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

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Weak environmental regulation has global consequences. When domestic regulation of carbon-intensive industries fails, the international community can intervene by targeting these industries with import tariffs. I argue that import tariffs must possess two features – coordination and commitment – in order to be effective. Without coordination across importers, tariffs are undermined by leakage to unregulated markets. Without commitment to upholding tariffs over the long term, tariffs are reduced over time as importers give in to static incentives. I develop a dynamic empirical framework for quantifying these forces in settings with incomplete regulation and sunk investment, and I apply it to the market for palm oil, a major driver of deforestation and one of the largest sources of emissions globally. In particular, I evaluate EU legislation targeting palm oil imports, primarily from Indonesia and Malaysia. I find coordinated, committed import tariffs to be effective, reducing carbon emissions relative to observed outcomes by 56% compared to 64% under a domestic palm oil tax. As coordination breaks down, emission reductions fall from 56% for action by all importers, to 17% for an EU-China-India coalition, to 2% for unilateral EU action, as tariff coverage falls from 80% to 35% to 12% of world consumption, respectively. As commitment breaks down, carbon reductions fall to as low as 0%. Finally, coordination and commitment interact. Achieving 95% of the full-commitment outcome requires a commitment period of only five years when importers coordinate, but more than twenty years when the EU acts unilaterally.

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1 Introduction

Carbon emissions have global consequences. The international community may therefore wish to intervene when countries fail to regulate emissions domestically. Indeed, domestic regulation often faces significant challenges: low incentives from free riding and political constraints (Oates and Portney 2003), and implementation barriers from administrative limits and potential corruption (Burgess et al. 2012; Oliva 2015). The conventional approach attempts to address these challenges, such as by improving enforcement (Duflo et al. 2018), but doing so at scale can be infeasible. Trade policy offers an alternative for regulating the 60% of global CO_2 emissions embodied in traded goods (Davis et al. 2011). In particular, import tariffs circumvent 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? This paper develops a dynamic empirical framework to answer this question quantitatively. I apply the framework to study the Indonesian and Malaysian palm oil industry, which accounts for a staggering 5% of global CO_2 emissions from 1990 to 2016 – more than the entire Indian economy (figure 1). I find that well designed import tariffs can be an effective substitute for a domestic palm oil tax, but that import tariffs generally faces two significant challenges: a leakage problem under incomplete regulation, and a commitment problem from static incentives to reduce tariffs over time.

I begin by discussing the leakage and commitment problems. First, when importers do not coordinate, incomplete regulation leads to demand-side "leakage" (Fowlie 2009). That is, although tariffs lower consumption in regulated markets, in doing so they lower world prices and encourage consumption in unregulated markets. This offsetting effect constrains the size of tariffs, as large tariffs lead to large leakage and therefore low net benefits. As a result, the losses are disproportionate as the tariff coalition shrinks. A small coalition covers a small proportion of global consumption, and leakage concerns further constrain it to small tariffs.

Second, importers face a commitment problem. Most traded emissions are from industries in which sunk investments make up the bulk of production costs: fossil fuels, manufacturing, mining, transportation, and agriculture (Peters et al. 2011). The result is a static incentive to reduce tariffs over time: when 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 often sunk, even if released gradually, because investment leads to low marginal costs up to capacity. For example, once the costs of identifying, exploring, and drilling an oil well have already been paid, extraction is cheap and thus likely to proceed to completion.

Palm oil and the resulting deforestation offer an ideal setting for studying environmental regulation by trade policy. I focus on palm oil from Indonesia and Malaysia, which together produce 84% of global supply. First, the industry is a major polluter. Land clearing for palm oil plantations in Indonesia and Malaysia threatens peatland forests that are particularly carbon-rich. Second, do-

Figure 1: CO_2 emissions from palm oil plantations over time

(a) Palm (Gt CO_2) **(b)** Global (Gt CO_2)

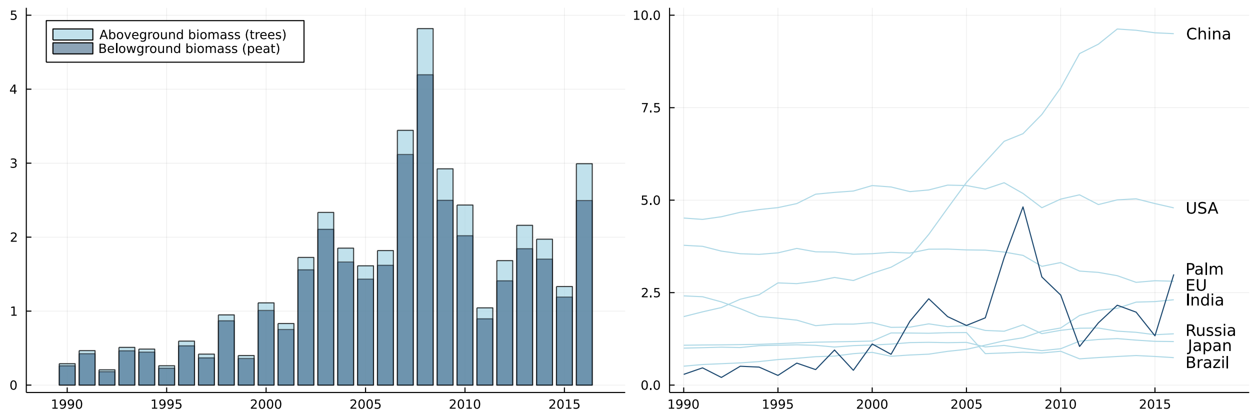


Figure 1a computes palm emissions using data on palm oil plantations (Xu et al. 2020; Song et al. 2018), tree biomass (Zarin et al. 2016), and peat deposits (Gumbricht et al. 2017). Figure 1b compares palm emissions to CO_2 emissions for the top seven emitters from 1990 to 2016. Palm emissions account for 4.95% of global emissions during this period. Global data come from the World Resources Institute and Global Carbon Atlas and include land-use change.

mestic incentives to regulate are limited. Despite its global consequences, palm oil is a major source of export revenue for Indonesia and Malaysia and has lifted millions out of poverty (Edwards 2019). 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, foreign governments are actively discussing trade-policy interventions, with the EU 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 build a quantitative empirical model for evaluating palm oil import tariffs. I divide land into individual sites, which I treat as firms representing potential entrants. Firms deforest land for plantations, plantations produce fruit for mills, mills process fruit into palm oil for domestic and foreign consumers, and foreign consumers in regulated markets pay import tariffs. The leakage problem depends on the elasticity of palm oil demand in unregulated markets. Demand responses in turn depend on consumers' substitution between palm and other vegetable oils. The commitment problem depends on the elasticity of palm oil supply, and how it differs between short- and long-term tariffs. Supply responses in turn depend on producers' expectations over future prices. The value of the structural model is that it accounts explicitly for cross-oil substitution on the demand side and price expectations on the supply side. A more reduced-form approach – that is, regressing palm oil demand and supply on prices (with instruments) – would account for neither, resulting in biased elasticity estimates in addition to ignoring equilibrium effects.

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). This product-space approach to demand estimation has two advantages: it allows for flexible patterns of substitution between palm and other vegetable oils, and it avoids the need to specify exactly which product characteristics consumers value. For estimation, I apply the iterated linear least squares approach 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 estimate the extent to which world demand for palm oil shifts over time, and I use these demand shifts – driven, for example, by changes in total vegetable oil consumption – as price instruments in estimating supply.

I model palm oil supply with a dynamic model of land development for palm oil. In the model, forward-looking firms make sunk investment decisions 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 develop into plantations. Data derived from satellite imagery allow me to observe these choices over time and at a high degree of spatial resolution. Firms' investments produce palm oil in each period and generate revenues as a function of world prices, which in turn depend on aggregate investment in palm oil production. Firms therefore play a dynamic competitive equilibrium as in the entry and investment game of Hopenhayn (1992). Modeling the dynamic investment decision allows me to infer firms' responses to hypothetical tariffs from their responses to observed price variation, while accounting for price expectations in a disciplined way. Intuitively, in the same way that price shocks today change both current revenues and expectations over future revenues, tariffs change revenues both today and in the future.

I take an Euler approach for estimating the supply model, combining standard continuous Euler methods for the intensive margin with more recent discrete Euler methods for the extensive margin (Hall 1978; Scott 2013). In both cases, I analyze the intertemporal trade-off in investing today versus tomorrow: investing today brings forward plantation revenues, but it also brings forward investment costs. On the intensive margin, I form an Euler equation from the first order condition for investment. On the extensive margin, I use discrete, short-term perturbations that hold long-term investment levels fixed. Continuation values difference out, and estimation reduces to linear regression with instruments. Identification comes from two sources: exogenous variation in world palm oil prices over time, as induced by the demand shifters discussed above, and exogenous variation in palm oil yields over space, as induced by differences in sunlight and precipitation. Prices and yields interact because high prices raise revenues most for high-yield plantations. Furthermore, while a conventional full-solution approach would need to specify exactly how firms expect the state of the economy to evolve over the long term, the Euler approach relies instead on the weaker assumption of rational expectations. The computational advantage is that the Euler approach avoids solving the model for estimation, while the full-solution approach requires solving repeatedly.

For counterfactuals, specifying firms' expectations and solving the model are unavoidable, and so I solve by backward induction from the steady state. The model assumes no exit and therefore reaches a steady state when all feasible lands are exhausted. The computational challenge is that it takes many periods to reach this point, and backward induction over long horizons suffers from a curse of dimensionality. I address this computational difficulty by iterating on two dimensions. In the outer loop, I solve over a manageable horizon treating the final period as the steady state. I then improve the solution by solving over a longer horizon, and I repeat until the solutions converge. In the inner loop, I backward induct with a limited look-ahead window, then I update the starting point based on the solution and repeat until finding a fixed point. To quantify emissions, I combine spatial data on carbon stocks with the model's spatial predictions for plantation development, and I assume a social cost of carbon of $40 per ton. I also make the strong assumption that non-palm deforestation does not expand in response to palm oil tariffs. The primary threat to this assumption is substitution from palm to acacia plantations, but I assess this substitution and find it to be empirically small.

I evaluate how coordination and commitment, both individually and in combination, influence the effects of import tariffs on carbon emissions and social welfare, and I benchmark these effects against a domestic palm oil tax implemented by Indonesia and Malaysia. The domestic tax avoids the leakage problem because it covers all production, and it avoids the commitment problem because it can be imposed upfront with a license fee for new development. In my baseline analysis, all regulation is set to maximize social welfare and is uniform across units of palm oil, although I also present extensions that relax each condition. I find that import tariffs can be an effective substitute for domestic regulation. When coordination and commitment hold, import tariffs reduce carbon emissions by 56% relative to observed outcomes under business as usual. By comparison, the domestic tax reduces emissions by 64%. The loss arises because import tariffs cannot regulate domestic consumption in Indonesia and Malaysia. However, the loss is not disproportionate because I find Indonesian and Malaysian demand to be inelastic, limiting leakage on this margin.

At the same time, emission reductions diminish as coordination and commitment weaken. Even under full commitment, relatively elastic demand among importers causes emission reductions to fall from 56% under full coordination among importers, to 17% under an EU-China-India coalition, to 2% under unilateral EU action. These emission reductions fall disproportionately more than tariff coverage – 80%, 35%, and 12% of world consumption, respectively – because leakage concerns lead to smaller tariffs. Even under full coordination, emission reductions fall from 56% under full commitment to 0% under no commitment. Time to build accounts for the stark no-commitment result: it is statically optimal to eliminate tariffs because tariffs today do not affect new development, which does not generate taxable production until a later period. Thus, both coordination and commitment are necessary. When either fails, import tariffs are low and have little effect.

Furthermore, coordination and commitment interact, with weak coordination increasing the importance of commitment. As a intermediate between full and no commitment, I consider a limited commitment scenario in which importers commit to a tariff regime over a fixed number of periods at a time – e.g., "five-year plans" – and revise tariffs at the end of each regime. Achieving 95% of full-commitment emission reductions requires a commitment period of only five years when importers coordinate, but more than twenty years when the EU acts unilaterally. The interaction between leakage and commitment arises because, anticipating the temptation to reduce tariffs in future periods, importers wish to increase tariffs today. However, leakage makes doing so difficult. Producers facing large tariffs in regulated markets can make investments and focus sales on unregulated markets. Then as tariffs are reduced – because investment is sunk – producers can shift sales to regulated markets. The more severe the leakage problem, the more unregulated markets can absorb, and thus the more easily producers can skirt tariffs.

The division of surplus among countries reveals why coordination and commitment are difficult to achieve in practice. Coordination is difficult because own-surplus-maximizing coalition members have an incentive to defect. For example, the EU-China-India coalition becomes fragile if China and India ignore carbon damages and focus on their consumer surplus alone: China and India lose consumer surplus when they impose tariffs, but they gain when they do not because leakage allows defectors to free ride on lower world prices. Commitment is difficult when countries value their consumer surplus alone because longer commitment demands larger sacrifices of consumer surplus for the sake of reducing emissions. Lastly, for Indonesia and Malaysia, under most tariff scenarios I find that imposing the socially optimal domestic tax leads to lower surplus. However, Indonesia and Malaysia prefer domestic regulation if threatened with fully coordinated import tariffs. In this scenario, the domestic tax has low marginal impact on producer surplus because the outside option is tariffs that are already high, and the domestic tax raises government revenue that would otherwise go abroad.

The main contribution of this paper is to develop an empirical framework for assessing trade policy as a means of environmental regulation. While Shapiro (2020) establishes the negative outcomes of emission-inattentive trade policy, I show what emission-attentive trade policy can achieve, and I quantify the challenges in implementing such policy. In particular, I study two problems – leakage and commitment – that are well recognized individually, and I provide novel analysis of how the two interact in an empirical setting. A rich literature on environmental regulation in trade-exposed markets documents how supply-side leakage undermines domestic regulation as polluters move to unregulated markets, motivating border adjustment taxes (Markusen 1975; Copeland and Taylor 1994, 1995; Hoel 1996; Rauscher 1997; Elliott et al. 2010; Fowlie et al. 2016; Kortum and Weisbach 2017). Similarly, demand-side leakage becomes a concern in my context, as free-riding makes the leakage problem fundamental and adds value to acting in coalition (Nordhaus 2015). I also build on a literature studying commitment problems in environmental regulation, in which the dynamic incentives to abate emissions depend critically on whether penalties are upheld over future periods (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).

Methodologically, my framework builds on dynamic 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. (2018), that develops Euler conditional choice probability (CCP) methods for estimating dynamic discrete choice models. Using standard dynamic discrete choice 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. In focusing on short-term perturbations in order to simplify dynamics, these Euler methods are closely related to moment-inequality techniques for revealed preference (Bajari et al. 2007; Pakes 2010; Pakes et al. 2015), with applications ranging from store placement to pension plans to export destinations (Holmes 2011; Illanes 2017; Morales et al. 2019). My contribution is to show how to combine both continuous and discrete Euler techniques in a single framework, with a model containing discrete entry choices on the extensive margin and continuous investment choices on the intensive margin. Indeed, many investment decisions involve a similar combination of extensive- and intensive-margin choices. I also show how to tractably solve my model in computing a set of counterfactuals unidentified by Euler methods alone.

More broadly, this paper contributes a quantitative analysis of environmental regulation for one of the world's largest sources of carbon emissions. Palm oil is ubiquitous, adding value to food and consumer products worldwide. But these benefits have come with severe costs: the industry accounts for an enormous 5% of global CO_2 emissions over the last three decades. Domestic regulations have failed to prevent these emissions, but trade policy offers an alternative set of tools for regulating this and other industries operating in low-regulation environments. Unlike the domestic programs evaluated in Burgess et al. (2019) and Souza-Rodrigues (2019), or the conservation contracting of Harstad (2012, 2016) and Harstad and Mideksa (2017), trade policy does not rely on a domestic government that is willing and able to enforce regulation. And unlike the payments for ecosystem services of Jayachandran et al. (2017) and Edwards et al. (2020), trade policy scales readily and does not rely on property rights that are well defined. Furthermore, swift action can still save vast swathes of forest that remain intact, particularly in Papua. Nonetheless, as with other forms of international climate action, coordination problems and dynamic concerns present fundamental challenges. This paper quantifies these challenges in an industry that is pivotal in the fight against climate change.

2 Illustrative Model

This section studies optimal tariffs for an emission-intensive traded good in a setting with incomplete regulation and sunk investment. It discusses the leakage and commitment problems.

2.1 Import tariffs under incomplete regulation and sunk investment

Consider two markets: an unregulated "domestic" market u and a regulated "foreign" market r. I study an agricultural good produced in u and consumed in both u and r. Consumers have consumption utility described by inverse demand curves $P_t^{Dr}(q)$ and $P_t^{Du}(q)$. Price-taking farmers produce the good by establishing plantations, subject to upfront development costs described by inverse supply curve $P_t^S(q)$. Investment in plantations is sunk and causes upfront emissions e via deforestation. Established plantations produce goods every period at zero marginal cost, do not depreciate, and have zero scrap value. Production begins one period after development.

I study tariffs on regulated consumption, with tariffs set to maximize social welfare. Social welfare is consumer and producer surplus net of emission damages, and it depends on old development $Q_{t+1}^o = Q_t^o + Q_t^n$, the path of new development $\{Q_t^n, Q_{t+1}^n, \ldots\}$ for $Q_t^n = Q_t^{rn} + Q_t^{un}$, and how the resulting production is allocated across markets. Given discrete time and discount factor β,

$$\begin{aligned} &W_t(Q_t^{rn}, Q_{t+1}^{rn}, \ldots, Q_t^{un}, Q_{t+1}^{un}, \ldots; Q_t^o) \\ &= \sum_{s=0}^{\infty} \beta^s \mathbb{E}_t \left[\int_0^{Q_{t+s}^{ro}} P_{t+s}^{Dr}(q)dq + \int_0^{Q_{t+s}^{uo}} P_{t+s}^{Du}(q)dq - \int_{Q_{t+s}^o}^{Q_{t+s}^o + Q_{t+s}^n} \left(P_{t+s}^S(q) + e \right) dq \right]. \end{aligned}$$

Domestic regulation

The first best is a domestic Pigouvian tax that reflects the full magnitude of the externality.

$$\tilde{\tau}_t^{\mathrm{FB}} = e\,,$$

where the tilde denotes net present value. There is no leakage problem because direct domestic regulation of supply achieves complete regulation. There is no commitment problem because the regulator can target new development with a license fee and thus impose the full tax upfront.

The leakage problem

Regulation is incomplete because import tariffs miss unregulated consumption. To isolate the leakage problem, suppose importers can commit to upholding tariffs. The optimal tariff is

$$\tilde{\tau}_t^{\mathrm{C}} = \left(\frac{\varepsilon_t^S}{\varepsilon_t^S - \frac{Q_{t+1}^{uo}}{Q_{t+1}^o} \varepsilon_{t+1}^{Du}} \right) e < \tilde{\tau}_t^{\mathrm{FB}},$$

where $\varepsilon_t^S > 0$ and $\varepsilon_{t+1}^{Du} < 0$ are elasticities of supply and unregulated demand, and "C" indicates full commitment. Even within the regulated market, the tariff is smaller than the first-best tax. First, leakage lowers the benefits of the tariff relative to the first best. Although tariffs decrease regulated consumption, net emission reductions are smaller because tariffs also increase unregulated consumption as they lower world prices. Second, leakage raises the costs of the tariff. Tariffs shift consumption from higher willingness-to-pay consumers in the regulated market to lower willingness-to-pay consumers in the unregulated market, and in doing so produce allocative inefficiency.

The commitment problem

Import tariffs tax consumption – not development directly – and thus are applied over time. But sunk investment, time to build, and leakage together induce a commitment problem. Tariffs have no benefit today: they cannot prevent prior development, which is sunk, and they cannot prevent new development, which under time to build does not generate taxable production until a future period. Furthermore, tariffs are costly: under leakage, they create allocative inefficiency in distorting consumption between markets. In combination, these forces make it statically optimal to set tariffs to zero. In the no-commitment case, importers follow these static incentives in each period and never levy tariffs at all.

Under limited commitment, I assume that importers can commit to upholding tariffs for L periods at a time. In other words, they revise tariffs every L periods. I consider a special case with time-invariant demand and supply curves in order to highlight intuition and solve for tariffs in closed form. The empirical exercise avoids these assumptions by solving numerically. Importers remove tariffs at the beginning of each L-period regime, and they set tariffs in other periods anticipating these periodic breaks. Tariffs have net present value

$$\tilde{\tau}_t^{\mathrm{LC}}(L) = \left(\frac{\varepsilon_t^S}{\varepsilon_t^S - \frac{Q_{t+1}^{uo}}{Q_{t+1}^{o}} \varepsilon_{t+1}^{Du} \left[1 + \Lambda(L, \varepsilon)\right]} \right) e \,,$$

for $\Lambda(L,\varepsilon) = \frac{(1-\beta)\beta^L}{\beta-\beta^L} \frac{P_{t+L}^{Du}}{P_{t+1}^{Du}} \big(1 - \frac{Q_{t+1}^{o} \varepsilon_t^S}{Q_{t+L}^{ro} \varepsilon_{t+1}^{Dr} + Q_{t+L}^{uo} \varepsilon_{t+1}^{Du}}\big) > 0$. Tariffs are increasing in L and approach full commitment as $L \to \infty$.

$$0 = \tilde{\tau}_t^{\mathrm{NC}} < \tilde{\tau}_t^{\mathrm{LC}}(L) < \tilde{\tau}_t^{\mathrm{C}} = \lim_{L \to \infty} \tilde{\tau}_t^{\mathrm{LC}}(L)$$

In the more general case, the statically optimal tariff also decreases over time because tariffs do less to reduce emissions as the stock of sunk investment grows. At the extreme, tariffs are set to zero when all lands are exhausted because tariffs cannot reduce emissions when there are no forests left to save. The above formula nests this case in which the elasticity of supply is zero.

The commitment problem is particularly stark in this setting with deforestation, which causes emissions to be released upon development. But note that the same framework can apply even when emissions are released over time, either in production or consumption. In particular, if sunk investment in a brown technology leads to permanently low marginal costs of production, then production continues in each period. Thus, emissions are committed upon investment, and externality e becomes the net present value of emission damages.

Table 1: Palm oil statistics by country (1988-2016)

	Production	Consumption	Exports	Imports
Indonesia	0.44	0.14	0.41	0.00
Malaysia	0.40	0.06	0.48	0.02
European Union	0.00	0.12	0.00	0.17
China	0.00	0.11	0.00	0.15
India	0.00	0.12	0.00	0.16
Rest of world	0.16	0.45	0.10	0.50

Data are from the USDA Foreign Agricultural Service. Columns show ratios of global totals and each sum to one.

How leakage and commitment interact

The key mechanism is that producers shift sales across markets as tariffs change. That is, producers focus on the unregulated market when tariffs are high, and shift toward the regulated market when tariffs are low. As a result, leakage and commitment interact. Intuitively, the regulator can only compensate for low future tariffs by imposing high tariffs while tariffs are in place. But these high tariffs suffer from leakage, and so the regulator cannot compensate fully. In particular, incomplete regulation allows producers to skirt high tariffs in any given period by directing sales to the unregulated market until tariffs fall. Thus, leakage exacerbates the commitment problem. The greater the leakage problem, the more the unregulated market can absorb, and thus the greater the loss from failures of commitment.

3 Empirical Setting and Data

This section provides institutional details and describes the data. Both make the world market for palm oil an ideal setting for studying environmental regulation by trade policy.

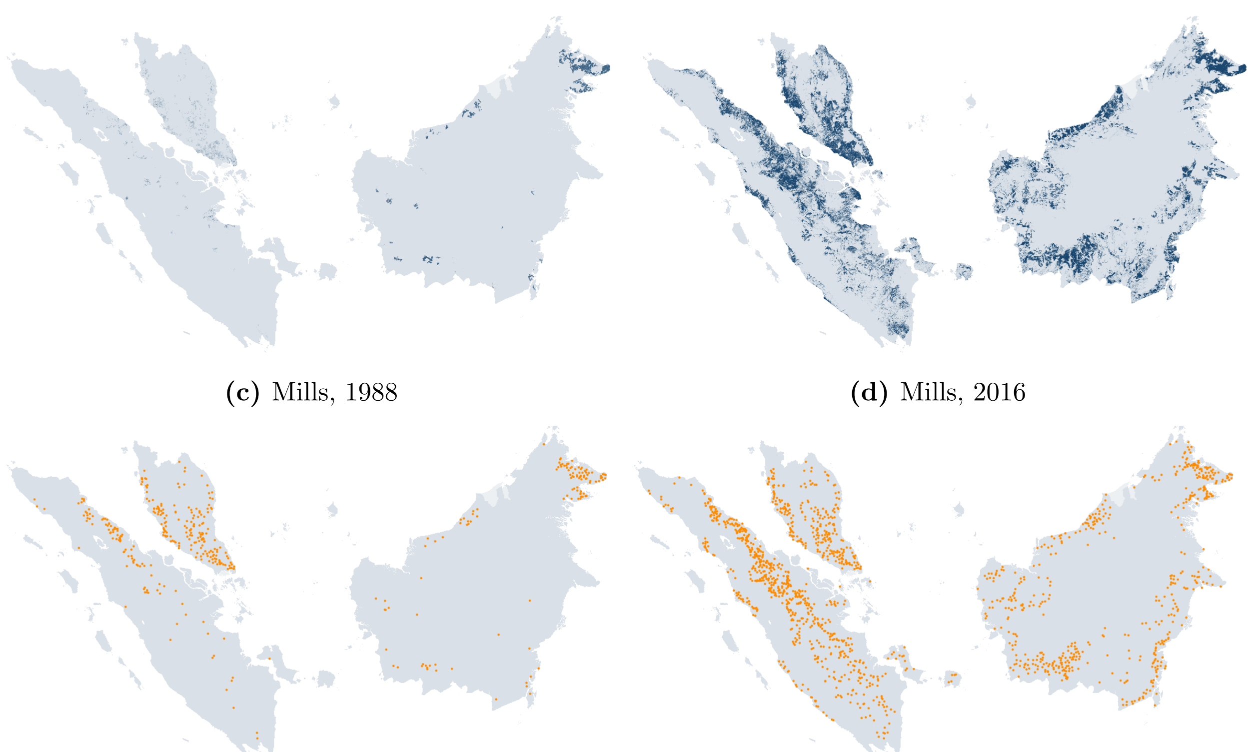
3.1 Empirical setting

Palm oil is among the most widely used plant products in the world. High yields drive its low price point, with oil palm producing more oil per hectare of land than any comparable oilseed. Palm oil is used as a cooking oil, particularly in Asia, and is a common ingredient in processed foods, where it has replaced trans fats. Palm oil also has non-food uses ranging from soaps to cosmetics to biofuels. At the country level, table 1 shows that Indonesia and Malaysia account for 84% of global production, 90% of exports, and 20% of consumption, with the European Union, China, and India accounting for another 35% of global consumption. At the firm level, the market is unconcentrated: the largest producer (FGV Holdings Berhad) accounts for 4% of global production (POA 2017), and the largest consumer (Unilever) accounts for 2% of global consumption (WWF 2016).

Figure 2: Palm oil plantations and mills over time

(a) Plantations, 1988 **(b)** Plantations, 2016

(c) Mills, 1988 **(d)** Mills, 2016



Data on plantations come from Xu et al. (2020) and Song et al. (2018), and data on mills come from the World Resources Institute and the Center for International Forestry Research. The study area is Sumatra, Kalimantan, and Riau of Indonesia and all of Malaysia, covering virtually all palm production in Indonesia and Malaysia.

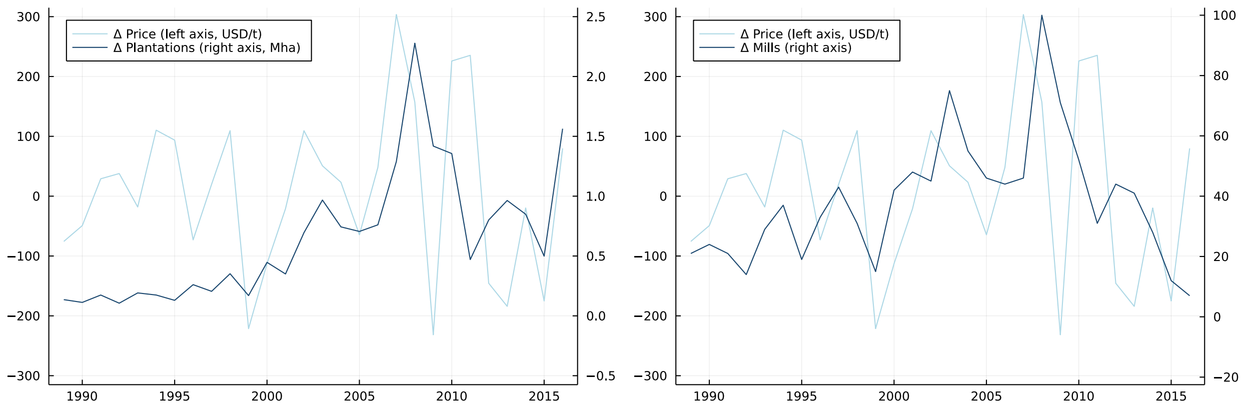
This empirical setting is appealing for several reasons. First, palm oil is among the largest sources of global carbon emissions. Deforestation for palm oil plantations has such severe consequences because Indonesia and Malaysia are rich in peatland forests, which contain deep layers of carbon-rich peat. I compute palm-related 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, with the goal of promoting domestic efforts to curb deforestation. As a case study, consider Indonesia's primary response: a 2011 moratorium on new forest concessions. Busch et al. (2015) cite problems of weak regulation and weak enforcement. The moratorium failed to regulate forests within existing concessions, and

[1] Converting peatlands to croplands involves draining peatlands and clearing the land with fire, releasing large amounts of carbon. Even without clearing by fire, unsubmerged peat releases carbon as it decomposes. Furthermore, fire spreads quickly on dried-out peat, and in 2015 slash-and-burn practices combined with dry El Niño conditions caused an estimated 100,000 deaths and $16 billion in damages (Koplitz et al. 2016; World Bank 2016).

Figure 3: Palm oil production vs. world prices over time

(a) New plantations **(b)** New mills



Data on plantation development come from Xu et al. (2020) and Song et al. (2018), and data on mill construction from the Universal Mill List. Prices combine palm and palm kernel oil prices from the International Monetary Fund.

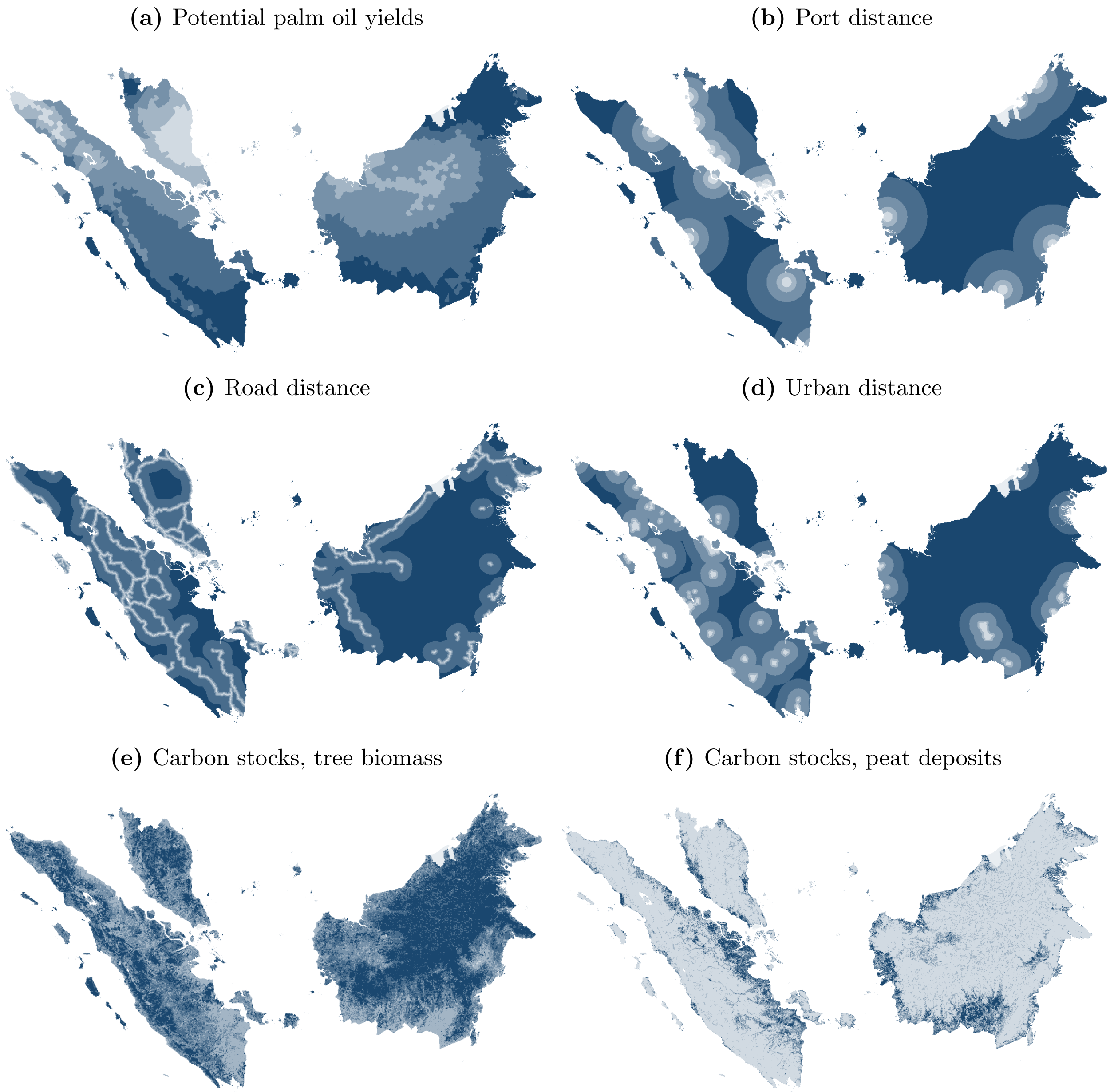
regulating all concessions would still have been insufficient because most deforestation occurred (illegally) outside of concessions, including in protected areas.

Third, foreign governments are actively discussing trade-policy interventions, particularly in Europe. French parliament debated a "Nutella" tax on palm oil in food products in 2016, although it failed to pass. Furthermore, the European Union initially provided green subsidies for palm-based biofuels, but policymakers later recognized the consequences of palm-driven deforestation. Recent policy therefore moves to eliminate green subsidies for palm-based biofuels, cap production, and achieve a complete phase-out by 2030. As well, palm-based biofuels face the further loss of green tax incentives in France and an outright ban in Norway, both by 2020. While none of these policies explicitly imposes tariffs across all palm oil imports, they all leverage European buying power to influence emissions abroad in the same way that tariffs do.

3.2 Data

I compile data on palm oil production and consumption, with data sources and construction detailed in appendix B. I measure production with spatial panel data at a resolution of 30 arc-seconds – approximately 1 km^2 – that records plantations and mills from 1988 to 2016 using satellite imagery. Figure 2 maps their widespread expansion over this period. For plantations, Xu et al. (2020) analyze PALSAR and MODIS satellite data to measure the expansion of palm oil plantations 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 manually cross-

Figure 4: Land characteristics



Darker blue indicates high yields, farther distances, and larger carbon stocks. Yields are computed with the PALMSIM agronomic model (Hoffmann et al. 2014). Ports and roads are from the 2019 World Port Index, World Port Source, and Global Roads Inventory Project. Urban areas are administrative cities (*kota*) in Indonesia and federal territories in Malaysia. Carbon stocks are from Zarin et al. (2016) and Gumbricht et al. (2017).

reference historical satellite data to identify construction dates back to 1988. The Indonesian data focus on Sumatra, Kalimantan, and Riau 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 fluctuations in 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 (Hoffmann et al. 2014) to compute potential palm oil yields as a function of climate. 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. I compute carbon stocks from geospatial data on tree biomass and peat deposits (Zarin et al. 2016; Gumbricht et al. 2017), which record how much carbon would be released in developing any given plot of land and thus link counterfactual production 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 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 Empirical Model

This section specifies empirical models of palm oil demand and supply. The resulting demand and supply curves correspond to the functions $P_t^{Dr}(q)$, $P_t^{Du}(q)$, and $P_t^S(q)$ of section 2.

4.1 Demand: an almost ideal demand system

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). First, consumers make an upper-level choice over total vegetable oil consumption. Second, 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, such 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. Market-specific demand curves allow me to obtain $P_t^{Dr}(q)$ and $P_t^{Du}(q)$ separately.

For a given consumer market, the specifications are as follows. For the lower level,

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

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

for expenditure shares ω_{it}, palm and other oil prices p_{jt}, total vegetable oil expenditures $X_t = Q_t P_t$, and translog price index P_t. For the upper level,

$$\ln Q_t = \alpha^0 + \alpha^1 t + \gamma \ln P_t + Z_t \beta + \varepsilon_t \,, \tag{2}$$

where Q_t is the quantity of total vegetable oil consumption, and P_t is the price index above. 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.

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

where $\frac{\partial \ln P_t}{\partial \ln p_{jt}} = \alpha_j^0 + \alpha_j^1 t + \frac{1}{2}\sum_k (\gamma_{jk} + \gamma_{kj}) \ln p_{kt}$, 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 changes in prices (via γ).

As is typical, prices are endogenous. 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.

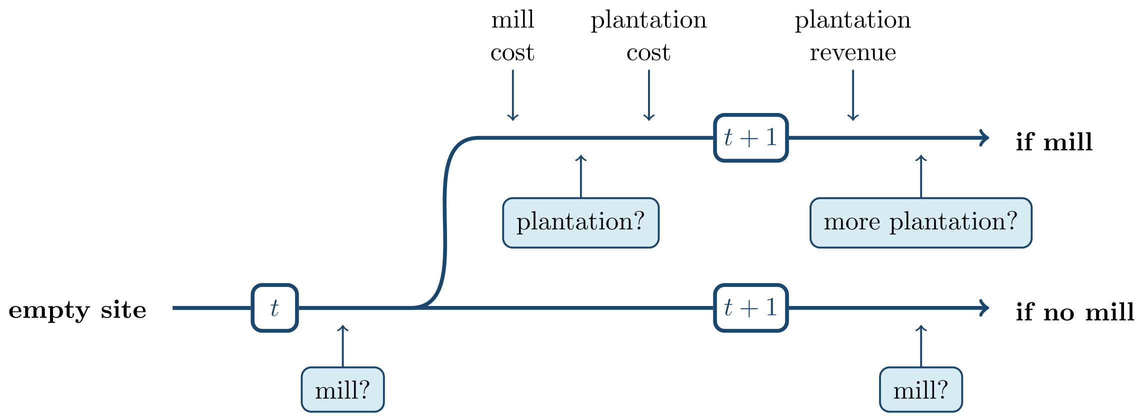
4.2 Supply: a dynamic model with sunk investment

Land is divided into sites, 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.

[2] An important 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.

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

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 binary choice in the following period. If so, then the site makes a continuous choice over how much land to develop into plantations. In future periods, the site faces more continuous choices over plantation expansion.

Intensive margin (plantation development)

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 development today affects plantation size s_{it} in all future periods according to law of motion $s_{it+1} = s_{it} + a_{it}$. Profits depend on publicly observed state $\boldsymbol{w}_{it} = \{Y_{it}, x_i, s_t, d_t\}$ and privately observed 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. Supply evolves endogenously, while demand evolves exogenously. Aggregate supply measures total production across plantations, with high supply leading to low prices. As in Hopenhayn (1992), atomistic sites affect world prices collectively but not individually, and firms play a dynamic competitive equilibrium in which collective action coincides with individual expectations. Aggregate demand captures world demand for palm oil, with high demand leading to high prices. Each period, sites with mills realize state $(\boldsymbol{w}_{it}, \varepsilon_{it})$ and make investment choice a_{it}, which incurs costs in the current period and begins generating revenues in the following one.

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

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

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

Expectations are over next-period state $(\boldsymbol{w}_{it+1}, \varepsilon_{it+1})$. Revenues are linear in plantation size and increasing in yields and world prices. Yields are affected by weather shocks ε^Y_{it} during production, but these shocks are unrealized at the time of investment 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 diseconomies of scale such as credit and local factor market constraints. Sites do not distinguish between upfront and future flow costs, and thus either interpretation is valid. Linear revenues and convex costs ensure unique optima. 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 (mill construction)

In each period t, sites i without mills make a binary choice a^e_{it} over whether to construct a mill. Plantations require mills because unmilled palm fruit decays quickly after harvest, and palm fruit is not consumed directly. Mills have no scrap value and are sunk, with law of motion $s^e_{it+1} = s^e_{it} + a^e_{it}$. Profits depend on publicly observed state $\boldsymbol{w}_{it} = \{Y_{it}, x_i, s_t, d_t\}$ and privately observed state ε^e_{it}, which captures mean-zero logit shocks $\{\varepsilon^e_{it0}, \varepsilon^e_{it1}\}$ with standard deviation σ^e. Each period, sites without mills realize state $(\boldsymbol{w}_{it}, \varepsilon^e_{it})$ and make investment choice a^e_{it}. 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 function, choice-specific conditional value functions, and cost function are

$$V^e(\boldsymbol{w}_{it}) = \mathbb{E}^e_{it}[\max\{v^e(0;\boldsymbol{w}_{it}) + \varepsilon^e_{it0}, v^e(1;\boldsymbol{w}_{it}) + \varepsilon^e_{it1}\}]\,, \tag{5a}$$

$$v^e(0;\boldsymbol{w}_{it}) = \beta\mathbb{E}^e_{it}[V^e(\boldsymbol{w}_{it+1})]\,, \tag{5b}$$

$$v^e(1;\boldsymbol{w}_{it}) = -c^e(\boldsymbol{w}_{it}) + \mathbb{E}^e_{it}[V(0;\boldsymbol{w}_{it}, \varepsilon_{it})]\,, \tag{5c}$$

$$c^e(\boldsymbol{w}_{it}) = x_i\gamma^e + \kappa^e_m + \alpha^e_m t\,, \tag{5d}$$

where the e superscript indicates the extensive margin with shorthand $\mathbb{E}^e_{it}[\cdot] \equiv \mathbb{E}^e[\cdot|\boldsymbol{w}_{it}]$. In equation 5a, expectations are over logit shocks ε^e_{it} that imply mill construction probabilities

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

more precisely written $p^e_m(\boldsymbol{w}_{it})$ given regional heterogeneity in the cost function. In equation 5b, choosing not to build leads to the same decision in the following period, subject to 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^e_{it}. In equation 5c, choosing to build incurs mill construction costs in return for the value of plantation development on the intensive margin, 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^e_m and time trends α^e_m accommodate unobserved heterogeneity by region. Cost shocks come from logit shocks ε^e_{it}, which are uncorrelated over time and across sites and also uncorrelated with intensive-margin shocks ε_{it}.

Unobserved heterogeneity and endogeneity

The primary restriction on both margins is that unobserved heterogeneity is allowed only at the regional level. Within regions, sites can receive differential shocks but otherwise have no persistent heterogeneity beyond that explained by observables. On the intensive margin, identifying site-level unobserved heterogeneity would require a long panel of plantation development decisions, which I only have for sites with early development. On the extensive margin, I would require multiple mill construction decisions per site, but each site constructs no more than one mill in the model.

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 a strong one. Instead, I instrument for prices with demand shifters d_t and for yields with potential yields Y_i^p. Demand shifters come from the estimated world demand curves in each period.

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

The intercept captures the level of demand over time, which I interpret as a demand shifter. Variation in total oil consumption $\ln Q_t$ drives this demand shifter, and indeed instrumenting directly with $\ln Q_t$ leads to similar results. 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 to be exogenous. Port distance considers only major ports, which predate plantations. Road distance considers only major roads, and not small roads that develop endogenously around plantations. Urban distance considers officially designated urban districts, which cover only major cities and do not include palm oil settlements. Carbon stocks are predetermined.

5 Estimation

This section describes how I estimate the demand and supply models specified in section 4. I take an iterated linear least squares approach for demand and an Euler approach for supply.

5.1 Demand: iterated linear least squares

I adopt the iterated linear least squares approach of Blundell and Robin (1999) to estimate the lower-level demand system. 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 and year, and I obtain standard errors with the delta method.

5.2 Supply: Euler approach

I take an Euler approach for estimation, focusing on the timing of observed investment 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 investment levels fixed. Continuation values difference out. I assume a discount factor of $\beta = 0.9$, as the discount factor is typically unidentified in dynamic discrete choice models (Magnac and Thesmar 2002). Estimation proceeds in three steps.

Step 1: defining site boundaries

I divide land into operational and potential 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, where the number of clusters k in each province is 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 results in 2,135 contiguous sites: 1,467 operational sites with one observed mill and some observed plantations, and 668 potential sites with zero observed mills or plantations.

Step 2: estimating the intensive-margin model (plantation development)

The first order condition for investment and the envelope theorem deliver an Euler equation.

$$
\begin{aligned}
c'(a_{it}; \boldsymbol{w}_{it}, \varepsilon_{it}) &= \beta \mathbb{E}_{it}[V'(s_{it+1}; \boldsymbol{w}_{it+1}, \varepsilon_{it+1})]\,, \\
V'(s_{it}; \boldsymbol{w}_{it}, \varepsilon_{it}) &= r'(s_{it}; \boldsymbol{w}_{it}) + \beta \mathbb{E}_{it}[V'(s_{it+1}; \boldsymbol{w}_{it+1}, \varepsilon_{it+1})]\,,
\end{aligned}
$$

where the first line is the first order condition for a_{it} and the second line applies the envelope theorem to equation 4a. Together, these equations imply the Euler equation

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

which captures the intertemporal trade-off in investing in period t compared to $t+1$. With the functional form assumptions of equation 4b, the Euler equation specializes to

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

with shorthand $P_t \equiv P(s_t, d_t)$ and $\tilde{t} \equiv t - \beta(t+1)$. Sites develop today instead of tomorrow when the marginal benefit is high and the marginal cost low. I implicitly assume an interior solution, otherwise the first order condition may not hold. Indeed, 99.5% of observed intensive-margin decisions are interior: 0.5% involve zero development, and 0% exceed sites' total area.

For estimation, 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

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

subject to shocks ε_{it} that are correlated across sites and over time, as well as expectational errors

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

Rational expectations are correct on average and use all available information, in which case expectational errors are mean-zero and orthogonal to sites' period-t information sets.[4] Investment choices, yields, prices, and cost factors are data, where cost factors include port, road, and urban distances, as well as carbon stocks. I cluster by region to address correlated cost shocks. I instrument for yields and prices with potential yields and demand shifters as discussed above, and I use lagged instruments that are within sites' period-t information sets. Figure 3 plots the time-series variation in world prices, and figure 4a plots the spatial variation in yields. Identification relies on both sources of variation: intuitively, price increases are more valuable for sites that produce more palm oil. Since revenues $Y_{it+1} P_{t+1}$ are measured directly, parameters γ, κ_m, and α_m are interpretable in dollar terms. While production begins one period after investment in this exposition, I instead impose the typical three-year lag for palm maturity in estimation.[5]

Step 3: Estimating the extensive-margin model (mill construction)

Discreteness precludes the use of a first order condition and the envelope theorem. Instead, I obtain an Euler equation by differencing and finite dependence. I compare sequences of actions, with differences in likelihoods reflecting differences in payoffs. Finite dependence facilitates the comparison: under finite dependence, I can choose sequences that lead to common states – and therefore common payoffs – in all future periods (Arcidiacono and Miller 2011).

As before, I compare investing today and tomorrow. More precisely, I compare two sequences of extensive- and intensive-margin actions: $(1, a^*_{it}, a^*_{it+1})$ and $(0, 1, a'_{it+1})$ for $a'_{it+1} = a^*_{it} + a^*_{it+1}$. The

[4] Equation 8 forms a telescoping series that implies $a_{it} = \sum_{t'=1}^{\infty} \frac{\beta^{t'}}{\delta} \mathbb{E}_{it}[Y_{it+t'} P_{t+t'}] - \frac{1}{\delta} x_i \gamma - \frac{1}{\delta} \kappa_m - \frac{1}{\delta} \alpha_m t - \frac{1}{\delta} \varepsilon_{it}$.

[5] Each year is one period. Y_{t+1} terms become Y_{it+3} and P_{t+1} terms become P_{t+3}, but a_{it+1} does not change because the intertemporal comparison is between developing today and tomorrow.

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 because, for both sequences, by period $t+2$ the mill is constructed and plantation size is $a^*_{it} + a^*_{it+1}$. To form the Euler equation, I first evaluate the payoffs for each sequence.

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

The continuation values align: $\beta^2 \mathbb{E}^e_{it}[V(a^*_{it} + a^*_{it+1}; \boldsymbol{w}_{it+2}, \varepsilon_{it+2})] = \beta^2 \mathbb{E}^e_{it}[V(a'_{it+1}; \boldsymbol{w}_{it+2}, \varepsilon_{it+2})]$ because $a'_{it+1} = a^*_{it} + a^*_{it+1}$. I then write these payoffs in terms of choice-specific conditional value functions $v^e(1; \boldsymbol{w}_{it})$ and $v^e(0; \boldsymbol{w}_{it})$, which the Hotz-Miller inversion links to choice probabilities.

$$\ln\left(\frac{p^e(\boldsymbol{w}_{it})}{1 - p^e(\boldsymbol{w}_{it})}\right) = v^e(1; \boldsymbol{w}_{it}) - v^e(0; \boldsymbol{w}_{it})\,, \tag{9}$$

as follows from equation 6 (Hotz and Miller 1993).

For the first sequence, $v^e(1; \boldsymbol{w}_{it}) = v^e(1, a^*_{it}, a^*_{it+1}; \boldsymbol{w}_{it})$ by definition, where $a^*_{it} \equiv a^*_{it}(0; \boldsymbol{w}_{it}, \varepsilon_{it})$ and $a^*_{it+1} \equiv a^*_{it+1}(a^*_{it}; \boldsymbol{w}_{it+1}, \varepsilon_{it+1})$. For the second sequence, $v^e(0, 1, a'_{it+1}; \boldsymbol{w}_{it})$ involves choices that may differ from the optimal choices implied by $v^e(0; \boldsymbol{w}_{it})$. The difference in payoffs is

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

where $a^*_{it+1} \equiv a^*_{it+1}(0; \boldsymbol{w}_{it+1}, \varepsilon_{it+1})$. Substituting into equation 9, I obtain an Euler equation in which continuation values cancel. Applying the functional forms of revenues and costs, and noting $a^*_{it+1}(a^*_{it}; \boldsymbol{w}_{it+1}, \varepsilon_{it+1}) = a^*_{it+1}(0; \boldsymbol{w}_{it+1}, \varepsilon_{it+1})$ given linear revenues,

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

for $\tilde{t} = t - \beta(t+1)$ and $I_{it+1} = [\beta Y_{it+1} P_{t+1} - (1-\beta)x_i\gamma - (1-\beta)\kappa_m - \alpha_m \tilde{t}]a^*_{it} + \delta[-\frac{1}{2}{a^*_{it}}^2 + \beta a^*_{it} a^*_{it+1}]$. Intuitively, developing earlier brings forward plantation revenues, but also investment costs.

I apply expectational errors η^e_{it} and substitute estimated values to obtain a regression equation.

$$\ln\left(\frac{\widehat{p^e}(\boldsymbol{w}_{it})}{1 - \widehat{p^e}(\boldsymbol{w}_{it})}\right) - \beta \ln \widehat{p^e}(\boldsymbol{w}_{it+1}) = \widehat{I}_{it+1} - (1-\beta)x_i\gamma^e - (1-\beta)\kappa^e_m - \alpha^e_m \tilde{t} + \eta^e_{it} \tag{10}$$

I estimate conditional choice probabilities $\widehat{p^e}(\boldsymbol{w}_{it})$ from the data. I use the predicted values from a logit regression of observed investment choices on a flexible set of basis terms: piecewise linear splines in Y_{it+1}, P_{t+1}, x_i, and $\tilde{t}$, as well as their interactions. I do so separately for each region and therefore account non-parametrically for regional heterogeneity. Consistent with the model, this procedure accommodates unobserved heterogeneity by region while allowing only observed heterogeneity by site. I estimate intensive-margin choices $\widehat{a}_{it}^{*}$ in the same way, but with OLS instead of a logit regression. Dollar-denominated intensive-margin profits $\widehat{I}_{it+1}$ provide a scale normalization that allows parameters γ^e, κ_m^e, and α_m^e to be interpreted in dollar terms. Intercepts κ_m^e are only identified relative to the outside option, as is typical with discrete choice models.

Discussion

This Euler approach to estimation has several advantages. I can address endogeneity concerns using standard instrumental variable techniques because estimation reduces to linear regression. Furthermore, while I do need to assume that agents have rational expectations, for estimation I do not need to model exactly what these expectations are. This flexibility is a significant advantage over a conventional full-solution approach that would require explicit structure on expectations. The full-solution approach also requires solving the model repeatedly for estimation, with each iteration involving the time-consuming calculation of continuation values. 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 the problem in my setting (Aguirregabiria and Mira 2007; Bajari et al. 2007; Pakes et al. 2007; Pesendorfer and Schmidt-Dengler 2008).

One disadvantage is that rational expectations can still be a strong assumption. Biased expectations load onto costs, with pessimism over future prices having the same effect as high costs. Regional effects κ_m capture cost heterogeneity across regions and therefore absorb expectational bias to the extent that it is fixed within regions. This approach is similar to Diamond et al. (2017), who difference out expectational bias by assuming that it is constant among individuals within a group. For counterfactuals, the assumption is that expectational bias remains uninfluenced by trade policy. A more careful treatment of expectations would require separate variation in actual and expected profits, as well as specifying how trade policy changes expectations.

Another disadvantage is that tractability relies on several assumptions that may also be strong. First, the Euler comparison between investing today or tomorrow implicitly assumes property rights. If delaying investment risks losing land claims, then sites will be biased toward investing today. Regional effects κ_m also help here: low costs make delayed investment less appealing, and so regions susceptible to land grabbing will appear to have low costs. Second, I assume independent, atomistic sites because finite dependence does not hold otherwise. If a price-maker delays investment, then competitors will respond, thereby changing the state of the economy in all future periods. Independence also rules out spatial competition. In particular, although sites are all price-takers in the global palm oil market, even small sites can be price-makers in local input markets for land, labor, and capital. Furthermore, spatial interdependence introduces a dimensionality problem that makes estimation intractable. Third, I assume that plantation age

Table 2: Weather shocks as price instruments

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

Each column is a regression, and the outcome variable is log prices. Data are annual and 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. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

does not affect profits, again such that finite dependence holds. If younger plantations are more productive, then delaying investment changes profits in all future periods.

6 Results

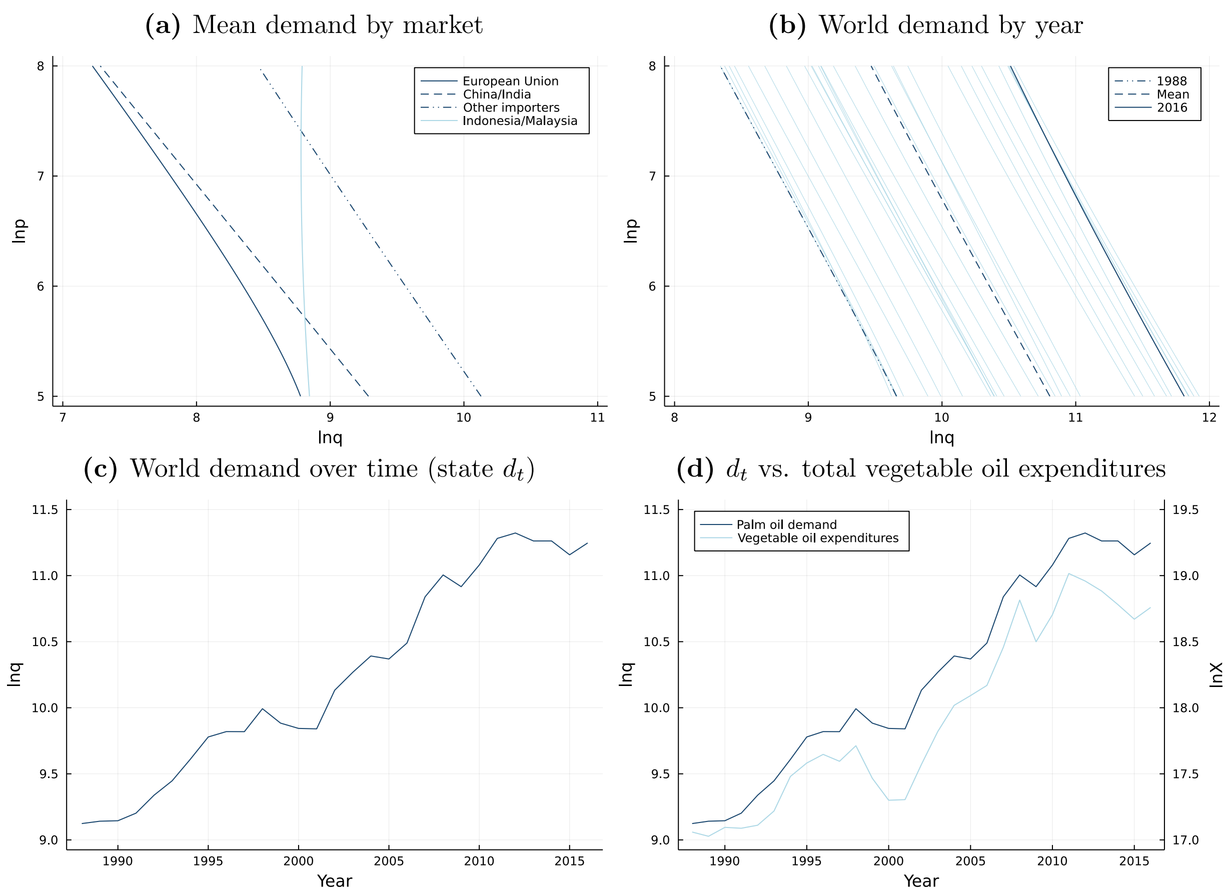
This section describes both demand and supply estimates. Demand estimates suggest inelastic Indonesian and Malaysian demand, while supply estimates quantify palm oil production costs.

6.1 Demand estimates

In the first stage, table 2 shows that both rainfall and temperature shocks significantly increase world oil prices. The first two columns pool across oil products and show that weather shocks have significant price effects, both controlling for year trends and not. The last two columns show estimates for palm and other oils separately. For palm oil, a smaller sample size means less precision, but the point estimates are relatively close to those of the pooled specifications, and the instruments remain strong. Temperature effects are perhaps imprecisely estimated because palm oil is grown in tropical climates with limited year-to-year variation in temperatures. Toward assessing the exclusion restriction, I show in the appendix that these weather shocks do not affect overall incomes or expenditures, both of which would influence demand directly.

Figure 6 plots the estimated demand curves and implied demand shifters. Price-responsive demand among non-EU importers suggests that unilateral EU action is susceptible to leakage, particularly because non-EU importers account for a substantial 68% of global consumption (table 1). By contrast, Indonesia and Malaysia have nearly perfectly inelastic demand, limiting leakage

Figure 6: Palm oil demand



(a) Mean demand by market **(b)** World demand by year **(c)** World demand over time (state d_t) **(d)** d_t vs. total vegetable oil expenditures

The demand estimation underlying these curves draws on annual data that cover coconut, olive, palm, rapeseed, soybean, and sunflower oils from 1988 to 2016, and it instruments for prices with weather shocks to oil production. Figures 6a and 6b show palm oil demand curves, with means computed over the study period. Figures 6c and 6d plot the world quantity demanded at price $\ln p = 6.25$ – roughly the mean price over the study period – in order to illustrate the rightward shift of the world demand curve over time.

if importers coordinate on regulation. As producers, Indonesia and Malaysia consume much more palm oil than other oils – consistent with home bias – and limited scope for substitution leads to inelastic palm oil demand.[6]

One limitation is that the demand model is static. I can rule out significant bias from stockpiling because I observe oil stocks held in storage facilities and find that they are small. However, demand may be sticky because switching between oils requires reformulating recipes and rewriting contracts with suppliers. If so, then larger long-run elasticities imply more leakage. Another concern is that palm oil tariffs may encourage unregulated markets to supply regulated markets with palm oil in other forms, such as palm-based biofuels. Static demand estimates do capture the short-term responses of existing industries, as the consumption data include palm oil used as inputs. However, static demand cannot capture the long-term response of new industries short of

[6] Palm oil accounts for 90% of vegetable oil expenditures in Indonesia and Malaysia, but only 20% in other markets.

Table 3: Intensive-margin supply regressions

	OLS	IV	First stage
	$a_{it} - \beta a_{it+1}$	$a_{it} - \beta a_{it+1}$	$Y_{it+3}P_{t+3}$
Yield × price ($Y_{it+3}P_{t+3}$)	0.113***	0.200***	
	(0.00714)	(0.0355)	
Potential yield × demand ($Y_i^p d_t$)			30.58***
			(1.220)
Province FE	x	x	x
Province-year trend	x	x	x
Observations	17,181	17,181	17,181
F-statistic			628

Each column is one regression, and each observation is a site-year. The dependent variables are shown in the column headings. The first column is OLS, and the second column IV. The IV specification uses the interaction of potential yields and demand shifters to instrument for the interaction of yields and prices, with the third column showing the first stage. Potential yields are computed using the agronomic model of Hoffmann et al. (2014). Demand shifters are computed during demand estimation. Prices combine palm and palm kernel oil prices and are inflation-adjusted to year 2000 dollars. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

modeling them. This concern is mitigated by the fact that most palm oil is exported in raw form, but nonetheless a simple response is for import tariffs to cover both palm oil and palm oil content.

6.2 Supply estimates

Tables 3 and 4 present supply estimates. Table 3 shows that higher revenues – whether they be from higher yields or higher prices – indeed lead to more development, with a larger effect in the IV specification. Table 4 shows the estimated model parameters, all of which are interpretable in dollar terms. On the intensive margin, I estimate the average lifetime costs of plantation development to be \$10 thousand per hectare in net-present-value terms, ranging from \$6 thousand at the 10th percentile to \$15 thousand at the 90th percentile across provinces. By comparison, accounting estimates suggest costs of \$7 thousand per hectare: \$4 thousand upfront and \$3 thousand for operations (Butler et al. 2009). I estimate costs to be decreasing at an annual rate of \$400 on average, again with some heterogeneity across provinces. Within provinces, I find costs to be similar across sites with different characteristics (conditional on mill construction).

On the extensive margin, I estimate lifetime mill construction costs of \$23 million on average, ranging from \$16 million at the 10th percentile to \$30 million at the 90th percentile. By comparison, accounting estimates suggest costs of \$20 million: \$5 million upfront and \$15 million for operations (Man and Baharum 2011). I estimate costs to be increasing at an annual rate of \$88 thousand on average, with large heterogeneity across provinces. I estimate the standard deviation of the logit shock to be \$3 million, suggesting that changing producer behavior requires incentives measured in the millions of dollars. Within provinces, site characteristics have a significant impact on costs,

Table 4: Supply model parameter estimates

	Mean	SE	10th percentile	90th percentile
Province-specific costs (κ_m)	9,674***	(856)	6,398	14,655
Province-specific cost trends (α_m)	-374***	(21)	-729	-99
Quadratic costs (δ)	4.50***	(0.80)	–	–
Cost factors (γ)				
Log port distance, km	-711	(486)	–	–
Log road distance, km	-333*	(199)	–	–
Log urban distance, km	-278	(278)	–	–
Log carbon in tree biomass, t	206	(540)	–	–
Log carbon in peat deposits, t	-93	(68)	–	–
Province-specific costs (κ_m^e)	22,881,886***	(391,964)	15,804,464	29,636,816
Province-specific cost trends (α_m^e)	88,477***	(15,261)	-483,608	625,779
Logit scale (σ^e)	3,075,006***	(107,831)	–	–
Cost factors (γ^e)				
Log port distance, km	685,682***	(194,359)	–	–
Log road distance, km	506,299***	(88,269)	–	–
Log urban distance, km	267,636**	(129,626)	–	–
Log carbon in tree biomass, t	706,172***	(174,548)	–	–
Log carbon in peat deposits, t	835	(30,598)	–	–

The top panel shows intensive-margin parameters, and the bottom panel shows extensive-margin parameters. All estimates are interpretable in dollar terms (inflation-adjusted to year 2000 dollars). For region-specific parameters, I include the 10th and 90th percentiles for estimates across regions. I report province-specific costs κ_m and κ_m^e for a mean year and at mean values for cost factors. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

which are increasing in distances from major ports, roads, and urban centers. This transportation-cost effect is smallest for distance from urban areas, with higher transportation costs partially offset by lower land and labor costs in remote regions. Furthermore, tree biomass does discourage mill construction, as entering heavily forested areas demands significant effort in land development and may face scrutiny from local governments and native populations. But peat deposits – the main source of carbon emissions – have little effect on mill construction. Indeed, palm oil producers fail to internalize their carbon externalities.

7 Counterfactuals: Assessing Coordination and Commitment

This section evaluates the individual and combined roles of coordination and commitment in determining the impacts of import tariffs. I find that import tariffs can be an effective substitute for domestic regulation, but only when both coordination and commitment hold.

7.1 Setting tariffs

I set tariffs to maximize social welfare, penalizing emission damages while also weighing consumer surplus from palm oil use and producer surplus for Indonesia and Malaysia. The domestic tax, which serves as a benchmark, is also set to maximize social welfare. Unlike the domestic tax, however, tariffs sidestep domestic obstacles to regulation by directly targeting the prices producers receive in world markets. In particular, prices equalize across markets in each period t.

$$P_t^{Dr}(Q_t^{ro}) - \tau_t = P_t^{Du}(Q_t^{uo})$$

For example, new EU tariffs cause revenues from EU sales to decline relative to other sales, and so producers respond by shifting sales to other markets. I assume zero trade costs for simplicity, but adding exogenous trade costs would be inconsequential because they would be invariant across tariffs. Furthermore, the above equation connects the three components of the empirical model: tariffs, demand, and supply. Tariff τ_t changes world price P_t depending on demand curves $P_t^{Dr}(q)$ and $P_t^{Du}(q)$, and world price P_t in turn affects the investments that produce supply $Q_t^{ro} + Q_t^{uo}$.

I focus on uniform tariffs that treat all palm oil equally. The alternative is to condition on the emissions specific to each unit of palm oil. For example, if palm oil can be certified as green, then tariffs can differentiate by certification status. In practice, however, tracking production histories to this extent is difficult. Similarly, I focus on a uniform domestic tax because of its administrative convenience: it can be applied at the point of sale without the need to monitor production. Indeed, uniform taxes are common despite being "second-best" relative to a Pigouvian tax. For example, fuel taxes are uniform despite heterogeneity across vehicles in tailpipe emissions (Knittel and Sandler 2018). Nonetheless, an alternative is to condition on emissions with site-specific license fees or ex-post penalties, and my framework can readily accommodate such policies.

I quantify the effects of coordination and commitment by studying the following scenarios. For coordination, I study tariffs set under three tariff coalitions: all importers together, an EU-China-India partnership, and the EU alone. For commitment, I study full, no, and limited commitment. Full commitment assumes that, once set, tariffs are upheld in perpetuity. No commitment assumes that tariffs are reset every period, with the result being sequential static optimization. Limited commitment assumes commitment to L-period tariff plans revised every L periods, similar to "five-year plans" in Indonesia and China or any policy based on decennial census results.

7.2 Solving the model

Counterfactuals require solving the supply model and thus involve an additional set of assumptions over how firms set expectations. I model the non-stationary evolution of demand d_t with an ARIMA process, and I assume firms' expectations are given by this process. Supply s_t is determined endogenously as the result of an entry game in which beliefs are correct in equilibrium.

Intuitively, if firms believe all other firms will enter, then they will anticipate low prices and not enter, in which case their beliefs are not consistent with reality. I assume that yields Y_{it} evolve at a constant and exogenous rate per year. Finally, I assume that while firms know current-period cost shocks ε_{it} and ε_{it}^{e}, they only know the distribution of future shocks. Note that estimation does not rely on these assumptions because the Euler approach estimates the model without solving it. And while I do need to solve the model for counterfactuals, I still avoid the computational burden of solving it repeatedly for estimation.

For a given set of tariffs, I solve the model by backward inducting from the steady state. Suppose the steady state is reached in period S. At this point, all feasible lands are developed and there is no further development, but plantations continue to generate revenues over the infinite horizon. Finite lands ensure that such a period exists, but the challenge is that it takes many periods to exhaust all available land. Backward induction over such a long horizon is computationally intensive. I address this computation burden in two ways. First, I solve each subproblem using an iterative algorithm that approximates the solution with a fixed look-ahead horizon instead of always looking ahead to the end of the game tree. This algorithm breaks the usual curse of dimensionality in which the state space grows exponentially in the length of the look-ahead window. Second, I approximate period S by choosing an arbitrary period $T < S$ and solving as if it were the steady state. This approach is biased if substantial development occurs after period T, but I resolve taking periods $T+5$, $T+10$, and so on as the steady state until the solutions converge. Intuitively, entry today becomes less appealing when competitors have a longer window of opportunity to enter, but discounting means a diminishing marginal impact of extending this window.

7.3 Quantifying emissions

I quantify carbon emissions by combining the model's site-level predictions for plantation development with site-level data on carbon stored both aboveground in trees and belowground in peat. Assuming plantation development releases carbon stocks completely, these data provide a direct link to counterfactual emissions.

On the demand side, I ignore the carbon effects of substitution to other oils. I therefore do not account for substitution to South American soybean oil, which potentially involves Amazonian deforestation. Three facts mitigate the resulting bias. First, South American soybean oil is only one of several close substitutes for palm oil: soybean oil is only 32% of total oil consumption, and South America supplies less than half of soybean crops globally. Second, South American soy does not destroy peatlands. Amazonian peatlands are concentrated deep in the Amazon, while deforestation is primarily at the Amazon's outskirts (Gumbricht et al. 2017; Song et al. 2018). Thus, the carbon consequences are smaller than those of palm oil, and indeed palm oil emissions would be five to ten times smaller without peatland destruction. Third, South American deforestation is driven primarily by cattle and not soy (Souza-Rodrigues 2019).

On the supply side, I ignore the carbon effects of substitution to other land uses. The primary threat is substitution to acacia plantations, which also destroy peatlands. I compile data on the acacia industry and estimate the reduced-form relationship between acacia and palm oil plantation development in appendix E.2. I find the magnitude of the relationship to be small, at least in partial equilibrium, with a one-percent reduction in palm oil plantation development corresponding to a 0.02% increase in acacia plantation development. Capturing general equilibrium effects would require a two-industry model in which producers first choose between palm oil and acacia, then proceed with the extensive- and intensive-margin investment decisions of the baseline model. But oil palm is more profitable than other crops – seven times more so than acacia (Sofiyuddin et al. 2012) – and thus acacia expansion is unlikely to fully offset palm reductions. Conceptually, substitution toward acacia plantations is a source of supply-side leakage that makes tariffs less effective, and the policy response is to levy acacia tariffs alongside palm oil tariffs. Mining and selective logging also drive deforestation in the region, but mining relies on the exogenous distribution of deposits, and selective logging does not destroy peatlands.

7.4 Import tariffs can be an effective substitute for domestic regulation

Table 5 shows that import tariffs can be effective in reducing carbon emissions. When importers coordinate on import tariffs, and when they commit to upholding them, carbon emissions are reduced by 56%. By comparison, the socially optimal domestic tax reduces carbon emissions by 64%. The difference arises from leakage to domestic consumption in Indonesia and Malaysia, which is not exported and therefore not subject to import tariffs. However, the loss is not disproportionate because demand in Indonesia and Malaysia is quite inelastic. Indeed, importers impose tariffs nearly as large as the domestic tax given limited leakage concerns. Finally, the magnitude of the emission externality leads to a domestic tax that is itself quite large at several times observed prices.

7.5 But only when both coordination and commitment hold

Emission reductions diminish as coordination and commitment weaken. Figure 7a plots emission reductions under each of the scenarios in table 5. First, weak coordination decreases the level of achievable emission reductions because importers have relatively elastic demand. Emissions fall by at most 56% under full coordination among all importers, 17% under an EU-China-India coalition, and 2% under unilateral EU action. These emission reductions fall disproportionately more than tariff coverage – 80%, 35%, and 12% of world consumption, respectively – because leakage concerns lead to smaller tariffs. Second, weak commitment can significantly undermine emission reductions. This effect is especially stark when the commitment period does not exceed time to build, in which case tariffs and emission reductions are zero. In this case, tariffs have no effect on new development because new development does not generate taxable production until after the commitment period has passed. Third, coordination and commitment interact. Figure 7b shows

Table 5: Counterfactual experiments

	$/t NPV	Δ%	Δ% surplus				$/t CO_2
Experiment	Tax	CO_2	EU	China India	Other	Indo Malay	Avg cost
Domestic regulation	20,487	-64	-93	-65	-31	-61	20
Import tariffs: full coordination							
Full commitment	19,718	-56	-86	-58	-25	-71	24
Limited commitment (20 years)	19,665	-56	-86	-58	-24	-71	24
Limited commitment (10 years)	19,476	-55	-85	-57	-24	-70	24
Limited commitment (5 years)	18,639	-53	-80	-54	-22	-67	24
Import tariffs: EU, China, India							
Full commitment	11,573	-17	-49	-32	45	-21	16
Limited commitment (20 years)	11,156	-16	-47	-30	43	-20	16
Limited commitment (10 years)	9,882	-14	-40	-25	38	-18	16
Limited commitment (5 years)	6,445	-9	-23	-13	25	-12	15
Import tariffs: EU only							
Full commitment	6,785	-2	-11	10	5	-3	10
Limited commitment (20 years)	6,445	-2	-10	10	5	-3	9
Limited commitment (10 years)	5,466	-2	-7	8	4	-2	9
Limited commitment (5 years)	3,197	-1	-3	5	2	-1	8

The first column shows the net present value of taxes or tariffs in dollars per ton of palm oil. The second column shows percentage changes in carbon emissions relative to observed net present values, and the third, fourth, fifth, and sixth columns show percentage changes in surplus by market. Figures for Indonesia and Malaysia combine consumer and producer surplus, and all figures include government tax or tariff revenue where applicable. The last column shows average social surplus losses per ton of carbon averted. The first panel is for a socially optimal domestic tax in Indonesia and Malaysia. The second, third, and fourth panels are for foreign import tariffs under full coordination among importers, under an EU-China-India coalition, and for the EU alone. Each shows several commitment scenarios: full commitment over all future periods, and limited commitment in which commitment is only for five, ten, or twenty years at a time. Under no commitment, tariffs have no effect because they do not affect new development given time to build. The discount factor is $\beta = 0.9$.

how weak coordination increases the importance of commitment. A five-year commitment period achieves 95% of full-commitment outcomes when all importers coordinate, but does much less under an EU-China-India coalition or unilateral EU action. These scenarios instead require twenty-year commitment periods to approach full-commitment outcomes.

The division of surplus highlights why coordination and commitment are difficult to achieve when countries focus only on their individual outcomes. For coordination, importers gain by defecting from the tariff coalition because they can free-ride on the emission reductions that the coalition achieves. Furthermore, defectors benefit from leakage as the tariff coalition cuts its consumption and world prices fall in response. For example, focusing on full commitment, other importers have 25% lower consumer surplus when they join the EU, China, and India in imposing tariffs, but 45% higher consumer surplus when they unilaterally defect. For commitment, acting importers

Figure 7: Counterfactual emissions

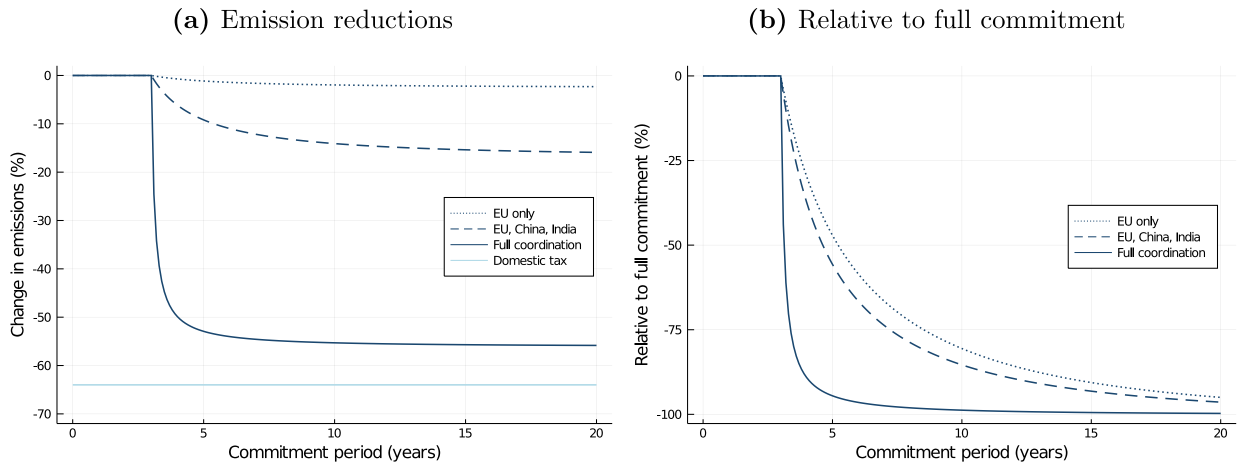


Figure 7a shows emission reductions under several scenarios. Starting at the top, the dotted line shows reductions under unilateral EU action for each of the commitment periods listed on the x-axis. Emission reductions are zero when the commitment period does not exceed time to build because otherwise tariffs do not influence new development. The dashed line shows emission reductions when the EU, China, and India coordinate on import tariffs. The solid line involves coordination among all importers, excluding domestic consumption in Indonesia and Malaysia. The light blue line corresponds to the socially optimal domestic tax. Figure 7b rescales emission reductions for the first three scenarios relative to their levels under full commitment.

have higher surplus when commitment levels are low because low commitment leads to low tariffs and thus limited sacrifices in consumer surplus. For example, focusing on full coordination, all importers have higher surplus under five-year commitment than they do under full commitment.

More broadly, the same considerations underscore why Indonesia and Malaysia have not implemented the socially optimal domestic tax. If importers cannot coordinate, then the domestic tax greatly reduces producer surplus, leaving Indonesia and Malaysia better off accepting import tariffs. But if importers threaten coordinated tariffs, then the domestic tax becomes appealing. It has low marginal impact on producer surplus since coordinated tariffs are already high, and it generates government revenue that would otherwise go to foreign governments.

7.6 Robustness and extensions

Table 6 shows that the qualitative results hold across a series of robustness checks. First, the baseline model assumes a discount factor of $\beta = 0.9$, but effects are larger for lower discount factors, which imply larger benefits from delaying development. Second, the baseline result relies on inelastic demand in Indonesia and Malaysia, but elastic demand increases leakage and lowers carbon reductions, although coordinated, committed tariffs continue to have large effects. Third, I allow importers under limited commitment to revise their L-year plans several years before the end of each plan. Early planning prevents tariffs from being set to zero at the start of each regime because of time to build, and thus lessens the difference between long and short commitment periods.

Table 6: Robustness and extensions, carbon emission reductions ($\Delta\%$ CO_2)

Coordination:	All importers		EU-China-India		EU alone	
Commitment:	20-year	5-year	20-year	5-year	20-year	5-year
Baseline	-56	-53	-16	-9	-2	-1
Discount factor						
$\beta = 0.8$	-75	-71	-21	-12	-3	-2
$\beta = 0.85$	-65	-61	-18	-11	-3	-1
$\beta = 0.95$	-48	-46	-14	-8	-2	-1
Demand elasticity, Indonesia/Malaysia						
$\varepsilon^{DI}, \varepsilon^{DM} = 0.22$	-50	-43	-13	-7	-2	-1
$\varepsilon^{DI}, \varepsilon^{DM} = 0.44$	-44	-34	-10	-5	-2	-1
$\varepsilon^{DI}, \varepsilon^{DM} = 0.66$	-39	-28	-8	-4	-1	-1
Limited commitment, early planning	-56	-55	-16	-14	-2	-2
Objective function, own surplus only	-57	-54	-3	-2	-0	-0
Conditioning on unit-specific emissions	-80	-75	-22	-12	-2	-1
Static supply	-5	-4	-1	-0	-0	-0

Each cell is one counterfactual experiment. The first panel corresponds to table 5. The second panel changes the discount factor. The third panel changes the elasticities of Indonesian and Malaysian demand, where 0.66 is the demand elasticity for other importers. The fourth panel allows planning for the next L-year plan under limited commitment to begin before the end of each plan. This early planning prevents tariffs from being set to zero at the beginning of each L-year tariff regime. The fifth panel assumes tariffs are set to maximize the surplus of the acting coalition, net of its own costs of carbon as computed by Ricke et al. (2018). The sixth panel allows import tariffs to condition on the emissions specific to each unit of palm oil. The last panel assumes a static supply model.

I also consider other extensions. First, I set tariffs to maximize the acting coalition's welfare rather than social welfare. I assume the coalition considers only its own proportion of the social costs of carbon: 1%, 17%, 80%, and 2% for the EU, China/India, other importers, and Indonesia/Malaysia, respectively, based on pooling the country-level estimates of Ricke et al. (2018). When importers coordinate, tariffs rise because they improve terms of trade – importers no longer value Indonesian and Malaysian producer surplus – and importers internalize nearly the full social cost of carbon. When importers do not coordinate, tariffs decline sharply because small coalitions internalize only a small part of the social cost of carbon. Second, baseline tariffs are uniform across all units of palm oil, but conditioning on unit-specific emissions leads to larger carbon reductions by more efficiently targeting peatland destruction. A non-uniform domestic tax achieves similar gains: a carbon reduction of 91% relative to 64% in the baseline. Finally, a static supply model leads to low supply elasticities and much smaller effects for tariffs. Dynamics matter quantitatively.

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 argues that trade policy requires both coordination and commitment to be effective. Without coordination, tariffs are undermined by leakage to unregulated markets. Without commitment, tariffs are reduced over time as importers give in to static incentives.

I develop an empirical framework for quantifying these forces, and I apply it to the market for palm oil. The palm oil industry is of first-order importance: deforestation for palm oil plantations accounts for more CO_2 emissions over the last three decades than the entire economy of India. My framework quantifies the extent to which import tariffs could have reduced these emissions. It accounts for leakage to unregulated consumer markets, and it captures firms' dynamic considerations over sunk investment in palm oil plantations and mills. Using data from satellite imagery, it delivers predictions of plantation development – and therefore deforestation – at a fine level of spatial disaggregation.

I find coordinated, committed trade policy to be effective, reducing carbon emissions by 56% compared to 64% under domestic regulation. In the case of Europe, where recent legislation has targeted palm oil imports, EU import 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. Coordination and commitment are complements: when either fails, EU action has limited effects. These findings underscore the significance of the Paris Agreement, as well as the implications of US withdrawal.

I leave several directions open for future work. First, despite its environmental consequences, oil palm yields significantly more oil per hectare than any comparable oilseed. Future work might take a global view of oilseed production and account more explicitly for substitution to other oilseed crops, including soybeans from the Amazon. Second, given my estimates of the social welfare gains from coordination, future work might study the dynamic bargaining game that the EU, China, and India face in deciding whether to form a coalition. Lastly, spatial interaction across palm oil plantations might create path dependence, which tariffs can leverage to protect carbon-rich regions by conditioning on where a given unit of palm oil is produced.

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A Appendix: Theory

I derive optimal tariffs, illustrating the leakage and commitment problems, and I consider extensions for heterogeneous emissions and terms-of-trade effects.

A.1 Import tariffs under incomplete regulation and sunk investment

Domestic regulation

In the absence of an unregulated market, I denote the total inverse demand curve by $P_t^D(q)$. Social welfare depends on the path of new development $\{Q_t^n, Q_{t+1}^n, \ldots\}$, as well as prior, old development Q_t^o, which is sunk. New development becomes old development by law of motion $Q_{t+1}^o = Q_t^n + Q_t^o$. For discount factor β,

$$W_t(Q_t^n, Q_{t+1}^n, \ldots; Q_t^o) = \sum_{s=0}^{\infty} \beta^s \mathbb{E}_t \Big[\int_0^{Q_{t+s}^o} P_{t+s}^D(q) dq - \int_{Q_{t+s}^o}^{Q_{t+s}^o + Q_{t+s}^n} \Big(P_{t+s}^S(q) + e \Big) dq \Big] ,$$

where $Q_{t+s}^o = Q_t^o + Q_t^n + Q_{t+1}^n + \cdots + Q_{t+s-1}^n$. Domestic regulation can directly target new development in the current period with an upfront development tax $\tilde{\tau}_t$. In equilibrium, new development equalizes marginal cost and expected revenue.

$$P_t^S\big(Q_{t+1}^{o*}(\tilde{\tau}_t)\big) = \sum_{s=1}^{\infty} \beta^s \mathbb{E}_t \big[P_{t+s}^D\big(Q_{t+s}^{o*}(\tilde{\tau}_t)\big)\big] - \tilde{\tau}_t \, .$$

Assuming an interior solution $Q_t^{n*}(\tilde{\tau}_t) > 0$, the first order condition and resulting tax are

$$\frac{dW_t}{d\tilde{\tau}_t} = (\tilde{\tau}_t - e) \frac{dQ_t^n}{d\tilde{\tau}_t} = 0 \, , \quad \tilde{\tau}_t^{\mathrm{FB}} = e \, ,$$

where upfront tax $\tilde{\tau}_t$ only directly affects contemporaneous new development Q_t^n, and where I apply the envelope theorem in ignoring second-order effects on new development in future periods.

The leakage problem

To isolate the leakage problem, I first suppose that importers are able to impose tariff $\tilde{\tau}_t$ on development directly, as is possible under domestic regulation. The difference is that producers can choose between regulated market r and unregulated market u. Social welfare is

$$\begin{aligned} &W_t(Q_t^{rn}, Q_{t+1}^{rn}, \ldots, Q_t^{un}, Q_{t+1}^{un}, \ldots; Q_t^o) \\ &= \sum_{s=0}^{\infty} \beta^s \mathbb{E}_t \Big[\int_0^{Q_{t+s}^{ro}} P_{t+s}^{Dr}(q) dq + \int_0^{Q_{t+s}^{uo}} P_{t+s}^{Du}(q) dq - \int_{Q_{t+s}^o}^{Q_{t+s}^o + Q_{t+s}^n} \Big(P_{t+s}^S(q) + e \Big) dq \Big]. \end{aligned}$$

New development equalizes marginal cost and revenue and is indifferent across markets.

$$P_t^S\big(Q_{t+1}^{o*}(\tilde{\tau}_t)\big) = \sum_{s=1}^{\infty} \beta^s \mathbb{E}_t \big[P_{t+s}^{Dr}\big(Q_{t+s}^{ro*}(\tilde{\tau}_t)\big)\big] - \tilde{\tau}_t = \sum_{s=1}^{\infty} \beta^s \mathbb{E}_t \big[P_{t+s}^{Du}\big(Q_{t+s}^{uo*}(\tilde{\tau}_t)\big)\big]$$

Development tariff $\tilde{\tau}_t^{\mathrm{L}}$ only directly affects new development Q_t^n. Assuming an interior solution, the first order condition and resulting tariff are

$$\frac{dW_t}{d\tilde{\tau}_t} = (\tilde{\tau}_t - e)\frac{dQ_t^{rn}}{d\tilde{\tau}_t} - e\frac{dQ_t^{un}}{d\tilde{\tau}_t} = 0\,, \quad \tilde{\tau}_t^{\mathrm{L}} = \left(\frac{\varepsilon_t^S}{\varepsilon_t^S - \frac{Q_{t+1}^{uo}}{Q_{t+1}^{o}}\varepsilon_{t+1}^{Du}}\right)e < \tilde{\tau}_t^{\mathrm{FB}}\,, \tag{11}$$

for elasticities $\varepsilon_t^S > 0$ and $\varepsilon_{t+1}^{Du} < 0$ evaluated at quantities $Q_{t+1}^o \equiv Q_{t+1}^{o*}(\tilde{\tau}_t^{\mathrm{L}})$ and $Q_{t+1}^{uo} \equiv Q_{t+1}^{uo*}(\tilde{\tau}_t^{\mathrm{L}})$, respectively. Elasticity of regulated demand $\varepsilon_{t+1}^{Dr} < 0$ does not enter the tariff itself, although tariffs do have smaller effects on quantities and welfare as ε_{t+1}^{Dr} shrinks. If $Q_{t+1}^{uo} = 0$, then $\tilde{\tau}_t^{\mathrm{L}} = \tilde{\tau}_t^{\mathrm{FB}}$.

The leakage problem is limited when supply is elastic or unregulated demand is inelastic. In the first case, tariffs have limited effects on world prices; in the second case, world prices do fall but unregulated consumption does not increase in response. In both cases, tariffs do not affect unregulated consumption, and so they approach the size of the first-best tax. The leakage problem is also limited when the unregulated share of consumption is small. Conversely, elastic unregulated demand leads to a severe leakage problem and pushes tariffs to zero. Tariffs also go to zero when supply is inelastic, in which case tariffs produce allocative inefficiency without reducing emissions.

The commitment problem

In reality, importers cannot impose an upfront tax $\tilde{\tau}_t$ directly on new development Q_t^n. Rather, they can only target individual units of consumption at each point in time. This constraint has two consequences. First, given time to build, this constraint means that tariffs today cannot target new development directly. Time to build implies that new development does not begin production until the next period, and so this new development is unaffected by tariffs on consumption today. New development is instead governed by the stream of future tariffs $\{\tau_{t+1}, \tau_{t+2}, \ldots\}$. Second, the allocation of consumption between markets can shift from period to period depending on the tariffs in place. This shifting occurs because producers reallocate sales toward higher-priced markets in each period until the prices they receive are equalized. Such reallocation does not occur with upfront tax $\tilde{\tau}_t$ because producers that have paid taxes upfront have no further cost of selling to the regulated market and therefore no incentive to reallocate sales.

To see the implications, it becomes convenient to rewrite social welfare as

$$\begin{aligned} &W_t(Q_t^{ro}, Q_{t+1}^{ro}, \ldots, Q_t^{uo}, Q_{t+1}^{uo}, \ldots; Q_t^o) \\ &= \sum_{s=0}^{\infty} \beta^s \mathbb{E}_t\Big[\int_0^{Q_{t+s}^{ro}} P_{t+s}^{Dr}(q)dq + \int_0^{Q_{t+s}^{uo}} P_{t+s}^{Du}(q)dq - \int_{Q_{t+s}^o}^{Q_{t+s+1}^o}\Big(P_{t+s}^S(q) + e\Big)dq\Big], \end{aligned}$$

with the following equilibrium conditions for all $s \geq 0$.

$$P_{t+s}^S\big(Q_{t+s+1}^{o*}(\tau)\big) = \sum_{s'=1}^{\infty}\beta^{s'}\mathbb{E}_t\big[P_{t+s+s'}^{Du}\big(Q_{t+s+s'}^{uo*}(\tau)\big)\big]\,, \quad P_{t+s}^{Dr}\big(Q_{t+s}^{ro*}(\tau)\big) - \tau_{t+s} = P_{t+s}^{Du}\big(Q_{t+s}^{uo*}(\tau)\big)\,.$$

The first order condition and resulting tariff for $s = 0$ show the source of the commitment problem.

$$\frac{dW_t}{d\tau_t} = \tau_t\frac{dQ_t^{ro}}{d\tau_t} = 0\,, \quad \tau_t = 0$$

From the perspective of time t, tariffs τ_t have no effect on new development because of time to build, and no effect on prior development because it is sunk. In the presence of leakage, tariffs distort the allocation of consumption across markets, and as such are set to zero. Importers that sequentially choose static optima in a no-commitment scenario will therefore never impose tariffs.

$$\tilde{\tau}_t^{\mathrm{NC}} = \tau_t^{\mathrm{NC}} = 0$$

In the absence of leakage, there is no such problem: $\frac{dQ_t^{ro}}{d\tau_t} = 0$, and the first order condition is satisfied without setting tariffs to zero.

Under limited commitment, I assume that importers commit to L-period tariff plans that get revised every L periods. Indeed, this scenario is common in practice: Indonesia and China both conduct national planning under "five-year plans," and the US revises many policies based on decennial census results. In each new commitment regime, importers treat prior development as sunk and thus set the regime's initial tariffs to zero.

$$\tau_t^{\mathrm{LC}} = \tau_{t+L}^{\mathrm{LC}} = \tau_{t+2L}^{\mathrm{LC}} = \cdots = 0$$

The remaining tariffs are set anticipating these periodic breaks. With the goal of highlighting intuition and obtaining manageable closed-form expressions, I simplify the problem by assuming that the demand and supply curves are constant over time. I relax this simplifying assumption in the empirical implementation by solving numerically.

Under time-invariant demand and supply curves, the problem simplifies because the non-zero tariffs will also be time-invariant. To see why, note that the first order condition for a tariff τ_{t+s} is

$$\frac{dW_t}{d\tau_{t+s}} = [\beta\tau_{t+s} - (1-\beta)e]\frac{dQ_{t+s}^{ro}}{d\tau_{t+s}} - (1-\beta)e\frac{dQ_{t+s}^{uo}}{d\tau_{t+s}} = 0\,,$$

nesting $\frac{dW_t}{d\tau_{t+s}} = \tau_{t+s}\frac{dQ_{t+s}^{ro}}{d\tau_{t+s}} = 0$ given $\frac{dQ_{t+s}^{o}}{d\tau_{t+s}} = 0$ for $s \in \{0, L, 2L, \ldots\}$. But $\frac{dQ_{t+s}^{ro}}{d\tau_{t+s}}$ and $\frac{dQ_{t+s}^{uo}}{d\tau_{t+s}}$ are time-invariant because the demand and supply curves are time-invariant, and thus $\tau_{t+s} = \tau$ for all $s \notin \{0, L, 2L, \ldots\}$. Furthermore, any response to announced tariffs will occur in the initial period. To see why, suppose not. Development in a later period must be profitable in that period, but if so then developing in the first period and generating revenues for the interceding periods is more profitable: flow profits do not decrease over time because demand, supply, and tariffs are fixed. Thus, development in a later period is not profit-maximizing.[7]

Social welfare therefore depends only on two allocations of consumption across markets: that under zero-tariff periods and that under non-zero-tariff periods. The key mechanism is that these allocations differ because producers can shift sales away from the regulated market where tariffs are in place, and toward the regulated market when they are not.

$$\begin{aligned}
&W_t(Q_{t+1}^{ro}, Q_{t+L}^{ro}, Q_{t+1}^{uo}, Q_{t+L}^{uo}; Q_t^{o}) \\
&= \left(\frac{\beta}{1-\beta} - \frac{\beta^L}{1-\beta^L}\right)\left[\int_0^{Q_{t+1}^{ro}} P^{Dr}(q)dq + \int_0^{Q_{t+1}^{uo}} P^{Du}(q)dq\right] \\
&\quad + \frac{\beta^L}{1-\beta^L}\left[\int_0^{Q_{t+L}^{ro}} P^{Dr}(q)dq + \int_0^{Q_{t+L}^{uo}} P^{Du}(q)dq\right] - \int_{Q_t^{o}}^{Q_{t+1}^{o}} \left(P^S(q) + e\right)dq\,,
\end{aligned}$$

[7] A benefit of developing later is that it delays development costs. But if firms prefer to delay, then they will do so forever given constant supply and demand over time. In this case, developing later is not optimal to begin with.

with $(Q^{ro}_{t+1}, Q^{uo}_{t+1})$ when tariffs are in place and $(Q^{ro}_{t+L}, Q^{uo}_{t+L})$ when they are not. In equilibrium,

$$P^S\big(Q^{o*}_{t+1}(\tau)\big) = \left(\frac{\beta}{1-\beta} - \frac{\beta^L}{1-\beta^L}\right) P^{Du}\big(Q^{uo*}_{t+1}(\tau)\big) + \frac{\beta^L}{1-\beta^L} P^{Du}\big(Q^{uo*}_{t+L}(\tau)\big)\,,$$

$$P^{Dr}\big(Q^{ro*}_t(\tau)\big) - \tau_t = P^{Du}\big(Q^{uo*}_t(\tau)\big) \quad \forall\, t, \text{ given } \tau_{t+s} = \begin{cases} 0 & \text{for } s \in \{0, L, 2L, \ldots\} \\ \tau & \text{otherwise} \end{cases}\,,$$

and $Q^{ro}_{t+1} + Q^{uo}_{t+1} = Q^{ro}_{t+L} + Q^{uo}_{t+L}$. The first order condition is

$$\frac{dW_t}{d\tau} = \left[\left(\frac{\beta}{1-\beta} - \frac{\beta^L}{1-\beta^L}\right)\tau - e\right]\frac{dQ^{ro}_{t+1}}{d\tau} - e\frac{dQ^{uo}_{t+1}}{d\tau}\,.$$

Assuming an interior solution, the net present value of the stream of tariffs given by τ is

$$\tilde{\tau}^{\mathrm{LC}}_t(L) = \left(\frac{\varepsilon^S_t}{\varepsilon^S_t - \frac{Q^{uo}_{t+1}}{Q^{o}_{t+1}}\varepsilon^{Du}_{t+1}\big[1 + \frac{(1-\beta)\beta^L}{\beta-\beta^L}\frac{P^{Du}_{t+L}}{P^{Du}_{t+1}}\big(1 - \frac{Q^{o}_{t+1}\varepsilon^S_t}{Q^{ro}_{t+L}\varepsilon^{Dr}_{t+1} + Q^{uo}_{t+L}\varepsilon^{Du}_{t+1}}\big)\big]}\right)e\,,$$

for elasticities $\varepsilon^S_t > 0$ and $\varepsilon^{Dr}_{t+1}, \varepsilon^{Dr}_{t+L}, \varepsilon^{Du}_{t+1}, \varepsilon^{Du}_{t+L} < 0$, and quantities and prices evaluated at τ^{LC}. For simplicity I assume constant elasticities of demand. Per-period tariff τ^{LC} is

$$\tau^{\mathrm{LC}}_t(L) = \left(\frac{\beta}{1-\beta} - \frac{\beta^L}{1-\beta^L}\right)^{-1}\tilde{\tau}^{\mathrm{LC}}_t(L)\,.$$

Total tariffs $\tilde{\tau}^{\mathrm{LC}}_t(L)$ are increasing in L, with $L \to \infty$ corresponding to full commitment and $L = 2$ to the minimum binding level of commitment.

$$\tilde{\tau}^{\mathrm{LC}}_t(L) < \left(\frac{\varepsilon^S_t}{\varepsilon^S_t - \frac{Q^{uo}_{t+1}}{Q^{o}_{t+1}}\varepsilon^{Du}_{t+1}}\right)e = \lim_{L\to\infty}\tilde{\tau}^{\mathrm{LC}}_t(L) = \tilde{\tau}^{\mathrm{C}}_t = \tilde{\tau}^{\mathrm{L}}_t\,.$$

Lastly, the same mechanism also applies in the more general case if tariffs are declining over time. Indeed, importers that take a sequential static approach to setting tariffs will be governed by equations 11, which imply declining tariffs if the elasticity of supply is declining over time. Such will be the case when the marginal costs of development are increasing as development progresses from more suitable lands to less suitable lands. At the extreme, tariffs are set to zero once all feasible lands are exhausted: at this point, tariffs cannot reduce emissions because prior development is sunk, and no new development is possible. Thus, as tariffs decline, producers will be able to reallocate sales toward the regulated market as shown above.

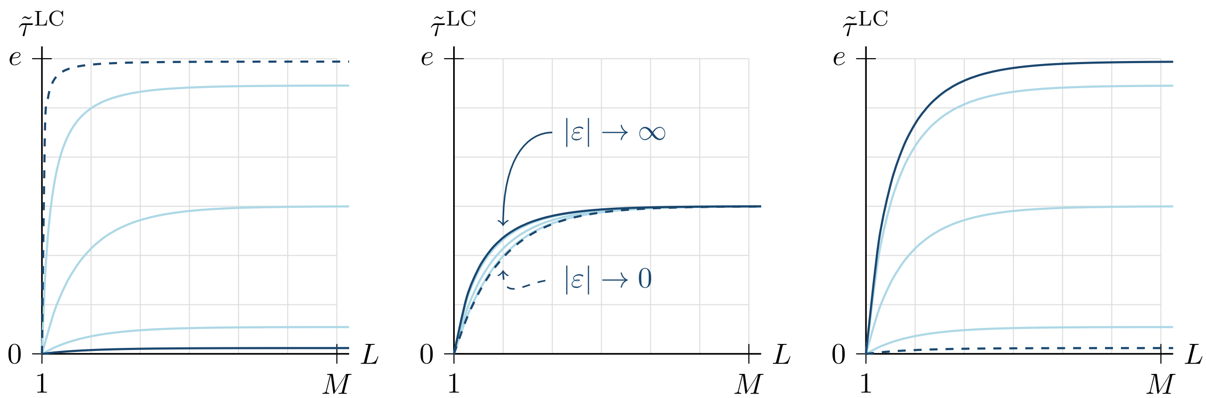
How leakage and commitment interact

I study how leakage (given ε^{Du}_{t+1}, ε^{Dr}_{t+1}, and ε^S_t) and commitment (given L) interact to determine total tariffs $\tilde{\tau}^{\mathrm{LC}}_t(L)$. First, $\tilde{\tau}^{\mathrm{LC}}_t(L)$ increases more rapidly in L for smaller $|\varepsilon^{Du}_{t+1}|$.

$$\lim_{\varepsilon^{Du}_{t+1}\to 0}\tilde{\tau}^{\mathrm{LC}}_t(L) = e > 0 = \lim_{\varepsilon^{Du}_{t+1}\to -\infty}\tilde{\tau}^{\mathrm{LC}}_t(L)$$

Figure A1: Total tariffs by leakage and commitment

(a) ε^{Du} **(b)** ε^{Dr} **(c)** ε^{S}



For various values of each leakage-relevant elasticity – namely elasticity of unregulated demand ε^{Du}, elasticity of regulated demand ε^{Dr}, and elasticity of supply ε^{S} – I plot the relationship between total tariffs $\tilde{\tau}^{\mathrm{LC}}$ and the length of commitment L. The solid navy lines show the relationship for large values of the elasticities, the dashed navy lines for small values, and the light blue lines for intermediate values. Each of the values differs by an order of magnitude. Emissions e represents the externality, and M is an arbitrarily large number.

Second, $\tilde{\tau}^{\mathrm{LC}}_t(L)$ increases more rapidly in L for larger $|\varepsilon^{Dr}_{t+1}|$, although this effect is relatively small.

$$\lim_{\varepsilon^{Dr}_{t+1}\to 0} \tilde{\tau}^{\mathrm{LC}}_t(L) = \left(\frac{\varepsilon^S_t}{\varepsilon^S_t - \frac{Q^{uo}_{t+1}}{Q^o_{t+1}}\varepsilon^{Du}_{t+1}\left[1+\frac{(1-\beta)\beta^L}{\beta-\beta^L}\frac{P^{Du}_{t+L}}{P^{Du}_{t+1}}\left(1-\frac{Q^o_{t+1}\varepsilon^S_t}{Q^{uo}_{t+L}\varepsilon^{Du}_{t+1}}\right)\right]}\right)e$$
$$< \left(\frac{\varepsilon^S_t}{\varepsilon^S_t - \frac{Q^{uo}_{t+1}}{Q^o_{t+1}}\varepsilon^{Du}_{t+1}\left[1+\frac{(1-\beta)\beta^L}{\beta-\beta^L}\frac{P^{Du}_{t+L}}{P^{Du}_{t+1}}\right]}\right)e = \lim_{\varepsilon^{Dr}_{t+1}\to -\infty}\tilde{\tau}^{\mathrm{LC}}_t(L)$$

Third, $\tilde{\tau}^{\mathrm{LC}}_t(L)$ increases more rapidly in L for larger ε^S_t.

$$\lim_{\varepsilon^S_t\to 0}\tilde{\tau}^{\mathrm{LC}}_t(L) = 0 < \left(\frac{1}{1+\frac{(1-\beta)\beta^L}{\beta-\beta^L}\frac{P^{Du}_{t+L}}{P^{Du}_{t+1}}\frac{Q^{uo}_{t+1}}{Q^o_{t+1}}\varepsilon^{Du}_{t+1}\left(\frac{Q^o_{t+1}}{Q^{ro}_{t+L}\varepsilon^{Dr}_{t+1}+Q^{uo}_{t+L}\varepsilon^{Du}_{t+1}}\right)}\right)e = \lim_{\varepsilon^S_t\to\infty}\tilde{\tau}^{\mathrm{LC}}_t(L)$$

Figure A1 graphs these relationships. As above, the leakage problem is most severe when unregulated demand is elastic or supply is inelastic. The elasticity of regulated demand plays a more limited role.[8]

A.2 Heterogeneous emissions

The baseline model treats emissions as homogeneous over space, but in reality there is spatial variation in carbon stocks. In the absence of leakage, the first-best regulation is Pigouvian, with higher tariffs for higher-emission goods. In practice, however, tracing goods to their emissions is

[8] It affects the scope for shifting but not the mechanism itself. In particular, commitment is more important when regulated demand is inelastic, in which case the need to shift toward the unregulated market is small: the tariff displaces only a small quantity, and regulated consumers bear the brunt of the tariff.

difficult and imperfect.[9] I therefore focus on a uniform tariff that treats all goods equally.

Consider incomplete regulation under commitment. The regulator considers consumption utility, for which clean and dirty products are perfect substitutes, and production costs, which vary both privately and socially. I again focus on the simple case of an initial period with no prior development and time-invariant demand and supply curves. Social welfare depends on the consumption of each good in each market.

$$
\begin{aligned}
W_1(Q_1^{rc}, Q_1^{rd}, Q_1^{uc}, Q_1^{ud}) = \frac{1}{1-\beta}\int_0^{Q_1^r} P^{Dr}(q)dq + \frac{1}{1-\beta}\int_0^{Q_1^u} P^{Du}(q)dq \\
- \int_0^{Q_1^c}\Big(P^{Sc}(q)+e^c\Big)dq - \int_0^{Q_1^d}\Big(P^{Sd}(q)+e^d\Big)dq\,,
\end{aligned}
$$

where $0 < e^c < e^d$. In equilibrium, new development – clean and dirty – equalizes marginal cost and marginal revenue. The equilibrium conditions bind when sales of a given product to a given market are positive, otherwise marginal cost exceeds marginal revenue. For per-period tariffs τ^k,

$$
\begin{aligned}
P^{Sk}\big(Q_1^{k*}(\tau^c,\tau^d)\big) &= \frac{1}{1-\beta}\Big(P^{Dr}\big(Q_1^{r*}(\tau^c,\tau^d)\big)-\tau^k\Big) \quad \text{if } Q_1^{rk*}(\tau^c,\tau^d) > 0 \text{ for } k\in\{c,d\}\,,\\
P^{Sk}\big(Q_1^{k*}(\tau^c,\tau^d)\big) &= \frac{1}{1-\beta}\Big(P^{Du}\big(Q_1^{u*}(\tau^c,\tau^d)\big)\Big) \quad \text{if } Q_1^{uk*}(\tau^c,\tau^d) > 0 \text{ for } k\in\{c,d\}\,,
\end{aligned}
$$

If clean and dirty consumption must face equal tariffs ($\tau^c = \tau^d = \tau$), then all four equilibrium conditions bind simultaneously. The first order condition and optimal tariff are

$$
\begin{aligned}
\frac{dW_1}{d\tau} &= \left(\frac{1}{1-\beta}\tau - e^c\right)\frac{dQ_1^{rc}}{d\tau} + \left(\frac{1}{1-\beta}\tau - e^d\right)\frac{dQ_1^{rd}}{d\tau} - e^c\frac{dQ_1^{uc}}{d\tau} - e^d\frac{dQ_1^{ud}}{d\tau} = 0\,,\\
\tau^{\mathrm{C}} &= (1-\beta)\left(\frac{\frac{Q_1^c}{Q_1}\varepsilon^{Sc}}{\frac{Q_1^c}{Q_1}\varepsilon^{Sc}+\frac{Q_1^d}{Q_1}\varepsilon^{Sd}-\frac{Q_1^u}{Q_1}\varepsilon^{Du}}\right)e^c + (1-\beta)\left(\frac{\frac{Q_1^d}{Q_1}\varepsilon^{Sd}}{\frac{Q_1^c}{Q_1}\varepsilon^{Sc}+\frac{Q_1^d}{Q_1}\varepsilon^{Sd}-\frac{Q_1^u}{Q_1}\varepsilon^{Du}}\right)e^d,
\end{aligned}
$$

for $\varepsilon^{Sc}, \varepsilon^{Sd} > 0$, $\varepsilon^{Du} < 0$, and $Q_1 = Q_1^c + Q_1^d = Q_1^r + Q_1^u$. The first best is special case $Q_1^u = 0$.

$$
\tau^{\mathrm{FB}} = (1-\beta)\left(\frac{\frac{Q_1^c}{Q_1}\varepsilon^{Sc}}{\frac{Q_1^c}{Q_1}\varepsilon^{Sc}+\frac{Q_1^d}{Q_1}\varepsilon^{Sd}}\right)e^c + (1-\beta)\left(\frac{\frac{Q_1^d}{Q_1}\varepsilon^{Sd}}{\frac{Q_1^c}{Q_1}\varepsilon^{Sc}+\frac{Q_1^d}{Q_1}\varepsilon^{Sd}}\right)e^d > \tau^{\mathrm{C}}
$$

In both cases, these "second-best" uniform tariffs are weighted averages of emission levels as in Diamond (1973), with weights given by level-specific supply elasticities.

A.3 Terms-of-trade effects

The baseline model also rules out terms-of-trade effects. This classic motivation for import tariffs arises because tariffs in large markets can change world prices and therefore improve terms of trade at the expense of other countries (Johnson 1953). The objective function in the baseline

[9] Several certification schemes exist for palm oil, with the Roundtable on Sustainable Palm Oil being most prominent. Two tiers of differentiation – certified or not – is common and insufficient for a Pigouvian tax that differentiates across emission levels. Furthermore, these schemes have their own commitment problems. A common criticism is that they certify palm oil from previously deforested lands on the grounds that it involves no new emissions.

model is global social welfare, and so the regulator fully internalizes these effects by construction.

Suppose instead that the regulator considers only consumer surplus in the regulated market alongside the emissions externality. For simplicity, I analyze an initial period with no prior development and time-invariant demand and supply curves. For per-period tariff τ under commitment, the objective function is

$$W_1(Q_1^r, Q_1^u) = \frac{1}{1-\beta}\int_0^{Q_1^r}\Big(P^{Dr}(q) - P^{Dr}(Q_1^r) + \tau\Big)dq - \int_0^{Q_1} e dq\,.$$

In equilibrium, marginal entry is indifferent between markets.

$$P^S\big(Q_1^*(\tau)\big) = \frac{1}{1-\beta}\Big(P^{Dr}\big(Q_1^{r*}(\tau)\big) - \tau\Big) = \frac{1}{1-\beta}\Big(P^{Du}\big(Q_1^{u*}(\tau)\big)\Big)$$

Assuming $Q_1^{r*}(\tau), Q_1^{u*}(\tau) > 0$, the first order condition and optimal per-period tariff are

$$\frac{dW_1}{d\tau} = -Q_1^r\frac{dP^{Dr}}{dQ_1^r}\frac{dQ_1^r}{d\tau} + \tau\frac{dQ_1^r}{d\tau} + Q_1^r - (1-\beta)e\frac{dQ_1}{d\tau} = 0\,,$$

$$\tau^{\mathrm{C}} = \underbrace{(1-\beta)\left(\frac{\varepsilon^S}{\varepsilon^S - \frac{Q_1^u}{Q_1}\varepsilon^{Du}}\right)e}_{\text{emissions}} + \underbrace{(1-\beta)\left(\frac{\frac{Q_1^r}{Q_1}P^S}{\varepsilon^S - \frac{Q_1^u}{Q_1}\varepsilon^{Du}}\right)}_{\text{terms of trade}},$$

for quantities $Q_1^k \equiv Q_1^{k*}(\tau)$, prices $P^S \equiv P^{S*}(\tau)$, and elasticities $\varepsilon^S > 0$ and $\varepsilon^{Du} < 0$. The first-best tariff is the special case with $Q_1^u = 0$.

$$\tau^{\mathrm{FB}} = (1-\beta)\left(e + \frac{P^S}{\varepsilon^S}\right) > \tau^{\mathrm{C}}$$

In both cases, I obtain an additional terms-of-trade term, although this term is dominated when the emissions externality is large.

B Appendix: Data

This section lists data sources and discusses the construction of data on palm oil plantations, mills, yields, and carbon stocks.

B.1 Data sources

Table B1: Palm oil plantations and mills

Source	Period	Coverage	Description
Xu et al. (2020)	2001-2016	Indonesia, Malaysia	Palm oil plantations over time, 100m resolution
Song et al. (2018)	1982-2016	World	Land cover change over time, 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 B2: 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 B3: 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 B4: 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

B.2 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 palm as well as both 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 B5 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 the predicted changes in plantation development with the 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 B5: Xu et al. (2020) plantation vs. Song et al. (2018) tree cover data, 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 observation is a 30-arc-second tile in a given year, and each column is a regression. The dependent variable is from Xu et al. (2020), which measures the ratio of each tile that has been developed into palm oil plantations over time. The independent variables come from Song et al. (2018), which measures the ratio of each tile that is covered by tree canopy over time. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Figure B1 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.

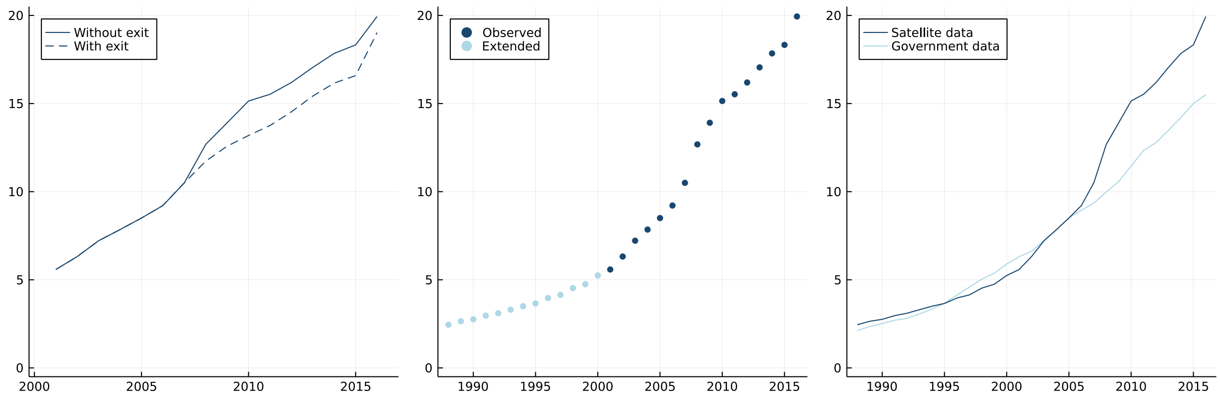
Spatial data on palm oil mills come from the 2018 Universal Mill List (UML), a joint effort led by the World Resources Institute and Rainforest Alliance that collects data from palm oil processors, traders, corporate consumers, and NGOs. Mills are geocoded and manually verified by satellite. I combine 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 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.[10] Table B6 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.

[10] 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).

Figure B1: Total plantations over time (Mha)

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



The left figure shows how imposing no exit affects the Xu et al. (2020) data. The middle figure shows the Xu et al. (2020) data in navy and the extended data in light blue, where I extend the data using tree cover data from Song et al. (2018) (based on table B5). The right figure compares the satellite data to USDA FAS data.

Table B6: Mill counts by region, mill data vs. government figures

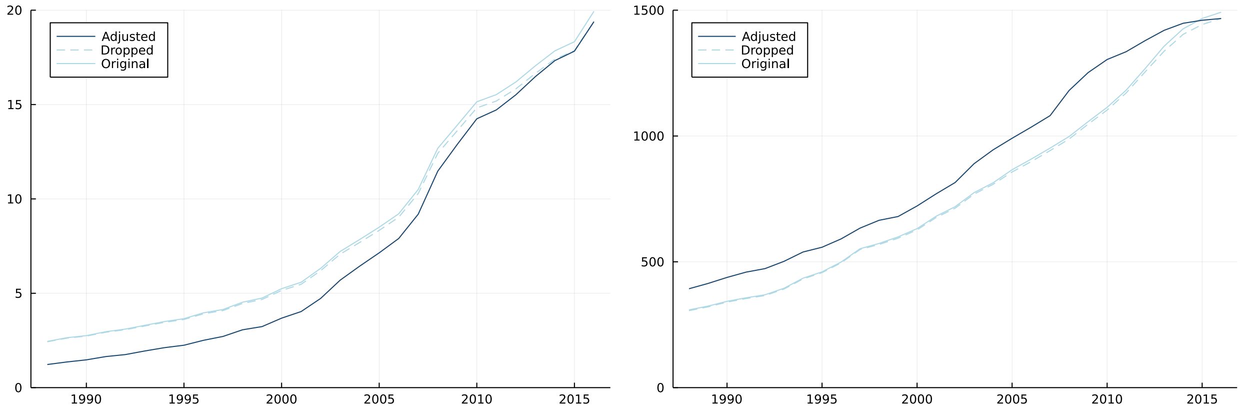
	Mill data	Government figures
Indonesia	1050	1070
Kalimantan	328	260
Central Sumatra	264	358
North Sumatra	225	237
South Sumatra	204	178
Sulawesi	21	30
Papua	8	7
Malaysia	471	453
Peninsular Malaysia	266	247
Sabah	132	129
Sarawak	73	77
Total	1521	1523

Mill data and government figures are both for 2016. Mill data come from the Universal Mill List and CIFOR. Indonesia government data come from the economic census, and Malaysian government data come from the Malaysian Palm Oil Board. Regions are in descending order by number of mills. Kalimantan includes the provinces of North, South, East, West, and Central Kalimantan; Central Sumatra includes West Sumatra, Riau, and Kepulauan Riau; North Sumatra includes North Sumatra and Aceh; South Sumatra includes South Sumatra, Bangka Belitung, Bengkulu, Jambi, and Lampung; Sulawesi includes North, South, Southeast, West, and Central Sulawesi, and Gorontalo; Papua includes Papua and West Papua. Peninsular Malaysia includes all states other than Sabah and Sarawak.

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

Figure B2: Harmonized plantation and mill data over time

(a) Total plantations (Mha) **(b)** Total mills



Light blue lines show unharmonized data, and navy lines harmonized data. Harmonization drops plantations and mills cannot be made consistent with each other, and dashed light blue lines show the effects of dropping these data.

Table B7: 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

The table shows the proportion of plantations and mills affected by harmonization. The first two columns assign plantations to the nearest existing mill within 50 kilometers, while the last two columns further impose that plantations be in the same province as their assigned mills. 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.

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 delaying plantation development against advancing mill construction.

Figure B2 and table B7 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 B7 shows that it has little marginal effect.[13]

[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.

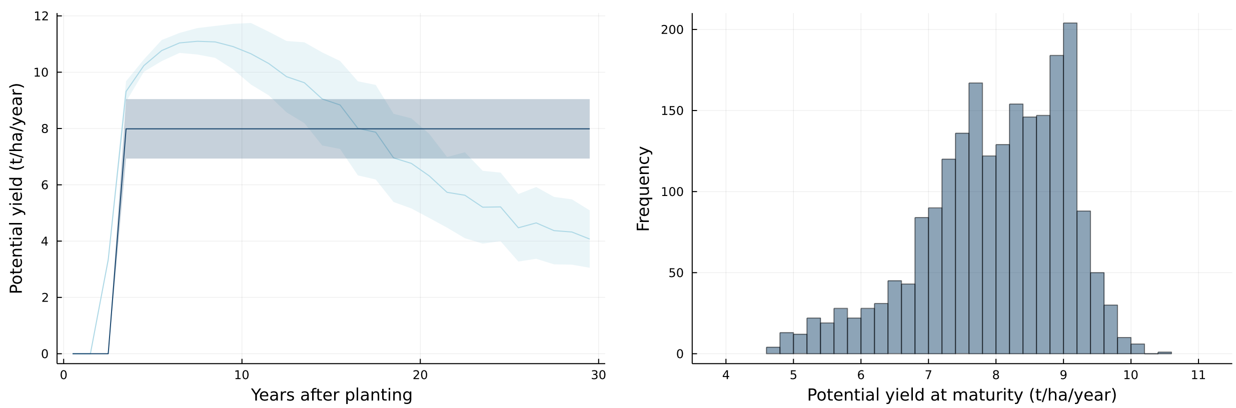
[12] The plantation data record when young palm trees have been established, and the mill data record when mill construction begins. Proximity to an under-construction mill ensures that young palm trees will have access to an operational mill by the time they reach maturity and begin to bear fruit.

[13] There is also anecdotal support for plantations' staying within these borders to avoid licensing with multiple regional governments. Since they are small and contain no mills, I combine Kuala Lumpur, Labuan, Perlis, and Putrajaya with neighboring states Selangor, Sabah, Kedah, and Selangor.

Figure B3: Potential palm oil yields

(a) Simulated vs. flattened yield curve

(b) Potential yield at maturity 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. To facilitate computation, I aggregate climate inputs and run the PALMSIM model at the site level, with sites defined in appendix section D.1. 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.

B.3 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 these variables at a resolution of 30 arc-seconds. I aggregate to the site level, where sites are as defined in appendix section D.1, and I run the PALMSIM model for each site. Figure B3a 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 B3b 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 B4a 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.[14] Across provinces and years, the average observed annual yield per hectare is 3.30 tons.

[14] Compositional changes in the age mix of palm oil crops may also account for changes in realized yields over time. However, there are two effects that potentially offset each other: newly planted crops increase average yields as they reach their peak yields, while aging crops decrease average yields as their yields decline with age.

Figure B4: Attained and attainable palm oil yields over time

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

On the left, each observation is the annual attained yield for a given province (Indonesia) or state (Malaysia) as recorded in government statistics. Data come from the Indonesian Ministry of Agriculture, World Bank INDO-DAPOER, and Malaysian Palm Oil Board. On the right, each observation is the annual attainable yield for a given site computed by combining site-level potential yields from PALMSIM with province-year-level attained yields from government statistics. For both, fitted lines show common time trends accounting for province/state fixed effects.

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

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

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

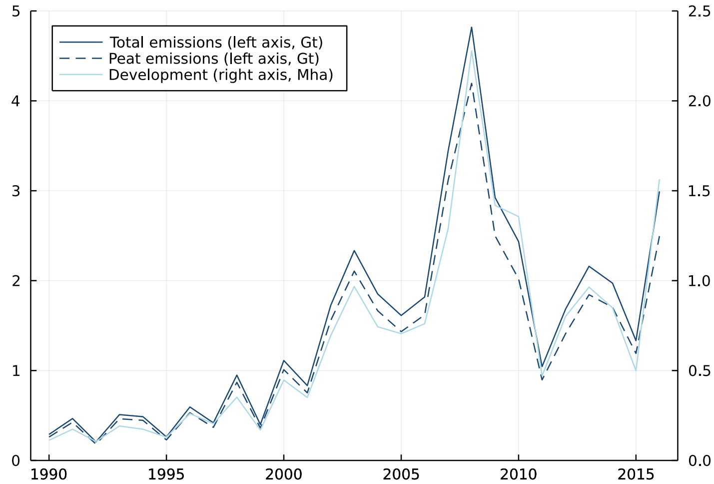
$$\gamma_{mt} = \alpha_m + \beta t + \varepsilon_{mt} \,,$$

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. Figure B4b shows the resulting estimates, which combine the uptrend of figure B4a with the site-level dispersion of figure B3b.

B.4 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

Figure B5: Plantation development vs. CO_2 emissions over time



Data on plantation development come from Xu et al. (2020) and Song et al. (2018), and data on carbon emissions from Zarin et al. (2016) and Gumbricht et al. (2017).

C/m^3 peat in Warren et al. (2017). I convert carbon to carbon dioxide emissions with a molecular-weight conversion factor of 3.67. I focus on CO_2 emissions because the carbon content of peatlands is well documented and because they account for 73% of total greenhouse gas emissions during the study period. Palm oil production also involves the release of methane and nitrous oxide, but precise estimates of these emissions are not yet well established.

I treat carbon stocks as predetermined, but they are not measured before the study period. Tree biomass is measured for the year 2000, and peat deposits for 2011. The data may therefore miss carbon stocks destroyed before these years. For tree biomass, I impute 1988 values by combining the 2000 values with the proportion of tree cover loss between 1988 and 2000, as measured in the Song et al. (2018) data. For peat deposits, bias is limited because Gumbricht et al. (2017) rely primarily on precipitation and topography – predetermined features – in order 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 B5 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.

B.5 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 B8 lists these countries for each oil (aggregating EU countries).

Table B8: 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%

Data are from the USDA Foreign Agricultural Service. Production pools over the study period (1988-2016), and for each oil I omit producers accounting for less than 5% of world production.

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 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.

C Appendix: 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. A choice between two products also allows me to 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 C1 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 C2 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 of aggregate demand curves.[15] Furthermore, the baseline instruments already target oil producers explicitly, and they pass the test above.

Table C3 presents demand elasticities for palm oil by market. Table C4 shows the lower- and upper-level parameter estimates that I use to compute these elasticities, and table C5 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 Malaysia, elasticities for other oils have larger standard errors because other oils account for only 3% of consumption in the data. Table C6 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. Figure C1 indicates why, with a high correlation between palm and other oil prices effectively dampening observed price variation. Instruments leverage differential weather shocks across oils, and indeed the instrumented price series are much less correlated.

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 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.

[15] 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 C1: Weather shocks vs. incomes and expenditures

Market	Outcome	Rainfall Estimate	Rainfall SE	Temperature Estimate	Temperature 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. Data are annual and 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. I control for oil fixed effects and oil-specific time trends, which differentiate between palm and other oils. Newey-West standard errors account for serial correlation. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table C2: 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. Data are annual and 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. I control for oil fixed effects and oil-specific time trends, which differentiate between palm and other oils. Newey-West standard errors account for serial correlation. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table C3: Mean demand elasticities for palm oil

Market	Estimate	SE	Market	Estimate	SE
European Union (E)	-0.510***	(0.181)	Importers (ECNR)	-0.555***	(0.134)
China/India (CN)	-0.667***	(0.210)	Producers (IM)	-0.026	(0.171)
Other importers (R)	-0.558***	(0.134)	EU/China/India (ECN)	-0.437***	(0.164)
Indonesia/Malaysia (IM)	-0.026	(0.171)	Not EU/China/India (RIM)	-0.482***	(0.129)
World (ECNRIM)	-0.447***	(0.133)	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. The demand estimation underlying these elasticities draws on annual data that cover coconut, olive, palm, rapeseed, soybean, and sunflower oils from 1988 to 2016. It instruments for prices with weather shocks to oil production, and it accounts for serial correlation with Newey-West standard errors. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table C4: Demand parameter estimates

	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. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table C5: Mean demand elasticities for vegetable oils

		Estimates		SEs	
Market		Palm	Other	Palm	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. The demand estimation underlying these elasticities draws on annual data that cover coconut, olive, palm, rapeseed, soybean, and sunflower oils from 1988 to 2016. It instruments for prices with weather shocks to oil production, and it accounts for serial correlation with Newey-West standard errors. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table C6: Mean demand elasticities for vegetable oils without price instruments

Market		Estimates		SEs	
		Palm	Other	Palm	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)

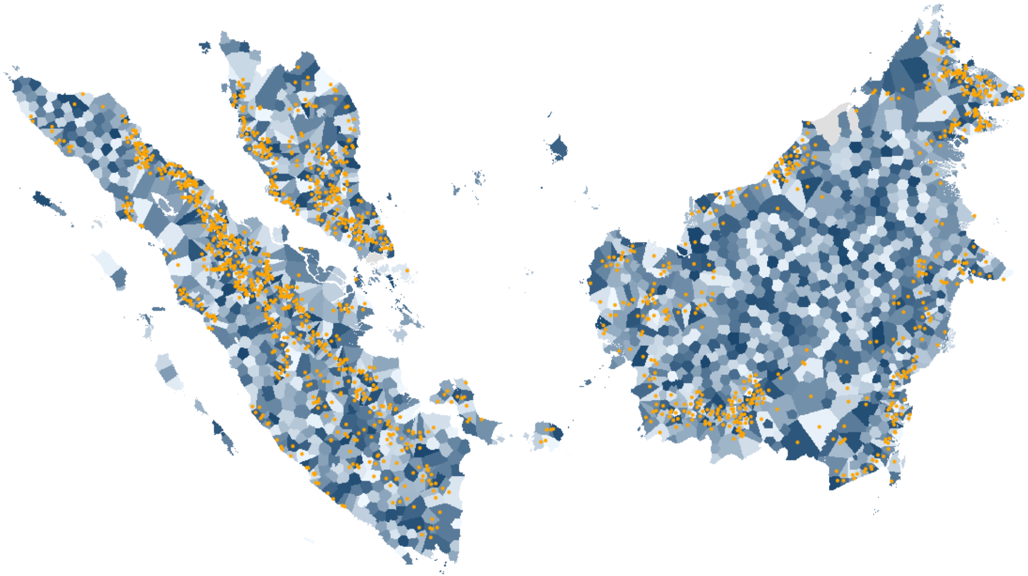
Each panel shows uncompensated price elasticities for a consumer market. I present mean elasticities over the study period, and I compute standard errors with the delta method. The demand estimation underlying these elasticities draws on annual data that cover coconut, olive, palm, rapeseed, soybean, and sunflower oils from 1988 to 2016. It does not instrument for prices, but it does account for serial correlation with Newey-West standard errors. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Figure C1: Vegetable oil prices over time

(a) Prices **(b)** Instrumented prices

Data on vegetable oil prices come from the International Monetary Fund and the World Bank. Palm oils aggregate palm and palm kernel, and other oils aggregate coconut, olive, rapeseed, soybean, and sunflower. I aggregate with a Stone price index, drawing on expenditure shares computed with data from the USDA Foreign Agricultural Service. The left figure shows observed prices, and the right figure shows predicted prices using weather shocks to oil production as instruments.

Figure D1: 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.

D Appendix: Supply

This section contains details on the defining of potential sites, the estimation of both intensive- and extensive-margin supply models, and the computation of supply elasticities.

D.1 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 that 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 D1 plots the potential sites.

D.2 Extensive-margin model (mill construction)

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

Proof. Comparing choice-specific conditional value functions $v^e(0;\boldsymbol{w}_{it})$ and $v^e(0,1;\boldsymbol{w}_{it})$,

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

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

Proof. Comparing choice-specific conditional value functions $v^e(1;\boldsymbol{w}_{it})$ and $v^e(1,a_{it};\boldsymbol{w}_{it})$,

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

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 first order condition that holds at a^*_{it} and the linearity of revenues. 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. $v^e(0;\boldsymbol{w}_{it}) - v^e(0,1,a'_{it+1};\boldsymbol{w}_{it}) = \frac{1}{2}\beta\mathbb{E}^e_{it}[c''(a'_{it+1};\boldsymbol{w}_{it+1},\varepsilon_{it+1})(a^*_{it+1} - a'_{it+1})^2] - \beta\mathbb{E}^e_{it}[\ln p^e(\boldsymbol{w}_{it+1})]$.

Proof. Comparing choice-specific conditional value functions $v^e(0;\boldsymbol{w}^e_{it})$ and $v^e(0,1,a'_{it+1};\boldsymbol{w}^e_{it})$,

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

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.

E Appendix: Counterfactuals

This section describes how I solve the model and quantify carbon emissions.

E.1 Solving the model

I impose additional assumptions on expectations over the evolution of the state variables, and I solve by backward induction.

Expectations over aggregate states d_t and s_t

Expectations over the evolution of demand d_t and supply s_t together determine the expected path of prices $P(s_t, d_t)$. I make explicit assumptions about expectations for demand d_t, which I describe below. Supply s_t is determined endogenously as the result of an entry game in which beliefs are correct in equilibrium.

I model the non-stationary evolution of demand d_t with an ARIMA process, and I assume expectations for all firms are given by this process. Table E1 evaluates log likelihoods over a range of ARIMA specifications and finds that an ARIMA$(2, 1, 2)$ process produces the best fit to the data. In this specification, changes $d_t - d_{t-1}$ in demand follow an ARMA(2,2) process.

$$d_t - d_{t-1} = c + \upsilon_t + \sum_{t'=1}^{2} \left(\varphi_{t'}(d_{t-t'} - d_{t-t'-1}) - \theta_{t'}\upsilon_{t-t'} \right)$$

Since the demand curve is specified in logs, this ARIMA process can sometimes predict infinite exponential growth in demand. Such unbounded growth leads to unrealistically stark predictions: exponentially rising demand (at a rate that dominates discounting β) implies infinite returns to development and therefore immediate development of all undeveloped lands. Thus, I shrink the ARIMA estimates toward a sigmoid function fit to observed demand. Expectations are therefore

$$\mathbb{E}_{it}[d_{t+t'}] = \left(\frac{\widehat{V}^{\text{SIG}}}{\widehat{V}^{\text{ARIMA}}_{t+t'} + \widehat{V}^{\text{SIG}}} \right) \widehat{d}^{\text{ARIMA}}_{t+t'} + \left(\frac{\widehat{V}^{\text{ARIMA}}_{t+t'}}{\widehat{V}^{\text{ARIMA}}_{t+t'} + \widehat{V}^{\text{SIG}}} \right) \widehat{d}^{\text{SIG}}_{t+t'} \quad \text{for } t' \geq 1\,, \tag{14}$$

where I weight by inverse variances, with the variance of the sigmoid predictions given by the mean squared error. The ARIMA predictions have increasing variance for expectations taken farther into the future, implying greater reliance on the fitted sigmoid function in these periods. Figure E1 plots both ARIMA and shrunk demand expectations. Indeed, shrinking toward the sigmoid function helps in bounding demand expectations.

Expectations over site-specific states Y_{it}, x_i, ε_{it}, and ε^e_{it}

I assume that yields Y_{it} evolve at a constant and exogenous rate per year. Thus, no expectational error arises from changes in yields. There is no need to define expectations over cost factors x_i because they are constant. I assume that while firms know current-period cost shocks ε_{it} and ε^e_{it}, they only know the distribution of future shocks.

I obtain estimates of intensive-margin cost shocks ε_{it} from the residuals of equation 8. The complication is that these residuals combine cost shocks and expectational errors.

$$\upsilon_{it} = -\frac{1}{\delta}\varepsilon_{it} + \eta_{it}$$

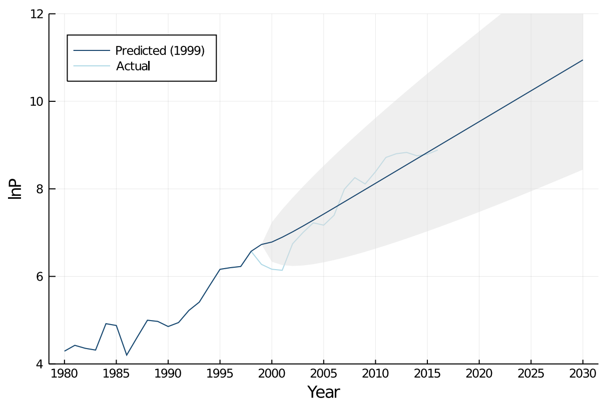
Table E1: ARIMA(p, d, q) log likelihoods for demand d_t

		ARMA(p, q)		
		(0,0)	(1,1)	(2,2)
	0	-69.17	-6.91	-6.37
Differencing (d)	1	-2.41	-0.53	1.44
	2	-14.82	-4.53	-0.37

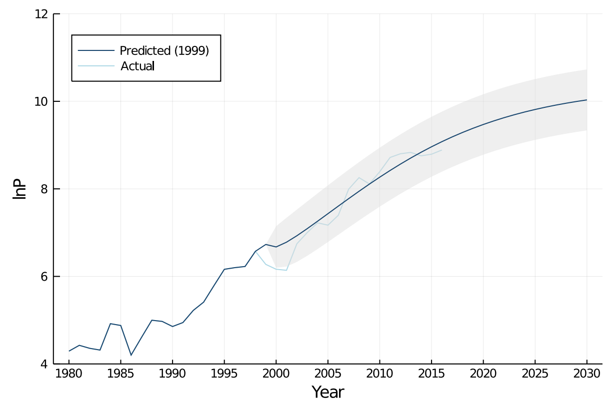
An ARIMA process with $d = 0$, the random variable is itself modeled as an ARMA process. For $d = 1$ it is the difference $x_t - x_{t-1}$, and for $d = 2$ it is the change in differences $(x_t - x_{t-1}) - (x_{t-1} - x_{t-2})$. I take $(p, d, q) = (2, 1, 2)$, which has the highest log likelihood, as my baseline specification.

Figure E1: Demand expectations $\mathbb{E}_{it}[d_{t+s}]$

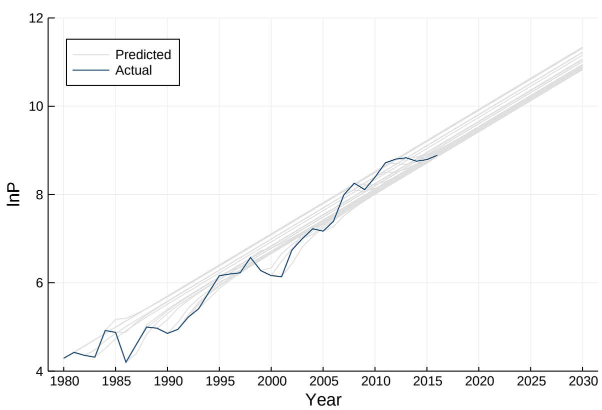
(a) ARIMA predictions, 1999



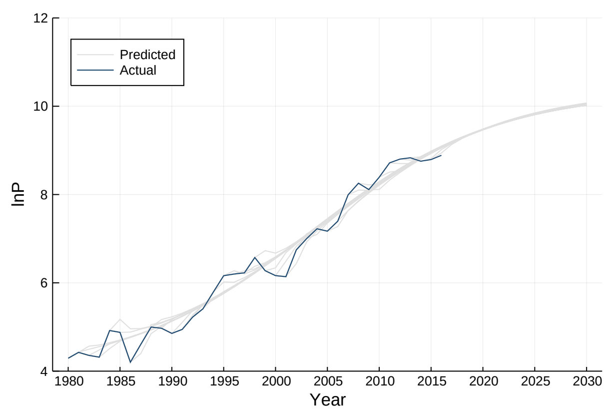
(b) Shrunk predictions, 1999



(c) ARIMA predictions, all years



(d) Shrunk predictions, all years



All figures show expectations for the evolution of demand state d_t. I estimate these demand states in section 5.1, and I plot the realized values as "actual." These realized values coincide with figure 6c. The top row shows predictions and the 95% confidence band from the perspective of a single year, while the bottom row shows such predictions for all years. The left column shows predictions arising from an ARIMA(2,1,2) process that I fit on observed values preceding each prediction year. This specification has the highest log likelihood among those tested in table E1. The right column shows the results of shrinking the ARIMA predictions toward a sigmoid function fit to realized values.

Substituting the expression for expectational errors and applying the above assumptions on expectations, I obtain

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

Thus, I can estimate cost shocks as a function of residuals υ_{it} and price expectations. The demand expectations of equation 14 translate into price expectations as a function of supply elasticities. Figure E1 shows that expectational errors for demand are relatively small in each period, so I approximate price expectations with the partial-equilibrium supply elasticities of table 3.

I do not obtain estimates of extensive-margin cost shocks ε^e_{kt}. Instead, counterfactuals evaluate the ex-ante value function and yield predicted probabilities of extensive-margin investment.

Backward induction from steady state

I solve the model by backward inducting from the steady state – period S – at which point all feasible lands have been developed. After period S, there is no further entry, but firms continue to generate revenues over the infinite horizon based on past entry. The existence of such a period is asymptotically guaranteed in my model: the total amount of development is non-decreasing given no exit, there are new cost shocks in each period, and there is a finite amount of land that can be developed. The challenge is that it may take many years for every hectare of available land to be developed.

I address this computation burden in two ways. First, I solve each subproblem using an iterative algorithm that uses a fixed look-ahead horizon instead of always looking ahead to the end of the game tree. Given initial state of development s_1, I backward induct from period S as follows.

1. Initialize the algorithm by solving for a_1 given s_1 assuming no further entry after period 1, then for a_2 given $s_2(a_1)$ assuming no further entry after period 2, and so on until a_S. With a_S and $s_S(a_{S-1})$, compute s_{S+1}. Note that $s_S(a_{S-1})$ is shorthand for $s_S(a_{S-1}, a_{S-2}, \ldots, a_1, s_1)$.
2. Taking s_{S+1} as fixed, work backward from period S. First, solve for a_{S-1} given s_{S-1} as a starting state and $\{s_S(a_{S-1}), s_{S+1}\}$ as the future states (with $s_{S+t'} = s_{S+1}$ for all $t' > 1$ given no future entry). Revise s_S given the previous solution to a_{S-1}. Second, solve for a_{S-2} given s_{S-2} as a starting state and $\{s_{S-1}(a_{S-2}), s_S, s_{S+1}\}$ as the future states. Revise s_{S-1} given the previous solution to a_{S-2}. Continue until a_1, noting that all states get revised except for initial state s_1, which must be taken as given.
3. To restart the chain of revisions, solve for a_S given s_S as the starting state and $s_{S+1}(a_S)$ as the future state given no further entry.
4. Repeat steps 2 and 3 until convergence in $\{a_1, a_2, \ldots, a_S\}$.

This algorithm breaks the usual curse of dimensionality in which the state space grows exponentially in the length of the look-ahead window.

Second, I approximate period S by choosing an arbitrary period $T < S$ and solving as if it were the steady state. In setting an earlier period T, computation is faster because the backward induction window is shorter, but there is more bias in ignoring post-T entry because there are more periods after T. My solution is to resolve taking periods $T+1$, $T+2$, and so on as the steady state until the solutions converge. Intuitively, entry today becomes less appealing when competitors have a longer window of opportunity to enter, but discounting means a diminishing marginal impact of extending this window.

Defining notation, world supply and entry in period t are functions of previous and new development, respectively.

$$s_t = \sum_i Y_{it} s_{it}\,, \quad a_t = \sum_i \Big(s^e_{it} a_{it} + (1 - s^e_{it}) p^e_{it} a_{it} \Big), \tag{15}$$

where for sites without mills in period t ($s^e_{it} = 0$), new development depends on both extensive-margin probability p^e_{it} of mill construction and intensive-margin choice a_{it} of plantation development. "Entry" involves plantation development in my context, so I refer to entry and development interchangeably. Entry determines future supply

$$s_{t+1} = s_t + a_t\,,$$

and therefore future world prices

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

To proceed, consider period T and suppose there is no further entry after this period. For sites with a mill in period T ($s^e_{iT} = 1$), the first order condition for a_{iT} determines development.

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

subject to constraint $0 \leq a_{iT} \leq \bar{s}_i - s_{iT}$. For sites without a mill in period T ($s^e_{iT} = 0$), development also depends on mill construction, which occurs with probability

$$p^e_{iT} = \frac{\exp\big(-x_i \gamma^e - \kappa^e_m - \alpha^e_m T + \mathbb{E}^e_{iT}[V(0; \boldsymbol{w}_{iT}, \varepsilon_{iT})] \big)}{1 + \exp\big(-x_i \gamma^e - \kappa^e_m - \alpha^e_m T + \mathbb{E}^e_{iT}[V(0; \boldsymbol{w}_{iT}, \varepsilon_{iT})] \big)}\,, \tag{17}$$

where the one in the denominator arises from $v^e(0; \boldsymbol{w}_{iT}) = 0$ since there is no further entry after period T (for an outside option normalized to zero).[16] In both cases, entry depends on world prices, which in turn depend on world supply.

The result is an entry game in which the returns to entry for a given firm depends on how many other firms enter. Intuitively, developing a given site has low returns when other sites develop extensively because high supply means low prices. In equilibrium, each firm's entry decision must be consistent with total entry. If all firms enter today, then future prices will be low and some firms are better off not entering; if no firm enters, then future prices will be high and some firms are better off entering. I solve by selecting an arbitrary level of total development a_T, computing the site-specific development choices by equations 16 and 17, and calculating the implied total a'_T by equation 15. If the implied total is higher (lower) than the initial total, then for the next iteration I start with a higher (lower) initial total. In this way, I obtain site-specific period-T development $\boldsymbol{a}_T = \{a_{iT}, a^e_{iT}\}$ as a function of previous development $\boldsymbol{s}_T = \{s_{iT}, s^e_{iT}\}$.

[16] To determine the probability of extensive-margin entry, I compute intensive-margin profits assuming $\mathbb{E}^e_{iT}[\varepsilon_{iT}] = 0$ because I assume that firms make extensive-margin decisions before observing intensive-margin shocks. When computing actual intensive-margin entry, however, I use realized intensive-margin shocks ε_{it}. Furthermore, since intensive-margin profits $\mathbb{E}^e_{iT}[V(0; \boldsymbol{w}_{iT})]$ are not linear in ε_{iT} (even though choices a_{iT} are), I cannot simply apply $\mathbb{E}^e_{iT}[\varepsilon_{iT}] = 0$ and must instead compute expected intensive-margin profits based on the distribution of ε_{iT}, which I assume firms know.

The problem is computationally fast to solve. First, prices are monotonically decreasing in total entry a_T, so the solution is unique and standard root-finding algorithms work well. Second, I can iterate on total development a_T instead of site-specific development $\boldsymbol{a}_T$ because world prices are influenced only by total supply and not the spatial distribution of supply. This simplification rules out spatial competition concerns, which would otherwise generate a severe curse of dimensionality by requiring iteration over the I-dimensional space $\boldsymbol{a}_T$. Third, as in Hopenhayn (1992), I invoke that firms are small enough to approximate a continuum: by the law of large numbers, the implied total is simply the expected value resulting from extensive-margin entry probabilities p^e_{iT}. By contrast, with a small number of large firms, the extensive-margin entry probabilities induce a binomial distribution over total entry. In dealing with a scalar instead of a distribution, I avoid the computational burden of computing outcomes over each point of the distribution.

Working backward, consider development $\boldsymbol{a}_{T-1}$ in period $T-1$. Taking previous development $\boldsymbol{s}_{T-1}$ as given, I solve for new development $\boldsymbol{a}_{T-1}$ as follows.

1. I make an initial guess for total new development a_{T-1}.
2. I divide this total new development a_{T-1} into site-specific new development $\boldsymbol{a}_{T-1}$. Since the first order condition is monotonic in prices, only one such division exists.
3. With $\boldsymbol{s}_{T-1}$ and $\boldsymbol{a}_{T-1}$, I obtain site-specific $\boldsymbol{s}_T$ and therefore total s_T.
4. Given $\boldsymbol{s}_T$, I solve the subproblem for $\boldsymbol{a}_T$ using the solution algorithm described above for entry in period T, after which there is no further entry. With $\boldsymbol{s}_T$ and $\boldsymbol{a}_T$, I obtain site-specific $\boldsymbol{s}_{T+1}$ and therefore total s_{T+1}.
5. Given totals s_T and s_{T+1}, I compute site-specific $\boldsymbol{a}_{T-1}$ with analogues of equations 16 and 17.[17]
6. Finally, I check if site-specific new development $\boldsymbol{a}_{T-1}$ sums to the guess for total new development a_{T-1}. If so, then $\boldsymbol{a}_{T-1}$ is the solution. If not, then I repeat the above steps with a different guess for a_{T-1}.

Solving for entry in period $T-2$ and in earlier periods follows similarly, where I can solve the subproblems in step four by recursively applying the same algorithm.

E.2 Quantifying carbon emissions

I account for substitution to paper pulp (*acacia*) plantations by estimating the observed relationship between paper pulp and palm oil plantation development. I estimate this relationship using data on paper pulp plantation development as of 2016 on the island of Borneo (Gaveau et al. 2019), as mapped in figure E2.

$$\text{acacia}_i = \beta_0 + \beta_1 \text{palm}_i + \beta_2 \text{mill\_distance}_i + \alpha_m + \varepsilon_i\,, \tag{18}$$

[17] For intensive-margin entry in equation 16, the analogue in period $T-1$ is similar except that prices depend on s_T in period T and s_{T+1} thereafter. A firm's expected development a_{iT} in period T does not enter. For extensive-margin entry probabilities in equation 17, the expression is simplified in period T because $v^e(0;\boldsymbol{w}_{iT}) = 0$ given no further entry. In earlier periods t, $v^e(0;\boldsymbol{w}_{it})$ is instead given by the logit log-sum formula

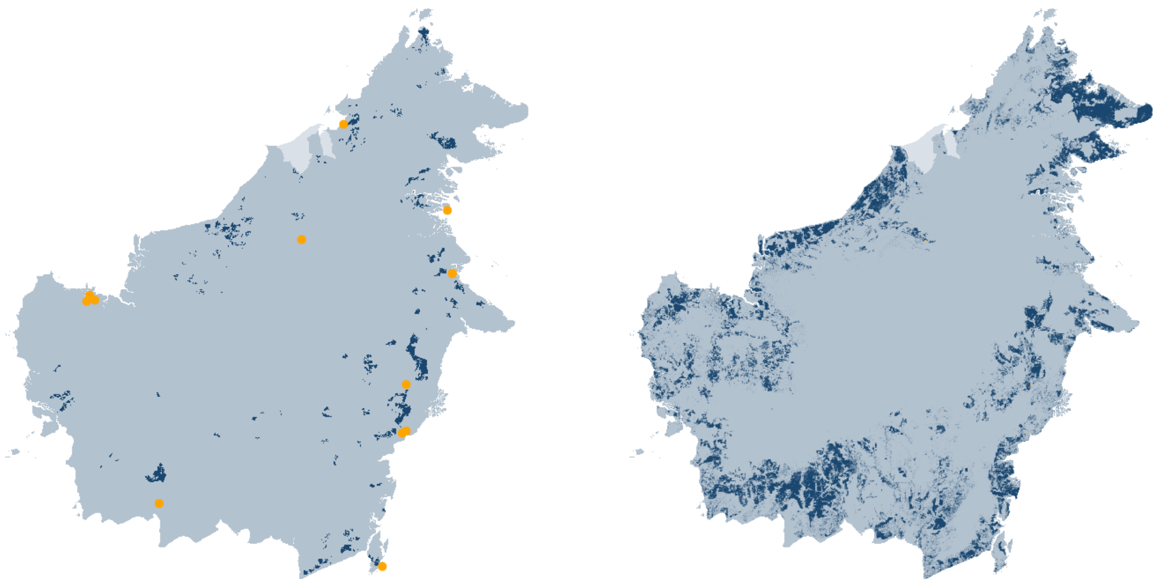
$$\begin{aligned} v^e(0;\boldsymbol{w}_{it}) &= \beta \mathbb{E}^e_{it}[V^e(\boldsymbol{w}_{it+1})] \\ &= \ln(e^{\mathbb{E}^e_{it}[v^e(1;\boldsymbol{w}_{t+1})]} + (e^{\mathbb{E}^e_{it}[v^e(1;\boldsymbol{w}_{t+2})]} + \cdots + (e^{\mathbb{E}^e_{it}[v^e(1;\boldsymbol{w}_{T})]})^{\beta})^{\beta})^{\beta}. \end{aligned}$$

I account explicitly for the distribution of future intensive-margin cost shocks ε_{it+s}, which do not fall out because intensive-margin profits $V(0;\boldsymbol{w}_{it},\varepsilon_{it})$ are not linear in ε_{it}, although development a_{it} is.

for sites i and regions m (provinces for Indonesia and states for Malaysia), and where I control for distance to the nearest paper pulp mill. Table E2 shows that lower levels of palm development are indeed associated with higher levels of paper pulp development, although the magnitude of the relationship does not seem to be large.

Figure E2: Plantation development, 2016

(a) Paper pulp **(b)** Palm oil



The figures map plantations as of 2016 for the island of Borneo, which is shared by Indonesia, Malaysia, and Brunei. The shaded out region is Brunei. On the left, data on paper pulp plantations come from Gaveau et al. (2019), and orange dots mark paper pulp mill locations based on information from the Indonesian Pulp and Paper Association. On the right, data on palm oil plantations come from Xu et al. (2020).

Table E2: Paper pulp vs. palm oil plantation development

Palm plantation development (%)	-0.0195***	-0.0235***
	(0.00610)	(0.00734)
Log paper pulp mill distance (km)	-0.0265***	-0.0210***
	(0.00447)	(0.00452)
Province FE		x
Observations	1,060	1,060

Each column is one cross-sectional regression using 2016 data, and each observation is a site. The sample is restricted to the island of Borneo, where data on paper pulp plantations are available (Gaveau et al. 2019). Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.