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 it to the market for palm oil, a major driver of deforestation and global emissions. Relative to business as usual, a domestic production tax of 50% reduces emissions by 7.5 Gt from 1988 to 2016, while coordinated, committed import tariffs of similar magnitude can achieve 5.4 Gt. The marginal abatement cost of import tariffs is as low as $15 per ton, even accounting for compensating transfers that recognize welfare losses for Indonesia and Malaysia. Unilateral EU tariffs are less effective, while domestic export taxes are equally effective. The latter are fiscally appealing independent of emission concerns, as Indonesia and Malaysia can exercise market power to improve their terms of trade. Import tariffs dampen these fiscal incentives, but a carbon border adjustment mechanism restores them.

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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; Burgess et al. 2012; Oliva 2015). The conventional approach attempts to address these difficulties, such as by improving enforcement (Duflo et al. 2018), but doing so at scale can be infeasible. Trade policy offers an alternative, circumventing these obstacles by targeting the prices 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 study the palm oil industry, which accounts for 5% of global CO_2 emissions from 1990 to 2016 – more than the entire Indian economy. 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.

Palm oil is an important empirical setting. The industry is a major polluter, as land clearing for palm oil plantations threatens carbon-rich peatland forests in Indonesia and Malaysia, which produce 83% of global supply. The industry also generates substantial domestic profits that have lifted millions out of poverty (Edwards 2019). This paper informs an active debate on whether foreign governments should intervene with trade policy, which includes recent action by the European Union (OJEU 2018). I quantify emission reductions under trade policy intervention, as well as the losses that Indonesia and Malaysia might claim as payment for ecosystem services.

I model palm oil demand by consumer market with an almost ideal demand system (Deaton and Muellbauer 1980). The model explicitly captures substitution between palm and other vegetable oils. Estimation applies iterated linear least squares as in Blundell and Robin (1999) to annual panel data on vegetable oil prices and consumption by country. I instrument for prices with weather shocks to vegetable oil production, which shift supply, and I obtain palm demand elasticities of 0.7 to 0.9.

I model palm oil supply with a dynamic discrete-continous choice model. Forward-looking firms invest in mills and plantations to produce palm oil. On the extensive margin, firms make a discrete choice over whether to build mills. On the intensive margin, firms make a continuous choice over how much land to deforest and develop into plantations. The model explicitly captures differential responses to long- and short-run policy. Estimation combines the continuous and discrete Euler methods of Hall (1978) and Scott (2013), and it reduces to linear regression with instruments. Continuation values difference out. I draw on fine-grained satellite data that measures palm oil investment over time and space, with identification from two sources: variation in world commodity prices over time and variation in palm oil yields over space. Intuitively, high prices raise revenues most for high-yield plantations. I obtain palm supply elasticities of 3.0 in the long run and 1.4 in the short run.

For counterfactuals, I quantify the impacts of regulation on emissions and welfare. I compare direct regulation with production taxes to trade policy with import tariffs, export taxes, and a carbon border adjustment mechanism. I compute emissions as a function of carbon stocks over space, which I observe, and counterfactual plantation development, which the model predicts. Welfare includes consumer surplus, producer surplus, and government revenue. I find that a production tax of 50% can reduce palm emissions by 7.5 Gt over the study period from 1988 to 2016, relative to business as usual. If feasible, this abatement is welfare-enhancing on net for Indonesia and Malaysia, as the production tax improves their terms of trade. By comparison, I find that EU-led import tariffs of similar magnitude can reduce emissions by 5.4 Gt. The cost to EU welfare is only $15 per ton, even accounting for full compensation for Indonesian and Malaysian losses. This compensation recognizes forgone profits and avoids worsening inequality.

However, import tariffs rely on coordination across importers and commitment to uphold tariffs over the long run. Both coordination and commitment are difficult. An alternative is unilateral EU action, which can still achieve 1 Gt of abatement at a marginal cost of $50 per ton. Another alternative is an export tax by Indonesia and Malaysia, which reduces emissions as effectively as coordinated tariffs. Even if direct regulation is infeasible, an export tax may be enforceable at international ports. This tax is fiscally appealing because it generates government revenue at the expense of foreign consumers, while also sparing domestic consumers. Import tariffs weaken these fiscal incentives to regulate, but a carbon border adjustment mechanism restores them.

This paper develops a new dynamic empirical framework for assessing emission-based trade policy. I build on a rich literature studying environmental regulation and trade, where free-riding and leakage motivate carbon coalitions (Nordhaus 2015; Böhringer et al. 2016; Farrokhi and Lashkaripour 2021) and border adjustment taxes (Markusen 1975; Copeland and Taylor 1994, 1995; Hoel 1996; Rauscher 1997; Fowlie 2009; Elliott et al. 2010; Fowlie et al. 2016; Kortum and Weisbach 2017, 2021), and where trade policy influences environmental incentives (Shapiro 2020; Harstad 2021). I also build on a literature studying commitment in environmental regulation (Marsiliani and Renström 2000; Abrego and Perroni 2002; Helm et al. 2003; Brunner et al. 2012; Harstad 2016, 2020; Battaglini and Harstad 2016; Acemoglu and Rafey 2019). 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), with empirical applications including Ryan (2012) and Collard-Wexler (2013). I draw on a growing literature, formalized by Aguirregabiria and Magesan (2013), Scott (2013), and Kalouptsidi et al. (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 et al. (2017), and Murphy (2018), I offer a simple estimation strategy that reduces to linear regression with instruments.

More broadly, trade policy enables regulation of 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 (Burgess et al. 2019; Souza-Rodrigues 2019; Araujo et al. 2021; Assunção et al. 2021; Domínguez-Iino 2023) or conservation contracting (Harstad 2012, 2016; Harstad and Mideksa 2017). It also scales readily, unlike direct payments for ecosystem services (Jayachandran et al. 2017; Edwards et al. 2020). I show that trade policy can greatly reduce emissions for an industry that is pivotal in the fight against climate change.

2 Background

Palm oil is a major source of global carbon emissions. It largely comes from 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.[1] 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.

Production involves the planting of oil palm seedlings, which mature into trees. These perennial crops bear fruit after three years and continue bearing fruit over a lifespan of 30 years. Plantations harvest fresh fruit bunches that mills process into palm and palm kernel oils, with further processing by refineries. These oils are exported widely. Indonesia and Malaysia account for 83% of global production and 89% of exports (table 1), and FGV Holdings Berhad is the single largest producer at 4% of global production (POA 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 cover 60% of production, vertical integration links plantations and mills directly. For smallholder plantations, which cover 40% of production, vertical contracting creates similar links. Smallholders receive investment support from mills – 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 contracting and integration coincide.[2]

Consumption takes many forms, as palm oil is among the most widely used

[1] 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.

[2] Recent work on agricultural value chains documents that market power over smallholder farmers is common across settings (Bergquist and Dinerstein 2020; Casaburi and Reed 2022; Van Patten and Méndez 2022; Zavala 2022; Chatterjee 2023; Domínguez-Iino 2023; Rubens 2023).

Figure 1: Emissions

(a) Global (Gt) **(b)** Palm (Gt)

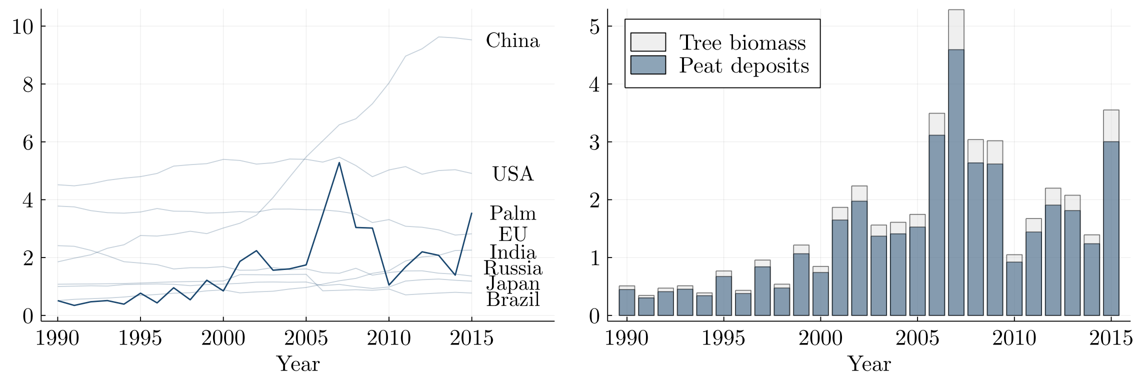


Figure 1a compares Indonesian and Malaysian palm oil to the top emitters, accounting for land-use change. Palm emissions are 4.95% of global emissions from 1990 to 2016. Figure 1b decomposes palm emissions from tree biomass and peat deposits. Emissions are in gigatons of CO_2 equivalents.

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 production and emissions. Palm oil expenditures in 2016 totaled $46 billion at 33% of 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.[3] Firms trade palm oil in global commodity markets, with Unilever as the largest consumer at 2% of global consumption (WWF 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 palm oil domestically (table 1).

Significant palm emissions motivate the need for 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 US $1 billion to Indonesia in cash incentives for domestic forest regulation, prompting a 2011 moratorium on new concessions. But the moratorium had little effect, failing to curb deforestation within existing concessions or otherwise, including in protected areas

[3] 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.

Table 1: Production, consumption, and trade

	Production	Exports	Consumption	Imports
	%	%	%	%
Indonesia	43	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

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

(Busch et al. 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% (USDA 2019a, 2019b).

Consequently, European policymakers have discussed intervening with trade policy. French parliament debated a "Nutella" tax on palm oil in food products in 2016. 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. Each policy uses European purchasing power to target emissions abroad. This paper considers the impacts of such policy.

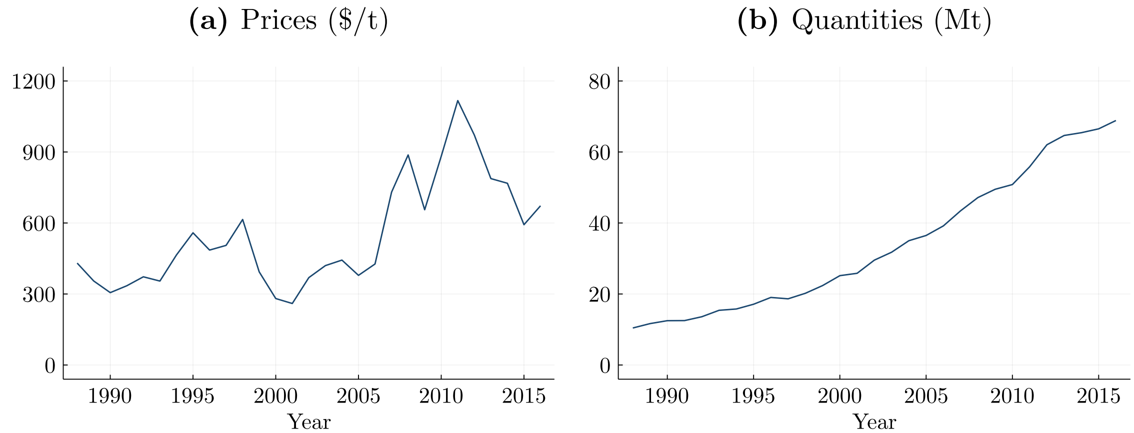
3 Data

I construct annual panel data on palm oil prices, consumption, and production from 1988 to 2016. Appendix A details data sources and each step of construction.

3.1 Demand

I measure annual prices and consumption of vegetable oils. World price data come from the International Monetary Fund and World Bank, and consumption data by country come from the USDA Foreign Agricultural Service. I compute total vegetable oil expenditures from these prices and quantities. The data span the study period from 1988 to 2016 and cover all major vegetable oils: palm, palm kernel, coconut,

Figure 2: Prices and quantities



World prices are in nominal USD per ton, and world quantities are in megatons. Each aggregates over palm and palm kernel oils.

olive, rapeseed, soybean, and sunflower. I use consumer price index data from the World Bank to adjust for inflation and denominate prices in year-2000 dollars.

I aggregate along two margins. First, I aggregate countries into consumer markets, which I define as the EU, China and India, Indonesia and Malaysia, and the rest of the world. Second, I focus on substitution between palm oils and other oils by aggregating individual oils into composites. Palm oils are palm and palm kernel oils, which palm fruit yields in fixed proportion, while other oils are those that remain. I use "palm oil" in reference to the composite. To aggregate, I compute total quantities and expenditure-weighted average prices.[4] Figure 2 plots these prices and quantities for palm oil, with prices rising over time despite a seven-fold increase in quantities traded. Concurrent growth in market prices and quantities indicates a large outward shift of the aggregate demand curve, and indeed palm oil was adopted for wide use in food products, consumer goods, and biofuels during this period.

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.

[4] For prices, I aggregate over individual oils o with 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}.

Choices

I capture plantations and mills with satellite-based measures. For plantations, Xu et al. (2020) use PALSAR and MODIS satellite data to map palm oil plantations at 1 km resolution from 2001 to 2016. I extend their measure back to 1988 with data on tree cover loss as a proxy for plantation development. I obtain these data from Song et al. (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 in 2018. With historical satellite data from Google Earth, I validate these locations and identify mills built by 2016.

With the plantation and mill data, I divide land into sites using observed plantations and mills in 2016 as a guide. Active sites have one mill supported by nearby plantation. Potential sites have no mills or plantations, but they represent potential entrants. To define potential sites, I identify provinces with the highest density of palm oil production – one mill per 521 km^2 on average – and I imagine all provinces at this density. For each province, I obtain site boundaries by k-means clustering on geographic coordinates, with the number of clusters k chosen to reach the target density. I impose that clusters separate observed mills and that observed plantations be assigned to clusters with observed mills. I obtain 2,050 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, assuming that sites build mills alongside their first plantations. I then lightly harmonize by dropping plantations without mills and mills without plantations observed by 2016. I find that my disaggregated data align well with aggregate government statistics. I focus on a study area that covers Sumatra and Kalimantan of Indonesia and all of Malaysia, capturing 97% of mills. Data construction assumes zero exit for both plantations and mills, and indeed exit is limited when I can observe it: Xu et al. (2020) measure cumulative plantation exit of only 5% between 2007 and 2016, perhaps

Table 2: Site statistics

Variable	Mean	SD	Min	Max	N
Mill	0.72	0.45	0	1	2,050
Plantations, ha	9,694	12,047	0	165,986	2,050
Yields, t/ha	3.37	0.57	1.99	5.19	2,050
Road distance, km	48	50	0	267	2,050
Port distance, km	191	100	7	468	2,050
Urban distance, km	125	90	0	417	2,050
Tree biomass CO_2, t/ha	386	157	26	753	2,050
Peat deposit CO_2, t/ha	1,240	2,079	0	16,217	2,050

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 ports, major roads, and administrative cities (Indonesia) or federal territories (Malaysia). Carbon stock densities, in tons per hectare, include aboveground tree biomass and belowground peat deposits.

because oil palm is a perennial crop with steady profits once planted.

The top panel of table 2 summarizes site choices by 2016. Of 2,050 total sites, 72% have an observed mill. The average plantation is large at nearly 10,000 ha in area. Over time, I observe plantation acreage increasing substantially from 1.2 Mha in 1988 to 19.4 Mha in 2016, relative to a study area of 134 Mha. That is, I measure 14% of total land being developed into palm oil plantations. Roughly half of the study area is too mountainous for agriculture, and so the proportion of arable land being developed is even higher. At the site level, 3% 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 711 ha of new plantation each year. Consistent with an interior solution, this new plantation development is non-zero for 99.5% of site-year observations and within the available land area for 100%.

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 Hoffmann et al. (2014) predicts potential yields under optimal growing conditions as a function of exogenous climate conditions. I run the model with WorldClim data on solar radiation and precipitation, which I aggregate by site. I thus obtain potential yields by site. Government statistics from the Indonesian Ministry of Agriculture and the Malaysian Palm Oil Board record actual yields by province-year. I calculate yield gaps as one minus the ratio of actual to potential yields, assuming sites within a province-year share a common gap, then I multiply by potential yields. I thus obtain actual yields by site-year. Variation across sites reflects differences in climate, while variation over time reflects technological progress that can vary by province.

I also consider cross-sectional variation in covariates that affect production costs. I calculate distance to markets as the sum of Euclidean distances to the nearest major port, road, and urban center. Each affects transport costs. I compute carbon stocks from geospatial data on tree biomass and peat deposits (Zarin et al. 2016; Gumbricht et al. 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.

The bottom panel of table 2 summarizes the state variables. Yields are high at 3.37 tons per hectare per year for the average site. Average annual revenues are $1,838 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 1,626 tons of CO_2 equivalents per hectare, with 386 from tree biomass and a much larger 1,240 from peat deposits. Even with recurring revenue, carbon damages far exceed revenues for reasonable social costs of carbon between $50 and $100.[5] 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. For each year, crop, and province, I compute weather shocks as total absolute

[5] For discount factor $\beta = 0.9$, annual revenue of $1,838 has a net present value of $18,380, ignoring production costs. For SCC = $50, carbon stores of 1,626 tons imply $81,300 in carbon damages.

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 Model

I model global consumption, production, and trade in palm oil. Consumers demand palm oil alongside other vegetable oils, and producers supply palm oil by investing in mills and plantations. World prices clear markets in equilibrium.

4.1 Demand

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 substitution patterns flexibly (Deaton and Muellbauer 1980).[6] For markets k, years t, and vegetable oils $o \in \{1, 2\} = \{\text{palm}, \text{other}\}$, demand is given by

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

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

Expenditure shares ω_{okt} depend on world prices p_{ot} for both palm and other oils, fixed effects γ^0_{ok} and time trends γ^1_{ok} that capture unobserved heterogeneity by market, total vegetable oil expenditures X_{kt}, price index P_{kt}, and shocks ε_{okt}. Own- and cross-price coefficients $\alpha_{o\hat{o}k}$ allow for flexible patterns of substitution. Translog price index P_{kt} aggregates over individual oil prices p_{ot}. It depends on market-specific parameters, and so it varies by market even if world prices do not. By definition of expenditure shares $\omega_{okt} = q_{okt} p_{ot} / X_{kt}$, quantities demanded are

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

[6] The characteristic-space approach of Berry et al. (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.

4.2 Supply

Sites produce palm oil by investing in 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 to construct a mill or not, 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

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

Three-year lags capture time to build for plantations, as newly planted crops do not yet bear fruit. Plantation acreage N_{it} thus tracks mature, fruit-bearing plantations. Furthermore, sites face constraints. First, each site supports no more than one mill, such that $M_{it}, m_{it} \in \{0, 1\}$. Second, sites can only develop plantations within their 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, and so $N_{it} = 0$ 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, and 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 ports, roads, and cities, none of which target individual sites.[7] These distances increase transport costs. Carbon stocks are predetermined and increase emissions that sites may internalize or not. Region g_i encodes the four regions of study – Sumatra, Kali-

[7] Major ports predate plantations, major roads exclude small roads built for plantations, and major cities exclude palm oil settlements.

mantan, Peninsular Malaysia, and East Malaysia – to allow for regional unobserved heterogeneity. Regional boundaries are fixed.

Unobserved states $\{\bar{\epsilon}_{it}, \bar{\varepsilon}_{it}, \varepsilon_{it}\}$ also affect choices $\{m_{it}, n_{it}\}$. Mill shocks $\bar{\epsilon}_{it}$ are logit-distributed and IID. 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} then proceed in two stages. First, sites construct mills. Sites with an existing mill do not face a choice, as sites can only support one mill. If $M_{it} = 1$, then $m_{it} = 0$. Sites otherwise face a choice. If $M_{it} = 0$, then they realize logit shock $\bar{\epsilon}_{it}$ and choose mill construction $m_{it} \in \{0, 1\}$. For sites i and years t, the ex-ante value function is

$$\bar{V}(s_{it}) = \mathbb{E}\big[\max_{m_{it}}\{\beta\bar{V}(s_{it+1}),\, -\bar{c}(s_{it}) + V(0, s_{it}) - \bar{\epsilon}_{it}\} \,\big|\, s_{it}\big]\,. \tag{4}$$

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 next year. Sites that choose $m_{it} = 1$ incur mill cost $\bar{c}(s_{it})$ 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 never constructing a mill, with utility normalized to zero.

Second, 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

$$V(N_{it}, s_{it}) = \mathbb{E}\big[\max_{n_{it}}\big\{r(N_{it}, s_{it}) - c(n_{it}, s_{it}) + \beta V(N_{it+1}, s_{it+1})\big\} \mid N_{it}, s_{it}\big]\,. \tag{5}$$

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.

Plantation acreage N_{it} determine quantities supplied. Production depends on yields y_{it} and acreage N_{it}, and so quantities supplied are

$$q_{it}^S = y_{it} N_{it} \,. \tag{6}$$

Because of dynamics, quantities in one year depend on states in every year. First, acreage is a stock of previous choices. By the laws of motion, current acreage N_{it} depends on year-one mill construction m_{i1} and, conditional on construction, plantation development n_{i1}. Second, previous choices are forward-looking. By equations 4 and 5, they depend on states s_{it} in every year. Thus, to calculate quantities from equations 4 and 5, I will need to specify the full expected path of states over time. Appendix C details this calculation. I can sidestep this challenge when estimating supply parameters and elasticities, but not when solving for equilibrium prices.

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

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

Revenues reflect prices p_t, yields y_{it}, and plantation acreage N_{it}. 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.[8] 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

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

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 model upfront costs, but it is isomorphic to consider flow costs.[9]

[8] 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 only support one mill each. I instead estimate regional effects, effectively pooling in the cross section rather than over time.

[9] Without exit or scrappage, sites effectively commit to paying flow costs upon investment. To this end, I can interpret the modeled costs as combining true upfront costs with the net present value of flow costs. Absent data on firm expenditures, formally separating these elements would require observing exit over time. Intuitively, entry followed by quick exit would imply low upfront costs

4.3 Equilibrium

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

1. World demand for palm and other oils is given by equations 1, 2, and 3. It depends on contemporaneous prices $\{p_{1t}, p_{2t}\}$ and total expenditures X_{kt}. Summing over markets k,

$$D_{ot}(p_{1t}, p_{2t}) = \sum_k q^D_{okt}(p_{1t}, p_{2t}; X_{kt}) \,.$$

2. World supply of palm oil is given by equations 4, 5, and 6. It depends on all prices $p^T_1 = \{p_{11}, \ldots, p_{1T}\}$ and yields $y^T_i = \{y_{i1}, \ldots, y_{iT}\}$. Sites are price takers individually, but will affect world prices collectively. Summing over sites i,

$$S_{1t}(p^T_1) = \sum_i q^S_{it}(p^T_1; y^T_i) \,.$$

3. World supply of other oils is given inelastically by quantities $\{S_{21}, \ldots, S_{2T}\}$.[10]
4. World markets clear.

$$D_{1t}(p_{1t}, p_{2t}) = S_{1t}(p^T_1) \,, \quad D_{2t}(p_{1t}, p_{2t}) = S_{2t} \quad \forall\, t \tag{7}$$

5 Estimation

I estimate parameters and elasticities by linear regression with instruments, drawing on iterative methods for demand and Euler methods for supply. I then solve for equilibrium prices and recover a measure of expectations.

5.1 Demand

I estimate the model by iterated linear least squares (Blundell and Robin 1999). The challenge is that equations 1 and 2 call for nonlinear estimation, as demand

but high flow costs. I observe limited exit that instead suggests low flow costs.

[10] I can alternatively assume perfectly elastic supply 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.

parameters enter nonlinearly through price index P_{kt}. But for fixed price index values P_{kt}^0, equation 1 is a linear regression equation.

$$\omega_{okt} = \sum_{\hat{o}} \alpha_{o\hat{o}k} \ln p_{\hat{o}t} + \gamma_{ok}^0 + \gamma_{ok}^1 t + \delta_{ok} \ln \left(\frac{X_{kt}}{P_{kt}^0} \right) + \varepsilon_{okt} \tag{8}$$

First, I compute initial price index values $\ln P_{kt}^0 = \ln X_{kt} - \ln Q_{kt}$ from data on total expenditures X_{kt} and quantities $Q_{kt} = \sum_o q_{okt}$. Second, I estimate equation 8 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 one, and I impose the standard adding-up, homogeneity, and symmetry restrictions.[11] 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.

I estimate equation 8 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.[12] Greater shocks correspond to lower yields, which lower 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 most relevant to vegetable oil production: deviations from optimal weather conditions for oilseed crops, specifically in the provinces and states that produce these crops, and only in the months of the growing season. 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, then I compute quantities demanded with equations 1, 2, and 3. I repeat with other oil prices, again holding

[11] With more products, estimation can apply seemingly unrelated regression to a system of equations. For 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 $\sum_o \omega_{okt} = 1$. For homogeneity, $\sum_{\hat{o}} \alpha_{o\hat{o}k} = 0$ for all o. It imposes that demand is unaffected by scaling prices and expenditures. For 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.

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

all else constant. I report percentage changes in total consumption over the study period, with standard errors given by the delta method.

5.2 Supply

I use Euler methods to estimate the model without the need to compute continuation values (Hall 1978; Scott 2013). I derive Euler equations that compare investment in years t and $t+1$. On the intensive margin, I differentiate equation 5 with respect to plantation development n_{it} and n_{it+1}. Continuation values align and difference out by the envelope theorem. On the extensive margin, I difference equation 4 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). That is, whether sites invest in year t or $t+1$, mills are operational and plantations have matured by year $t+4$. Appendix C presents derivations.

I obtain two linear regression equations that I stack and estimate jointly. Estimation is straightforward and computationally light.

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

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

for structural errors $\{\mu_{it}, \bar{\mu}_{it}\}$ and expectational errors $\{\eta_{it}, \bar{\eta}_{it}\}$. Each equation captures an intertemporal trade-off. In equation 9, earlier plantation development n_{it} brings added revenue $p_{t+3}y_{it+3}$ and avoids rising cost trends γ_g^1, but later development n_{it+1} delays costs $(\gamma_g^0 + \gamma_g^1 t + x_i\delta)$ and discounts them. In equation 10, earlier mill construction π_{it} brings added plantation profits, as embodied by n_{it}^2, while later construction π_{it+1} delays costs. Observed choices capture future payoffs and thus stand in for continuation values, echoing the typical intuition for conditional choice probability estimation.

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 $\{\psi, \bar{\gamma}_g^0, \bar{\gamma}_g^1, \bar{\delta}\}$, and isolating ψ gives $\{\alpha, \gamma_g^0, \gamma_g^1, \delta\}$ in levels. Variation in prices and yields jointly identify price coefficient α. High-yield sites benefit more from high prices than low-yield sites, as revenues reflect both prices and yields. If supply is very elastic, then high-yield sites develop much more aggressively than low-yield sites when prices rise.[13]

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. I discuss the error terms, which motivate instrumenting and clustering. First, expectational error η_{it} is the difference between expectations and realizations. Plantation development depends on unobserved expectation $\mathbb{E}[p_{t+3}y_{it+3}|s_{it}]$, which I proxy for with observed realization $p_{t+3}y_{it+3}$. Expectational error captures the difference. It is mechanically correlated with future $p_{t+3}y_{it+3}$, and so I instrument with current $p_t y_{it}$. I appeal to rational expectations, which condition on all information known at time t, such that $p_t y_{it}$ is orthogonal to η_{it}. Second, structural error $\mu_{it} = -\frac{1}{\psi}\varepsilon_{it} + \frac{\beta}{\psi}\varepsilon_{it+1}$ reflects unobserved costs. It is uncorrelated with observed states $\{p_t, y_{it}, x_i, g_i\}$, which sites take as given. Individual, idiosyncratic costs affect neither world prices nor site fundamentals like crop yields, market access, or regional boundaries. But costs may themselves be correlated across sites or over time. I cluster standard errors by district to accommodate this 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 again smooth over observed choices, assuming that unobserved mill and plantation costs are uncorrelated. Second, I discuss the error terms, which motivate clustering. Structural error $\bar{\mu}_{it} = -\bar{\varepsilon}_{it} + \beta\bar{\varepsilon}_{it+1}$ is uncorrelated with observed states but may be autocorrelated, and so I cluster standard errors by district. It is uncorrelated with n_{it}, again assuming that unobserved mill and plantation costs are uncorrelated. Expectational error $\bar{\eta}_{it}$ is uncorrelated with observed states by rational expectations.

[13] 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.

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 appendix C. I do so instead of computing quantities from equations 4 and 5, 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 Expectations

Having estimated demand and supply parameters $\hat{\theta} = \{\hat{\theta}^d, \hat{\theta}^s\}$, I invert the model to recover a measure of long-run expectations. I focus on expected future demand by assuming that total expenditures X_{kt} take exponential form with growth rate λ beyond the study period.

$$X_{kt+1} = (1 + \lambda)X_{kt}$$

High demand growth implies high future prices, encouraging current entry and affecting current prices. I choose candidate expectations $\hat{\lambda}$, solve for equilibrium prices with parameter estimates $\hat{\theta}$, then repeat to match observed palm oil prices. Importantly, parameter estimates do not depend on long-run expectations, even though long-run expectations affect quantities and prices. The reason is that equations 9 and 10 estimate investment in changes, differencing out the long-run expectations that rationalize investment in levels. In specifying expectations, I can compute investment in levels directly from equations 4 and 5. I avoid this issue when computing supply elasticities by restricting attention to small price changes.

I solve for equilibrium prices with conditions 7 and several further assumptions. First, I set terminal year $T = 2050$, discount factor $\beta = 0.9$, unobservables $\bar{\varepsilon}_{it} = \varepsilon_{it} = \varepsilon_{okt} = 0$, and expectational errors $\bar{\eta}_{it} = \eta_{it} = 0$. Second, beyond the study period, palm oil yields grow linearly at observed rates, as does the supply of other oils, and annual inflation is 2%. Third, palm production in Indonesia and Malaysia is proportional to palm production elsewhere.[14] Each confounds demand expectations

[14] Indonesia and Malaysia account for 83% of palm production during the study period (table 1), which limits bias from not directly modeling production elsewhere. I treat Indonesia and

Table 3: 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)	0.046	(0.043)	-0.001	(0.040)	0.047	(0.032)
γ^0	0.084	(0.282)	-0.252	(0.292)	-0.447*	(0.256)	1.054***	(0.186)
γ^1	0.004***	(0.001)	0.003	(0.002)	0.004***	(0.001)	0.012***	(0.002)
δ	0.008	(0.028)	0.046	(0.029)	0.061***	(0.023)	-0.022	(0.021)

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, and it instruments for prices with weather shocks to vegetable oil production. Newey-West standard errors account for serial correlation. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

$\hat{\lambda}$, but the goal is simply to match prices in a manner consistent with equilibrium – not to isolate the precise nature of long-run expectations. Counterfactuals will maintain the same assumptions.

6 Estimates

I describe demand estimates by consumer market and supply estimates over the short and long run. I discuss implications for coordination and commitment, and I report measures of model fit.

6.1 Demand

Table 3 presents estimated demand parameters. 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. The implication is that quantities fall as prices rise, otherwise higher prices would mechanically lead to higher expenditure shares. Intercepts γ^0 and time trends

Malaysia as representative palm 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 conditions 7 for market-clearing prices. 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 production elsewhere as fixed, with very similar results in terms of model fit.

Table 4: Demand elasticities

	IV		OLS	
	Estimate	SE	Estimate	SE
European Union	-0.721***	(0.210)	-0.208**	(0.102)
China/India	-0.697***	(0.167)	-0.282	(0.735)
Other importers	-0.876***	(0.130)	-0.529	(0.687)
Indonesia/Malaysia	-0.925***	(0.046)	-0.907***	(0.144)

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. The IV columns instrument for prices with weather shocks to vegetable oil production, while the OLS columns do not. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

γ^1 capture observed differences in palm oil consumption across markets. Indonesia and Malaysia have a large, positive intercept. They consume more palm oil than other oils across years, as is consistent with home bias and their role as major producers. All markets have positive time trends, rationalizing rising consumption in spite of rising prices (figure 2). Expenditure coefficients δ govern how consumption responds as expenditures rise. Other importers shift toward higher palm oil shares, while other markets respond more neutrally.

Table 4 presents demand elasticities for palm oil by consumer market. I report elasticities of total consumption over the study period. I find elasticities that are roughly similar across markets and all less than one, suggesting relatively inelastic demand. Inelastic demand helps to reduce leakage concerns and thus the losses from a failure to coordinate. At the same time, leakage concerns remain as long as demand is less than perfectly inelastic. Without price instruments, I obtain estimates with strong upward bias, particularly for the EU, China, and India. As is typical, this upward bias arises because prices are positively correlated with unobserved demand shocks. Appendix B shows the strong first stage for weather shocks as instruments, and it presents demand elasticities for other oils, which I find are similar in magnitude to demand elasticities for palm oil.

While static demand estimation greatly simplifies computation, ignoring dynamics may lead to bias. On one hand, switching costs will lead to underestimated demand elasticities and understated leakage concerns. If switching among vegetable oils is a

Table 5: Supply parameters

		Intensive				Extensive			
		θ^s	Unit	Estimate	SE	$\bar{\theta}^s$	Unit	Estimate	SE
Revenue	Price	α	10^{-8}	3.148**	(1.511)				
Cost	Median	γ^0/α	\$1K	8.052***	(0.330)	$\bar{\gamma}^0/\alpha$	\$1M	86.70**	(37.56)
	Trend	γ^1/α	\$1K	-0.404***	(0.036)	$\bar{\gamma}^1/\alpha$	\$1M	1.285***	(0.353)
	Distance	δ/α	\$1K	0.001	(0.002)	$\bar{\delta}/\alpha$	\$1M	0.329**	(0.154)
	Carbon	δ/α	\$1K	-0.000**	(0.000)	$\bar{\delta}/\alpha$	\$1M	0.002	(0.001)
	Convexity	ψ/α	\$1	6.240***	(0.566)				

The top panel is the price coefficient. The bottom panel divides cost parameters by the price coefficient, such that magnitudes are interpretable as inflation-adjusted, year-2000 dollars. 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 road, port, and urban distances, while carbon stocks sum over above- and below-ground carbon stocks. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

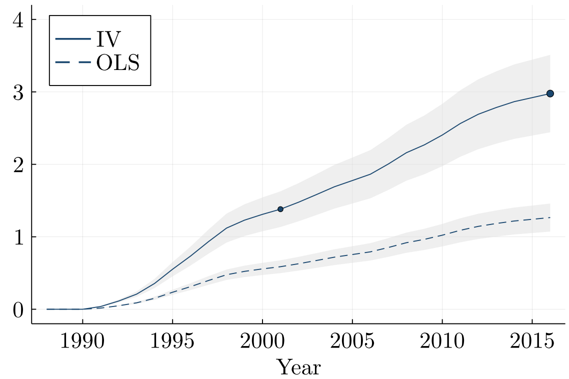
gradual process, with new recipes and new suppliers, then contemporaneous price responses will be attenuated. Appendix B applies price lags and leads and finds similar estimates across specifications. On the other hand, stockpiling behavior will lead to overestimated demand elasticities and overstated leakage concerns. If consumers stockpile to take advantage of temporary price drops, then short-run price responses will be exaggerated. Appendix B measures stockpiling and finds it to be limited.

6.2 Supply

Table 5 presents estimated supply parameters, 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 \$8,052 per hectare of plantation and \$86.70 million per mill, with an additional \$1,445 per hectare from cost convexity.[15] Accounting estimates are smaller at \$7,000 and \$20 million (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 that I do not model explicitly, including urban

[15] Estimated cost convexity is \$6.24 per hectare (times $\frac{1}{2}$), and average n_{it} is 463 hectares.

Figure 3: 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 band is computed from IV estimates, and the bottom band from OLS estimates. I plot 95% confidence bands.

boundaries. Plantation costs fall by a meaningful 5% of median costs per year, while mill costs rise by 1.5%. Appendix C presents regional costs.

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 proxy for a lack of competing claims on land. However, on both margins, the effects of carbon stocks are small in magnitude.

Figure 3 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 1.4, and those from 1988 to 2016 give a long-run elasticity of 3.0. Very short-run price changes from 1988 to 1990 have no effect because I take 1988 as the initial year, and production responds with a three-year lag based on time to mature. 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 et al. 2021). 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.

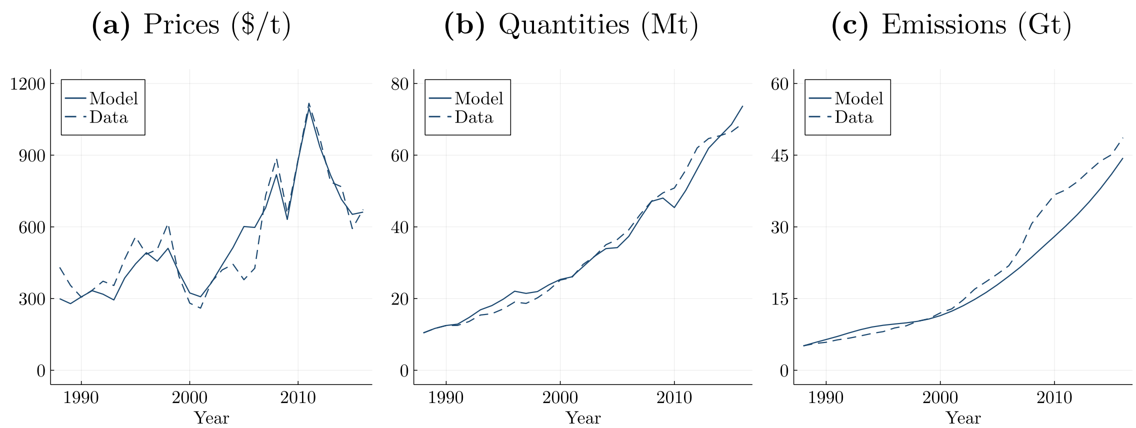
Figure 3 also shows the attenuated elasticities I obtain from estimation without instruments. In equation 9, large realizations of future revenue imply smaller expectational errors, leading to downward bias in the estimated impact of revenues on plantation development. Instruments correct for this bias, and appendix C shows a strong first stage. Appendix C also estimates a static version of the model and finds elasticities that are small and negative. It regresses on current prices, which are noisy measures of future prices, and this noise leads to attenuation. 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, appendix C presents additional specifications with disaggregated cost factors and alternative basis functions for smoothing. It also explores the baseline assumption that unobserved mill costs are uncorrelated with unobserved plantation costs. I estimate similar supply elasticities across specifications.

Euler estimation has several important advantages. This approach greatly simplifies computation, as it avoids the need to compute continuation values. And because estimation reduces to linear regression, I can address endogeneity and autocorrelation concerns with standard tools. Although I need to assume rational expectations, I do not need to specify expectations more precisely, and I note that regional terms $\gamma = \{\gamma_g^0, \gamma_g^1, \bar{\gamma}_g^0, \bar{\gamma}_g^1\}$ can 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 is stronger than assuming rational expectations.[16]

At the same time, estimation relies on several assumptions. First, I compare in-

[16] Other approaches have similar computational advantages in the discrete case, but cannot directly accommodate the non-stationarity of my setting (Aguirregabiria and Mira 2007; Bajari et al. 2007; Pakes et al. 2007; Pesendorfer and Schmidt-Dengler 2008). Besides Scott (2013), other recent applications of discrete Euler methods include Diamond et al. (2017), De Groote and Verboven (2019), Traiberman (2019), and Almagro and Domínguez-Iino (2020). Hsiao (2023) develops an alternative approach with similar advantages, appealing to price data and efficient markets in place of finite dependence.

Figure 4: 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 equivalents.

vesting today or tomorrow, but weak property rights may promote land grabbing and thus bias toward investing today. Regional terms γ help by absorbing some variation in property rights. Second, sites are independent and atomistic. Otherwise, finite dependence does not hold: if price-makers delay investment, then competitors respond, altering the evolution of the economy such that continuation values do not align. World production is indeed unconcentrated, with the largest producer accounting for 4% and the largest ten for 21%. But I must rule out spatial competition, including in local factor markets, because spatial interaction 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.

6.3 Model fit

Figure 4 compares model-implied values to observed data during the study period. Model-implied values are fitted values that I compute with structural and expectational errors set to zero and estimated demand growth rate $\hat{\lambda} = 0.10$. I find that the model matches the data for palm oil relatively well, noting that equilibrium prices are directly targeted. Prices and quantities are tied by conditions 7, and I match data on each in both level and trend.[17] Quantities and emissions are tied by

[17] The model can err from observed prices and quantities in the same or opposite directions. If the demand model is overly optimistic in a particular year, then I overpredict both price and quantity.

plantation development choices, but quantities depend on yields and emissions 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 welfare relative to the model-implied baseline presented here.

7 Counterfactuals

I compare direct regulation with domestic policy to indirect regulation with trade policy. I quantify impacts on emissions and welfare, and I discuss general lessons.

7.1 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 $\{\tau^D_{kt}, \tau^S_{gt}\}$, equilibrium condition 7 for palm oil becomes

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

Estimation has treated baseline taxes as negligible.[18] I study coordination by introducing taxes across regions and markets. Incomplete regulation across regions induces supply-side leakage, as production shifts toward unregulated regions. Similarly, incomplete regulation across markets induces demand-side leakage. I study commitment by introducing taxes upheld over time. Commitment resists static incentives to set taxes to zero, given sunk investment and time to build. That is, taxes are costly today, but they prevent neither past development, which is sunk, nor new

If the supply model is overly optimistic, then I underpredict price and overpredict quantity.

[18] Indeed, EU tariffs are only 3.8% for crude palm oil (WTO 2023), and Indonesian regulation is not consistently enforced (Busch et al. 2015). However, estimation accommodates existing taxes with unobserved market heterogeneity $\{\gamma^0_{ok}, \gamma^1_{ok}\}$ for demand and regional heterogeneity $\{\gamma^0_g, \gamma^1_g, \bar{\gamma}^0_g, \bar{\gamma}^1_g\}$ for supply. I interpret counterfactuals as taxation beyond this baseline.

development, which does not yet produce taxable output.[19]

I quantify emission and welfare effects. Emissions depend on carbon stock density, which I observe, and the extent of plantation development, which I model. Welfare is consumer surplus, producer surplus, and government revenue. I compute total welfare over the study period from 1988 to 2016. Welfare beyond the study period depends 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. Appendix D provides formal expressions for each and tabulates effects for policy of varying intensity.

Several restrictions simplify computation. First, tax paths are announced at the outset and taken as given. I abstract from the dynamic game between policymakers and producers. Second, tax paths 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.[20] 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, ignoring emissions from demand substitution to other oils or supply substitution to other deforesting activities. 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 production.

7.2 Domestic regulation

Domestic regulation taxes production directly. Table 6 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

[19] The regulator can levy an immediate fine at the full cost of emissions, but enforcement still requires commitment. Large fines can prompt legal challenges and lobbying that undercut commitment.

[20] 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.

Table 6: Emissions (Gt) and welfare ($1B)

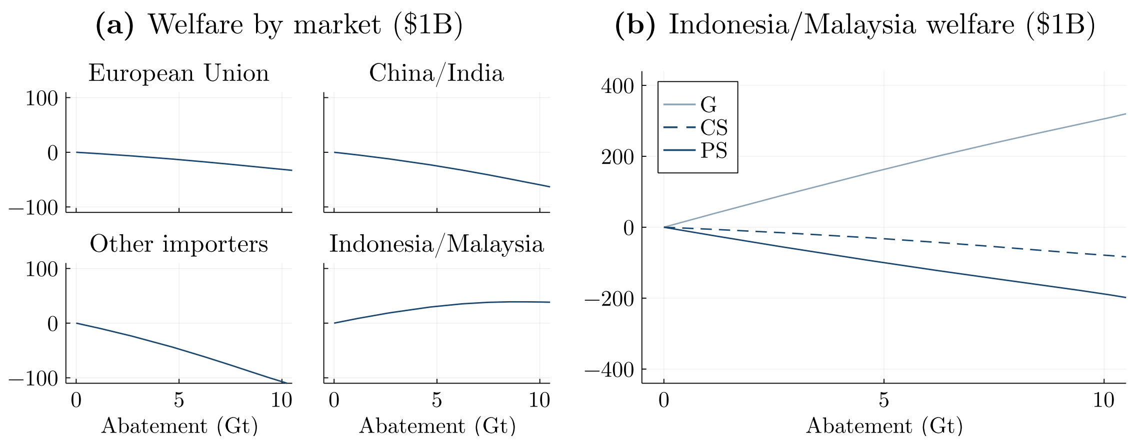
	τ	ΔE		ΔW^{EU}		ΔW^{CI}		ΔW^{OI}		ΔW^{IM}	
	%	2016	2001	2016	2001	2016	2001	2016	2001	2016	2001
Production taxes											
All exporters	50	-7.5	-0.8	-22	-5.5	-41	-9.0	-76	-22	38	6.7
Indonesia only	50	-4.8	-0.9	-6.7	-1.6	-12	-2.7	-22	-6.6	13	0.8
Malaysia only	50	-1.7	-0.1	-3.7	-1.1	-6.9	-1.8	-12	-4.7	7.2	0.9
Import tariffs											
All importers	100	-5.4	-0.5	8.4	2.1	9.1	1.2	12	5.7	-89	-38
EU, China, India	100	-2.1	-0.1	-1.7	-0.1	-7.3	-0.6	26	7.7	-32	-11
EU only	100	-0.7	-0.1	-9.7	-1.6	4.9	0.9	9.6	3.5	-13	-6.2

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 equivalents, and welfare is in billions of inflation-adjusted, year-2000 dollars. 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. 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.

short-run taxes from 1988 to 2001. I find that coordinated, long-run taxes reduce emissions by 7.5 Gt from 1988 to 2016. Unilateral and short-run taxes have smaller effects. 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.

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 the terms of trade, leveraging producer market power to elevate world prices and raise tax revenue at the expense of foreign consumers. That is, production taxes simulta-

Figure 5: Production taxes



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

neously reduce emissions and raise welfare for Indonesia and Malaysia. If enforceable, domestic regulation is fiscally appealing even absent international pressures to abate.

Figure 5 plots welfare against abatement for production taxes of varying intensity, focusing on coordinated, long-run taxes. Figure 5a 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 8.5 Gt of abatement. Abatement at this level corresponds to a 55% production tax. Figure 5b 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. That is, Indonesian and Malaysian producers suffer losses that far exceed Norway's $1B USD in cash incentives to encourage forest regulation. Indeed, these distributional effects shape agricultural policy broadly (Hsiao et al. 2024).

7.3 Import tariffs

Import tariffs tax traded consumption. Table 6 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, short-run tariffs from 1988 to 2001, and medium-run tariffs in between. I find that coordinated, long-run tariffs reduce emissions by 5.4 Gt from 1988 to 2016. This reduction is smaller than the 7.5 Gt reached by production taxes, as import tariffs fail to regulate Indonesian and Malaysian consumers. Unilateral and short-run import tariffs also 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 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 importers can manipulate the terms of trade, leveraging consumer market power to lower world prices and raise tax revenue at the expense of foreign producers. This market power is strongest when importers act together, and coordinated tariffs – both long- and short-run – raise welfare for all importers. Smaller tariff coalitions have less market power, and so welfare instead falls because government revenue does not offset the direct consumer surplus losses from import tariffs. But non-coalition importers 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, including in poor, rural communities. In curbing emissions, these countries forgo local profits for global benefit. Second, these transfers help navigate legal and diplomatic concerns. Import tariffs of 100% are substantial, although some precedents exist. 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.[21] Nonetheless,

[21] For sugar, beef, and milk, I compute ad valorem equivalents by combining non-ad valorem rates with primary commodity prices for 2020 (WTO 2023; IMF 2023). 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

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.

I evaluate import tariffs by imagining the EU as tariff coalition leader, then calculating EU welfare net of the proposed transfers. I suppose transfers are to the point of indifference – for all non-EU markets – between EU-led import tariffs and business as usual. For example, for long-run tariffs by the EU, China, and India in table 6, the EU itself incurs \$1.7B 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 \$7.3B 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 \$26B 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 desire emission reductions.[22]

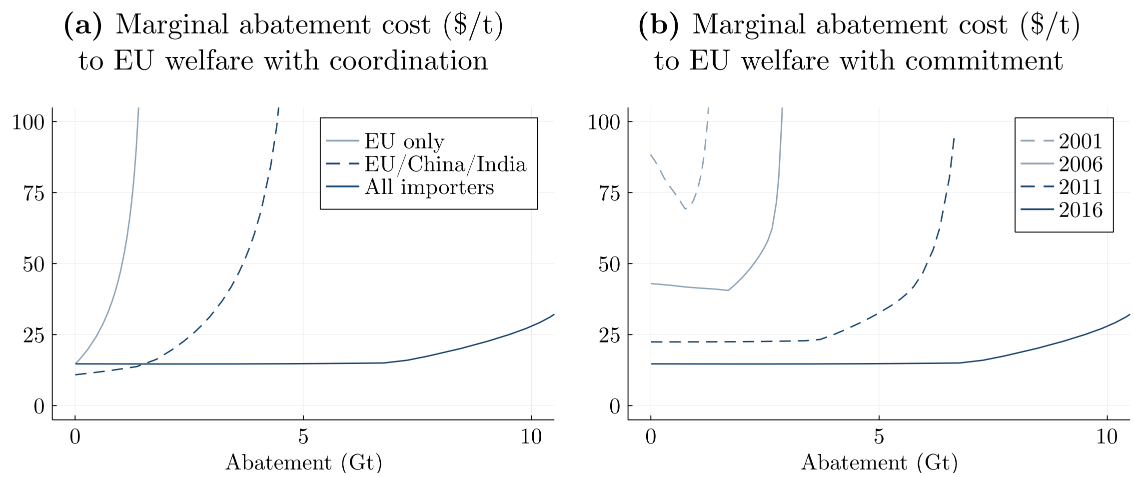
Figure 6 presents the results. Even accounting for compensating transfers, I find that EU-led import tariffs reduce emissions by up to 9.5 Gt from 1988 to 2016 at a marginal cost to EU welfare of less than \$25 per ton. Abatement at 9.5 Gt calls for coordinated, long-run import tariffs of 350%, noting that compensating transfers offset Indonesian and Malaysian welfare losses from these large tariffs, at least in principle. Import tariffs of 100%, as in table 6, achieve 5.4 Gt of abatement at a marginal cost of less than \$15 per ton. Palm oil tariffs thus compare favorably to other forms of abatement, including those receiving active EU investment.[23] However,

retail selling price of cigarettes released for consumption" since 2014 (OJEU 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.

[22] Indeed, China and India bear 18% of the social costs of carbon. Ricke et al. (2018) construct country-level social costs of carbon with damage functions derived from historical climate-growth impacts, as estimated by Burke et al. (2015) (BHM) and Dell et al. (2012) (DJO). I compute average country-specific estimates across five damage function specifications: four from BHM (short- vs. long-run impacts that pool vs. distinguish rich and poor countries) and one from DJO. I aggregate into the coalition groups of interest, and I normalize to compute shares. I find that the EU, China/India, other importers, and Indonesia/Malaysia bear 1%, 18%, 79%, and 2% of the social costs of carbon.

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

Figure 6: Import tariffs



I simulate EU-led import tariffs of increasing intensity. I compute effects on total EU welfare and total palm abatement from 1988 to 2016, and I plot marginal welfare costs of abatement. Costs are in inflation-adjusted, year-2000 dollars per ton, and abatement is in gigatons of CO_2 equivalents. EU welfare includes consumer surplus, government revenue, and compensating transfers to other markets. Figure 6a shows long-run tariffs with coordination among all importers, an EU-China-India coalition, or the EU alone. Figure 6b shows coordinated tariffs with long-run commitment from 1988 to 2016 or shorter-run commitment from 1988 to 2011, 1988 to 2006, or 1988 to 2001.

the effectiveness of tariffs relies on coordination and commitment.

Figure 6a plots marginal abatement costs across levels of coordination, focusing on long-run tariffs. For a target marginal abatement cost of $25 per ton, an EU-China-India coalition achieves only 2.4 Gt of abatement with tariffs of 125%, and the EU itself only 0.5 Gt with tariffs of 50%. Larger tariffs increase abatement, but with marginal abatement costs that rise rapidly because of leakage. I also note that EU-China-India tariffs are somewhat less costly at low 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 6b plots marginal abatement costs across levels of commitment, focusing on coordinated tariffs. For medium-run tariffs upheld from 1988 to 2011, marginal abatement costs remain below $25 per ton until 4 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 shorter-run tariffs, abatement is much costlier. Tariffs upheld from 1988 to 2006 at 300% achieve 2.2 Gt of abatement at marginal cost of $50 per ton. Tariffs upheld from 1988 to 2001 at 350% achieve 1 Gt at $75 per ton. Forward-looking producers do not react strongly to short-run tariffs, and so these tariffs create welfare losses with little abatement. The initial fall in marginal costs is because small, short-run tariffs are even less effective at abatement, which raises marginal costs.

Comparing figures 6a and 6b, I highlight the importance of commitment. In particular, I find 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 marginal costs of $50, $75, and $100 per ton, while the latter achieves only 0 Gt, 1 Gt, and 1.2 Gt at the same costs. Even with full coordination across importers, short-run policy leads to little abatement. The 14-year period from 1988 to 2001 is not especially short, and less commitment yields even less abatement. Unilateral EU action may offer a more feasible route to long-run policy.

7.4 Export taxes

Export taxes also target traded consumption. They may appeal to Indonesia and Malaysia to 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 require monitoring individual mills and plantations, while export taxes only require enforcement at international ports. Moreover, export taxes achieve the same emission reductions as import tariffs, which also tax foreign consumption alone.[24] But government revenue goes to Indonesia and Malaysia rather than abroad.

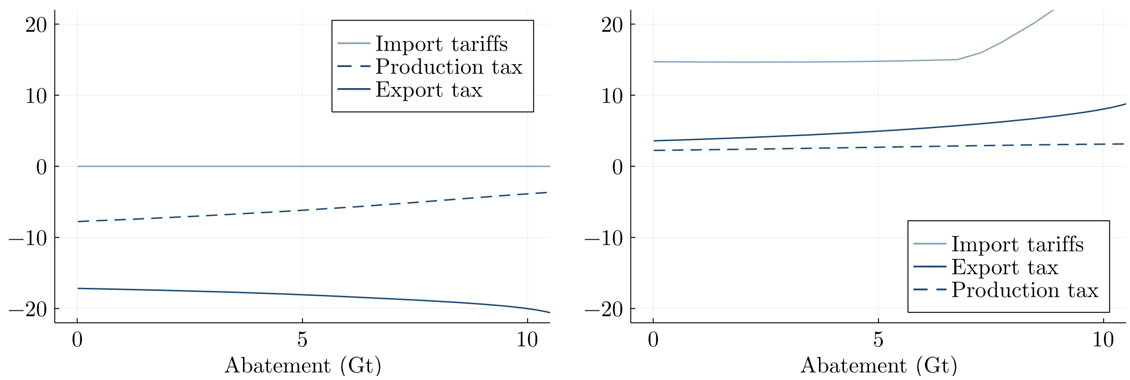
Figure 7a plots the marginal impacts of abatement on Indonesian and Malaysian welfare. I find that even high levels of abatement are welfare-enhancing, with welfare gains that grow larger – not smaller – with export taxes. High export taxes lead to low foreign consumption, which becomes increasingly inelastic as price-sensitive

[24] I compare export taxes by Indonesia and Malaysia to import tariffs by other markets. They are symmetric in targeting the same set of goods – those that leave Indonesia and Malaysia for world markets. They are not symmetric in the sense of Lerner (1936).

Figure 7: Export taxes

(a) Marginal abatement cost ($/t) to Indonesia/Malaysia welfare

(b) Marginal abatement cost ($/t) to European Union welfare



I simulate coordinated, long-run export taxes of increasing intensity by Indonesia and Malaysia. I compute effects on total welfare by market and total palm abatement from 1988 to 2016, and I plot marginal welfare costs of abatement. Costs are in inflation-adjusted, year-2000 dollars per ton, and abatement is in gigatons of CO_2 equivalents. I compare these costs to those under coordinated, long-run production taxes and coordinated, long-run import tariffs. Figure 7a shows Indonesian and Malaysian welfare, which includes consumer surplus, producer surplus, and government revenue. Figure 7b shows EU welfare, which includes consumer surplus and government revenue. Import tariffs additionally include compensating transfers from the EU to Indonesia and Malaysia.

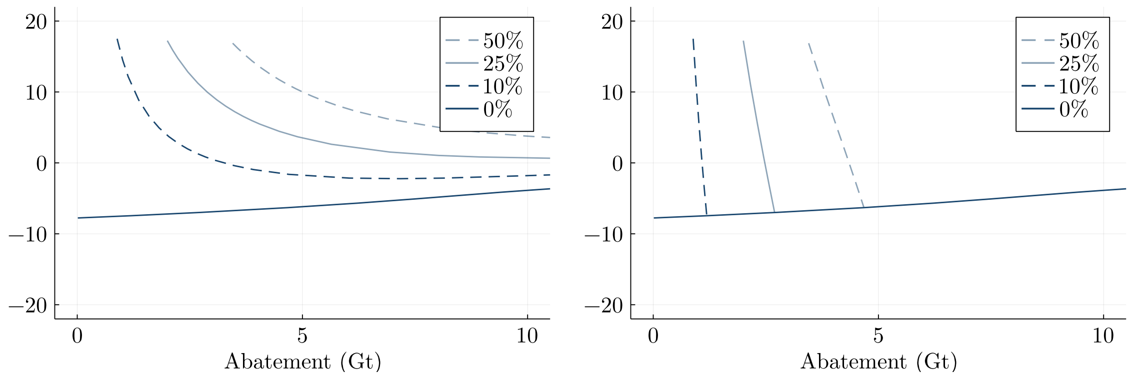
consumers exit. They also lead to high domestic consumption, which becomes increasingly elastic as domestic consumption reaches satiation. High export taxes thus shift the tax burden to foreign consumers, thereby reducing welfare costs for Indonesia and Malaysia. Export taxes are more appealing than production taxes, which are also welfare-enhancing given Indonesian and Malaysian market power, because export taxes avoid taxing domestic consumers. Import tariffs are least attractive, even with compensating transfers from the EU that offset welfare losses. Without these compensating transfers, import tariffs would be even less attractive.

Figure 7b illustrates the European perspective. Production taxes dominate export taxes, as Indonesian and Malaysian consumers share in the tax burden when production is taxed domestically. Export taxes thus imply larger losses for EU consumer surplus at all levels of abatement. But export taxes also dominate import tariffs, which call for large compensating transfers to other markets. The EU benefits from accepting Indonesian and Malaysian export taxes in place of EU-led import tariffs, even if export taxes are less effective than taxing production directly.

Figure 8: Carbon border adjustments

(a) Marginal abatement cost ($/t) to IM welfare without border adjustment

(b) Marginal abatement cost ($/t) to IM welfare with border adjustment



I simulate coordinated, long-run production taxes of increasing intensity by Indonesia and Malaysia. I compute effects on total Indonesian and Malaysian welfare and total palm abatement from 1988 to 2016, and I plot marginal welfare costs of abatement. Costs are in inflation-adjusted, year-2000 dollars per ton, and abatement is in gigatons of CO_2 equivalents. I study how these costs interact with coordinated, long-run import tariffs led by the EU, which I simulate at levels of 0%, 10%, 25%, and 50%. Indonesian and Malaysian welfare includes consumer surplus, producer surplus, and government revenue. It does not include compensating transfers from the EU. Figure 8a shows import tariffs that do not adjust with domestic regulation. Figure 8b shows a carbon border adjustment mechanism that combines import tariffs with credits for domestic regulation.

7.5 Carbon border adjustments

A concern is that import tariffs may crowd out domestic regulation. Figure 8a plots the marginal costs to Indonesian and Malaysian welfare of abatement with production taxes. Focusing on coordinated, long-run production taxes and coordinated, long-run import tariffs, the figure shows that production taxes are costlier in the presence of import tariffs. Absent import tariffs, Indonesia and Malaysia can exercise market power to draw tax revenue from foreign consumers. Welfare rises, even as emissions fall. With modest import tariffs of 25%, Indonesia and Malaysia experience welfare losses with production taxes at any level, as import tariffs push the tax burden onto domestic consumers. At the extreme, infinite tariffs eliminate imports and thus Indonesian and Malaysian influence in world markets. Production taxes become costlier as they fall solely on domestic consumers and producers.

A carbon border adjustment mechanism addresses this friction by combining import tariffs with credits for domestic regulation. Figure 8b shows that this mechanism restores Indonesian and Malaysian welfare gains from taxing production. Import tariffs fall as production taxes rise, maintaining Indonesian and Malaysian market power and thus the incentive to tax production. When taxing production at high levels, Indonesia and Malaysia are exempt from import tariffs, and so outcomes align with those absent import tariffs. An alternative mechanism would allow credits for export taxes, rather than domestic regulation. The story is similar to that of figure 8. The typical carbon border adjustment mechanism does not credit export taxes, which are not carbon taxes. But export taxes are less costly to EU welfare than import tariffs (figure 7b), and so the EU might consider such credits in this setting.

7.6 General lessons

Palm oil has important carbon implications. Average annual palm emissions were 1.5 Gt from 1988 to 2016, relative to 5.2 Gt for China, 5.0 Gt for the US, 3.4 Gt for the EU, and 1.2 Gt for India (figure 1). I find that a production tax of 50% would have reduced total emissions by up to 7.5 Gt over this period. By comparison, import tariffs of similar magnitude would have achieved up to 5.4 Gt – nearly five years of Indian emissions – at marginal abatement costs as low as $15 per ton, even accounting for transfers to ensure equity.

I discuss 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 71% of manufacturing GDP and 51% of agricultural GDP (World Bank 2023; WTO 2023b). Among fossil fuels, global exports range from 55% of crude oil production, to 28% for natural gas, to 14% for coal (EIA 2023). In the Amazon, Brazilian exports are 48% of soy production but only 14% for beef (USDA 2023).[25]

Second, a commitment problem arises from sunk emissions, which create static

[25] I compute export-to-production ratios covering the period from 1990 to 2018. From the World Bank, I obtain global GDP, as well as agricultural and service value added measures as a percentage of GDP. I then compute agricultural and manufacturing GDP, defining manufacturing as non-agricultural, non-service activity. From the WTO, I obtain global values of total and agricultural merchandise exports. I then compute the value of manufacturing exports as the difference between these measures. From the EIA, I obtain global volumes of fossil fuel production and exports. From the USDA, I obtain production and export volumes of cattle and soy for Brazil, pooling oilseed, oil, and meal by weight for soy.

incentives to deregulate. Without commitment, firms anticipate deregulation and proceed to emit. Committed trade policy can help, and indeed emissions are sunk in many sectors, including those accounting for the majority of traded emissions: agriculture, manufacturing, fossil fuels, mining, and transportation (Davis et al. 2011; Peters et al. 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.

Third, trade policy need not be punitive. Compensating transfers can ensure equity, recognizing the global good that targeted markets provide in curbing emissions. These transfers act as payment for ecosystem services at national scale. Moreover, targeted markets may have 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.

Nonetheless, trade policy faces several challenges. Direct regulation can tax palm oil in raw form, but trade policy encounters palm oil in many other forms. It should therefore target palm oil content, but this approach raises practical questions. 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, but there is no precedent in the cookie domain. Carbon border adjustment mechanisms face similar questions in assigning dollar values to domestic regulation. 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.

8 Conclusion

The conventional approach to environmental regulation focuses on domestic intervention, but domestic regulation can face major difficulties. Governments may prioritize local profits over global consequences or lack the capacity to enforce regulation. Trade policy offers the international community a set of tools to intervene when domestic policies fail. This paper develops a dynamic empirical framework to quantify the effects of such policy on emissions and welfare. I use it to evaluate EU tariffs on imports of palm oil, a major driver of deforestation and global emissions.

I find large scope to reduce emissions at low cost. Direct regulation with a production tax of 50% can reduce emissions by 7.5 Gt. Import tariffs of similar magnitude can reduce emissions by 5.4 Gt at a marginal abatement cost of $15 per ton, inclusive of compensating transfers to Indonesia and Malaysia as payment for ecosystem services. But to achieve these outcomes, EU import tariffs must be coordinated with other importers and upheld over the long run. Tariffs achieve little without coordination and commitment. These results underscore the significance of the Paris Agreement and the implications of US withdrawal. If tariff coalitions fail, unilateral EU action can still achieve 1 Gt of abatement at a marginal cost of $50 per ton. Alternatively, an export tax is net positive for Indonesia and Malaysia and reduces emissions as effectively as import tariffs. A carbon border adjustment mechanism combines both options.

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ONLINE APPENDIX

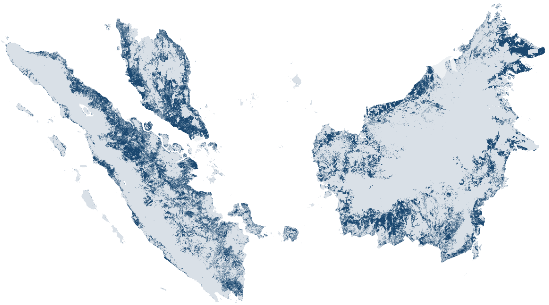
A Data

Table A1: Data sources

Source	Period	Coverage	Description
USDA Foreign Agricultural Service	1960-2019	World	Annual consumption, production, area harvested, imports, and exports by country and oilcrop
IMF, World Bank	1980-2019	World	Monthly prices by oilcrop
Global Meteorological Forcing Dataset	1980-2016	World	Daily precipitation and temperature, 28km resolution
Database of Global Administrative Areas	2018	World	GIS maps of administrative boundaries
Xu et al. (2020)	2001-2016	Indonesia, Malaysia	Palm oil plantations, 100m resolution
Song et al. (2018)	1982-2016	World	Land cover change, 5.6km resolution
WRI Universal Mill List	2018	Indonesia, Malaysia	List of mill coordinates
CIFOR mill list	2017	Indonesia	List of mill coordinates
Economic census	2016	Indonesia	Palm oil firms by village
Malaysian Palm Oil Board	2016	Malaysia	Palm oil mills by region
Google Earth	1987-2018	Indonesia	Historical satellite images of mill coordinates
WorldClim	1970-2000	World	Average monthly solar radiation and precipitation
World Bank INDO-DAPOER	1996-2010	Indonesia	Annual yields by province
Indonesian Ministry of Agriculture	2011-2017	Indonesia	Annual yields by province
Malaysian Palm Oil Board	1990-2018	Malaysia	Annual yields by state
World Port Index	2019	World	Port coordinates
Global Roads Inventory Project	2018	World	Road networks
Gumbricht et al. (2017)	2011	World	Peatlands and depth, 231m resolution
Zarin et al. (2016)	2000	World	Aboveground biomass, 30m resolution

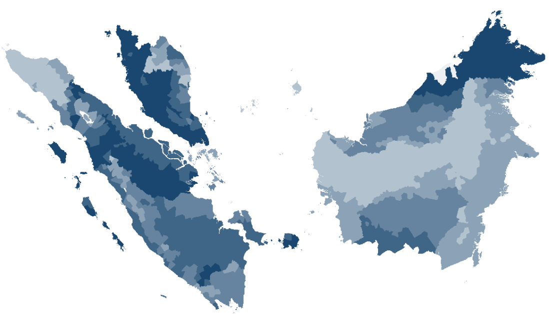
Figure A1: Plantations, mills, yields, and cost factors

(a) Plantations, 2016

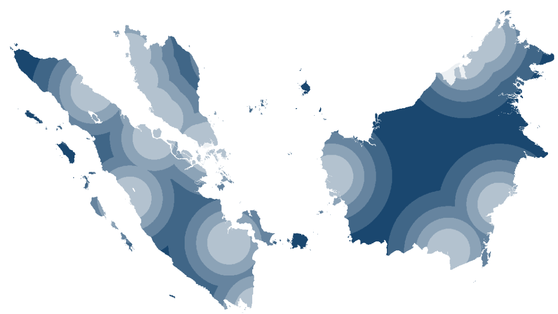


(b) Mills, 2016

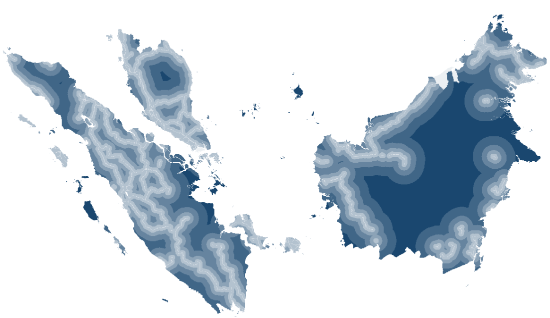
(c) Potential palm oil yields



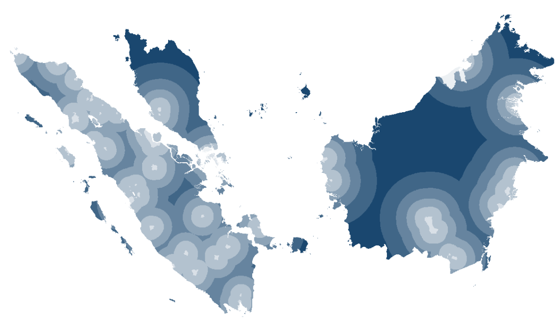
(d) Port distance



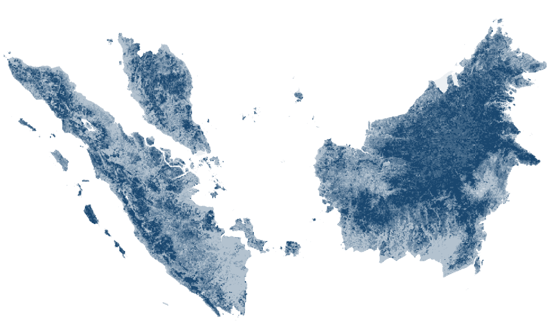
(e) Road distance



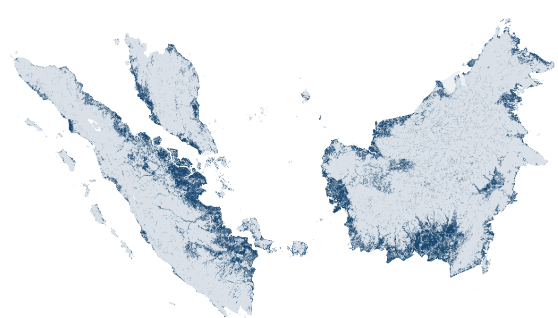
(f) Urban distance



(g) Carbon stocks, tree biomass



(h) Carbon stocks, peat deposits



I study Sumatra, Kalimantan, Peninsular Malaysia, and East Malaysia, which together total 134 Mha in surface area. Darker blue indicates higher yields, farther distances, and larger carbon stocks. Urban areas include administrative cities (Indonesia) and federal territories (Malaysia).

Table A2: Plantations vs. tree cover (2001-2016)

	ΔPlantation$_t$	ΔPlantation$_t$	ΔPlantation$_t$
ΔTree cover$_t$	-0.00314***	-0.00253***	-0.00261***
	(0.000156)	(0.000155)	(0.000153)
ΔTree cover$_{t-1}$	-0.00524***	-0.00441***	-0.00435***
	(0.000192)	(0.000191)	(0.000190)
ΔTree cover$_{t-2}$	-0.00102***	0.000203	0.000414**
	(0.000194)	(0.000193)	(0.000193)
ΔTree cover$_{t-3}$	-0.000672***	6.42e-05	7.27e-05
	(0.000162)	(0.000161)	(0.000160)
Year FE	x	x	x
District FE		x	
Tile FE			x
Observations	9,098,040	9,098,040	9,098,040

Each column is a regression, and each observation is a tile-year. I regress plantation development on tree canopy cover. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Plantations and mills

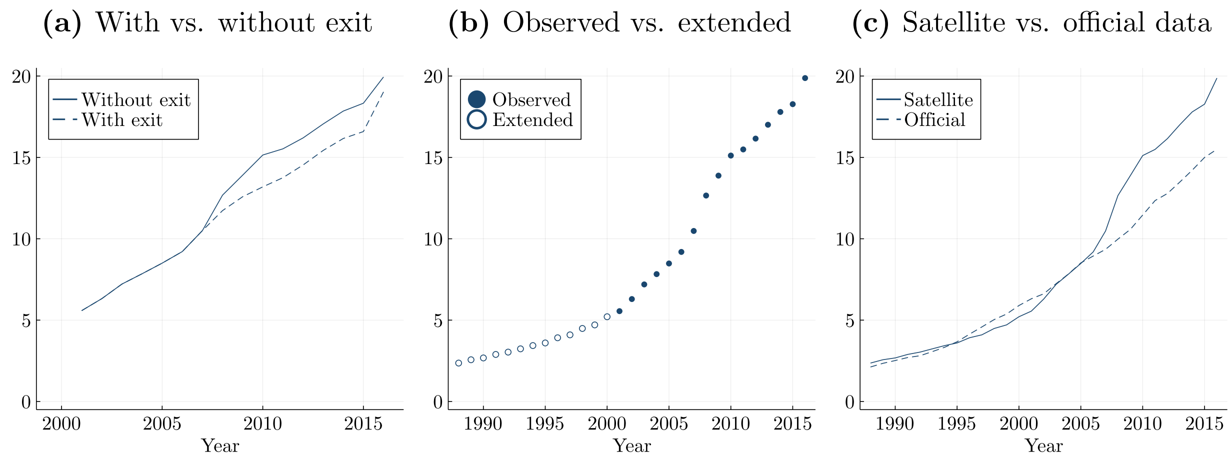
Spatial panel data on palm oil plantations from 2001 to 2016 come from Xu et al. (2020), who construct the data at 100m resolution from Phased Array type L-band Synthetic Aperture Radar (PALSAR), PALSAR-2, and Moderate Resolution Imaging Spectroradiometer (MODIS) satellite imagery. The data measure how much of each tile is covered by palm oil plantations, inclusive of both young and mature as well as industrial and smallholder plantations. I use midpoints of the upper and lower bounds in years where bounds are provided, and point estimates otherwise. I aggregate the data to 1km resolution by averaging. As discussed in Xu et al. (2020), I impose that development is uni-directional, such that plantation area for each tile is non-decreasing over time. Xu et al. (2020) restrict their attention to Sumatra, Kalimantan, Peninsular Malaysia, and East Malaysia, and I do the same in my analysis. These regions cover virtually all palm production in Indonesia and Malaysia during the study period.

I extend the plantations data back to 1988 using data on tree canopy cover from Song et al. (2018), who analyze satellite imagery from the Advanced Very High Resolution Radiometer (AVHRR), MODIS, and Landsat Enhanced Thematic Mapper Plus (ETM+). These data extend from 1982 to 2016, overlapping the Xu et al. (2020) data from 2001 to 2016. Focusing on tiles that the Xu et al. (2020) data identify as having plantations, I estimate the empirical relationship between plantation development and tree cover loss during the period of overlap, and I use these estimates to impute plantations prior to 2001. For tiles i in years t,

$$\Delta\text{Plantation}_{it} = \sum_{s=0}^{3} \beta_s \Delta\text{Tree cover}_{it-s} + \varepsilon_{it} \,,$$

where $\Delta\text{Plantation}_{it}$ is new plantation development and $\Delta\text{Tree cover}_{it-s}$ terms are tree cover loss in preceeding years. The Song et al. (2018) data are at 5.6km resolution, so I downscale them to match the 1km resolution of the aggregated Xu et al. (2020) data. Table A2 shows the resulting estimates. Significant, negative coefficients indicate that tree cover loss, especially in the preceeding

Figure A2: Total plantations (Mha)



The left figure imposes no exit, the middle figure extends the plantation data using tree cover data, and the right figure shows official aggregate data. Plantation area is in megahectares.

two years, is predictive of plantation development. I take third column, which includes tile fixed effects, as my preferred specification. For each tile, I combine predicted plantation development with observed levels in 2001 to impute pre-2001 plantations, imposing a minimum of zero for plantation development. The downscaling of the coarser Song et al. (2018) implies that the imputed data should not be analyzed below 5.6km resolution, and indeed my core analysis analyzes aggregated sites and not individual tiles.

Figure A2 plots the resulting data. First, imposing uni-directional development rules out exit. Limited exit makes this assumption reasonable: Xu et al. (2020) measure cumulative exit of 5% between 2007 and 2016, noting that exit can include misclassified oil palm. Second, the tree cover data imply a reasonable pattern of plantation development pre-2001. Third, I verify the quality of the satellite data, both observed and imputed, by comparing them to aggregate figures from government statistics. The data match well, although the satellite data reveals modestly higher levels of plantation development in later years.

Spatial data on palm oil mills come from the 2018 Universal Mill List (UML), a joint effort led by the World Resources Institute and Rainforest Alliance that collects data from palm oil processors, traders, corporate consumers, and NGOs. Mills are geocoded and manually verified by satellite. I combine these data with the 2017 Center for International Forestry Research (CIFOR) database, an independent effort that combs traceability reports for major palm oil processors and also verifies coordinates manually by satellite. I merge the datasets spatially, matching mills within one kilometer of each other, and I validate mills with Landsat and DigitalGlobe satellite images from Google Earth by identifying nearby plantations, storage tanks, and effluent ponds. I omit mills in Java, which houses refineries and administrative offices but few plantations. I correct coordinates where necessary, and I use historical satellite images from Google Earth to identify mills constructed by 2016.

In this way, I identify 1,521 mills in 2016. I verify the data by comparing them to official government data from the Indonesian economic census and Malaysian Palm Oil Board. The 2016 Indonesian economic census contains 1,248 palm-oil establishments, of which 1,154 are located outside of Java. Focusing on firms involved in extracting crude oil from crops, I obtain 1,070 firms

Table A3: Mill counts by region (2016)

	Mill data	Government figures
Indonesia	1,050	1,070
Sumatra	693	773
Kalimantan	328	260
Sulawesi, Papua	29	37
Malaysia	471	453
Peninsular Malaysia	266	247
East Malaysia	205	206
Total	1,521	1,523

Government figures come from the Indonesian census and the Malaysian Palm Oil Board.

that produce either crude palm or palm kernel oil (KBLI codes 10431 and 10432, respectively). Table A3 shows that the total number of mills matches well, as does the overall spatial distribution. Discrepancies in regional counts are concentrated in the Indonesian data, where the census often records firm locations based on administrative offices and not milling facilities. From here, I drop the small set of mills in Sulawesi and Papua, which the plantation data do not capture.

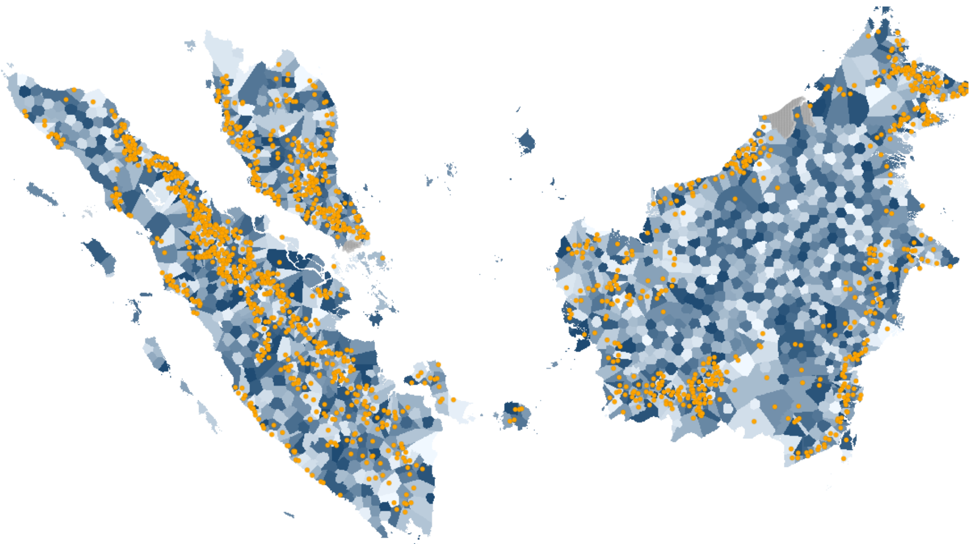
Sites

To divide land into sites, I first compute the maximum number of sites $\bar{k}$ for each province: $\bar{k} = \max\{\text{floor(area/521)}, \text{number of observed mills}\}$. I use a benchmark site size of 521 km^2, which I obtain as the average of three calculations. First, I consider provinces with high mill density in 2016, the last year of the study period. Among provinces, the density at the 75th percentile is one mill per 455 km^2. Second, I consider provinces without mill construction between 2011 and 2016, reflecting plateaued expansion. The median such province has one site per 553 km^2. These two methods imagine bringing site density for all provinces to the level of the most developed provinces. A third method considers circular sites that reflect the upper end of plantation-mill distances observed in the data. For each province, I compute the average distance between plantations and their closest mills in 2016. Among provinces, the distance at the 75th percentile implies radii of 13.3 km and site sizes of 553 km^2.

Second, I define sites by k-means clustering on geographic coordinates. I ensure consistency with the plantations and mills observed in 2016 by imposing (1) that observed mills be assigned to unique sites and (2) that observed plantations be clustered with observed mills. I do so with a version of the constrained k-means clustering algorithm described in Wagstaff et al. (2001), and I apply multiple starts because convergence is to local optima.

1. Choose initial cluster centers $C_1, C_2, \ldots, C_k$.
2. For the m mills observed in the data, move the m closest centers to the mill coordinates.
3. Assign points to the nearest cluster centers.
4. Update each cluster center by averaging over the points assigned to it.
5. Repeat (2) to (4) until convergence.
6. For clusters without mills but with at least 10 km^2 of plantations, reassign all points to nearest clusters with mills.

Figure A3: Potential sites



Blue shading indicates different potential sites. Orange dots are palm oil mills observed by 2016.

Step (2) ensures consistency with observed mills, and step (6) with observed plantations. Figure A3 maps the resulting 2,050 potential sites.

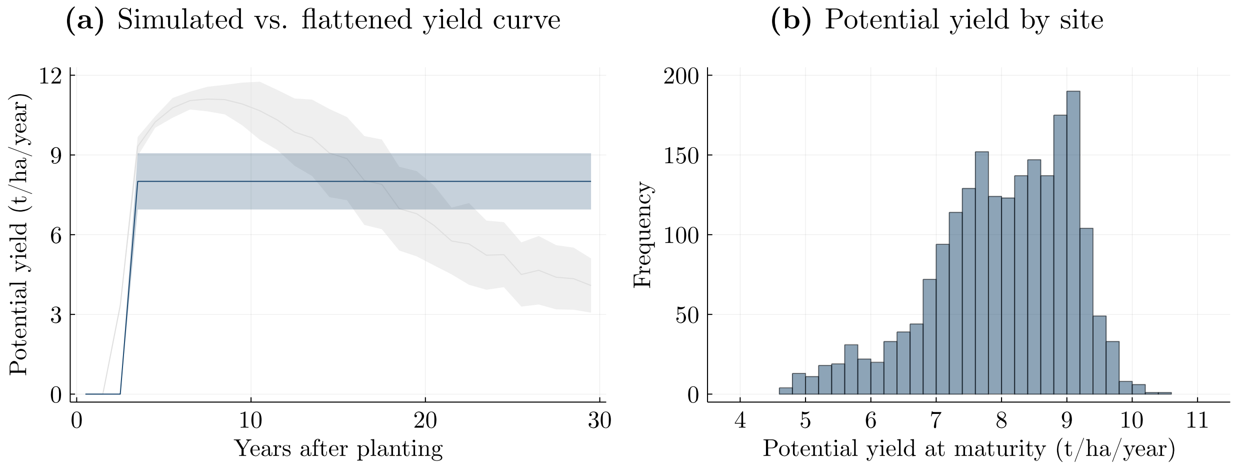
I overlay plantations and mills with the site boundaries to construct a panel of palm oil investment by site and year. From the panel data on plantations, I compute plantation area for each site, and I define plantation development as the change in area each year. From the cross-sectional data on mills, I define mill construction as the first year in which I observe meaningful plantations. I define the cutoff for "meaningful" to be 413 hectares, which I choose so that average plantation development in the year of mill construction is equal to average plantation development in the years after mill construction. A cutoff of zero hectares would yield little variation on the extensive margin, as measurement error in the satellite data and classification error in clustering sites each place small patches of plantations on most sites, even in early years. From here, I lightly harmonize by dropping plantations with mills and dropping mills without plantations. In doing so, I drop 0.4% of plantations and 1% of mills observed in 2016.

Yields

I construct site-level data on palm oil yields over time, combining site-level data on potential yields from the PALMSIM model of Hoffmann et al. (2014) with province-level data on actual yields over time from government statistics.

First, I compute potential yields by site using the agronomic PALMSIM model of Hoffmann et al. (2014), which predicts yields under optimal growing conditions as a function of climate. As inputs, I use average monthly solar radiation and precipitation from WorldClim, which measures these variables at 1km resolution. To facilitate computation, I aggregate climate inputs and run the PALMSIM model by site. Figure A4a shows the resulting 30-year yield curve, which starts at zero before increasing steeply then declining gradually. Because the data on actual yields distinguish only between "immature" and "mature" crops, I flatten the curve to these levels while fixing average yields over time. Figure A4b plots these flattened yields at maturity. The yields are time-invariant because yields under optimal conditions are an inherent characteristic of the oil palm plant.

Figure A4: Potential palm oil yields



Yield curves are computed from the PALMSIM model (Hoffmann et al. 2014) using site-level average monthly solar radiation and precipitation from WorldClim. On the left, the gray curve shows the average output of the PALMSIM model, and the navy blue line flattens the curve to two levels – "immature" (zero-yield) and "mature" – while maintaining the same average over time. Shaded areas show standard deviations. On the right, I show the dispersion of (flattened) mature yields across sites. Yields are in tons per hectare per year.

Second, I compile data on actual yields by province and year from government statistics, namely the Indonesian Ministry of Agriculture, the World Bank INDO-DAPOER database (via the Indonesian Ministry of Agriculture), and the Malaysian Palm Oil Board. Each reports yields for mature crops, omitting immature crops that do not yet produce fruit. Figure A5a shows that, on average, actual yields are increasing over time as technology improves, although they fall far short of potential yields in all provinces and years. Crop age mix also affects yields over time, but two effects are potentially offsetting: young crops approaching their peak have increasing yields, while aging crops past their peak have decreasing yields. Across provinces and years, the average observed annual yield per hectare is 3.30 tons.

Lastly, I combine these data to compute actual yields y_{it} by site i and year t. I assume that y_{it} combines yield gaps γ_{mt} and potential yields y_i^p, where yield gaps are fixed across sites within a given province m and year t.

$$y_{it} = (1 - \gamma_{mt}) y_i^p \tag{11}$$

I observe actual yields y_{mt} by province-year, which aggregate over site-years as follows.

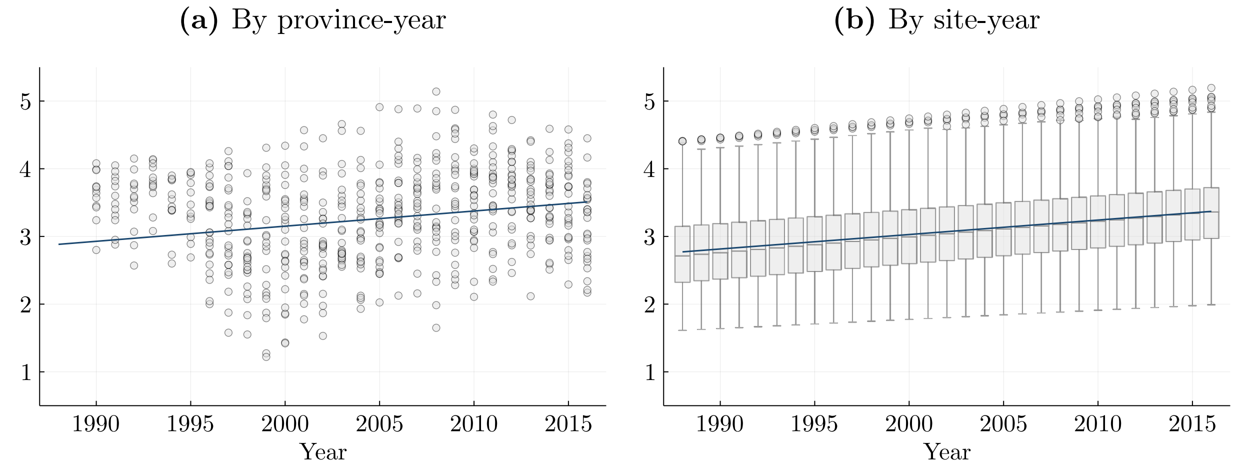
$$y_{mt} = \frac{\sum_{i \in \mathcal{I}_m} y_{it} N_{it}}{\sum_{i \in \mathcal{I}_m} N_{it}}$$

for plantation acreage N_{it}. I substitute equation 11 and rearrange to obtain yield gaps γ_{mt}.

$$\gamma_{mt} = 1 - y_{mt} \left(\frac{\sum_{i \in \mathcal{I}_m} y_i^p N_{it}}{\sum_{i \in \mathcal{I}_m} N_{it}} \right)^{-1}$$

Thus, I can compute yield gaps as a function of observed quantities: actual yields y_{mt}, potential yields y_i^p, and plantation acreage N_{it}. I then isolate the underlying levels and trends of these yield

Figure A5: Actual palm oil yields (t/ha/year)



The left figure shows annual yields by province (Indonesia) or state (Malaysia) as recorded in government statistics. The right figure shows annual yields by site as computed with potential yields by site from PALMSIM and actual yields by province from government statistics. Yields are in tons per hectare per year.

gaps with the specification

$$\gamma_{mt} = \alpha_m + \beta t + \varepsilon_{mt} \,,$$

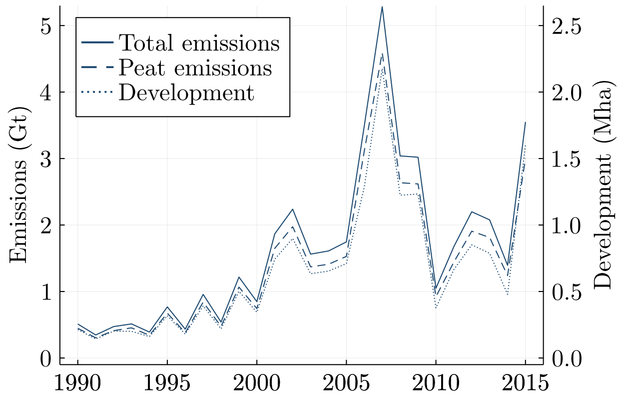
which also allows me to extrapolate back to 1988 and beyond 2016. I compute fitted values and substitute into equation 11 to obtain actual yields y_{it} by site-year. Figure A5b shows the resulting estimates, which combine the uptrend of figure A5a with the site-level dispersion of figure A4b.

Carbon stocks

I compute carbon stocks over space using two datasets, which I aggregate to 1km resolution: Zarin et al. (2016) measures aboveground tree biomass at 30m resolution, and Gumbricht et al. (2017) measures belowground peat biomass at 231m resolution. Plantation development releases both. To convert aboveground biomass to carbon, I use a biomass-to-carbon conversation factor of 0.5. To convert belowground biomass, I use the conversation factor of 65.1 kg C/m^3 peat in Warren et al. (2017). I convert carbon to carbon dioxide emissions with a molecular-weight conversion factor of 3.67. I focus on CO_2 emissions because the carbon content of peatlands is well documented and because they account for 73% of total greenhouse gas emissions during the study period. Palm oil production also involves the release of methane and nitrous oxide, but precise estimates of these emissions are not yet well established.

I treat carbon stocks as predetermined, but they are not measured before the study period. Tree biomass is measured for the year 2000, and peat deposits for 2011. The data may therefore miss carbon stocks destroyed before these years. For tree biomass, I impute 1988 values by combining the 2000 values with the proportion of tree cover loss between 1988 and 2000, as measured in the Song et al. (2018) data. For peat deposits, bias is limited because Gumbricht et al. (2017) rely primarily on precipitation and topography – predetermined features – to identify wetlands as areas where water is likely to pool because precipitation exceeds evapotranspiration. MODIS satellite imagery from 2011 then allow the authors to distinguish between different kinds of wetlands. Indeed, figure A6 shows that the relationship between plantation development and the resulting emissions is

Figure A6: Plantation development vs. emissions



Emissions are in gigatons of CO_2 equivalents, and plantation development area is in megahectares.

consistent over time. If the data missed peatlands destroyed before 2011, then peatland emissions would be much smaller for plantation development before 2011.

Weather shocks to vegetable oil production

Weather data come from the Global Meteorological Forcing Dataset, which records daily rainfall and average surface temperature from 1988 to 2016 at 0.25° resolution. I use these data to construct annual measures of weather shocks to the production of coconut, olive, palm, rapeseed, soybean, and sunflower oils over the study period. I omit cottonseed and peanut oils given a lack of price data and relatively small volumes at 5% of vegetable oil consumption volume in 2016.

First, I isolate day-tile observations within oil-producing regions and during the growing season. I define oil-producing regions as countries that account for at least 5% of world production for any of the aforementioned oils during the study period, as measured by data from the USDA Foreign Agricultural Service. Table A4 lists these countries for each oil (aggregating EU countries). For Argentina, Brazil, Canada, China, India, Indonesia, Malaysia, Russia, and the United States, I further consider subnational regions – namely states and provinces – using data from both the USDA and local government sources. I define the growing season for rapeseed, soybean, and sunflower oils to be those specified by country-specific crop calendars from the USDA, and I take the growing season for coconut, olive, and palm oils to be year-round.

Second, I compute crop-specific weather shocks at the year-tile level. For rainfall, I first aggregate from daily to monthly values for each tile, as daily variation in rainfall is not detrimental to crop growth in the same way that daily variation in temperatures can be. I then compute shocks as absolute deviations from optimal levels for each crop. The FAO Crop Ecological Requirements Database records optimal windows by crop for both rainfall and temperature, and I take the midpoint of these windows as optimal levels. The FAO database specifies optimal annual rainfall, which I divide by twelve to obtain optimal monthly rainfall. Having computed monthly deviations from optimal levels for rainfall, as well as daily deviations for temperature, I aggregate over time to obtain average deviations by year for each tile.

Third, I aggregate to obtain annual weather shocks by vegetable oil. I average over tiles for each oil-producing region, then average across oil-producing regions for each oil in proportion

Table A4: Oil producers

Oil	Producers
Coconut	Philippines 52%, Indonesia 33%, India 15%
Olive	EU 86%, Tunisia 8%, Turkey 6%
Palm	Indonesia 49%, Malaysia 45%, Nigeria 6%
Rapeseed	EU 36%, China 27%, Canada 23%, India 14%
Soybean	US 44%, Brazil 29%, Argentina 18%, China 8%
Sunflower	EU 29%, Russia 23%, Ukraine 23%, Argentina 17%, China 8%

Each row sums to 100% and covers 1988 to 2016. I omit producers below 5% of world production.

to production volumes. I weight by total production over the study period rather than annual production, as annual production is a direct function of annual weather.

B Demand

Table B1 shows that weather shocks increase world vegetable oil prices in the first stage. The first two columns pool across oil products, and the last two consider palm and other oils separately. The instruments remain strong for palm oil despite a smaller sample size, although imprecise temperature estimates reflect limited temperature variation in the palm-producing tropics. Table B2 shows that weather shocks do not have domestic income or expenditure effects, which would violate the exclusion restriction by influencing demand beyond the price channel. These results also provide reassurance that the instruments do not simply capture idiosyncratic fluctuations in macroeconomic conditions. Table B3 shows that own-price elasticities for other oils are similar to those for palm oil. Elasticities for other oils are more precisely estimated for the EU, China, India, and other importers, where observed consumption of other oils is high. They are much less precisely estimated for Indonesia and Malaysia, where observed consumption of other oils is particularly low.

I take a static approach to estimating demand, which can lead to bias in either direction. I underestimate price elasticities if substitution involves slow transitions. In this case, consumers respond to price changes with a delay or in anticipation, such that contemporaneous responses are attenuated. However, table B3 finds limited evidence for such effects. I apply price lags and leads, and I obtain similar estimates across specifications. At the same time, I overestimate price elasticities if consumers engage in stockpiling. In this case, consumers stockpile when prices fall temporarily, such that short-run responses are exaggerated. However, data from the USDA Foreign Agricultural Service show that stockpiling is limited, with average stockpiles at only 12% of consumption by volume, relative to 342% and 188% in other contexts (Erdem et al. 2003; Hendel and Nevo 2006). These studies document weekly, individual-level stockpiling, but this behavior aggregates out in my annual, national-level measures of consumption.

Table B1: Weather shocks as price instruments

	All	All	Palm	Other
Rainfall shocks (100 mm)	0.208***	0.212***	0.139***	0.224***
	(0.0317)	(0.0278)	(0.0325)	(0.0318)
Temperature shocks (°C)	0.297***	0.308***	0.681	0.315***
	(0.0335)	(0.0315)	(0.804)	(0.0334)
Oil FE	x	x		
Oil-year trend		x		
Year trend			x	x
Observations	174	174	29	145
F-statistic	40.94	49.25	10.56	48.90

Each column is a regression, and the outcome variable is log prices. Annual data cover coconut, olive, palm, rapeseed, soybean, and sunflower oils from 1988 to 2016. Weather shocks are absolute deviations from optimal conditions during the growing season, aggregated over producing provinces and states. Oil fixed effects and oil-specific time trends differentiate between palm and other oils. Newey-West standard errors account for serial correlation. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table B2: Weather shocks vs. incomes and expenditures

		Rainfall		Temperature		
Market	Outcome	Estimate	SE	Estimate	SE	Obs
European Union	CPI	0.00362	(0.00275)	0.00264	(0.00245)	174
	GDP	0.00530	(0.00762)	0.00408	(0.00736)	174
	GDE	0.00587	(0.00783)	0.00437	(0.00748)	174
China/India	CPI	0.00632	(0.0109)	0.00346	(0.0113)	174
	GDP	8.10e-05	(0.0103)	-0.00344	(0.00986)	174
	GDE	-0.00163	(0.00969)	-0.00434	(0.00922)	174
Other importers	CPI	0.00571	(0.00776)	0.000995	(0.00787)	174
	GDP	0.00360	(0.00448)	0.00180	(0.00411)	174
	GDE	0.00429	(0.00415)	0.00235	(0.00373)	174
Indonesia/Malaysia	CPI	-0.0231	(0.0246)	-0.0221	(0.0242)	174
	GDP	0.0113	(0.0154)	0.00539	(0.0157)	174
	GDE	0.00920	(0.0147)	0.00424	(0.0152)	174

Each row is a regression. Annual data cover coconut, olive, palm, rapeseed, soybean, and sunflower oils from 1988 to 2016. For outcome variables, GDPs and GDEs are in logs, and CPIs aggregate national data weighted by household GDE. Weather shocks are absolute deviations from optimal conditions during the growing season, aggregated over producing regions. Oil fixed effects and oil-specific time trends differentiate between palm and other oils. Newey-West standard errors account for serial correlation. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table B3: Demand elasticities for other oils

	Palm		Other	
	Estimate	SE	Estimate	SE
European Union	-0.721***	(0.210)	-0.943***	(0.024)
China/India	-0.697***	(0.167)	-0.870***	(0.043)
Other importers	-0.876***	(0.130)	-0.890***	(0.037)
Indonesia/Malaysia	-0.925***	(0.046)	-0.525*	(0.309)

Each pair of columns shows own-price elasticities by consumer market. I report elasticities of total consumption with respect to a 1% increase in prices during the study period. Other oils aggregate over non-palm vegetable oils. Demand estimation draws on annual data covering coconut, olive, palm, rapeseed, soybean, and sunflower oils from 1988 to 2016. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table B4: Demand elasticities with price lags and leads

Price lags	None		One-year		Two-year		Three-year	
	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE
European Union	-0.721***	(0.210)	-0.570**	(0.249)	-0.545**	(0.239)	-0.499*	(0.265)
China/India	-0.697***	(0.167)	-0.659***	(0.158)	-0.791***	(0.108)	-0.734***	(0.101)
Other importers	-0.876***	(0.130)	-0.789***	(0.134)	-0.765***	(0.134)	-0.763***	(0.151)
Indonesia/Malaysia	-0.925***	(0.046)	-0.948***	(0.040)	-0.949***	(0.033)	-0.964***	(0.032)
Price leads	None		One-year		Two-year		Three-year	
	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE
European Union	-0.721***	(0.210)	-0.843***	(0.170)	-0.871***	(0.191)	-0.848***	(0.187)
China/India	-0.697***	(0.167)	-0.649***	(0.171)	-0.726***	(0.179)	-0.732***	(0.222)
Other importers	-0.876***	(0.130)	-0.886***	(0.120)	-0.856***	(0.140)	-0.813***	(0.150)
Indonesia/Malaysia	-0.925***	(0.046)	-0.940***	(0.052)	-0.937***	(0.047)	-0.989***	(0.033)

Each pair of columns shows own-price elasticities for palm oil by consumer market. I compute elasticities of total consumption with respect to a 5% increase in prices during the study period. The top and bottom panels include price lags and leads of zero, one, two, and three years. Demand estimation draws on annual data covering coconut, olive, palm, rapeseed, soybean, and sunflower oils from 1988 to 2016, and it instruments for prices with weather shocks to vegetable oil production. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

C Supply

Model

Figure C1 illustrates the model timeline. I define choice-specific conditional value functions

$$\bar{v}(0, s_{it}) = \beta \mathbb{E}[\bar{V}(s_{it+1}) \,|\, s_{it}] \,, \tag{12a}$$

$$\bar{v}(1, s_{it}) = -\bar{c}(s_{it}) + V(0, s_{it}) \,. \tag{12b}$$

To lighten notation, I denote arguments with subscripts for the rest of this section. By the logit shocks of equation 4, mill construction probabilities are

$$\pi_{it} = \frac{\exp[\bar{v}_{it}(1)]}{\exp[\bar{v}_{it}(0)] + \exp[\bar{v}_{it}(1)]} \,, \tag{13}$$

and expected utility is given by the log-sum formula

$$\bar{V}_{it} = \ln\{\exp[\bar{v}_{it}(0)] + \exp[\bar{v}_{it}(1)]\} = \bar{v}_{it}(1) - \ln \pi_{it} \,. \tag{14}$$

Arcidiacono and Ellickson (2011) document this expression as the logit special case of Arcidiacono and Miller (2011) Lemma 1. For linear revenue function r_{it}, I can rewrite equation 5 as

$$V_{it}(N_{it}) = \alpha p_t y_{it} N_{it} + \mathbb{E}_{it}\left[\max_{n_{it}} \left\{ - c_{it}(n_{it}) + \sum_{s=3}^{T-t} \alpha \beta^s p_{t+s} y_{it+s} n_{it} \right\} + \beta V_{it+1}(N_{it}) \right]. \tag{15}$$

I express flow revenues for new development n_{it} as a net present value, while keeping revenues for mature plantations N_{it} in recursive form. For quadratic cost function c_{it}, the first-order condition gives plantation development

$$n_{it} = \frac{1}{\psi}\left(- \gamma_g^0 - \gamma_g^1 t - x_i \delta - \varepsilon_{it} + \sum_{s=3}^{T-t} \alpha \beta^s \mathbb{E}_{it}[p_{t+s} y_{it+s}] \right). \tag{16}$$

Substituting back into equation 15, I obtain

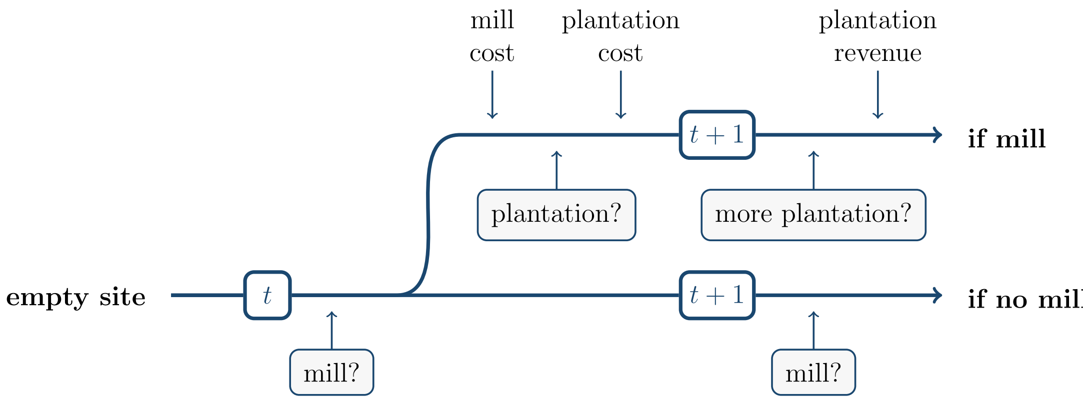
$$V_{it}(0) = \frac{1}{2}\psi n_{it}^2 + \beta \mathbb{E}_{it}[V_{it+1}(0)] = \sum_{s=0}^{T-t} \beta^s \mathbb{E}_{it}\left[\frac{1}{2} \psi n_{it+s}^2 \right]. \tag{17}$$

Production

I can compute production by site from supply parameters $\{\alpha, \gamma_g^0, \gamma_g^1, \delta\}$ and states $\{s_{i1}, \ldots, s_{iT}\}$. First, I calculate mill construction probabilities and plantation development $\{\pi_{it}, n_{it}\}$.

1. Compute $\{n_{i1}, \ldots, n_{iT}\}$ with equation 16.
2. Compute $\{V_{i1}(0), \ldots, V_{iT}(0)\}$ with equation 17.
3. Compute $\{\bar{v}_{i1}(1), \ldots, \bar{v}_{iT}(1)\}$ with equation 12b.
4. Compute $\{\pi_{i1}, \ldots, \pi_{iT}\}$ backward from terminal year T. In year T, $\bar{v}_{iT}(0) = 0$ by normalization, and π_{iT} follows from equation 13. In prior years, $\bar{v}_{it}(0) = \beta \mathbb{E}_{it}[\bar{v}_{it+1}(1) - \ln \pi_{it+1}]$ by equations 12a and 14, and π_{it} again follows from equation 13.

Figure C1: Supply model timeline



An empty site makes a binary choice over whether to construct a mill. If not, then the site faces the same choice next year. 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.

Second, I calculate expected mill stocks and plantation acreage $\{\hat{M}_{it}, \hat{N}_{it}\}$.

$$\hat{M}_{it+1} = \hat{M}_{it} + (1 - \hat{M}_{it})\pi_{it}\,, \quad \hat{N}_{it+3} = \hat{N}_{it} + \hat{M}_{it+1}n_{it}\,, \tag{18}$$

where initial conditions $\{M_{i1}, N_{i1}\}$ are as observed in the data. For sites that contain a mill initially, $M_{i1} = 1$ implies $\pi_{it} = 0$ and thus $\hat{M}_{it} = 1$. For other sites, I obtain expected mill investment $\hat{M}_{it} \in [0, 1)$ as a function of investment probabilities π_{it}. These expected values are continuous, unlike the binary observed values of mill stocks $M_{it} \in \{0, 1\}$, and I sum over sites to compute aggregate production in each year. As in Hopenhayn (1992), atomistic firms and the law of large numbers imply that realized production is given simply by expected production, which equations 18 deliver in closed form. Without atomistic firms, calculating realized production is more computationally intensive. It requires simulating discrete realizations of mill construction choices m_{it} with choice probabilities π_{it}, then integrating over the distribution of potential realizations.

Estimation

I derive regression equations for estimating the supply model. On the intensive margin, differentiating equation 5 gives first-order conditions for plantation development (n_{it}, n_{it+1}).

$$[n_{it}] \quad \frac{\partial c_{it}}{\partial n_{it}} = \beta^3 \mathbb{E}_{it}\left[\frac{\partial r_{it+3}}{\partial n_{it}}\right] + \beta^4 \mathbb{E}_{it}\left[\frac{\partial V_{it+4}}{\partial n_{it}}\right], \qquad [n_{it+1}] \quad \beta \mathbb{E}_{it}\left[\frac{\partial c_{it+1}}{\partial n_{it+1}}\right] = \beta^4 \mathbb{E}_{it}\left[\frac{\partial V_{it+4}}{\partial n_{it+1}}\right].$$

By the envelope theorem, impacts on future actions are negligible. Differencing gives Euler equation

$$\frac{\partial c_{it}}{\partial n_{it}} - \beta \mathbb{E}_{it}\left[\frac{\partial c_{it+1}}{\partial n_{it+1}}\right] = \beta^3 \mathbb{E}_{it}\left[\frac{\partial r_{it+3}}{\partial n_{it}}\right],$$

which compares payoffs of plantation development in year t relative to year $t+1$. Specializing with r_{it} and c_{it}, the difference in revenues is $\mathbb{E}_{it}[\frac{\partial r_{it+3}}{\partial n_{it}}] = \alpha \mathbb{E}_{it}[p_{t+3} y_{it+3}]$. The difference in costs is

$$\frac{\partial c_{it}}{\partial n_{it}} - \beta \mathbb{E}_{it}\left[\frac{\partial c_{it+1}}{\partial n_{it+1}}\right] = (1-\beta)(\gamma_g^0 + \gamma_g^1 t + x_i\delta) - \beta\gamma_g^1 + \psi n_{it} + \varepsilon_{it} - \beta \mathbb{E}_{it}[\psi n_{it+1} - \varepsilon_{it+1}]\,.$$

Defining structural error $\mu_{it} = -\frac{1}{\psi}\varepsilon_{it} + \frac{\beta}{\psi}\varepsilon_{it+1}$ and expectational error

$$\eta_{it} = \mathbb{E}_{it}\left[\beta n_{it+1} + \frac{\alpha\beta^3}{\psi}p_{t+3}y_{it+3} + \frac{\beta}{\psi}\varepsilon_{it+1}\right] - \beta n_{it+1} - \frac{\alpha\beta^3}{\psi}p_{t+3}y_{it+3} - \frac{\beta}{\psi}\varepsilon_{it+1}\,,$$

I substitute and rewrite to obtain regression equation 9.

On the extensive margin, $\bar{v}_{it}(1) = -\bar{c}_{it} + V_{it}(0)$ by definition, and $\bar{v}_{it}(0) = \beta\mathbb{E}_{it}[\bar{v}_{it+1}(1) - \ln\pi_{it+1}]$ by equations 12a and 14. Inverting equation 13 and substituting gives

$$\begin{aligned}\ln\pi_{it} - \ln(1-\pi_{it}) &= \bar{v}_{it}(1) - \bar{v}_{it}(0)\\ &= -\bar{c}_{it} + V_{it}(0) + \beta\mathbb{E}_{it}[\bar{c}_{it+1} - V_{it+1}(0) + \ln\pi_{it+1}]\,,\end{aligned}$$

which compares payoffs of mill construction in year t relative to year $t+1$. Specializing with r_{it}, c_{it}, and $\bar{c}_{it}$, the difference in revenues is $V_{it}(0) - \beta\mathbb{E}_{it}[V_{it+1}(0)] = \frac{1}{2}\psi n_{it}^2$ by equation 17. The linear separability of equation 17 admits a finite-dependence argument, as the only gain from mill construction in year t relative to $t+1$ is the flow revenue from plantation development n_{it}, net of its upfront costs. Future development choices and payoffs remain unaffected, such that continuation values align and difference out. The difference in costs is

$$-\bar{c}_{it} + \beta\mathbb{E}_{it}[\bar{c}_{it+1}] = \beta\bar{\gamma}_g^1 - (1-\beta)(\bar{\gamma}_g^0 + \bar{\gamma}_g^1 t + x_i\bar{\delta}) - \bar{\varepsilon}_{it} + \beta\mathbb{E}_{it}[\bar{\varepsilon}_{it+1}]\,.$$

Defining structural error $\bar{\mu}_{it} = -\bar{\varepsilon}_{it} + \beta\bar{\varepsilon}_{it+1}$ and expectational error

$$\bar{\eta}_{it} = \mathbb{E}_{it}[\beta\ln\pi_{it+1} + \beta\bar{\varepsilon}_{it+1}] - \beta\ln\pi_{it+1} - \beta\bar{\varepsilon}_{it+1}\,,$$

I substitute and rewrite to obtain regression equation 10.

Finally, a static model would ignore the durability of mills and plantations, as well as time to build. To this end, I consider laws of motion $M_{it} = m_{it}$ and $N_{it} = n_{it}$ that eliminate long-run continuation values. Equations 5 and 4 yield intensive- and extensive-margin conditions

$$\frac{\partial c_{it}}{\partial n_{it}} = \frac{\partial r_{it}}{\partial n_{it}}\,, \quad \ln\pi_{it} - \ln(1-\pi_{it}) = \bar{v}_{it}(1) - \bar{v}_{it}(0) = -\bar{c}_{it} + V_{it}(0)\,.$$

I substitute and rewrite to obtain regression equations that can be estimated without instruments.

$$\begin{aligned}n_{it} &= \frac{\alpha}{\psi}p_t y_{it} - \frac{1}{\psi}(\gamma_g^0 + \gamma_g^1 t + x_i\delta) - \frac{1}{\psi}\varepsilon_{it}\,,\\ \ln\pi_{it} - \ln(1-\pi_{it}) &= \frac{1}{2}\psi n_{it}^2 - \bar{\gamma}_g^0 - \bar{\gamma}_g^1 t - x_i\bar{\delta} - \bar{\varepsilon}_{it}\,.\end{aligned}$$

Elasticities

For small price changes within the study period, I can compute production by site from supply parameters $\{\alpha, \psi\}$. I do not need to specify states beyond the study period. These price changes have no direct effect on forward-looking choices $\{\hat{n}_{iS}, \hat{\pi}_{iS}\}$, where S is the final year of the study period, and so I can read these choices from data $\{n_{iS}, \pi_{iS}\}$. I then compute counterfactual choices

Table C1: Lagged instruments

	Intensive
	$\beta^3 p_{t+3} y_{it+3}$
$p_t y_{it}$	0.265***
	(0.00420)
Region FE	x
Region-year trend	x
Observations	37,754
F-statistic	3985

The table shows the first stage for current revenues as an instrument for future revenues. I control for cost factors and cluster standard errors by district. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

$\{\hat{n}_{it}, \hat{\pi}_{it}\}$ for all preceding years directly from estimating equations 9 and 10. For differences

$$\Delta n_{it} = n_{it} - \beta n_{it+1} \,, \tag{19a}$$

$$\Delta \pi_{it} = \ln \pi_{it} - \ln(1 - \pi_{it}) - \beta \ln \pi_{it+1} \,, \tag{19b}$$

I proceed as follows for price changes from observed p_t to counterfactual $\hat{p}_t$, holding all else constant.

1. Compute Δn_{it} by equation 19a.
2. Compute $\Delta \hat{n}_{it}$. By equations 9 and 19a, $\Delta \hat{n}_{it} = \Delta n_{it} + \frac{\alpha \beta^3}{\psi}(\hat{p}_{t+3} - p_{t+3}) y_{it+3}$.
3. Compute $\hat{n}_{it}$. By equation 19a, $\hat{n}_{it} = \Delta \hat{n}_{it} + \beta n_{it+1}$, where $\hat{n}_{iS}$ is data.
4. Compute $\Delta \pi_{it}$ by equation 19b.
5. Compute $\Delta \hat{\pi}_{it}$. By equations 10 and 19b, $\Delta \hat{\pi}_{it} = \Delta \pi_{it} + \frac{1}{2}\psi(\hat{n}_{it} - n_{it})^2$.
6. Compute $\hat{\pi}_{it}$. By equation 19b, $\ln \hat{\pi}_{it} - \ln(1 - \hat{\pi}_{it}) = \Delta \hat{\pi}_{it} + \beta \ln \hat{\pi}_{it+1}$, where $\hat{\pi}_{iS}$ is data.
7. Compute $\{\hat{M}_{it}, \hat{N}_{it}\}$ by equations 18.

Estimates

Table C1 presents the first stage regression and shows that current revenue is a strong instrument for future revenue. Table C2 presents average costs and time trends by region. Peninsular Malaysia has the highest costs of plantation development, but the lowest costs of mill construction. This combination rationalizes widespread but slow growth in palm oil production, which originates in this region but remains limited by land constraints during the study period. Other regions, which make up the bulk of the study area, have lower plantation costs and higher mill costs that rationalize spatially concentrated but rapid growth in production. Low plantation costs encourage intensive-margin expansion, while high mill costs discourage extensive-margin expansion. These effects strengthen over time with falling plantation costs and rising mill costs.

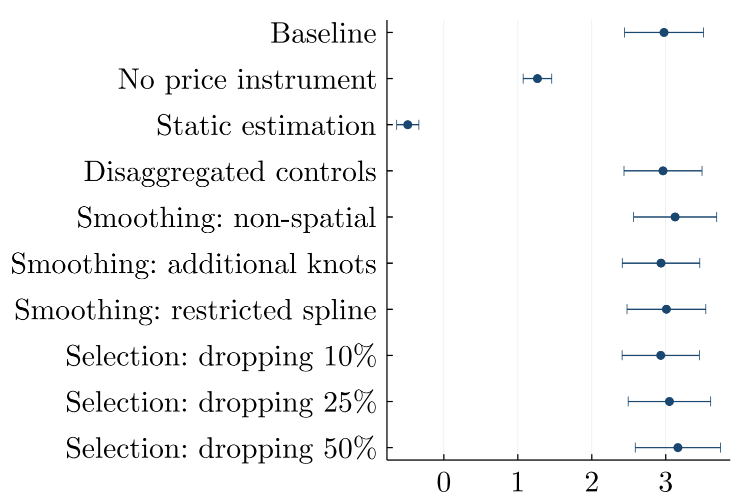
Figure C3 shows that estimation without instruments leads to attenuated estimates, as expected. For intensive-margin equation 9, larger revenue $p_{t+3} y_{it+3}$ implies smaller expectational error η_{it}, which attenuates the effect of an increase in $p_{t+3} y_{it+3}$ on the dependent variable. Static estimation also leads to biased estimates, which I find are small and negative. Static estimation regresses on current prices, even though forward-looking investment depends on future prices. Current prices are noisy measures of future prices, and this noise leads to attenuation. Furthermore, investment may even slow when prices are high, as mean reversion implies that high prices today

Table C2: Supply parameters by region

	γ_g^0/α (\$1K)		γ_g^1/α (\$1K)		$\bar{\gamma}_g^0/\alpha$ (\$1M)		$\bar{\gamma}_g^1/\alpha$ (\$1M)	
	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE
Indonesia, Sumatra	6.701***	(0.180)	-0.470***	(0.021)	95.66**	(42.47)	1.642***	(0.632)
Indonesia, Kalimantan	8.110***	(0.998)	-0.174*	(0.101)	78.51**	(33.43)	1.574***	(0.373)
Malaysia, Peninsular	10.35***	(0.980)	-0.295***	(0.091)	34.36**	(15.57)	-0.316	(0.621)
Malaysia, East	7.041***	(0.726)	-0.678***	(0.027)	138.2**	(66.91)	2.242***	(0.644)

Each row shows cost parameters in dollar terms for a producing region. The first pair of columns is the fixed cost of plantation development in thousands of inflation-adjusted, year-2000 dollars. The second pair is the annual trend in these costs. Similarly, the third pair of columns is the fixed cost of mill construction in millions of dollars. The fourth pair is the annual trend in these costs. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table C3: Supply elasticities, alternative specifications



Each point presents an elasticity of total production during the study period with respect to a 1% increase in prices throughout the study period. The first three points show dynamic IV, dynamic OLS, and static IV estimation. The fourth point shows estimation with cost factors defined as road, port, and urban distances and above- and below-ground carbon stocks. The "smoothing" points show alternative basis functions for smoothing in extensive-margin estimation. The "selection" points show alternative samples for smoothing, again for extensive-margin estimation, where I compute plantation development for sites without mills from varying subsamples of sites with a mill. I plot 95% confidence intervals.

portend lower prices tomorrow.

Figure C3 also shows robustness to alternative specifications. First, I treat cost factors parsimoniously, but I obtain similar estimates with disaggregated cost factors that include road, port, and urban distances and above- and below-ground carbon stocks. Second, extensive-margin estimation involves smoothing over observed choices to compute mill construction probabilities π_{it} and plantation development n_{it} for sites without mills. I smooth spatially with one-knot cubic basis splines, but I obtain similar estimates when smoothing non-spatially (omitting latitude and longitude as basis variables), with three knots, and with three-knot restricted cubic splines.

Third, I assume that unobserved mill and plantation costs $\{\bar{\varepsilon}_{it}, \varepsilon_{it}\}$ are uncorrelated with each other. Correlation most directly threatens estimates of parameter ψ in equation 10. Suppose these unobserved costs are positively correlated, as is natural. On one hand, sites with a mill are positively selected on plantation development n_{it}, and so I overestimate n_{it} for sites without mills. This bias leads me to underestimate ψ. On the other hand, plantation development n_{it} is positively correlated with structural error $\bar{\mu}_{it}$, as n_{it} contains ε_{it} and $\bar{\mu}_{it}$ contains $\bar{\varepsilon}_{it}$. This correlation leads me to overestimate ψ. Figure C3 shows that these forces seem to be inconsequential in my sample. In particular, I identify sites that are likely to have extreme values for unobserved costs. Sites with a mill despite low probabilities π_{it} of mill construction must have low costs $\bar{\varepsilon}_{it}$. Correlated costs then imply low costs ε_{it} that encourage high development n_{it}. I calculate π_{it} for all sites, and I drop those with a mill despite low π_{it}. These sites are most selected. I smooth over the remaining sites with a mill, and I obtain $\hat{n}_{it}$ for sites without mills. I then estimate elasticities as in baseline. I obtain similar estimates when dropping the 10, 25, and 50% of sites with lowest π_{it}. More generally, however, the potential for correlation across margins remains a challenge for discrete-continuous models.

D Counterfactuals

Welfare

I compute undiscounted total consumer surplus, producer surplus, government revenue, and emissions over the study period. For a given year t,

$$CS_t = \sum_k \Big(X(p_{1t}, p_{2t}; u^0_{kt}) - X(p^0_{1t}, p^0_{2t}; u^0_{kt}) \Big),$$

$$PS_t = \sum_i \Big(r(N_{it}, s_{it}) - \frac{1}{\alpha}[c(n_{it}, s_{it})M_{it+1} + \bar{c}(s_{it})\pi_{it}(1 - M_{it})] \Big),$$

$$G_t = \sum_k p_{1t} q^D_{1kt} \tau^D_{kt} + \sum_i p_{1t} q^S_{1it} \tau^S_{gt}\,, \quad E_t = \sum_i e_i n_{it} M_{it+1}\,.$$

Consumer surplus is the increase in expenditures X_{kt} needed to maintain utility $u_{kt} = (\ln X_{kt} - \ln P_{kt})(\prod_o p_{ot}^{\delta_{ok}})^{-1}$, as derived in Deaton and Muellbauer (1980). It is relative to baseline prices $\{p^0_{1t}, p^0_{2t}\}$ and utility u^0_{kt}. Producer surplus is relative to the outside option. In net-present-value terms, producer surplus is simply $\bar{V}(s_{it})$. I compute revenue net of costs to obtain producer surplus in undiscounted terms. Government revenue is from ad valorem taxes on world prices p_{1t}. Emissions depend on carbon stock density e_i, as measured in tons per hectare. I observe carbon stocks, and so I can read counterfactual emissions directly from data.

Emissions

On the demand side, I ignore emissions from substitution to other vegetable oils. The primary threat is South American soybean oil, which contributes to Amazonian deforestation. The resulting bias is small because Amazonian deforestation is driven primarily by cattle, not soy (Souza-Rodrigues 2019), and it does not destroy peatlands, which are located away from the deforested outskirts of the forest (Gumbricht et al. 2017; Song et al. 2018). Furthermore, South American soybean oil is only 13% of total oil consumption. To capture these emissions, I would need to model the supply of soybean oil. I would then impose joint tariffs on palm and soybean oils.

On the supply side, I ignore emissions from substitution to other drivers of deforestation. I leave aside mining, which is governed by the exogenous distribution of deposits, and selective logging, which does not destroy peatlands. The primary threat that remains is substitution to acacia (paper pulp) plantations, which do destroy peatlands. The resulting bias is small because palm oil is seven times more profitable than acacia, which requires replanting upon harvest, such that switching to acacia is unappealing for many palm oil producers (Sofiyuddin et al. 2012). To capture these emissions, I would need to model the choice between palm and acacia development. I would then impose joint tariffs on palm oil and acacia.

Indeed, palm development greatly exceeds acacia development, and I find limited substitution between the two historically. Gaveau et al. (2019) measure palm and acacia plantations for the island of Borneo in five-year intervals from 1990 to 2015. For the average site, I observe 257 ha of palm development per year, relative to only 42 ha of acacia development per year. These measures align with the baseline data, which capture 288 ha of palm development per year. I test for substitution between palm and acacia as follows. For sites i and years t, I compare palm and acacia development with the specification

$$\Delta \text{acacia}_{it} = \beta \Delta \text{palm}_{it} + \alpha_i + \alpha_t + \varepsilon_{it}\,.$$

Acacia_{it} is total acacia plantation, and so Δacacia_{it} is new acacia development. I include site and year fixed effects, and I cluster standard errors by district. Table D1 shows that palm development has very small effects on acacia development. Palm development does not displace acacia development and if anything slightly increases it, perhaps by opening up new lands. That is, palm and acacia are not substitutes and may even be weak complements. I isolate intensive-margin investments by focusing on sites with nonzero initial palm development, and I allow for cross-site effects by aggregating to the district level. Each gives similar estimates.

Policy

Tables D2 and D3 summarize the impacts of domestic regulation and trade policy on global emissions and welfare by market. They correspond to table 6 and figures 5, 6, and 7.

Table D1: Acacia vs. palm development

	All sites		1990 sites		All districts		1990 districts	
	Acacia	Acacia	Acacia	Acacia	Acacia	Acacia	Acacia	Acacia
Palm	0.0235***	0.0134	0.0233*	0.0125	0.0350**	-0.0160	0.0293	-0.0189
	(0.00888)	(0.00859)	(0.0116)	(0.0124)	(0.0159)	(0.0345)	(0.0191)	(0.0422)
Site FE		x		x		x		x
Year FE		x		x		x		x
Observations	5,700	5,700	1,254	1,254	528	528	270	270

Each column is one regression. I measure palm and acacia development in hectares of new plantation. In the first four columns, each observation is a site-year. I consider the full sample and the sample with nonzero palm development in 1990. In the last four columns, each observations is a district-year. I again consider the full and 1990 samples. Standard errors are clustered by district. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table D2: Domestic regulation

	20% tax		33% tax		50% tax		67% tax	
	2016	2001	2016	2001	2016	2001	2016	2001
Production taxes (I + M)								
Emissions	-3	-0	-5	-0	-7	-1	-11	-1
Welfare: European Union	-7	-2	-12	-3	-22	-6	-34	-8
Welfare: China, India	-12	-3	-23	-5	-41	-9	-65	-13
Welfare: Other importers	-24	-8	-44	-14	-77	-23	-115	-31
Welfare: Indonesia	5	-1	5	-3	-1	-7	-12	-12
Welfare: Malaysia	14	5	25	9	39	14	50	17
Production taxes (I)								
Emissions	-2	-0	-4	-1	-5	-1	-6	-1
Welfare: European Union	-3	-1	-5	-1	-7	-2	-8	-2
Welfare: China, India	-6	-2	-10	-2	-13	-3	-15	-3
Welfare: Other importers	-12	-4	-18	-6	-23	-7	-27	-7
Welfare: Indonesia	-26	-17	-38	-28	-45	-32	-51	-32
Welfare: Malaysia	34	18	50	29	58	33	65	33
Production taxes (M)								
Emissions	-1	0	-1	-0	-2	-0	-2	-0
Welfare: European Union	-2	-1	-3	-1	-4	-1	-4	-1
Welfare: China, India	-4	-1	-6	-2	-7	-2	-8	-2
Welfare: Other importers	-8	-3	-11	-4	-13	-5	-14	-5
Welfare: Indonesia	26	15	34	23	38	25	40	25
Welfare: Malaysia	-21	-14	-28	-22	-31	-24	-33	-24

I compute total changes in global emissions and market-specific welfare from 1988 to 2016. Emissions are in gigatons of CO_2 equivalents, and welfare is in billions of inflation-adjusted, year-2000 dollars. Production taxes are levied in Indonesia (I), Malaysia (M), or both (I + M). Welfare for Indonesia and Malaysia includes consumer surplus, producer surplus, and government revenue. Welfare elsewhere includes consumer surplus. Columns are taxes of different levels, upheld from 1988 to 2016 or from 1988 to 2001.

Table D3: Trade policy

	25% tax		50% tax		100% tax		200% tax	
	2016	2001	2016	2001	2016	2001	2016	2001
Import tariffs (all imports)								
Emissions	-2	-0	-3	-0	-5	-0	-8	-1
Welfare: European Union	5	1	8	2	8	2	4	2
Welfare: China, India	7	1	10	1	9	1	-3	-0
Welfare: Other importers	13	4	17	6	13	6	-14	1
Welfare: Indonesia, Malaysia	-34	-15	-58	-25	-89	-39	-121	-54
Import tariffs (EU + CI)								
Emissions	-1	-0	-1	-0	-2	-0	-3	-0
Welfare: European Union	2	1	2	1	-2	-0	-14	-3
Welfare: China, India	3	0	1	0	-7	-1	-34	-4
Welfare: Other importers	9	2	16	4	27	8	41	12
Welfare: Indonesia, Malaysia	-12	-4	-21	-7	-32	-11	-46	-16
Import tariffs (EU)								
Emissions	-0	-0	-0	-0	-1	-0	-1	-0
Welfare: European Union	-0	0	-2	-0	-10	-2	-28	-5
Welfare: China, India	2	0	3	1	5	1	7	1
Welfare: Other importers	3	1	6	2	10	4	15	6
Welfare: Indonesia, Malaysia	-5	-2	-9	-4	-14	-6	-19	-9
Export taxes (all exports)								
Emissions	-2	-0	-3	-0	-5	-0	-8	-1
Welfare: European Union	-8	-2	-15	-4	-28	-7	-48	-11
Welfare: China, India	-15	-3	-28	-6	-51	-10	-91	-17
Welfare: Other importers	-28	-9	-53	-17	-96	-29	-165	-48
Welfare: Indonesia, Malaysia	35	12	61	21	99	34	146	51

I compute total changes in global emissions and market-specific welfare from 1988 to 2016. Emissions are in gigatons of CO_2 equivalents, and welfare is in billions of inflation-adjusted, year-2000 dollars. Import tariffs are levied on all imports, imports to the EU, China, and India (EU + CI), or imports to the EU alone (EU). Export taxes are levied on all exports from Indonesia and Malaysia. Welfare for Indonesia and Malaysia includes consumer surplus and producer surplus, as well as government revenue from export taxes. Welfare elsewhere includes consumer surplus, as well as government revenue from import tariffs. Columns are taxes of different levels, upheld from 1988 to 2016 or from 1988 to 2001.