Coordination and Commitment in International Climate Action: Evidence from Palm Oil

Allan Hsiao*

Princeton University

February 22, 2022

(most recent version here)

Weak environmental regulation has global consequences. When domestic regulation fails, the international community can intervene by targeting emitters with import tariffs. I develop a dynamic empirical framework for evaluating import tariffs as a substitute for domestic regulation, and I apply it to the market for palm oil, a major driver of deforestation and one of the largest sources of emissions globally. Coordinated, committed tariffs reduce emissions by 39% relative to 40% under domestic regulation, but free-riding concerns undermine coordination and static incentives undermine commitment. Alternatives include unilateral EU action and a domestic export tax, which reduce emissions by up to 6% and 39%. The export tax generates significant revenue at the expense of foreign consumers and is fiscally appealing independent of emission concerns.

*Email: ajhsiao@princeton.edu. I am grateful to Nikhil Agarwal, Esther Duflo, Ben Olken, and Rob Townsend for their guidance and encouragement throughout this project. I have also benefited from helpful conversations with Daron Acemoglu, David Atkin, Clare Balboni, Abhijit Banerjee, Arnaud Costinot, Dave Donaldson, Namrata Kala, Jing Li, Rachael Meager, Will Rafey, Mar Reguant, Tobias Salz, and Tavneet Suri. I acknowledge generous support from the National Science Foundation Graduate Research Fellowship, Jerry Hausman Graduate Dissertation Fellowship, George and Obie Shultz Fund, and Weiss Fund for Research in Development Economics.

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. Import tariffs offer an alternative, circumventing domestic obstacles to regulation by directly targeting the prices emitters receive in world markets.

How effective are international import tariffs as a substitute for domestic regulation? I develop a dynamic empirical framework to answer this question quantitatively, and I apply it to studying the palm oil industry. This industry accounts for a staggering 5% of global CO_2 emissions from 1990 to 2016 – more than the entire Indian economy (figure 1) – and traded goods more broadly embody 60% of global emissions (Davis et al. 2011). I find import tariffs to be effective subject to two challenges: (1) a coordination problem because defectors can free-ride on emission reductions achieved by the tariff coalition and (2) a commitment problem because imposing tariffs is not statically optimal once emissions are sunk.

Palm oil offers an ideal empirical setting, and I focus on Indonesia and Malaysia, which together produce 84% of global supply. First, the industry is a major polluter. Land clearing for palm oil plantations threatens peatland forests that are particularly carbon-rich. Second, local benefits limit domestic incentives to regulate. Despite its global consequences, palm oil is a major source of export revenue and has lifted millions out of poverty (Edwards 2019). Third, foreign governments are actively discussing trade-policy interventions, with the European Union passing recent legislation targeting palm oil imports (OJEU 2018). Fourth, satellite imagery provides a rich source of spatial data capturing the evolution of the industry over time and at a granular level.

I model palm oil demand by consumer market with an almost ideal demand system in which consumers choose between palm and other vegetable oils (Deaton and Muellbauer 1980). For estimation, I apply the iterated linear least squares approach

Figure 1: Palm emissions (Gt CO_2)

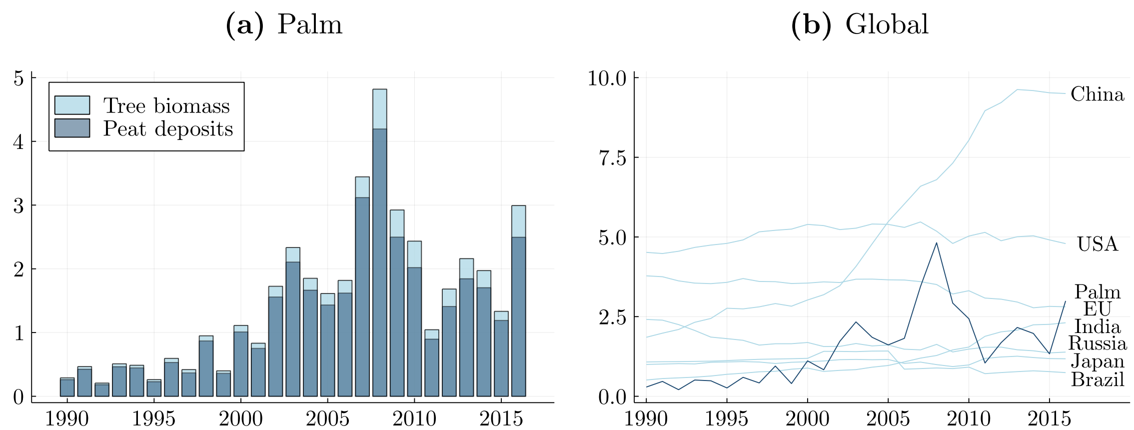


Figure 1a computes emissions from palm oil plantations. Figure 1b compares palm emissions to CO_2 emissions, including from land-use change, for the top seven emitters from 1990 to 2016. Palm emissions account for 4.95% of global emissions during this period. Data: Xu et al. (2020), Song et al. (2018), Zarin et al. (2016), Gumbricht et al. (2017), World Resources Institute.

of Blundell and Robin (1999) using annual panel data on vegetable oil prices and consumption by country. I address price endogeneity by instrumenting with weather shocks to oil production, which shift supply. I then obtain world palm oil demand curves, which shift right over time as demand expands.

I model palm oil supply with a dynamic model of sunk investment. Forward-looking firms invest along two margins. On the extensive margin, firms make a discrete choice over whether to build mills – a prerequisite for plantations. On the intensive margin, firms with mills make a continuous choice over how much land to deforest and develop into plantations. Once operational, plantations generate palm oil revenues each period as a function of world prices. For estimation, I combine standard continuous Euler methods for the intensive margin with more recent discrete Euler methods for the extensive margin (Hall 1978; Scott 2013). Continuation values difference out, simplifying computation and reducing estimation to linear regression with instruments. Identification comes from two sources: exogenous variation in world palm oil prices over time, given shifts in the world demand curve estimated above, and exogenous variation in palm oil yields over space, given differences in climate. Intuitively, high prices raise revenues most for high-yield plantations.

For counterfactuals, I evaluate the effects of regulation on emissions. Tariffs lower world prices, discouraging investment in palm oil production and deforestation. I set tariffs to maximize social welfare, and I quantify emissions by combining the model's spatial predictions with a map of carbon stocks. Coordinated, committed tariffs are very effective, reducing emissions by 39% relative to 40% under domestic regulation, although emission reductions fall as coordination and commitment weaken. Coordination is achievable with modest transfers, as China, India, and other importers enjoy large, direct benefits from emission reductions. Commitment is achievable with strong institutions, as commitment is optimal ex-ante.

An alternative to coordinated, committed tariffs is unilateral EU action, which still reduces emissions by up to 6%. Because coordination and commitment are substitutes, the EU can draw on strong institutions and compensate for weak coordination with strong commitment. Indeed, committed, unilateral action is nearly as effective as less-committed action by larger coalitions. Another alternative is an export tax by Indonesia and Malaysia, which is arguably more feasible than direct domestic regulation. This policy reduces emissions by up to 39% while generating substantial government revenue at the expense of foreign consumers. Thus, Indonesia and Malaysia have strong fiscal incentives to regulate even absent international pressures.

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 concerns 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 affects environmental incentives more broadly (Shapiro 2020). 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 the rich dynamics and fine-grained spatial heterogeneity missed by the computable general equilibrium models that are common in this literature.

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 show how to combine both continuous and discrete Euler techniques in a single framework, with a generalizable model containing discrete entry choices on the extensive margin and continuous investment choices on the intensive margin.

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) or conservation contracting (Harstad 2012, 2016; Harstad and Mideksa 2017), and it scales readily, unlike direct payments for ecosystem services (Jayachandran et al. 2017; Edwards et al. 2020). Harstad (2021) and Domínguez-Iino (2021) provide important insights on trade policy for deforestation, but focus on theoretical and static settings, respectively. I quantify the effectiveness of trade policy in an empirical, dynamic setting, and I do so for an industry that is pivotal in the fight against climate change.

2 Background

Palm oil is among the most widely used plant products in the world, with uses ranging from cooking and baking to cosmetics and biofuels. According to USDA data, palm oil expenditures in 2016 totaled $46 billion – 33% of vegetable oil expenditures, and more than any other oil. Table 1 shows that Indonesia and Malaysia account for 84% of global production, 90% of exports, and 20% of consumption. The EU, China, and India account for another 35% of global consumption. The largest individual producer (FGV Holdings Berhad) is 4% of global production (POA 2017), and the largest consumer (Unilever) is 2% of global consumption (WWF 2016).

This empirical setting is appealing for several reasons. First, palm oil is among the largest sources of global carbon emissions. Deforestation for palm oil plantations is particularly consequential because Indonesia and Malaysia are rich in peatland

Table 1: Palm oil by country (%)

	Production	Consumption	Exports	Imports
Indonesia	44	14	41	0
Malaysia	40	6	48	2
European Union	0	12	0	17
China	0	11	0	15
India	0	12	0	16
Rest of world	16	45	10	50

Each column sums to 100%. Data: USDA Foreign Agricultural Service, 1988-2016.

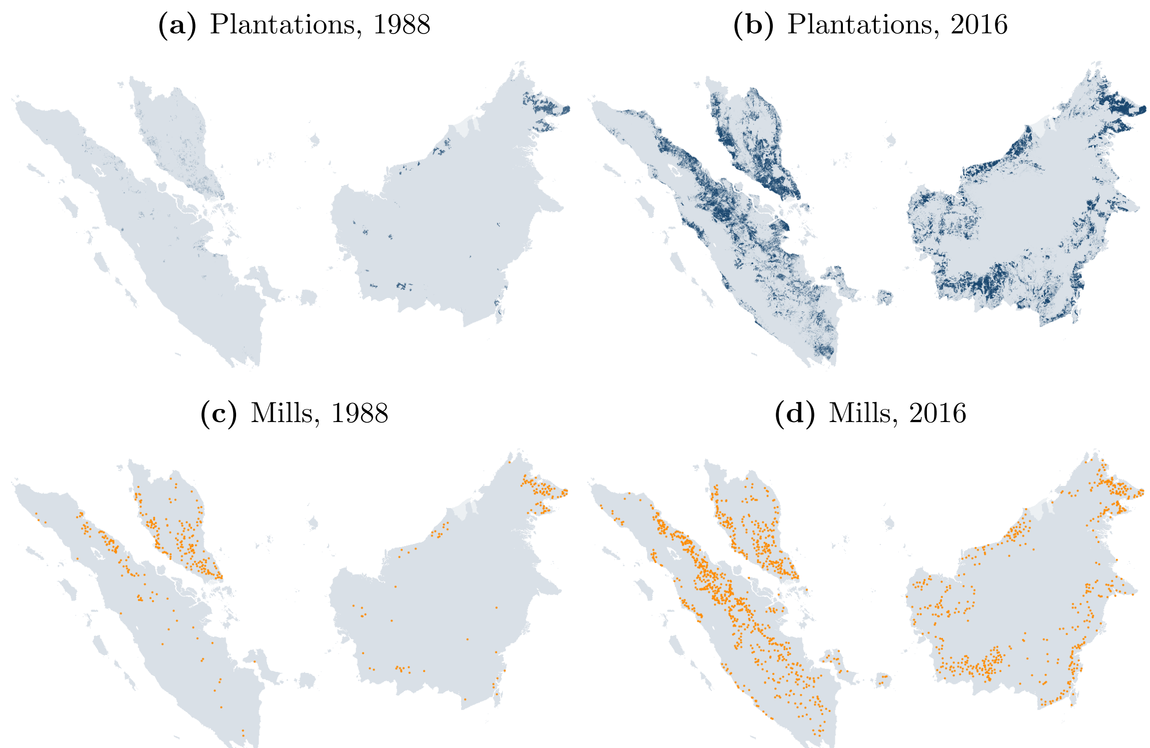
forests, which contain deep layers of carbon-rich peat. I compute palm emissions in figure 1a and find that emissions from peat deposits exceed those from tree biomass by five to ten times.[1] Figure 1b shows that palm emissions account for more CO_2 from 1990 to 2016 than the entire Indian economy.

Second, there are significant challenges in implementing regulation domestically. Free-riding limits 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 forest concessions. But the moratorium had little effect, failing to curb both (legal) deforestation within existing concessions and (illegal) deforestation outside of concessions, including in protected areas (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%, respectively (USDA 2019a, 2019b).

Third, European policymakers are actively discussing trade-policy interventions. 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. As with import tariffs, each policy uses European buying power to reduce emissions abroad.

[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.

Figure 2: Palm oil production

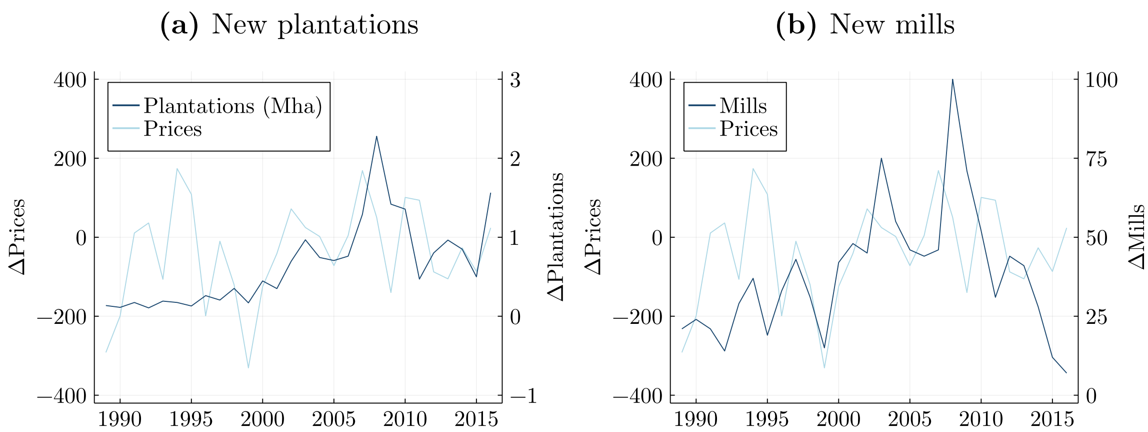


The study area is Sumatra, Kalimantan, and Riau of Indonesia and all of Malaysia. Data: Xu et al. (2020), Song et al. (2018), World Resources Institute.

3 Data

Spatial panel data record palm oil plantations and mills from 1988 to 2016 using satellite imagery at a resolution of 30 arc-seconds – approximately 1 km^2. Figure 2 maps the expansion of production over this period. For plantations, Xu et al. (2020) analyze PALSAR and MODIS satellite data to capture plantation development from 2001 to 2016. Using data on tree cover loss from 1988 to 2016 from Song et al. (2018), who draw on Landsat and MODIS satellite data, I estimate the (positive) relationship between plantation development and tree cover loss, and I use this relationship to impute plantation development back to 1988. For mills, I rely on geocoded data on present-day mills from the World Resources Institute and the Center for International Forestry Research, and I use historical satellite data to manually identify construction dates back to 1988. The Indonesian data focus on Sumatra, Kalimantan, and Riau

Figure 3: Palm oil production vs. prices ($/t)



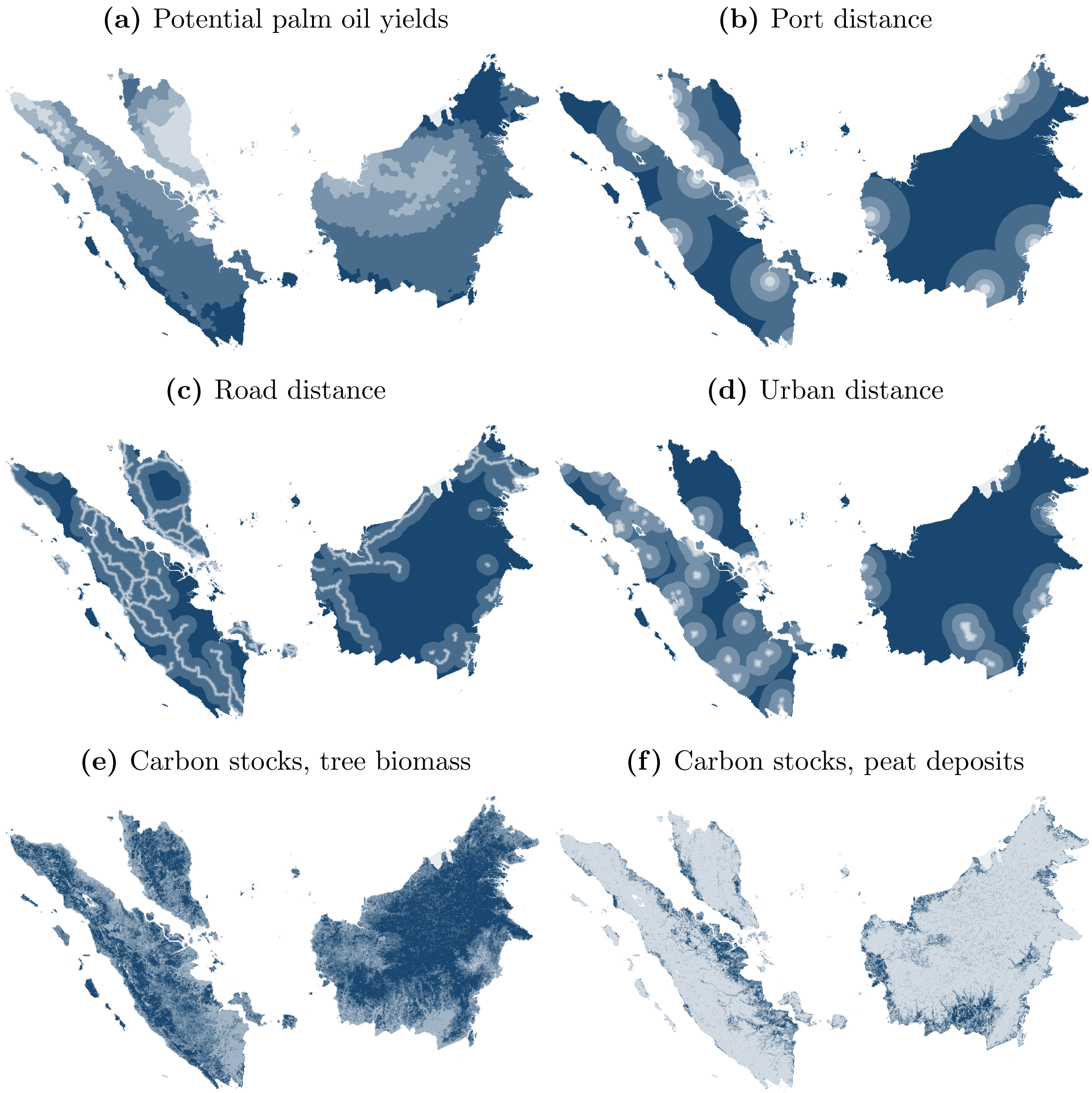
Prices combine world palm and palm kernel oil prices, weighting by expenditures. Data: Xu et al. (2020), Song et al. (2018), World Resources Institute, International Monetary Fund.

but remain exhaustive, covering 97% of mills. I compare my measures of plantations and mills to aggregate government statistics and find that they align closely. Figure 3 compares investment in plantations and mills to world prices over time, with world price data from the International Monetary Fund and World Bank.

Figure 4 maps land characteristics, which I measure at a resolution of 30 arc-seconds. I use an agronomic model of the oil palm plant to compute potential palm oil yields as a function of climate (Hoffmann et al. 2014). These potential yields are time-invariant but computable at high resolution, allowing me to downscale data on actual yields over time from provincial government statistics. Euclidean distances to the nearest major port, road, and urban district generate spatial heterogeneity via transport costs. Carbon stocks, which I compute from geospatial data on tree biomass and peat deposits (Zarin et al. 2016; Gumbricht et al. 2017), link counterfactual plantation development to emissions.

For consumption, I compile annual panel data from 1988 to 2016 on palm oil and its substitutes. Consumption data by country come from the USDA Foreign Agricultural Service. Palm oils include palm and palm kernel, and other oils include coconut, olive, rapeseed, soybean, and sunflower. To address price endogeneity, I measure weather shocks to oil production. Rainfall and temperature data come from the Global Meteorological Forcing Dataset, which includes daily measures during the study period at 0.25° resolution. I identify producing regions – primarily states and

Figure 4: Land characteristics



Darker blue indicates high yields, farther distances, and larger carbon stocks. Urban areas include administrative cities (Indonesia) and federal territories (Malaysia). Data: Hoffmann et al. (2014), World Port Index, Global Roads Inventory Project, Zarin et al. (2016), Gumbricht et al. (2017).

provinces – with production data from the USDA Foreign Agricultural Service. For each crop, year, and region, I compute weather shocks as total absolute deviations from optimal levels during the growing season, with optimal levels given by the FAO Crop Ecological Requirements Database (ECOCROP). I then aggregate over regions, weighting by production, to obtain shocks by crop and year.

4 Model

4.1 Demand

I model aggregate demand for vegetable oils with a two-stage almost ideal demand system as in Deaton and Muellbauer (1980) and Hausman et al. (1994). Consumers make an upper-level choice over total oil consumption. Given this total, they make a lower-level choice between palm and other oils, aggregated by Stone price index $\ln p_{it} = \sum_j \omega_{jt} \ln p_{jt}$. Relative to the characteristic-space approach, as in Berry et al. (1995), this product-space approach allows for flexible substitution patterns and avoids the need to specify which product characteristics consumers value.

For each consumer market, the specifications are as follows. The lower level is

$$\omega_{it} = \alpha_i^0 + \alpha_i^1 t + \sum_j \gamma_{ij} \ln p_{jt} + \beta_i \ln \left(\frac{X_t}{\tilde{P}_t} \right) + \epsilon_{it} \, , \tag{1a}$$

$$\ln \tilde{P}_t = \alpha_0 + \sum_j (\alpha_j^0 + \alpha_j^1 t) \ln p_{jt} + \frac{1}{2} \sum_j \sum_k \gamma_{jk} \ln p_{jt} \ln p_{kt} \, , \tag{1b}$$

for expenditure shares ω_{it}, palm and other oil prices p_{jt}, total oil expenditures $X_t = \tilde{Q}_t \tilde{P}_t$, and translog price index $\tilde{P}_t$. The upper level is

$$\ln \tilde{Q}_t = \alpha^0 + \alpha^1 t + \gamma \ln \tilde{P}_t + Z_t \beta + \epsilon_t \, , \tag{2}$$

for quantity $\tilde{Q}_t$ of total oil consumption and translog price index $\tilde{P}_t$. Demand shifters Z_t include GDP and the CPI, which capture overall income and prices.[2]

Both specifications are standard. For the upper level, an alternative is to specify total consumption in expenditure shares as in the lower level. However, vegetable oil expenditures are only 0.15% of GDP, and the resulting elasticities are unstable with expenditure shares so close to zero. Furthermore, the uncompensated price elasticities show why both levels are necessary.

[2] Part of EU demand for palm oil is for biofuels. I do not include fossil fuels in the choice set because the EU has biofuel targets, such as for 14% of fuel for transportation to be renewable by 2030. Thus, higher palm oil prices arguably require substitution toward other vegetable oils rather than to fossil fuels. Including fossil fuels in the choice set would allow me to account for the substitution that occurs in the absence of these targets.

$$\frac{\partial \ln q_{it}}{\partial \ln p_{jt}} = -\delta_{ij} + \frac{\gamma_{ij}}{\omega_{it}} + \left(\frac{\beta_i \gamma}{\omega_{it}} + \gamma + 1\right)\left(\frac{\partial \ln \tilde{P}_t}{\partial \ln p_{jt}}\right), \tag{3}$$

where $\frac{\partial \ln \tilde{P}_t}{\partial \ln p_{jt}} = \alpha_j^0 + \alpha_j^1 t + \frac{1}{2}\sum_k (\gamma_{jk} + \gamma_{kj}) \ln p_{kt}$, Kronecker $\delta_{ij} = \mathbb{1}[i = j]$, and $q_{it} = \frac{\omega_{it} X_t}{p_{it}}$. The lower level allows substitution between palm and other oils (via γ_{ij}), and the upper level allows total category demand to respond to price changes (via γ).

Prices are endogenous, as unobservables ϵ_{it} and ϵ_t shift demand and therefore affect equilibrium prices p_{jt}. I instrument with weather shocks to oil production as a supply shifter. The exclusion restriction is that these shocks affect vegetable oil demand only through their impact on prices. However, domestic shocks might also affect demand by impacting incomes or expenditures more broadly. I address this concern by isolating shocks to crops in producing states and provinces during the growing season, and also by directly testing for income and expenditure effects.

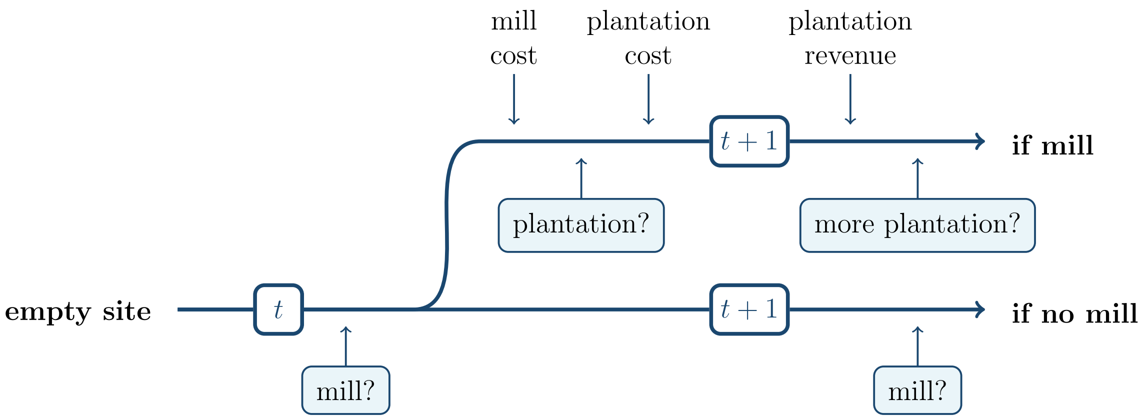
Unlike supply, demand is static. First, I miss dynamics from stockpiling, although stored oil stocks are observably small. Second, I miss stickiness in switching among oils, which requires reformulating recipes and recontracting with suppliers. Thus, long-run demand may be more elastic than estimated, and I analyze this case explicitly in counterfactuals. Third, while most palm oil is exported in raw form today, palm processors may attempt to avoid tariffs with exports in other, more processed forms. Capturing these responses would require a multi-industry dynamic model, and so I focus on tariffs that also cover palm oil content.

4.2 Supply

Land is divided into sites, which represent potential entrants and which I assume are small, independent, and managed by long-lived owners. Forward-looking sites generate profits by making sunk investments on two margins. On the extensive margin, sites make a binary choice over whether to build a mill. On the intensive margin, sites with mills make a continuous choice over how much land to develop into plantations.[3] Figure 5 shows the timeline.

[3] This model abstracts away from negotiations with smallholders, which account for 40% of production but are often vertically integrated into the production chain. In particular, smallholders are commonly bound by contracts that require selling harvests to specific mills in exchange for investment support (Cramb and McCarthy 2016). Even without vertical contracting, the intensive-margin model holds as long as investment is efficient, and the extensive-margin model holds as long as mills extracts all surplus from plantations. Indeed, the perishability of harvest

Figure 5: 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 period. If so, then the site makes a continuous choice over how much land to develop into plantations. The site can then expand its plantation in future periods.

Intensive margin

In each period t, sites i with mills make a continuous choice a_{it} over how much land to develop into plantations. Plantations have no scrap value and are sunk, such that plantation size s_{it} is given by law of motion $s_{it+1} = s_{it} + a_{it}$. Profits depend on observed state $\boldsymbol{w}_{it} = \{Y_{it}, x_i, s_t, d_t\}$ and unobserved state ε_{it}. Site-specific yields Y_{it} affect revenues, while site-specific cost factors x_i and shocks ε_{it} affect costs. Aggregate supply $s_t = \sum_i Y_{it} s_{it}$ and aggregate demand d_t affect world prices $P(s_t, d_t)$, which in turn affect revenues. Aggregate supply evolves endogenously: as in Hopenhayn (1992), firms reach a dynamic competitive equilibrium in which atomistic sites act as price takers but affect world prices collectively. Aggregate demand evolves exogenously. Each period, sites with mills realize state $(\boldsymbol{w}_{it}, \varepsilon_{it})$ and make investment choice a_{it}, incurring costs today to generate future revenues.

The value, revenue, and cost functions are as follows, with $\mathbb{E}_{it}[\cdot] \equiv \mathbb{E}[\cdot | s_{it}, \boldsymbol{w}_{it}, \varepsilon_{it}]$.

$$V(s_{it}; \boldsymbol{w}_{it}, \varepsilon_{it}) = \max_{a_{it}} \left\{ r(s_{it}; \boldsymbol{w}_{it}) - c(a_{it}; \boldsymbol{w}_{it}, \varepsilon_{it}) + \beta \mathbb{E}_{it}[V(s_{it+1}; \boldsymbol{w}_{it+1}, \varepsilon_{it+1})] \right\}, \tag{4a}$$

$$r(s_{it}; \boldsymbol{w}_{it}) = Y_{it} P(s_t, d_t) s_{it}, \quad c(a_{it}; \boldsymbol{w}_{it}, \varepsilon_{it}) = \left(\frac{1}{2} \delta a_{it} + x_i \gamma + \kappa_m + \alpha_m t + \varepsilon_{it} \right) a_{it} \tag{4b}$$

Expectations are over next-period state $(\boldsymbol{w}_{it+1}, \varepsilon_{it+1})$, and I suppress function sub-

fruit gives mills spatial market power that helps in extracting rents.

scripts m. Linear revenues and convex costs ensure unique optima. Revenues are linear in plantation size and increasing in yields and world prices. Weather shocks ε_{it}^{Y} affect yields during production, but they are unrealized ex ante and thus do not enter here: sites invest based on climate and not weather. Costs are quadratic and convex in investment, spreading investment over time and reflecting credit and local factor market constraints, although upfront and future flow costs are not separately identified. Cost factors x_i capture observed heterogeneity by site, while fixed effects κ_m and time trends α_m accommodate unobserved heterogeneity by region. Cost shocks ε_{it} can be correlated across sites and over time.

Extensive margin

In each period t, sites i without mills make a binary choice a_{it}^{e} over whether to construct a mill. Plantations require mills because unmilled palm fruit decays quickly after harvest and is not consumed directly. Mills have no scrap value and are sunk, with law of motion $s_{it+1}^{e} = s_{it}^{e} + a_{it}^{e}$. Profits depend on observed state $\boldsymbol{w}_{it} = \{Y_{it}, x_i, s_t, d_t\}$ and unobserved state ε_{it}^{e}, which captures mean-zero logit shocks $\{\varepsilon_{it0}^{e}, \varepsilon_{it1}^{e}\}$ with standard deviation σ^{e}. Each period, sites without mills realize state $(\boldsymbol{w}_{it}, \varepsilon_{it}^{e})$ and make investment choice a_{it}^{e}. If they choose not to invest, then the period ends. If they choose to invest, then they immediately face the intensive-margin problem, realizing shock ε_{it} and making choice a_{it} before the period ends.

The ex-ante value, choice-specific conditional value, and cost functions are

$$\begin{aligned}
V^{e}(\boldsymbol{w}_{it}) &= \mathbb{E}_{it}^{e}[\max\{v^{e}(0;\boldsymbol{w}_{it}) + \varepsilon_{it0}^{e}, v^{e}(1;\boldsymbol{w}_{it}) + \varepsilon_{it1}^{e}\}]\,, && \text{(5a)}\\
v^{e}(0;\boldsymbol{w}_{it}) &= \beta\mathbb{E}_{it}^{e}[V^{e}(\boldsymbol{w}_{it+1})]\,, && \text{(5b)}\\
v^{e}(1;\boldsymbol{w}_{it}) &= -c^{e}(\boldsymbol{w}_{it}) + \mathbb{E}_{it}^{e}[V(0;\boldsymbol{w}_{it}, \varepsilon_{it})]\,, && \text{(5c)}\\
c^{e}(\boldsymbol{w}_{it}) &= x_i\gamma^{e} + \kappa_m^{e} + \alpha_m^{e} t\,, && \text{(5d)}
\end{aligned}$$

with $\mathbb{E}_{it}^{e}[\cdot] \equiv \mathbb{E}^{e}[\cdot|\boldsymbol{w}_{it}]$ and e superscripts referring to the extensive margin. In equation 5a, expectations are over logit shocks ε_{it}^{e} that imply mill construction probabilities

$$p^{e}(\boldsymbol{w}_{it}) = \frac{\exp[v^{e}(1;\boldsymbol{w}_{it})]}{\exp[v^{e}(0;\boldsymbol{w}_{it})] + \exp[v^{e}(1;\boldsymbol{w}_{it})]}\,. \tag{6}$$

In equation 5b, choosing not to build leads to the same decision in the following period given expectations over next-period state $\boldsymbol{w}_{it+1}$. The outside option is never constructing a mill, with utility normalized to zero given mean-zero shocks ε_{it}^{e}. In equation 5c, choosing to build incurs mill construction costs in return for the intensive-margin value of plantation development, where new plantations start with size $s_{it} = 0$. Expectations are over intensive-margin shock ε_{it}. In equation 5d, cost factors x_i capture observed heterogeneity by site, while fixed effects κ_m^e and time trends α_m^e accommodate unobserved heterogeneity by region. Logit cost shocks ε_{it}^e are uncorrelated across sites and over time, and also uncorrelated with intensive-margin shocks ε_{it}.

Discussion

Both margins only allow for regional unobserved heterogeneity, and sites otherwise differ only in observables and shocks. Identifying site-level unobserved heterogeneity would require multiple plantation development and mill construction decisions over time. The former exists only for early sites, and the latter is inconsistent with a model in which sites construct no more than one mill each.

There is also an endogeneity problem on the intensive margin: both prices P_t and yields Y_{it} are correlated with cost shocks ε_{it}. First, collectively low costs induce entry, raising supply and lowering prices. Second, attained yields depend on unobserved, costly effort. Assuming uncorrelated cost shocks across sites addresses the first concern, but this assumption is strong. Instead, I instrument for prices with demand shifters d_t and for yields with potential yields Y_i^p. From estimated world demand

$$\ln p_t = -\widehat{\phi} \ln q_t + \widehat{d}_t \, ,$$

I obtain shifters $\widehat{d}_t$ that capture changes in the level of demand over time. Potential yields are a function of climate, which is exogenous, and instrumenting also mitigates bias from mismeasured yields. These concerns do not arise on the extensive margin because mills themselves do not affect prices or yields, and because extensive- and intensive-margin cost shocks are assumed to be uncorrelated with each other.

I take cost factors x_i as exogenous. Port distance is to major ports, which predate plantations. Road distance is to major roads, and not to small roads that develop endogenously around plantations. Urban distance is to major cities, which do not include palm oil settlements. Carbon stocks are predetermined.

5 Estimation

5.1 Demand

I estimate the lower-level demand system with iterated linear least squares as in Blundell and Robin (1999). I start by estimating a linear approximate version, using a Stone price index instead of translog. I then construct the translog price index with the resulting estimates and iterate until convergence, thereby avoiding nonlinear estimation. Each iteration imposes the standard adding-up, homogeneity, and symmetry restrictions. Given the lower-level estimates, I estimate the upper level by linear IV. Throughout, I instrument for prices with weather shocks to oil production, and Newey-West standard errors account for serial correlation. I compute demand elasticities by market-year and obtain standard errors with the delta method.

5.2 Supply

I estimate the supply model with Euler methods as in Hall (1978) and Scott (2013). On the intensive margin, I form Euler equations from the first order conditions for investment; on the extensive margin, I compare discrete, short-term perturbations that hold long-term investments fixed. Continuation values difference out.

Step 1: defining sites

I divide land into sites using observed mills and plantations as a guide. I identify the palm oil industry's most developed provinces and imagine bringing all provinces to this level of development. By several metrics, I obtain a target density of one mill per 521 km^2. I then define sites by k-means clustering on geographic coordinates, with the number of clusters in each province chosen to reach this target density. I impose that clusters separate observed mills and that observed plantations be assigned to clusters with observed mills. This procedure yields 2,135 contiguous sites, of which 1,467 have one observed mill and some observed plantations by 2016.

Step 2: intensive margin

The first order condition for investment delivers an Euler equation. Investing in period t instead of period $t + 1$ increases revenues, as production begins earlier, but it also increases costs, which are otherwise delayed and discounted.[4]

$$c'(a_{it};\boldsymbol{w}_{it},\varepsilon_{it}) = \beta\mathbb{E}_{it}[r'(s_{it+1};\boldsymbol{w}_{it+1}) + c'(a_{it+1};\boldsymbol{w}_{it+1},\varepsilon_{it+1})] \tag{7}$$

I set $\beta = 0.9$, as the discount factor is typically unidentified in dynamic discrete choice models (Magnac and Thesmar 2002). By equation 4b, the Euler equation becomes

$$a_{it} - \beta\mathbb{E}_{it}[a_{it+1}] = \frac{\beta}{\delta}\mathbb{E}_{it}[Y_{it+1}P_{t+1}] - \frac{1-\beta}{\delta}x_i\gamma - \frac{1-\beta}{\delta}\kappa_m - \frac{1}{\delta}\alpha_m\tilde{t} - \frac{1}{\delta}\varepsilon_{it} + \frac{\beta}{\delta}\mathbb{E}_{it}[\varepsilon_{it+1}]\,,$$

with $P_t \equiv P(s_t, d_t)$ and $\tilde{t} \equiv t - \beta(t+1)$. In using the first order condition, I implicitly assume an interior solution. Indeed, 99.5% of observed intensive-margin decisions are interior: 0.5% involve zero development, and 0% exceed sites' total area.

I take realized values as noisy measures of expectations, which are unobserved, subject to expectational errors η_{it} as in Hall (1978). I obtain the regression equation

$$a_{it} - \beta a_{it+1} = \frac{\beta}{\delta}Y_{it+1}P_{t+1} - \frac{1-\beta}{\delta}x_i\gamma - \frac{1-\beta}{\delta}\kappa_m - \frac{1}{\delta}\alpha_m\tilde{t} - \frac{1}{\delta}\varepsilon_{it} + \frac{\beta}{\delta}\varepsilon_{it+1} + \eta_{it}\,. \tag{8}$$

Rational expectations are correct on average and use all available information. Thus, expectational errors are mean-zero and orthogonal to sites' period-t information sets.

$$\begin{aligned}\eta_{it} &= \beta\mathbb{E}_{it}[a_{it+1}] - \beta a_{it+1} + \frac{\beta}{\delta}\mathbb{E}_{it}[Y_{it+1}P_{t+1}] - \frac{\beta}{\delta}Y_{it+1}P_{t+1} + \frac{\beta}{\delta}\mathbb{E}_{it}[\varepsilon_{it+1}] - \frac{\beta}{\delta}\varepsilon_{it+1} \\ &= \sum_{t'=1}^{\infty}\frac{\beta^{t'}}{\delta}\Big(\mathbb{E}_{it}[Y_{it+t'}P_{t+t'}] - \mathbb{E}_{it+1}[Y_{it+t'}P_{t+t'}]\Big)\end{aligned} \tag{9}$$

The last line follows from equation 8.[5] Investment choices, yields, prices, and cost factors are data, where cost factors include port, road, and urban distances, as well as carbon stocks. I instrument for yields and prices with lagged, period-t values for potential yields and the demand shifters discussed above. Figures 3 and 4a plot the time-series variation in world prices and spatial variation in yields. Identification relies on both sources of variation: intuitively, price increases are more valuable for sites that produce more palm oil. I cluster by region given correlated cost shocks. Since revenues $Y_{it+1}P_{t+1}$ are measured directly, parameters γ, κ_m, and α_m are interpretable

[4] By equation 4a, the first order condition for a_{it} is $c'(a_{it};\boldsymbol{w}_{it},\varepsilon_{it}) = \beta\mathbb{E}_{it}[V'(s_{it+1};\boldsymbol{w}_{it+1},\varepsilon_{it+1})]$, and the envelope theorem gives $V'(s_{it};\boldsymbol{w}_{it},\varepsilon_{it}) = r'(s_{it};\boldsymbol{w}_{it}) + \beta\mathbb{E}_{it}[V'(s_{it+1};\boldsymbol{w}_{it+1},\varepsilon_{it+1})]$.

[5] Telescoping implies $a_{it} = \sum_{t'=1}^{\infty}\frac{\beta^{t'}}{\delta}\mathbb{E}_{it}[Y_{it+t'}P_{t+t'}] - \frac{1}{\delta}x_i\gamma - \frac{1}{\delta}\kappa_m - \frac{1}{\delta}\alpha_m t - \frac{1}{\delta}\varepsilon_{it}$.

in dollar terms. Production begins one period after investment in this exposition, but in estimation I impose the typical three years to reach crop maturity.[6]

Step 3: extensive margin

As before, I compare investing today and tomorrow. In this discrete case, differencing stands in for the first order condition, and finite dependence for the envelope theorem. My comparison is between two sequences of actions: $(1, a^*_{it}, a^*_{it+1})$ and $(0, 1, a'_{it+1})$ for $a'_{it+1} = a^*_{it} + a^*_{it+1}$. The first constructs a mill today, then develops a^*_{it} plantations today and a^*_{it+1} plantations tomorrow; the second constructs a mill tomorrow, then develops a'_{it+1} plantations tomorrow. Finite dependence holds when actions lead to common states – and thus common payoffs – in all future periods (Arcidiacono and Miller 2011). It holds here because, for both sequences, by period $t+2$ the mill is constructed and the plantation is of size $a^*_{it} + a^*_{it+1}$. The payoffs are

$$\begin{aligned} v^e(1, a^*_{it}, a^*_{it+1}; \boldsymbol{w}_{it}) &= -c^e(\boldsymbol{w}_{it}) + \mathbb{E}^e_{it}[-c(a^*_{it}; \boldsymbol{w}_{it}, \varepsilon_{it}) + \beta r(a^*_{it}; \boldsymbol{w}_{it+1}) - \beta c(a^*_{it+1}; \boldsymbol{w}_{it+1}, \varepsilon_{it+1})] \\ &\quad + \beta^2 \mathbb{E}^e_{it}[V(a^*_{it} + a^*_{it+1}; \boldsymbol{w}_{it+2}, \varepsilon_{it+2})]\,, \\ v^e(0, 1, a'_{it+1}; \boldsymbol{w}_{it}) &= -\beta \mathbb{E}^e_{it}[c^e(\boldsymbol{w}_{it+1}) + c(a'_{it+1}; \boldsymbol{w}_{it+1}, \varepsilon_{it+1})] + \beta^2 \mathbb{E}^e_{it}[V(a'_{it+1}; \boldsymbol{w}_{it+2}, \varepsilon_{it+2})]\,. \end{aligned}$$

The continuation values align: $V(a^*_{it} + a^*_{it+1}; \boldsymbol{w}_{it+2}, \varepsilon_{it+2}) = V(a'_{it+1}; \boldsymbol{w}_{it+2}, \varepsilon_{it+2})$. By the Hotz-Miller inversion (Hotz and Miller 1993), equation 6 implies

$$\ln\left(\frac{p^e(\boldsymbol{w}_{it})}{1 - p^e(\boldsymbol{w}_{it})}\right) = v^e(1; \boldsymbol{w}_{it}) - v^e(0; \boldsymbol{w}_{it})\,. \tag{10}$$

While $v^e(1; \boldsymbol{w}_{it}) = v^e(1, a^*_{it}, a^*_{it+1}; \boldsymbol{w}_{it})$ by definition, $v^e(0; \boldsymbol{w}_{it})$ and $v^e(0, 1, a'_{it+1}; \boldsymbol{w}_{it})$ generally differ because the latter imposes particular choices.[7] The difference is

$$v^e(0; \boldsymbol{w}_{it}) - v^e(0, 1, a'_{it+1}; \boldsymbol{w}_{it}) = \frac{1}{2}\beta \mathbb{E}^e_{it}[c''(a'_{it+1}; \boldsymbol{w}_{it+1}, \varepsilon_{it+1})(a^*_{it+1} - a'_{it+1})^2] - \beta \mathbb{E}^e_{it}[\ln p^e(\boldsymbol{w}_{it+1})]\,.$$

Substituting into equation 10 and applying the revenue and cost functions, I obtain an Euler equation in which continuation values difference out.

$$\ln\left(\frac{p^e(\boldsymbol{w}_{it})}{1 - p^e(\boldsymbol{w}_{it})}\right) - \beta \mathbb{E}^e_{it}\big[\ln p^e(\boldsymbol{w}_{it+1})\big] = \mathbb{E}^e_{it}[I_{it+1}] - (1-\beta)x_i\gamma^e - (1-\beta)\kappa^e_m - \alpha^e_m \tilde{t}\,,$$

[6] For year t, $\beta Y_{t+1} P_{t+1}$ becomes $\beta^3 Y_{t+3} P_{t+3}$, and $s_{it} = s_{it-1} + a_{it-3}$.

[7] $v^e(1, a^*_{it}, a^*_{it+1}; \boldsymbol{w}_{it})$ has $a^*_{it}(0; \boldsymbol{w}_{it}, \varepsilon_{it})$ and $a^*_{it+1}(a^*_{it}; \boldsymbol{w}_{it+1}, \varepsilon_{it+1})$, while $v^e(0; \boldsymbol{w}_{it})$ has $a^*_{it+1}(0; \boldsymbol{w}_{it+1}, \varepsilon_{it+1})$. But $a^*_{it+1}(a^*_{it}; \boldsymbol{w}_{it+1}, \varepsilon_{it+1}) = a^*_{it+1}(0; \boldsymbol{w}_{it+1}, \varepsilon_{it+1})$ for linear revenues.

for $\tilde{t} = t - \beta(t+1)$ and $I_{it+1} = [\beta Y_{it+1} P_{t+1} - (1-\beta) x_i \gamma - (1-\beta)\kappa_m - \alpha_m \tilde{t}] a^*_{it} + \delta[-\frac{1}{2} {a^*_{it}}^2 + \beta a^*_{it} a^*_{it+1}]$.

Substituting expectational errors and estimated values yields regression equation

$$\ln\left(\frac{\widehat{p^e}(\boldsymbol{w}_{it})}{1-\widehat{p^e}(\boldsymbol{w}_{it})}\right) - \beta \ln \widehat{p^e}(\boldsymbol{w}_{it+1}) = \widehat{I}_{it+1} - (1-\beta) x_i \gamma^e - (1-\beta)\kappa^e_m - \alpha^e_m \tilde{t} + \eta^e_{it}\,. \quad (11)$$

I estimate conditional choice probabilities $\widehat{p^e}(\boldsymbol{w}_{it})$ non-parametrically by regressing observed investment choices on a flexible set of basis terms: piecewise linear splines in Y_{it+1}, P_{t+1}, x_i, and $\tilde{t}$. I do so separately for each region to account for regional unobserved heterogeneity, and I estimate intensive-margin choices $\widehat{a}^*_{it}$ similarly. Dollar-denominated intensive-margin profits $\widehat{I}_{it+1}$ provide a scale normalization that allows parameters γ^e, κ^e_m, and α^e_m to be interpreted in dollar terms, with intercepts κ^e_m identified relative to the outside option.

Discussion

Euler estimation has several advantages. First, I can address endogeneity concerns using standard instrumental variable techniques because estimation reduces to linear regression. Second, while I need to assume rational expectations, I do not need to specify what expectations are. By contrast, the conventional full-solution approach requires explicit structure on expectations over the long-run horizon. Rational expectations remains a strong assumption, but regional effects κ_m absorb expectational bias to the extent that it is fixed within regions. Third, the full-solution approach requires solving the model repeatedly and computing continuation values with each iteration. The Euler approach sidesteps this computational burden because it estimates the model without solving it. Other methods have similar computational advantages in the discrete case, but they cannot accommodate the non-stationarity of my setting (Aguirregabiria and Mira 2007; Bajari et al. 2007; Pakes et al. 2007; Pesendorfer and Schmidt-Dengler 2008).[8]

Estimation relies on several other assumptions. First, I compare investing today or tomorrow, but weak property rights may promote land grabbing and thus bias toward investing today. Regional effects κ_m help by absorbing regional variation in

[8] Besides Scott (2013), recent applications of discrete Euler methods include Diamond et al. (2017), De Groote and Verboven (2019), Traiberman (2019), and Almagro and Domínguez-Iino (2020).

Table 2: Supply shifters as 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 regions. Oil fixed effects and oil-specific time trends differentiate between palm and other oils. Newey-West standard errors account for serial correlation. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

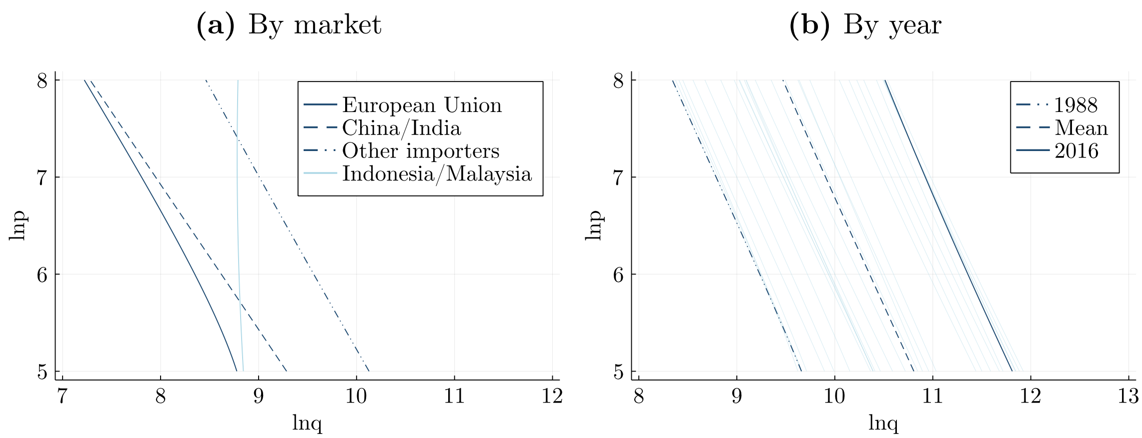
property rights. Second, sites are independent and atomistic. Otherwise, finite dependence does not hold: if price-makers delay investment, then competitors respond, altering the evolution of the economy such that continuation values do not align. World production is indeed unconcentrated, with the largest producer accounting for 4% and the largest ten for 21%, but I must rule out spatial competition, including in local factor markets, as spatial interaction makes estimation intractable. Third, plantation age does not affect profits. Otherwise, delayed investment affects profits in all future periods, and finite dependence again does not hold.

6 Estimates

6.1 Demand

Table 2 and figure 6 present demand estimates. Table 2 shows that weather shocks significantly increase world oil prices in the first stage. The first two columns pool across oil products, and the last two consider palm and other oils separately. For palm oil, a smaller sample size means less precision, but point estimates are relatively close to those of the pooled specifications, and instruments remain strong. Tempera-

Figure 6: Palm oil demand curves



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 oil production. The left figure averages over the study period for each market. The right figure shows demand over time, and each faded line is one year between 1988 and 2016.

ture estimates are perhaps imprecise because variation is limited in tropical climates where palm oil is grown. Toward assessing the exclusion restriction, I also find that weather shocks do not directly affect overall incomes or expenditures. Figure 6 plots the estimated demand curves. Demand elasticities are less than one, particularly for Indonesia and Malaysia, which as producers consume palm oil almost exclusively – consistent with home bias. Globally, demand for palm oil is rising rapidly over time as the demand curve shifts rightward in log scale.

6.2 Supply

Tables 3 and 4 present supply estimates. Table 3 shows that higher revenues increase development, with a larger IV estimate and a strong instrument. Table 4 shows parameter estimates in dollar terms. I estimate average lifetime costs of $8,000 per hectare of plantation (including quadratic costs) and $23 million per mill, both of which decrease over time. Accounting estimates are similar at $7,000 and $20 million (Fairhurst and McLaughlin 2009; Man and Baharum 2011). On the intensive margin, producers treat all land similarly and simply develop around constructed mills. On the extensive margin, distance from major ports, roads, and urban centers discourages production, but tree biomass and peat deposits do not. Producers internalize their private transport costs, but not their emission externalities.

Table 3: Demand shifters as instruments

	OLS	IV	First stage
	$a_{it} - \beta a_{it+1}$	$a_{it} - \beta a_{it+1}$	$Y_{it+3}P_{t+3}$
Yield × price ($Y_{it+3}P_{t+3}$)	0.111***	0.279**	
	(0.00677)	(0.117)	
Potential yield × demand ($Y_i^p d_t$)			17.53***
			(0.719)
Province FE	x	x	x
Province-year trend	x	x	x
Observations	22,914	22,914	22,914
F-statistic			594

Each column is one regression, and each observation is a site-year. Column headings denote specifications and outcome variables. Potential yields and demand shifters instrument for yields and prices. Potential yields are computed with the agronomic model of Hoffmann et al. (2014), and demand shifters are computed in demand estimation. Prices combine palm and palm kernel oil prices, weighting by expenditures. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 4: Palm oil supply parameters

	Intensive-margin		Extensive-margin	
	Estimate	SE	Estimate	SE
Province-specific costs ($\bar{\kappa}_m, \bar{\kappa}_m^e$)	7,412***	(167)	22,745,198***	(2,019,229)
Province-specific cost trends ($\bar{\alpha}_m, \bar{\alpha}_m^e$)	-384***	(18)	-1,370,062***	(153,467)
Cost factors (γ, γ^e)				
Log port distance, km	-303	(324)	3,974,558***	(824,272)
Log road distance, km	-98	(129)	2,605,341***	(398,823)
Log urban distance, km	109	(212)	2,133,386***	(471,598)
Log carbon in tree biomass, t	381	(302)	959,958*	(500,588)
Log carbon in peat deposits, t	-58	(40)	-152,701	(111,080)
Quadratic costs (δ)	3**	(1)	–	–
Logit scale (σ^e)	–	–	6,718,816***	(663,730)

Estimates are interpretable as inflation-adjusted, year-2000 dollars. I report averages of province-specific costs and cost trends. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

7 Counterfactuals

7.1 Regulation and emissions

I study a palm oil consumption tax, subject to coordination among consumers and commitment to uphold the tax. For coordination, domestic regulation covers all consumers by taxing exports alongside domestic consumption. I also study three import tariffs coalitions: all importers together, an EU-China-India partnership, and the EU alone. Import tariffs offer an alternative when domestic regulation is infeasible, but small coalitions suffer from incomplete coverage and potential leakage. For commitment, I study full, limited, and no commitment.[9] Under full commitment, tariffs are set and upheld in perpetuity. Under limited commitment, tariffs are upheld for L periods before lapsing to no commitment. Under no commitment, sunk investment and time to build make it statically optimal to set tariffs to zero in each period. The reason is that tariffs impose costs without immediate benefit: they act as a price wedge, but they prevent neither past development, which is sunk, nor new development, which takes time to generate taxable production.[10]

For a given set of tariffs, I quantify the effects on emissions. Unlike estimation, counterfactuals require solving the model. I take year 2100 as terminal, noting that the results are insensitive to this particular choice. I then solve for prices over time as a fixed point: the demand model connects quantities produced to prices, and the supply model connects prices to quantities produced. Tariffs enter as follows.

$$P_t^{DR}(Q_t^R) - \tau_t = P_t^{DU}(Q_t^U)$$

Tariffs τ_t push sales to unregulated markets until prices equalize given quantity produced Q_t, which in turn depends on prices over time. With prices and quantities, I

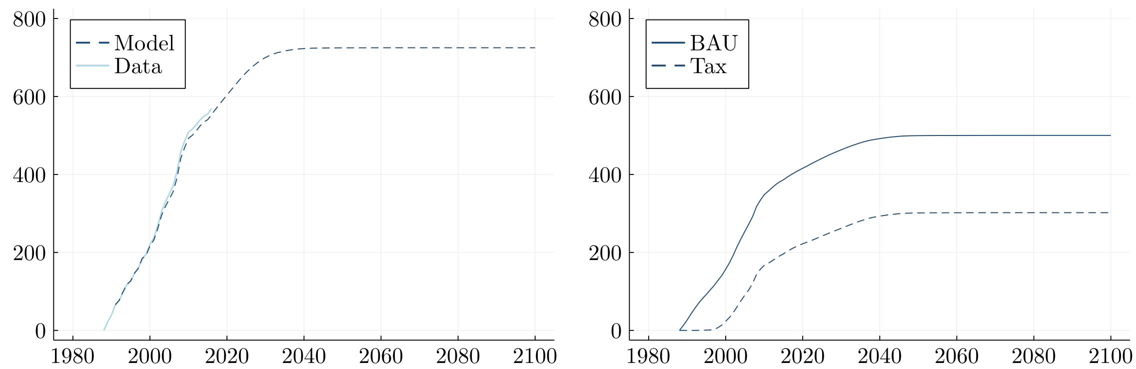
[9] In principle, domestic regulation can avoid commitment problems by taxing production, imposing the full cost of emissions as an immediate fine. In practice, however, such large fines may encourage legal challenges to delay payment, including until a political regime change.

[10] Indeed, most traded emissions are from industries in which production relies on sunk investment: fossil fuels, manufacturing, mining, transportation, and agriculture (Peters et al. 2011). As investments are sunk, so too are emissions. For agriculture, emissions are sunk because they are released upon investment. Once land is cleared, the forest is gone. For other sectors, emissions are sunk, even if released gradually, when investment results in low marginal costs. Once an oil well has been identified, explored, and drilled, extraction is cheap and proceeds to completion.

Figure 7: Cumulative emission costs ($1B)

(a) Model fit

(b) Business as usual vs. domestic regulation



Both figures show cumulative emission damages in dollar terms, computed as net present values from the initial period. The left shows emissions under realized mill construction and illustrates model fit. The right shows emissions under expected mill construction and compares business as usual to the optimal tax under domestic regulation and full commitment.

compute consumer and producer surplus and government revenue. I quantify carbon emissions by combining predicted plantation development with spatial data on carbon stocks, assuming development releases all carbon. Indeed, trees must be cut to make space for plantations, and the peat layer must be cleared to access the underlying soil. I monetize emission damages with a social cost of carbon of $75. Figure 7 plots emissions over time: those under realized mill construction show the close fit of the model to observed data, and those under expected mill construction incorporate the effects of regulation on both intensive and extensive margins.

For each coordination and commitment scenario, I choose tariffs to maximize social welfare, resolving the model for each candidate tariff. Two simplifications facilitate the optimization problem. First, I focus on tariffs that are constant during the commitment period. Such tariffs are straightforward to administer and can replicate the net present values of more complex tariff paths. Second, I focus on tariffs that treat all palm oil uniformly. Although palm emissions are heterogeneous, Pigouvian tariffs would require monitoring production and tracking sales, as well as commitment not to "greenwash" palm oil produced with sunk deforestation. Furthermore, uniform tariffs sidestep reshuffling concerns in which tariffs on dirty palm oil simply reallocate it toward unregulated markets rather than decrease its production.

On the demand side, I ignore the carbon effects of substitution to other oil products. 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 one of several substitutes at 13% of total oil consumption.

On the supply side, I ignore the carbon effects of substitution to other drivers of deforestation. The primary threat is substitution to acacia (paper pulp) plantations, which also destroy peatlands. The resulting bias is small because palm oil is seven times more profitable than acacia, which requires replanting after harvest, such that switching to acacia is unappealing for many palm oil producers (Sofiyuddin et al. 2012). Indeed, I do not find that palm displaces acacia development in the data, at least in partial equilibrium, although other settings may require multi-product tariffs. Other drivers of deforestation include mining, which relies on the exogenous distribution of deposits, and selective logging, which does not destroy peatlands.

7.2 Results

Table 5 shows counterfactual results. Domestic regulation with full commitment is first best, reducing emissions by 40% and increasing social welfare by $115 billion. Tariffs are nearly as effective as first-best regulation, but only when coordinated and committed. Weak coordination constrains emission reductions, as low coverage limits the influence of tariffs on world prices. Leakage exacerbates this effect, but only modestly so given relatively inelastic demand. Weak commitment leads to temporary tariffs that do less to dissuade palm production.

How achievable are coordination and commitment? Consider China, India, and other importers – markets that are crucial for the efficacy of tariffs. For coordination, the challenge is that defectors can free-ride on both the emission reductions and lower world prices induced by the coalition. But coordination remains preferable to China, India, and other importers because they benefit greatly from emission reductions. Unifying other importers requires transfers to those for whom emissions matter little – particularly in the short run – and large welfare gains provide an abundant source of funds for these transfers. For commitment, the challenge is that it is always statically

Table 5: Counterfactual experiments

	%	$1B	ΔW ($1B)				ΔW ($1B)			
	ΔE	ΔW	CS	PS	G	E	EU	CI	OI	IM
Domestic regulation										
Full commitment	39.62	115	-207	-70	194	198	-21	0	74	62
30-year commitment	32.63	95	-157	-58	147	163	-17	3	67	41
10-year commitment	7.87	26	-30	-18	35	39	-4	3	18	8
Tariffs: all importers										
Full commitment	38.92	108	-165	-65	143	195	-3	24	138	-51
30-year commitment	31.84	89	-123	-53	105	160	-3	20	113	-41
10-year commitment	7.49	22	-25	-17	27	38	0	5	29	-12
Tariffs: EU, China, India										
Full commitment	15.20	39	-87	-22	72	76	-8	0	64	-18
30-year commitment	11.68	30	-61	-16	49	58	-6	1	49	-14
10-year commitment	2.13	6	-12	-3	11	11	-1	0	9	-3
Tariffs: EU only										
Full commitment	6.10	15	-28	-9	22	30	-8	6	25	-8
30-year commitment	5.03	12	-23	-7	17	25	-7	4	21	-6
10-year commitment	1.27	3	-6	-2	5	6	-1	1	5	-2

Each row is one experiment. Columns show changes relative to business as usual in emissions (E) and social welfare (W). I break welfare into consumer surplus (CS), producer surplus (PS), government revenue (G), and emissions (E), as well as welfare for the EU (EU), China and India (CI), other importers (OI), and Indonesia and Malaysia (IM). Each is a net present value from the initial period. The EU, China/India, other importers, and Indonesia/Malaysia bear 1%, 17%, 80%, and 2% of the social costs of carbon, respectively, based on pooled estimates from Ricke et al. (2018).

optimal to set tariffs to zero. But weak commitment is an issue of institutions and not incentives, as full commitment is optimal ex-ante.

Absent coordination, unilateral EU action can still meaningfully reduce emissions. In particular, the EU can take advantage of substitutability between coordination and commitment. While coordination is preferable, political constraints may make even ten-year commitment difficult for some importers. But strong institutions give the EU commitment power, and committed, unilateral action is nearly as effective as less-committed action by larger coalitions. Note, however, that EU action requires an interest in reducing emissions globally. The EU bears only a small fraction of emission damages directly, and thus suffers losses in all tariffs scenarios. Nonetheless, these losses are modest compared to emission reductions and consistent with current EU efforts to combat climate change.

More generally, tariffs reduce emissions at reasonable average costs ranging from \$30 to \$40 per ton (and marginal costs of \$75), where costs are foregone consumer and producer surplus net of government revenue. Import tariffs may therefore be appealing for climate-conscious governments that have exhausted low-cost options domestically. At the same time, tariffs impose large losses on Indonesian and Malaysian producers that may motivate compensatory transfers. Consistent with the magnitude of emissions at stake, tariffs are twice as large as observed palm oil prices during the study period tariffs, ranging from \$1,000 to \$2,000 across scenarios.

An alternative is a renewed focus on domestic regulation, which generates government revenue at the primary expense of foreign consumers given relatively inelastic demand. While direct domestic regulation may be infeasible, an export tax requires enforcement only at ports. Such a tax is equivalent to tariffs imposed by all importers, except that government revenue goes to Indonesia and Malaysia rather than abroad. Emission reductions are nearly as large as those under domestic regulation, and the gains to Indonesia and Malaysia (IM + G) are even greater because domestic consumption remains unregulated. Thus, domestic regulation is fiscally appealing even absent international pressures.

7.3 Robustness

Table 6 shows alternative specifications. First, I consider more elastic demand by rotating demand curves around business-as-usual outcomes. More elastic regulated demand increases emission reductions by boosting the effect of regulation on world prices. More elastic unregulated demand undercuts emission reductions by increasing leakage. Second, I apply objective functions that ignore unregulated markets and producers. Doing so increases tariffs and thus emission reductions, as tariffs improve terms of trade, but only when governments consider global emission damages. An EU focused on EU damages alone will undervalue emission reductions and act modestly. Third, a larger social cost of carbon implies larger emission reductions, although reductions remain substantial with a smaller social cost. Fourth, more discounting leads to larger emission reductions by upweighting the initial reductions achieved by regulation. Fifth, solving with later terminal years has little effect given discounting.

Table 6: Counterfactual experiments, robustness (%ΔE)

	Domestic		EU only	
	Full	10-year	Full	10-year
Baseline	39.62	7.87	6.10	1.27
Demand elasticity				
Regulated $\varepsilon^{\mathrm{DR}}$ + 50%	49.91	9.47	9.08	1.98
Unregulated $\varepsilon^{\mathrm{DU}}$ + 50%	39.62	7.87	5.87	1.25
Objective function				
$\Delta\mathrm{CS}^{\mathrm{R}} + \Delta\mathrm{G} + \Delta\mathrm{E}$	43.63	8.48	6.60	1.50
$\Delta\mathrm{CS}^{\mathrm{R}} + \Delta\mathrm{G} + \Delta\mathrm{E}^{\mathrm{R}}$	43.63	8.48	0.53	0.15
Social cost of carbon				
$50	35.20	7.76	4.66	1.06
$100	44.62	8.25	7.25	1.50
Discount factor				
0.85	59.04	22.84	12.41	5.19
0.95	22.56	2.32	1.98	0.17
Terminal year				
2125	39.62	7.87	6.10	1.27
2150	39.62	7.87	6.10	1.29

Each cell is one experiment and shows emission reductions in percentage terms relative to business as usual. Columns indicate coordination and commitment, and rows indicate deviations from baseline.

8 Conclusion

The conventional approach to environmental regulation focuses on domestic intervention, but domestic regulation can face major challenges. 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 for evaluating the effects of such policy on emissions. I apply it to studying proposed EU tariffs on imports of palm oil, which drives deforestation accounting for more emissions over the last three decades than the entire economy of India.

I find that EU tariffs are most effective when coordinated with other major importers like China and India, and when regulators can commit to upholding them over the long term. Coordinated, committed tariffs are comparable to domestic regulation, reducing carbon emissions by 39% compared to 40%. But free-riding and leakage concerns undermine coordination, and static incentives to remove tariffs undermine commitment. These results underscore the significance of the Paris Agreement, as well as the implications of US withdrawal. If tariff coalitions fail, an alternative is unilateral EU action that reduces emissions by up to 6%. Another alternative is partial domestic regulation with an export tax, which generates enough government revenue to be net positive for Indonesia and Malaysia, requires enforcement only at domestic ports, and reduces emissions by up to 39%.

I leave several directions open for future work. First, trade policy may interact with domestic regulation in settings where domestic regulation is at least partially feasible. Second, dynamic bargaining considerations could influence the formation and stability of tariff coalitions in ways that I do not explicitly capture here. Third, spatial interaction among plantations might create path dependence that amplifies the effects of regulation. Each direction invites more work on this important topic, as policymakers can still protect the vast forests that remain intact for now.

References

Abrego, Lisandro and Carlo Perroni. Investment Subsidies and Time-Consistent Environmental Policy. Oxford Economic Papers, 54(4):617–635, 2002.

Acemoglu, Daron and Will Rafey. Mirage on the Horizon: Geoengineering and Carbon Taxation Without Commitment. 2019.

Aguirregabiria, Victor and Arvind Magesan. Euler Equations for the Estimation of Dynamic Discrete Choice Structural Models. Advances in Econometrics, 31:3–44, 2013.

Aguirregabiria, Victor and Pedro Mira. Sequential Estimation of Dynamic Discrete Games. Econometrica, 75(1):1–53, 2007.

Almagro, Milena and Tomás Domínguez-Iino. Location Sorting and Endogenous Amenities: Evidence from Amsterdam. 2020.

Araujo, Rafael, Francisco Costa, and Marcelo Sant'Anna. Efficient Forestation in the Brazilian Amazon: Evidence from a Dynamic Model. 2021.

Arcidiacono, Peter and Paul Ellickson. Practical Methods for Estimation of Dynamic Discrete Choice Models. Annual Review of Economics, 3:363–394, 2011.

Arcidiacono, Peter and Robert Miller. Conditional Choice Probability Estimation of Dynamic Discrete Choice Models With Unobserved Heterogeneity. Econometrica, 79(6):1823–1867, 2011.

Assunção, Juliano, Robert McMillan, Joshua Murphy, and Eduardo Souza-Rodrigues. Optimal Environmental Targeting in the Amazon Rainforest. 2021.

Bajari, Patrick, C. Lanier Benkard, and Jonathan Levin. Estimating Dynamic Models of Imperfect Competition. Econometrica, 75(5):1331–1370, 2007.

Battaglini, Marco and Bård Harstad. Participation and Duration of Environmental Agreements. Journal of Political Economy, 124(1):160–204, 2016.

Berry, Steven, James Levinsohn, and Ariel Pakes. Automobile Prices in Market Equilibrium. Econometrica, 63(4):841–890, 1995.

Blundell, Richard and Jean Marc Robin. Estimation in Large and Disaggregated Demand Systems: An Estimator for Conditionally Linear Systems. Journal of Applied Econometrics, 14(3):209–232, 1999.

Böhringer, Christoph, Jared Carbone, and Thomas Rutherford. The Strategic Value of Carbon Tariffs. American Economic Journal: Economic Policy, 8(1):28–51, 2016.

Brunner, Steffen, Christian Flachsland, and Robert Marschinski. Credible Commitment in Carbon Policy. Climate Policy, 12(2):255–271, 2012.

Burgess, Robin, Matthew Hansen, Benjamin Olken, Peter Potapov, and Stefanie Sieber. The Political Economy of Deforestation in the Tropics. Quarterly Journal of Economics, 127(4):1707–1754, 2012.

Burgess, Robin, Francisco Costa, and Benjamin Olken. The Brazilian Amazon's Double Reversal of Fortune. 2019.

Busch, Jonah, Kalifi Ferretti-Gallon, Jens Engelmann, Max Wright, Kemen Austin, Fred Stolle, Svetlana Turubanova, Peter Potapov, Belinda Margono, Matthew Hansen, and Alessandro Baccini. Reductions in Emissions from Deforestation from Indonesia's Moratorium on New Oil Palm, Timber, and Logging Concessions. Proceedings of the National Academy of Sciences of the United States of America, 112(5):1328–1333, 2015.

Collard-Wexler, Allan. Demand Fluctuations in the Ready-Mix Concrete Industry. Econometrica, 81(3):1003–1037, 2013.

Copeland, Brian and M. Scott Taylor. North-South Trade and the Environment. Quarterly Journal of Economics, 109(3):755–787, 1994.

Copeland, Brian and M. Scott Taylor. Trade and Transboundary Pollution. American Economic Review, 85(4):716–737, 1995.

Cramb, Rob and John McCarthy, editors. The Oil Palm Complex: Smallholders, Agribusiness and the State in Indonesia and Malaysia. NUS Press, Singapore, 2016.

Davis, Steven, Glen Peters, and Ken Caldeira. The Supply China of CO2 Emissions. Proceedings of the National Academy of Sciences, 108(45):18554–18559, 2011.

De Groote, Olivier and Frank Verboven. Subsidies and Time Discounting in New Technology Adoption: Evidence from Solar Photovoltaic Systems. American Economic Review, 109 (6):2137–2172, 2019.

Deaton, Angus and John Muellbauer. An Almost Ideal Demand System. American Economic Review, 70(3):312–326, 1980.

Diamond, Rebecca, Tim McQuade, and Franklin Qian. The Effects of Rent Control Expansion on Tenants, Landlords, and Inequality: Evidence from San Francisco. 2017.

Domínguez-Iino, Tomás. Efficiency and Redistribution in Environmental Policy: An Equilibrium Analysis of Agricultural Supply Chains. 2021.

Duflo, Esther, Michael Greenstone, Rohini Pande, and Nicholas Ryan. The Value of Regulatory Discretion: Estimates from Environmental Inspections in India. Econometrica, 86 (6):2123–2160, 2018.

Edwards, Ryan. Export Agriculture and Rural Poverty: Evidence from Indonesian Palm Oil. 2019.

Edwards, Ryan, Walter Falcon, Gracia Hadiwidjaja, Matthew Higgins, Rosamond Naylor, and Sudarno Sumarto. Fight Fire with Finance: A Randomized Field Experiment to Curtail Land-clearing Fire in Indonesia. 2020.

Elliott, Joshua, Ian Foster, Samuel Kortum, Todd Munson, Fernando Pérez Cervantes, and David Weisbach. Trade and Carbon Taxes. American Economic Review: Papers & Proceedings, 100:465–469, 2010.

Erdem, Tülin, Susumu Imai, and Michael Keane. Brand and Quantity Choice Dynamics Under Price Uncertainty. Quantitative Marketing and Economics, 1:5–64, 2003.

Ericson, Richard and Ariel Pakes. Markov-Perfect Industry Dynamics: A Framework for Empirical Work. Review of Economic Studies, 62(1):53–82, 1995.

Fairhurst, Thomas and David McLaughlin. Sustainable Oil Palm Development on Degraded Land in Kalimantan. Technical report, World Wildlife Fund, 2009.

Farrokhi, Farid and Ahmad Lashkaripour. Can Trade Policy Mitigate Climate Change? 2021.

Fowlie, Meredith. Incomplete Environmental Regulation, Imperfect Competition, and Emissions Leakage. American Economic Journal: Economic Policy, 1(2):72–112, 2009.

Fowlie, Meredith, Mar Reguant, and Stephen Ryan. Market-Based Emissions Regulation and Industry Dynamics. Journal of Political Economy, 124(1):249–302, 2016.

Gaveau, David, Bruno Locatelli, Mohammad Salim, Husna Yaen, Pablo Pacheco, and Douglas Sheil. Rise and Fall of Forest Loss and Industrial Plantations in Borneo (2000–2017). Conservation Letters, 12(3):e12622, 2019.

Gumbricht, Thomas, Rosa Maria Roman-Cuesta, Louis Verchot, Martin Herold, Florian Wittmann, Ethan Householder, Nadine Herold, and Daniel Murdiyarso. An Expert System Model for Mapping Tropical Wetlands and Peatlands Reveals South America as the Largest Contributor. Global Change Biology, 23:3581–3599, 2017.

Hall, Robert. Stochastic Implications of the Life Cycle-Permanent Income Hypothesis: Theory and Evidence. Journal of Political Economy, 86(6):971–987, 1978.

Hansen, Lars Peter and Kenneth Singleton. Generalized Instrumental Variables Estimation of Nonlinear Rational Expectations Models. Econometrica, 50(5):1269–1286, 1982.

Hansen, M. C., P. V. Potapov, R. Moore, M. Hancher, S. A. Turubanova, A. Tyukavina, D. Thau, S. V. Stehman, S. J. Goetz, T. R. Loveland, A. Kommareddy, A. Egorov, L. Chini, C. O. Justice, and J. R. G. Townshend. High-Resolution Global Maps of 21st-Century Forest Cover Change. Science, 342(6160):850–853, 2013.

Harstad, Bård. Buy Coal! A Case for Supply-Side Environmental Policy. Journal of Political Economy, 120(1), 2012.

Harstad, Bård. The Market for Conservation and Other Hostages. Journal of Economic Theory, 166:124–151, 2016.

Harstad, Bård. Technology and Time Inconsistency. Journal of Political Economy, 128(7): 2653–2689, 2020.

Harstad, Bård. Trade and Trees. 2021.

Harstad, Bård and Torben Mideksa. Conservation Contracts and Political Regimes. Review of Economic Studies, 84:1708–1734, 2017.

Hausman, Jerry, Gregory Leonard, and J. Douglas Zona. Competitive Analysis with Differenciated Products. Annales d'Economie et de Statistique, 34:159–180, 1994.

Helm, Dieter, Cameron Hepburn, and Richard Mash. Credible Carbon Policy. Oxford Review of Economic Policy, 19(3):438–450, 2003.

Hendel, Igal and Aviv Nevo. Measuring the Implications of Sales and Consumer Inventory Behavior. Econometrica, 74(6):1637–1673, 2006.

Hoel, Michael. Should a Carbon Tax Be Differentiated Across Sectors? Journal of Public Economics, 59:17–32, 1996.

Hoffmann, Munir, Alba Castañeda-Vera, Mark van Wijk, Ken Giller, Thomas Oberthuer, Christopher Donough, and Anthony Whitbread. Simulating Potential Growth and Yield of Oil Palm (Elaeis Guineensis) with PALMSIM: Model Description, Evaluation and Application. Agricultural Systems, 131:1–10, 2014.

Hopenhayn, Hugo. Entry, Exit, and Firm Dynamics in Long Run Equilibrium. Econometrica, 60(5):1127–1150, 1992.

Hotz, V. Joseph and Robert Miller. Conditional Choice Probabilities and the Estimation of Dynamic Models. Review of Economic Studies, 60(3):497–529, 1993.

Jayachandran, Seema, Joost de Laat, Eric Lambin, Charlotte Stanton, Robin Audy, and Nancy Thomas. Cash for Carbon: A Randomized Trial of Payments for Ecosystem Services to Reduce Deforestation. Science, 357:267–273, 2017.

Kalouptsidi, Myrto, Paul Scott, and Eduardo Souza-Rodrigues. Linear IV Regression Estimators for Structural Dynamic Discrete Choice Models. Journal of Econometrics, 222 (1):778–804, 2021.

Kortum, Samuel and David Weisbach. The Design of Border Adjustments for Carbon Prices. National Tax Journal, 70(2):421–446, 2017.

Kortum, Samuel and David Weisbach. Optimal Unilateral Carbon Policy. 2021.

Magnac, Thierry and David Thesmar. Identifying Dynamic Discrete Decision Pro- cesses. Econometrica, 70(2):801–816, 2002.

Man, Elaine Lau Ying and Adam Baharum. A Qualitative Approach of Identifying Major Cost Influencing Factors in Palm Oil Mills and the Relations towards Production Cost of Crude Palm Oil. American Journal of Applied Sciences, 8(5):441–446, 2011.

Markusen, James. International Externalities and Optimal Tax Structures. Journal of International Economics, 5:15–29, 1975.

Marsiliani, Laura and Thomas Renström. Time Inconsistency in Environmental Policy: Tax Earmarking as a Commitment Solution. Economic Journal, 110(462):C123–C138, 2000.

Nordhaus, William. Climate Clubs: Overcoming Free-riding in International Climate Policy. American Economic Review, 105(4):1339–1370, 2015.

Oates, Wallace and Paul Portney. The Political Economy of Environmental Policy. Handbook of Environmental Economics, 1:325–354, 2003.

Official Journal of the European Union. European Parliament Resolution of 4 April 2017 on Palm Oil and Deforestation of Rainforests, 2018.

Oliva, Paulina. Environmental Regulations and Corruption: Automobile Emissions in Mexico City. Journal of Political Economy, 123(3):686–724, 2015.

Pakes, Ariel, Michael Ostrovsky, and Steven Berry. Simple Estimators for the Parameters of Discrete Dynamic Games (with Entry/Exit Examples). RAND Journal of Economics, 38(2):373–399, 2007.

Palm Oil Analytics. Essential Palm Oil Statistics. Technical report, 2017.

Parks, Richard. Efficient Estimation of a System of Regression Equations when Disturbances are Both Serially and Contemporaneously Correlated. Journal of the American Statistical Association, 62(318):500–509, 1967.

Pesendorfer, Martin and Philipp Schmidt-Dengler. Asymptotic Least Squares Estimators for Dynamic Games. Review of Economic Studies, 75:901–928, 2008.

Peters, Glen, Jan Minx, Christopher Weber, and Ottmar Edenhofer. Growth in Emission Transfers via International Trade from 1990 to 2008. Proceedings of the National Academy of Sciences, 108(21):8903–8908, 2011.

Rauscher, Michael. International Trade, Factor Movements, and the Environment. Oxford University Press, Oxford, 1997.

Ricke, Katharine, Laurent Drouet, Ken Caldeira, and Massimo Tavoni. Country-Level Social Cost of Carbon. Nature Climate Change, 8:895–900, 2018.

Ryan, Stephen. The Costs of Environmental Regulation in a Concentrated Industry. Econometrica, 80(3):1019–1061, 2012.

Scott, Paul. Dynamic Discrete Choice Estimation of Agricultural Land Use. 2013.

Shapiro, Joseph. The Environmental Bias of Trade Policy. 2020.

Sofiyuddin, Muhammad, Arief Rahmanulloh, and S. Suyanto. Assessment of Profitability of Land Use Systems in Tanjung Jabung Barat District, Jambi Province, Indonesia. Open Journal of Forestry, 2(4):252–256, 2012.

Song, Xiao-Peng, Matthew Hansen, Stephen Stehman, Peter Potapov, Alexandra Tyukavina, Eric Vermote, and John Townshend. Global Land Change from 1982 to 2016. Nature, 560:639–643, 2018.

Souza-Rodrigues, Eduardo. Deforestation in the Amazon: A Unified Framework for Estimation and Policy Analysis. Review of Economic Studies, 86:2713–2744, 2019.

Traiberman, Sharon. Occupations and Import Competition: Evidence from Denmark. American Economic Review, 109(12):4260–4301, 2019.

USDA Foreign Agricultural Service. Indonesia Biofuels Annual Report 2019. Technical report, 2019a.

USDA Foreign Agricultural Service. Malaysia Biofuels Annual Report 2019. Technical report, 2019b.

Wagstaff, Kiri, Claire Cardie, Seth Rogers, and Stefan Schroedl. Constrained K-means Clustering with Background Knowledge. Proceedings of the Eighteenth International Conference on Machine Learning, 1:577–584, 2001.

Warren, Matthew, Kristell Hergoualc'h, J. Boone Kauffman, Daniel Murdiyarso, and Randall Kolka. An Appraisal of Indonesia's Immense Peat Carbon Stock Using National Peatland Maps: Uncertainties and Potential Losses from Conversion. Carbon Balance and Management, 12:12, 2017.

World Wildlife Fund. Palm Oil Buyers Scorecard: Measuring the Progress of Palm Oil Buyers. Technical report, 2016.

Xu, Yidi, Le Yu, Wei Li, Philippe Ciais, Yuqi Cheng, and Peng Gong. Annual Oil Palm Plantation Maps in Malaysia and Indonesia from 2001 to 2016. Earth System Science Data, 12:847–867, 2020.

Zarin, Daniel, Nancy Harris, Alessandro Baccini, Dmitry Aksenov, Matthew Hansen, Claudia Azevedo-Ramos, Tasso Azevedo, Belinda Margono, Ane Alencar, Chris Gabris, Adrienne Allegretti, Peter Potapov, Mary Farina, Wayne Walker, Varada Shevade, Tatiana Loboda, Svetlana Turubanova, and Alexandra Tyukavina. Can Carbon Emissions from Tropical Deforestation Drop by 50% in 5 Years? Global Change Biology, 22:1336–1347, 2016.

ONLINE APPENDIX

A Data

Sources

Table A1: Palm oil plantations and mills

Source	Period	Coverage	Description
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

Table A2: Yields

Source	Period	Coverage	Description
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

Table A3: Land characteristics

Source	Period	Coverage	Description
World Port Index	2019	World	Port coordinates
World Port Source	2020	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
Hansen et al. (2013)	2001-2018	World	Tree cover loss, 30m resolution

Table A4: Consumption and world prices

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
World Bank	1980-2019	World	Inflation
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

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 a resolution of 100 meters 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 the 30-arc-second resolution (approximately 1 km^2) by averaging. As discussed in Xu et al. (2020), I impose that development is uni-directional, such that the proportion of development for each tile is non-decreasing over time. Xu et al. (2020) restrict their attention to Sumatra, Kalimantan, Riau, and Malaysia, and I do the same in my analysis. These regions cover virtually all palm production in Indonesia and Malaysia during the period of study, although Papua and Sulawesi remain important frontiers for future expansion.

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 plantation development, I estimate the empirical relationship between plantation development and tree cover loss during the period of overlap, and I use these estimates to impute plantation development prior to 2001. For tiles i in years t,

$$\Delta\text{Plantation}_{it} = \sum_{s=0}^{3} \beta_s \Delta\text{Tree cover}_{it-s} + \varepsilon_{it}\,, \tag{12}$$

where $\Delta\text{Plantation}_{it}$ is new plantation development and $\Delta\text{Tree cover}_{it-s}$ terms are tree cover loss in the preceeding periods. The Song et al. (2018) data are at 5.6-km resolution, so I downscale them to match the 1-km resolution of the aggregated Xu et al. (2020) data. Table A5 shows the resulting estimates: negative coefficients indicate that more plantation development corresponds to higher tree cover loss, especially over the preceeding two years. For each tile, I combine predicted changes in plantation development with observed levels in 2001 to impute pre-2001 plantation development, 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 a resolution of 5.6km, and indeed my core analysis analyzes aggregated sites and not individual tiles.

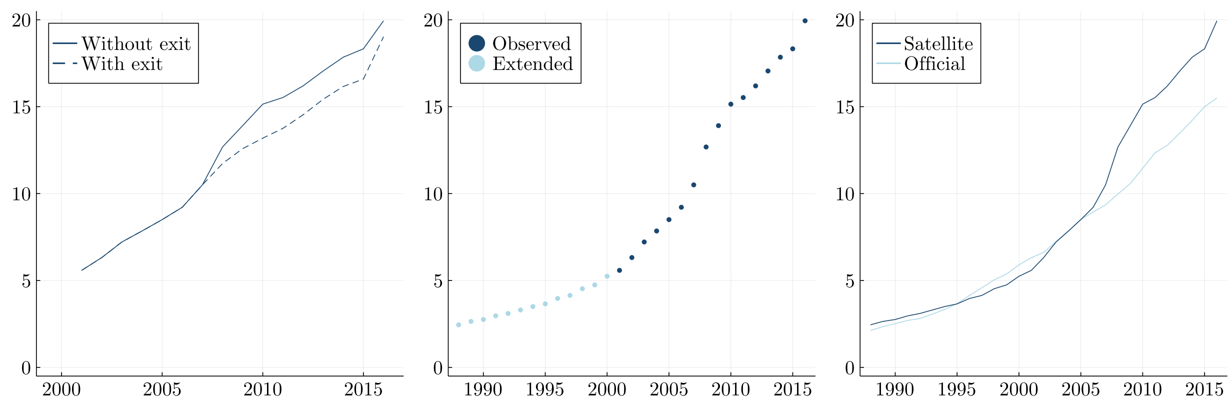
Table A5: Plantations vs. tree cover (2001-2016)

	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. Data: Xu et al. (2020), Song et al. (2018). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Figure A1: Total plantations (Mha)

(a) With vs. without exit **(b)** Observed vs. extended **(c)** Satellite vs. official data



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. Data: Xu et al. (2020), Song et al. (2018), USDA FAS.

Figure A1 plots the resulting data. First, imposing uni-directional development rules out exit. Indeed, there is little exit in the data to begin with, and in any case plantation development releases carbon emissions irreversibly. 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

Table A6: Mill counts by region (2016)

	Mill data	Government figures
Indonesia	1,050	1,070
Kalimantan	328	260
Central Sumatra	264	358
North Sumatra	225	237
South Sumatra	204	178
Sulawesi	21	30
Papua	8	7
Malaysia	471	453
Peninsular Malaysia	266	247
Sabah	132	129
Sarawak	73	77
Total	1,521	1,523

For Sumatra, Central is West Sumatra, Riau, and Kepulauan Riau; North is North Sumatra and Aceh; and South is South Sumatra, Bangka Belitung, Bengkulu, Jambi, and Lampung. Data: World Resources Institute, Indonesian economic census, Malaysian Palm Oil Board.

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 determine the timing of mill construction. For each mill, I record the first year in which I observe mill construction.

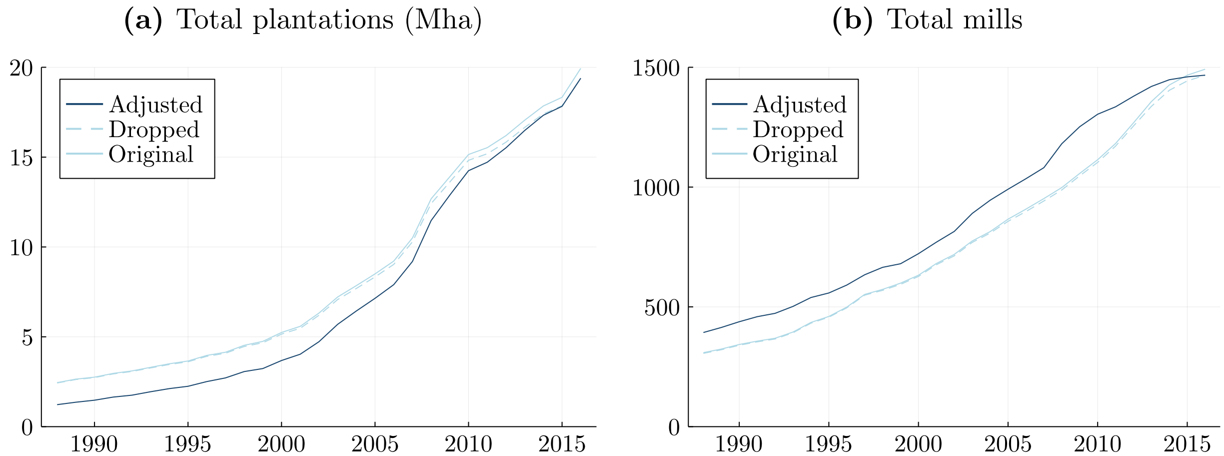
In this way, I identify 1,521 palm mills as of 2016. I verify the data by comparing them to official government data from the Indonesian economic census and Malaysian Palm Oil Board. The 2016 Indonesian economic census contains 1,248 palm-oil establishments, of which 1,154 are located outside of Java. Focusing on firms involved in extracting crude oil from crops, I obtain 1,070 firms that produce either crude palm or palm kernel oil (KBLI codes 10431 and 10432, respectively). Table A6 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.

I lightly harmonize to ensure consistency between the plantation and mill data. First, I assign plantations to the nearest mill in 2016, and I assume these assignments are consistent over time. Second, I drop plantations and mills that do not meet industry standards. Plantations must be within 50 kilometers of a mill, as oil palm fruit deteriorates rapidly after harvest and thus cannot be processed without nearby mills. Mills must have at least 1,000 hectares of plantations, which is the minimum required to run a small mill at capacity.[11] Third, I adjust the data to avoid plantations that pre-date their assigned mills.[12] I weight the plantation and mill data equally, which balances

[11] Each year, 1,000 hectares with a yield of 3 tons of palm oil per hectare will produce 3,000 tons, matching the capacity of a small mill that processes 1 ton per hour for 10 hours per day for 300 days per year.

[12] The plantation data record when young palm trees have been established, and the mill data record when mill construction begins. Proximity to an under-construction mill ensures that young palm trees will have access to an operational mill by the time they reach maturity and begin to bear fruit.

Figure A2: Harmonized plantation and mill data



Light blue lines show unharmonized data, and navy lines harmonized data. Harmonization drops plantations and mills inconsistent with each other, and dashed light blue lines show the effects of dropping these data.

Table A7: Proportion of data impacted by harmonization

	All		Within province	
	Plantations	Mills	Plantations	Mills
Dropped (%)	1.83	0.91	2.06	1.06
Adjusted (%)	11.98	12.23	11.95	11.95
Total (%)	13.80	13.14	14.00	13.01

I assign plantations to the nearest existing mill within 50 kilometers and – in the last two columns – within the same province. Harmonization adjusts the timing of plantation and mill investment to avoid plantations that predate their assigned mills, dropping data that cannot be reconciled in this way.

delaying plantation development against advancing mill construction.

Figure A2 and table A7 show the modest impacts of harmonization. I further impose that plantations be linked to mills within the same province (Indonesia) or state (Malaysia). This assumption simplifies computation in defining potential sites because it allows me to define sites separately by region, and table A7 shows that it has little marginal effect. Kuala Lumpur, Labuan, Perlis, and Putrajaya are small and lack yields data, so I combine them with neighboring states Selangor, Sabah, Kedah, and Selangor, respectively.

Yields

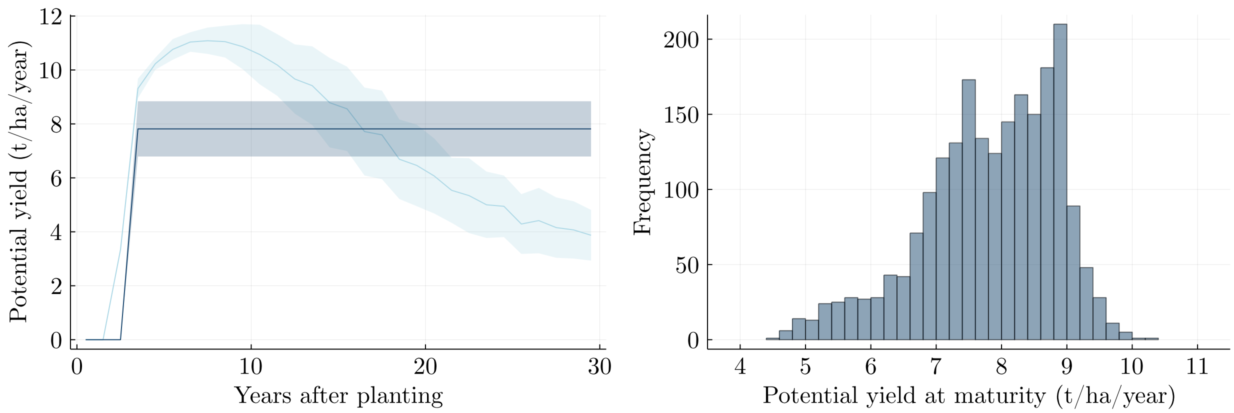
I construct data on palm oil yields by site over time by combining cross-sectional, site-level data on potential yields from the PALMSIM model of Hoffmann et al. (2014) with panel, province-level data on attained yields from government statistics.

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

Figure A3: Potential palm oil yields

(a) Simulated vs. flattened yield curve

(b) Potential yield by site



Yield curves are computed from the PALMSIM model (Hoffmann et al. 2014) using field-level average monthly solar radiation and precipitation from WorldClim. On the left, the light blue 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.

these variables at a resolution of 30 arc-seconds. To facilitate computation, I aggregate climate inputs and run the PALMSIM model by site. Figure A3a shows the resulting 30-year yield curve, which starts at zero before increasing steeply then declining gradually. Because the data on attained yields distinguish only between "immature" and "mature" crops, I flatten the curve to these levels while holding fixed the average yield over time. Figure A3b shows the variation in the flattened yields at maturity. These data are time-invariant because yields under optimal conditions are an inherent characteristic of the oil palm plant.

Second, I compile data on attained yields by province and year from government statistics, namely the Indonesian Ministry of Agriculture, the World Bank INDO-DAPOER database (via the Indonesian MoA), and the Malaysian Palm Oil Board. Each reports yields for mature crops, omitting immature crops that do not yet produce fruit. Figure A4a shows that, on average, these yields are increasing over time as technology improves, although attained yields fall far short of the maximum potential yields in all provinces and years. Crop age mix also affects yields over time, but two effects potentially offset each other: 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 produce estimates of attainable yields by site and year. Suppose the desired attainable yields Y_{it} in sites i and years t are products of site-specific, time-invariant potential yields Y_i^p and province-specific, time-varying yield gaps γ_{mt}.

$$Y_{it} = (1 - \gamma_{mt})Y_i^p \tag{13}$$

The underlying restriction is that, while potential yields are allowed to vary by site, yield gaps are

Figure A4: Attained and attainable palm oil yields (t/ha/year)

(a) Attained yields by province-year **(b)** Attainable yields by site-year

The left figure shows annual attained yields by province (Indonesia) or state (Malaysia) as recorded in government statistics. Data: Indonesian Ministry of Agriculture, World Bank, Malaysian Palm Oil Board. The right figure shows annual attainable yields by site as computed by combining site-level potential yields from PALMSIM with province-year attained yields from government statistics.

fixed across sites in a given province-year. Yield gaps are then a function of known quantities.

$$\frac{\sum_{i\in\mathcal{I}_m} Y_{it}s_{it}}{\sum_{i\in\mathcal{I}_m} s_{it}} = Y_{mt} \quad \Rightarrow \quad \gamma_{mt} = 1 - Y_{mt}\left(\frac{\sum_{i\in\mathcal{I}_m} Y_i^p s_{it}}{\sum_{i\in\mathcal{I}_m} s_{it}}\right)^{-1},$$

where attained yields Y_{mt}, potential yields Y_i^p, and plantation development s_{it} are known. I isolate the underlying levels and trends of these yield gaps with the specification

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

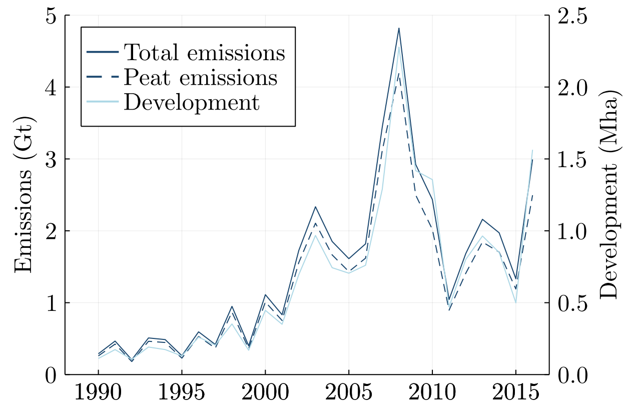
and I use the fitted values to estimate attainable yields Y_{it} with equation 13. In doing so, I extrapolate back before 1990 for Malaysia and 1996 for Indonesia. I also extrapolate past 2016 to obtain future yields, which I use in computing counterfactuals. Figure A4b shows the resulting estimates, which combine the uptrend of figure A4a with the site-level dispersion of figure A3b.

Carbon stocks

I compute carbon stocks over space using two datasets, which I aggregate to a resolution of 30 arc-seconds: Zarin et al. (2016) measures aboveground tree biomass at a resolution of 30m, and Gumbricht et al. (2017) measures belowground peat biomass at a resolution of 231m. 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.

Figure A5: Plantation development vs. CO_2 emissions



Data: Xu et al. (2020), Song et al. (2018), Zarin et al. (2016), Gumbricht et al. (2017).

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 A5 shows that the relationship between plantation development and the resulting emissions is 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 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-pixel 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 A8 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-pixel level. For rainfall, I first aggregate from daily to monthly values for each pixel, 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

Table A8: 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%

For each oil, I omit producers below 5% of world production. Data: USDA FAS, 1988-2016.

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 pixel.

Third, I aggregate to obtain annual weather shocks by oil. I do so by averaging over pixels for each oil-producing region, then averaging across oil-producing regions for each oil in proportion 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. In this final step, I can isolate foreign shocks for each consumer market by omitting shocks to domestic oil-producing regions, and I do so in checking robustness.

B Demand

In estimating the lower-level demand system, I impose the standard adding-up, homogeneity, and symmetry restrictions. The adding-up restrictions are $\sum_i \alpha_i^0 = 1$, $\sum_i \alpha_i^1 = 0$, $\sum_i \beta_i = 0$, $\sum_i \gamma_{ij} = 0 \; \forall \, j$ and are automatically satisfied since expenditure shares sum to one. Homogeneity imposes $\sum_j \gamma_{ij} = 0 \; \forall \, i$, such that proportional changes in prices and income have no impact on demand. Symmetry imposes $\gamma_{ij} = \gamma_{ji} \; \forall \, i, j$. Given a choice between two products – palm vs. other oils – imposing homogeneity imposes symmetry, and vice versa. With two products, I can also estimate the demand system on palm oil expenditure shares alone, as the adding-up restriction requires the dropping of one product. Thus, I apply linear IV and use Newey-West standard errors to account for serial correlation in the error terms. The typical case with more than two products applies seemingly unrelated regression to estimate a system of regression equations. Serial correlation can then by accounted for with a Prais-Winsten transformation as in Parks (1967).

On instruments, table B1 shows that weather shocks do not affect domestic incomes or expenditures for any consumer market. Such effects would influence demand directly – as opposed to through the channel of oil prices – and therefore violate the exclusion restriction. These results also provide reassurance that the instruments do not simply capture idiosyncratic fluctuations in macroeconomic conditions. Table B2 shows the first stage for foreign weather shocks, which are also strong instruments. In omitting domestic shocks within a given consumer market, these instruments go one step further toward avoiding violations of the exclusion restriction. However, the baseline analysis favors the use of all weather shocks because they greatly simplify the construction

Table B1: 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
	GDE (hh)	0.000190	(0.000257)	0.000147	(0.000245)	174
	GDE (gov)	0.000241	(0.000303)	0.000169	(0.000292)	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
	GDE (hh)	-5.51e-05	(0.000343)	-0.000148	(0.000327)	174
	GDE (gov)	4.56e-05	(0.000281)	-6.68e-05	(0.000263)	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
	GDE (hh)	0.000138	(0.000130)	8.12e-05	(0.000117)	174
	GDE (gov)	0.000181	(0.000182)	9.07e-05	(0.000162)	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
	GDE (hh)	0.000384	(0.000536)	0.000202	(0.000555)	174
	GDE (gov)	0.000283	(0.000769)	5.96e-05	(0.000798)	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, GDEs measure total, household, and government expenditures, 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 B2: Foreign weather shocks as price instruments

	European Union	China	India	Other importers	Indonesia	Malaysia
Rainfall shocks (100 mm)	0.000499	0.217***	0.197***	0.111**	0.185***	0.199***
	(0.0419)	(0.0179)	(0.0307)	(0.0443)	(0.0236)	(0.0297)
Temperature shocks (°C)	0.150***	0.343***	0.275***	0.240***	0.295***	0.300***
	(0.0523)	(0.0178)	(0.0356)	(0.0514)	(0.0302)	(0.0327)
Observations	174	174	174	174	174	174
F-statistic	12.76	200.5	30.12	12.22	48.22	45.83

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. Foreign weather shocks are absolute deviations from optimal conditions during the growing season, aggregated over foreign 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 palm oil

Market	Estimate	SE
European Union (E)	-0.510***	(0.181)
China/India (CN)	-0.667***	(0.210)
Other importers (R)	-0.558***	(0.134)
Indonesia/Malaysia (IM)	-0.026	(0.171)
World (ECNRIM)	-0.447***	(0.133)

Market	Estimate	SE
Importers (ECNR)	-0.555***	(0.134)
Producers (IM)	-0.026	(0.171)
EU/China/India (ECN)	-0.437***	(0.164)
Not EU/China/India (RIM)	-0.482***	(0.129)
Not EU (CNRIM)	-0.602***	(0.113)

Each row of each table shows the palm oil demand elasticity for an individual or group of consumer markets. I present mean elasticities over the study period, and I compute standard errors with the delta method. 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 oil production. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table B4: Demand parameters

	European Union		China/India		Other importers		Indonesia/Malaysia	
Parameter	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE
α_1^0	0.162	(0.155)	0.328*	(0.168)	0.345***	(0.069)	0.662***	(0.127)
α_1^1	0.003***	(0.001)	0.004	(0.003)	0.005***	(0.001)	0.009***	(0.002)
γ_{11}	0.038	(0.026)	0.027	(0.030)	0.017	(0.016)	0.022	(0.029)
β_1	0.012	(0.029)	0.035	(0.032)	0.033***	(0.011)	-0.025	(0.024)
γ	-0.198	(0.122)	-0.416	(0.339)	-0.090	(0.235)	0.215	(0.159)

Each pair of columns is a demand system, and subscript $i = 1$ refers to palm oil. The first four rows describe the lower level of demand, and the last row the upper level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

of aggregate demand curves.[13] Furthermore, the baseline instruments already target oil producers explicitly, and they pass the test above.

Table B3 presents demand elasticities for palm oil by market. Table B4 shows the lower- and upper-level parameter estimates that I use to compute these elasticities, and table B5 shows demand elasticities for vegetable oils in general. I obtain reasonable estimates with negative own-price elasticities that are statistically significant and positive cross-price elasticities. For Indonesia and Malaysia, elasticities for other oils have larger standard errors because other oils account for only a small fraction of consumption in the data. Table B6 shows elasticities computed without price instruments, indicating clear bias in the form of positive own-price and negative cross-price elasticities, some of which are statistically significant.

Finally, I observe oil stockpiles and find that they are limited in this context. In particular, stockpiles are 12.5% of average annual consumption by volume, compared to an estimated 342% of average weekly consumption for ketchup in Erdem et al. (2003) and 188% of median weekly

[13] For example, to estimate demand for the combined Indonesian-Malaysian market, I can aggregate their consumption data then estimate an aggregate curve directly. With foreign weather shocks, I must estimate separate curves for Indonesia and Malaysia then aggregate the curves themselves. Each demand curve relies heavily on the AIDS functional form at its extremes, and aggregating curves exacerbates this problem, particularly for markets with different consumption levels. Aggregating curves is also theoretically inconsistent with AIDS microfoundations.

Table B5: Demand elasticities for vegetable oils

Market		Estimates: Palm	Estimates: Other	SEs: Palm	SEs: Other
European Union	Palm	-0.510***	0.290	(0.181)	(0.206)
	Other	0.105	-0.301*	(0.148)	(0.171)
China/India	Palm	-0.667***	0.172	(0.210)	(0.302)
	Other	0.187	-0.584***	(0.159)	(0.224)
Other importers	Palm	-0.558***	0.454**	(0.134)	(0.180)
	Other	0.350***	-0.436***	(0.113)	(0.149)
Indonesia/Malaysia	Palm	-0.026	0.234*	(0.171)	(0.120)
	Other	0.707	-0.416	(0.474)	(0.478)

Each panel shows uncompensated price elasticities for a consumer market. I present mean elasticities over the study period, and I compute standard errors with the delta method. 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 oil production. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

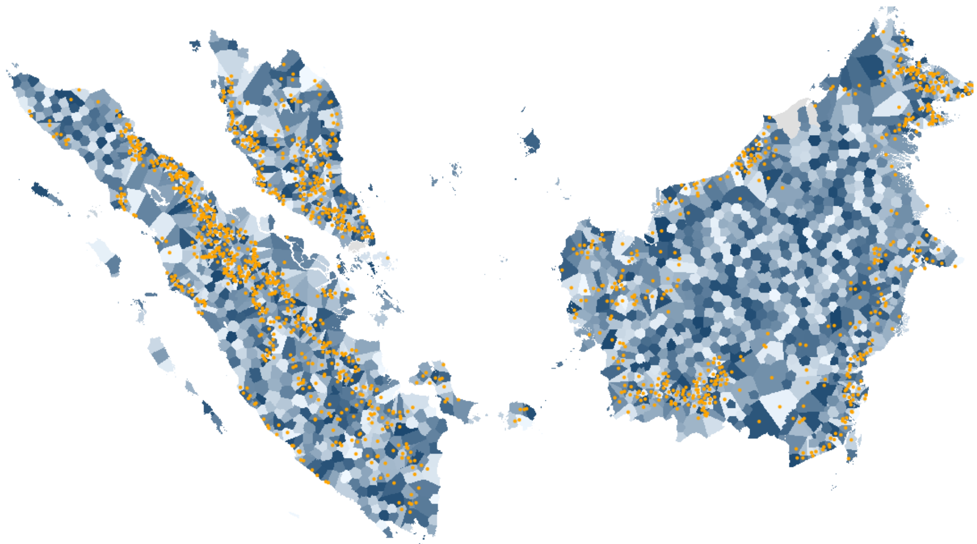
Table B6: Demand elasticities for vegetable oils without price instruments

Market		Estimates: Palm	Estimates: Other	SEs: Palm	SEs: Other
European Union	Palm	-0.075	0.018	(0.116)	(0.150)
	Other	-0.347**	0.196	(0.149)	(0.184)
China/India	Palm	0.606	-0.113	(0.693)	(0.556)
	Other	0.850**	-0.617*	(0.342)	(0.359)
Other importers	Palm	-0.484***	0.224	(0.051)	(0.143)
	Other	-0.279**	-0.139	(0.135)	(0.221)
Indonesia/Malaysia	Palm	0.730*	-0.685*	(0.424)	(0.403)
	Other	0.417	-0.477	(0.576)	(0.518)

Each panel shows uncompensated price elasticities for a consumer market. I present mean elasticities over the study period, and I compute standard errors with the delta method. Demand estimation draws on annual data covering coconut, olive, palm, rapeseed, soybean, and sunflower oils from 1988 to 2016. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

consumption for laundry detergent in Hendel and Nevo (2006). Temporal aggregation explains the difference: the vegetable oil data measure annual consumption, and substitution across years may be less salient than substitution across weeks for consumer products sold for regular discounts. As well, national consumption aggregates over the stockpiling of individual consumers.

Figure C1: Potential sites



Blue shading indicates different potential sites, and gray shading indicates omitted regions. Orange dots are palm oil mills observed by 2016. There are 2,135 sites and 1,467 observed mills.

C Supply

Defining sites

To divide land into sites, I first compute the maximum number of sites $\bar{k}$ for each province: $\bar{k} = \max\{\text{floor}(\text{area}/521), \text{number of observed mills}\}$. 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. At the 75th percentile, there is one mill per 455 km^2. Second, I consider provinces without mill construction in the last five years of the study period, reflecting plateaued expansion. The median such province has one site per 553 km^2. These two methods thus 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. The 75th percentile of these distances 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 significant plantations, reassign points to clusters with mills.

Step (2) ensures consistency with observed mills, and step (6) observed plantations. In step (6), I define clusters with more than 10 30-arc-second tiles of plantations as having "significant" plantations. I drop the 0.3% of plantations that remain unassigned to clusters with mills. A lower cutoff would drop fewer plantations at the cost of losing more clusters. This procedure results in 2,135 sites, of which 1,467 contain an observed mill by 2016. Figure C1 plots the potential sites.

Extensive margin

Lemma 1. $v^e(0; \boldsymbol{w}_{it}) - v^e(0, 1; \boldsymbol{w}_{it}) = -\beta \mathbb{E}^e_{it}[\ln p^e(\boldsymbol{w}_{it+1})]$.

$$\begin{aligned} v^e(0; \boldsymbol{w}_{it}) - v^e(0, 1; \boldsymbol{w}_{it}) &= \beta \mathbb{E}^e_{it}[\ln(\exp(v^e(0; \boldsymbol{w}_{it+1})) + \exp(v^e(1; \boldsymbol{w}_{it+1})))] - \beta \mathbb{E}^e_{it}[v^e(1; \boldsymbol{w}_{it+1})] \\ &= \beta \mathbb{E}^e_{it}[v^e(1; \boldsymbol{w}_{it+1}) - \ln p^e(\boldsymbol{w}_{it+1})] - \beta \mathbb{E}^e_{it}[v^e(1; \boldsymbol{w}_{it+1})] \\ &= -\beta \mathbb{E}^e_{it}[\ln p^e(\boldsymbol{w}_{it+1})] \,. \end{aligned}$$

The first line applies the logit log-sum formula for expected utilities, and the second line applies the expression for logit choice probabilities. Arcidiacono and Ellickson (2011) document this result as the logit special case of Arcidiacono and Miller (2011) Lemma 1.

Lemma 2. $v^e(1; \boldsymbol{w}_{it}) - v^e(1, a_{it}; \boldsymbol{w}_{it}) = \frac{1}{2} \mathbb{E}^e_{it}[c''(a_{it}; \boldsymbol{w}_{it}, \varepsilon_{it})(a^*_{it} - a_{it})^2]$.

$$\begin{aligned} & v^e(1; \boldsymbol{w}_{it}) - v^e(1, a_{it}; \boldsymbol{w}_{it}) \\ &= \mathbb{E}^e_{it}[-c(a^*_{it}; \boldsymbol{w}_{it}, \varepsilon_{it}) + c(a_{it}; \boldsymbol{w}_{it}, \varepsilon_{it}) + \beta V(a^*_{it}; \boldsymbol{w}_{it+1}, \varepsilon_{it+1}) - \beta V(a_{it}; \boldsymbol{w}_{it+1}, \varepsilon_{it+1})] \\ &= \mathbb{E}^e_{it}\left[- c'(a_{it}; \boldsymbol{w}_{it}, \varepsilon_{it})(a^*_{it} - a_{it}) - \frac{1}{2} c''(a_{it}; \boldsymbol{w}_{it}, \varepsilon_{it})(a^*_{it} - a_{it})^2 + \beta V'(a_{it}; \boldsymbol{w}_{it+1}, \varepsilon_{it+1})(a^*_{it} - a_{it}) \right] \\ &= \mathbb{E}^e_{it}\left[- c'(a_{it}; \boldsymbol{w}_{it}, \varepsilon_{it})(a^*_{it} - a_{it}) - \frac{1}{2} c''(a_{it}; \boldsymbol{w}_{it}, \varepsilon_{it})(a^*_{it} - a_{it})^2 + c'(a^*_{it}; \boldsymbol{w}_{it}, \varepsilon_{it})(a^*_{it} - a_{it}) \right] \\ &= \frac{1}{2} \mathbb{E}^e_{it}[c''(a_{it}; \boldsymbol{w}_{it}, \varepsilon_{it})(a^*_{it} - a_{it})^2], \end{aligned}$$

where $a^*_{it} \equiv a^*_{it}(0; \boldsymbol{w}_{it}, \varepsilon_{it})$. The first equality is definitional. The second equality applies that costs are quadratic and revenues linear. The third equality applies the linearity of revenues and the first order condition that holds at a^*_{it}. The last equality again applies that costs are quadratic, and thus that c' is linear. For convex costs, the last line is positive, and indeed $v^e(1; \boldsymbol{w}_{it}) \geq v^e(1, a_{it}; \boldsymbol{w}_{it})$.

Result. $v^e(0; \boldsymbol{w}_{it}) - v^e(0, 1, a'_{it+1}; \boldsymbol{w}_{it}) = \frac{1}{2} \beta \mathbb{E}^e_{it}[c''(a'_{it+1}; \boldsymbol{w}_{it+1}, \varepsilon_{it+1})(a^*_{it+1} - a'_{it+1})^2] - \beta \mathbb{E}^e_{it}[\ln p^e(\boldsymbol{w}_{it+1})]$.

$$\begin{aligned} v^e(0; \boldsymbol{w}_{it}) - v^e(0, 1, a'_{it+1}; \boldsymbol{w}_{it}) &= v^e(0, 1; \boldsymbol{w}_{it}) - v^e(0, 1, a'_{it+1}; \boldsymbol{w}_{it}) - \beta \mathbb{E}^e_{it}[\ln p^e(\boldsymbol{w}_{it+1})] \\ &= \beta \mathbb{E}^e_{it}[v^e(1; \boldsymbol{w}_{it+1})] - \beta \mathbb{E}^e_{it}[v^e(1, a'_{it+1}; \boldsymbol{w}_{it+1})] - \beta \mathbb{E}^e_{it}[\ln p^e(\boldsymbol{w}_{it+1})] \\ &= \frac{1}{2} \beta \mathbb{E}^e_{it}[c''(a'_{it+1}; \boldsymbol{w}_{it+1}, \varepsilon_{it+1})(a^*_{it+1} - a'_{it+1})^2] - \beta \mathbb{E}^e_{it}[\ln p^e(\boldsymbol{w}_{it+1})] \,, \end{aligned}$$

where $a^*_{it+1} \equiv a^*_{it+1}(0; \boldsymbol{w}_{it+1}, \varepsilon_{it+1})$. The first line substitutes Lemma 1, the second line is definitional, and the third line substitutes Lemma 2.

Estimates

Table C1 presents the regional estimates underlying the means in table 4. Regions include provinces in Indonesia and states in Malaysia, grouped to maintain at least 25 sites each. I combine island provinces Kepulauan Riau and Bangka Belitung with nearby mainland provinces in Indonesia, and I do the same for island territory Labuan in Malaysia. I also group the peninsular Malaysian states, which are relatively small, into three regions.

Table C1: Supply parameters by region

	Intensive-margin		Extensive-margin	
	κ_m	α_m	κ_m^e	α_m^e
Indonesia				
Aceh	5,736	-352	53,596,558	302,761
Bengkulu	7,245	-297	40,924,622	787,098
Jambi	7,745	-160	24,223,003	-249,858
Kalimantan Barat	8,008	85	14,456,470	-1,986,743
Kalimantan Selatan	4,562	-354	41,312,107	1,538,485
Kalimantan Tengah	7,255	-203	2,013,060	-2,760,063
Kalimantan Timur	6,202	-117	31,511,180	-2,700,773
Lampung	6,311	-280	17,420,535	-2,403,876
Riau, Kepulauan Riau	7,492	-362	25,060,550	-482,428
Sumatera Barat	6,164	-314	37,892,067	6,227
Sumatera Selatan, Bangka Belitung	7,836	-201	19,767,987	-831,927
Sumatera Utara	6,873	-491	31,213,840	-227,949
Malaysia				
Johor, Kuala Lumpur, Melaka, Negeri Sembilan, Putrajaya, Selangor	7,067	-526	68,729,952	1,933,534
Kedah, Penang, Perak, Perlis	8,196	-522	53,353,791	1,333,236
Kelantan, Pahang, Terengganu	8,855	-277	30,593,456	660,323
Sabah, Labuan	8,890	-566	14,166,323	-1,020,647
Sarawak	4,558	-571	-9,776,962	-2,362,619

Estimates are interpretable as inflation-adjusted, year-2000 dollars. Parameters κ_m and κ_m^e denote mean costs, and α_m and α_m^e denote cost trends.

D Counterfactuals

Firms play a dynamic entry game taking tariffs as given. Boldfaced $\boldsymbol{s}_{it} = \{s_{it}, s_{it}^e\}$ and $\boldsymbol{a}_{it} = \{a_{it}, p_{it}^e\}$ denote site-specific supply and entry. Total supply and entry in period t are

$$s_t = \sum_i Y_{it} s_{it}\,, \quad a_t = \sum_i \Big(s_{it}^e a_{it} + (1 - s_{it}^e) p_{it}^e a_{it} \Big). \tag{14}$$

For sites without mills ($s_{it}^e = 0$), entry depends on mill construction probability p_{it}^e and plantation development a_{it}. Entry affects future supply and thus prices.

$$s_{t+1}(a_t, s_t) = s_t + a_t\,, \quad P(s_{t+1}(a_t, s_t), d_{t+1}, \tau_{t+1}) \tag{15}$$

Prices depend on supply, demand, and tariffs. Only total supply enters; tracking supply over space is much harder computationally. Plantation development and mill construction probabilities are

$$a_{it} = \sum_{t'=1}^{\infty} \frac{\beta^{t'}}{\delta} \mathbb{E}_{it}\Big[Y_{it+t'} P(s_{t+t'}, d_{t+t'}, \tau_{t+t'}) \Big] - \frac{1}{\delta} x_i \gamma - \frac{1}{\delta}\kappa_m - \frac{1}{\delta}\alpha_m t - \frac{1}{\delta}\varepsilon_{it}\,, \tag{16}$$

$$p_{it}^e = \frac{\exp\big(-\frac{1}{\sigma^e} x_i \gamma^e - \frac{1}{\sigma^e}\kappa_m^e - \frac{1}{\sigma^e}\alpha_m^e t + \frac{1}{\sigma^e}\mathbb{E}_{it}^e[V(0; \boldsymbol{w}_{it}, \varepsilon_{it})]\big)}{1 + \exp\big(-\frac{1}{\sigma^e} x_i \gamma^e - \frac{1}{\sigma^e}\kappa_m^e - \frac{1}{\sigma^e}\alpha_m^e t + \frac{1}{\sigma^e}\mathbb{E}_{it}^e[V(0; \boldsymbol{w}_{it}, \varepsilon_{it})]\big)}\,, \tag{17}$$

subject to bounds $a_{it} \in [0, \bar{s}_i - s_{it}]$ and an outside option normalized to zero. Entry depends on expected future supply, demand, and yields, as well as current cost shocks.

The residuals of equation 8 capture future expectations and current cost shocks. For residuals $\upsilon_{it} = -\frac{1}{\delta}\varepsilon_{it} + \frac{\beta}{\delta}\varepsilon_{it+1} + \eta_{it}$, I compute the discounted sum over time and apply equation 9 to obtain

$$\tilde{\upsilon}_{it} \equiv \sum_{t'=0}^{\infty} \beta^{t'} \upsilon_{it+t'} = -\frac{1}{\delta}\varepsilon_{it} + \sum_{t'=1}^{\infty} \frac{\beta^{t'}}{\delta} \Big(\mathbb{E}_{it}[Y_{it+t'} P_{t+t'}] - Y_{it+t'} P_{t+t'} \Big).$$

I can then rewrite equation 16 in terms of observed values.

$$a_{it} = \sum_{t'=1}^{\infty} \frac{\beta^{t'}}{\delta} Y_{it+t'} P(s_{t+t'}, d_{t+t'}, \tau_{t+t'}) - \frac{1}{\delta} x_i \gamma - \frac{1}{\delta}\kappa_m - \frac{1}{\delta}\alpha_m t + \tilde{\upsilon}_{it}\,.$$

For long-term yields and demand, I extrapolate from the sample period assuming that yields grow at fixed rates and that demand follows a fitted sigmoid curve. In-sample residuals match changes $a_{it} - \beta a_{it+1}$, and I choose long-term residuals to match levels a_{it}. On the extensive margin, firms invest before realizing intensive-margin cost shocks, which are uncorrelated with extensive-margin shocks. I assume that sites with zero observed development remain undeveloped in counterfactuals, but this assumption is weak as counterfactuals each tax development.

The entry game determines supply. Given price-taking firms and terminal year 2100, I solve for prices over time as a fixed point: prices induce production via the supply model, and production pins down prices via the demand model. Prices decrease monotonically in total entry, such that the solution is unique. As in Hopenhayn (1992), atomistic firms and the law of large numbers lead to expected extensive-margin entry that equals probability p^e_{it}. Otherwise, solving requires integrating over a distribution of potential outcomes. Large tariffs push prices to zero in some periods, with negative prices ruled out by free disposal for producers. Consumer surplus and government revenue depend on quantity consumed, which is less than quantity produced when prices are zero. I take the study region as representative of global supply.

For each tariff coalition and commitment period, I choose tariffs to maximize social welfare. Table D1 shows the optimal tariffs, and figure D1 illustrates the optimization problem. Larger coalitions have lower tariffs (but larger overall effects), as emission reductions hit diminishing returns at scale. Similarly, limited commitment leads to lower tariffs, as temporary tariffs do less to reduce emissions. Lower tariffs induce less leakage and tend to involve lower average costs of foregone emissions, except that limited commitment raises these costs regardless of tariff level.

Substitution to acacia may bias emission estimates. Data from Gaveau et al. (2019) measure acacia and palm oil plantations for the island of Borneo in five-year intervals from 1990 to 2015. For sites i, provinces m, and years t, I compare new palm and acacia development with the specification

$$\text{acacia}_{it} = \beta \text{palm}_{it} + \alpha_i + \alpha_{mt} + \varepsilon_{it}\,. \tag{18}$$

Table D2 shows that palm development has very small effects on acacia development. Palm does not displace acacia and if anything slightly increases acacia investment, perhaps in opening up new lands. That is, palm and acacia are not substitutes, but rather weak complements. I can isolate intensive-margin investments by focusing on sites with nonzero initial development, and I can allow for cross-site effects by aggregating over sites within provinces. Both lead to similar results.

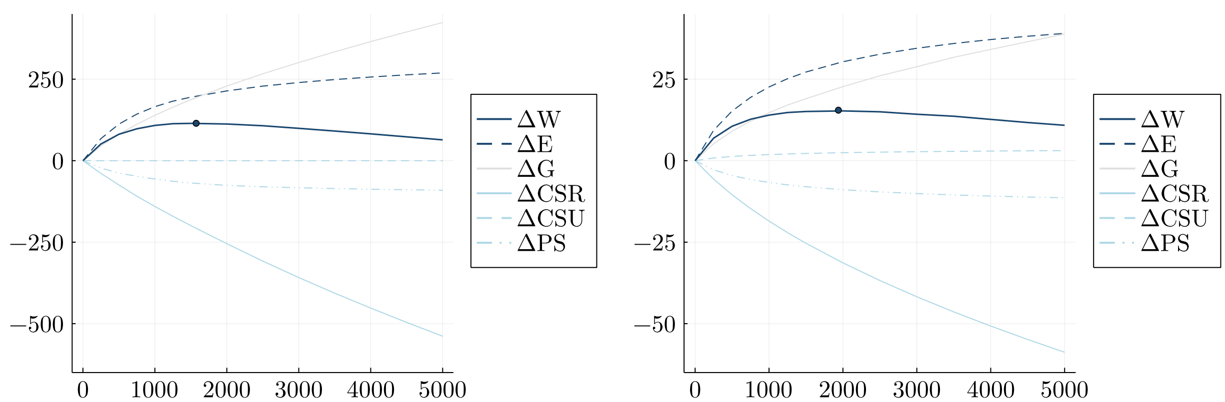
Table D1: Counterfactual experiments, taxes/leakage/costs

	Optimal tax ($/t)			ΔCS^U ($1B)			Cost ΔE ($/t)		
	Full	30-year	10-year	Full	30	10	Full	30	10
Domestic regulation	1,574	1,531	852	0	0	0	32	31	26
All importers	1,919	1,849	1,135	10	8	4	33	33	31
EU, China, India	2,240	1,956	1,285	5	3	1	37	36	34
EU only	1,939	1,939	1,149	2	2	1	36	38	34

Rows are levels of coordination, and columns are levels of commitment. For each scenario, the table shows welfare-maximizing taxes, leakage as captured by increases in unregulated consumer surplus, and costs per ton of emissions averted. Costs are foregone consumer and producer surplus net of government revenue.

Figure D1: Social welfare ($1B) by tax ($1K), full commitment

(a) Domestic regulation **(b)** EU only



Lines show changes in social welfare, emissions, government revenue, regulated consumer surplus, unregulated consumer surplus, and producer surplus relative to business as usual. Dots mark optimal tariffs.

Table D2: Acacia vs. palm oil plantation development

	Acacia	Acacia	Acacia	Acacia
Palm development (ha)	0.0221***	0.0155**	0.0113	0.0115
	(0.00682)	(0.00776)	(0.00782)	(0.00792)
Site FE		x	x	x
Year FE			x	
Province-year FE				x
Observations	6,018	6,018	6,018	6,018

Each column is one regression, and each observation is a site-year. Standard errors are clustered by site. Data: Gaveau et al. (2019). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.