environmental policy, the Cobb-Douglas specification used by most of the production function literature is overly restrictive since it imposes a unitary substitution elasticity. Therefore, I use the more flexible CES specification (Doraszelski and Jaumandreu, 2018). Fact 3 suggests agribusiness firms plausibly hold buyer market power over farmers, especially in remote locations on the agricultural frontier. Therefore, I model agribusiness firms as oligopsonists in local upstream markets.
6 Model

On the supply side, atomistic farmers choose between leaving their land in its natural state, or converting it to agriculture and producing a specific commodity. Demand consists of consumers who are distributed across domestic and foreign markets. However, farmers cannot access consumer markets directly—they must sell their output to intermediating firms with buyer market power.

6.1 Supply

Farmers

A county is indexed by $i$ and contains a continuum of fields indexed $\omega$. Each field is owned by a farmer, who chooses a land use from a discrete choice set containing a natural-use option $N$ and a nest of agricultural commodities $C$. Field $\omega$'s output of a specific commodity $c \in C$ is,

$$Q_c^i(\omega) = A_c^i(\omega)L_c^i(\omega),$$

where $A_c^i(\omega)$ is the field’s productivity in commodity $c$ and $L_c^i(\omega)$ is its acreage. Productivity is decomposed into a county-level mean $A_c^i$ and a field-level shock $\epsilon_c^i(\omega)$,

$$A_c^i(\omega) = A_c^i \exp(\epsilon_c^i(\omega)).$$

The county mean $A_c^i$ is observable to the econometrician from the FAO-GAEZ agronomic data, while the field-idiosyncratic component $\epsilon_c^i(\omega)$ is unobservable and is distributed extreme value with dispersion parameter $\sigma$.\textsuperscript{33} Given a farm-gate price of $p_c^i$ per unit of output, farmers obtain a payoff of $p_c^iA_c^i(\omega)$ per unit of land from choosing commodity $c$. The payoff per unit of land of leaving the field in its natural state is $A_N^i(\omega)$, which is defined analogously as in 1. The key nesting assumption is that the unobservable productivity shocks are correlated between agricultural

\textsuperscript{33}Specifically, $\epsilon_c^i(\omega)$ is distributed type I EV with location parameter 0 and standard deviation $\sigma \frac{\pi}{\sqrt{6}}$, which is equivalent to having $A_c^i(\omega)$ distributed type II EV (Fréchet) with location parameter 0, scale parameter $\Gamma(1 - \sigma)^{-1}A_c^i$ and shape parameter $\sigma^{-1}$. Either case implies $E[A_c^i(\omega)] = A_c^i$. The type I EV formulation casts the nested choice problem as a nested logit model.
commodities, but not between a commodity and the natural-use option.\textsuperscript{34}

Taking logs of payoffs and re-scaling them by a constant $\theta \equiv \sigma^{-1}$ (the inverse of field dispersion), we obtain a nested logit model of land-use with the following log returns per unit of land:\textsuperscript{35}

$$r^k_i(\omega) = \begin{cases} 
\theta \ln (p^c_i A^c_i) + \epsilon^c_i(\omega)^* & \text{if } k = c \in C \\
\theta \ln (A^N_i) + \epsilon^N_i(\omega)^* & \text{if } k = N.
\end{cases}$$

Under these assumptions, the probability commodity $c$ is chosen, conditional on the farmer choosing the agricultural nest, is

$$\pi^{c|c}_i = \frac{(p^c_i A^c_i)^{\theta} \lambda}{\sum_{c' \in C} (p'^c_i A'^c_i)^{\theta} \lambda}.$$  \hfill (CCP)

The choice probabilities of the two nests are

$$\pi^C_i = \frac{\left(\sum_{c' \in C} (p'^c_i A'^c_i)^{\theta} \lambda\right)}{(A^N_i)^{\theta} + \left(\sum_{c' \in C} (p'^c_i A'^c_i)^{\theta} \lambda\right)} \quad \text{and} \quad \pi^N_i = \frac{(A^N_i)^{\theta}}{(A^N_i)^{\theta} + \left(\sum_{c' \in C} (p'^c_i A'^c_i)^{\theta} \lambda\right)}.$$  \hfill (NCP)

and the unconditional choice probability of commodity $c$, which corresponds to land shares in the data, is given by $\pi_i = \pi^{c|c}_i \pi^C_i$.

$\theta$ governs the dispersion of productivity across fields within a county, and thus determines the county-level supply elasticity: as $\theta \to \infty$, marginal fields become identical to inframarginal fields, so county-level supply curves become flat. $\lambda \in (0, 1]$ governs the correlation of productivity between commodities: as $\lambda \to 1$, correlation goes to zero and the nested logit model collapses into a multinomial logit model, the often-used specification in Ricardian models of agriculture.\textsuperscript{36}

\textsuperscript{34}In the benchmark Eaton and Kortum (2002) model, each country chooses the lowest cost trading partner for each good it imports. Since productivity draws are independent, the choice problem corresponds to a multinomial discrete choice model over trading partners. Recent work has extended the framework to admit flexible correlation patterns between countries’ productivities (Lind and Ramondo, 2018). In the same way that correlation between countries allows for heterogeneity in trade elasticities across different groups of trading partners, correlation between land use activities allows for heterogeneity in land-use change elasticities across different land use categories.

\textsuperscript{35}Derivations are in Appendix section D.1. The re-scaling by $\sigma^{-1}$ implies $\epsilon^c_i(\omega)^*$ is a standardized type I EV error: its location parameter is 0 and its standard deviation is $\frac{\pi}{\sqrt{6}}$.

\textsuperscript{36}As $\lambda \to 1$ and nests disappear, the land share equation is given by equation CCP, which is identical to the land
The nested structure is crucial in my setting, because a multinomial model would restrict substitution between commodities to be as easy as substitution between agricultural- and natural-land use.\footnote{In the nested model, substitution patterns between commodities are stronger than between a commodity and natural use, \[
\left| \frac{d \ln \pi^c_i}{d \ln p^c_i} \right| > \left| \frac{d \ln \pi^N_i}{d \ln p^c_i} \right| \quad \text{for } c \neq c'.
\]
Within nest $C$, the proportional substitution property holds: \[
\frac{d \ln \pi^c_i}{d \ln p^c_i} = -\frac{\theta}{\pi^c_i} \frac{\pi^c_i}{\pi^c_{i'}}. \]
In a multinomial model, proportional substitution holds across all choices, including the natural-use option. For the exact formulas of the unconditional choice probabilities and substitution patterns, see Appendix section D.2.}

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, commodity-blind deforestation fines versus commodity-specific subsidies. Under these assumptions, the county-level output of commodity $c$ has the following closed form:

\[
Q^c_i = \int_\omega A^c_i(\omega) L^c_i(\omega) d\omega = A^c_i \left( \pi^{c|C}_i \right)^{-\frac{1}{\lambda}} L^c_i. \tag{S-C}
\]

Notice a county’s output is not simply average yield multiplied by acreage, $A^c_i L^c_i$, because we have field heterogeneity, and therefore a selection effect: only fields with high draws of $A^c_i(\omega)$ actually choose to produce $c$.\footnote{The magnitude of this selection effect can be seen by observing that a field’s mean yield in $c$, conditional on $c$ being chosen, is higher than its unconditional mean (see Appendix section D.3 for derivations), \[
E \left[ A^c_i(\omega) \bigg| p^c_i A^c_i(\omega) \right] = \max_{c' \in C} \left\{ p^c_i A^c_i(\omega) \right\} = A^c_i \left( \pi^{c|C}_i \right)^{-\frac{1}{\lambda}} > A^c_i = E \left[ A^c_i(\omega) \right].
\]
This point has been made by Costinot et al. (2016); however in this case, the selection effect can also disappear as productivity becomes perfectly correlated across commodities ($\lambda \to 0$). Field dispersion going to zero ($\theta \to \infty$) means every field in the county is identical in the sense that $\varepsilon^c_i(\omega) = \varepsilon^c_i(\omega')$ for any two fields $\omega$ and $\omega'$. Perfect correlation ($\lambda \to 0$) is a weaker restriction because any two fields $\omega$ and $\omega'$ can differ in levels, in the sense that $\varepsilon^c_i(\omega) \neq \varepsilon^c_i(\omega')$, but it restricts the idiosyncratic shocks to be equal across choices, that is, $\varepsilon^c_i(\omega) = \varepsilon_i^c(\omega)$ for any two commodities $c$ and $c'$. This implies all fields within a county order their choice set in the same way; that is, they are identical in terms of their choices.}

Finally, it is worth clarifying that the commodity set $C$ includes pasture as a “commodity”. Pasture land differs from the rest of the crop commodities in that it is not tradable: it is consumed as an input by the ranching sector in the county where it is supplied.

\[\text{share equations from Costinot et al. (2016) and Sotelo (2020).}\]
Ranchers

Ranchers rent pasture land $L_i$ and purchase feed crops $M_i$ from farmers, which they feed to their cattle $K_i$. They combine these inputs to produce finished beef with the following technology,\footnote{Because the rest of the model is static, I abstract from dynamic aspects of cattle breeding. In Appendix section B.2 I discuss the implications of cattle dynamics and the long-standing literature on cattle cycles (Jarvis, 1974; Rosen et al., 1994). Whereas a dynamic model would be useful for studying transitional dynamics between steady states (which can be interesting in their own right due to the peculiarity of cattle cycles), how it would fundamentally change the steady states themselves, which are what ultimately matter from an environmental standpoint, is unclear. Apart from substantially complicating the rest of the model, estimation of a dynamic cattle model would require data that are typically not available in developing-country agricultural contexts (producer-level cattle stocks or field-level land-use data). For all these reasons, I opt for the static approach.}

$$F_i (K_i, L_i, M_i) = \min \left\{ z_{Ki} K_i \left[ \left( \frac{z_{Li} L_i}{z_{Mi} M_i} \right)^{-\sigma} + \left( \frac{z_{Mi} M_i}{z_{Li} L_i} \right)^{\frac{1}{\sigma}} \right] \right\},$$

where $\sigma$ is the elasticity of substitution between pasture and feed, and $z_{Xi}$ is factor $X$-augmenting technology.\footnote{An example of an increase in $z_L$ would be an improvement in pasture management techniques—by raising the available biomass per unit of land, this would reduce the amount of land needed to deliver a given amount of beef. An example of an increase in $z_K$ would be an improvement in veterinary care, because mortality rates would be reduced, which would reduce the amount of cattle required to yield the same output. An example of an increase in $z_M$ would arise from an improvement in feed quality, which would reduce the amount of feed required to yield the same output.}

This production function implies cattle is not substitutable in beef production, whereas feed crops and pasture are substitutable with each other as part of cattle’s diets.\footnote{In Appendix section D.4, I discuss alternative specifications of the production function.} Given pasture-land rental rates $p_{Li}$, feed prices $p_{Mi}$, and cattle prices $p_{Ki}$, profit maximization implies the optimal feed-to-pasture ratio depends on relative input prices,\footnote{Derivations are in Appendix section D.4.}

$$\frac{M_i}{L_i} = \left( \frac{p_{Li}^{pL} + p_{Ki}^{pK}}{p_{Mi}^{pM} + p_{Ki}^{pK}} / z_{Ki} \right)^{\sigma} \left( \frac{z_{Mi}}{z_{Li}} \right)^{\sigma-1}. \quad \text{(FOC-ML)}$$

6.2 Demand

Consumers are located in destination locations indexed $j \in J$, and they demand commodities from source locations indexed $i \in I$. Trade between source and destination is intermediated by agribusiness firms.
**Intermediaries**

The following holds for each commodity, so I abstract from commodity-specific superscripts in this section to keep notation clean. An intermediary firm purchases a good from source $i$ at farm-gate price $p_i$ and sells it in destination $j$ at final price $p_{ij}$. Trade costs are of the iceberg type: a firm needs to purchase $\tau_{ij} > 1$ units at source $i$ for 1 unit to arrive at destination $j$. A finite number $N_{ij}$ of these firms compete along each “route” $ij$. Intermediaries hold market power as buyers in upstream market $i$, but take prices as given in downstream market $j$. Assuming competition along each route is in quantities, each firm solves the following problem:

$$\max_{q_{ij}} \frac{p_{ij}}{\tau_{ij}} q_{ij} - p_i (Q_i) q_{ij},$$

where $p_i (Q_i)$ is source $i$’s inverse supply equation and $Q_i$ is its total output. The specific form of $p_i (Q_i)$ and consequently, the supply elasticity $\frac{\partial p_i}{\partial Q_i} Q_i p_i$, are microfounded by the supply model. The intermediary firm’s FOC results in the following:

$$p_i = \frac{p_{ij}}{\tau_{ij}} \mu_{ij} \quad \text{with} \quad \mu_{ij} = \left(1 + \frac{\partial p_i}{\partial Q_i} \frac{Q_i}{p_i} s_{ij} \right)^{-1},$$

where $\mu_{ij}$ is the ratio of input price to marginal revenue product and $s_{ij}$ is the share of output produced in source $i$ going to destination $j$.\(^{44}\) The interpretation of $\mu_{ij}$ is that for every dollar the intermediary makes from selling the commodity in market $j$, the farmer obtains $\mu_{ij}$ cents. The markdown is defined as the difference between the marginal revenue product and the input price, as a fraction of the input price,

$$\frac{p_{ij}/\tau_{ij} - p_i}{p_i} = \frac{\partial p_i}{\partial Q_i} \frac{Q_i}{p_i} \frac{s_{ij}}{N_{ij}}.$$

This result is the monopsony analogue of the Lerner index: sources with relatively inelastic supply face larger markdowns. A lower value of $\mu_{ij}$ therefore corresponds to a larger markdown. In the case with perfectly competitive intermediaries, the markdown is 0, the input price to marginal revenue product ratio is 1, and the farm-gate price is simply the destination market price adjusted

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\(^{44}\)See Appendix section D.5 for derivations.
by trade costs, \( p_i = \frac{p_{ij}}{\tau_{ij}} \).

**Consumers**

I model consumers with a three-level CES demand system. In the upper level, consumers substitute between goods (e.g., maize vs. wheat). In the middle level, they substitute between source countries of a given good (e.g., Brazilian maize vs. US maize). In the lower level, they substitute between source counties within a source country (e.g., maize from Northern Brazil vs. maize from Southern Brazil). The lower level is the non-standard part of consumer demand in this paper, and is required for an equilibrium analysis at the county-level. Specifically, I assume each destination \( j \) has a representative consumer with the following three-level CES utility function:

\[
U_j = \left( \sum_n (a^n_j)^{1/(\epsilon)} (C^n_j)^{\epsilon-1} \right)^{1/\epsilon}, \text{ where } C^n_j = \left( \sum_l (a^n_{lj})^{1/(\eta)} (C^n_{lj})^{\eta-1} \right)^{1/\eta} \text{ and } C^n_{lj} = \left( \sum_i (C^n_{ij})^{\rho-1} \right)^{\rho}. \]

\( C^n_j \) is consumption of good \( n \) aggregated across source countries indexed \( l \). \( C^n_{lj} \) is consumption of good \( n \) aggregated across source counties indexed \( i \) belonging to country \( l \). \( \epsilon \) is the elasticity of substitution between goods, \( \eta \) is the elasticity of substitution between source countries, and \( \rho \) is the 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: \(45\)

\[
C^n_{ij} = \left( \frac{p^n_{ij}}{P^n_{ij}} \right)^{-\rho} a^n_{ij} \left( \frac{P^n_{ij}}{p^n_{ij}} \right)^{-\eta} a^n_{ij} \left( \frac{p^n_{ij}}{P^n_{ij}} \right)^{-\epsilon} \frac{X_j}{P_j} \forall i \in l, \tag{D-N} \]

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

\[
P^n_{ij} \equiv \left( \sum_{i \in l} (p^n_{ij})^{1-\rho} \right)^{1/\rho}, \quad P^n_{ij} \equiv \left( \sum_{i \in l} (a^n_{ij})^{1-\eta} \right)^{1/\eta}, \quad P_j \equiv \left( \sum_n (a^n_{ij})^{1-\epsilon} \right)^{1/\epsilon}.
\]

### 6.3 Equilibrium

An equilibrium is a set of farm-gate prices for commodities such that,

\(45\)See Appendix section D.6 for derivations.
• markets for each final good $n$ (beef and crops) clear globally,

$$Q^n_i = \sum_j C^n_{ij} \tau_{ij} \quad \forall i, n,$$

• markets for pasture land clear locally at the county level,

$$Q^L_i = L_i \quad \forall i,$$

• and the destination $j$ price of the final good $n$ sourced from $i$ is given by,

$$p^n_{ij} = \frac{p^n_i}{\mu_{ij}} \tau_{ij}.$$
7 Estimation

7.1 Land-use change and commodity substitution elasticities

Our first estimating equation is the odds ratio between commodities within the agricultural nest \( C \);

\[
\ln \left( \frac{\pi_{c}^{i}t}{\pi_{c'}^{i}t} \right) = \frac{\theta}{\lambda} \ln \left( \frac{p_{c}^{it}A_{i}^{c}r_{t}}{p_{c'}^{it}A_{i}^{c'}r_{t}} \right) + \varepsilon_{cc}^{c'i},
\]

where \( \pi_{c}^{i}t \) is county \( i \)'s land share in commodity \( c \) at time \( t \), \( p_{c}^{it} \) is the farm-gate price, \( A_{i}^{c} \) is the observable component of productivity, and \( \varepsilon_{cc}^{c'i} \) is an unobservable supply shifter of \( c \) relative to \( c' \). The composite parameter \( \frac{\theta}{\lambda} \) is the elasticity of substitution between commodities, i.e., within the agricultural nest. A useful interpretation of 2 is as a supply equation of commodity \( c \) relative to \( c' \), in which case \( \frac{\theta}{\lambda} \) can be interpreted 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 correlated across commodities \( (\lambda \to 0) \). Thus, identifying this supply elasticity is not enough to separately identify \( \theta \) from \( \lambda \).

The additional restriction needed for separate identification exploits variation across nests: it is the odds ratio between nest \( C \) and natural use \( N \),

\[
\ln \left( \frac{\pi_{C}^{i}t}{\pi_{N}^{i}t} \right) = \lambda \ln \left( \sum_{c \in C} (p_{c}^{it}A_{i}^{c})^{\frac{\theta}{\lambda}} \right) - \theta \ln \left( A_{i}^{N} \right) + \varepsilon_{it},
\]

where \( \ln \left( \sum_{c \in C} (p_{c}^{it}A_{i}^{c})^{\frac{\theta}{\lambda}} \right) \) 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 I estimate it as a county fixed effect, and \( \varepsilon_{it} \) is an unobservable supply shifter of agricultural land. The parameter \( \lambda \) is the deforestation elasticity, i.e., the substitution elasticity across nests. Given the composite parameter \( \frac{\theta}{\lambda} \) estimated from 2, we can construct the inclusive value term in 3, and then \( \lambda \) is identified.

---

\(^{46}\) 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.
OLS estimates of equation 2 will be biased toward zero due to simultaneity bias because the unobservable supply shocks $\varepsilon_{it}^{cc'}$ will be correlated with relative land shares and relative returns.\footnote{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 $\lambda$ downwards.} 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,

$$z_{it}^{cc'} = \sum_j s_{ij}^{cc'} d_{jt}^{cc'},$$

where $s_{ij}^{cc'}$ is the share of commodity $c$ output produced in county $i$ that historically goes to destination $j$, and $d_{jt}^{cc'}$ 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 $d_{jt}^{cc'}$, 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 $\Delta \varepsilon_{it}^{cc'}$, whereas correlation with levels $\varepsilon_{it}^{cc'}$ is allowed (Goldsmith-Pinkham et al., 2020).\footnote{For example, 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 $c'$.}

### 7.1.1 Discussion of results

OLS and IV estimates of $\lambda$, 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. For example, Costinot et al. (2016) estimate a value of 2.46 and Sotelo (2020) estimates a value of 1.66.\footnote{Also, Pellegrina (2019) conducts his estimation separately for each product category (fruits, cereals, etc.), with an estimate of 3.64 for cereals. His larger estimates are possibly due to productivity dispersion being lower within categories than across.} 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 such as the Amazon.
Table 3: Nested model - substitution elasticity between commodities (within-nest)

<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>$\frac{\delta}{\lambda}$</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>$\frac{\delta}{\lambda} \times$ frontier region</td>
<td>0.181</td>
<td>-0.842**</td>
<td>(0.356)</td>
<td>(0.382)</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>9,547</td>
<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>
</tbody>
</table>

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

Table 4 shows estimates of $\lambda$, the deforestation elasticity. The estimates are broadly 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 on the order of 0.3. Within Brazil and focusing on the Amazon, 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.50

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

<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>$\lambda$</td>
<td>0.121***</td>
<td>0.418**</td>
<td>0.120***</td>
<td>0.399**</td>
</tr>
<tr>
<td></td>
<td>(0.013)</td>
<td>(0.180)</td>
<td>(0.013)</td>
<td>(0.165)</td>
</tr>
<tr>
<td>$\lambda \times$ frontier region</td>
<td>0.019</td>
<td>-0.217</td>
<td>(0.061)</td>
<td>(0.153)</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>8,285</td>
<td>8,285</td>
<td>8,285</td>
<td>8,285</td>
</tr>
<tr>
<td>Adjusted R²</td>
<td>0.445</td>
<td>0.365</td>
<td>0.445</td>
<td>0.376</td>
</tr>
</tbody>
</table>

Note: First stage F-statistic = 577.9. *p<0.1; **p<0.05; ***p<0.01.

How important is the nesting structure? If we imposed a multinomial model, we would as-

---

50 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 long time horizon, I interpret the results as long-run elasticities.
sume $\lambda = 1$ and estimate 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

<table>
<thead>
<tr>
<th></th>
<th>OLS (1)</th>
<th>IV (2)</th>
<th>OLS (3)</th>
<th>IV (4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\theta$</td>
<td>0.242***</td>
<td>0.167***</td>
<td>0.252***</td>
<td>0.174***</td>
</tr>
<tr>
<td></td>
<td>(0.007)</td>
<td>(0.008)</td>
<td>(0.007)</td>
<td>(0.008)</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,

$$\frac{d \ln \pi_i^c}{d \ln p_i^c} = \theta (1 - \pi_i^c).$$

Because estimates of $\theta$ are well above 1 in the trade literature, the multinomial model estimates 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 allows for changes in a commodity’s acreage to
be decomposed into both margins:

\[
\frac{d \ln \pi_i^c}{d \ln p_i^c} = \frac{d \ln \pi_i^{C|C}}{d \ln p_i^{C|C}} + \frac{d \ln \pi_i^c}{d \ln p_i^c}.
\]

where \(\pi_i^c\) is the inclusive value of the agricultural nest—a measure of agriculture’s payoff as a whole. By separating the two margins, the model can reconcile relatively large high substitution elasticities identified from variation within the agricultural nest (high \(\frac{\theta}{\lambda}\)) with relatively low land-use change elasticities identified from variation across nests (low \(\lambda\)).

Finally, Figures 9 and 10 display the within-sample fit of the nested and multinomial models, in terms of the land shares they predict from the observed prices, and how these predictions compare to the observed land shares. The nested model is more flexible than the multinomial model by definition, so it fits the data better by construction. How much better though, is an empirical question: the nested model’s fit, as measured by R-squared, is twice as good. Note that the multinomial model is especially poor at predicting how agricultural land is divided between different commodities (right hand side panel of Figure 10). Because the multinomial model’s single parameter \(\theta\) is significantly lower than the nested model’s within-nest parameter \(\frac{\theta}{\lambda}\)—and recall these parameters are the ones determining how farmers respond to differential returns across commodities in each model—the multinomial model predicts very little variation in land shares across commodities. Another way to see this is that as \(\theta \to 0\), agricultural returns become irrelevant for farmer’s decisions and agricultural land is divided equally among all commodities.
Agricultural share of total land: \( \ln(\pi^C_i) \)

Commodity share of agricultural land: \( \ln\left(\pi^i_{\cdot|C}\right) \)

Figure 9: Nested model within-sample fit. Bubble sizes are proportional to total acreage.

Agricultural share of total land: \( \ln(\pi^C_i) \)

Commodity share of agricultural land: \( \ln\left(\pi^i_{\cdot|C}\right) \)

Figure 10: Multinomial model within-sample fit. Bubble sizes are proportional to total acreage.
7.2 Input substitution elasticities

Our estimating equation comes from the rancher’s demand for feed relative to pasture land,

\[
\ln \left( \frac{M_{it}}{L_{it}} \right) = \sigma \ln \left( \frac{p_{it}^L + p_{it}^K / z_{Kit}}{p_{it}^M + p_{it}^K / z_{Kit}} \right) + \varepsilon_{it} \quad \text{where} \quad \varepsilon_{it} \equiv (\sigma - 1) \ln \left( \frac{z_{Mit}}{z_{Lit}} \right),
\]

where \( \varepsilon_{it} \) is the unobservable relative productivity between feed and pasture.\(^{51}\) OLS estimation of equation 4 suffers from simultaneity bias: relative input prices are positively correlated with unobserved relative productivity, biasing the OLS estimate of \( \sigma \) toward zero. I instrument for the relative land price in equation 4 with a shifter of land available to ranchers.\(^{52}\) I exploit temporal variation from the soybean boom documented in section 5 with cross-sectional soybean soil suitability to construct a shift-share instrument, \( Z_{it} \equiv A_{i}^{S}p_{t}^{S} \). \( A_{i}^{S} \) is the natural soybean-suitability of county \( i \), as measured by the FAO-GAEZ agronomic data, and \( p_{t}^{S} \) is the international soybean price. Given land markets clear locally because of the non-tradability of land, a soybean price boom raises land prices relative to feed prices, and more so in soybean-suitable areas, thus satisfying the relevance condition. The exclusion restriction is that natural soybean-suitability is not systematically correlated with changes in the relative productivity between pasture land and feed inputs for beef production.\(^{53}\)

7.2.1 Discussion of results

OLS and IV estimates are shown in Table 6. The first-stage is strong by conventional standards and OLS results are downward biased, as expected with simultaneity bias. Values lie within reasonable bounds compared to the production function estimation literature and suggest inputs are complements. For example, Doraszelski and Jaumandreu (2018) assume a CES technology us-

---

\(^{51}\)For example, \( \varepsilon_{it} \) would vary in the cross-section if there is variation in feed quality relative to pasture land quality across counties.

\(^{52}\)A common solution in production function estimation is to assume a stochastic process for productivity with some finite dependence, which, combined with timing assumptions on the input decisions, delivers internal instruments, typically lagged variables (Arellano and Bond, 1991). For example, Doraszelski and Jaumandreu (2018) estimate a CES production function using first-order conditions similar to the ones above by instrumenting with lagged output and input prices. I take a different approach because I do not have firm-level production data, but I do have quasi-experimental variation available.

\(^{53}\)This assumption allows beef production in historically soybean-suitable areas to become systematically more productive in the Hicks-neutral sense. It does not allow beef production in these areas to experience systematic factor-biases in technological change. For example, it allows feed and pasture land productivity to increase in tandem in soybean-suitable areas, as long as the change in relative productivities isn’t systematically different in these areas.
Estimating how substitutable land and non-land inputs are with each other is important to evaluate policies that promote intensification as a way to reduce environmental damages. For example, consider a subsidy on maize whose goal is to have ranchers substitute away from pasture towards maize-based animal feed, with the goal of reducing land-use change emissions. This subsidy tilts the ratio of clean-to-dirty inputs favorably, but may increase the level of all inputs if they are poorly substitutable and demand is highly elastic, leading to higher equilibrium output and emissions—the Jevons paradox. On the other hand, if inputs are highly substitutable and demand is inelastic, the subsidy has a land-saving effect—the Borlaug hypothesis. Thus, the critical empirical objects are the production function’s elasticity of substitution and the beef demand elasticity.

Figure 11 shows the hypothetical subsidy’s effects under different combinations of input substitution elasticity and demand elasticity.\(^54\) Land use declines only when demand is sufficiently inelastic and inputs are highly substitutable. The worst-case scenario, in terms of increasing land use, increasing emissions, and defeating the policy’s goal, is when demand is very elastic and inputs are poor substitutes. There is a range of parameter combinations for which a subsidy on environmentally friendly inputs can backfire and lead to higher emissions, hence the importance of quantifying the input substitution margin.

\(^{54}\)This is a partial equilibrium exercise for illustrative purposes. The full equilibrium results are presented in section 8.
Figure 11: Effect of a feed subsidy under different combinations of elasticity of substitution ($\sigma$) and demand elasticity ($\epsilon^B$) on feed ($M$) and land ($L$). Each point on the surface is the percentage change between the post-subsidy and the pre-subsidy equilibrium, for a fixed {$\epsilon^B, \sigma$} pair.

7.3 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 $p_i$. The agribusiness sourcing data allows me to obtain origin-destination prices $p_{ij}$, 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,

$$\frac{p_{ij}}{p_i} = \tau_{ij}. \quad (5)$$

However, if intermediaries hold market power, the price gap identifies a combination of trade costs and markdowns (Atkin and Donaldson, 2015),

$$\frac{p_{ij}}{p_i} = \frac{\tau_{ij}}{\mu_{ij}}. \quad (6)$$

Without further assumptions, trade costs and markdowns cannot be separately identified from price gaps. The conduct assumption in the intermediary sector therefore serves as an identifying
restriction: it pins down $\mu_{ij}$ as a function of supply elasticities and number of competitors, so that $\tau_{ij}$ becomes identified.

7.3.1 Discussion of results

Figure 12 shows the distribution of the input price to marginal revenue product ratio $\mu_{ij}$, which is a necessary input to inferring trade costs. The results suggest agribusiness market power is more significant in the beef sector.

![Figure 12: Distribution of input price to marginal revenue product $\mu_{ij}$](image)

The markdown estimates have implications for measuring trade costs, since they are combined with origin prices $p_i$ and destination prices $p_{ij}$ to back out trade costs using equation 6. Figure 13 shows the distribution of trade costs implied by the estimated markdowns, while also comparing it to the distribution of trade costs implied by perfectly competitive markets. 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 (see Figure 14), the upward bias in trade costs is larger in these regions.
7.4 Demand elasticities

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

$$
\ln \left( \frac{X_{ij}^n}{X_{ij}^n} \right) = (1 - \rho) \ln \left( p_{ij}^n \right) + \lambda_{ij}^n + \epsilon_{ij}^n \quad \forall i \in l,
$$

(7)

where $X_{ij}^n$ is destination $j$’s expenditure on good $n$ from county $i$ and $X_{ij}^n = \sum_{i \in l} X_{ij}^n$. Because 7 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 $i$, $s_{ij}^n$,

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

(8)

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.

---

55 Full derivations for the estimating equations presented in this section are in Appendix section D.6. Here, $\lambda_{ij}^n \equiv - \ln \left( \sum_{i' \in l} (p_{ij}^{n, i'})^{1-\rho} \right)$ is treated as a good-source-destination-time fixed effect.
Figure 14: Input price to marginal revenue product ratio (averaged across products)
The exclusion restriction is that these origin-destination specific supply shocks are uncorrelated with origin-destination specific demand shocks.\textsuperscript{56}

The middle-level elasticity $\eta$ is identified from expenditure variation across countries:

$$\ln \left( \frac{X_{njt}^n}{X_{jt}^n} \right) = (1 - \eta) \ln \left( P_{njt}^n \right) + \lambda_{njt}^n + \epsilon_{njt}^n, \quad (9)$$

where $X_{njt}^n$ is destination $j$’s total expenditure on good $n$ across all source countries.\textsuperscript{57} Since 9 is a demand equation, I again instrument for price by constructing a supply shifter as in equation 8, however at the country rather than county level.

Finally, the upper-level elasticity $\epsilon$ is identified from expenditure variation across goods,

$$\ln \left( \frac{X_{jt}^n}{X_{jt}} \right) = (1 - \epsilon) \ln \left( P_{njt}^n \right) + \lambda_{jt} + \epsilon_{jt}^n, \quad (10)$$

where $X_{jt}$ is destination $j$’s total expenditure on all imports.\textsuperscript{58} 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 $A_{jt}^n$,

$$Z_{jt}^n = \ln \left( A_{jt}^n W_{jt} \right). \quad (11)$$

7.4.1 Discussion of results

Substitution elasticity estimates for each level of the demand system are shown in Table 7.

As expected, IV estimates are larger than the OLS estimates for each level of the demand system, and the results indicate stronger substitution patterns across product sources than across products. Furthermore, substitution elasticities across counties are substantially larger than across countries, as would be expected. At the country and good levels, the implied CES parameter values are $\eta = 6.52$ and $\epsilon = 1.88$. These results are similar to those in the related literature. For

\textsuperscript{56}More specifically, a destination market’s exposure measure is not predictive of future supply shocks.

\textsuperscript{57}The term $\lambda_{njt}^n \equiv - \ln \left( \sum_l a_{nlj}^n (P_{nlj}^n)^{1-\eta} \right)$ and $\epsilon_{njt}^n \equiv \ln \left( a_{njt}^n \right)$.

\textsuperscript{58}To construct the price indices required for the upper-level estimation I use the residuals from the middle-level equation 9. That is, $P_{njt}^n \equiv \left( \sum_l a_{nlj}^n \left( P_{nlj}^n \right)^{1-\eta} \right)^{\frac{1}{n}}$, where $a_{njt}^n = \exp \left( \epsilon_{njt}^n \right)$. Furthermore, $\lambda_{jt} \equiv - \ln \left( \sum_n a_{njt}^n \left( P_{njt}^n \right)^{1-\eta} \right)$ is treated as a destination-time fixed effect and $a_{njt}^n = \exp \left( \epsilon_{njt}^n \right)$. 

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Table 7: Demand substitution elasticities

<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.

example, Costinot et al. (2016) estimate demand substitution across countries and goods, finding values of $\eta = 5.40$ and $\epsilon = 2.82$. 

45
8 Policy counterfactuals

8.1 Environmental tariffs

Given the infeasibility of a first-best carbon tax levied by developing world governments on their agricultural sectors, foreign trading partners may intervene with environmental tariffs. A recent example is the EU’s potential veto of its free trade agreement with the South American trade bloc, with the stated goal of reducing deforestation and emissions.\(^{59}\)

Efficiency: Efforts to reduce emissions are substantially undermined by leakage

In a benchmark trade model without market failures, tariffs distort consumption and production decisions away from the efficient allocation. However, once we add an environmental externality, tariffs have a corrective potential to move the economy towards the *socially* efficient allocation.

Figure 15: Effect of an EU environmental tariff on beef imports from South America

\(^{59}\)Source: Deutsche Welle.
Figure 15 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 unregulated markets. The tariff’s corrective potential is therefore substantially limited by this “leakage effect”: over 80% of the emissions reductions achieved by the drop in EU consumption are offset by increased trade flows to non-EU markets (Figure 16).

![Figure 16: Effect of an EU environmental tariff on net emissions](image)

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 a 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 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.

---

60 The tariff is based on a carbon price of 30 USD per tn.
**Redistribution: Farmers from poorer regions bear a larger burden of regulation**

Beyond the limited effectiveness of the EU tariff, what are the distributional effects on farmers? Figure 17 shows the policy’s effect on farm-gate beef prices across regions and the farmer tax burden (defined as the drop in farm-gate prices relative to the increase in consumer prices). In the frontier agricultural regions—which are also the poorest—farm-gate prices drop more and the regulatory burden is larger because supply is more inelastic. Hence, apart from increasing food prices for consumers, the tax has an extra layer of regressivity on the supply side: farmers in poor regions lose more than farmers in rich regions.

**Figure 17: Distributional effects across space**

![Bar chart showing distributional effects across space](image)

**Role of market structure**

To isolate the role of market power, I repeat the counterfactual policy analysis under two market structures: perfectly competitive and imperfectly competitive agribusiness intermediaries. First,
the reduction in quantities is smaller when intermediaries have market power. Therefore, the effectiveness of the policy, in terms of reducing quantities and thus emissions, is lower when market power is present. Second, the percentage drop in farm-gate prices, which we can interpret as the effective income tax on farmers, is larger.\textsuperscript{61} In this sense, the regressive effects of the policy are exacerbated by market power. Figure 18 shows the percentage drop in farm-gate prices of beef under each market structure.

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{figure18.png}
\caption{Effects on farm-gate prices under each market structure}
\end{figure}

\subsection{Domestic regulation}

\textbf{Deforestation policies versus commodity-targeted policies}

The supply model’s nested structure allows us to evaluate policies targeting different emissions margins: anti-deforestation policies targeting the extensive margin of land clearing, and commodity-

\footnote{The percentage drop in prices differs from the pass-through rate, which is defined as the change in farm-gate price per dollar of tariff. Even though pass-through rates can be lower with market power, the percentage change in price can be higher because the initial pre-tariff prices are lower.}

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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 19 compares the effects of these two policies on land shares.

Figure 19: Effect of a deforestation tax (left) compared with a livestock tax (right) 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 parameter $\frac{\theta}{\lambda}$. 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 margins, and thus allow for the evaluation of targeted policies.

One could imagine two polar-opposite worlds delivering different policy implications. In the first world, substitution across nests is low ($\lambda \to 0$) and within-nests is high ($\frac{\theta}{\lambda} \to \infty$). 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 world, substitution across nests is high ($\lambda \to 1$) and within-nests is low ($\frac{\theta}{\lambda} \to 1$). In this case, the extensive margin is the responsive one, so a deforestation tax will be more effective.

**Input substitution policies**

Beyond attempting to reduce emissions by taxing agriculture, an alternative is to subsidize the use of environmentally friendlier inputs in specific agricultural activities. In the case of beef production, an important margin is the rancher’s decision to fatten cattle exclusively on pasture or to complement diets with animal feed, which is typically maize-based. Using animal feed is a form of agricultural intensification, as it reduces land requirements per unit of output, thus having potential environmental benefits by reducing deforestation.

Policies subsidizing maize have been recently implemented in Argentina for example, with intensification objectives in mind.\(^{62}\) While such subsidies reduce land *per unit of output* by inducing a substitution effect away from pasture to feed, they can also have a scale effect that increases the *levels* of inputs and production. Thus, the net environmental damage can increase if the substitution effects are dominated by such scale effects. In our case, the livestock production function estimates from section 7 indicate pasture and feed are relative complements, suggesting that substitution effects may likely be dominated by scale effects.

Figure 20 shows the effects of a counterfactual maize subsidy on emissions, decomposed by source: land-use change emissions from deforestation, on-farm emissions from maize and beef...\(^{62}\)Source: Reuters.
production, and the overall net emissions change. While the ratio of pasture-to-feed falls with the maize subsidy, the levels of pasture and feed increase, resulting in positive net emissions from increased deforestation, maize production and beef production. However, if the maize subsidy is combined with a deforestation tax (black bars of Figure 20), net emissions can be reduced while increasing maize and beef output. The deforestation tax neutralizes the undesirable scale effects of the subsidy while preserving the desired substitution effects away from pasture.

Figure 20: Effects of input substitution policies

8.3 Extensions

Before concluding, I briefly discuss counterfactuals that my current framework can and cannot accommodate, and which of those I plan to incorporate.

Interactions between environmental and antitrust policy

Thus far, the way I use my framework to study the interaction between the two distortions in this economy—the environmental externality and market power—has been to evaluate how the effects of environmental policy are modified by the presence of market power. Alternatively, it
is possible to do the reverse analysis under the current framework, which is to understand the effects of antitrust policy in the presence of environmental externalities. For example, policies that change the degree of competition, such as allowing a merger of agribusiness firms. While in such a scenario we would expect more deadweight loss from increased market power as well as negative distributional effects for farmers, there can be some environmental benefits because quantities drop. Optimal policy design would have to take into account that both distortions push in opposite directions: the environmental externality leads to overproduction and market power leads to underproduction. If we assume the environmental externality is larger than the deadweight loss from market power, then the first-best solution would be a carbon-tax, but it would have to be set at a rate smaller than the social cost of carbon because market power already reduces quantities part of the way towards the social optimum.

**Targeting across space**

Since the environmental cost of agriculture varies across locations due to variation in carbon stocks, a reasonable margin to target is space. Recent examples include the Brazilian government’s “Priority List” policy in 2008, where specific municipalities were subject to increased anti-deforestation monitoring. The equilibrium and internal geography features of my model can be used to study the effects of such policies on the reallocation of agricultural activities to non-targeted regions—a form of production leakage.

**Targeting intermediaries**

In the agricultural context the main source of the environmental externality is at production, which is atomistic and geographically dispersed, making it logistically challenging to directly regulate at the producer level. Since concentration increases as one moves downstream the supply chain, regulation at the agribusiness firm level can be less costly. However, to fully understand the environmental effects of regulation at the agribusiness level we need to know how firms respond by modifying their sourcing network. In my current setup, the intermediaries’ sourcing network is fixed, therefore they respond to policy interventions by adjusting quantities along their given network. Alternatively, they could modify the network itself. While allowing for endogenous network choice is an interesting intersection between the environmental economics literature and
the trade literature on multinationals and global sourcing, I leave this extension for future work.
9 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 margins driving agriculture’s environmental impact on the supply-side: the choice of which specific agricultural activity is conducted 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 can reconcile relatively high land-use change elasticities implied by trade elasticities with relatively low values found by recent work in agricultural economics and empirical IO. I also allow a third emissions margin—input substitution—through a model of livestock production, which I estimate from data covering 20% of the world’s cattle stock. Through counterfactual exercises, I show how each margin—deforestation, commodity choice, and input substitution—responds to different policy tools, and the policy implications of not taking these separate margins into account.

Second, I document concentration among agribusiness firms and incorporate buyer market power into my framework 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 the demand side. Supply-side distributional effects are highly relevant in agriculture, where policy is often designed with redistribution towards farmers as an explicit goal, thus 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. Finally, agribusiness market power plays a role by exacerbating the distributional effects. Thus, in the presence of
multiple market failures, policies targeting a single externality can exacerbate other distortions—not only in efficiency terms, but also in skewing the distribution of the remaining surplus.
References


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Appendix A. Environmental science background

A.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 m$^2$. 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 ton of the gas absorbs over a given time period, relative to the emissions of 1 ton of CO$_2$. Thus, the GWP of CO$_2$ is 1 by definition. For example, methane (CH$_4$) is over 80 times as effective at trapping heat as CO$_2$ over a period of 20 years (i.e., GWP$_{20}$ $\approx$ 80). In order to add up different GHGs into a single emissions inventory, GWPs are used to convert non-CO$_2$ gases into CO$_2$-equivalent (CO$_2$e) units. Under this aggregation method, CO$_2$ represents 75% of all GHG emissions, while CH$_4$ 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 CO$_2$ is notoriously difficult to pin down, it is typically reported to be in the order of centuries to millenia (Inman, 2008). Specifically, about 50% of CO$_2$ 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 et al., 2007). By contrast, the atmospheric lifetime of CH$_4$ is approximately 12 years, after which it breaks down into CO$_2$ and water.

A.2 Distinction between agricultural emissions and fossil fuel emissions

The burning of fossil fuels adds “new” CO$_2$ to the atmosphere because it releases CO$_2$ which had made its way deep underground over millions of years. Because of this and the long atmospheric lifetime of CO$_2$, 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$_4$ offers an opportunity to reduce radiative forcing quickly, in a way CO$_2$ 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$_2$ abatement strategies with CH$_4$ abatement, the probability of the climate irreversibly entering tipping point scenarios in the near future can be reduced (Montzka et al., 2011). Given the largest source of global anthropogenic CH$_4$ emissions is the livestock in-
dustry, abatement strategies in this sector can mitigate climate-change damages in a substantial way (Ripple et al., 2013).

A.3 Emissions pricing

Conceptually, calculating the social cost of carbon consists of evaluating the present value of the future damages from releasing one ton of CO$_2$ 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 ton of CO$_2$, 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 ton of CO$_2$.

A.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.

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.
Appendix B. Agronomy background

B.1 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.*

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 coincides with the season of the year when grassland is most abundant, which varies by region but is typically the spring.

B.2 Dynamic aspects of cattle production

The livestock industry has the peculiar feature that animals are both a capital and a consumption good: animals are used to breed new animals, and they are also slaughtered for consumption (Jarvis, 1974). This creates an inherent dynamic problem for ranchers, as they face an intertemporal trade-off between slaughtering their animals today to collect revenue, or retaining animals to grow their herds for the future. Beef cattle in particular have a biological cycle that is longer than any other animal agriculture sector: the production lag from birth to slaughter is typically over 2 years, substantially longer than poultry or pork. The “time-to-build” feature of the production technology results in cyclical variations in cattle stocks and prices. Indeed, “cattle stocks are among the most periodic time series in economics” (Rosen et al., 1994).

Cattle cycles show up clearly in aggregate data, and they display remarkable regularity across major beef producing countries despite important differences in technology and institutions (Mundlak and Huang, 1996). Figures 21 and 22 show the cattle cycle for the United States, Argentina, and Brazil.

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63 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. County-level data distinguishing between first- and second-harvest crops is only available for recent years and not for the 1990s. Therefore, throughout the paper I use the aggregated values. Bustos et al. (2016) encounter the same issue and calculate land shares using aggregated first- and second-harvest maize acreage for Brazil.

64 Such hysteresis is also present in other industries with important production lags. For example, in more recent work, Kalouptsidi (2014) shows this also holds for shipbuilding.
Figure 21: Cattle stock time series for major beef producing countries.
Figure 22: Detrended cattle stock and real beef price time series for major beef producing countries.
Appendix C. Institutional details

C.1 Agricultural land ownership and employment

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.\textsuperscript{65} According to Brazil’s agricultural census, there 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.\textsuperscript{66} As of 2006, agriculture’s share of employment was 15.7% in Brazil and 1.05% in Argentina.\textsuperscript{67}

C.2 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.\textsuperscript{68} 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 (Pierri 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 et al., 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.\textsuperscript{69}

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

\textsuperscript{65}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.

\textsuperscript{66}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.

\textsuperscript{67}Source: World Bank.

\textsuperscript{68}Source: MAGYP.

\textsuperscript{69}Source: IBGE Table 6957, Table 6959, and TRASE.
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 sub-national/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.

C.3 Beef supply chain

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 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. 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 et al., 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. As in Argentina, the supply chain is vertically unintegrated and divided into three parts: breeders, finishers, and slaughterhouses.

C.4 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 et al., 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 sugar-

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70 Source: SENASA.
71 Vertical 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).
72 Sources: IBGE Table 6783 and Table 6910 and Table 6783.
cane 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.

C.5 Export restrictions in Argentina (2005-2008): Short- and long-run effects

Figures 23 shows beef exports, cattle stock, and domestic beef consumption and prices for Argentina. Between 2001 and 2005 production, exports, and domestic consumption increased as the country recovered from its 2001 economic crisis. Under these favorable conditions, cattle ranchers invested in growing their herds, with the national cattle stock reaching its highest level in 25 years.

By 2005, annual inflation had risen above 10%. As a means to control inflation, the government decided to intervene in specific industries whose products were an important component of the consumer price index, one of which was the beef industry. Between 2005 and 2008 the government implemented a host of measures to restrict beef exports, with the objective of diverting supply to the domestic market and curbing the rise in domestic beef prices. These measures ranged from export taxes to direct quantity restrictions such as export quotas and outright bans on certain cuts of meat. Guevara and Grunwaldt (2012) provide a summary of the major beef export restrictions during this period:

- November 2005: beef export taxes are increased from 5% to 15%.
- March 2006: beef exports are banned for 180 days, except Hilton quota cuts.
- June-November 2006: exports restricted to 40% of the volume exported in the same period of the previous year (June-November 2005).
- May 2008: restriction of exports to 540,000 tons per year.

The stated objectives of the restrictions were achieved in the short run, as exports fell by 50%, domestic consumption increased by 12.5%, and domestic real beef prices were flat during most of 2005-2008. However, the long term effect of these measures were not seen until several years later due to the industry’s production lags. Given the negative profitability implied by the export restrictions, ranchers disinvested in their herds by increasing slaughter rates, leading to a short run increase in beef production. This disinvestment period ended with an 18% drop in the cattle stock between 2007 and 2010—the fastest and largest contraction in the cattle cycle ever recorded in Argentina. From 2010 to 2013, with beef supply constrained by the historically low cattle stock, real beef prices increased by over 50%. Thus, the short-run success of these restrictions were undone by their long-run failure.
Figure 23: Case study for Argentina. Beef export restrictions were implemented between 2005-2008 (shaded region). The dashed horizontal line in the bottom right panel is the female share of slaughtered cattle that maintains a constant herd size (0.43).
Appendix D. Theory

D.1 Derivations of the nested logit model

Field productivity for a land use $k$ is decomposed into a common component $A^k_i$ and a field-idsiosyncratic deviation $\varepsilon^k_i(\omega)$ distributed type I EV with location parameter 0 and standard deviation $\sigma/\sqrt{6}$,

$$A^k_i(\omega) = A^k_i \exp(\varepsilon^k_i(\omega)) \quad \forall k \in \mathcal{N} \cup \mathcal{C}$$

Let $R^k_i(\omega)$ denote field $i$’s return per unit of land from choice $k$,

$$R^k_i(\omega) = \begin{cases} \frac{c_i}{A^c_i(\omega)} & \text{if } k = c \in \mathcal{C} \\ A^N_i(\omega) & \text{if } k = N \end{cases}$$

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,

$$r^k_i(\omega) = \begin{cases} \ln \left( \frac{c_i}{A^c_i(\omega)} \right) + \varepsilon^c_i(\omega) & \text{if } k = c \in \mathcal{C} \\ \ln A^N_i(\omega) + \varepsilon^N_i(\omega) & \text{if } k = N \end{cases}$$

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 $\sigma/\sqrt{6}$ (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 ($\theta \equiv \sigma^{-1}$), $r^k_i(\omega)^* = \theta r^k_i(\omega)$, $\varepsilon^k_i(\omega)^* \equiv \theta \varepsilon^k_i(\omega)$, which delivers

$$r^k_i(\omega)^* = \begin{cases} \theta \ln \left( \frac{c_i}{A^c_i(\omega)} \right) + \varepsilon^c_i(\omega)^* & \text{if } k = c \in \mathcal{C} \\ \theta \ln A^N_i(\omega) + \varepsilon^N_i(\omega)^* & \text{if } k = N \end{cases}$$

D.2 Choice probabilities and substitution patterns

The unconditional choice probabilities (the land use shares) are,

$$\pi^k_i = \frac{\left( \frac{p^c_i A^c_i}{\sum_{j \in \mathcal{C}} p^j_i A^j_i} \right)^{\frac{\theta}{2}} \left( \frac{\sum_{j \in \mathcal{C}} \left( p^j_i A^j_i \right)^{\frac{\theta}{2}}}{\sum_{j \in \mathcal{C}} \left( p^j_i A^j_i \right)^{\frac{\theta}{2}}} \right)^{\frac{\theta}{2} - 1}}{\left( \frac{c_i A^c_i}{\sum_{j \in \mathcal{C}} c_j A^j_i} \right)^{\theta/2} + \left( \frac{\sum_{j \in \mathcal{C}} \left( p^j_i A^j_i \right)^{\theta/2}}{\sum_{j \in \mathcal{C}} \left( p^j_i A^j_i \right)^{\theta/2}} \right)^{\theta/2}} = \pi^c_i \pi^C_i \quad \text{for } k = c \in \mathcal{C}$$

$$\pi^k_i = \frac{\left( \frac{A^N_i}{\sum_{j \in \mathcal{C}} A^j_i} \right)^{\theta/2} \left( \frac{\sum_{j \in \mathcal{C}} \left( p^j_i A^j_i \right)^{\theta/2}}{\sum_{j \in \mathcal{C}} \left( p^j_i A^j_i \right)^{\theta/2}} \right)^{\theta/2}}{\left( \frac{c_i A^c_i}{\sum_{j \in \mathcal{C}} c_j A^j_i} \right)^{\theta/2} + \left( \frac{\sum_{j \in \mathcal{C}} \left( p^j_i A^j_i \right)^{\theta/2}}{\sum_{j \in \mathcal{C}} \left( p^j_i A^j_i \right)^{\theta/2}} \right)^{\theta/2}} = \pi^N_i \quad \text{for } k = N.$$
The cross-price elasticities of land use are,

\[
\frac{d \ln \pi_k^i}{d \ln p_i^c} = \begin{cases} 
-\theta \pi_i^c + \theta \pi_i^c \left( \frac{\lambda - 1}{\lambda} \right) & \text{for } k = c \in C \\
-\theta \pi_i^c & \text{for } k = N.
\end{cases}
\]

The own-price elasticities of land use for a specific commodity \( c \) are,

\[
\frac{d \ln \pi_c^i}{d \ln p_i^c} = \frac{\theta}{\lambda} \left( 1 - \pi_i^c \right) + \frac{\theta \pi_i^c \lambda}{\lambda} \left( 1 - \pi_i^c \right)
\]

and the own-price elasticities of agricultural land use overall are,

\[
\frac{d \ln \pi_C^i}{d \ln p_i^c} = \lambda \left( 1 - \pi_i^c \right)
\]

The term \( \ln p_i^c \) measures the return from all agricultural uses—technically, it is the agricultural nest’s inclusive value. The own-price elasticities of output for a specific commodity \( c \) are,

\[
\frac{\partial \ln p_i^c}{\partial \ln Q_i^c} = \begin{cases} 
\frac{1}{(\theta - 1)(1 - \pi_i^c)} + \theta \pi_i^c \left( 1 - \pi_i^c \right) & \text{for } \lambda < 1 \\
\frac{1}{(\theta - 1)(1 - \pi_i^c)} & \text{for } \lambda = 1.
\end{cases}
\]

Therefore, the supply curve becomes more inelastic when \( \theta \) falls, since field heterogeneity increases. Furthermore, given \( \theta \), the supply elasticity is not constant—it is increasing in the own price (since the land shares for commodity \( c \) are increasing in \( p_i^c \)). Thus, as we move up the supply curve, supply becomes more inelastic. We can then plug these supply elasticities in the markdown formula,

\[
\mu_{ij}^c = \left( 1 + \frac{\partial \ln p_i^c}{\partial \ln Q_i^c N_{ij}^c} \right)^{-1},
\]

which delivers,

\[
\mu_{ij}^c = \begin{cases} 
\left( 1 + \frac{1}{(\theta - 1)(1 - \pi_i^c)} \left( 1 - \pi_i^c \right) \frac{\delta_j}{N_{ij}} \right)^{-1} & \text{for } \lambda < 1 \\
\left( 1 + \frac{1}{(\theta - 1)(1 - \pi_i^c)} \frac{\delta_j}{N_{ij}} \right)^{-1} & \text{for } \lambda = 1.
\end{cases}
\]
D.3 Selection effect

The expected payoff of a nested discrete choice problem, conditional on choosing a nest, is equal to the inclusive value of the nest multiplied by the nest’s correlation parameter $\lambda$ (Train (2009), Chapter 4). To obtain the payoff in dollar units one must then divide by the coefficient on price (in our case, $\theta$). Applying the appropriate transformation from the type I EV to the type II EV setting we obtain,

$$E \left[ \max_{c \in C} p^c_i A^c_i(\omega) \right] = \left[ \sum_c (p^c_i A^c_i) \right]^\frac{1}{\theta}$$ \hspace{1cm} (12)

$$\sum_c E \left[ p^c_i A^c_i(\omega) \right] = \max_{l \in C} p^l_i A^l_i(\omega) \times \pi^c_i = \left[ \sum_c (p^c_i A^c_i) \right]^\frac{1}{\theta}$$ \hspace{1cm} (13)

$$\sum_c E \left[ p^c_i A^c_i(\omega) \right] = \max_{l \in C} p^l_i A^l_i(\omega) \times \pi^c_i = \left[ \sum_c (p^c_i A^c_i) \right]^\frac{1}{\theta} \times \pi^c_i = 1$$ \hspace{1cm} (14)

$$\sum_c E \left[ A^c_i(\omega) \right] = \max_{l \in C} p^l_i A^l_i(\omega) \times \pi^c_i = \left[ \sum_c (p^c_i A^c_i) \right]^\frac{1}{\theta} \times \pi^c_i = 1$$ \hspace{1cm} (15)

We want to show 15 implies,

$$E \left[ A^c_i(\omega) \right] = \max_{l \in C} p^l_i A^l_i(\omega) = A^c_i \left( \pi^c_i \right)^{-\frac{1}{\theta}} \forall c$$

Suppose this is not the case. Then, for 15 to hold there must exist a good $c$ and a good $c'$ such that,

$$\frac{E \left[ A^c_i(\omega) \left| p^c_i A^c_i(\omega) = \max_{l \in C} p^l_i A^l_i(\omega) \right. \right]}{A^c_i \left( \pi^c_i \right)^{-\frac{1}{\theta}}} \neq 1 < \frac{E \left[ A^{c'}(\omega) \left| p^{c'} A^{c'}(\omega) = \max_{l \in C} p^l_i A^l_i(\omega) \right. \right]}{A^{c'} \left( \pi^{c'} \right)^{-\frac{1}{\theta}}}$$
Now consider good $c$,
\[
E \left[ A^c(\omega) \bigg| p^c A^c(\omega) = \max_{l \in C} p^l_i A^l_i(\omega) \right] < 1
\]
\[
A^c \left( \pi^c_i \right)^{-\frac{1}{\sigma}}
\]
\[
E \left[ A^c(\omega) \bigg| p^c A^c(\omega) = \max_{l \in C} p^l_i A^l_i(\omega) \right] \times \pi^c_i < 1
\]
\[
A^c \left( \pi^c_i \right)^{-\frac{1}{\sigma}}< 1
\]
\[
\frac{E \left[ A^c(\omega) \right]}{A^c \left( \pi^c_i \right)^{1-\frac{1}{\sigma}}} < 1
\]
\[
1 < \left( \pi^c_i \right)^{1-\frac{1}{\sigma}}
\]

But this last line cannot hold because $\pi^c_i \in [0, 1]$ and $\frac{1}{\sigma} \in (0, 1)$.

D.4 Production function details

The baseline production function is,
\[
F_i(\bar{K}_i, \bar{L}_i, \bar{M}_i) = \min \left\{ z_{K}^i \bar{K}_i, \left[ (z_{L}^i \bar{L}_i)^{\frac{\sigma - 1}{\sigma}} + (z_{M}^i \bar{M}_i)^{\frac{\sigma - 1}{\sigma}} \right]^{\frac{1}{\sigma - 1}} \right\}
\]

The FOC of the rancher’s problem is,
\[
p^b_i \left[ (z_{L}^i \bar{L}_i)^{\frac{\sigma - 1}{\sigma}} + (z_{M}^i \bar{M}_i)^{\frac{\sigma - 1}{\sigma}} \right]^{\frac{1}{\sigma - 1}} z_{X}^i X_i^{-\frac{1}{\sigma}} = p^L_i + \frac{p^K_i}{z_{K}^i} \quad \text{for } X = L, M,
\]

which after rearranging implies,
\[
\frac{M_i}{L_i} = \left( \frac{p^L_i + p^K_i}{z_{K}^i} \right) \left( \frac{z_{M}^i \bar{M}_i}{z_{L}^i \bar{L}_i} \right)^{\sigma - 1}.
\]

Whereas factor intensities are determined by relative factor prices, factor levels are indeterminate because technology is constant returns to scale—given factor intensities, the rancher’s FOC with respect to $L_i$ delivers a flat inverse demand curve for land,
\[
p^b_i z_{L}^i \left[ 1 + \left( \frac{z_{M}^i \bar{M}_i}{z_{L}^i \bar{L}_i} \right)^{\frac{\sigma - 1}{\sigma}} \right]^{\frac{1}{\sigma - 1}} = p^L_i + \frac{p^K_i}{z_{K}^i}.
\]

Therefore, the scale of production, and thus input levels, will be pinned down by equilibrium conditions—in this case, by farmers’ supply of pasture land.
Alternative production function

An alternative CES production function, where all inputs are equally substitutable is,

$$F_i(K_i, L_i, M_i) = \left[ (z_{Ki}K_i)^{\frac{\sigma-1}{\sigma}} + (z_{Li}L_i)^{\frac{\sigma-1}{\sigma}} + (z_{Mi}M_i)^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}}.$$

Given pasture-land rental rates $p^L_i$, cattle prices $p^K_i$, and feed prices $p^M_i$, profit maximization implies a factor’s intensity per unit of land depends on the factor’s price relative to the land price,

$$k_i = \left( \frac{p^L_i}{p^K_i} \right)^{\sigma} z_{ki}^{\sigma-1}, \quad (18)$$

$$m_i = \left( \frac{p^L_i}{p^M_i} \right)^{\sigma} z_{mi}^{\sigma-1}, \quad (19)$$

where $x_i \equiv X_i / L_i$ and $z_{xi} \equiv z_{X_i} / z_{Li}$. The rancher’s FOC with respect to $L_i$ delivers a flat inverse demand curve for land,

$$p^L_i = p^B_i z_{Li} \left[ 1 + (z_{ki}k_i)^{\sigma-1} + (z_{mi}m_i)^{\sigma-1} \right]^{\frac{1}{\sigma-1}}.$$

The following table shows the estimates for the elasticity of substitution under this functional form.

| Table 8: Elasticity of substitution - Livestock production function |
|-----------------|-----------------|-----------------|-----------------|-----------------|
|                 | Argentina OLS   | Argentina IV    | Brazil OLS      | Brazil IV       |
| $\sigma$        | 0.192***        | 0.523***        | 0.364***        | 0.439***        |
|                  | (0.045)         | (0.088)         | (0.016)         | (0.016)         |
| Observations     | 558             | 538             | 2,922           | 2,922           |
| Adjusted R$^2$   | 0.715           | 0.711           | 0.842           | 0.838           |
| 1st stage F-stat | -               | 463,757         | -               | 331,269         |
| **Note:**        | $^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01. |

D.5 Intermediary sector derivations

The following holds for each final good $n$, so I abstract from $n$ superscripts in this section to keep notation clean. An intermediary firm $f$ purchases a good from source $i$ at farm-gate price $p_i$ and sells it in destination $j$ at final price $p_{ij}$. Trade costs are firm specific and are of the iceberg type: a firm needs to purchase $\tau_{ij}^f > 1$ units at source $i$ for 1 unit to arrive at destination $j$. There
is a finite number \( N_{ij} \) of these firms competing on "route" \( ij \)—they hold market power in the upstream market \( i \), but take prices as given in the downstream market \( j \). Assuming firms compete in quantities, each firm’s solves the following problem,

\[
\max_{q_{ij}} \frac{p_{ij}}{\tau_{ij}} q_{ij}^f - p_i(Q_i) q_{ij}^f
\]

where \( p_i(Q_i) \) is the inverse market supply curve of the good, which is increasing in the source’s total production \( Q_i \equiv \sum_j \sum_f q_{ij}^f \). The firm’s FOC is,

\[
\frac{p_{ij}}{\tau_{ij}^f} = p_i + \frac{\partial p_i}{\partial Q_i} \frac{Q_i}{p_i} s_{ij} \quad \text{where} \ s_{ij} \equiv \frac{q_{ij}^f}{Q_i}
\]

Aggregating the above over firms gives us,

\[
\frac{p_{ij}}{p_i} \sum_f \tau_{ij}^{f - 1} = N_{ij} + \frac{\partial p_i}{\partial Q_i} \frac{Q_i}{p_i} s_{ij} \quad \text{where} \ s_{ij} \equiv \sum_f s_{ij}^f
\]

\[
\frac{N_{ij}}{\sum_f \tau_{ij}^{f - 1}} \left( 1 + \frac{\partial p_i}{\partial Q_i} \frac{Q_i}{p_i} \frac{s_{ij}}{N_{ij}} \right) = p_i
\]

Therefore,

\[
p_i = \frac{p_{ij}}{\tau_{ij}^f} \mu_{ij} \quad \text{where} \ \tau_{ij} = \frac{N_{ij}}{\sum_f \tau_{ij}^{f - 1}} \quad \text{and} \ \mu_{ij} = \frac{1}{\left( 1 + \frac{\partial p_i}{\partial Q_i} \frac{Q_i}{p_i} \frac{s_{ij}}{N_{ij}} \right)}
\]

### D.6 Demand side derivations

Consumer demand is CES with three-levels. In the upper level, consumers substitute between goods (maize vs. wheat). In the middle level, they substitute between origin countries of a given good (Brazilian maize vs. US maize). In the lower level, they substitute between origin counties within a country (maize from a county in Northern Brazil vs. maize from a county in Southern Brazil). The lower level is the non-standard part of consumer demand in this paper, and is required for an equilibrium analysis at the county-level. Estimating the lower level substitution elasticity requires domestic trade flow data, which is often not available but in my case I can obtain from the supply chain data. Utility of the representative consumer in location \( j \) is given by,

\[
U_j = \left( \sum_n (a^n_{ij})^{\frac{1}{\tau}} (C^n_{ij})^{\frac{\tau - 1}{\tau}} \right)^{\frac{\tau}{\tau - 1}}, \quad \text{where} \ C^n_{ij} = \left( \sum_i (a^n_{ij})^{\frac{1}{\tau}} (C^n_{ij})^{\frac{\tau - 1}{\tau}} \right)^{\frac{\tau}{\tau - 1}} \quad \text{and} \ C_{ij}^{\rho} = \left( \sum_{i \in l} (C^n_{ij})^{\frac{\tau - 1}{\tau}} \right)^{\frac{\tau}{\tau - 1}}.
\]
$C^n_i$ is good $n$ consumption aggregated over different source countries indexed $l$. $C^n_{ij}$ is good $n$ consumption aggregated over different source counties indexed $i$ within country $l$. $\epsilon$ is the elasticity of substitution between different goods. $\eta$ is the elasticity of substitution between source countries of a given good. $\rho$ is the elasticity of substitution between the counties within a country. The $a$'s are preference shifters across goods and sources. The representative consumer has income $X_j$ and solves the following problem,

$$\max_{C^n_{ij}} U_j \text{ s.t. } \sum_n p^n_{ij} C^n_{ij} \leq X_j.$$  

The first order condition with respect to $C^n_{ij}$ is,

$$\left( \sum_n (a^n_{ij})^{\frac{1}{\epsilon}} (C^n_{ij})^{\frac{\epsilon-1}{\epsilon}} \right)^{\frac{1}{1-\epsilon}} (a^n_{ij})^{\frac{1}{\rho}} (C^n_{ij})^{\frac{\rho-1}{\rho}} (C^n_{ij})^{\frac{1}{\rho}} = p^n_{ij}.$$  

(20)

**Lower level**

Combining the FOC 20 for $C^n_{ij}$ and $C^n_{ij}$ delivers,

$$\frac{C^n_{ij}}{C^n_{i'j}} = \left( \frac{p^n_{ij}}{p^n_{i'j}} \right)^{\rho},$$

$$(p^n_{ij})^{\rho} C^n_{ij} (p^n_{i'j})^{1-\rho} = p^n_{ij} C^n_{ij},$$

$$(p^n_{ij})^{\rho} C^n_{ij} \sum_{i' \in l} (p^n_{i'j})^{1-\rho} = \sum_{i' \in l} p^n_{i'j} C^n_{ij}.$$  

Define expenditure on good $n$ from county $i$ as $X^n_{ij}$ and from country $l$ as $X^n_{ij}$. Then,

$$C^n_{ij} = \frac{(p^n_{ij})^{-\rho}}{\sum_{i' \in l} (p^n_{i'j})^{1-\rho}} X^n_{ij} = \left( \frac{p^n_{ij}}{P^n_{i'j}} \right)^{-\rho} \frac{X^n_{ij}}{P^n_{ij}} \forall i \in l,$$  

(21)

where $P^n_{ij} = \left( \sum_{i' \in l} (p^n_{i'j})^{1-\rho} \right)^{\frac{1}{1-\rho}}$ is the price index for good $n$ imports from $l$.\(^73\) This gives us our first estimating equation, for the lower level substitution elasticity between counties,

$$\ln \left( \frac{X^n_{ij}}{X^n_{ij}} \right) = (1-\rho) \ln \left( p^n_{ij} \right) - \ln \left( \sum_{i' \in l} (p^n_{i'j})^{1-\rho} \right) \forall i \in l.$$  

(22)

\(^73\)This implies $p^n_{ij} C^n_{ij} = X^n_{ij}$. 

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Middle level

Next, to obtain the middle level, we plug our solution for $C_{ij}^n$ into 20,

$$\left( \sum_n (a_{ij}^n)^{1/2} (C_{ij}^n)^{-1/2} \right)^{1/2} (a_{ij}^n)^{1/2} (C_{ij}^n)^{-1/2} (a_{ij}^n)^{1/2} (C_{ij}^n)^{-1/2} (P_{ij}^n)^{1/2} (X_{ij}^n)^{-1/2} = 1 \quad (23)$$

Combining the above for $l$ and $l'$ and using $P_{lj}^n C_{lj}^n = X_{lj}^n$ we obtain,

$$\frac{(a_{ij}^n)^{1/2} (C_{ij}^n)^{-1/2} + (P_{ij}^n)^{1-\rho} (X_{ij}^n)^{-1}}{a_{ij}^n} = \frac{(a_{ij}^n)^{1/2} (C_{ij}^n)^{-1/2} + (P_{ij}^n)^{1-\rho} (X_{ij}^n)^{-1}}{a_{ij}^n} \left( \frac{P_{ij}^n}{P_{ij}^n} \right)^{1-\eta} = \frac{X_{ij}^n}{X_{ij}^n} \left( \frac{P_{ij}^n}{P_{ij}^n} \right)^{1-\eta} \sum_{l'} a_{lj}^n \left( \frac{P_{lj}^n}{P_{lj}^n} \right)^{1-\eta} = \sum_{l'} X_{lj}^n$$

This gives us our second estimating equation, for the middle level’s substitution elasticity between countries,

$$\ln \left( \frac{X_{ij}^n}{X_{ij}^n} \right) = \ln \left( a_{ij}^n \right) + (1 - \eta) \ln \left( P_{ij}^n \right) - \ln \left( \sum_{l'} a_{lj}^n (P_{lj}^n)^{1-\eta} \right) \quad (24)$$

It will be useful to express $X_{ij}^n$ as follows,

$$X_{ij}^n = a_{ij}^n \left( \frac{P_{ij}^n}{P_{ij}^n} \right)^{1-\eta} X_{ij}^n,$$

where $P_j^n \equiv \left( \sum_{l'} a_{lj}^n (P_{lj}^n)^{1-\eta} \right)^{1/\eta}$. 

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81
Upper level

To obtain the upper level we start from equation 23.

\[
\left( \sum_n (a^n_j)^{1/2} (C^n_j)^{\epsilon_n/2} \right)^{1/2} \left( \sum_n (a^n_j)^{1/2} (C^n_j)^{\epsilon_n/2} \right)^{1/2} = 1
\]

\[
\left( \sum_n (a^n_j)^{1/2} (C^n_j)^{\epsilon_n/2} \right)^{1/2} \left( a^n_j \right) \left( C^n_j \right)^{1/2} + \frac{1}{2} (a^n_j)^{1/2} (P^n_j)^{1/2} (X^n_j)^{1/2} = 1
\]

Next, we combine the expression above for good \( n \) and good \( m \),

\[
\frac{a^n_j (P^n_j)^{1-\epsilon}}{a^n_j (P^n_j)^{1-\epsilon} X^n_j} = X^n_j
\]

\[
\sum_m a^n_j (P^n_j)^{1-\epsilon} X^n_j = \sum_m X^n_j
\]

\[
X^n_j = \frac{a^n_j (P^n_j)^{1-\epsilon} X_j}{\sum_m a^n_j (P^n_j)^{1-\epsilon}} = a^n_j \left( \frac{P^n_j}{P_j} \right)^{1-\epsilon} X_j
\]

where \( X_j \) is the location \( j \) expenditure and its price index is \( P_j \). The upper level estimating equation is thus,

\[
\ln \left( \frac{X^n_j}{X_j} \right) = \ln \left( a^n_j \right) + (1 - \epsilon) \ln \left( P^n_j \right) - \ln \left( \sum_m a^n_j (P^n_j)^{1-\epsilon} \right). \quad (25)
\]
Summary

County-level demand is given by,

\[ C_{ij}^n = \left( \frac{p^n_{ij}}{P^n_{ij}} \right)^{-\rho} a_{ij} \left( \frac{P^n_{lj}}{P^n_{j}} \right)^{-\eta} \left( \frac{p^n_{lj}}{P^n_{j}} \right)^{-\epsilon} \frac{X_j}{P_j} \quad \forall i \in I. \tag{26} \]

where,

\[ P^n_{lj} \equiv \left( \sum_{i \in I} (p^n_{ij})^{1-\rho} \right)^{\frac{1}{1-\rho}} \quad P^n_{j} \equiv \left( \sum_{l} a^n_{lj}(P^n_{lj})^{1-\eta} \right)^{\frac{1}{1-\eta}} \quad P_j \equiv \left( \sum_{n} a^n_{j}(P^n_{j})^{1-\epsilon} \right)^{\frac{1}{1-\epsilon}} \]

The estimating equations, from lower to top level are,

\[ \ln \left( \frac{X^n_{ij}}{X^n_{lj}} \right) = (1 - \rho) \ln \left( p^n_{ij} \right) - \ln \left( \sum_{i' \in I} (p^n_{i'j})^{1-\rho} \right) \quad \forall i \in I. \tag{27} \]

\[ \ln \left( \frac{X^n_{lj}}{X^n_{j}} \right) = \ln \left( a^n_{lj} \right) + (1 - \eta) \ln \left( P^n_{lj} \right) - \ln \left( \sum_{l'} a^n_{l'j}(P^n_{l'j})^{1-\eta} \right) \tag{28} \]

\[ \ln \left( \frac{X^n_{j}}{X_j} \right) = \ln \left( a^n_{j} \right) + (1 - \epsilon) \ln \left( P^n_{j} \right) - \ln \left( \sum_{m} a^n_{mj}(P^n_{mj})^{1-\epsilon} \right). \tag{29} \]
Appendix E. Data

E.1 Geographic unit of analysis

The geographic unit of analysis for Argentina is the “departamento” and for Brazil it is the “município”. Throughout the paper I refer to both of these geographic units as “counties”.

Table 9: Comparison of geographic units

<table>
<thead>
<tr>
<th></th>
<th>Argentine counties</th>
<th>Brazilian municipalities</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Population</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>- Mean</td>
<td>78,782</td>
<td>34,570</td>
</tr>
<tr>
<td>- Minimum</td>
<td>17</td>
<td>806</td>
</tr>
<tr>
<td>- Quartile 1</td>
<td>10,889</td>
<td>5,254</td>
</tr>
<tr>
<td>- Median</td>
<td>25,796</td>
<td>11,020</td>
</tr>
<tr>
<td>- Quartile 3</td>
<td>64,280</td>
<td>23,644</td>
</tr>
<tr>
<td>- Maximum</td>
<td>2,891,082</td>
<td>11,316,119</td>
</tr>
<tr>
<td>- Sum</td>
<td>40,336,576</td>
<td>192,379,287</td>
</tr>
<tr>
<td><strong>Land area (ha)</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>- Mean</td>
<td>544,906</td>
<td>152,831</td>
</tr>
<tr>
<td>- Minimum</td>
<td>3,000</td>
<td>356</td>
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<tr>
<td>- Quartile 1</td>
<td>152,500</td>
<td>20,425</td>
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<tr>
<td>- Median</td>
<td>325,900</td>
<td>41,829</td>
</tr>
<tr>
<td>- Quartile 3</td>
<td>640,700</td>
<td>102,680</td>
</tr>
<tr>
<td>- Maximum</td>
<td>6,378,400</td>
<td>15,953,326</td>
</tr>
<tr>
<td>- Sum</td>
<td>279,536,900</td>
<td>851,576,705</td>
</tr>
<tr>
<td><strong>Count</strong></td>
<td>513</td>
<td>5,572</td>
</tr>
</tbody>
</table>

Notes: Population data is from 2010 for Argentina and 2011 for Brazil. As a reference point, the 3,242 counties in the USA have a mean population of 100,813 and land area of 2,825 km².

E.2 Agronomic data

Data on agricultural productivity for the world’s major crops are available from the Food and Agriculture Organization’s Global Agro-Ecological Zones project (FAO-GAEZ) at 5 arc-minute resolution for over one million grid cells around the globe (IIASA/FAO, 2012). The key feature of the FAO-GAEZ data is agricultural productivity is measured as potential yields predicted by an agronomic model based on agro-climatic fundamentals, rather than with realized yields. The distinction is important because realized yields deliver upward-biased productivity measures because

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74 A 5 arc-minute grid cell is approximately a 10 × 10 km grid cell near the equator and becomes smaller as one moves toward the poles.
cause locations select into producing the crops they are especially productive in.\textsuperscript{75} The potential yields are reported separately for a range of time periods (baseline 1961-1990, and specific years between 1990-2000, 2020s, 2050s, 2080s) as well as for three levels of farmer inputs:

- **Low-level:** under the low input, traditional management assumption, the farming system is largely subsistence based and not necessarily market oriented. Production is based on the use of traditional cultivars, labor intensive techniques, and no application of nutrients, no use of chemicals for pest and disease control and minimum conservation measures.

- **Intermediate-level:** Under the intermediate input, improved management assumption, the farming system is partly market oriented. Production for subsistence plus commercial sale is a management objective. Production is based on improved varieties, on manual labor with hand tools and/or animal traction and some mechanization. It is medium labor intensive, uses some fertilizer application and chemical pest, disease and weed control, adequate fallows and some conservation measures.

- **High-level:** Under the high input, advanced management assumption, the farming system is mainly market oriented. Commercial production is a management objective. Production is based on improved high yielding varieties, is fully mechanized with low labor intensity and uses optimum applications of nutrients and chemical pest, disease and weed control.

Figures 24 and 25 show the FAO-GAEZ potential yields are positively correlated with realized yields from census data. Since potential yields aim to capture the natural component of productivity, there remains substantial variation in realized yields that is unexplained by the FAO-GAEZ measure. By isolating the exogenous component of productivity, the FAO-GAEZ data provides useful quasi-experimental variation that has been exploited in recent applied work such as Nunn and Qian (2011), Bustos et al. (2016), Costinot et al. (2016), Sotelo (2020), Pellegrina (2019), and Bustos et al. (2020).

\textsuperscript{75}The agronomic model’s parameters are based on estimates from field and lab experiments in the agronomic literature, and its specific inputs are: soil characteristics, land gradient, elevation, average temperature, rainfall, and sun exposure.
Figure 24: Average annual realized yield and FAO-GAEZ potential yields across counties in Argentina. Bubble sizes are proportional to crop output. FAO-GAEZ yields are at the intermediate level of inputs.
Figure 25: Average annual realized yield and FAO-GAEZ potential yields across counties in Argentina and Brazil. Bubble sizes are proportional to crop output. FAO-GAEZ yields are at the intermediate level of inputs.
E.3 Land-use data

Land-use data are from the agricultural censuses of Argentina and Brazil. Higher frequency land use data are from the Datos Agroindustriales database (DA) for Argentina, and from the Produção Agrícola Municipal database (PAM) for Brazil. Although satellite data for Brazilian deforestation exists, I use the agricultural census data. Satellite data cannot distinguish between land that is left temporarily fallow or permanently fallow for reforestation, and in many cases cannot distinguish between different commodities. Given an important part of this project is about land use substitution between different commodities, I opt for the census data since crop-specific land use can be consistently compared with deforestation data. Since the census data is based on farmer self-reports one may worry deforestation rates may be downward biased. Souza-Rodrigues (2019) uses the census data and describes the methods the Brazilian statistical institute uses to deal with such biases in a supplemental appendix, showing the census deforestation data is consistent with satellite data in robustness exercises. Recent work using the Brazilian agricultural census data includes Bustos et al. (2016), Pellegrina (2019), Souza-Rodrigues (2019), and Bustos et al. (2020). Recent work using the PAM data includes Assunção et al. (2015) and Bustos et al. (2020).

E.4 Livestock sector data

Cattle stocks, pasture land, and maize production data are available at the county level from the agricultural censuses. Higher frequency data on cattle stocks for Argentina is from the National Food Safety Agency (SENASA), and for Brazil is from the Pesquisa da Pecuária Municipal (PPM) survey.

E.5 Agribusiness and trade flow data

TRASE provides supply chain data linking South American counties to exporting firms, ports, and importing firms in foreign markets, for major agricultural commodities for Argentina and Brazil. Exporting firms are identified from customs data and linked to source counties using asset location data (for example, slaughterhouses or soybean crushing facilities owned by exporters). The trade flows are reported at the firm-origin county-destination country level in trade quantities and trade value. Trade values are calculated from port of export FOB prices. I therefore interpret the TRASE prices as the price the agribusiness firm receives per unit of commodity shipped, which in the model corresponds to the origin-destination prices \( p_{ij} \).

I use the TRASE data to construct domestic firm-level trade flows. Further details can be found at trase.earth/about/methods-and-data, and an example of recent published work using the data is Rajão et al. (2020). For country-level international trade flows I use data from FAOSTAT, which has been used extensively in the trade literature, for example by Costinot et al. (2016).
E.6 Price data

For Brazil, farm-gate prices of crops are obtained from production quantity and value data from PAM. Cattle prices are from cattle transaction quantities and values reported in the agricultural census. Pasture land prices are from farm values and acreage (specifically those in the ranching sector), also reported in the agricultural census. For Argentina, farm-gate prices are from DA. Cattle prices are from cattle transaction microdata from DA. Land prices are obtained from sale values from Márgenes Agropecuarios (MA). The origin-destination prices, $p_{ij}$, come from the TRASE data. To assess the representativeness of the TRASE prices, Figure 26 shows how they compare to price data from external sources, such as FRED, FAOSTAT, and the Brazilian PAM survey.

Figure 26: Comparison of TRASE prices to external data sources
The upper panel of Figure 26 aggregates the TRASE prices to the annual level and shows they follow the same time trends as the external sources. The lower panel of Figure 26 aggregates the TRASE origin-destination prices to the origin county-level and compares it to the county-level farm gates prices from the Brazilian PAM survey. Over 94% of the observations lie above the 45 degree line, which is consistent with the interpretation of the TRASE prices being the prices agribusiness firms receive.

E.7 Weather data

Data on extreme temperatures at the country level are from FAOSTAT. I use the “Temperature change” and “Standard deviation” series. I construct local county level weather data from the National Centers for Environmental Prediction’s Climate Forecast System Reanalysis (CFSR) database.

E.8 Emissions data

Land-use change emissions are computed 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 products I use the datasets from Poore and Nemecek (2018) and Clark et al. (2020).
## Appendix F. Tables

### F.1 Additional tables

Table 10: Land use summary statistics

<table>
<thead>
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<tbody>
<tr>
<td><strong>Acreage (million ha)</strong></td>
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<td></td>
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<tr>
<td>Total surface area</td>
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<td>279.54</td>
<td>851.58</td>
<td>851.58</td>
<td>851.58</td>
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<td>508.90</td>
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<td>110.48</td>
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<td>57.03</td>
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<td>- Natural</td>
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<td>28.54</td>
<td>105.12</td>
<td>86.95</td>
<td>92.79</td>
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<tr>
<td>- Planted</td>
<td>2.19</td>
<td>0.89</td>
<td>5.37</td>
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<td>0.35</td>
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<tr>
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<td>78.21</td>
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<td>44.29</td>
<td>56.18</td>
<td>68.35</td>
<td>6.04</td>
<td>11.69</td>
<td>18.83</td>
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<td><strong>Share of total surface area</strong></td>
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<tr>
<td>Private land</td>
<td>0.63</td>
<td>0.57</td>
<td>0.41</td>
<td>0.39</td>
<td>0.42</td>
<td>0.23</td>
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<tr>
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<td>0.01</td>
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<td>0.01</td>
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<td>0.20</td>
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<td>0.11</td>
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<tr>
<td>Forest</td>
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<td>0.32</td>
<td>0.28</td>
<td>0.28</td>
<td>0.48</td>
<td>0.37</td>
<td>0.36</td>
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<tr>
<td>- Natural</td>
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<td>0.26</td>
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<td>0.35</td>
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<tr>
<td>- Planted</td>
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<td>0.02</td>
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<td>0.51</td>
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<td>0.49</td>
<td>0.43</td>
<td>0.49</td>
<td>0.48</td>
</tr>
<tr>
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<td>0.19</td>
<td>0.20</td>
<td>0.13</td>
<td>0.17</td>
<td>0.19</td>
<td>0.05</td>
<td>0.10</td>
<td>0.14</td>
</tr>
<tr>
<td><strong>Share of cropland</strong></td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Soybean</td>
<td>0.37</td>
<td>0.57</td>
<td>0.21</td>
<td>0.30</td>
<td>0.33</td>
<td>0.30</td>
<td>0.39</td>
<td>0.34</td>
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<td>Maize</td>
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<td>0.11</td>
<td>0.24</td>
<td>0.17</td>
<td>0.18</td>
<td>0.18</td>
<td>0.13</td>
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Table 11: Descriptive regressions - Argentina and Brazil

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<th>Δ Grazing land share</th>
<th>Δ Establishments</th>
<th>Δ Cattle p/ha</th>
<th>Δ Cattle p/establishment</th>
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</thead>
<tbody>
<tr>
<td>Δ Soybean land share</td>
<td>−0.535*** (0.035)</td>
<td>−380.147*** (85.475)</td>
<td>0.397*** (0.111)</td>
<td>76.845** (33.452)</td>
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<td>Observations</td>
<td>1,215</td>
<td>1,210</td>
<td>1,222</td>
<td>1,220</td>
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<tr>
<td>R²</td>
<td>0.188</td>
<td>0.013</td>
<td>0.012</td>
<td>0.006</td>
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</table>

<table>
<thead>
<tr>
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<th>Δ Grazing land share</th>
<th>Δ Establishments</th>
<th>Δ Cattle p/ha</th>
<th>Δ Cattle p/establishment</th>
</tr>
</thead>
<tbody>
<tr>
<td>Potential soybean yield</td>
<td>−0.030*** (0.007)</td>
<td>−304.340*** (15.051)</td>
<td>−0.137*** (0.021)</td>
<td>64.804*** (5.590)</td>
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<tr>
<td>Observations</td>
<td>1,243</td>
<td>1,239</td>
<td>1,246</td>
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<tr>
<td>R²</td>
<td>0.014</td>
<td>0.179</td>
<td>0.030</td>
<td>0.099</td>
</tr>
</tbody>
</table>

*Note:*  
*p<0.1; **p<0.05; ***p<0.01*
Appendix G. Figures

G.1 Additional figures

Figure 27: Share of global emissions (CO$_2$e) for major emitting industries. “Electricity and heat production” refers to the burning of coal, natural gas, and oil for electricity and heat. “Transportation” consists of fossil fuels burned for road, rail, air, and marine transportation, i.e., these are “tailpipe” emissions resulting from operating vehicles. “Livestock” represents all emissions along the livestock supply chain (enteric methane accounts for 40% of these emissions). Source: EPA and Gerber et al. (2013).
Figure 28: Share of livestock emissions (CO$_2$e) for each stage of the supply chain. “Fertilizer use” consists of emissions from manure applied to feed crops and pasture, as well as synthetic fertilizers applied to feed crops. “Direct land-use change” consists of emissions resulting from pasture expansion. “Indirect land-use change” consists of emissions resulting from the expansion of cropland for feed production. “Energy use” refers to emissions from energy use on the animal production unit (heating, ventilation, etc.), as well as the construction of the animal production buildings and equipment. “Postfarm” refers to emissions related to the processing and transportation of livestock products between the production and retail point. Source: Gerber et al. (2013).

Figure 29: Emissions footprints of food products. Source: OWID and Poore and Nemecek (2018).
Figure 30: Agricultural area allocated to major crops in Argentina and Brazil. As of 2017, 91% of all planted land in Argentina was concentrated among four crops: soybeans (46%), maize (24%), wheat (16%), and sunflower (5%). As of 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%). Source: Datos Agroindustriales (Argentina) and CONAB (Brazil).
Figure 31: Evolution of the global cattle stock, and decomposition by region. Source: FAOSTAT.

96
Figure 32: Argentina and Brazil’s share of world agricultural output. Source: FAOSTAT.
Figure 33: Argentina and Brazil’s share of South American agricultural output. Source: FAOSTAT.
Figure 34: International commodity prices are defined as “benchmark prices which are representative of the global market. They are determined by the largest exporter of a given commodity”. Source: FRED.
Figure 35: Size distribution of cattle establishments along the supply chain.
Figure 36: Share of cattle transactions by subspecies. Bos Taurus (European breeds) are well-suited to temperate climates, while Bos Indicus (Indian breeds) adapt better to tropical climates and are prevalent in Northern Argentina and Brazil. The Taurus breeds in the data are Aberdeen Angus, Jersey, Hereford, Polled Hereford, Shorthorn, West Highland, Belted Galloway, Fleckvieh Simmental, Argentine Holando, Blonde d’Aquitaine, Charolais, Limousin, Piemontese, and Retinta. The Indicus breeds are Brahman, Braford, Brangus, Santa Gertrudis, and Zebu.

Figure 37: Share of cattle transactions that take place within-province (left) and within-county (right).
Figure 38: Female share of cattle stock by age group
Appendix H. Additional results

H.1 Measuring monopsony power

Moving beyond the concentration measures from section 5, a straightforward approach to measure buyer market power is to estimate the residual supply curve each agribusiness firm faces,

\[
\ln \left( p_{fit} \right) = \mu \ln \left( Q_{fit} \right) + \lambda_i + \lambda_t + \lambda_f + \epsilon_{fit},
\]

where \( p_{fit} \) is the price paid by firm \( f \) in county \( i \), \( Q_{fit} \) is the total quantity purchased, and the \( \lambda \)'s are fixed effects. If \( \mu = 0 \), the residual supply curve is flat and agribusiness firms have no market power. Since equation 30 regresses prices on quantities, OLS estimates will be biased towards zero due to simultaneity. As our goal is to recover a residual supply elasticity, we need instruments that shift residual demand, i.e., firm-level demand shocks. I exploit data on each firm’s export network from TRASE to construct a shift-share instrument \( Z_{fit} \) as follows,

\[
Z_{fit} \equiv \sum_j s_{ij}^f \times d_{jt},
\]

where \( s_{ij}^f \) is the share of \( f \)'s total purchases from \( i \) that go to destination \( j \) in a baseline period, and \( d_{jt} \) is a time-varying measure of demand conditions in destination \( j \). Figure 39 shows a sample path from a source county to various destination countries through a specific firm.

Figure 39: A snapshot of TRASE data. In this example, the red links represent the beef volume exported by JBS from source municipality Ribas do Rio Pardo to all destination importing firms and countries.

Intuitively, if demand in destination \( j \) increases, firms that historically exported to \( j \) are more
“exposed” and increase their demand from upstream farmers more than other firms. I use destination \( j \)'s imports from every country except Argentina and Brazil as the demand measure \( d_{jt} \). Under this research design, the identifying assumption is the cross-sectional exposure measure \( s_{ij} \) is uncorrelated with changes in the error term \( \Delta \epsilon_{it} \), while correlation with levels \( \epsilon_{it} \) is allowed (Goldsmith-Pinkham et al., 2020).

Table 12 shows the OLS and IV estimates of the inverse elasticity of residual supply faced by beef and soybean exporters. OLS estimates are biased towards zero as expected, and the first stage is strong by conventional standards. The IV estimates range between 0.09-0.15 and are slightly lower than those found in recent studies of monopsonistic labor markets: Azar et al. (2019)'s median estimate across various occupations is 0.17, while Goolsbee and Syverson (2019)'s estimate is 0.19.

<table>
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<th>Table 12: Inverse elasticity of residual supply</th>
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<tr>
<td></td>
</tr>
<tr>
<td>( \mu )</td>
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<tr>
<td></td>
</tr>
<tr>
<td>Year FE</td>
</tr>
<tr>
<td>County FE</td>
</tr>
<tr>
<td>Firm FE</td>
</tr>
<tr>
<td>Observations</td>
</tr>
<tr>
<td>Adjusted R(^2)</td>
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<td>1st stage F-stat</td>
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</tbody>
</table>

Note: \*p<0.1; \**p<0.05; \***p<0.01.

While upward sloping residual supply indicates the existence of buyer market power, it does not imply firms choose to exploit it, which is a matter of conduct. If we assume monopsony conduct, the estimates imply ranchers face a markdown of 0.15, i.e., they receive 0.86 of their marginal revenue product. Related to my setting is Rubens (2019), who finds Chinese tobacco

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76For example, the assumption allows for farmers with high unobservable productivity from a given source county to selectively supply firms that export to specific destinations. The assumption would fail if farmers’ subsequent productivity growth is predicted by the firm’s historic destinations from that specific source county, beyond overall firm characteristics we can control for with firm fixed effects.

77It is well known that identification of oligopoly conduct cannot be attained by a shift in the demand curve, but rather by a rotation (Bresnahan, 1982, 1989). The mirror image of this result is that identification of the oligopsony conduct parameter can be attained by a rotation in supply curves. This exact intuition has been applied as early as Just and Chern (1980) to identify buyer conduct in agricultural markets, where market power is often suspect on the buyer side—for example, large food processors facing atomistic farmers. Given conduct assumptions, one can then use the supply elasticity estimates to infer the markdowns implied by the model’s equilibrium conditions. In the standard monopsony model, with input price \( w \), input quantity \( L \) and marginal revenue product \( R'(L) \), the markdown is defined as \( \frac{R'(L)-w}{w} \) and is equal to the inverse elasticity of supply \( \frac{\partial w}{\partial L} \frac{L}{w} \) in equilibrium. The input price to marginal revenue product ratio \( \frac{w}{R(L)} \) is equal to \( \left(1 + \frac{\partial w}{\partial L} \frac{L}{w} \right)^{-1} \).
farmers receive only 0.35 of their marginal revenue product. A possible reason for his relatively large markdowns compared to mine and those of the labor market studies has to do with the unique institutional setting he describes. Internal migration in China, especially from rural to urban regions, is restricted by the Chinese Communist Party via the Hukou system. Hence, farmers are plausibly more captive in their home regions than in Argentina and Brazil, where formal migration restrictions are non-existent.