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COORDINATION AND COMMITMENT IN INTERNATIONAL CLIMATE ACTION: EVIDENCE FROM PALM OIL

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Weak environmental regulation has global consequences. When domestic regulation fails, the international community can target emitters with trade policy. I develop a dynamic empirical framework for evaluating trade policy as a substitute for domestic regulation, and I apply the framework to the market for palm oil, a major driver of deforestation and global CO_2 emissions. Relative to business as usual, a domestic production tax of 50% reduces CO_2 emissions by 7.4 Gt from 1988 to 2016, amounting to 0.26 Gt annually. Coordinated, committed import tariffs of similar magnitude reduce emissions by 5.4 Gt over the same period. The cost of these import tariffs is only \$15 per ton of CO_2, even accounting for compensating transfers that recognize welfare losses for producing countries. Without coordination and commitment, import tariffs have more limited effects. Alternative policies include domestic export taxes, which are fiscally appealing independent of emission concerns, and a carbon border adjustment mechanism, which encourages domestic regulation.

KEYWORDS: Climate change, environmental regulation, trade policy, palm oil, European Union, Indonesia, Malaysia.

1. INTRODUCTION

CARBON EMISSIONS have global consequences. The international community may therefore wish to intervene when domestic regulation fails. Indeed, free-riding incentives, political constraints, administrative limits, and potential corruption each undermine domestic regulation (Oates and Portney (2003), BHOP+ (2012), Oliva (2015)). The conventional approach attempts to address these difficulties by strengthening regulatory capacity (Greenstone and Hanna (2014), Duflo, Greenstone, Pande, and Ryan (2018)), but doing so at scale is often infeasible. Trade policy offers an alternative, circumventing these obstacles by targeting the prices that carbon emitters receive in world markets.

How effective is trade policy as a substitute for direct regulation? I develop a dynamic empirical framework to answer this question quantitatively. I highlight two challenges: (1) a coordination problem because of leakage to unregulated markets and (2) a commitment problem because regulation is not statically optimal once emissions are sunk.[1] I apply this framework to studying the palm oil industry, which accounts for 5% of global CO_2 emissions from 1990 to 2016 (Figure 1). By comparison, the European Union (EU) accounts for 11% and Russia for 6% over the same period.

Palm oil is an important empirical setting. The industry is a major polluter: land clearing for palm oil plantations threatens carbon-rich peatland forests in Indonesia and

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[1]"Leakage" arises under incomplete regulation. Regulation reduces consumption in regulated markets. But in doing so, regulation also reduces world prices and raises consumption in unregulated markets. This response of unregulated markets attenuates the net effect on global consumption.

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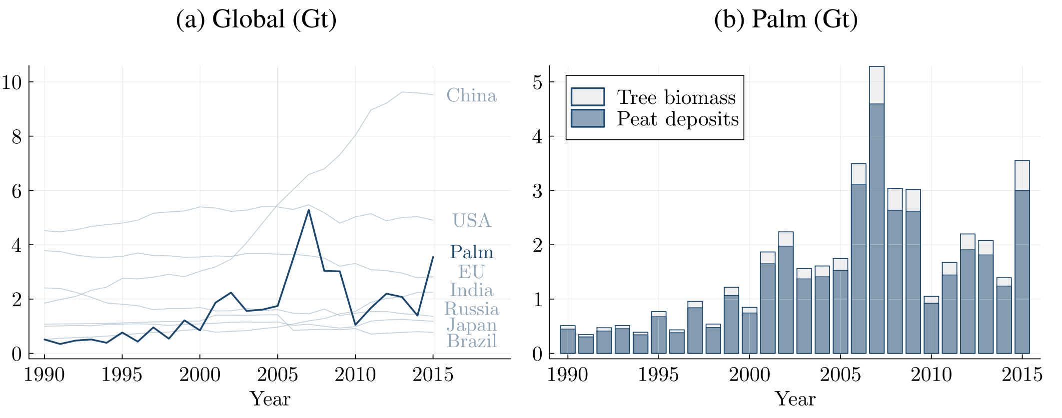

FIGURE 1.—Emissions. Figure 1a compares Indonesian and Malaysian palm oil to the top emitters, accounting for land-use change. Palm emissions are 5.45% of global emissions from 1990 to 2016. Figure 1b separates palm emissions from tree biomass and peat deposits. Emissions are in gigatons of CO_2. Country emissions are from Climate Watch (2020).

Malaysia, which together account for 84% of global palm oil production. At the same time, the industry generates substantial domestic profits that have lifted millions out of poverty (Edwards (2026)). This paper informs an active debate on whether foreign governments should intervene with trade policy. The leading example is the EU Regulation on Deforestation-free Products, which will soon restrict EU imports of palm oil (Official Journal of the EU (2023)). I quantify emission reductions under such trade policy intervention, as well as the losses that Indonesia and Malaysia might claim as payment for ecosystem services.

I characterize palm oil demand with an almost ideal demand system (Deaton and Muellbauer (1980)) and annual panel data on vegetable oil consumption by consumer market. The model explicitly captures substitution between palm oil and other vegetable oils in response to price changes. Demand estimation applies iterated linear least squares, as in Blundell and Marc Robin (1999). Prices are endogenous. I instrument for palm oil prices with weather shocks to palm oil production, and I instrument for other vegetable oil prices with weather shocks to other vegetable oil production. These instruments act as supply shifters. I estimate palm oil demand elasticities of 0.7 to 0.9, which indicate relatively inelastic demand for this staple food product. These estimates determine the losses from non-coordination, as leakage is exacerbated by elastic demand in unregulated markets.

I characterize palm oil supply with a dynamic discrete-continuous choice model and granular satellite data on palm oil production over time and space. The model explicitly captures differential responses to long- and short-run price changes. In the model, forward-looking firms invest in mills and plantations to produce palm oil for sale in world markets. I consider two margins of investment. On the extensive margin, firms make a discrete choice to build a mill or not. On the intensive margin, firms make a continuous choice over how much land to deforest and develop into plantations. Deforestation releases carbon emissions.

Supply estimation combines the continuous and discrete Euler methods of Hall (1978) and Scott (2013). Continuation values difference out, and estimation simplifies to linear regression with instruments. That is, I estimate the model without solving it. For identification, I combine variation in world prices over time with variation in yields across space. Revenues are the product of prices and yields. Thus, if supply is elastic, then high-yield plantations respond more strongly to prices than low-yield plantations. If supply is instead inelastic, then high- and low-yield plantations have similarly muted responses. Prices are again endogenous. I instrument for palm oil prices with total vegetable oil consumption and weather shocks to other vegetable oil production. These instruments act as demand shifters. Total consumption raises the category budget for vegetable oils overall, and weather shocks affect residual demand for palm oil. I estimate palm oil supply elasticities of 2.8 in the long run and 1.3 in the short run, reflecting that firms respond weakly to temporary price changes. These estimates determine the losses from non-commitment, as temporary regulation induces temporary price changes with limited effects.

For counterfactuals, I quantify the global impacts of regulation. I simulate direct regulation with production taxes, as well as trade policy with import tariffs, export taxes, and a carbon border adjustment mechanism. For each policy, I solve the model for equilibrium prices, production, and consumption. Emissions depend on the spatial distribution of plantation development, which I model, and carbon stocks, which I observe. Welfare in each market is the sum of consumer surplus, producer surplus, and government revenue. For a given social cost of carbon, global social welfare is the sum of welfare across markets and the value of global emission reductions. I find that a palm oil production tax of 50% can reduce CO_2 emissions by 7.4 Gt over the study period from 1988 to 2016, relative to business as usual. If feasible, this production tax generates net welfare gains for Indonesia and Malaysia by improving their terms of trade. By comparison, EU-led import tariffs of similar magnitude can reduce emissions by 5.4 Gt over the same period. The cost to the EU is only $15 per ton of CO_2, even accounting for compensating transfers that recognize profit losses for Indonesia and Malaysia.

Import tariffs rely on an EU that can coordinate across importers and commit to long-run enforcement. Coordination and commitment are difficult. The challenge with coordination is free-riding in two forms. Import tariffs reduce both global emissions and world prices, such that unregulated importers enjoy double benefits without bearing the burden of regulation. The challenge with commitment is the temptation to eliminate import tariffs once emissions are sunk. Present-biased governments may find it difficult to resist this temptation, seeking short-run gain at long-run cost. I find that emission reductions are smaller and substantially costlier when either coordination or commitment fails. Neither is independently sufficient for achieving the largest environmental gains. Both are necessary.

I consider several alternative policies. First, if international coordination fails, the EU can act unilaterally. Unilateral action can still achieve 1 Gt of abatement over the study period, although the cost to the EU rises to $50 per ton of CO_2. Second, Indonesia and Malaysia can impose export taxes. Export taxes target the same goods as import tariffs and thus achieve the same emission reductions. Export taxes require enforcement only at international ports, unlike direct regulation. And export taxes have fiscal appeal because they generate government revenue at the expense of foreign consumers, while also sparing domestic consumers. Third, importers can implement a carbon border adjustment mechanism, which combines import tariffs with a credit for domestic regulation. This credit strengthens the fiscal incentive for Indonesia and Malaysia to regulate.

This paper develops a new dynamic empirical framework for assessing green trade policy. I build on a rich literature that studies environmental regulation and trade, where free-riding and leakage motivate carbon coalitions (Nordhaus (2015), Böhringer, Carbone, and Rutherford (2016), Farrokhi and Lashkaripour (2025)) and border adjustment taxes (Markusen (1975), Copeland and Taylor (1994, 1995), Hoel (1996), Rauscher

(1997), Fowlie (2009), EFKM+ (2010), Fowlie, Reguant, and Ryan (2016), Kortum and Weisbach (2017, 2024)), and where trade policy influences environmental incentives (Shapiro (2021), Harstad (2024)). I also build on a literature studying commitment in environmental regulation (Marsiliani and Renström (2000), Abrego and Perroni (2002), Helm, Hepburn, and Mash (2003), Brunner, Flachsland, and Marschinski (2012), Harstad (2020), Acemoglu and Rafey (2023)). I quantify the challenges of coordination and commitment jointly and in an important empirical setting. By focusing on one industry, I can leverage detailed microdata to capture rich dynamics and fine-grained spatial heterogeneity.

Methodologically, I build on models of industry dynamics in the tradition of Hopenhayn (1992) and Ericson and Pakes (1995). I draw on a growing literature, formalized by Aguirregabiria and Magesan (2013), Scott (2013), and Kalouptsidi, Scott, and Souza-Rodrigues (2021), that develops Euler conditional choice probability methods for estimating dynamic discrete choice models. Using techniques from Hotz and Miller (1993) and Arcidiacono and Miller (2011), this literature adapts classic continuous Euler methods from Hall (1978) and Hansen and Singleton (1982) to the discrete setting. I combine discrete and continuous Euler techniques to estimate a dynamic discrete-continuous choice model of entry and investment. Relative to other such models, including Blevins (2014), Iskhakov, Jørgensen, Rust, and Schjerning (2017), and Murphy (2018), I offer a simple estimation strategy that is computationally light and straightforward to implement.

More broadly, trade policy enables regulation in otherwise low-regulation environments. For deforestation, trade policy does not rely on domestic governments that are willing and able to enforce regulation, unlike domestic policies (Souza-Rodrigues (2019), Assunção, McMillan, Murphy, and Souza-Rodrigues (2023), Burgess, Costa, and Olken (2024), Araujo, Costa, and Sant'Anna (2025), Domínguez-Iino (2025)) or conservation contracting (Harstad (2012), Harstad and Mideksa (2017)). Trade policy also scales readily, unlike direct payments for ecosystem services (JLLS+ (2017), EFHH+ (2022)). I show that trade policy can greatly reduce emissions in an industry that is crucial in the fight against climate change.

2. BACKGROUND

Palm oil is a major source of global carbon emissions. Production is concentrated in Indonesia and Malaysia, where slash-and-burn practices have transformed the natural landscape. Sweeping plantations emerge from widespread deforestation, including of the peatland forests prevalent in the region. These forests house vast amounts of carbon in the form of peat, with layers of decomposing organic matter that extend as deep as ten meters belowground.[2] Palm-driven deforestation is thus particularly consequential, as it destroys both tree biomass and peat deposits. Figure 1 shows that palm emissions account for more CO_2 from 1990 to 2016 than the entire Indian economy, with peat destruction generating the vast majority of emissions.

Palm oil production begins with the planting of oil palm seedlings, which mature into trees. These trees bear fruit after three years and continue to do so over a lifespan of 30 years. Plantations harvest fresh fruit bunches that mills process into palm oil and palm kernel oil, with further processing by refineries. Roughly 90% of the oil in palm fruit is

[2]Converting peatlands to croplands involves draining peatlands and clearing the land with fire. Even without clearing by fire, unsubmerged peat releases carbon as it decomposes, and dried-out peat is likely to ignite from slash-and-burn activity in surrounding areas.

TABLE I

PRODUCTION, CONSUMPTION, AND TRADE.

	Production %	Exports %	Consumption %	Imports %
Indonesia	44	41	15	0
Malaysia	40	48	8	3
European Union	0	0	12	18
China	0	0	10	15
India	0	0	11	15
Rest of world	16	10	44	49

Note: Each column sums to 100% and covers 1988 to 2016. I pool palm oil and palm kernel oil by volume.

extracted from the flesh as palm oil, while the remaining 10% is extracted from the seed as palm kernel oil. These oils are exported widely. Indonesia and Malaysia account for 84% of global production and 89% of exports (Table I). Production is unconcentrated at the firm level, with the largest firm accounting for only 4% of global production (Palm Oil Analytics (2017)).

Plantations and mills operate in tandem, as unmilled fruit decays within one day of harvest and is not consumed directly. For industrial plantations, which are 60% of production, vertical integration links plantations and mills directly. For smallholder plantations, which are 40% of production, vertical contracting creates similar links. Smallholders receive investment support from mills, which are nearly all industrial, in exchange for exclusive contracting (Cramb and McCarthy (2016)). Mills exercise market power in setting contract terms, as smallholders face credit constraints and crop perishability that limit their bargaining power. Mills thus extract rents from plantations. If mills extract rents fully, then vertical integration and contracting coincide.[3]

Consumption takes many forms, as palm oil is among the most widely used plant products in the world. Its uses range from cooking and baking to cosmetics and biofuels, and this ubiquity has driven continued growth in palm oil production and emissions. In 2016, palm oil expenditures were $45 billion and 32% of total vegetable oil expenditures—more than any other vegetable oil. Substitutes include coconut, olive, rapeseed, soybean, and sunflower oils, but versatility in use and a low price point have helped palm oil maintain its market share.[4] Firms trade palm oil in competitive global commodity markets, with the largest firm accounting for only 2% of global consumption (World Wildlife Fund (2016)). At the country level, the EU, China, and India account for 33% of global consumption and 48% of imports, while Indonesia and Malaysia consume 23% of the world's palm oil domestically (Table I).

Significant palm emissions motivate regulation, but domestic regulation faces challenges. Palm oil profits limit incentives to pass regulation, and weak enforcement hampers regulation that does pass. In 2010, Norway pledged $1 billion to Indonesia in cash incentives for domestic forest regulation, prompting the Indonesian government to issue

[3]Indeed, market power over smallholder farmers is common in agricultural value chains (Bergquist and Dinerstein (2020), Chatterjee (2023), Rubens (2023), Zavala (2024)).

[4]For the EU, biofuels have driven an important part of palm oil demand. I abstract from substitution between palm oil and fossil fuels because of EU biofuel targets. For example, 14% of fuel for transportation must be renewable by 2030. Where binding, these targets prevent increased fossil fuel use and thus encourage substitution from palm oil to other vegetable oils.

a moratorium on new forest concessions in 2011. But the moratorium had little effect, failing to curb deforestation within existing concessions or elsewhere, including in protected areas (BFEW+ (2015)). Some policies even promote palm oil production rather than restricting it: for transportation, Indonesia and Malaysia mandate that fossil fuels be blended with palm-based biofuels at rates of 30% and 20%, respectively (USDA Foreign Agricultural Service (2019a,b)).

Consequently, European policymakers have discussed intervening with regulation. The EU is set to eliminate green subsidies for palm-based biofuels, cap production, and achieve a complete phase-out by 2030. Palm-based biofuels face the further loss of green tax incentives in France and an outright ban in Norway. French parliament debated a "Nutella tax" in 2016, highlighting the copious use of palm oil in Nutella and other food products. Each policy uses European purchasing power to target emissions abroad. This paper considers the impacts of such policy.

3. DATA

I construct annual panel data on palm oil prices, consumption, and production from 1988 to 2016. Supplemental Appendix A (Hsiao (2026)) details data sources and construction.

3.1. *Demand*

I measure annual prices and consumption of vegetable oils. The data span the study period from 1988 to 2016 and cover all major vegetable oils: palm, palm kernel, coconut, olive, rapeseed, soybean, and sunflower. World price data come from the International Monetary Fund (2023). Palm oil prices derive from forward contract prices at Bursa Malaysia Derivatives Berhad, which is the primary global exchange market for palm oil futures. I use consumer price index data from the World Bank (2023) to adjust for inflation and denominate prices in year-2000 dollars. Consumption data by country come from the USDA Foreign Agricultural Service (2025). I compute total vegetable oil expenditures from these prices and quantities.

I aggregate along two margins. First, I aggregate countries into four consumer markets: the EU, China and India, Indonesia and Malaysia, and the rest of the world. For each consumer market, I compute total quantities and expenditure-weighted average inflation.[5] Second, I aggregate individual vegetable oils into two product groups: palm oils and other oils. Palm oils include palm oil and palm kernel oil, while other oils include coconut, olive, rapeseed, soybean, and sunflower oils. For each product group, I compute total quantities and expenditure-weighted average prices.[6] From here, I will use "palm oil" in reference to the palm oils product group. Figure 2 shows that palm oil prices have risen over time despite a seven-fold increase in quantities traded. Concurrent growth in prices and quantities indicates an outward shift of the aggregate demand curve, and indeed palm oil was adopted widely for use in food products, consumer goods, and biofuels during this period.

[5]For inflation, I aggregate over the countries in each market. I average over the consumer price index data, weighting by each country's household final consumption expenditures.

[6]For prices, I aggregate over individual oils o within each product group. I use Stone price index $\ln p_t = \sum_o \omega_{ot} \ln p_{ot}$ for years t, world expenditure shares ω_{ot}, and world prices p_{ot}.

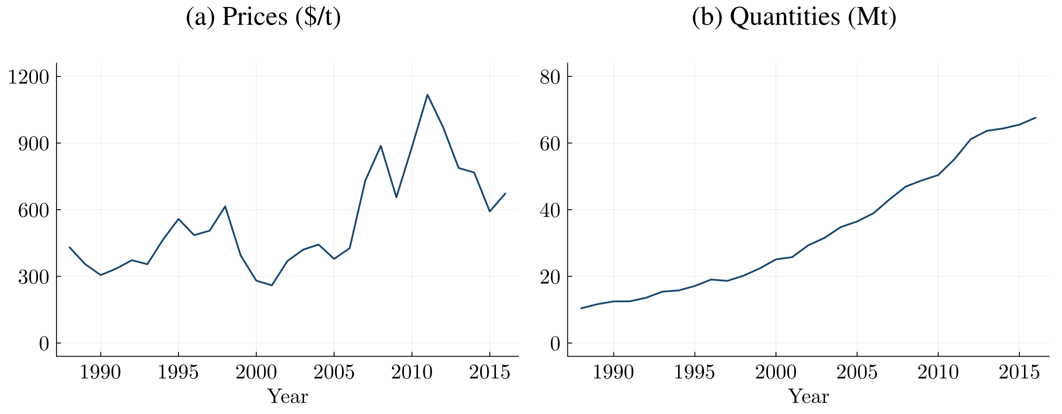

FIGURE 2.—Prices and quantities. World prices are in nominal USD per ton, and world quantities are in megatons. Each aggregates over palm oil and palm kernel oil.

3.2. *Supply*

I measure Indonesian and Malaysian palm oil production by site and year. I define sites as groupings of plantations and mills, and I treat sites as firms. Sites choose to invest in plantations and mills, subject to state variables that affect profits.

Choices

I capture plantations and mills with satellite-based measures. The study area is Sumatra and Kalimantan of Indonesia and all of Malaysia. For plantations, XYLC+ (2020) use PALSAR and MODIS satellite data to map palm oil plantations in the study area at 1 km resolution from 2001 to 2016. I extend their measure back to 1988 using data on tree cover loss as a proxy for plantation development. I obtain these data from SHSP+ (2018), who construct tree cover loss from 1988 to 2016 with Landsat and MODIS satellite data. I estimate the relationship between tree cover loss and plantation development in the overlapping period from 2001 to 2016, and I find that tree cover loss is strongly predictive of plantation development. I then apply the estimated relationship to extend the plantation development data into the non-overlapping period from 1988 to 2000. For mills, data from the World Resources Institute and the Center for International Forestry Research record palm oil mill locations for all of Indonesia and Malaysia in 2018 (Okarda and Manalu (2017), World Resources Institute (2019)). With historical satellite data from Google Earth, I confirm each location and identify 1526 mills. I drop the 29 mills that lie outside of the study area.

I use the plantation and mill data to divide the study area into independent plots, which I call "sites." Active sites have one mill with nearby plantations. Potential sites have no mills or plantations, but they represent potential entrants. In the data, the provinces with the highest density of palm oil production contain one mill per 535 km^2 of land area in 2016. I treat this ratio as a target density. For each province, I obtain site boundaries by k-means clustering on geographic coordinates, where the number of clusters k is given by land area divided by the target density. I impose that no cluster contain more than one observed mill and that observed plantations be assigned to clusters with an observed mill. I obtain 2050 contiguous sites.

I overlay plantations, mills, and site boundaries to construct a panel by site and year. I use the plantation data to identify the timing of mill construction by assuming that sites

TABLE II
SITE STATISTICS.

Variable	Mean	SD	Min	Max	N
Mill	0.72	0.45	0	1	2050
Plantations, ha	9694	12,047	0	165,986	2050
Yields, t/ha	3.37	0.57	1.99	5.21	2050
Road distance, km	48	50	0	267	2050
Port distance, km	191	100	7	468	2050
Urban distance, km	125	90	0	417	2050
Tree biomass CO_2, t/ha	386	157	26	753	2050
Peat deposit CO_2, t/ha	1240	2079	0	16,217	2050

Note: Each observation is an Indonesian or Malaysian site in year 2016. Plantations are in hectares, and palm oil yields are in tons per hectare per year. Distances in kilometers are to major roads, major ports, and administrative cities (Indonesia) or federal territories (Malaysia). Carbon stock densities, in tons per hectare, include aboveground tree biomass and belowground peat deposits.

build mills alongside their first plantations. I drop the 0.3% of plantations without mills and the 1% of mills without plantations observed by 2016. I assume zero exit for both plantations and mills, and indeed exit is limited where observable. XYLC+ (2020) measure cumulative plantation exit of only 4.6% between 2007 and 2016, perhaps because oil palm is a perennial crop with steady profits once planted. I compare the cleaned data to government statistics, and I find that the data align well. Supplemental Appendix A shows that I match the large growth in plantation area over time, as well as the distribution of mills across space.

The top rows of Table II summarize site choices by 2016. Of 2050 total sites, 72% have an observed mill. The average plantation is large, at nearly 10,000 hectares in area. Over time, I observe plantation acreage increasing substantially from 2.4 Mha in 1988 to 19.9 Mha in 2016, relative to a study area of 134 Mha. That is, 15% of total land is developed into palm oil plantations. Roughly half of the study area is too mountainous for agriculture, and so the proportion of arable land developed is even higher. At the site level, 2.6% of sites without a mill choose to construct a new mill in an average year. Sites with a mill choose to develop an average of 464 ha of new plantation each year. Consistent with interior solutions, which I will assume for estimation, new plantation development is non-zero for 99.6% of site-year observations and never exceeds the available land area.

States

Palm oil profits depend on prices and yields. I use the same palm oil prices described previously for demand, and I compute palm oil yields over time with an agronomic model and government statistics. The PALMSIM model of HCWG+ (2014) predicts potential yields under optimal growing conditions as a function of exogenous climate conditions.[7] I run the model with WorldClim data on solar radiation and precipitation to obtain potential yields by site (Fick and Hijmans (2017)). Government statistics from the Indonesian Ministry of Agriculture and the Malaysian Palm Oil Board record actual yields by province-year (Direktorat Jenderal Perkebunan (2018), Malaysian Palm Oil Board

[7]The model includes plant growth and radiation modules, which simulate fresh fruit bunch production as the outcome of frond, trunk, root, and flower growth. HCWG+ (2014) validate the model with observed yields under optimal conditions from 13 sites that span my study area.

(2018)). I calculate yield gaps as 1 minus the ratio of actual to potential yields. I assume that sites within a province-year share a common yield gap, which I apply to potential yields to obtain actual yields by site-year. Yields vary across space, reflecting climate conditions that can differ by site. Yields also vary over time, reflecting technological progress that can differ by province.

I also consider cross-sectional variation in covariates that potentially affect production costs. I calculate distance to markets as the sum of Euclidean distances to the nearest major road, port, and urban area (Meijer, Huijbregts, Schotten, and Schipper (2018), National Geospatial-Intelligence Agency (2019), World Port Source (2020)). These distances proxy for transport costs. I compute carbon stocks from geospatial data on tree biomass and peat deposits (ZHBA+ (2016), GMRVH+ (2017)), which allow me to link plantation development to emissions. Administrative boundaries delineate the four major producing regions: Sumatra, Kalimantan, Peninsular Malaysia, and East Malaysia (GADM (2021)).

The bottom rows of Table II summarize the state variables. Yields are high at 3.37 tons per hectare per year for the average site. Average annual revenues are therefore \$1840 per hectare at an average price of \$546 per ton, among years plotted in Figure 2. Carbon externalities are also large. The average site stores 1626 tons of CO_2 per hectare, with 386 tons from tree biomass and a much larger 1240 tons from peat deposits. Even with recurring revenue, carbon damages outweigh revenues for any social cost of carbon that exceeds \$12 per ton.[8] Carbon damages are most severe for peat-rich sites, where carbon stores can exceed 10,000 tons per hectare.

Shifters

For supply shifters, I consider crop yields by vegetable oil. The direct measure for palm oil combines agronomic modeling and government statistics, but it is difficult to replicate this approach for every vegetable oil. Thus, I instead construct an indirect measure that isolates weather shocks to oil crop production. I collect daily rainfall and temperature data at 0.25° resolution from the Global Meteorological Forcing Dataset, which I combine with crop-specific optimal growing conditions from the FAO Ecocrop Database, as well as province-specific production from the USDA Foreign Agricultural Service (Sheffield, Goteti, and Wood (2006), USDA Foreign Agricultural Service (2021), Food and Agriculture Organization (2025)). For each year, crop, and province, I compute weather shocks as total absolute deviations from optimal levels during the growing season. Then, for each year and vegetable oil, I aggregate over crops and provinces while weighting by production. These weather shocks proxy for yields.

4. DEMAND

I model consumers that demand palm oil and other vegetable oils. I use iterative methods for estimation, which simplifies to linear regression with instruments. I describe demand estimates by consumer market, and I discuss the implications for coordination.

4.1. *Model*

Consumers choose between palm and other vegetable oils. I model demand in product space with an almost ideal demand system, which allows me to capture cross-product

[8]For discount factor $\beta = 0.9$, annual revenue of \$1840 has a net present value of \$18,400, ignoring production costs. For SCC = \$12, carbon stores of 1626 tons imply \$19,512 in carbon damages.

substitution patterns flexibly (Deaton and Muellbauer (1980)).[9] For markets k, years t, and vegetable oils $o \in \{1, 2\} = \{\text{palm}, \text{other}\}$, demand is given by

$$\omega_{okt} = \sum_{\hat{o}} \alpha_{o\hat{o}k} \ln p_{\hat{o}t} + \gamma_{ok}^0 + \gamma_{ok}^1 t + \delta_{ok} \ln\left(\frac{X_{kt}}{P_{kt}}\right) + \varepsilon_{okt}, \tag{1}$$

$$\ln P_{kt} = \frac{1}{2} \sum_o \sum_{\hat{o}} \alpha_{o\hat{o}k} \ln p_{ot} \ln p_{\hat{o}t} + \sum_o \left(\gamma_{ok}^0 + \gamma_{ok}^1 t\right) \ln p_{ot}. \tag{2}$$

In equation (1), expenditure shares ω_{okt} depend on world prices p_{ot} for both palm and other oils, fixed effects γ_{ok}^0 and time trends γ_{ok}^1 that capture unobserved heterogeneity by market, total vegetable oil expenditures X_{kt}, price index P_{kt}, and shocks ε_{okt}. Unobservables accommodate existing tariffs, which in any case are limited.[10] Own- and cross-price coefficients $\alpha_{o\hat{o}k}$ allow for flexible patterns of substitution. In equation (2), translog price index P_{kt} aggregates over individual oil prices p_{ot}.[11] By definition of expenditure shares $\omega_{okt} = q_{okt} p_{ot} / X_{kt}$, quantities demanded are

$$q_{okt}^D = \frac{\omega_{okt} X_{kt}}{p_{ot}}. \tag{3}$$

4.2. *Estimation*

I estimate the model by iterated linear least squares (Blundell and Marc Robin (1999)). The challenge is that equations (1) and (2) call for nonlinear estimation, as demand parameters enter nonlinearly through price index P_{kt}. But for fixed price index values P_{kt}^0, equation (1) becomes a linear regression equation:

$$\omega_{okt} = \sum_{\hat{o}} \alpha_{o\hat{o}k} \ln p_{\hat{o}t} + \gamma_{ok}^0 + \gamma_{ok}^1 t + \delta_{ok} \ln\left(\frac{X_{kt}}{P_{kt}^0}\right) + \varepsilon_{okt}. \tag{4}$$

First, I compute initial price index values $\ln P_{kt}^0 = \ln X_{kt} - \ln Q_{kt}$ using data on total expenditures X_{kt} and quantities $Q_{kt} = \sum_o q_{okt}$. Second, I estimate equation (4) taking these price index values as given. I do so on palm oil expenditure shares alone, noting that other oil shares are collinear because shares sum to 1, and I impose the standard adding-up, homogeneity, and symmetry restrictions.[12] Regression coefficients identify demand parameters. Third, I use estimated demand parameters to compute price index values by equation (2). Fourth, I repeat from step two until convergence.

[9]The characteristic-space approach of Berry, Levinsohn, and Pakes (1995) restricts patterns of substitution to operate through product characteristics. It also requires specifying the product characteristics that consumers value. But unlike the product-space approach, it is tractable with many products.

[10]EU tariffs are only 3.8% for crude palm oil (World Trade Organization (2023a)). Unobservables also absorb physical trade costs, including shipping costs for palm oil from Indonesia and Malaysia.

[11]Price index P_{kt} depends on market-specific parameters, and so it varies by market even though world prices p_{ot} do not.

[12]With more products, estimation can apply seemingly unrelated regression to a system of equations. Under adding-up, $\sum_o \alpha_{o\hat{o}k} = 0$ for all $\hat{o}$, $\sum_o \gamma_{ok}^0 = 1$, $\sum_o \gamma_{ok}^1 = 0$, and $\sum_o \delta_{ok} = 0$. It is automatically satisfied if $\sum_o \omega_{okt} = 1$. Under homogeneity, $\sum_{\hat{o}} \alpha_{o\hat{o}k} = 0$ for all o, such that demand is unaffected by scaling prices and expenditures. Under symmetry, $\alpha_{o\hat{o}k} = \alpha_{\hat{o}ok}$ for all o, $\hat{o}$. With two products, imposing homogeneity imposes symmetry and vice versa.

I estimate equation (4) for each market separately. Prices p_{ot} are endogenous, as unobserved shocks ε_{okt} affect prices by increasing demand. Thus, I instrument for prices with crop yields as a supply shifter. I use weather shocks to vegetable oil production as a measure of yields, as I can construct these shocks for every vegetable oil.[13] Greater shocks correspond to lower yields, which reduce supply and increase prices. The exclusion restriction is that these shocks affect vegetable oil demand only through their impact on prices, and not through their impact on income or expenditures more broadly. To this end, I isolate the weather shocks that are most relevant to vegetable oil production: deviations from optimal weather conditions for oil crops, specifically in the provinces and states that produce these crops, and only in the months of the growing season. Supplemental Appendix B tests for and rules out income and expenditure effects. Moreover, unobserved shocks ε_{okt} may be correlated over time, and so I account for serial correlation with Newey–West standard errors.

With the estimated parameters, I can compute demand elasticities. I raise palm oil prices by 1% in each year, holding all else constant. I then compute quantities demanded with equations (1), (2), and (3). I report percentage changes in total consumption over the study period, with standard errors given by the delta method.

4.3. *Estimates*

Table III presents demand parameter estimates. Interpretation is indirect because equation (1) is specified in expenditure shares and not in quantities. For palm oil, own-price coefficients α suggest that expenditure shares do not react strongly to prices. When palm oil prices rise by 1%, EU palm oil expenditure shares rise by only 0.041 percentage points. This modest effect on expenditure shares implies that quantities fall as prices rise. Intercepts γ^0 and time trends γ^1 capture observed differences in palm oil consumption across markets. Indonesia and Malaysia have a large, positive intercept of 1.060, which rationalizes observed expenditure shares for palm oil that exceed 90%. Indonesia and Malaysia are major palm oil producers, and these high expenditure shares for palm oil are consistent with home bias. All markets have positive time trends, rationalizing rising consumption in spite of rising prices, as in Figure 2. Expenditure coefficients δ govern how

TABLE III

DEMAND PARAMETERS.

	European Union		China/India		Other importers		Indonesia/Malaysia	
θ^d	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE
α	0.041	(0.030)	0.045	(0.043)	−0.001	(0.038)	0.047	(0.032)
γ^0	0.082	(0.283)	−0.269	(0.294)	−0.444	(0.244)	1.060	(0.188)
γ^1	0.004	(0.001)	0.002	(0.002)	0.004	(0.001)	0.012	(0.002)
δ	0.008	(0.028)	0.048	(0.029)	0.061	(0.022)	−0.023	(0.021)

Note: Each pair of columns shows parameters for a consumer market: α_{11k}, γ^0_{1k}, γ^1_{1k}, and δ_{1k}. Parameters for other oils follow from the adding-up, homogeneity, and symmetry restrictions. Demand estimation draws on annual data covering coconut, olive, palm, rapeseed, soybean, and sunflower oils from 1988 to 2016.

[13] If I were to restrict demand estimation to palm oil alone, then I could directly apply the detailed yields that I obtain for palm oil. These yields enter the supply model as y_{it}.

TABLE IV

DEMAND ELASTICITIES.

	IV		OLS	
	Estimate	SE	Estimate	SE
European Union	−0.723	(0.209)	−0.209	(0.109)
China/India	−0.692	(0.168)	−0.271	(0.763)
Other importers	−0.876	(0.128)	−0.521	(0.646)
Indonesia/Malaysia	−0.925	(0.046)	−0.905	(0.151)

Note: Each pair of columns shows own-price elasticities for palm oil by consumer market. I report elasticities of total consumption with respect to a 1% increase in prices from 1988 to 2016. Demand estimation draws on annual data covering coconut, olive, palm, rapeseed, soybean, and sunflower oils from 1988 to 2016. IV estimation instruments for prices with weather shocks to vegetable oil production, while OLS estimation does not.

consumption responds as expenditures rise. Other importers shift toward higher palm oil shares, while the remaining markets respond more neutrally.

Table IV presents demand elasticities for palm oil by consumer market. I estimate elasticities that are roughly similar across markets and all less than 1, such that demand is relatively inelastic. Inelastic demand reduces leakage concerns and thus the losses from a failure to coordinate. However, leakage concerns remain as long as demand is less than perfectly inelastic. Without price instruments, I obtain estimates with upward bias, particularly for the EU, China, and India. This upward bias arises because prices are positively correlated with unobserved demand shocks. Supplemental Appendix B shows the strong first stage for weather shocks as instruments and presents demand elasticities for other oils, which I find are similar in magnitude to demand elasticities for palm oil.

I model demand as static, which simplifies estimation at the cost of potential bias. The bias can go in either direction. If switching among vegetable oils is a gradual process that involves new recipes and suppliers, then contemporaneous price responses will be attenuated. I will underestimate demand elasticities and understate leakage concerns. If consumers stockpile to take advantage of temporary price drops, then contemporaneous price responses will be exaggerated. I will overestimate demand elasticities and overstate leakage concerns. In both cases, the underlying issue is that estimation relies on annual variation in prices, but consumers may not be responding to short-run prices. Supplemental Appendix B evaluates these concerns with price lags and leads, as well as rolling variation over decadal horizons. I obtain similar estimates across specifications.

5. SUPPLY

I model producers that supply palm oil by investing in mills and plantations. World prices clear markets in equilibrium. I use Euler methods for estimation, which simplifies to linear regression with instruments. I describe supply estimates over the short and long run, and I discuss the implications for commitment.

5.1. *Model*

Sites produce palm oil with mills and plantations. These sites are small, independent, and forward-looking with rational expectations. Long-lived owners manage sites without exit or scrappage. I model dynamics explicitly, as I seek to connect short-run responses in the data to long-run responses in counterfactuals.

Choices and States

Sites i make choices $\{m_{it}, n_{it}\}$. In each year t, sites without mills choose whether to construct a mill, and then sites with a mill choose how much land to develop into plantations. Mill construction m_{it} is a binary, extensive-margin choice to enter into production or not, while plantation development n_{it} is a continuous, intensive-margin choice over the scale of production.

Observed states $\{M_{it}, N_{it}\}$ track choices $\{m_{it}, n_{it}\}$. Each is within the control of individual sites. Mill stock M_{it} and plantation acreage N_{it} follow laws of motion

$$M_{it+1} = M_{it} + m_{it}, \qquad N_{it+3} = N_{it+2} + n_{it}.$$

Plantation acreage N_{it} tracks mature, fruit-bearing plantations. Newly planted crops require three years to bear fruit, and so plantation acreage grows with a three-year lag. Sites face three constraints. First, each site supports no more than one mill, such that $M_{it}, m_{it} \in \{0, 1\}$. Second, sites must develop plantations within their own lands, such that $N_{it} \in [0, L_i]$ and $n_{it} \in [0, L_i - N_{it+2}]$ for land area L_i. Third, plantations cannot operate without mills, such that $N_{it} = 0$ if $M_{it} = 0$.

Observed states $\{p_t, y_{it}, x_i, g_i\}$ affect choices $\{m_{it}, n_{it}\}$. Sites take each as given. Individual sites are price takers for world palm oil prices p_t, where $p_t = p_{1t}$ of equations (1) and (2). Yields y_{it} depend on climatic conditions that sites cannot change. These prices and yields determine revenues. Cost factors x_i include distance to markets and carbon stocks. Distance to markets sums over distances to major roads, ports, and urban areas, none of which target individual sites.[14] I will estimate the extent to which this distance raises transport costs. Carbon stocks are predetermined and increase emissions, which sites may or may not internalize. Region g_i encodes the four regions of study—Sumatra, Kalimantan, Peninsular Malaysia, and East Malaysia—to allow for regional unobserved heterogeneity. Regional boundaries are fixed.

Unobserved states $\{\bar{\upsilon}_{it}, \bar{\varepsilon}_{it}, \varepsilon_{it}\}$ also affect choices $\{m_{it}, n_{it}\}$. Mill shocks $\bar{\upsilon}_{it}$ are logit-distributed and i.i.d. Unobserved mill and plantation costs $\{\bar{\varepsilon}_{it}, \varepsilon_{it}\}$ are more flexible: they are uncorrelated with each other, but individually can be correlated across sites and over time. I collect states with the notation

$$s_{it} = \{p_t, y_{it}, x_i, g_i, \bar{\varepsilon}_{it}, \varepsilon_{it}\}.$$

Timing and Production

Each year, sites realize state s_{it} and then proceed in two stages. Figure 3 illustrates. In the first stage, sites construct mills. Sites with an existing mill do not face a choice, as sites can support only one mill. If $M_{it} = 1$, then $m_{it} = 0$. Sites otherwise face a choice. If $M_{it} = 0$, then they realize logit shock $\bar{\upsilon}_{it}$ and choose mill construction $m_{it} \in \{0, 1\}$. For sites i and years t, the ex ante value function is

$$\bar{V}(s_{it}) = \mathbb{E}\Big[\max_{m_{it}}\big\{\beta\bar{V}(s_{it+1}),\ -\bar{c}(s_{it}) + V(0, s_{it}) - \bar{\upsilon}_{it}\big\} \,|\, s_{it}\Big]. \tag{5}$$

Sites that choose $m_{it} = 0$ receive next-year value $\bar{V}(s_{it+1})$. They do not construct a mill, and they face the same choice the next year. Sites that choose $m_{it} = 1$ incur mill cost $\bar{c}(s_{it})$

[14]Major roads exclude small roads built for plantations, major ports predate plantations, and major urban areas exclude palm oil settlements.

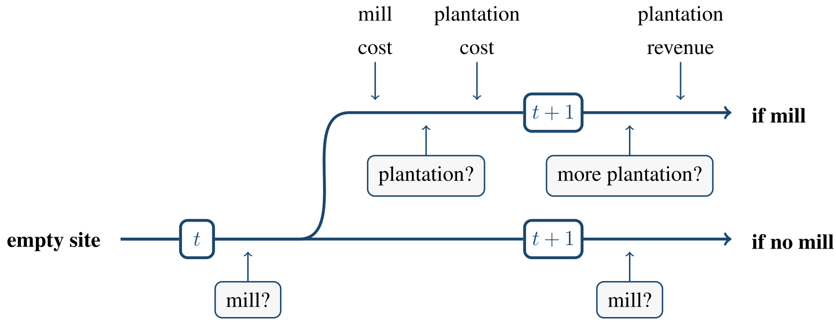

FIGURE 3.—Supply model timeline. An empty site makes a binary choice to construct a mill or not. If not, then the site faces the same choice in the next period. If so, then the site makes a continuous choice over how much land to develop into plantations. The site can then expand its plantation in future years.

for plantation value $V(0, s_{it})$, starting from $N_{it} = 0$. That is, they construct a mill and begin to develop plantations, which eventually generate revenues. The outside option is to never construct a mill, with utility normalized to zero.

In the second stage, sites develop plantations. Sites without an existing or new mill do not face a choice, as plantations require mills. If $M_{it} + m_{it} = 0$, then $n_{it} = 0$. Sites otherwise face a choice. If $M_{it} + m_{it} = 1$, then they choose plantation development n_{it}. I assume interior solutions $n_{it} \in (0, L_i - N_{it+2})$ for land area L_i. For sites i and years t, the ex ante value function is

$$V(N_{it}, s_{it}) = \mathbb{E}\Big[\max_{n_{it}}\big\{r(N_{it}, s_{it}) - c(n_{it}, s_{it}) + \beta V(N_{it+1}, s_{it+1})\big\} \,\big|\, N_{it}, s_{it}\Big]. \tag{6}$$

Mature plantations N_{it} generate revenues $r(N_{it}, s_{it})$, while plantation development n_{it} incurs costs $c(n_{it}, s_{it})$. Next-year value $V(N_{it+1}, s_{it+1})$ captures future profits, including the option value of future plantation development.

I specify revenues and costs as follows. For plantations, linear revenues and convex costs ensure unique optima:

$$r(N_{it}, s_{it}) = \alpha p_t y_{it} N_{it}, \qquad c(n_{it}, s_{it}) = \left(\gamma_g^0 + \gamma_g^1 t + x_i\delta + \varepsilon_{it} + \frac{1}{2}\psi n_{it}\right) n_{it}.$$

Revenues reflect prices p_t, yields y_{it}, and plantation acreage N_{it}. Parameter α governs how strongly development responds to higher revenues.[15] Costs depend on fixed effects γ_g^0 and time trends γ_g^1 that capture unobserved heterogeneity by region, cost factors x_i that capture observed heterogeneity by site, and unobserved costs ε_{it} by site.[16] Unobservables accommodate existing regulation, which in any case is limited and weakly enforced (BFEW+ (2015)). Quadratic costs ψ encourage plantation development over time, capturing credit constraints and local factor market congestion. For mills, there are no direct revenues. Costs are

$$\bar{c}(s_{it}) = \bar{\gamma}_g^0 + \bar{\gamma}_g^1 t + x_i\bar{\delta} + \bar{\varepsilon}_{it}.$$

[15] It is equivalent to set $\alpha = 1$, treat revenues as numeraire, and estimate a logit scale parameter.

[16] To identify unobserved heterogeneity by site, I must observe multiple choices per site. But multiple plantation choices are observed only for early sites, and multiple mill choices are ruled out because sites support only one mill each. I instead estimate regional effects, effectively pooling in the cross section rather than over time.

They again depend on fixed effects $\bar{\gamma}_g^0$, time trends $\bar{\gamma}_g^1$, observed costs x_i, and unobserved costs $\bar{\varepsilon}_{it}$ that capture regional and site heterogeneity. I interpret costs as upfront costs.[17]

Production depends on yields y_{it} and plantation acreage N_{it}. Quantities supplied are

$$q_{it}^S = y_{it} N_{it}. \tag{7}$$

Because of dynamics, quantities in one year depend on states in every year. By the laws of motion, current acreage N_{it} is a stock that depends on all past choices. And by equations (5) and (6), these past choices are forward-looking and in turn depend on states in every future year. Thus, to solve the model, I will need to specify the full expected path of states over time. Supplemental Appendix C details this calculation.

Equilibrium

For terminal year T and vegetable oils $o \in \{1, 2\} = \{\text{palm}, \text{other}\}$, a dynamic competitive equilibrium is defined by prices $p^* = \{p_{11}^*, p_{21}^*, \dots, p_{1T}^*, p_{2T}^*\}$ such that:

1. World demand for palm and other oils is given by equations (1), (2), and (3). Demand depends on contemporaneous prices $\{p_{1t}, p_{2t}\}$ and total expenditures X_{kt}. Summing over markets k, world demand is $D_{ot}(p_{1t}, p_{2t}) = \sum_k q_{okt}^D(p_{1t}, p_{2t}; X_{kt})$.
2. World supply of palm oil is given by equations (5), (6), and (7). Supply depends on all prices $p_1^T = \{p_{11}, \dots, p_{1T}\}$ and yields $y_i^T = \{y_{i1}, \dots, y_{iT}\}$. Sites are price takers individually, but they affect world prices collectively. Summing over sites i, world supply is $S_{1t}(p_1^T) = \sum_i q_{it}^S(p_1^T; y_i^T)$.
3. World supply of other oils is given inelastically by quantities $\{S_{21}, \dots, S_{2T}\}$.[18]
4. World markets clear. For world demand and supply defined above,

$$D_{1t}(p_{1t}, p_{2t}) = S_{1t}\big(p_1^T\big), \qquad D_{2t}(p_{1t}, p_{2t}) = S_{2t} \quad \forall t. \tag{8}$$

5.2. *Estimation*

I use Euler methods to estimate the model without the need to compute continuation values (Hall (1978), Scott (2013)). I obtain two linear regression equations that I stack and estimate jointly. Estimation is straightforward and computationally light:

$$n_{it} - \beta n_{it+1} = \frac{\alpha\beta^3}{\psi} p_{t+3} y_{it+3} + \frac{\beta}{\psi}\gamma_g^1 - \frac{1-\beta}{\psi}\big(\gamma_g^0 + \gamma_g^1 t + x_i\delta\big) + \mu_{it} + \eta_{it}, \tag{9}$$

$$\ln\left(\frac{\pi_{it}}{1-\pi_{it}}\right) - \beta \ln \pi_{it+1} = \frac{1}{2}\psi n_{it}^2 + \beta\bar{\gamma}_g^1 - (1-\beta)\big(\bar{\gamma}_g^0 + \bar{\gamma}_g^1 t + x_i\bar{\delta}\big) + \bar{\mu}_{it} + \bar{\eta}_{it}. \tag{10}$$

The dependent variables include plantation development $\{n_{it}, n_{it+1}\}$ and conditional choice probabilities $\{\pi_{it}, \pi_{it+1}\}$, which are the probabilities of mill construction. The residuals include structural errors $\{\mu_{it}, \bar{\mu}_{it}\}$ and expectational errors $\{\eta_{it}, \bar{\eta}_{it}\}$, where structural

[17] In practice, costs combine upfront costs, flow costs, and scrap values. Limited exit in the data suggests that upfront costs are relatively large. If upfront costs were small relative to flow costs or scrap values, then I would instead observe entry followed by exit at higher rates. Separating flow costs and scrap values is difficult without additional data.

[18] I can alternatively assume perfectly elastic supply of other oils and treat prices p_{2t} as fixed. It is more difficult to estimate a model of other oils alongside the present model of palm oil. An intermediate option is to calibrate the elasticity of supply of other oils.

errors reflect unobserved costs $\{\varepsilon_{it}, \bar{\varepsilon}_{it}\}$:

$$\mu_{it} = -\frac{1}{\psi}\varepsilon_{it} + \frac{\beta}{\psi}\varepsilon_{it+1}, \qquad \bar{\mu}_{it} = -\bar{\varepsilon}_{it} + \beta\bar{\varepsilon}_{it+1}.$$

Regression coefficients identify supply parameters. The coefficients of equation (9) identify parameters $\{\frac{\alpha}{\psi}, \frac{\gamma_g^0}{\psi}, \frac{\gamma_g^1}{\psi}, \frac{\delta}{\psi}\}$ if discount factor β is known. The discount factor is not identified, as is typical of dynamic discrete choice models (Magnac and Thesmar (2002)), and so I set $\beta = 0.9$. The coefficients of equation (10) identify $\{\psi, \bar{\gamma}_g^0, \bar{\gamma}_g^1, \bar{\delta}\}$, thereby isolating ψ and giving $\{\alpha, \gamma_g^0, \gamma_g^1, \delta\}$ in levels. The main parameter of interest is revenue coefficient α, which captures the elasticity of development with respect to prices. I note that price and yield variation jointly identify α. That is, I benefit from granular spatial variation in yields, rather than relying solely on time-series variation in world prices. Intuitively, high-yield sites benefit more from high prices than low-yield sites, as revenues reflect both prices and yields. If supply is elastic, then high-yield sites develop more aggressively than low-yield sites when prices rise.[19]

I derive the regression equations from Euler equations, which compare investment in years t and $t+1$. Supplemental Appendix C presents derivations. On the intensive margin, I differentiate equation (6) with respect to plantation development n_{it} and n_{it+1}. Continuation values align and difference out by the envelope theorem. I obtain equation (9), which captures an intertemporal trade-off: earlier plantation development n_{it} brings added revenue $p_{t+3}y_{it+3}$ and avoids rising cost trends γ_g^1, while later development n_{it+1} delays costs $(\gamma_g^0 + \gamma_g^1 t + x_i\delta)$ and discounts them. On the extensive margin, I difference equation (5) with respect to mill construction m_{it} and m_{it+1}. Continuation values align and difference out by finite dependence, which holds because mill construction and plantation development are terminal actions that lead to common future states and payoffs (Arcidiacono and Miller (2011)). Whether sites invest in year t or $t+1$, mills are operational, and plantations have matured by year $t+4$. I obtain equation (10), which also captures a trade-off: earlier mill construction brings added plantation profits, as embodied by n_{it}^2, while later mill construction delays costs. Conditional choice probabilities $\{\pi_{it}, \pi_{it+1}\}$ are the probabilities of earlier and later mill construction. Observed choices capture future payoffs and stand in for continuation values, echoing the typical intuition for conditional choice probability estimation.

I estimate equation (9) on the sample of sites with a new or existing mill ($M_{it} + m_{it} = 1$). It is these sites that face a plantation development decision. There are three problems. First, future revenue $p_{t+3}y_{it+3}$ may be correlated with structural error μ_{it}, which includes unobserved costs ε_{it}. These unobserved costs may contain aggregate shocks that affect future supply and thus future prices p_{t+3}. The structural error remains uncorrelated with observed states $\{y_{it}, x_i, g_i\}$, which are site fundamentals. Second, future revenue is correlated with expectational error η_{it}. This expectational error is the difference between unobserved expectations and observed realizations. It includes $\mathbb{E}[p_{t+3}y_{it+3}|s_{it}] - p_{t+3}y_{it+3}$, which is mechanically correlated with $p_{t+3}y_{it+3}$. Third, the structural error is autocorrelated. It is correlated over time because both μ_{it} and μ_{it+1} contain ε_{it+1}, and furthermore ε_{it+1} may be correlated across sites.

I address these problems by instrumenting and clustering. For the first problem, I instrument with demand shifters. In particular, I instrument for $p_{t+3}y_{it+3}$ with $Z_t y_{it}$, where

[19]This high- to low-yield comparison gives identification only in relative terms. But zero-yield sites offer a natural normalization, as they receive zero benefit from price increases.

Z_t includes total vegetable oil consumption and weather shocks to other vegetable oil production. Total consumption raises the category budget and thus demand for palm oil. I focus on total consumption outside of Indonesia and Malaysia, as Indonesian and Malaysian consumption may not be excluded from palm oil production. Weather shocks to other oils affect the supply of other oils and thus residual demand for palm oil. Other oils are produced outside of Indonesia and Malaysia, and so these weather shocks are foreign and arguably excluded from palm oil production. For the second problem, I use lagged instruments. Under rational expectations, sites condition on all information known at time t, such that $Z_t y_{it}$ is orthogonal to η_{it}. For the third problem, I cluster standard errors by district to accommodate autocorrelation, at least in some form.

I estimate equation (10) on the sample of sites without mills ($M_{it} = 0$). It is these sites that face a mill construction decision. First, I discuss the choice terms, which I must compute from data. I compute conditional choice probabilities π_{it} non-parametrically, smoothing spatially over observed choices with cubic splines in latitude, longitude, cost factors, and time. I also compute plantation development n_{it}. I must do so because I estimate equation (10) for sites without mills, but I observe development only for sites with a mill. I smooth over observed choices, assuming that unobserved mill and plantation costs are uncorrelated. Second, I discuss the error terms, which motivate clustering. Structural error $\bar{\mu}_{it}$ is uncorrelated with observed states x_i but is correlated over time, and so I cluster standard errors by district. The structural error is uncorrelated with n_{it}, again assuming that unobserved mill and plantation costs are uncorrelated. Expectational error $\bar{\eta}_{it}$ is uncorrelated with x_i and n_{it} by rational expectations.

With the estimated parameters, I can compute supply elasticities. I raise palm oil prices by 1% over shorter and longer periods within the study period, holding all else constant. Small price changes within the study period do not affect plantation development n_{it} or mill construction probabilities π_{it} at the end of the study period, and so I can read these values from data. I then compute quantities supplied directly from regression equations (9) and (10), as described in Supplemental Appendix C. I do so instead of solving the model and computing quantities from equations (5) and (6), which require specifying expectations beyond the study period. I report percentage changes in total production over the study period, with standard errors given by the delta method.

5.3. *Estimates*

Table V presents supply parameter estimates, which I compute from regression coefficients. A positive price coefficient gives an upward-sloping supply curve, and dividing parameters by this coefficient gives magnitudes in dollar terms. I estimate relatively high median costs of \$8039 per hectare of plantation and \$91.15 million per mill, with an additional \$1522 per hectare from cost convexity.[20] Accounting estimates are smaller at \$7000 and \$20 million, respectively (Fairhurst and McLaughlin (2009), Man and Baharum (2011)). These accounting estimates include planting and operating costs but abstract from capital and land acquisition, which my estimates capture. My estimates also capture other lifetime costs, including replanting and capital replacement, as well as constraints to expansion, including urban boundaries, that I do not model explicitly. Plantation costs fall by a meaningful 5% of median costs per year, while mill costs rise by 1.5%. Supplemental Appendix C presents regional costs.

[20]Estimated convexity is \$6.56 per hectare (times $\frac{1}{2}$), multiplied by an average n_{it} of 464 hectares.

TABLE V

SUPPLY PARAMETERS.

		Intensive				Extensive			
		θ^s	Unit	Estimate	SE	$\bar{\theta}^s$	Unit	Estimate	SE
Revenue	Price	α	10^{-8}	2.994	(1.469)				
Cost	Median	γ^0/α	\$1K	8.039	(0.347)	$\bar{\gamma}^0/\alpha$	\$1M	91.15	(40.26)
	Trend	γ^1/α	\$1K	−0.400	(0.038)	$\bar{\gamma}^1/\alpha$	\$1M	1.352	(0.380)
	Distance	δ/α	\$1K	0.001	(0.001)	$\bar{\delta}/\alpha$	\$1M	0.346	(0.167)
	Carbon	δ/α	\$1K	−0.000	(0.000)	$\bar{\delta}/\alpha$	\$1M	0.002	(0.001)
	Convexity	ψ/α	\$1	6.560	(0.773)				

Note: The revenue row is the price coefficient. The cost rows divide cost parameters by the price coefficient, such that magnitudes are interpretable as inflation-adjusted, year-2000 USD. Costs describe median costs for sites with observed construction, as well as annual cost trends across regions, costs of market distance and carbon stocks, and cost convexities. Market distance sums over distances to major roads, ports, and urban areas, while carbon stocks sum over above- and belowground carbon stocks.

I find that producers internalize their private transport costs, but not their emission externalities. Distance from markets increases costs on the extensive margin, given transport costs from mills to markets. These distance costs are large: an additional kilometer from a major road, port, or urban area increases mill costs by 0.38% of median costs. If an additional kilometer of remoteness increases road, port, and urban distances simultaneously, then mill costs increase by 1.14%. At the same time, distance to markets has no impact on the intensive margin. Once a mill has been constructed, plantation development proceeds unhindered. Carbon stocks also have no impact on production. If anything, carbon stocks decrease costs on the intensive margin, as forests and peat may proxy for a lack of competing land claims. However, on both margins, the effects of carbon stocks are small in magnitude.

Figure 4 presents supply elasticities for palm oil. I report elasticities of total production over the study period. Dots mark the short- and long-run price changes that I will consider in counterfactuals. Price changes sustained from 1988 to 2001 give a short-run elasticity of 1.3, and those from 1988 to 2016 give a long-run elasticity of 2.8. Very short-run price changes from 1988 to 1990 have no effect because I take 1988 as the initial year, and pro-

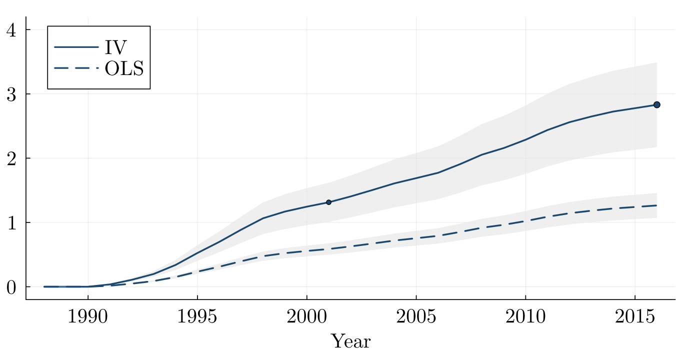

FIGURE 4.—Supply elasticities. I plot elasticities of total production with respect to a 1% increase in prices from 1988 to the years shown on the x-axis. That is, the small dot marks how total production from 1988 to 2016 responds to a 1% increase in prices from 1988 to 2001. The large dot marks how total production from 1988 to 2016 responds to a 1% increase in prices from 1988 to 2016. The top curve is computed from IV estimates, and the bottom curve from OLS estimates. I plot 95% confidence bands.

duction responds with a three-year lag based on the time between planting and bearing fruit. My long-run estimate is consistent with those from the Amazon, where others have estimated long-run price elasticities of 4.1 and 6.3 (Sant'Anna (2024), Araujo, Costa, and Sant'Anna (2025)). Each far exceeds the Scott (2013) estimate of 0.3 for the US. Large long-run elasticities highlight the need to commit to long-run policy, as forward-looking sites consider revenues over time. Without instruments, I obtain estimates with downward bias. This downward bias arises because revenues are negatively correlated with the error terms in equation (9). Revenues $p_{t+3}y_{it+3}$ enter expectational error η_{it} negatively, and unobserved costs ε_{it} raise prices p_{t+3} and enter structural error μ_{it} negatively. Supplemental Appendix C shows the strong first stage for demand shifters as instruments.

Supplemental Appendix C also estimates a static version of the model and finds elasticities that are smaller in magnitude and negative. Static estimation regresses on current prices, which are noisy measures of future prices. This noise biases estimates toward zero. Furthermore, investment can slow in response to short-run price spikes if expectations are mean-reverting, such that high prices today prompt expectations of lower prices tomorrow. For robustness, Supplemental Appendix C presents additional specifications with disaggregated cost factors and alternative basis functions for smoothing. It also evaluates the potential selection bias from assuming that unobserved mill costs are uncorrelated with unobserved plantation costs. I obtain similar estimates across specifications.

Euler estimation has important advantages.[21] I avoid the need to compute continuation values, which greatly simplifies computation. Because estimation reduces to linear regression, I can address endogeneity and autocorrelation concerns with standard tools. And although I need to assume rational expectations, I do not need to specify expectations more precisely. I do not need to assume perfect foresight, and I note that regional terms $\gamma = \{\gamma_g^0, \gamma_g^1, \bar{\gamma}_g^0, \bar{\gamma}_g^1\}$ accommodate common expectational bias. By comparison, the full-solution approach requires computing continuation values in every iteration. It also requires explicitly specifying long-run expectations, which involves stronger assumptions than rational expectations.

At the same time, estimation relies on several assumptions. First, sites consider investing today or tomorrow. Weak property rights may encourage land grabbing and bias toward investing today, although regional terms γ help by absorbing some variation in property rights. Second, sites are independent and atomistic. Otherwise, finite dependence does not hold: if large sites delay investment, then competitors respond and alter the evolution of the economy, such that continuation values do not align. It helps that world production is unconcentrated, with the largest producer accounting for 4% and the largest ten for 21% (Palm Oil Analytics (2017)). But I must rule out local spatial interaction, which makes estimation intractable. Third, the age of mills and plantations does not affect profits. Otherwise, delayed investment affects profits in all future years, and finite dependence again does not hold.

6. COUNTERFACTUALS

I solve the model for counterfactuals, which compare direct regulation with domestic policy to indirect regulation with trade policy. I quantify impacts on emissions, consumer and producer surplus, and government revenue. I close with general lessons.

[21] Other discrete Euler applications include De Groote and Verboven (2019), Diamond, McQuade, and Qian (2019), Traiberman (2019), and Almagro and Domínguez-Iino (2025). Hsiao (2025) develops an alternative approach with similar advantages, appealing to price data in place of finite dependence.

6.1. *Solving the Model*

I solve for equilibrium prices and quantities with conditions (8). I set discount factor $\beta = 0.9$, unobservables $\bar{\varepsilon}_{it} = \varepsilon_{it} = \varepsilon_{okt} = 0$, and expectational errors $\bar{\eta}_{it} = \eta_{it} = 0$, and I assume that palm oil production in Indonesia and Malaysia is proportional to global production.[22] In solving the model, I compute supply in levels with equations (5) and (6). I do so by specifying long-run expectations and computing continuation values until terminal year $T = 2050$. Beyond the study period, I assume linear growth in palm oil yields and the supply of other oils at the rates observed during the study period, as well as annual inflation of 2%. I also assume annual growth in total vegetable oil expenditures X_{kt} at a rate of λ, such that $X_{kt+1} = (1 + \lambda)X_{kt}$. I interpret λ as expected growth in aggregate demand over time.

I recover demand growth λ by matching the data in levels. Having already estimated demand and supply parameters $\hat{\theta} = \{\hat{\theta}^d, \hat{\theta}^s\}$, I choose a candidate value for λ and solve for equilibrium prices. Intuitively, demand growth affects future prices, which in turn affect current entry and thus current prices. I repeat to find the candidate value that best fits the palm oil prices in the data. I obtain $\hat{\lambda} = 0.106$.[23] This procedure effectively inverts the model to recover an implied measure of long-run expectations. I did not need to work with long-run expectations when estimating parameters θ, as estimation relied instead on equations (9) and (10). These estimating equations difference out long-run expectations and avoid solving the model, but they match the data only in changes. I must specify expectations and solve the model to match the data in levels, as is needed for counterfactuals.

Figure 5 assesses model fit by comparing model-implied values to observed data during the study period. The model matches the data well, noting that prices are directly targeted. Prices and quantities are linked by equilibrium conditions (8), and I match data on each in both levels and trends. Quantities and emissions are linked by plantation development choices. However, quantities depend on yields, while emissions depend instead on carbon stocks. These values need not align. I miss the particularly large emission episodes of the late 2000s, but I otherwise capture the trajectory of emissions over the study period. Counterfactuals will impose regulation and study changes in outcomes relative to this model-implied baseline.

6.2. *Policy Evaluation*

I evaluate policy in the form of palm oil taxes on the supply side, the demand side, and both in combination. Domestic regulation imposes production taxes $\tau^S_{gt} > 0$, which can vary by producing region g_i. Import tariffs and export taxes impose consumption taxes $\tau^D_{kt} > 0$, which can vary by consumer market k. Carbon border adjustments combine import tariffs with credits for domestic regulation. For ad valorem taxes $\{\tau^D_{kt}, \tau^S_{gt}\}$,

[22]Indonesia and Malaysia account for 84% of palm oil production during the study period (Table I), which limits the bias from not directly modeling production elsewhere. I treat Indonesia and Malaysia as representative producers, and I scale their production accordingly. I compute multiplicative adjustment factors Ω_t, such that $D_{1t} = S_{1t}\Omega_t$, and I apply these adjustments when solving equilibrium conditions (8). During the study period, I observe world demand D_{1t} and Indonesian and Malaysian supply S_{1t}. Beyond the study period, I apply $\Omega_{2016} = 1.1$ based on the last year of the study period. Alternatively, additive adjustment factors treat palm oil production elsewhere as fixed, with very similar results in terms of model fit.

[23]Other long-run expectational assumptions, such as linear growth in palm oil yields, will be confounded with this demand growth. But the goal is simply to match the data in levels, rather than to isolate the precise nature of long-run expectations.

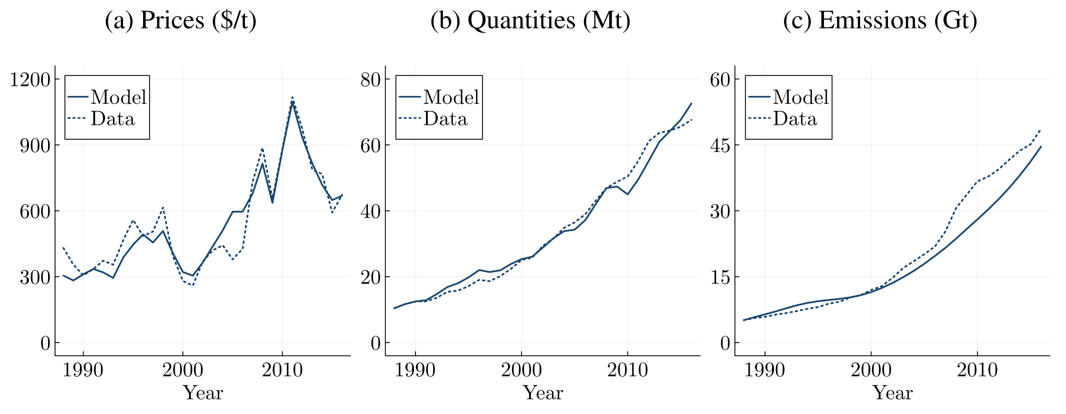

FIGURE 5.—Model fit. I plot equilibrium prices, quantities, and cumulative emissions for palm oil, comparing model-implied values to observed data from 1988 to 2016. Prices are in nominal USD per ton, quantities in megatons, and emissions in gigatons of CO_2.

equilibrium conditions (8) for palm oil become

$$\sum_k q^D_{1kt}\big((1+\tau^D_{kt})p_{1t}, p_{2t}\big) = \sum_i q^S_{1it}\big((1-\tau^S_{g1})p_{11}, \dots, (1-\tau^S_{gT})p_{1T}\big) \quad \forall t.$$

I assess the value of coordination and commitment. I simulate coordination by applying taxes across regions and markets. Complete regulation across regions prevents supply-side leakage, by which production shifts toward unregulated regions. Complete regulation across markets prevents demand-side leakage, by which consumption shifts. I simulate commitment by applying taxes over time. Commitment resists the static incentive to set taxes to zero, given sunk investment and time to build. This static incentive arises because taxes today are costly, but they do not prevent emissions. That is, taxes today do not prevent existing development, which is sunk, or new development, which does not yet produce taxable output.[24]

I quantify impacts on emissions, consumer and producer surplus, and government revenue. Emissions depend on carbon stock density, which I observe, and the extent of plantation development, which I model. Surplus and revenue depend on equilibrium prices and quantities, which I solve for. I focus on impacts within the study period from 1988 to 2016, as those beyond the study period depend more heavily on the expectational assumptions required for solving the model. Consumer surplus is the compensating variation needed to maintain baseline utility, producer surplus is revenue net of costs, and government revenue is the product of tax rates, prices, and quantities. Supplemental Appendix D provides formal expressions for each. I report welfare effects for each market as the sum of consumer surplus, producer surplus, and government revenue. A global social

[24]New development responds only to taxes tomorrow—after time to build has elapsed. But new development today becomes sunk development tomorrow. Without commitment, taxes tomorrow are again set to zero. Only commitment to non-zero taxes tomorrow can prevent development today. I note that these taxes are output taxes. The regulator could instead tax land development itself by imposing an immediate fine, rather than taxing output over time. But the regulator must still commit to enforcing the fine, which will be large if it imposes the full cost of emissions. A large fine may prompt legal challenges and lobbying that complicate commitment to enforcement.

planner evaluates regulation by asking whether the benefits of emission reductions exceed the costs for welfare across markets.

Several restrictions simplify computation. First, tax rates are announced at the outset and taken as given. I abstract from the dynamic game between policymakers and producers. Second, tax rates are constant during an initial commitment period, then lapse to zero afterwards—as is statically optimal. More complex paths are more computationally intensive to evaluate and more difficult to administer in practice. Third, I tax palm oil uniformly. Palm emissions are not uniform, but heterogeneous taxes would require monitoring production and tracking sales.[25] Fourth, plantation development releases carbon stocks fully. Trees must be cut to make space for plantations, and the peat layer must be cleared to access the underlying soil. Fifth, I focus on palm emissions. I ignore emissions from demand substitution to other oils or supply substitution to other deforesting activities. Supplemental Appendix D argues that the resulting bias is limited: other oils involve limited or non-peat deforestation, and other deforesting activities are much less profitable than palm oil production.

6.3. *Domestic Regulation*

Domestic regulation taxes production directly. Table VI simulates production taxes of 50%. I consider coordinated taxes by Indonesia and Malaysia and unilateral taxes by either alone, as well as commitment to long-run taxes from 1988 to 2016 and short-run taxes from 1988 to 2001. I find that coordinated, long-run taxes reduce CO_2 emissions by 7.4 Gt from 1988 to 2016. The cost to global consumer and producer surplus, net of government revenue, is \$13 per ton of CO_2. That is, this policy improves global social welfare

TABLE VI

EMISSIONS (GT), WELFARE (\$1B), AND ABATEMENT COSTS (\$/T).

	τ	ΔE		ΔW^{EU}		ΔW^{CI}		ΔW^{OI}		ΔW^{IM}		$\Delta W/\Delta E$	
	%	2016	2001	2016	2001	2016	2001	2016	2001	2016	2001	2016	2001
Production taxes													
All exporters	50	−7.4	−0.8	−21	−5.5	−40	−9.0	−73	−22	38	6.7	13	38
Indonesia only	50	−4.8	−0.9	−6.8	−1.7	−12	−2.9	−22	−6.8	13	0.8	5.9	11
Malaysia only	50	−1.7	−0.1	−3.7	−1.2	−6.9	−1.9	−12	−4.7	7.3	0.9	9.2	58
Import tariffs													
All importers	100	−5.4	−0.5	8.6	2.1	9.4	1.2	13	5.9	−88	−38	10	60
EU, China, India	100	−2.1	−0.1	−1.5	−0.1	−6.9	−0.6	27	7.8	−32	−11	6.5	29
EU only	100	−0.7	−0.1	−9.7	−1.6	4.9	0.9	9.6	3.5	−13	−6.3	12	53

Note: Each row is one counterfactual. I compute total changes in global emissions and market-specific welfare from 1988 to 2016, relative to business as usual, for the European Union (EU), China and India (CI), other importers (OI), and Indonesia and Malaysia (IM). Emissions are in gigatons of CO_2, and welfare is in billions of inflation-adjusted, year-2000 USD. Indonesia and Malaysia are exporters, and welfare includes consumer surplus, producer surplus, and government revenue. Other countries are importers, and welfare includes consumer surplus and government revenue. Abatement costs divide welfare costs, summed across markets, by emission reductions. The units are USD per ton of CO_2. Production taxes of 50% target some or all production, while import tariffs of 100% target some or all imports. Taxes are upheld from 1988 to 2016 or from 1988 to 2001.

[25]Heterogeneous taxes also require commitment not to "greenwash" palm oil produced with sunk deforestation. Moreover, uniform taxes avoid reshuffling concerns. Taxing dirty palm oil alone pushes dirty palm oil to unregulated markets and clean palm oil to regulated markets. With sufficient unregulated demand, the result is pure reallocation and zero decrease in dirty production.

for any social cost of carbon that exceeds $13 per ton. Unilateral and short-run taxes have smaller effects on emissions. For long-run action, emissions fall by 4.8 Gt when Indonesia acts alone and by 1.7 Gt when Malaysia acts alone. Unilateral Malaysian action is prone to leakage, as elastic Indonesian supply increases rapidly when Malaysian taxes drive up world prices. Unilateral Indonesian action is more effective, as it pushes production toward Malaysia, where higher yields increase efficiency. For short-run action, this compositional shift even leads to slightly larger emission reductions for unilateral Indonesian taxes relative to coordinated taxes. Higher yields and foregone profits in Malaysia also explain higher abatement costs for Malaysia-only regulation.

Domestic regulation reduces welfare for the EU, China, India, and other importers. Production taxes raise world prices and lower consumer surplus in these markets. Losses for other importers are twice as large as losses for China and India, which in turn are twice as large as losses for the EU. At the same time, production taxes increase welfare for Indonesia and Malaysia. These countries can manipulate their terms of trade, as their producer market power allows them to elevate world prices and raise tax revenue at the expense of foreign consumers. That is, production taxes simultaneously reduce emissions and raise welfare for Indonesia and Malaysia. If enforceable, domestic regulation is fiscally appealing even absent international pressures to abate.

Figure 6 plots welfare against abatement for production taxes of varying intensity, focusing on coordinated, long-run taxes. Figure 6a shows that increasing abatement also increases welfare losses for the EU, China, India, and other importers, where consumer surplus falls as world prices rise. Indonesia and Malaysia experience welfare gains as they exercise market power, with welfare maximized at 9.3 Gt of abatement. Abatement at this level corresponds to a 60% production tax. Figure 6b shows that welfare gains for Indonesia and Malaysia come from substantial government revenue, collected in part from foreign consumers. This revenue offsets consumer surplus losses from higher prices, as well as producer surplus losses that amount to hundreds of billions of dollars. Indonesian and Malaysian producers suffer losses that far exceed Norway's $1 billion in cash compensation for forest regulation.

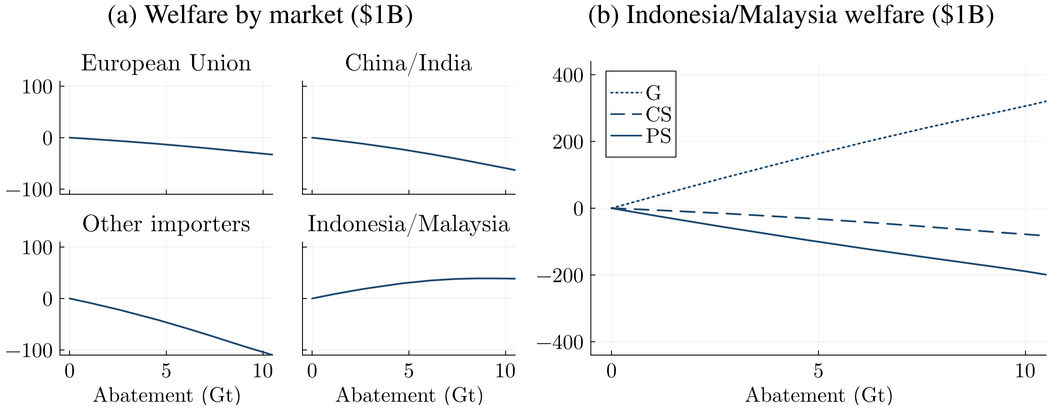

FIGURE 6.—Production taxes. I simulate coordinated, long-run production taxes of increasing intensity by Indonesia and Malaysia. I plot effects on market-specific welfare and total abatement from 1988 to 2016. Abatement is palm emission reductions. Welfare is in billions of inflation-adjusted, year-2000 USD, and abatement is in gigatons of CO_2. Welfare for Indonesia and Malaysia includes consumer surplus, producer surplus, and government revenue. Welfare elsewhere includes consumer surplus.

6.4. *Import Tariffs*

Import tariffs tax traded consumption. Table VI simulates import tariffs of 100%. I thus match the production taxes above: consumers pay twice the amount that producers receive when taxing demand at 100%, and the same holds when taxing supply at 50%. I consider coordinated tariffs by all importers, multilateral tariffs by an EU-China-India coalition, and unilateral tariffs by the EU alone, as well as commitment to long-run tariffs from 1988 to 2016 and short-run tariffs from 1988 to 2001. I note that precedents exist for import tariffs of 100%. For the EU, tariffs of 162% on sugar, 88% on beef, and 62% on milk aim to protect domestic agriculture, while tariffs of 257% on cigarettes act as excise duties on harmful goods.[26] More broadly, Hsiao, Moscona, and Sastry (2025) document that governments commonly use trade policy to intervene in agricultural markets.

I find that coordinated, long-run tariffs reduce CO_2 emissions by 5.4 Gt from 1988 to 2016, amounting to 0.19 Gt annually. This reduction is smaller than the 7.4 Gt achieved by production taxes, as import tariffs fail to regulate Indonesian and Malaysian consumers. But import tariffs still have large effects. Average annual palm emissions were 1.6 Gt from 1990 to 2016, relative to 5.0 Gt for the US, 5.0 Gt for China, 3.5 Gt for the EU, and 1.1 Gt for India (Figure 1). Coordinated, long-run tariffs therefore reduce emissions by an amount equal to 17% of Indian emissions annually. However, unilateral and short-run import tariffs have smaller effects. For long-run action, emissions fall by 2.1 Gt under an EU-China-India coalition and by 0.7 Gt when the EU acts alone. Each is prone to leakage, as unregulated demand rises when import tariffs drive down world prices. For short-run action, temporary tariffs do little to dissuade palm oil production, as producers look toward high prices in post-tariff years. Emissions fall by no more than 0.5 Gt.

Import tariffs can increase welfare for the EU, China, India, and other importers. These countries can manipulate their terms of trade, as their consumer market power allows them to lower world prices and raise tax revenue at the expense of foreign producers. This market power is strongest when importers act together, as coordinated tariffs—both long- and short-run—raise welfare for all importers. Smaller tariff coalitions have less market power, and so coalition importers suffer welfare losses because government revenue does not offset the direct consumer surplus losses from import tariffs. But non-coalition importers still enjoy welfare gains because import tariffs lead to lower world prices.

At the same time, Indonesia and Malaysia suffer large welfare losses across import tariff scenarios. To this end, I consider compensating transfers in the spirit of payments for ecosystem services. First, these transfers promote equity. Palm oil fuels economic development in Indonesia and Malaysia, especially in poor, rural communities. In curbing emissions, these countries forgo local profits for global benefit. Second, these transfers help to navigate legal and diplomatic concerns. Indonesia and Malaysia have criticized EU trade policy for palm oil, arguing that it penalizes palm oil relative to the “like goods” of rapeseed and sunflower oils, which the EU produces domestically. Transfers act as compensation.

[26]For sugar, beef, and milk, I compute ad valorem equivalents by combining non-ad valorem rates with primary commodity prices for 2020 (International Monetary Fund (2023), World Trade Organization (2023a)). I choose 2020 to capture ad valorem equivalents before the recent inflationary period. For cigarettes, EU legislation requires that “the overall excise duty on cigarettes shall represent at least 60% of the weighted average retail selling price of cigarettes released for consumption” since 2014 (Official Journal of the EU (2011)). The European Commission offers the following sample calculation: a pre-tax price of 0.70 EUR, an excise duty of 1.80 EUR, and a post-duty 20% VAT of 0.50 EUR together yield a retail price of 3.00 EUR. The excise duty is 60% of the retail price and 257% of the pre-tax price.

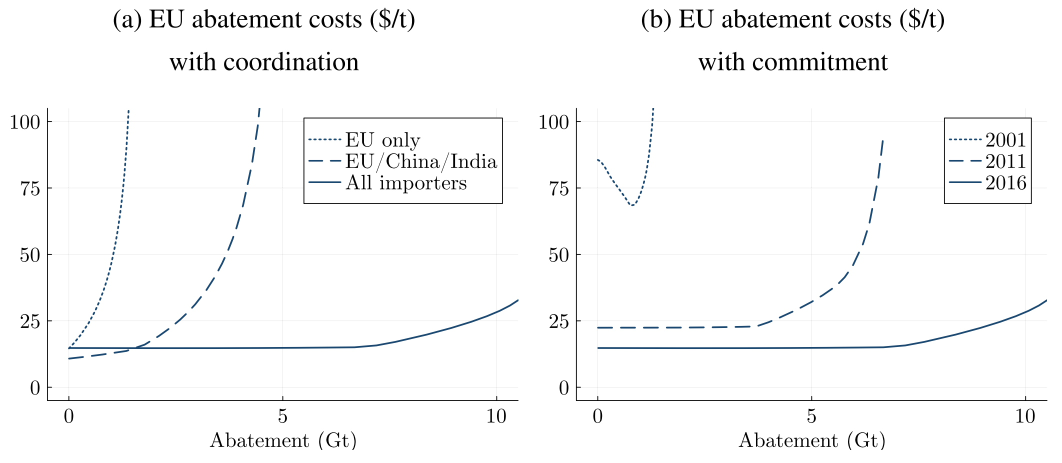

FIGURE 7.—Import tariffs. I simulate EU-led import tariffs of increasing intensity. EU costs include losses to EU consumer surplus, net of tariff revenue and compensating transfers to other markets. Abatement is palm emission reductions. Costs are in inflation-adjusted, year-2000 USD per ton of CO_2, and abatement is in gigatons of CO_2. Both are totals from 1988 to 2016. Figure 7a shows long-run tariffs with coordination among all importers, an EU-China-India coalition, or the EU alone. Figure 7b shows coordinated tariffs with commitment from 1988 to 2016, 1988 to 2011, or 1988 to 2001.

I evaluate import tariffs by imagining the EU as tariff coalition leader, and I calculate costs for the EU inclusive of the proposed transfers. I suppose transfers are to the point that all non-EU markets at least weakly prefer EU-led import tariffs to business as usual. For example, for long-run tariffs by the EU, China, and India in Table VI, the EU itself incurs \$1.5B in welfare losses across EU consumer surplus and government revenue. I additionally consider EU transfers of \$32B to Indonesia and Malaysia as payment for ecosystem services, as well as \$6.9B to China and India for their participation as coalition members. There is no need for a transfer to other importers, who enjoy a welfare gain of \$27B through lower world prices. I then ask whether emission reductions are large enough to justify EU action. In doing so, I aim to assess import tariffs with distributional equity in mind, noting that I may overstate the feasibility of transfers, which are large and international, or conversely the need for transfers, which ignore that non-EU markets also benefit from emission reductions.[27]

Figure 7 presents the results. Even accounting for compensating transfers, I find that EU-led import tariffs reduce CO_2 emissions by up to 9.4 Gt from 1988 to 2016 at a cost to the EU of less than \$25 per ton of CO_2. Abatement at 9.4 Gt calls for coordinated, long-run import tariffs of 350%, noting that transfers serve as compensation for the welfare losses that these large tariffs impose on Indonesia and Malaysia, at least in principle. Import tariffs of 100%, as in Table VI, reduce emissions by 5.4 Gt at a cost to the EU of \$15 per ton. Palm oil tariffs thus compare favorably to other means of abatement, including those receiving active EU investment.[28] However, the effectiveness of tariffs relies on coordination and commitment.

[27]Ricke, Drouet, Caldeira, and Tavoni (2018) calculate that India bears 21% of the global social cost of carbon. The US and Saudi Arabia each bear 11%, and Brazil and China each bear 6%.

[28]For now, direct air capture costs still far exceed the industry target of \$100 per ton (International Energy Agency (2022)).

Figure 7a plots EU abatement costs for long-run tariffs across levels of coordination. For a target abatement cost of \$25 per ton of CO_2, an EU-China-India coalition achieves only 2.4 Gt of abatement with tariffs of 125%, while the EU itself achieves only 0.5 Gt with tariffs of 50%. Larger tariffs increase abatement, but at much higher cost because of leakage. I also note that EU-China-India tariffs are somewhat less costly at the lowest levels of abatement. At these levels, coordinated tariffs are costlier because they are more punitive for Indonesia and Malaysia and thus require larger compensating transfers. Unilateral tariffs are costlier because they lack the market power of a larger coalition.

Figure 7b plots EU abatement costs for coordinated tariffs across levels of commitment. For medium-run tariffs upheld from 1988 to 2011, abatement costs remain below \$25 per ton of CO_2 until 4.0 Gt of abatement with tariffs of 175%. Costs then rise convexly with a kink where the tariff coalition's initial welfare gains, which derive from market power, turn into welfare losses. At this point, the EU begins compensating transfers to China, India, and other importers to maintain the coalition. For short-run tariffs, abatement is much costlier. Tariffs upheld from 1988 to 2001 at 350% achieve 1.0 Gt of abatement at a cost of \$74 per ton. Forward-looking producers do not react strongly to short-run tariffs, and so these tariffs impose welfare costs with little abatement. The smallest tariffs impose welfare costs with nearly zero abatement, elevating abatement costs.

Comparing Figures 7a and 7b, I highlight the importance of commitment. In particular, I note that unilateral EU tariffs upheld from 1988 to 2016 dominate coordinated tariffs upheld from 1988 to 2001. The former achieves 1 Gt, 1.2 Gt, and 1.3 Gt of abatement at target costs of \$50, \$75, and \$100 per ton of CO_2, while the latter achieves 0 Gt, 1.0 Gt, and 1.3 Gt at the same costs. Even with full coordination across importers, abatement relies on commitment over the long run. The 14-year period from 1988 to 2001 is already not especially short, and shorter commitment would yield even less abatement. Commitment to long-run policy will be difficult, especially globally. Unilateral EU action may offer a more feasible path forward.

6.5. *Export Taxes*

Export taxes also target traded consumption. They may appeal to Indonesia and Malaysia for several reasons. First, they allow these countries to exercise market power and raise tax revenue from foreign consumers. Second, they tax foreign but not domestic consumers, and so they raise domestic consumer surplus by shielding domestic consumers from foreign competition. Third, they are implementable with relatively limited administrative burden. Directly taxing production requires monitoring individual mills and plantations, while taxing exports requires enforcement only at international ports. Fourth, they are better than import tariffs. Export taxes by Indonesia and Malaysia and import tariffs by other markets are both aimed at the same set of goods: those that leave Indonesia and Malaysia for world markets.[29] Thus, both impose the same pressures to abate, but only the export taxes generate government revenue for Indonesia and Malaysia.

Figure 8a plots the costs of abatement for Indonesia and Malaysia. Negative costs imply that export taxes are welfare-enhancing, rather than welfare-reducing, for Indonesia and Malaysia. Export taxes reduce foreign consumption, which becomes increasingly inelastic as price-sensitive consumers exit. Export taxes also raise domestic consumption,

[29]Note that symmetry in the sense of Lerner (1936) would instead compare export taxes by a given market to import tariffs by the same market.

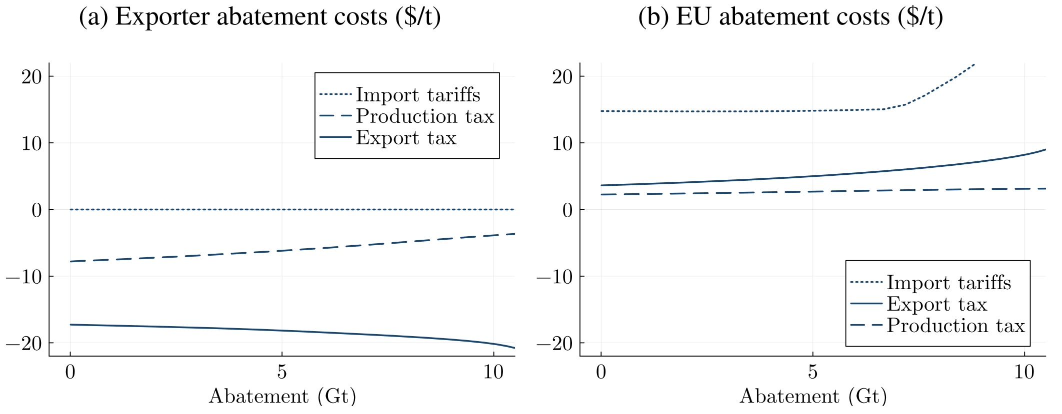

FIGURE 8.—Export taxes. I simulate coordinated, long-run export taxes of increasing intensity by Indonesia and Malaysia. I compare these export taxes to coordinated, long-run production taxes by Indonesia and Malaysia and coordinated, long-run import tariffs led by the EU. Figure 8a shows exporter costs, which include losses to Indonesian and Malaysian consumer and producer surplus, net of tax revenue and compensating transfers from the EU. Figure 8b shows EU costs, which include losses to EU consumer surplus, net of tariff revenue and compensating transfers to Indonesia and Malaysia. Abatement is palm emission reductions. Costs are in inflation-adjusted, year-2000 USD per ton of CO_2, and abatement is in gigatons of CO_2. Both are totals from 1988 to 2016.

which becomes increasingly elastic as domestic consumption reaches satiation. As a result, domestic losses are modest because the burden of export taxes falls primarily on foreign consumers—the inelastic party. Production taxes are also welfare-enhancing because of Indonesian and Malaysian market power, but export taxes avoid taxing domestic consumers and thus are more attractive. Import tariffs are the least attractive, even with compensating transfers from the EU that make import tariffs welfare-neutral. Without these compensating transfers, import tariffs would be welfare-reducing and even less attractive.

Figure 8b illustrates the European perspective. The EU prefers production taxes to export taxes because Indonesian and Malaysian consumers share in the tax burden when production is taxed domestically. Export taxes target EU consumers, leading to larger losses for EU consumer surplus at all levels of abatement. But the EU still prefers export taxes to import tariffs, which call for large compensating transfers to other markets. It is better for the EU to accept Indonesian and Malaysian export taxes in place of EU-led import tariffs, even if these export taxes are less effective than production taxes.

6.6. *Carbon Border Adjustment Mechanism*

A concern is that EU-led import tariffs may crowd out domestic regulation in Indonesia and Malaysia. Figure 9a plots the costs of abatement for Indonesia and Malaysia when they impose production taxes against the backdrop of import tariffs. Focusing on coordinated, long-run production taxes and coordinated, long-run import tariffs, I find that import tariffs raise the domestic costs of production taxes. Absent import tariffs, Indonesia and Malaysia can exercise market power to draw tax revenue from foreign consumers. Welfare rises at all levels of abatement, even as emissions fall. When importers impose tariffs of 10%, production taxes at modest levels lead to welfare losses for Indonesia and Malaysia. With import tariffs of 50%, production taxes at all levels lead to welfare losses.

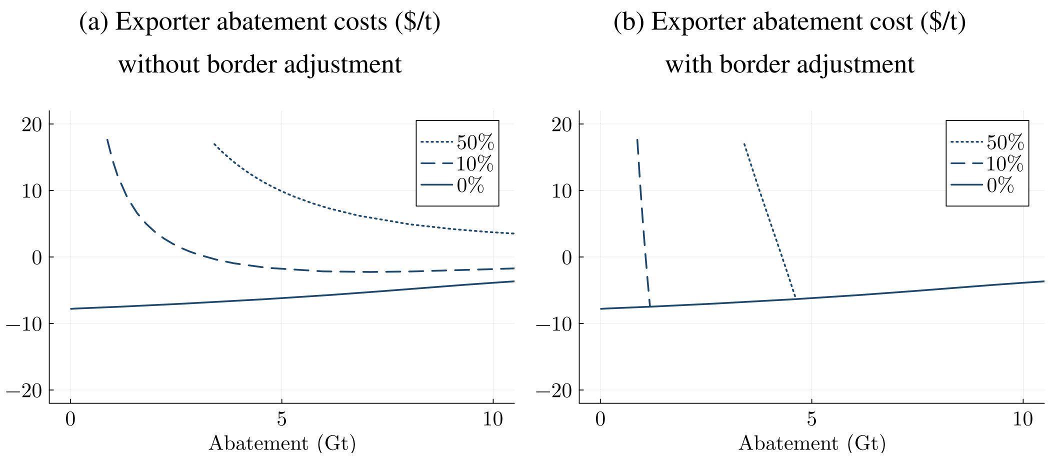

FIGURE 9.—Carbon border adjustment mechanism. I simulate coordinated, long-run production taxes of increasing intensity by Indonesia and Malaysia. Exporter costs include losses to Indonesian and Malaysian consumer and producer surplus, net of tax revenue but without compensating transfers from the EU. I study how these costs interact with coordinated, long-run import tariffs led by the EU, which I simulate at levels of 0%, 10%, and 50%. Abatement is palm emission reductions. Costs are in inflation-adjusted, year-2000 USD per ton of CO_2, and abatement is in gigatons of CO_2. Both are totals from 1988 to 2016. Figure 9a shows import tariffs that do not adjust with domestic regulation. Figure 9b shows a carbon border adjustment mechanism that combines import tariffs with credits for domestic regulation.

The reason is that import tariffs push the burden of production taxes onto domestic consumers. The intuition is clear at the extreme: if importers shut down imports by imposing infinite tariffs, then Indonesia and Malaysia lose their market power as exporters. Production taxes are then especially costly for Indonesia and Malaysia because these taxes fall solely on domestic consumers and producers.

A carbon border adjustment mechanism addresses this concern by combining import tariffs with credits for domestic regulation. Figure 9b shows that this mechanism restores Indonesian and Malaysian welfare gains from taxing production. When import tariffs fall as production taxes rise, Indonesia and Malaysia maintain market power and thus the incentive to tax production. When import tariffs fall to zero for production taxes at high levels, the three curves align on abatement at negative cost. The EU could also credit export taxes to similar effect, rather than crediting production taxes alone. Although the typical carbon border adjustment mechanism would not credit export taxes, export taxes and production taxes are similarly attractive for the EU in this setting (Figure 8b).

6.7. *General Lessons*

I discuss general lessons for green trade policy. First, a leakage problem arises from incomplete regulation. Coordinated trade policy can help, but only for traded goods. For palm oil, Indonesia and Malaysia export 80% of production, and so import tariffs have wide scope for impact. More broadly, global exports account for 68% of manufacturing GDP and 51% of agricultural GDP (World Bank (2023), World Trade Organization (2023b)). Both export shares are relatively large and indicate a role for trade policy. Among fossil fuels, global exports range from 54% of crude oil production to 28% for natural gas to 14% for coal (Energy Information Administration (2023)). Trade policy will be less effective at curbing coal emissions. The Amazon is another important frontier of deforestation, and Brazilian exports amount to 46% of soy production but only 14% of beef production (USDA Foreign Agricultural Service (2025)).[30] If soy expansion occurs on land previously deforested for cattle pasture, then trade policy can still play a role despite limited beef exports.

Second, a commitment problem arises from sunk emissions, which create static incentives to deregulate. Indeed, emissions are sunk in many sectors, including those accounting for the majority of traded emissions: agriculture, manufacturing, fossil fuels, mining, and transportation (Davis, Peters, and Caldeira (2011), Peters, Minx, Weber, and Edenhofer (2011)). For agriculture, including palm oil, emissions are sunk upon investment. Once land is cleared, the forest is gone. For other sectors, emissions are sunk—even if released gradually—if upfront investment yields low marginal costs. Once an oil well has been identified, explored, and drilled, extraction is cheap and proceeds to completion. Once older ships are built, they continue to operate and emit, even if new shipbuilding faces new regulation (Peters (2024)). Committed trade policy helps by imposing long-run regulation and resisting the temptation to deregulate after emissions are sunk.

Third, trade policy need not be punitive. Compensating transfers can ensure equity, recognizing the global good that targeted markets provide by curbing emissions. These transfers act as payment for ecosystem services at global scale. Moreover, targeted markets may have their own fiscal incentives to regulate, even independent of emission concerns. Market power encourages domestic regulation, and export taxes avoid targeting domestic consumers. Trade policy can undercut these domestic incentives to regulate, but a carbon border adjustment mechanism restores the incentives.

Fourth, trade policy also faces challenges. Trade policy for palm oil should tax palm oil in all forms, but palm oil takes many forms indeed. Must a cookie importer be taxed for the 7 grams of palm oil in a 28-gram chocolate chip cookie? There is precedent for palm-based biofuels, which EU trade policy already covers: palm oil repackaged as biofuel remains subject to tariffs. But there is no such precedent in the cookie domain. Trade policy also faces political obstacles. Coordination and commitment must navigate complex, dynamic, multilateral bargaining environments. Palm oil tariffs may lead to trade disputes and escalation that I do not model, although I compute compensating transfers that acknowledge these frictions.

7. CONCLUSION

Trade policy allows the international community to intervene when domestic policies fail. This paper develops a dynamic empirical framework to quantify the impacts of such policy. I use the framework to evaluate EU tariffs on imports of palm oil, a major driver of deforestation and global emissions. I document opportunities to achieve large emission reductions at low cost. Direct regulation with a production tax of 50% can reduce CO_2 emissions by 7.4 Gt. By comparison, EU import tariffs of similar magnitude can reduce emissions by 5.4 Gt if coordinated with other importers and upheld over the long run. The cost of these tariffs is only $15 per ton of CO_2, inclusive of compensating transfers to Indonesia and Malaysia as payment for ecosystem services.

[30] I compute export-to-production ratios for the study period from 1988 to 2016. World Bank data give global agricultural and manufacturing GDP, WTO data give global total and agricultural export values, EIA data give global fossil fuel production and export volumes, and USDA data give Brazilian production and export volumes for cattle and soy. For global manufacturing, I define manufacturing as non-agriculture. For Brazilian soy, I pool oilseed, oil, and meal by weight.

Green trade policy will be an important tool for protecting the vast forests that remain intact, at least for now. More broadly, international climate action will be crucial for meeting our global climate targets. But it relies on coordination and commitment, which are fundamentally difficult. And it imposes economic costs on lower-income countries that must also prioritize economic growth. How can we make progress in this increasingly fragmented and unequal world? Future work grounded in political realities will help to chart the path forward.

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