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DEFORESTATION: A GLOBAL AND DYNAMIC PERSPECTIVE

Farid Farrokhi
Elliot Kang
Heitor S. Pellegrina
Sebastian Sotelo

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ABSTRACT

We study deforestation in a dynamic world trade system. We first document that between 1990-2020: (i) global forest area has decreased by 7.1 percent, with large heterogeneity across countries, (ii) deforestation is associated with expansions of agricultural land use, (iii) deforestation is larger in countries with a comparative advantage in agriculture, and (iv) population growth causes deforestation. Motivated by these facts, we build a model in which structural change and comparative advantage determine the extent, location, and timing of deforestation. Using the model, we obtain conditions under which reductions in trade costs and tariffs reduce global deforestation. Quantitatively, eliminating global agricultural tariffs has limited impacts on global forest area, leads to substantial forest reallocation across countries, and results in net welfare benefits

Farid Farrokhi
Boston College
Department of Economics
farid.farrokhi@bc.edu

Heitor S. Pellegrina
University of Notre Dame
Department of Economics
hpelleg3@nd.edu

Elliot Kang
University of Michigan
emkang@umich.edu

Sebastian Sotelo
University of Michigan
Department of Economics
and NBER
ssotelo@umich.edu

An online appendix is available at http://www.nber.org/data-appendix/w34150

1 Introduction

Global deforestation has gathered speed in recent decades, bringing the adverse impacts of human activity on biodiversity and the world's climate to the forefront of public debate. The expansion of agriculture—strengthened by global markets where producers expand their land use to meet international demand—is one of the key drivers of deforestation. This confluence of factors, along with the resulting calls from policymakers to restrict agricultural trade and curb deforestation, underscore the need to evaluate how trade barriers affect the extent, location, and timing of land-use changes. Such an evaluation is also necessary to determine whether agricultural trade liberalization, a traditional stumbling block in trade negotiations, is desirable when its climate costs are considered.

We offer an approach that emphasizes the global and dynamic nature of deforestation. The global dimension is crucial because international trade connects the demand for land across countries. For example, an increase in food demand in China can be met with an expansion in Brazil's agricultural frontier, instead of that of China itself. Similarly, population growth in one region can put pressure on land use not just locally, but also abroad. A global perspective makes such spatial linkages explicit and acknowledges that changes to policy or market conditions in one location will have repercussions elsewhere. In turn, a dynamic approach distinguishes between movements in the land frontier, which cause deforestation, and the existing stock of land, which is used in production. This distinction is key for understanding the timing of deforestation and associated carbon emissions, one of the main climate damages stemming from it. An approach that is both global and dynamic is therefore important to design policies that have a bearing on deforestation, especially if they are to be applied simultaneously by many countries.

We start by collecting cross-country data on land use, sectoral production, international trade, and population growth. Using these data, we document four empirical patterns that describe the geography of forests and how it relates to international agricultural markets and population growth. First, since 1990 global forest area declined by 7.1 percent—an area the size of Argentina—with substantial heterogeneity across countries. Tropical countries experienced especially large rates of deforestation and, put together, account for about 90 percent of the world's forest loss in this period. At the same time, forest area expanded in other regions, such as Europe and China. Countries with more initial forest deforested more in this period, suggesting that land-clearing becomes costlier as forests dwindle. Second, agricultural land expansion was strongly associated with deforestation across countries. This observation suggests that understanding the incentives to use land for agricultural production is crucial to studying deforestation. Third, countries that had a revealed comparative advantage in agriculture in 1990 experienced both a larger increase in agricultural land and larger forest loss between 1990 and 2020. This pattern suggests that international trade distributes global pressures on land across countries in line with their comparative advantage in agriculture. Fourth, deforestation in a country follows from its own population growth and that of its main trading partners. This fact is important on its own right, as population growth looms large in certain regions; but it is also informative about the ease with which the land frontier expands and how trade connects demand for land across countries—features of the data that we exploit in our model calibration.

Motivated by these empirical patterns, we develop a dynamic, general equilibrium model to evaluate the quantitative response of deforestation to trade policy across the world and over time. The model incorporates many countries that differ in multiple dimensions such as productivity and endowments. It also includes three broad sectors, agriculture, manufacturing, and services that are complementary in consumption. There is also a market and, therefore, a price for new land. New land is supplied by a land-clearing sector that employs labor to transform open-access forests into land. Landowners, who are forward looking, incorporate new land to their existing stock of land, which they rent to other sectors in the economy. The reallocation of labor between sectors is subject to frictions.

The equilibrium stocks of land and forests in our model are shaped by three mechanisms: (i) structural change determines the size of the agricultural sector and the aggregate demand for land; (ii) comparative advantage distributes pressures on agricultural land and forests across countries, and together with absolute advantage, determines whether trade alleviates pressures on forests globally; and (iii) forward-looking land accumulation decisions control the pace of forest adjustments to shocks.

Using a stylized version of our model, we present a set of analytical results that apply in steady state. Our first two results indicate that the geographic scope of the analysis is key for understanding the impact of changes in trade costs on deforestation. Specifically, reducing agricultural iceberg export costs unilaterally for a small open economy leads to deforestation there (Proposition 1). This is because the country expands its production and land use, taking advantage of the high within-sector substitutability of varieties across countries. In contrast, a multilateral reduction in agricultural iceberg trade costs increases global forest area (Proposition 2). Focusing on a collection of symmetric economies—which shuts down the comparative advantage channel—we show that the change in global land use is determined by the demand elasticity across sectors. In the empirically relevant case, agriculture is complementary in consumption with non-agricultural goods, and so the trade shock drives structural change away from agriculture, increasing global forest area.

Unlike reductions in iceberg trade costs, which act as export-oriented productivity shocks, reductions in tariffs do not entail such productivity gains. We therefore characterize the conditions under which agricultural trade liberalization increases global forest area. Still in a symmetric world, our findings show that the forces of structural change are strong enough to ensure that a global tariff reduction leads to an increase in global forest area, but only if agricultural trade is sufficiently protected to begin with (Proposition 3). Lastly, we study the role of comparative advantage when the elasticity of substitution between agriculture and non-agriculture is equal to one—which shuts down the structural change channel. We show that when the correlation between comparative and absolute advantage in agriculture is positive, countries with an absolute advantage in agriculture specialize in agriculture, making the move from autarky to free trade globally land-saving (Proposition 4).[1]

Propositions 1–4 identify the mechanisms through which trade affects global deforestation in our model, but they do not yield a definitive prediction. We therefore develop a quantitative model that incorporates the mechanisms highlighted by these propositions and key features of reality, including those documented in our empirical patterns. We bring our quantitative model to data on production, trade, land use, and forest area. We disaggregate the world into 33 countries and 7 regions, and classify goods into agriculture, manufacturing, and service sectors—further dividing agriculture into main staple crops, pasture-related products, and a bundle of other agricultural goods. Our calibration measures three sets of parameters that shape the model's quantitative predictions. First, we draw on established literature to set the parameters that govern the substitution in demand across and within sectors, as well as workers' sectoral mobility. Second, we use standard model inversion methods to recover productivities and trade costs. Third, we calibrate the parameters governing land dynamics—the novel component in our model. Here, we calibrate the conversion technology of forest into land, following the logic of indirect inference, so that the model replicates the reduced-form impact of population growth on forest area over different time horizons.[2]

Having calibrated our model, we examine two counterfactual scenarios. We first examine a counterfactual policy scenario in which all agricultural tariffs on Brazilian exports are eliminated. On net, global forest area drops by roughly 0.1 percentage points, in a slow process that takes decades to unfold. Behind this global change, there is a sharp decline in forest area within Brazil, while forest leakage—the forest gain in the rest of the world for each unit of deforestation in Brazil—is large and amounts to about 50 percent.

[1] Taken together, these results extend Borlaug's famed hypothesis—that agricultural productivity growth is land-saving in a closed economy Borlaug (2000)—to the domain of international trade, explaining the consequences of changes in different types of trade barriers and highlighting that trade can lead to global forest gains.

[2] Our quantitative model features, in addition, a fallow land sector. We introduce this additional block to capture the fact that in the data fallow land is a sizable share of total land and an important source of expansion in agricultural land.

We then consider a scenario of global agricultural tariff removal. In contrast to the Brazil-specific case, removing tariffs worldwide leads to an increase of about 0.2 percentage points in global forest area. Beneath this modest aggregate gain lies a substantial reallocation of forest area across countries: deforestation occurs in countries with extensive boreal forests as well as in Brazil, but these losses are more than offset by forest gains elsewhere, particularly in other tropical countries.

We use our second policy scenario—full agricultural tariff liberalization—to illustrate the quantitative importance of the mechanisms highlighted by our theoretical propositions. First, the forces of structural change, governed by sectoral demand elasticity and emphasized in Propositions 2 and 3, are crucial. When the sectoral demand elasticity is sufficiently high, agricultural trade liberalization drives economic activity towards the agricultural sector and thus leads to global forest loss, rather than gain. Second, we show that comparative advantage in agriculture shapes the cross-sectional pattern of deforestation: countries with higher agricultural productivity relative to manufacturing experience greater forest loss (or less forest gain) in response to agricultural trade liberalization. Moreover, our calibration reveals a positive correlation between absolute and comparative advantage in agriculture. This finding underscores the relevance of Proposition 4 and implies that moving toward free trade alleviates global pressure on forests from the agricultural sector.

After establishing the quantitative importance of the key mechanisms in our model, we consider a new Business-as-usual (BAU) scenario in which each country's population grows until 2100, according to UN projections. In this new BAU scenario, many African countries experience large rates of deforestation since their growing population increases local demand for food. We find that the scope for tariff reductions to mitigate the effects of population growth on deforestation is limited, as the direct impact of population growth on food demand outweighs the reallocations induced by trade policy. Nevertheless, as we discuss next, a trade-induced reallocation of deforestation away from Africa's dense tropical forests would help reduce its environmental costs.

We conclude by evaluating the welfare gains from agricultural tariff liberalization, explicitly accounting for the carbon emission costs associated with deforestation. A multilateral liberalization of agricultural tariffs leads to 0.13 percent increase in global, aggregate real consumption. When factoring in a social cost of carbon of 200 ($\$/tCO_2$), the net global welfare gain drops to 0.09 percent. This net gain remains positive under a broad range of assumptions and measurement methods, including scenarios with higher social costs of carbon, the potential for carbon sequestration through forest regrowth, and different approaches to discounting the future. Nevertheless, this aggregate result conceals considerable heterogeneity in net welfare gains across countries. The largest gains are realized in countries that, in response to agricultural trade liberalization, expand their agricultural land at the expense of forests.

Related Literature. We contribute to three strands of research. First, our paper speaks to research at the intersection of trade, spatial economics, and the environment, such as Costinot et al. (2016), Gouel and Laborde (2021), Shapiro (2016), Farrokhi and Lashkaripour (2024), Kortum and Weisbach (2024), and Nath (2025). Closer to our research, a few recent papers study quantitatively the relations between trade and natural resources. For example, Farrokhi (2020) studies the impact of trade-related policies in global oil markets, and Carleton et al. (2025) examine the relation between agricultural trade and the allocation of water use across the world. Focusing on deforestation, Dominguez-Iino (2025) examines the effects of environmental policies along supply chains in South America, while Hsiao (2025), also in a dynamic context, studies international cooperation and commitment in the market for palm oil. See Copeland and Taylor (2004) and Copeland et al. (2022) for a review of previous work. Hertel (2012) also points out that the impact of agricultural technological innovations on land use and emissions depends on the elasticity of demand faced by farmers. Relative to this literature, our multi-country equilibrium approach demonstrates the role of structural change and comparative advantage in shaping the deforestation impact of trade openness. We also incorporate deforestation dynamics into a quantitative general equilibrium framework to study how aggregate economic forces and international trade policy shape land use around the world.[3]

Second, we contribute to research examining the welfare impacts of agricultural trade (Donaldson, 2018; Sotelo, 2020; Pellegrina, 2022) and how agriculture relates to structural change and development (Tombe, 2015; Gollin et al., 2021; Fajgelbaum and Redding, 2022; Farrokhi and Pellegrina, 2023). Our work gives deforestation a central role in the analysis of agricultural trade, focusing on how structural change determines worldwide pressures on land use and how the resulting impact on deforestation evolves over time. We also relate to a long-standing and rich tradition, reviewed in Hertel (2002), that formulates computational general equilibrium (CGE) models to study global agricultural markets. Relative to the latter, we introduce dynamics in land development and provide an analytical characterization of the mechanisms driving global deforestation.

Lastly, we complement a large literature that uses detailed micro-data to study different drivers and consequences of deforestation, such as national institutions (Burgess et al., 2019), land use taxes and payment programs for forest conservation (Jayachandran et al., 2017;

[3] Other recent studies have formulated dynamic trade and migration models to evaluate the consequences of climate change (e.g. Conte et al., 2021; Desmet et al., 2021; Balboni, 2025).

Souza-Rodrigues, 2019; Assunção et al., 2020; Araujo et al., 2025b), roads and access to markets (Pfaff, 1999; Asher et al., 2020; Gollin and Wolfersberger, 2024; Araujo et al., 2025a), regional trade agreements (Abman and Lundberg, 2020; Abman et al., 2024), China's demand for food (Hansen and Wingender, 2023), the demand for wood and forest products (Foster and Rosenzweig, 2003), spatial misallocation in agricultural deforestation (Mishra, 2025), and the externalities generated by forest fires (Balboni et al., 2024). We examine how incentives to deforest transmit across countries through international trade, emphasizing that government policies and market conditions in one country have the potential to drive or curb deforestation elsewhere.

2 Data sources

We combine data on global deforestation and carbon content of forests with other, more standard country-level information on trade, production, and factor employment required in global trade models. After merging these data sets, we have 150 countries in five periods (1990, 2000, 2010, 2015 and 2020). In some of our empirical facts, we present results for an aggregation of 33 countries and 7 regional aggregates, which is the sample we use in our model calibration.[4] Below we summarize our data. Appendix A provides additional details about each data source.

Forests and Forest Carbon Stock Since 1948, FAO has published a periodic report called Forest Resource Assessment (FRA), which reflects the FAO's efforts to measure country-level forest area from national forest inventories. We focus on this data set for two reasons. First, they are publicly available and they offer ample coverage in time and space. The data that we use come from the latest edition of FRA, which covers a 30-year period between 1990 and 2020 (FAO, 2020). Second, it is a key reference for policy debate on global deforestation and for assessments of the impact of deforestation on climate change (Brown and Zarin, 2013).[5]

We also employ FAO-FRA information on the carbon content of living biomass above ground—which includes all living biomass above the soil—as well as below ground—which incorporates all biomass of living roots.

[4] Appendix Table F.1 lists the individual countries that constitute each of our regional aggregates.

[5] These data are used, for example, for the estimation of CO_2 emissions from deforestation by the Intergovernmental Panel on Climate Change (IPCC). Since the 1990s, the methodology used by FAO has been improved to ensure that the measurement of forest areas are comparable over years. This is the earliest year for which we can build consistent time series.

Other Country-level Data. We use data on agricultural production, land use, and international trade, disaggregated by agricultural commodity, from FAOSTAT. For agriculture, manufacturing and services, we take data on employment from UN-ILO and value added, final and intermediate-input expenditures, and international trade from the GTAP database.

3 Four Empirical Patterns about Global Deforestation

This section documents four empirical patterns about global deforestation that motivate our modeling approach. We first document the evolution of deforestation between 1990 and 2020. Second, we show that deforestation has been strongly associated with expansions in agricultural land use. Third, deforestation was larger in countries with a comparative advantage in agriculture. Fourth, population growth within a country and also among its main trade partners drives deforestation in that country.

Pattern 1. Between 1990 and 2020, global forest area dropped by 7.1%. While in the tropics, forest area dropped substantially, in several non-tropical regions there was forest regrowth.

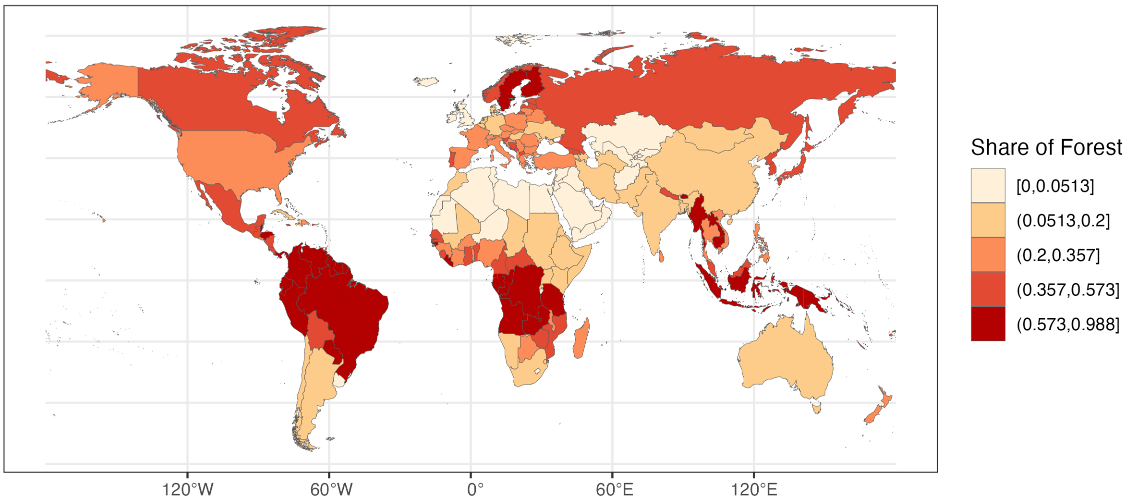
In what follows, we use "country area" as a shorthand for total area of a country net of deserts, glaciers, and lakes. Panel (a) in Figure 1 shows the share of country area covered by forest. Countries with higher forest concentration tend to be close to the North Pole, including Canada, Russia, and the Nordic countries that host large boreal forests, or near the equator, where the tropical forests of the Amazon, Congo Basin, and Southeast Asia are located. Panel (b) depicts global deforestation in 2020 relative to 1990 (as percentage points of the each country's area). The 7.1 percent loss of global forest area—from 4.07 to 3.78 billion hectares—amounts to the size of a country larger than Argentina. Deforestation was particularly large in tropical countries such as Brazil, Congo, and Indonesia where forest area fell by 17, 16, and 26 percent during this period.[6] Other countries, primarily China and many European countries, reforested over this period.

The correlation between a country's forest share in 1990 and its deforestation between 1990-2020 is sizable, equal to 0.57. In our quantitative model, we introduce a land-clearing technology whose productivity depends on the current share of forest, so as to respect this feature of the data.

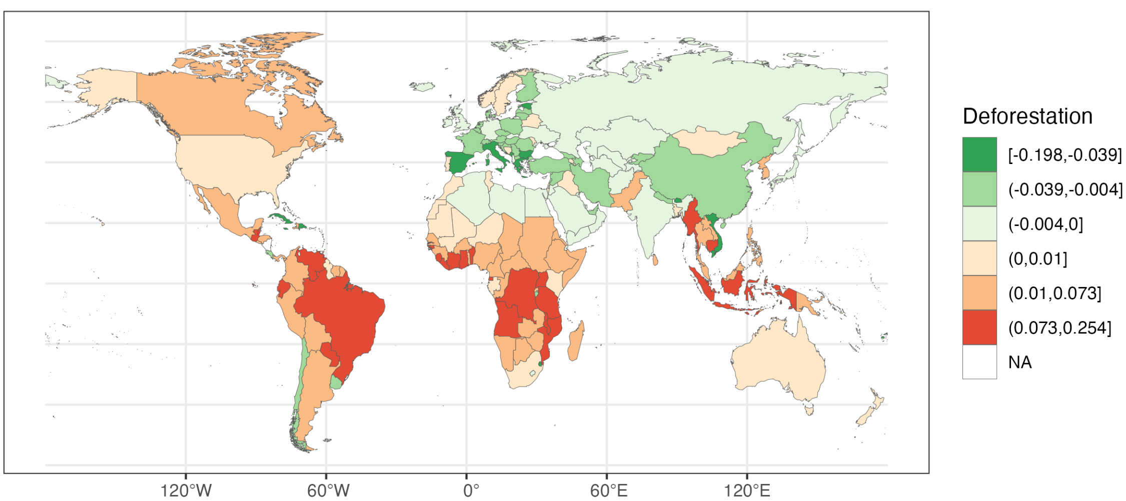
[6] The figure shows these numbers in terms of the percentage point (p.p.) change in each country's forest share rather than percentage change since the latter gives uninformatively large magnitudes in countries where forest share is tiny. The p.p. change in forest share (multiplied by 100) was -2.2 at the global level and -12.0, -10.8, and -16.4 in Brazil, Congo, and Indonesia.

Figure 1: Forest and Deforestation across the World (1990-2020)

(a) Forest Share in Country Area (1990)



(b) Deforestation (2020 relative to 1990)



Notes: Panel (a) shows "forest share" for each country—as the share of a country's area covered by forest in 1990. Panel (b) shows the percentage point change in forest share for each country between 1990 and 2020.

Appendix Table F.2 provides an accounting of global deforestation disaggregated by the 33 countries plus 7 aggregate regions we bring to data for quantitative analysis.[7] The table shows for each country the forest share in country area in 1990, percentage point change in forest share and percentage change in forest area during 1990-2020. It also shows each country's contribution to the global deforestation during 1990-2020. Brazil alone accounts

[7]Appendix Table F.3 reports these deforestation-related variables at the individual country level.

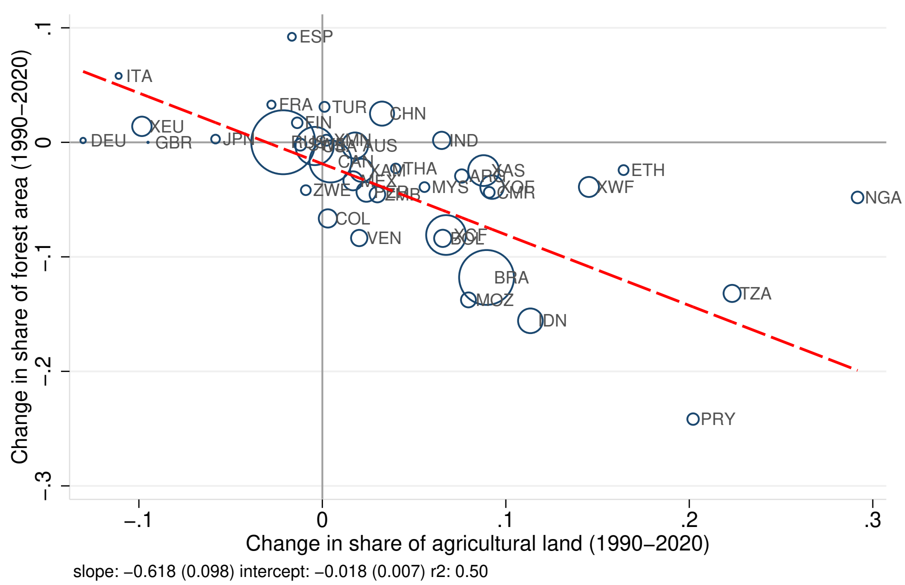
for one-third of global deforestation, followed by Central African countries and Indonesia which account together for one-fourth of global deforestation.

Before moving on, we note that forests are heterogeneous in their carbon content. Figure F.1 in the appendix depicts each country's forest carbon intensity (tons of carbon stock per hectare of forest), suggesting that the carbon emissions caused by deforestation depend on where it occurs. We incorporate this heterogeneity into our analysis of the climate costs of different trade integration scenarios, following the IPCC and FAO guidelines (Tubiello et al., 2020).

Pattern 2. Changes in forest area are negatively correlated with changes in agricultural land use.

Figure 2 plots the change in forest area against the change in agricultural land use across our 40 regional aggregates, both measured as a share of their corresponding region area. The two variables are strongly and negatively correlated, with the share of forest area decreasing at a slope of -0.62 with respect to the share of agricultural land. That the slope is less than one in absolute value suggests that expansions in agricultural land come from other sources, in addition to forests. These findings are consistent with previous work focusing on the tropics (Pendrill et al., 2022).

Figure 2: Change in Share of Land in Forest versus Share of Land in Agriculture (1990-2020)

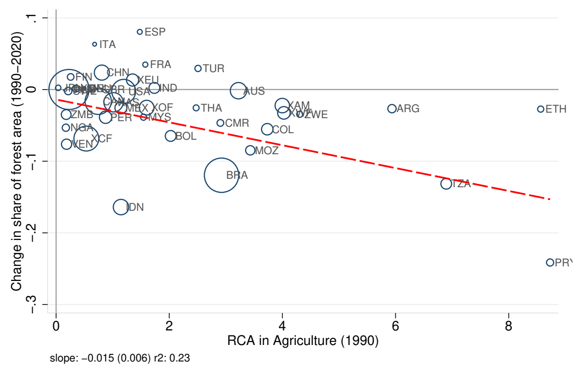


Notes: This figure shows the relationship between changes from 1990 to 2020 in agricultural land use and changes in forest area across countries, each as a share of country area, in percentage changes from 1990 to 2020. The size of circles represents the total forest area in each country. The red dashed line shows the linear fit weighting the observations by each country's forest area in 1990.

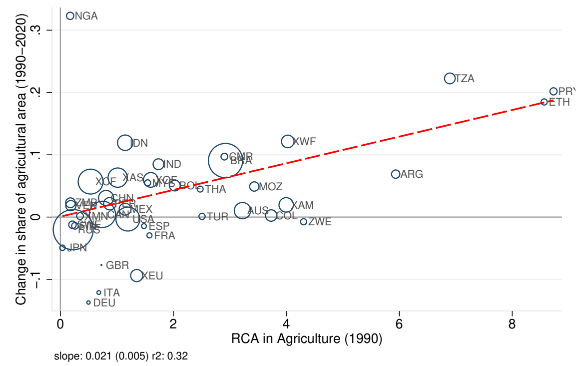
This empirical regularity motivates us to design a land-use model in which expansions in land use, particularly from agriculture, may come at the cost of deforestation.[8] We next turn to two mechanisms driving the demand for agricultural land in a country, namely, agricultural trade and population growth.

Figure 3: Change in Agricultural Land and Forest Area against Comparative Advantage in Agriculture

(a) Forest Area



(b) Agricultural Area



Notes: This figure shows the 1990-2020 change in forest share in country area (Panel a) and agricultural land share in country area (Panel b) against the index of revealed comparative advantage (measured in 1990) across countries.

Pattern 3. Between 1990 and 2020, countries with a comparative advantage in agriculture experienced a larger expansion in their agricultural land use and a larger reduction in their forest area.

We next examine countries' change in agricultural and forest area in relation to their comparative advantage in agriculture. To this end, we employ Balassa's index of revealed comparative advantage for each country i, defined as:

$$\mathrm{RCA}_i^{(\mathrm{Agr})} = \frac{(\text{Agr Exports})_i/(\text{Total Exports})_i}{(\text{World Agr Exports})/(\text{World Total Exports})},$$

i.e., the degree to which a country i's exports specialize in agriculture, relative to the world's exports. Panels (a) and (b) of Figure 3 show that in countries with a higher RCA (measured in 1990) the expansion agricultural land and the reduction of forest area was larger between

[8]See in Appendix Figure F.2 the country-level share of land under forest, agriculture, and a residual "fallow land" category that we construct as the difference between country area and the sum of forests and agricultural land (excluding water bodies and other non-productive areas, such as deserts). Fallow land takes as much as fifty percent of the land in Argentina or Australia but less than ten percent in Nigeria or Colombia. Later in the paper, we incorporate data on fallow land in the calibration of our quantitative model.

1990 and 2020. This pattern motivates a model in which comparative advantage governs the relative demand for land, and therefore the pressure on forests, across countries.

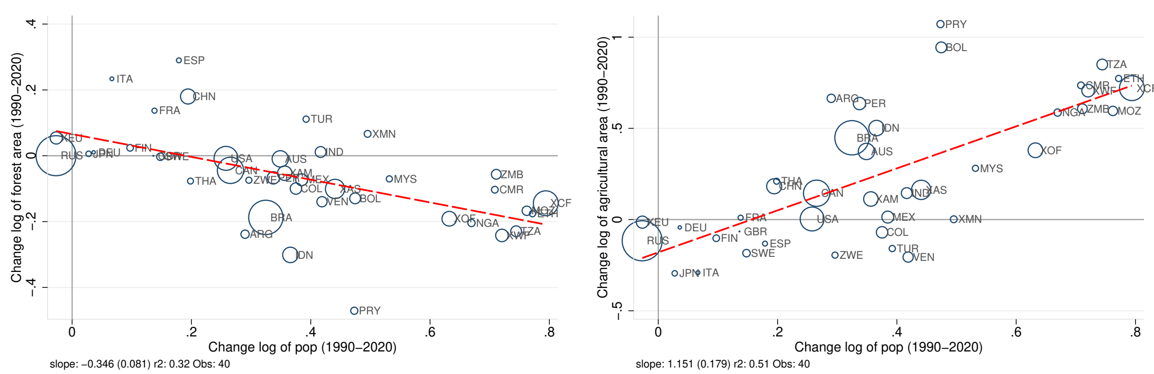
Pattern 4. Domestic population growth and that of top trading partners leads to agricultural land expansion and deforestation.

Figure 4, Panels (a) and (b) show that population growth in a country is associated with reductions in forest area and increases in agricultural land. In addition, Figure 5, Panels (a) and (b) show that when population grows in a country's top five trade partners, that country's forest area shrinks and its agricultural area expands, as well.

Figure 4: Change in Forest and Agricultural Area and Domestic Population Growth

(a) Forest Area

(b) Agricultural Area

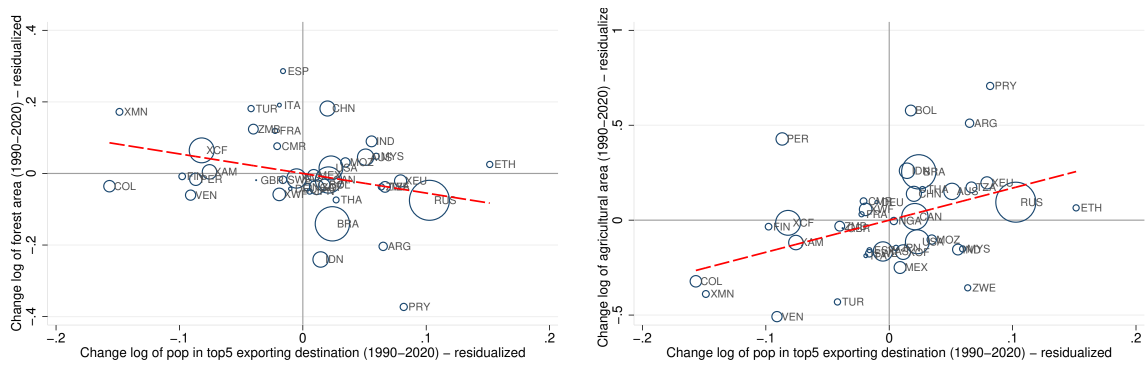


Notes: This figure shows the 1990-2020 change in log forest land area (Panel a) and log agricultural area (Panel b) against the 1990-2020 change in log population across countries.

Figure 5: Change in Forest and Agricultural Area and Top Trade Partner's Population Growth

(a) Forest Area

(b) Agricultural Area



Notes: This figure shows the 1990-2020 change in log forest area (Panel a) and log agricultural land area (Panel b) against the 1990-2020 change in log population across countries. We residualize the y- and x-axis variables based on the population growth of a country's own population.

To explore this relationship more systematically, we consider the following equation:

$$\Delta \ln y_{i,t} = \beta_0 + \beta_1 s^{\text{Own}}_{i,t-1} \Delta \ln \text{Own Population}_{i,t} + \beta_2 s^{\text{Partner}}_{i,t-1} \Delta \ln \text{Partner Population}_{i,t} + \beta_X \mathbf{X}_{i,t} + \epsilon_{i,t} \quad (1)$$

where $y_{i,t}$ represents either agricultural land or forest area; Own Population$_{i,t}$ and Partner Population$_{i,t}$ measure country i's population and that of its top five trade partners, and $\mathbf{X}_{i,t}$ and $\epsilon_{i,t}$ denote control variables—see description in Table 1—and the error term for country i at time t. The Δ operator denotes 30-year time differences. The coefficients of interest are β_1 and β_2, which capture the impact of domestic population growth and that of country i's top five trade partners on net forest or agricultural land growth. We adjust these variables by the share of agricultural sales of a country to itself $s^{\text{Own}}_{i,t-1}$ and share of sales to top trading partners $s^{\text{Partern}}_{i,t-1}$ in year $t-1$, which is 1990.

An OLS estimation of equation (1) may suffer from endogeneity bias. For example, shocks to agricultural productivity can lead to a change to both population and deforestation, creating a correlation between population growth and the error term. We therefore instrument $\Delta \ln \text{Own Population}_{i,t}$ with the median age of the population, the crude birth rate per 1000 individuals, and the average age for child bearing at time period $t-1$. Likewise, we instrument $\Delta \ln \text{Partner Population}_{i,t}$ with these same three variables in country i's top trading partners.[9] Our identifying assumption is that, conditional on our set of controls (which include GDP per capita and measures of forest area protection) past demographic structure is uncorrelated with current unobserved shocks such as those to productivity, so the instruments predict population growth for purely biological reasons.

Table 1 shows the OLS and IV estimates of equation (1). Overall, Panel (a) reports negative elasticities of forest area to both population variables, for both OLS and IV, without any controls (Columns (1) and (4)), with controls for initial forest and agricultural area (Columns (2) and (5)) and with additional controls for natural areas under reservation and GDP per capita (Columns (3) and (6)). Our specification adjusts the population growth shock by a revenue share, so that the regressors of interest can be interpreted as local and foreign shocks to agricultural demand. Our specification also implies that the elasticity of the dependent variables to population growth is heterogenous across countries. For the average country in the sample, the share of domestic sales in total agricultural sales is 0.85, while the share of sales to its top trading partners is 0.12. Thus, the IV estimate under Column (6) implies that a 10 percent increase in own population growth reduces its forest area by $3.6 \times 0.85 = 3.06$ percent, while a 10 percent increase in the country's trading partners'

[9] To construct the population growth in partner countries, we aggregate the total population across the 5 top trading partners of a country in every year, effectively making it a larger geographic unit. To construct the instruments and controls, we take the average of the these values at $t-1$ across trading partners.

population reduces its forest area by $11.9 \times 0.12 = 1.43$ percent. This comparison shows that the elasticity of forest area to local demand is about twice as large as that in response to foreign demand.

Panel (b) retains the same structure, only placing agricultural area as a dependent variable. Across specifications, the coefficient is positive and statistically significant. For the average country in our sample, the IV estimate in Column (6) indicates that a 10 percent increase in population leads to a $8.8 \times 0.85 = 7.48$ percent increase in agricultural land use, while a 10 percent increase in population of the country's top trading partners leads to a $29.9 \times 0.12 = 3.59$ percent increase in agricultural land use. Once again, we can see that the impact of local demand on local agricultural land is about twice as large as the effect of foreign demand. Appendix Table F.6 shows that our qualitative results are largely the same if we use the full sample of countries.

Table 1: The Relationship between Population Growth and Forest Area (30 years interval)

	OLS (1)	OLS (2)	OLS (3)	IV (4)	IV (5)	IV (6)
a. DV is the log of forest area						
$s^{\text{Own}} \times \Delta$ Log(Own Pop)	-0.380***	-0.357***	-0.257*	-0.436***	-0.408***	-0.360*
	(0.072)	(0.065)	(0.151)	(0.095)	(0.084)	(0.197)
$s^{\text{Partner}} \times \Delta$ Log(Partner Pop)	-1.325*	-1.209	-1.030	-1.416**	-1.295*	-1.190*
	(0.727)	(0.742)	(0.766)	(0.708)	(0.711)	(0.721)
R2 or K-P	0.310	0.360	0.403	34.995	32.726	12.313
Obs	40	40	40	40	40	40
b. DV is the log of agricultural area						
$s^{\text{Own}} \times \Delta$ Log(Own Pop)	1.409***	1.368***	1.136***	1.427***	1.375***	0.879***
	(0.106)	(0.111)	(0.225)	(0.107)	(0.102)	(0.297)
$s^{\text{Partner}} \times \Delta$ Log(Partner Pop)	3.809***	3.629***	3.177***	3.864***	3.632***	2.986***
	(0.872)	(0.952)	(0.888)	(0.840)	(0.913)	(0.904)
R2 or K-P	0.746	0.761	0.815	34.995	32.726	12.313
Obs	40	40	40	40	40	40
Controls (Initial period value in logs)						
- Share of Agricultural area	-	Y	Y	-	Y	Y
- Share of Forest area	-	Y	Y	-	Y	Y
- Natural reserve area	-	-	Y	-	-	Y
- GDP p.c.	-	-	Y	-	-	Y

Notes: * / ** / *** denotes significance at the 10 / 5 / 1 percent level. Robust standard errors clustered at the country level in parenthesis. Instrument in columns (4) to (6) are (1) the log of the median age of the population, (2) the birth rate, and (3) the average age of child bearing in the baseline year. Kleinberg-Paap weak instrument statistic is reported in columns (4) to (6) instead of R2.

These results are important for three reasons. First, because the world population is expected to grow by 35 percent between 2020 and 2100, our results are informative about the impact of a shock that looms large in the future. Second, the estimated impact of foreign population growth cements the notion that international trade distributes pressures on land demand across countries. Third, through the lens of our model, changes in population map transparently into land use pressures, both by raising the demand for food and increasing the supply of labor. We will therefore target these reduced-form results to calibrate the parameters of our land-producing sector, which governs the response of deforestation to shocks that shift agricultural demand, including those induced by changes in trade costs.

Toward a model of trade and deforestation. In sum, we have established four empirical patterns that motivate a dynamic model of global trade and land use. The pace of deforestation depends, among other forces, on a country's current forest stock (Pattern 1). Deforestation across countries is closely tied to the expansion of agricultural land (Pattern 2). Countries exploit their comparative advantage in agriculture, in part, by deforesting (Pattern 3). Lastly, international trade contributes to deforestation by connecting population dynamics in export markets, as well as domestically, to changes in forest cover (Pattern 4).

We will develop a quantitative model that incorporates these empirical patterns, along with well-established features of global production and trade. While our quantitative model is intended for careful calibration and detailed policy analysis, it is useful to first examine a simplified version. This stylized model deliberately leaves out some of these patterns to explain the core mechanisms that link trade to land use as clearly as possible. In the next section, we introduce this stylized model and derive sharp theoretical results on how trade influences deforestation. After establishing these results, we then present our full quantitative model in Section 6.

4 The Stylized Model

Consider a global economy consisting of multiple countries, indexed by $i, j = 1, ..., I$, and three sectors: agriculture (A), manufacturing (M), and land-clearing (T). Time is continuous and denoted by $t \in [0, \infty)$. Each country i is endowed with (i) a fixed amount of land H_i, which consists of agricultural land, $L_i(t)$, and forest area, $F_i(t)$, such that $H_i = L_i(t) + F_i(t)$, and (ii) a labor force $N_i(t)$, which evolves exogenously over time. Labor is perfectly mobile within each country and immobile between countries. Markets are perfectly competitive. Hereafter we drop the time index with the understanding that all variables may vary over time, and we denote the time derivative of any variable x by $\dot{x}$.

Households. Each country has a representative consumer with a two-tier constant elasticity of substitution (CES) demand. In the lower tier, national varieties of $g = \{A, M\}$ are aggregated with an elasticity of substitution η into a composite bundle of g. In the upper tier, the composite bundles of agriculture (A) and manufacturing (M) are combined into an aggregate consumption bundle, with an elasticity of substitution σ.

The lower tier gives rise to international trade flows in agriculture and manufacturing. Specifically, country j's share of expenditure on origin i's variety of $g = \{A, M\}$ equals:

$$\pi_{ij,g} = \left(\frac{p_{ij,g}}{P_{j,g}}\right)^{1-\eta}, \tag{2}$$

where $p_{ij,g}$ is the price of country i's variety delivered in country j and $P_{j,g}$ is the consumer price of g in country j:

$$P_{j,g} = \left(\sum_{n=1}^{N} p_{nj,g}^{1-\eta}\right)^{1/(1-\eta)} \tag{3}$$

The upper tier, in turn, determines the expenditure across broad sectors in the economy. Specifically, country j's expenditure share on sector $g = \{A, M\}$ is given by:

$$\beta_{j,g} = \left(\frac{P_{j,g}}{P_j}\right)^{1-\sigma}, \tag{4}$$

where P_j is the final consumer price index:

$$P_j = \left(P_{j,A}^{1-\sigma} + P_{j,M}^{1-\sigma}\right)^{\frac{1}{1-\sigma}}. \tag{5}$$

Production. Technologies are given by:

$$Q_{i,A} = Z_{i,A} L_i, \qquad Q_{i,M} = Z_{i,M} N_{i,M}, \qquad Q_{i,T} = Z_{i,T} N_{i,T}, \tag{6}$$

where agriculture uses only land, L_i, while manufacturing and land-clearing use only labor, $N_{i,M}$ and $N_{i,T}$. $Z_{i,A}$, $Z_{i,M}$, and $Z_{i,T}$ are exogenous productivity parameters. In each country, the land-clearing sector converts the forest area into the agricultural land.[10] The products of agriculture and manufacturing can be traded internationally between each origin i and destination j subject to trade costs $\tau_{ij,g} = (1 + t_{ij,g})\, d_{ij,g}$ for each $g = \{A, M\}$, where $t_{ij,g}$ denotes ad valorem import tariff rates charged by country j to country i, and $d_{ij,g} \geq 1$ represents iceberg trade costs for shipping goods from i to j (with $t_{ii,g} = 0$ and $d_{ii,g} = 1$). Consequently, the price of $g = \{A, M\}$ from origin i at destination j equals:

$$p_{ij,A} = \frac{\tau_{ij,A} r_i}{Z_{i,A}}, \qquad p_{ij,M} = \frac{\tau_{ij,M} w_i}{Z_{i,M}}; \tag{7}$$

[10] In the corner case of $F_i = 0$, the production flow of the new land becomes zero, $Q_{i,T} = 0$.

where r_i is the rental rate of land, and w_i is the wage rate in country i. In turn, the price of new land, denoted by q_i, is set domestically in the land-clearing (T) sector,[11]

$$q_i = \frac{w_i}{Z_{i,T}}. \tag{8}$$

Landowners. A continuum of symmetric landowners, who are risk-neutral and have perfect foresight, connect the land-clearing sector to the agricultural sector. Each landowner owns one unit of land that can be rented out at the rate r_i to agricultural producers. Landowners discount the future at a rate of ρ, and each unit of land "depreciates" back into forest at a rate of δ_L. Under these assumptions, the value of a plot to a landowner, v_i^L, can be expressed as:

$$\rho v_i^L = r_i - \delta_L v_i^L + \dot{v}_i^L.$$

Potential entrants purchase new land produced by the T sector when v_i^L is greater than or equal to the price of new land, q_i. We assume free entry into landowning, which ensures that $v_i^L = q_i$. Hence, the price of new land, q_i, satisfies the following asset pricing equation:

$$(\rho + \delta_L)\, q_i = r_i + \dot{q}_i. \tag{9}$$

Solving this equation delivers the price of new land as the present value of future land rents, discounted by $(\rho + \delta_L)$, a rate that accounts for both time preference and forest regrowth.[12]

Finally, agricultural land grows with the inflow of new land converted from forest by the T sector, $Q_{i,T}$, and shrinks with the outflow due to forest regrowth, $\delta_L L_i$,

$$\dot{L}_i = Q_{i,T} - \delta_L L_i. \tag{10}$$

Market clearing. National expenditure in country i, E_i, equals net payments to labor and land plus tariff revenues, T_i:

$$E_i = w_i N_i + (r_i L_i - w_{i,T} N_{i,T}) + T_i,$$

where

$$T_i = \sum_{g \in \{A,M\}} \sum_n \frac{t_{ni,g}}{1 + t_{ni,g}} X_{ni,g}.$$

[11] We write the pricing conditions (7) and (8) under the assumption that both M and T are operational, which will always be true with Armington differentiation.

[12] Specifically, $q_i(t) = \int_t^\infty e^{-(\rho+\delta_L)(s-t)} r_i(s)\, \mathrm{d}s$.

Total payments to land come from sales across the world:

$$r_i L_i = \sum_j \frac{X_{ij,A}}{1 + t_{ij,A}}, \tag{11}$$

and, likewise, for manufacturing labor:

$$w_i N_{i,M} = \sum_j \frac{X_{ij,M}}{1 + t_{ij,M}}. \tag{12}$$

Static Equilibrium. Given (i) technologies, iceberg trade costs, tariffs, and preferences $\{Z_{i,g}, d_{ij,g}, t_{ij,g}, \sigma, \eta\}$, (ii) agricultural land and national labor supplies $\{L_i, N_i\}$, and (iii) the price of new land $\{q_i\}$, a static equilibrium consists of factor rewards $\{w_i, r_i\}$, and labor allocations $\{N_{i,T}, N_{i,M}\}$, such that land markets clear according to equation (11) and labor markets clear according to equations (8) and (12).

Dynamic Equilibrium. Given (i) paths of technologies, iceberg trade costs, tariffs, preferences and national labor supplies, and (ii) initial agricultural land $\{L_i(0)\}$, a dynamic equilibrium consists of the paths of static equilibrium variables as well as price of new land and stock of agricultural land $[\{q_i(t), L_i(t)\}]$ that evolve according to equations (9) and (10).

A Steady-State Equilibrium. A steady-state equilibrium is a dynamic equilibrium in which $\dot{q}_i = \dot{L}_i = 0$.

In Section 6, we extend this stylized model in several ways to bring it to data for quantitative analysis.[13] Before doing so, however, in Section 5 we will use our model to derive four key analytical results under steady-state equilibrium. To that end, we conclude this section by showing how the steady values of the rental rate and total area of agricultural land depend on labor market outcomes. In the steady state, equations (8) and (9) imply that the rental rate of land is proportional to the wage rate through the following relationship:

$$r_i = \frac{(\rho + \delta_L) w_i}{Z_{i,T}}. \tag{13}$$

[13]These extensions include: (i) incorporating a service sector and disaggregating the agricultural sector, (ii) introducing an input-output structure to production technologies, (iii) forward-looking labor decisions with sectoral switching costs, (iv) adding a third category of land, which we refer to as "fallow," and (v) allowing the productivity in the land-clearing sector to depend on the available stock of forest and fallow land. Crucially, we also solve for the entire transitional path when evaluating policy responses.

Furthermore, replacing $Q_{i,T}$ from equation (6) into the steady state version of equation (10) establishes a link between agricultural land area and employment in the land-clearing sector,

$$L_i = \frac{1}{\delta_L} Z_{i,T} N_{i,T}. \tag{14}$$

Equations (13) and (14) arise because the agricultural land is ultimately produced using labor. In this sense, the steady state reflects the long-run outcome of the balance between human-driven, economic incentives to expand agricultural land and the natural tendency of forests to regrow.

5 Analytical Results

Using our stylized model, this section provides four analytical results regarding the impact of trade on deforestation. First, when a small open economy experiences reductions in its export costs, it loses forests. Second, in a world consisting of symmetric countries, a multilateral reduction in iceberg agricultural trade costs results in global forest gain. Third, a global reduction in agricultural tariffs results in global forest gain if (and only if) the initial level of tariffs is sufficiently high. Fourth, in a world consisting of asymmetric economies, trade leads to a global forest gain if comparative and absolute advantage in agriculture align across countries. Appendix B collects the proofs.

Our first proposition clarifies the context in which a conventional intuition—that trade leads to deforestation—can be most clearly understood. To this end, we consider country i as a small open economy á la Alvarez and Lucas (2007).

Proposition 1. *A unilateral reduction in the agricultural export costs of a small open economy i leads to an increase in its stock of land, L_i, governed by:*

$$\frac{\mathrm{d} \ln L_i}{\mathrm{d} \ln d_{i,A}} = \frac{N_{i,M}}{N_i} (1 - \eta) < 0 \quad for \quad \eta > 1. \tag{15}$$

The response in the stock of land of the country that experiences reductions in export costs is governed by the elasticity of substitution between domestic and foreign varieties, η. Specifically, the elasticity of derived demand for land coincides with the elasticity of import demand, $(1 - \eta)$. In the empirically relevant case, this elasticity is negative. Consequently, a reduction in export costs in a small open economy leads to deforestation there.

Expanding the scope of policy to the global level, the deforestation impact of multilateral trade cost reductions depends on the sectoral demand elasticity $(1-\sigma)$ rather than the import demand elasticity, $(1-\eta)$. To illustrate this point, suppose that all countries in the world are symmetric, in the sense that they have the same endowments, geography and productivity, and that there are no tariffs. Under symmetry, we can drop the country indicator i:

Proposition 2. *A global reduction in agricultural trade costs in a system of symmetric economies leads to a decrease in the global stock of land, governed by:*

$$\frac{\mathrm{d}\log L}{\mathrm{d}\log d_A} = \frac{N_M}{N}\left(1-\sigma\right)\left(1-\pi_A^D\right) > 0 \quad \textit{for} \quad \sigma < 1; \tag{16}$$

where π_A^D is the domestic expenditure share in the agricultural sector.

Here, the response of the land stock is governed by the elasticity of substitution between agriculture and manufacturing sectors, σ. In the empirically relevant case, agriculture and manufacturing are complements, i.e. $\sigma \in (0,1)$, and so, a multilateral trade cost reduction results in a reduction in agricultural land and hence an expansion of forest area. The reason is that, in response to the change in prices, structural change reallocates resources away from agriculture and land clearing. In other words, at the global level, because demand for land is sufficiently inelastic, the productivity gains from trade cost reductions lead to land savings.

This result highlights one of the key mechanisms in the model—that at the global scale, the pressure on land is governed by the sectoral demand elasticity. The result relies, however, on the assumption of iceberg trade costs, so that payments for agricultural trade costs are fully received by farmers, and as a result, entirely allocated to land. Because a reduction in iceberg-type agricultural trade costs is an export-biased productivity gain, it can reduce land use beyond its impact on the land content of agricultural consumption.

The response of forests to iceberg trade costs is useful as a baseline, but does not speak to the impacts of changes in trade policy. Revisiting Proposition 1 with tariffs instead of iceberg trade costs requires replacing $(1-\eta)$ with $(-\eta)$ in equation (15), yielding the same conclusion that the country experiencing reductions in export barriers would lose forests. Revisiting Proposition 2 yields a more nuanced outcome. The next result provides conditions under which a global tariff reduction leads to either forest gain or loss.

Proposition 3. *Consider a worldwide change in agricultural (ad valorem) import tariffs in a system of symmetric economies. As a result:*

(i) The global stock of land changes according to:

$$\frac{\mathrm{d}\ln L}{\mathrm{d}\ln(1+t_A)} = \frac{N_M}{N}\left[\underbrace{\left(1-\sigma\right)\left(1-\pi_A^D\right)}_{(+)\ \textit{if}\ \sigma<1} + \underbrace{\left(\eta-1\right)\left(s_A^D-\pi_A^D\right)}_{(+)\ \textit{if}\ \eta>1} + \underbrace{\left[-\left(1-s_A^D\right)\right]}_{(-)}\right], \tag{17}$$

where s_A^D is the fraction of farmers' revenue that comes from domestic demand.

(ii) Provided that $\eta > \sigma$, the global stock of land is an increasing function of tariffs when tariffs are sufficiently low, $t_A \in [0, t_A^*)$. Conversely, it is a decreasing function of tariffs when tariffs are sufficiently high, $t_A \in (t_A^*, \infty)$. The critical tariff rate, t_A^*, satisfies:

$$t_A^* \pi_A^D \left(t_A^*\right) = \frac{\sigma}{\eta - \sigma}, \qquad \textit{with} \qquad \pi_A^D \left(t_A\right) = \left[\left(I-1\right)\left(d_A\left(1+t_A\right)\right)^{1-\eta} + 1\right]^{-1}$$

Proposition 3 introduces two new terms to equation (16), both related to changes in the share of expenditure in agriculture that is ultimately received by farmers, net of tariffs. Specifically, from each dollar spent on agriculture, the fraction collected as tariffs equals $h_A = \frac{t_A}{1+t_A}\left(1-\pi_A^D\right)$, while the remaining share, $(1-h_A)$, is received by farmers—i.e., the "pass-through" rate to farmers and ultimately to land. Of each dollar received by farmers, the share coming from domestic consumers is $s_A^D = \frac{\pi_A^D}{1-h_A}$, which, by construction, is larger than the domestic expenditure share, π_A^D, as long as $t_A > 0$.[14]

The pass-through rate, $(1-h_A)$, changes for two reasons. First, holding fixed $\frac{t_A}{1+t_A}$, a higher tariff shifts agricultural demand from foreign to domestic varieties, thereby raising the pass-through to farmers. This effect corresponds to $(\eta - 1)\left(s_A^D - \pi_A^D\right)$ in equation (17), which is positive for $\eta > 0$. Second, holding fixed the imported expenditure share, $\left(1-\pi_A^D\right)$, a higher tariff increases the fraction collected by the governments, $\frac{t_A}{1+t_A}$, lowering the pass-through rate. This effect corresponds to $\left(1-s_A^D\right)$ in equation (17), which captures the share of farmers' revenue dependent on foreign demand. Proposition 3 shows that the stock of land has a U-shaped relationship with respect to the agricultural tariff. Specifically, a multilateral agricultural trade liberalization saves land—that is, the first two terms outweigh the last term in equation (17)—if and only if agricultural trade is sufficiently protected by tariffs.

Propositions 2 and 3 assume symmetric countries to highlight how structural change shapes the impact of trade costs on deforestation. In an asymmetric world, countries specialize according to their comparative advantage. Trade liberalization, therefore, can lead these countries to expand their agricultural frontier, which may reinforce or mitigate the above results. To shed light on this matter, we next illustrate the role of comparative advantage.

To state our next result in the clearest way, we consider a continuum of countries $i \in [0, 1]$ that have heterogenous productivities in agriculture and manufacturing, but are otherwise identical. In addition, we shut down the mechanism behind Proposition 2 by assuming that the elasticity of substitution between agriculture and manufacturing equals one ($\sigma = 1$) and

[14] For instance, suppose from one dollar spent on agriculture, 60 cents are purchased domestically (setting $\pi_A^D = 0.60$) and the remaining 40 cents are imported at a tariff rate of 25%. The amount collected as tariffs equals 8 cents ($h_A = \frac{0.25}{1.25} \times 40$). Out of the remaining 92 cents, the share coming from domestic sales equals 0.65 ($s_A^D = \frac{60}{92}$).

the additional mechanisms behind Proposition 3 by assuming that goods within each sector are homogenous ($\eta \to \infty$). Without loss of generality, we order countries in decreasing order of comparative advantage in agriculture, i.e. $Z_{i,A}/Z_{i,M}$ decreases with i.

Proposition 4. *(Comparative and absolute advantage) Suppose goods within each sector are homogeneous and preferences are Cobb-Douglas (i.e., $\eta \to \infty$ and $\sigma = 1$). A reduction of trade costs that brings the world economy from autarky to free trade has the following consequences.*

(i) Comparative advantage drives international specialization: There is a cutoff country i^* such that all countries $i < i^*$ specialize in agriculture, and the rest specialize in manufacturing.

(ii) Comparative and absolute advantage in agriculture are aligned: If $Z_{i,M}$ decreases in i, so does $Z_{i,A}$ (as implied by our assumption that $Z_{i,A}/Z_{i,M}$ is decreasing in the country index i), meaning that comparative and absolute advantage align in agriculture but not in manufacturing. In this case, global forest area expands when moving to free trade.

(iii) Comparative and absolute advantage in agriculture are not aligned: If $Z_{i,A}$ increases in i, so does $Z_{i,M}$, meaning comparative and absolute advantage align in manufacturing but not in agriculture. In this case, global forest area shrinks when moving to free trade.

Proposition 4 carries two main messages. The first message, in line with standard results from trade theory, is that comparative advantage is a key determinant of cross-country patterns of specialization. The second message, to the best of our knowledge, is novel. It states that the correlation between absolute and comparative advantage determines whether trade increases global land use. In particular, when countries whose comparative advantage lies in agriculture also have an absolute advantage in agriculture (and an absolute disadvantage in manufacturing), agricultural production is undertaken by the most efficient agricultural producers in the free-trade equilibrium. This specialization pattern makes free trade a land-saving policy.

Relation to Borlaug's Hypothesis. The above four propositions extend to an international setting the famed hypothesis put forward by Borlaug (2000), namely, that agricultural productivity growth in a closed economy protects forests because the demand for food is inelastic, and so is the derived demand for land. Our results show that international trade can also act as a technological improvement that leads to a lower global demand for land, whether through reductions in trade costs—modeled as export-biased productivity increases or tariff reductions—or through efficiency gains brought about by alignment between comparative and absolute advantage.

Toward a Quantitative Analysis. Propositions 1 through 4 highlight two key considerations for the impact of trade on deforestation. First, Propositions 1 and 2 show that the effect of agricultural trade policy on deforestation depends on the geographic scope of the analysis. Second, when the scope is global, Propositions 3 and 4 indicate that agricultural trade liberalization can lead to either forest gain or loss—depending, in Proposition 3, on the degree of protection in agricultural trade, and in Proposition 4, on whether countries with a comparative advantage in agriculture also possess an absolute advantage. Taken together, these propositions do not provide a definite answer, but rather clarify the conditions under which trade leads to forest loss or gain. We now take these insights to a quantitative model, which incorporates incorporates quantitatively important features of reality and which we calibrate carefully to data, to study the effects of trade on deforestation. We will return to the above propositions when interpreting our quantitative results.

6 The Quantitative Model

Our quantitative model extends the stylized model of Section 4 in five important dimensions, as outlined below. Appendix C presents the Quantitative Model in detail.

First, we incorporate a more detailed set of industries, denoted by g, consisting of a manufacturing industry, a service industry, and multiple agricultural industries, each differentiated into varieties by country of origin. Demand is structured in three CES tiers: the lower tier aggregates national varieties of each industry g with substitution elasticity η_g; the middle tier combines the agricultural industries into an agricultural composite with substitution elasticity κ; and the upper tier aggregates the composites of agriculture, manufacturing, and services into final consumption with substitution elasticity σ.

Second, we incorporate labor, land and intermediate input use into Cobb-Douglas production technologies for each good g,

$$Q_{i,g} = Z_{i,g} \left(N_{i,g}^{\gamma_{i,g}} L_{i,g}^{1-\gamma_{i,g}} \right)^{\alpha_{i,g}} (M_{i,g})^{1-\alpha_{i,g}} \,,$$

where $Z_{i,g}$ is total factor productivity, $N_{i,g}$, $L_{i,g}$, and $M_{i,g}$ are, respectively, the use of labor, land, and intermediate inputs. The latter is in turn an aggregate over all industries using a tiered CES structure similar to that of final consumption, but with factor intensities specific to each using industry g. The parameter $\alpha_{i,g}$ measures the value added share, which is further divided between land and labor with shares $\gamma_{i,g}$ and $(1 - \gamma_{i,g})$.

Third, we include an additional category of land, which we refer to as "fallow land". Specifically, the cleared land L_i is divided into *usable* land U_i and *fallow* land O_i, such that

$L_i = U_i + O_i$ (and, as before, the country's total area consists of cleared land and forests, $H_i = L_i + F_i$). Accordingly, the usable land may depreciate to both forest area and fallow land.

Fourth, we allow the productivity in the land-clearing sector to depend on the available stock of forest and fallow land. Specifically, let z_i denote the share of cleared land in total country area, $z_i \equiv L_i/H_i$, and $u_i \equiv U_i/L_i$ be the share of usable land within cleared land. Usable land is generated by converting forest (F) and fallow land (O) employing labor as an input. The corresponding production technologies are expressed as:

$$Q_{i,T}^{FU} = \underbrace{\zeta_{i,F}\left(1-z_i\right)^{\lambda}}_{\equiv J_i(z_i)}\left(N_{i,T}^{FU}\right)^{\gamma_F}, \qquad Q_{i,T}^{OU} = \underbrace{\zeta_{i,O}\left(z_i\left(1-u_i\right)\right)^{\lambda}}_{\equiv \tilde{J}_i(z_i(1-u_i))}\left(N_{i,T}^{OU}\right)^{\gamma_O}, \tag{18}$$

where $Q_{i,T}^{FU}$ and $Q_{i,T}^{OU}$ denote the usable land produced from forests and fallow land, and $N_{i,T}^{FU}$ and $N_{i,T}^{OU}$ denote the corresponding input uses. Total production and employment of the land-clearing sector are given by:

$$Q_{i,T} = Q_{i,T}^{FU} + Q_{i,T}^{OU}, \qquad N_{i,T} = N_{i,T}^{FU} + N_{i,T}^{OU}.$$

In our specification, $J_i(\cdot)$ and $\tilde{J}_i(\cdot)$ represent the productivity of converting forest and fallow land into usable land, and $\{\gamma_F, \gamma_O\}$ denote the output elasticities with respect to labor. Furthermore, $\{\zeta_{i,F}, \zeta_{i,O}\}$ are exogenous parameters and λ is the elasticity of productivity $J_i(.)$ and $\tilde{J}_i(.)$ with respect to the available stock of forest and fallow land. The productivity $J_i(.)$ is a decreasing function, reflecting the rising cost of deforestation as a shorthand for stricter policies, terrain variability, or greater distances to markets. This property introduces convexity into the cost function, meaning that within each country, the marginal cost of deforestation is not equal to the average cost. Moreover, $J_i(1) = 0$ as no new land can be produced from forest if the entire forest is depleted. Similar properties apply to the productivity function $\tilde{J}_i(\cdot)$. The representative land-clearing producer treats these productivities as fixed and does not internalize the effects of its production decisions on them.[15]

Fifth, we introduce forward-looking workers à la Artuç et al. (2010) and Caliendo et al. (2019). Workers can switch between agriculture, manufacturing, services, and the land-clearing sector, conditional on receiving a move opportunity (which arrive with intensity ψ). Upon receiving an opportunity, they draw preference shocks from a Type-I extreme value distribution, with dispersion parameter ν, and decide whether to move from sector s to s',

[15] Our specification is rooted in the literature on renewables, e.g., Brander and Taylor (1997), who assume $Q_{i,T} \propto (1-z_i) N_{i,T}$. This corresponds to a special case of our specification where $J_i(z_i) = 1 - z_i$ and $\gamma_F = 1$, and the category of fallow land is assumed away.

Table 2: Parameter calibration

Parameter	Value	Source
a. Technology and Preferences		
Cost share of VA and labor, $\alpha_{i,g}, \gamma_{i,g}$	–	GTAP, FAOSTAT
Elast. of substitution between goods	$\sigma = \sigma^I = 0.5$, $\kappa = \kappa^I = 3$	Comin et al. (2021), Costinot et al. (2016)
Trade elasticity	$\eta = 5$	Simonovska and Waugh (2014)
Trade costs and productivity	$d_{ij,g}, Z_{i,g}$	Model inversion in 2010
b. Technology for the production of new-land		
Forest regrowth rate, δ_f	0.5%	Brazil's data (Mapbiomas)
Fallow land regrowth rate, δ_o	5.0%	Brazil's data (Mapbiomas)
	$\zeta_{i,F}$	L_i and F_i in 2010 to be at SS
$Q^{FU}_{i,T} = \zeta_{i,F} \left(1 - z_i\right)^{\lambda} \left(N^{FU}_{i,T}\right)^{\gamma_F}$	$\lambda = 0.9$	Population and deforestation reg.
	$\gamma_F = 0.95$	Population and deforestation reg.
	$\zeta_{i,O}$	L_i and F_i in 2010 to be at SS
$Q^{OU}_{i,T} = \zeta_{i,O} \left(\left(1 - u_i\right) z_i\right)^{\lambda} \left(N^{OU}_{i,T}\right)^{\gamma_O}$	$\lambda = 0.9$	Population and deforestation reg.
	$\gamma_O = 0.9$	Population and deforestation reg.
c. Dynamics of Labor and Land		
Transition costs for labor, $f^N_{i,ss'}$	$5 \cdot (\text{annual income}_{US})$	Artuc et al. (2010) in SS
Discount rate, ρ	0.05	
T1EV dispersion for labor	$\nu = 0.5$	Artuc et al. (2010) in SS
Arrival rates	$\psi = 1$	–

incurring a moving cost $f^N_{i,ss'}$.

7 Taking the Model to Data

This section explains how we calibrate our model calibration and bring it to data. We disaggregate the world into the 40 countries or regional aggregates, as described in Section 3. We calibrate our model parameters in three steps. First, we calibrate the parameters related to the static equilibrium using data circa 2010. Second, we calibrate the labor-dynamics parameters based on previous literature. Third, we calibrate the technology in the land-producing sector so that the model matches reduced-form relationships between population growth and growth in agricultural land and forest area (which we presented as motivation in Section 3). We next explain each step. Table 2 summarizes our calibrated parameters.

7.1 Calibration of static equilibrium

In this first step we exploit the property that, in each time t, our model behaves like a static trade model with fixed employment of labor and land. We set the elasticity of substitution between agriculture, manufacturing, and services, both in production and consumption, at $\sigma = \sigma^I = 0.5$, following Comin et al. (2021), the trade elasticity in each of the sectors,

$\eta - 1 = 4$, following Simonovska and Waugh (2014), and the elasticity of substitution between crops at $\kappa = \kappa^I = 3$, following Costinot et al. (2016). For the cost share parameters, we use GTAP database to directly calibrate the share of value added in gross output $\{\alpha_{i,g}\}$ for all sectors and the labor share in value added $\{\gamma_{i,g}\}$ for agriculture. For non-agricultural sectors, the GTAP dataset does not provide information on the land share in value added. We, therefore, set the land share in value added $(1 - \gamma_{i,g})$ to match the global land share of urban areas (available from FAOSTAT).

Then, taking GTAP database from 2014 on international trade flows, gross output by industry and input-output matrices, we apply standard inversion methods to back out productivity shifters $\{Z_{i,g}\}$, and demand shifters, given trade costs $\{\tau_{ij,g}\}$, which we explain how we parameterize next.

Trade Costs. The contrast between Propositions 2 and 3 motivates us to distinguish between policy and non-policy components of trade costs. Specifically, we express trade costs $\tau_{ij,g}$ as:

$$\tau_{ij,g} = \tau_{ij,g}^{\text{(non-policy)}} \times \tau_{ij,g}^{\text{(policy)}},$$

where tariffs are included in the policy component, $\tau_{ij,g}^{\text{(policy)}}$, and other barriers, such as distance, are included in the non-policy component, $\tau_{ij,g}^{\text{(non-policy)}}$. In the agriculture sector, due to the widespread use of specific tariffs and the frequent occurrence of missing tariff entries in standard data sources, reported ad valorem tariff rates are not reliable indicators of effective ad valorem tariff levels (Teti, 2024; Bouët et al., 2008). For this reason, we adopt a gravity estimation approach, similar to Nath (2025), to estimate the policy component of trade costs. Specifically, we regress our calibrated trade costs $\tau_{ij,g}$ on observable policy variables, such as tariff rates, free trade agreements, and import fees to isolate $\tau_{ij,g}^{\text{(policy)}}$. We then bring in data on the ratio of tariff revenues to imports to pin down the level of effective ad valorem tariff equivalents, which result in an unweighted average of 13%. See Appendix D.1 for details.

7.2 Calibration of labor dynamics

In this second step, we set the sectoral labor supply elasticity at $1/\nu = 2$ and the labor mobility costs, $f_{ss'}^N = f^N$, in line with previous work on labor mobility.[16] We also set arrival

[16] Caliendo et al. (2019) report that the yearly equivalent of their labor elasticity equals our choice of $1/\nu = 2$. For the labor mobility cost, f^N, we follow McLaren (2017) who reports estimates of about five times yearly real income, which we target for US service workers in the steady state.

rates of move opportunities ψ to 1.[17]

7.3 Calibration of the land dynamics

The land dynamics module is the new component that we integrate into the standard modules of production, trade, and labor mobility. Motivated by Pattern 4, we choose parameters so that the model can replicate the empirical relations between population growth, land use, and deforestation.

In the third and final step, our calibration of the parameters in the land-producing sector follows a nested approach. In the inner nest, given values of the elasticities $\{\lambda, \gamma_F, \gamma_O\}$, we recover the productivity shifters $\{\zeta_{i,F}, \zeta_{i,O}\}$ that ensure that the model's steady state values of agricultural land, fallow land, and forest area match their observed values in the initial year of our sample. In the outer nest, in the spirit of indirect inference, we search for the values of the elasticities $\{\lambda, \gamma_F, \gamma_O\}$ so that our model mimics the reduced-form dynamic responses of deforestation and land use to population shocks.

Specifically, after recovering $\{\zeta_{i,F}, \zeta_{i,O}\}$, (i) we shock the model with the UN population growth projection until 2100, and (ii) using these simulated data, we run a set of regressions along the lines of equation (1) in Empirical Pattern 4 but exploiting the timing of the impact of the population shock:

$$\underbrace{\log\left(y_{i,t}\right) - \log\left(y_{i,1990}\right)}_{\text{different time lags}} = \beta_0 + \beta_t^y \underbrace{\left[\log\left(\text{Pop}_{i,2020}\right) - \log\left(\text{Pop}_{i,1990}\right)\right]}_{\text{30 years lag}} + \epsilon_i,$$

where we choose $t = \{2000, 2010, 2020\}$ allowing for the dependent variables to vary at 10, 20, and 30 year horizons, and $y_{i,t}$ is either forest area or agricultural land area. The different coefficients β_t^y across time horizons t allow us to capture the total response of agricultural land and forests to the shock, as well as how quickly this response unfolds. The distinction between the two allows us to separate $\{\gamma_F, \gamma_O\}$ from λ.

Stacking all the coefficients $\{\beta_t^y\}_{t,y}$ in a vector β, we search for values of $\{\lambda, \gamma_F, \gamma_O\}$ to minimize

$$\left(\beta^{(\text{data})} - \beta^{(\text{model})}\right)^\top \left(\beta^{(\text{data})} - \beta^{(\text{model})}\right),$$

where $\beta^{(\text{data})}$ is the vector of parameters estimated using the actual data, and $\beta^{(\text{model})}$ is the vector of parameters estimated using model-generated data.

[17] Our calibration approach imposes that the stock of cleared land in the initial year equals its steady-state value in the absence of any changes in fundamentals. The stock of workers in each sector, however, is not constrained and does evolve from the starting point to the steady state. Appendix Figure F.9 documents this aspect of our calibration.

Our procedure separately pins down the three above elasticity parameters. First, in the data fallow land accounts for a sizable share of a country area, and it is a source of expansion of agricultural land (recall Appendix Figure F.2). Therefore, in response to population growth, agricultural land may expand partly at the expense of forests and partly by converting fallow land. This distinction separately identifies the parameters that govern the expansion from forest, γ_F, from those that control the expansion from fallow land, γ_O. Second, our regressions reveal that land expansions respond differently at various time horizons to a 30-year change in population, capturing the persistence built into the land conversion function via $J_i(.)$ and $\tilde{J}_i(.)$. This variation helps us pin down the labor elasticities separately from the initial condition elasticity, i.e., λ. Higher labor elasticities scale up the overall deforestation responses, whereas higher area elasticities, λ, reduce future land-clearing productivity, and makes short-run responses relatively larger.[18]

7.4 Model validation

Before moving on to the quantitative analysis, we briefly discuss four exercises that validate the performance of our model. First, we show that the fallow land module is essential to match the reduced-form evidence on the impact of population on agricultural land. Without fallow land as an additional source of agricultural land expansion, the model substantially underestimates the response of cleared land to population growth (Appendix Figure F.6).

Second, although our calibration only targets the impact of own population growth, the model closely reproduces the reduced-form impact of foreign population growth, as documented in Pattern 4 (Appendix Table F.8). This finding means that the role of international trade as a transmission mechanism of land pressures across countries—a central mechanism in our paper—is aligned in the quantitative model and our reduced-form results.

Third, the calibrated values of the forest conversion productivity shifters, $\zeta_{i,F}$, effectively capture cross-country variation in institutional regulations that protect forests (Appendix Figure F.7). That is, in the absence of a richer formulation of institutional differences across countries, the calibrated values of productivity of land-clearing sector reflect real-world differences in the ease to deforest.

Fourth, the model-implied yields correlate well with actual data on yields, which we do not use in calibration (Appendix Figure F.8). This means that our calibrated model captures actual cross-country differences in the productivity and land intensity of agriculture, a sector that is key to studying deforestation.

[18] Appendix Figures F.4 and F.5 show the objective function as a function of γ_O, γ_F and λ. They indicate a clear local minimum.

Overall, our calibrated model replicates key features of the data (including several untargeted moments) on trade, land productivity, forest protection, and deforestation dynamics, making it a useful laboratory to study the impact of trade barriers on forests.

8 Counterfactual Policy Analysis

In this section, we examine the quantitative consequences of reducing agricultural trade barriers on land use and deforestation around the world. We focus on scenarios that eliminate agricultural import tariffs, as such scenarios are rooted in policy considerations.[19] We present results, first, starting from a baseline without population growth, and then incorporate population growth forecasts up to the year 2100. We conclude by evaluating the welfare gains from agricultural trade liberalization net of the climate costs of deforestation.

8.1 Removing agricultural import tariffs

We conduct two counterfactual policy scenarios, both of them involving the elimination of agricultural tariffs.

Counterfactual Scenario 1. We consider what would happen if every country removed its import tariffs only on agricultural products coming from Brazil.

Counterfactual Scenario 2. We examine the impact of removing all agricultural import tariffs globally.

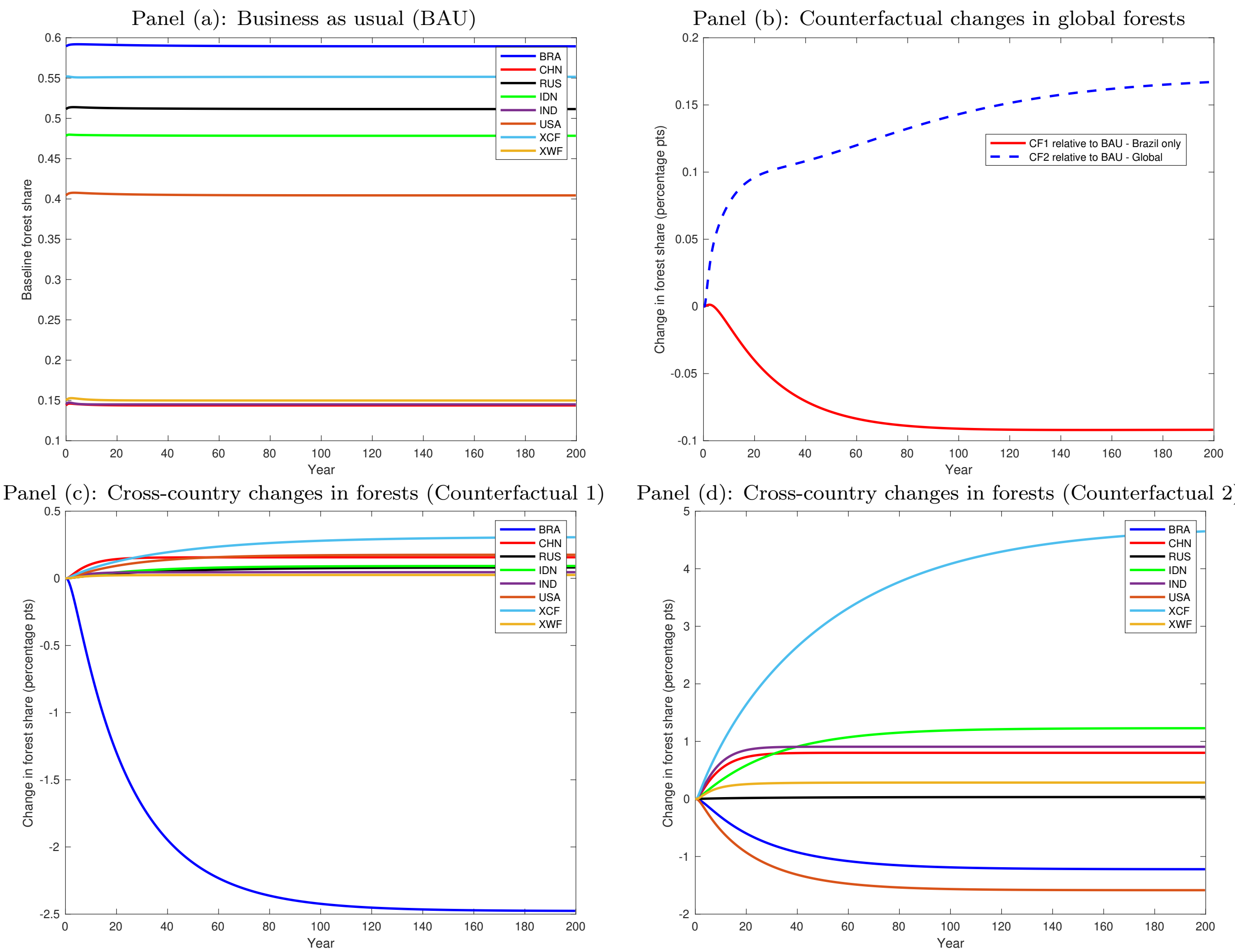
These two scenarios are important in their own right, as they illustrate different ways trade liberalization could take place in agricultural markets. Scenario 1 examines unilateral integration for a country like Brazil, a global leader in agricultural exports and home to vast rainforests. Scenario 2 reflects the outcome of a multilateral agreement, with all countries reducing their agricultural tariffs. The different geographic scopes of the two scenarios—local in Scenario 1, global in Scenario 2—also highlight the quantitative importance of general equilibrium adjustments, via structural change and comparative advantage, as fleshed out in Propositions 1 through 4.

8.1.1 The path of forests

We begin by reporting the frontier of cleared land in the business as usual (BAU) scenario—which is the baseline outcome of our model where no policy change or any other

[19]For comparison, we also report the effects of lowering iceberg trade costs in in Appendix E.

Figure 6: Multilateral vs Unilateral Tariff Elimination: Change in Forest Area Relative to Baseline (Global and Selected Countries)



Notes: Panel (b), (c) and (d) shows at time t the difference in forest share in the counterfactual relative to BAU shown in Panel (a). XCF and XWF stand for the aggregate regions in Central Africa and the rest of West Africa. See Table F.1 for the mapping of individual countries to aggregate regions.

shock is introduced. Panel (a) in Figure 6 shows this path for select countries. As a consequence of our approach to calibration, the land frontier remains almost constant across countries and globally.[20]

Figure 6 displays the percentage point changes in forest share relative to the BAU, both at the level of the world and for select countries. As shown in Panel (b), removing tariffs only on Brazilian agricultural exports leads to a reduction in global forest area. In contrast, eliminating agricultural tariffs worldwide results in an expansion of global forest area.

Recall from Proposition 3 that a global reduction in tariffs has an ambiguous effect on global forest area. Our quantitative findings show that the land-saving forces, primarily driven by structural change, dominate the negative, direct effect of tariff reductions on forest area.[21]

Panels (c) and (d) show the heterogeneous responses of forests in a selected set of countries. In Scenario 1 (Brazil only), the forest area falls sharply in Brazil whereas it increases elsewhere. The forest loss in Brazil amounts to 1 p.p. after 14 years, 2 p.p. after 42 years, and 2.5 p.p. at the steady state—the reduction in tariff equals 8.6 p.p. An important benefit of our global and dynamic perspective is that it is well-suited to capture leakage effects. The steady-state forest-leakage, i.e., the long-run forest gain in the rest of the world for each unit of forest loss in Brazil, equals about 50 percent (see Appendix Figure F.12). This response comes about because Brazil displaces other countries in agricultural markets, and the optimal response of these countries is to devote less resources to agriculture. Leakage is larger in the short run, as Brazil cannot immediately reallocate workers to land-clearing in response to the shock.

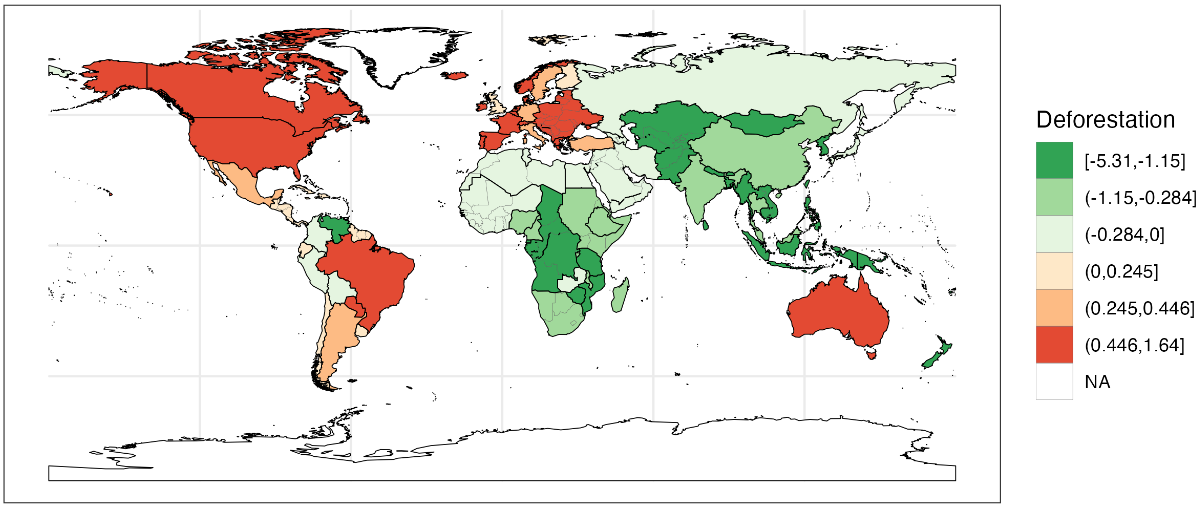
Panel (d) reports analogous results for Scenario 2 (multilateral tariff liberalization). The forest area expands in Central Africa (labeled as "XCF") and South East Asia, whereas North America and Brazil experience relatively large rates of deforestation. Although structural change leads to aggregate reforestation, countries that have a comparative advantage in agriculture or that are geographically well positioned to serve economies that specialize in non-agriculture, take advantage of the tariff reduction by expanding their agricultural sector at the expense of their forests.

To illustrate the geography of deforestation in response to multilateral agricultural tariff removals, Figure 7 shows the steady-state changes in forest area (as a share of country area)

[20] We emphasize that this baseline is not a forecast based on our model. In our baseline scenario, productivity, population, and land remain constant over time, while one would need to know their future paths to forecast the future of forests.

[21] Analogous reductions in iceberg trade costs, instead of import tariffs, result in a larger increase in global forest area (see Appendix E). This quantitative finding is consistent with Propositions 2 and 3, which highlight the attenuating effect of tariff reductions compared to iceberg trade cost reductions.

Figure 7: The Impact of Eliminating Tariffs on Forests Across the World



Notes: This figure shows the changes in forest area in the steady state following a multilateral reduction in global agricultural tariffs. Bold lines indicate the 40 regions analyzed in the paper, while thinner lines denote country-level boundaries.

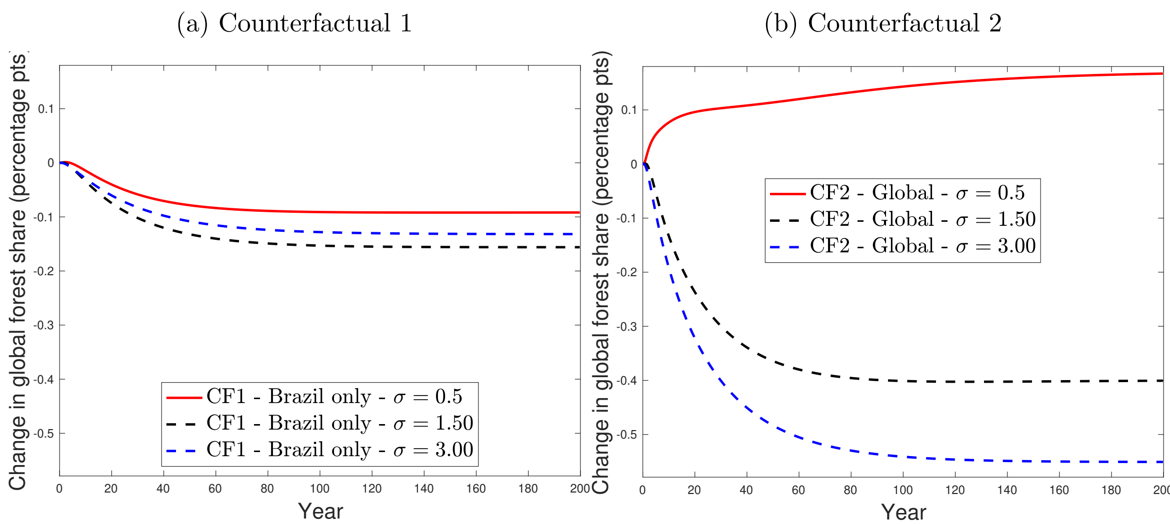
on a global map. Forest area increases in all tropical countries except Brazil, which has a particularly strong comparative advantage in agriculture. For a similar reason, boreal forests tend to experience significant forest loss. This pattern stands in sharp contrast to the actual deforestation of recent decades, which was widespread across tropical countries and less prevalent in boreal regions.

8.1.2 The roles of structural change and comparative advantage

We examine the quantitative importance of structural change and comparative advantage as adjustment mechanisms in response to the multilateral trade liberalization of agriculture. To do so, we focus on Scenario 2, whose global scope makes it an ideal lab to study these general-equilibrium mechanisms.

Structural Change To illustrate the contribution of structural change, in Figure 8 we display the counterfactual path of forests under three values of the sectoral elasticity of substitution, $\sigma \in \{0.5, 1.5, 3.0\}$. Increasing σ limits the scope of structural change for reducing land demand, by muting the complementarity and turning it into higher substitutability between the agricultural and non-agricultural sectors. A larger value of σ reverts the path of global forest area in Scenario 2 but does not qualitatively change that of Scenario 1. These quantitative results show that the relevant elasticity of demand for agricultural goods depends on the geographic scope of trade-cost shock. For an individual exporter, demand is elastic due to trade, and largely unrelated to structural change; but in the global economy, demand is largely inelastic, precisely due to structural change.

Figure 8: The Role of the Sectoral Elasticity of Substitution, σ



Notes: This figure reports counterfactual changes in forest share across alternative values of the sectoral elasticity of substitution. Panel (a) displays the change in global forest share under Scenario 1, whereas Panel (b) presents the change in global forest share under Scenario 2. In both panels, changes are expressed in percentage points.

Comparative Advantage To explore quantitatively the role of comparative advantage, Figure 9, Panel (a) relates the comparative advantage in agriculture relative to manufacturing as measured in the model (on the x-axis) and the counterfactual change in the forest share in the steady state (on the y-axis) for our main specification at $\sigma = 0.5$. Comparative advantage governs the cross-sectional responses: Upon a reduction in trade costs, countries with a comparative advantage in agriculture take advantage of the new trade opportunities and, to expand their agricultural sector, they clear their forests.

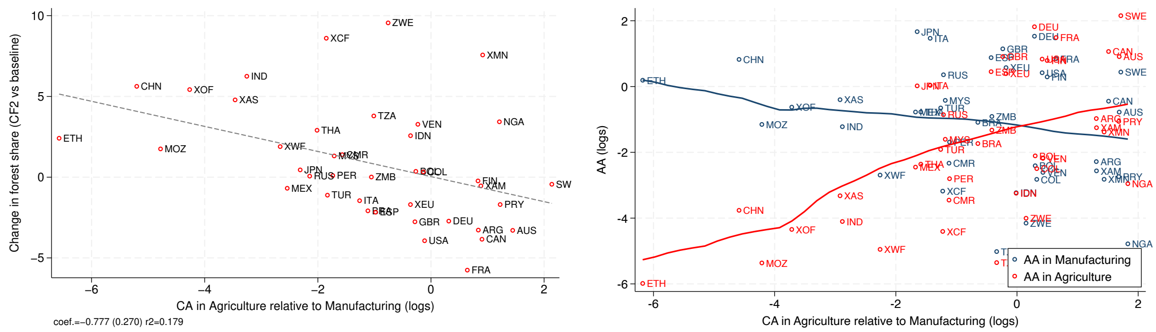
In addition, Figure 9, Panel (b) shows that across countries relative productivity in agriculture, $Z_{i,A}/Z_{i,M}$, is positively correlated with absolute agricultural productivity, $Z_{i,A}$, while it is only weakly correlated with absolute manufacturing productivity, $Z_{i,M}$, (both recovered via model inversion), which means that trade reallocates agricultural production to the most efficient agricultural producers. Through the lens of Proposition 4, the figure suggests that expanding agricultural trade leads to global land savings.[22]

[22] Given our calibrated trade costs, our calibration procedure pins down the set of productivities, $Z_{i,A}$ and $Z_{i,M}$, that make our baseline economy match observed trade flows and production. Altering the distribution of productivities, in an attempt to isolate the role of the absolute advantage channel, would also induce other changes in our baseline economy and prevent us from isolating this channel.

Figure 9: The Role of Comparative Advantage

(a) Deforestation in the cross-section

(b) Absolute and Comparative Advantage in Agriculture



Notes: Panel (a) shows the correlation between the comparative advantage of a country in agriculture (average of implied TFPs across goods) relative to manufacturing and the change in forest area in steady state between BAU and a multilateral reduction in global agricultural tariffs. Panel (b) shows the correlation between comparative and absolute advantage in agriculture, relative to manufacturing.

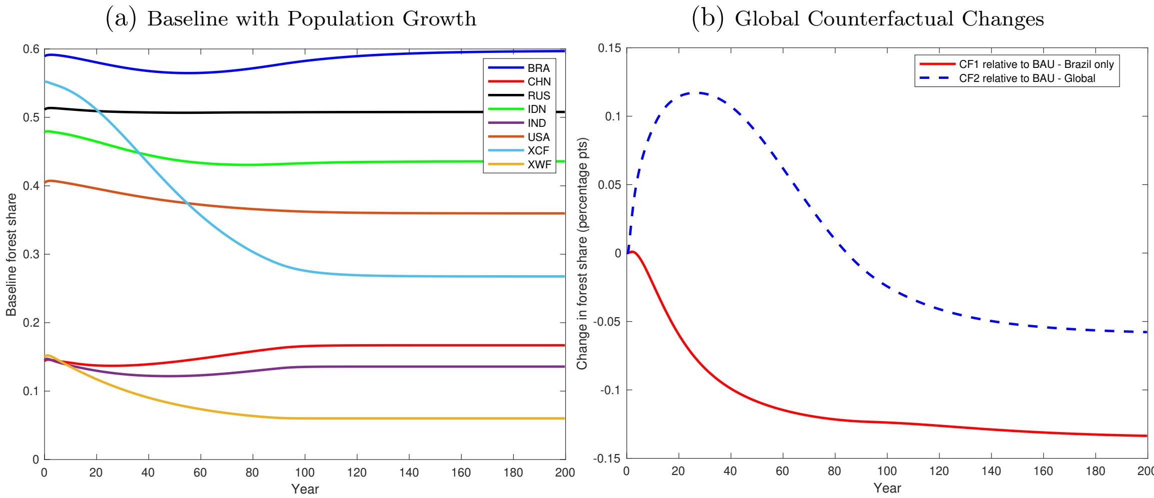
8.2 Incorporating population growth

This section expands our analysis in two directions. First, we examine the impact of population growth on deforestation, by focusing on an alternative business-as-usual scenario that incorporates UN population growth projections until 2100. Average population growth will be large and uneven across countries: The average will be 35 percent, and it will range from population reductions in Japan to more than 300 percent increases in parts of Africa, where large forests areas remain untouched. Since population growth, as we discuss below, is a key determinant of pressures on land, understanding this new scenario is important in itself. Second, we reevaluate the scope of trade policy to mitigate deforestation and its associated costs, under this new BAU scenario, showing that although its impact on global forests is small, it induces important reallocation across countries.

Panel (a) of Figure 10 displays our new BAU scenario. There are large increases in the amount of cleared land (and hence, reductions in forest) in countries in which population growth is projected to be largest. Countries such as Brazil and Indonesia, where population growth is smaller, experience early but moderate expansion in their cleared land, which is then partially reverted as countries with higher population growth develop new land to serve their growing domestic demand for agricultural goods. This is in line with the theoretical predictions of our model, which suggest that population size is one of the key drivers of land stock in equilibrium.[23] Appendix Figure F.13 shows, for our whole sample, that countries

[23] Consider, for example, Appendix equation (B.13), which implies that the elasticity of land stock to population is equal to 1, in the context of a collection of symmetric economies. In our quantitative model, these effects are modulated by the curvature of the function $J(.)$.

Figure 10: The Role of Population Growth



Notes: Panel (a) shows the path of forest share for individual countries under the baseline incorporating population growth. Panel (b) reports the counterfactual changes in global forest share under Scenarios 1 and 2.

with larger population growth experience larger deforestation (steady-state relative to 2010) in the new BAU. Table F.4 in the Appendix reports the corresponding values.

Panel (b) of Figure 10 shows that, relative to this new BAU, our counterfactual scenarios remain qualitatively similar to those without population growth: Global forest area shrinks with the elimination of tariffs faced by Brazil, whereas a global tariff elimination leads to much smaller, albeit slightly positive, global deforestation. That trade policy has limited scope for curbing global deforestation reflects, in part, the larger importance of population growth as a driver of deforestation. Equally important for our results, however, in the multilateral tariff elimination scenario, there is substantial reallocation of land pressure—and, therefore, of reforestation—across countries. As we show below, this reallocation yields a reduction in the deforestation costs of the policy (relative to a scenario without population growth), because on average forests with higher carbon content are protected, even if global forest cover decreases marginally.

Our results show the different impacts on forest area globally and across countries in response to trade costs, highlighting the importance of general-equilibrium forces, such as structural change and comparative advantage. In particular, starting from both our BAU scenarios with and without population, our simulations show that tariff elimination induces substantial reallocation of deforestation across countries (see Figure 6, Panel (d) and Appendix Figure F.11, Panel (b)). Together with the substantial heterogeneity in carbon content of forests we have documented (Appendix Figure F.1), such reallocation suggests that the welfare costs of tariff elimination will depend on the details of which countries end up deforesting more. We turn now to an evaluation of the costs of deforestation, comparing them with the welfare gains of trade liberalization implied in these scenarios.

8.3 Carbon heterogeneity, dynamics, and reforestation

In this section, we evaluate the welfare implications of agricultural trade liberalization. We first consider the climate costs of deforestation resulting from the two policy scenarios presented earlier. This is calculated as the welfare cost of CO_2 emissions released from deforestation, following the IPCC guidelines.[24] Each hectare of forest loss in a country and year results in a corresponding CO_2 emission released to the atmosphere.[25] We assign a monetary value to these emissions at each point in time by applying a social cost of CO_2 of either \$200 or \$350 per ton.[26] We obtain the discounted present value of the stream of these costs using a 5 percent discount rate, and to put them in context, we express them as a fraction of US GDP in 2010. Next, we use these climate costs to compute climate-adjusted welfare gains from agricultural trade liberalization. These gains are calculated as the change in the present discounted value of aggregate real consumption, adjusted for the climate costs of deforestation, at the global level.[27]

Table 3 presents both the climate costs and climate-adjusted welfare gains for the world as a whole, across several specifications. Panels (a) and (b) correspond to Scenarios 1 and 2. In our main specification, the sectoral elasticity σ is set to 0.5. To illustrate the impact of structural change, Panel (c) shows results for Scenario 2 with a higher sectoral elasticity of $\sigma = 1.5$.

As a starting point, Column (1) evaluates the effects of tariff reductions under the assumption of a zero social cost of carbon. This scenario simply elicits the real consumption gains. In Scenario 1, Brazil experiences real consumption gains, but these are more than

[24]Our evaluation does not incorporate other costs associated with deforestation. These other costs stem from the loss of wildlife endemic to each forest, the change in landscape that increases the likelihood of flooding, the amenity value of forests, and desertification. Additionally, we abstract away from the costs associated with reforestation such as the adverse health effects of pollen.

[25]Specifically, following the guidelines described in Tubiello et al. (2020), we use the following equation to compute CO_2 emissions from deforestation: $NFC_{i,t} = -\frac{B_{i,t-1}}{A_{i,t-1}} \min\left[A_{i,t} - A_{t,t-1}, 0\right] \frac{44}{12}$, where $NFC_{i,t}$ is the net deforestation, expressed in tonnes of CO_2. The term $\frac{44}{12}$ converts C to CO_2—it is the ratio of the molecular weight of carbon dioxide, which equals 44, to that of carbon, which equals 12. Note that this is a somewhat pessimistic approach since (i) it assumes when a hectare of forest is lost, all the carbon previously stored in that hectare is immediately released, and (ii) it does not account for reforestation.

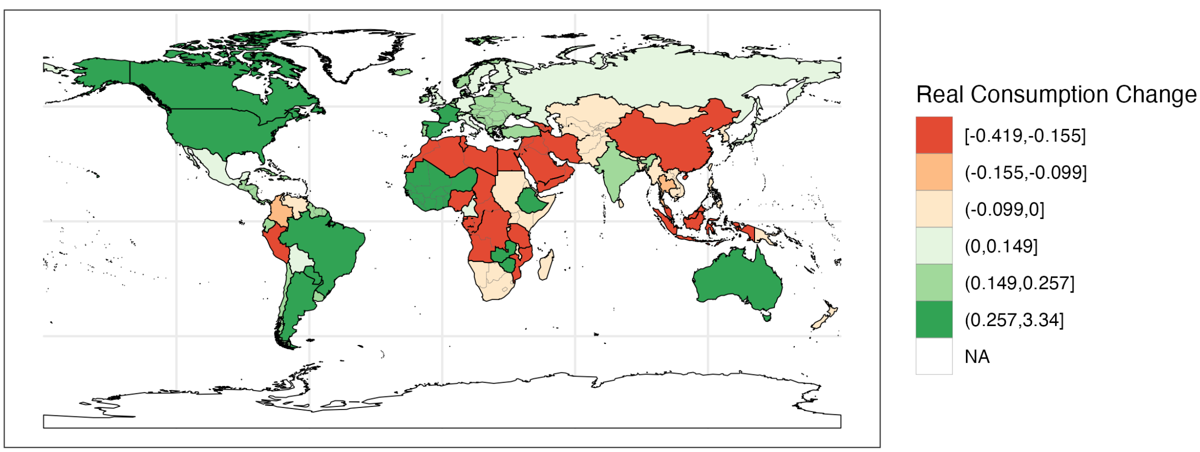
[26]The values of 200 and 350 (\$/tCO2) are consistent with the the latest release of the United States Environmental Protection Agency (EPA)'s Final Report on the Social Cost of Greenhouse Gas.

[27]We specify the global climate-adjusted welfare as $C - \varphi Z$, where C represents world real consumption, Z denotes global emissions, and φ measures the marginal disutility per unit of global emissions. Assuming a constant marginal disutility allows for a simple calibration of the social cost of carbon, and a transparent calculation of climate-adjusted welfare gains for each scenario of deforestation-related changes to emissions. See Appendix D.2 for details.

offset by losses elsewhere, leading to an aggregate loss overall. In Scenario 2, which features multilateral liberalization, real consumption gains around the world outweigh the losses, resulting in an aggregate gain.

Column (2) repeats the analysis, this time applying a social cost of 200 (\$/tCO_2). In both policy scenarios, some countries experience forest loss compared to the business-as-usual (BAU) case, while others see forest regrowth. For countries with regrowth, we make the assumption that there is no carbon sequestration (consistent with Tubiello et al., 2020). Consequently, overall climate costs are positive, even in Scenario 2, which features a modest global increase in forest area. These climate costs amount to about 2 in Scenario 1 and 9 in Scenario 2, as percent of the US GDP in 2010. In Scenario 2, the climate costs are outweighed by the benefits of trade liberalization, resulting in a net positive gain.

Figure 11: Real Consumption Change from Multilateral Agricultural Trade Liberalization



Notes: This figure displays the change in real consumption between the steady state in the BAU scenario versus the counterfactual scenario in which there is a full agricultural trade liberalization.

Figure 11 illustrates that there is significant variation across countries in the welfare gains from eliminating agricultural tariffs. These gains are positively correlated with the extent of deforestation in response to the policy change. This relationship arises because, as a country reduces the size of its agricultural sector, its land stock declines, leading to lower real GDP per worker. Thus, while global tariff elimination increases aggregate real consumption, the gains are unevenly distributed and some countries may still experience losses.

We consider two additional scenarios, both of which suggest that a multilateral liberalization brings larger benefits than climate costs. Column (3) repeats the analysis, by pricing carbon at 350 ($/t$CO_2$), and shows that the climate-adjusted welfare gains remain positive. Column (4) uses this higher price of carbon in the BAU that includes population growth. Note that the climate costs become smaller now, i.e., in Column (4) relative to (3), even if global forest area decreases (as shown in Figure 10). The reason is that, with population growth, deforestation occurs in the BAU in countries that are relatively forest intensive, such as those in Africa. A multilateral trade liberalization shifts deforestation away from these countries to forests that are on average less dense in carbon content, lowering the overall climate costs. In this new scenario, a multilateral tariff liberalization continues to generate a net positive welfare gain.

Remarks and robustness Although these simulations suggest that, across several scenarios, the net impact of multilateral liberalizations on global welfare is positive, we emphasize that our approach brings broader messages. One of our key messages is the role of general equilibrium forces in determining the impact of deforestation. To shore up this message, we recompute our counterfactual scenarios setting $\sigma = 1.5$, which changes the direction in which structural change operates (See Propositions 2 and 3). Doing so suggests, wrongly, much larger deforestation and associated climate costs in response to multilateral trade liberalizations.[28] We also consider non-homothetic preferences, using the formulation from Comin et al. (2021), and find little change in our quantitative findings. Results are reported in Appendix Table F.13.

A second message is that, given our calibration of the structural change and comparative advantage forces, tariff hikes lead to worse global outcomes, especially when applied broadly. As shown in Appendix Table F.9, Panel B, in our main calibration a 10 fold increase in tariff rates worldwide leads to net welfare losses, across all carbon cost and population growth scenarios.

Third, a general feature of our simulations is that the responses of forests vary across countries, with some of them often regrowing their forests. On the one hand, such heterogeneity suggests that to obtain a full picture of the evaluation of a policy, one must incorporate the responses of all countries involved (as we do in our calculations). On the other hand, it also suggests that the details of the valuation of forests will have a bearing on our final calculations. Following IPCC guidelines, our main specification calculates the costs of deforestation assuming no sequestration, meaning that forest regrowth does not capture carbon from the atmosphere. In a less extreme calibration, in which we assume a 30 percent sequestration, our model suggests even larger gains from a multilateral liberalization

[28] While we report the welfare outcomes for completeness, note that since the elasticity of substitution is different, one cannot compare the welfare outcomes between the two specifications.

(Appendix Table F.10).[29]

Finally, Appendix Table F.12 presents the climate costs and net welfare gains under different assumptions about discount rates, to decompose the importance of dynamics. We measure the climate costs and welfare gains for several horizons truncated at $t \in \{5, 10, 20, 50, 200\}$. The table shows that, because deforestation unfolds over many years, a substantial fraction of the costs and gains from liberalization occur well into the future. For example, the first 5 years after the shock account for only one tenth of the entire present value of the total climate costs associated with global tariff reductions. Even for the first 20 years, only 78 percent of the full costs are realized. These results underscore the importance of properly accounting for the dynamics of land use when measuring the impacts of trade liberalization on forests and, through them, on welfare.

Table 3: Costs and Benefits of Eliminating Agricultural Tariffs

	(1)	(2)	(3)	(4)
Panel A: Brazil				
Climate Costs (as fraction of US GDP)	0.000	1.977	3.460	4.827
Welfare gains (percentual change)	-0.090	-0.100	-0.107	-0.009
Panel B: All countries				
Climate Costs (as fraction of US GDP)	0.000	8.788	15.380	4.535
Welfare gains (percentual change)	0.131	0.086	0.053	0.159
Panel C: All countries ($\sigma = 1.5$)				
Climate Costs (as fraction of US GDP)	0.000	37.456	65.548	67.763
Welfare gains (percentual change)	1.267	1.144	1.052	-0.171
Economic Assumptions				
- SCC = 0	Y	-	-	-
- SCC = 200	-	Y	-	-
- SCC = 350	-	-	Y	Y
- Population Growth	-	-	-	Y

Notes: This table shows the present value of the gains in real GDP and the present value of the costs in terms of carbon emissions of different policy counterfactuals using different assumptions on the costs of carbon emissions from deforestation. Column (1) and (2) compute such gains and costs by comparing the counterfactual scenario with the baseline trajectory of GDP and environmental costs in a scenario with no population growth. Columns (3) and (4) proceeds analogously using the baseline scenario in which there is population growth. To compute costs and gains, we weight countries based on their population.

9 Conclusions

We have developed a framework to study—analytically and quantitatively—the impact of trade policy on deforestation. The key insight of our paper is that in a trading world, structural change and comparative advantage interact to determine aggregate land use and how

[29] Specifically, we assume that forest regrowth sequestrate carbon from the atmosphere at a 30 percent rate, which means that, relative to the initial carbon stock per hectare in the data, every hectare of forest recovered absorbs 30 percent of that initial carbon density.

it is distributed across countries. Our results provide a new rationale for international cooperation in trade policy, by showing that multilateral trade liberalization can help circumvent trade offs between the gains from trade and preservation of the forests.

References

Abman, R. and Lundberg, C. (2020). Does free trade increase deforestation? the effects of regional trade agreements. *Journal of the Association of Environmental and Resource Economists*, 7(1):35–72.

Abman, R., Lundberg, C., and Ruta, M. (2024). The effectiveness of environmental provisions in regional trade agreements. *Journal of the European Economic Association*, 22(6):2507–2548.

Alvarez, F. and Lucas, R. J. (2007). General equilibrium analysis of the eaton-kortum model of international trade. *Journal of Monetary Economics*, 54(6):1726–1768.

Araujo, R., Assunção, J., and Bragança, A. (2025a). Transportation infrastructure and deforestation in the amazon. *Journal of Development Economics*, page 103559.

Araujo, R., Costa, F., and SantAnna, M. (2025b). Efficient conservation of the brazilian amazon: Estimates from a dynamic model. *Review of Economic Studies*, page rdaf031.

Artuç, E., Chaudhuri, S., and McLaren, J. (2010). Trade shocks and labor adjustment: A structural empirical approach. *American Economic Review*, 100(3):1008–45.

Asher, S., Garg, T., and Novosad, P. (2020). The ecological impact of transportation infrastructure. *The Economic Journal*, 130(629):1173–1199.

Assunção, J., Gandour, C., Rocha, R., and Rocha, R. (2020). The effect of rural credit on deforestation: evidence from the brazilian amazon. *The Economic Journal*, 130(626):290–330.

Balboni, C. (2025). In harm's way? infrastructure investments and the persistence of coastal cities. *American Economic Review*, 115(1):77–116.

Balboni, C., Burgess, R., and Olken, B. A. (2024). The origins and control of forest fires in the tropics. *Review of Economic Studies*, Forthcoming.

Borlaug, N. (2000). The green revolution revisited and the road ahead. Special 30th Anniversary Lecture, The Norwegian Nobel Institute, Oslo.

Bouët, A., Decreux, Y., Fontagné, L., Jean, S., and Laborde, D. (2008). Assessing applied protection across the world. *Review of International Economics*, 16(5):850–863.

Brander, J. and Taylor, S. (1997). International trade and open-access renewable resources: The small open economy case. *The Canadian Journal of Economics*, 30(3).

Brown, S. and Zarin, D. (2013). What does zero deforestation mean? *Science*, 342(6160):805–807.

Burgess, R., Costa, F., and Olken, B. A. (2019). The brazilian amazon's double reversal of fortune.

Caliendo, L., Dvorkin, M., and Parro, F. (2019). Trade and Labor Market Dynamics: General Equilibrium Analysis of the China Trade Shock. *Econometrica*, 87(3):741–835.

Carleton, T., Crews, L., and Nath, I. (2025). Agriculture, trade, and the spatial efficiency of global water use. *Working Paper*.

Comin, D., Lashkari, D., and Mestieri, M. (2021). Structural change with long-run income and price effects. *Econometrica*, 89(1):311–374.

Conte, B., Desmet, K., Nagy, D. K., and Rossi-Hansberg, E. (2021). Local sectoral specialization in a warming world. *Journal of Economic Geography*, 21(4):493–530.

Copeland, B. R., Shapiro, J. S., and Scott Taylor, M. (2022). Globalization and the environment. In Gopinath, G., Helpman, E., and Rogoff, K., editors, *Handbook of International Economics: International Trade, Volume 5*, volume 5 of *Handbook of International Economics*, pages 61–146. Elsevier.

Copeland, B. R. and Taylor, M. S. (2004). Trade, growth, and the environment. *Journal of Economic literature*, 42(1):7–71.

Costinot, A., Donaldson, D., and Smith, C. (2016). Evolving comparative advantage and the impact of climate change in agricultural markets: Evidence from 1.7 million fields around the world. *Journal of Political Economy*, 124(1):205–248.

Desmet, K., Kopp, R. E., Kulp, S. A., Nagy, D. K., Oppenheimer, M., Rossi-Hansberg, E., and Strauss, B. H. (2021). Evaluating the economic cost of coastal flooding. *American Economic Journal: Macroeconomics*, 13(2):444–486.

Dominguez-Iino, T. (2025). Efficiency and redistribution in environmental policy: An equilibrium analysis of agricultural supply chains. *Journal of Political Economy*, Forthcoming.

Donaldson, D. (2018). Railroads of the raj: Estimating the impact of transportation infrastructure. *American Economic Review*, 108(4-5):899–934.

Fajgelbaum, P. and Redding, S. J. (2022). Trade, structural transformation, and development: Evidence from argentina 1869–1914. *Journal of political economy*, 130(5):1249–1318.

FAO (2020). Guide for country reporting for fra 2015. *FRA 2020 Working Paper 184*.

Farrokhi, F. (2020). Global sourcing in oil markets. *Journal of International Economics*, page 103323.

Farrokhi, F. and Lashkaripour, A. (2024). Can trade policy mitigate climate change? *Working Paper*.

Farrokhi, F. and Pellegrina, H. S. (2023). Trade, technology, and agricultural productivity. *Journal of Political Economy*, 131(9):2509–2555.

Foster, A. D. and Rosenzweig, M. R. (2003). Economic Growth and the Rise of Forests*. *The Quarterly Journal of Economics*, 118(2):601–637.

Gollin, D., Hansen, C. W., and Wingender, A. M. (2021). Two blades of grass: The impact of the green revolution. *Journal of Political Economy*, 129(8):2344–2384.

Gollin, D. and Wolfersberger, J. (2024). Agricultural trade and deforestation: the role of new roads. *Working Paper*.

Gouel, C. and Laborde, D. (2021). The crucial role of domestic and international market-mediated adaptation to climate change. *Journal of Environmental Economics and Management*, 106:102408.

Hansen, C. W. and Wingender, A. (2023). Who fed china? Technical report, CEPR Discussion Papers.

Hertel, T. (2012). Implications of agricultural productivity for global cropland use and ghg emissions: Borlaug vs jevons". Technical Report 69, GTAP.

Hertel, T. W. (2002). Applied general equilibrium analysis of agricultural and resource policies. *Handbook of agricultural economics*, 2:1373–1419.

Hsiao, A. (2025). Coordination and Commitment in International Climate Action: Evidence from Palm Oil. *Working Paper*.

Jayachandran, S., De Laat, J., Lambin, E. F., Stanton, C. Y., Audy, R., and Thomas, N. E. (2017). Cash for carbon: A randomized trial of payments for ecosystem services to reduce deforestation. *Science*, 357(6348):267–273.

Kortum, S. and Weisbach, D. A. (2024). Optimal unilateral carbon policy. *Working Paper*.

McLaren, J. (2017). Globalization and labor market dynamics. *Annual Review of Economics*, 9:177–200.

Mishra, P. (2025). The global allocative efficiency of deforestation. *Working Paper*.

Nath, I. (2025). Climate change, the food problem, and the challenge of adaptation through sectoral reallocation. *Journal of Political Economy*, 133(6):1705–1756.

Pellegrina, H. S. (2022). Trade, productivity, and the spatial organization of agriculture: Evidence from brazil. *Journal of Development Economics*, 156:102816.

Pendrill, F., Gardner, T. A., Meyfroidt, P., Persson, U. M., Adams, J., Azevedo, T., Bastos Lima, M. G., Baumann, M., Curtis, P. G., De Sy, V., et al. (2022). Disentangling the numbers behind agriculture-driven tropical deforestation. *Science*, 377(6611):eabm9267.

Pfaff, A. S. (1999). What drives deforestation in the brazilian amazon?: Evidence from satellite and socioeconomic data. *Journal of Environmental Economics and Management*, 37(1):26–43.

Shapiro, J. S. (2016). Trade costs, CO2, and the environment. *American Economic Journal: Economic Policy*, 8(4):220–54.

Simonovska, I. and Waugh, M. E. (2014). The elasticity of trade: Estimates and evidence. *Journal of International Economics*, 92(1):34–50.

Sotelo, S. (2020). Domestic trade frictions and agriculture. *Journal of Political Economy*, 128(7):2690–2738.

Souza-Rodrigues, E. (2019). Deforestation in the amazon: A unified framework for estimation and policy analysis. *The Review of Economic Studies*, 86(6):2713–2744.

Teti, F. (2024). Missing tariffs. Technical Report 11590, CESifo Working Paper Series.

Tombe, T. (2015). The missing food problem: Trade, agriculture, and international productivity differences. *American Economic Journal: Macroeconomics*, 7(3):226–258.

Tubiello, F. N., Pekkarinen, A., Marklund, L., Wanner, N., Conchedda, G., Federici, S., Rossi, S., and Grassi, G. (2020). Carbon emissions and removals by forests: New estimates 1990. *Sci. Data Discuss.*