E.U. Trade Restrictions, Heterogeneity among Malaysian Oil Palm Farmers, and Limiting Deforestation

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Abstract

Market-level environmental policies may be easier to implement than targeted alternatives, but can suffer from within-market leakage when competing firms are heterogeneous, potentially undermining policy effectiveness. I examine this phenomenon in Malaysian regional markets by analyzing the 2017 EU trade resolution that phases out palm oil imports to reduce upstream deforestation. These markets contain two distinct producer types — smallholders and large estates — whose land expansion decisions are linked through equilibrium prices, creating potential for within-market leakage when one type reduces production in response to policy, thereby incentivizing expansion by the other type and partially offsetting intended environmental benefits. I develop and estimate a dynamic single-agent supply-side model of oil palm land-use using aggregate market data. Results show that large estate expansion substantially offsets deforestation reductions from decreased smallholder activity, as large estates benefit from lower entry costs and access to more profitable alternative land uses. Counterfactual analysis reveals that while a targeted per-unit tax on large estates would enhance deforestation reduction, large estates have strong incentives to block such policies even with full tax revenue redistribution. In contrast, sanctioning supplier quantity coordination emerges as a superior policy alternative that simultaneously prevents further deforestation by both producer types while increasing intensive margin profits for each, making it both environmentally effective and politically feasible.

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1 Introduction

In recent years, the European Union has begun using trade policies restricting palm oil imports to combat global deforestation and climate change. Such policies are mistargeted in that they work through affecting downstream commodity prices rather than directly aligning the internalized cost of deforestation with its social cost. While easier to implement than more targeted policies requiring upstream country or producer cooperation, these market-level policies can generate within-market leakage when heterogeneous upstream producers compete. When differences in extensive margin expansion costs coincide with differences in internalized deforestation costs, reduced expansion by one producer type may lead to increased expansion by another type, diminishing policy effectiveness.

Absent an enforceable command-and-control policy dictating socially optimal deforestation levels, a first-best approach would directly internalize deforestation costs by pricing them according to their social cost. However, such policies are difficult to implement for both technological and political economy reasons, especially in developing economies where deforestation is a major concern (Oates and Portney, 2003; Hahn and Stavins, 1992; Keohane et al., 2019). Regulators may not be able to collect fees from agents specifically responsible for given occurrences of deforestation, making it difficult to achieve correct price internalization. Moreover, governments may face internal political opposition to enforcing such policies. Consequently, this paper examines "second best" but more feasible counterfactual policies that could be more favorable to supplier countries and more effective at reducing deforestation. In particular, I focus on the implications of a targeted per-unit tax on large estates and allowing producers to coordinate on quantity restrictions.

A targeted tax enables policymakers to better align internalized and social deforestation costs when different producer types face different costs. Consider large estates that face lower deforestation costs due to better technology access and smallholders that face higher deforestation costs. Targeting taxes at large estates may reduce deforestation more efficiently than the EU policy while addressing distributional concerns that smallholders could bear a disproportionate policy burden relative to their share of oil palm land expansion and deforestation. Consequently, the threat of a tariff could incentivize producer countries to levy a domestic targeted tax that reduces deforestation by at least as much, potentially protecting smallholders

while reducing deforestation at lower total economic cost than a coarser international trade restriction.

However, large estates still have incentives to block a targeted tax. "Interest groups" play a large role in determining which environmental policies regulators ultimately implement (Oates and Portney, 2003). Even though a targeted tax could better limit deforestation and improve long-run payoffs to smallholders, large estates experience losses under this policy. Furthermore, tax revenues collected may not be sufficient to offset large estate losses, and large estates may not trust their governments to redistribute collected taxes. Following Asker et al. (2024)'s finding that one benefit of OPEC's market power was reduced carbon emissions, I explore to what extent allowing Malaysian oil palm farmers to form a trade organization can limit deforestation. Unlike individual farmers, a trade organization facilitating price coordination could exercise market power and consequently face incentives to limit production to maintain higher prices. Since yield per farm is difficult to externally specify and enforce, one main way for a trade organization to limit quantity is to restrict total productive land, which would also directly limit deforestation. Such a policy could be more attractive to all incumbent farmers by allowing them to jointly maintain higher prices, while potential entrants are much less likely to be sufficiently organized to block such policies.

Notably, Malaysia has actually supported a similar policy in the past, though it has not come to fruition (*Malaysian Palm Oil Board: Good move to replicate Opec for palm oil industry*, 2019). Moreover, supply restrictions more generally have an established role in agricultural policy, making this form of policy potentially more palatable. For example, in the US, there has been some form of government-led supply restriction ranging from the New Deal's Agricultural Adjustment Act of 1933 to more recent iterations of the Farm Bill that include mandatory production controls and government payments to keep large percentages of cropland idle (Gardner, 1992).

I focus specifically on evaluating the European Union's 2017 resolution to restrict palm oil imports on Malaysia's upstream oil palm industry. Malaysia is the second largest global exporter of palm oil after Indonesia, and the European Union has consistently ranked among Malaysia's top three importers. Moreover, Malaysia's oil palm farmers are heterogeneous, with small farms of, on average, 3.9 hectares (smallholders) producing about 40% of the country's

oil palm (Ellis-Petersen, 2018). Palm oil's profitability has historically played an important role in Malaysian poverty alleviation (*Malaysian Farmers Protest Europe's Push to Curb Palm Oil Imports*, 2018), with the government creating multiple programs to help rural farmers gain access to the crop. The EU policy is cause for concern because it correlates with observed slowdowns in land area expansions and sometimes even contractions across regions, indicating potential effects on farmer profits. Notably, palm oil's economic influence extends well beyond Malaysia, with 3 million smallholders growing oil palm and 2.9 million related downstream jobs globally (Voora et al., 2020).

To estimate the long-run effects of the 2017 EU trade policy on smallholders, I obtain data on aggregate oil palm land flows by farm type from the Malaysian government. In these data, I observe land areas by administrative region and year for independent smallholders, organized smallholders, and large estates. Such distinctions are not generally available from the geospatial satellite data used in other papers (Hsiao, 2020; Domínguez-Iino, 2022). I also collect price, quantity, and other data that allow me to estimate aggregate oil palm supply and demand.

Using land areas, prices, quantities, and other characteristics (e.g., rainfall, prices of substitutes), I estimate and simulate a model with two key components: 1) static short-run aggregate supply and demand for oil palm fruit, and 2) oil palm farmer entry and exit decisions by farm type. Aggregate supply and demand are needed to estimate and simulate the dynamic portion of the model, as they predict equilibrium static profits in different states of the world. I use a single agent dynamic model of entry and exit decisions similar to Rust (1987) and Scott (2014) with an additional restriction on agent beliefs over equilibrium price changes. This dynamic structural model allows me to recover stationarity from the farmers' perspective even when some underlying variables determining equilibrium prices such as total productive land are generally increasing and nonstationary in my period of analysis.

I use simulated method of moments to estimate parameters that rationalize observed land flows by farmer type across regions. This methodology, in contrast to CCP estimation methods which require observing individual agent decisions to estimate policy functions, can be implemented using only aggregate data. Using my model and estimated parameters, I solve counterfactuals that explore the impacts of: (i) the EU policy, (ii) a targeted tax on large estates, and (iii) supplier quantity coordination. This structural framework is useful because

the trade policies are non-randomly assigned and affect all markets in my setting.

Consistent with large farms having access to better (cheaper) land clearing and planting technologies (Kailany, 2011), I estimate that large estates face lower entry costs than smallholders. Moreover, I also estimate that large estates have higher value alternative uses of their farmland, as reflected in higher scrap values. These differences in estimated entry cost and scrap value distributions translate into smallholders experiencing larger losses in long-run discounted flow payoffs, tying together environmental concerns with equity concerns. Lower entry costs mean that it is easier for large estates to enter the oil palm market and benefit from higher prices if prices increase again in the future. Lower scrap values imply a lower outside option for small estates. Thus, smallholders who exit due to a negative demand shock are worse off because they accept, on average, much lower scrap values.

From 2017 to 2019, I find that the EU trade restriction decreased total land area farmed by smallholders but increased total land area farmed by large estates. Reduced entry (and increased exit) by smallholders generates increased entry (and decreased exit) by large estates because the decrease in smallholders leads to higher counterfactual prices for incumbent and entrant large estates.[1] Similarly, participating smallholders on average experience losses in long-run discounted payoffs while large estates on average experience gains, driven by equilibrium prices decreasing in regions where more smallholders survive and increasing in regions where more smallholders exit.

Examining counterfactual "second best" policies that better align heterogeneous farmer incentives with deforestation costs, I find that a roughly 0.9% per-unit tax targeted at only large estates could reduce deforestation by the same amount as the EU trade policy. This targeted tax leads to higher long-run equilibrium prices for smallholders, generating an increase of almost $7.4 million USD in intensive margin long-run discounted flow payoffs. However, this counterfactual also potentially explains why the Malaysian government has not yet implemented a targeted tax. After accounting for tax revenues collected, total losses summed across smallholders and large estates are larger than under the negative demand shock associated with the EU policy, implying that the EU policy may not have been large enough of a threat to induce uptake of a domestic targeted tax. Moreover, large estates face even greater long-run losses

[1] The increase in large estate entry is not large enough to offset increases in equilibrium prices due to decreased smallholder entry and increased exit.

under the targeted tax than under the EU trade restriction. Consequently, such a targeted tax may be politically infeasible because large estates have substantial economic incentives to block such policies and may not trust the government to redistribute tax revenues.

I then examine another counterfactual under which all incumbent producers find it incentive compatible to reduce deforestation. I consider allowing Malaysian producers to restrict quantity and increase long-run equilibrium prices by restricting oil palm production entry as part of a trade organization similar to OPEC. My calculations suggest that this policy is promising. Allowing coordination could increase total long-run payouts to incumbent Malaysian farmers while decreasing deforestation by more than the EU trade restriction does. This holds under demand elasticities assuming that Indonesia's global trade share remains relatively constant as well as under higher elasticities taken from the literature that account for substitution across oils (Hsiao, 2020).

This paper connects and extends the literature on market-based environmental policies[2] and the links between rural poverty and land use.[3] In particular, I consider how producer heterogeneity: (i) shapes the impact of market-based environmental policies, and (ii) makes rural poverty and differences in productivity relevant for evaluating environmental policy.

Under the umbrella of market-based environmental policies, this paper ties most directly into the discussion of optimal policies for managing deforestation. Souza-Rodrigues (2019) and Assunção et al. (2023), for instance, explore the efficiency of domestic policies, both command-and-control and economic instruments, in preventing deforestation in the Amazon and the general social benefits from resulting reduced carbon emissions. Hsiao (2020) examines the efficacy of various tariff structures in limiting deforestation, focusing on leakage across importer countries.[4] Domínguez-Iino (2022) provides a counterpart to Souza-Rodrigues (2019) by examining geographic variation in policy impacts and finds that poorer regions do indeed bear the brunt of policy costs. This project extends the discussion of heterogeneity by analyzing leakage across different types of farmers within the same geographic regions.

[2]See Stavins (2003) for a general discussion.

[3]See Dasgupta (2003) for a general discussion.

[4]The current discussion among international policymakers about how to address deforestation and climate change also largely focuses on entire industries or countries. For example, the 2022 iteration of the EU's policy against deforestation targets a broad class of imported goods associated with deforestation, including cocoa, coffee, palm oil, and rubber. While the EU plans to work with other countries to help them "improve their regulation capacity," how to do so given heterogeneity of upstream producers across and within countries is not well defined Radford (2022).

With respect to rural poverty and land use, this project builds on the literature examining agricultural inequality in developing economies (Chen et al., 2023; Adhvaryu et al., 2021). I extend this discussion by modeling and estimating how farmers adjust in the long run to shocks they perceive as being more persistent. This contrasts with Chen et al. (2023)'s focus on controlling for transitory shocks when estimating factor misallocation and Adhvaryu et al. (2021)'s analysis of how households smooth short-run consumption shocks from global commodity price fluctuations by temporarily engaging in enterprise ownership. Adding to the discussion on how farm size distribution impacts productivity (Aragn et al., 2022; Adamopoulos et al., 2022; Da-Rocha et al., 2023), I illustrate how selection based on differences in productivity can lead to larger environmental externalities because these productivity differences are driven, in part, by varying access to more efficient land-clearing technologies.

The rest of the paper is organized as follows: Section 2 provides further background on the palm oil industry and Malaysia. Section 3 describes the data. Section 4 provides descriptive statistics. Section 5 describes the model in detail. Section 6 discusses estimation and identification. Section 7 presents estimation results. Section 8 discusses counterfactuals eliminating the trade policy and taxing large estates. Section 9 concludes with a brief discussion. Figures and Tables are included in sections 10 and 11.

2 Background

Developing countries in Southeast Asia, Africa, and Latin America are the primary sources of palm oil. In 2022, the estimated value of the global palm oil market was $67.91 billion USD (Precedence-Research, 2023). Malaysia accounts for roughly 34% of world exports and has been the second largest global exporter, after Indonesia, of various forms of palm oil (e.g., crude, kernel, refined) and its byproducts (MPOC, 2023). Consequently, palm oil plays a large role in the Malaysian economy, accounting for between 5 and 7 percent of Malaysia's annual GDP (Nambiappan et al., 2018). Of Malaysia's main commercial crops (cocoa, kenaf, oil palm, pepper, rubber, and sago), oil palm plantations occupy the vast majority of land area as shown in Figure 1.

Production Palm oil originates from fresh fruit bunches (FFB) growing on oil palm trees. Due to the trees' lifespan and tropical climate allowing year-round FFB production, farmers practice monoculture and dedicate land exclusively to FFB cultivation. The average bunch weighs between 20 and 55 pounds and must be transported to a mill and processed into oil within 24 to 48 hours of harvesting. All FFB harvesting must be done by hand, implying minimal returns to scale in short-run harvesting. Due to these transportation constraints, initial processing of oil palm into crude palm oil (CPO) must be done locally.

Farmers sell FFB either directly to CPO processing mills or to middlemen called oil palm dealers who then sell to mills. According to the Directory of Malaysian Palm Oil Processing sectors, there are on average 39 palm oil mills per region (Malaysian Palm Oil Board, 2019). The Directory of Malaysian Oil Palm Fresh Fruit Dealers from 2016 lists an average of 186 oil palm dealers per region (Malaysian Palm Oil Board, 2016). After pressing, CPO is sold to regional refineries, which then process the oil for export. Further downstream, palm oil can be found in biofuels, retail foods and snacks, and cosmetics. The World Wide Fund for Nature notes that palm oil is "in close to 50% of the packaged products we find in supermarkets."

Production occurs in distinct regional markets across Malaysia. Malaysia spans two main land masses: Peninsular Malaysia and Malaysian Borneo. Peninsular Malaysia is divided into 10 administrative regions (Johor, Kedah, Kelantan, Melaka, Negeri Sembilan, Pahang, Perak, Pulau Pinang, Selangor, and Terengganu), while Malaysian Borneo includes two regions (Sabah and Sarawak).

Heterogeneous Producers Given its large downstream demand, palm oil has played an important role in Malaysian poverty alleviation since its introduction as a commercial crop by the French in 1917. Smallholders produce about 40% of Malaysian palm oil (Ellis-Petersen, 2018). The Malaysian government defines smallholdings as all farms under 40 hectares (Yew, 2021). However, most smallholdings are far below this cutoff, with an average size of 3.9 hectares—less than 10% of the maximum (Ahmad et al., 2023). There are two types of smallholders in Malaysia: independent smallholders and organized smallholders who participate in government programs (e.g., FELDA, FELCRA). Independent smallholders manage approximately 17% of total oil palm cultivation area in Malaysia. While independent smallholders face market prices, organized smallholders receive substantial government subsidies and benefit from other market

protections. One of palm oil's advantages is that its yields are 5 to 10 times those of other vegetable crops (Voora et al., 2020), making it a relatively efficient land use for small farms.

Combined with growing demand, palm oil's efficiency has made it a historically important means of poverty alleviation in Malaysia.[5] Organized smallholders originated from early land resettlement schemes designed to reduce poverty. The Federal Land Development Authority (FELDA), formed in the late 1950s, was one of the earliest such programs. Some estimates suggest the program reduced poverty among participants from 50% in the 1960s to 5% today (Rahman, 2020).

Large estates produce the remaining 60% of Malaysian palm oil. Unlike smallholders, which are often individual family units, large estates are typically publicly traded companies with more than 2000 acres of land on average. The largest company associated with large estates is Sime Darby, which owns roughly 5% of oil palm land in Malaysia (743,854 acres) (*Sime Darby Annual Report*, n.d.). Moreover, land owned by the same firm is generally split into many smaller, separately managed plantations. While large estates are hundreds of times larger than smallholdings, no individual large estate produces a majority market share.

Differences in landholdings mean that large estates (and organized smallholders making collective decisions) have different alternative land uses, even though the oil palm production process is relatively homogeneous across farm sizes. Given that oil palm yields are 5–10 times higher than those of other crops, independent smallholders may not own enough land to profitably produce alternative crops. However, large estates or organized smallholders pooling land are less likely to face this constraint. Consequently, the relevant outside options for independent smallholders—often individual family groups—would be switching to subsistence farming or selling the land and migrating to urban areas for employment (Hassan et al., 2018). This contrasts with the possibility of converting a palm oil plantation into another exportable cash crop (e.g., rapeseed oil).

Scale differences between large estates and smallholdings also generate differences in the entry costs of clearing each acre of land. For independent smallholders, replanting occurs on a small scale, meaning their access to land-clearing technology—whether for removing old trees

[5]The president of Malaysia's National Association of Smallholders described the importance of palm oil as follows: "Smallholders rely on palm oil income to buy food and send their children to school. We have cultivated palm for decades, (and) it has brought development. The country is rich because of palm oil" (*Malaysian Farmers Protest Europe's Push to Curb Palm Oil Imports*, 2018).

or preparing new land for planting—differs from other groups (organized smallholders, large estates) who can clear and plant large swaths of land simultaneously (Kailany, 2011). For example, a survey of oil palm smallholders found that their main method of managing clearing waste was to stack it around their farms after manually cutting it up or using small cutting machines (Herdiansyah and Frimawaty, 2021). In contrast, large estates often have access to or own large mechanical devices for processing and managing waste, such as various tractors and mulchers (Abubakar et al., 2021). Accordingly, Gutirrez-Vlez et al. (2011) find that large farms prefer large concessions in forested regions while smallholders prefer already cleared land. Lee et al. (2014) note that large estates have the capital and expertise to drain and cultivate peat swamps that independent smallholders might not access.

Moreover, evidence suggests that better access to land-clearing technologies correlates with large estates being more responsible for deforestation than smallholders. Lee et al. (2014) find that 88.3% of deforestation in Sumatra, Indonesia from 2000 to 2010 was driven by large-scale oil palm plantations, compared to 10.7% attributed to smallholdings. Large enterprises convert 16.7 times more peat swamp forests—which release more carbon than other land types—into oil palm plantations compared to smallholdings. Similarly, Gutirrez-Vlez et al. (2011) find that in Peru, 75% of oil palm land expansion by industrial-scale plantations involved deforestation, whereas only 30% of smallholder expansion did.

2017 E.U. Palm Oil Resolution Between 2002 and 2019, Malaysia exported on average 90.3% of the palm oil it produced.[6] Through 2019, the EU was generally one of the two largest importers of Malaysian palm oil, accounting for between 9% and 12% of all exports (Chu, 2023; Tan, 2019). Given its large palm oil imports, the EU resolved in 2017 to phase out the use of palm biodiesel by 2020 (Keong, 2017). The European Parliament cites concerns about illegal deforestation of rainforests and climate change as the main reasons behind its import restrictions (E.U., 2017). Since 2020, the EU's policies have evolved into a certification scheme for palm oil entering the EU.

As the world's two largest exporters of palm oil, Malaysia and Indonesia reacted with alarm to the resolution. Skeptical observers worried that these policies constituted protectionism framed as environmentalism, noting that the resolution "indirectly favored Europe's homegrown

[6]Calculated using data from the MPOB collected from the Oil World Annual report.

products like rapeseed and sunflower oils." Malaysia and Indonesia have filed separate suits with the World Trade Organization against the EU (Tan, 2019). Discussions of Malaysia and Indonesia jointly banning all palm oil exports to the EU have been ongoing from 2017 through 2023 (Chu, 2023).

Notably, the EU's resolutions are not the only policies addressing deforestation and sustainability concerns in the oil palm industry. Starting in 2004, sustainability certifications have been available to oil palm farmers, including the Roundtable on Sustainable Palm Oil (RSPO), Indonesian Sustainable Palm Oil (ISPO), and Malaysian Sustainable Palm Oil (MSPO). The ISPO was launched in 2011 by the Indonesian government and the MSPO in 2013 by the Malaysian government. The rollout and uptake of these certifications have been gradual and sometimes coupled with government assistance, making assessment of their direct implications on farmer profits difficult. I abstract away from these existing schemes in my model and analysis.

3 Data

My main data source is the Ministry of Plantation Industries and Commodities (MPIC). They provide me with annual total palm oil land area by administrative region and farmer type from 2006 to 2019. Figure 2 displays aggregate land flows by region over time and changes in land use composition with respect to the fraction of land independent smallholders farm. In contrast to satellite geospatial data, these data differentiate land use by farmer type. This allows me to study implications of aggregate demand shocks within a specific country and industry for inequality. In particular, I can observe within-region compositional changes in the types of farmers growing oil palm, unlike work focusing primarily on the extensive margin of land use (Hsiao, 2020; Domínguez-Iino, 2022). I supplement these data with regional data on primary forest loss and carbon emissions from Global Forest Watch (2025) to tie extensive margin expansion to deforestation in my analyses. All additional data are similarly collected for 2006 to 2019 (when available), since my main goal is to rationalize changes in the composition of farm types underlying extensive margin land expansion over time.

The Malaysian Palm Oil Board (MPOB) is a sub-agency under the MPIC that collects and reports information on monthly prices and yields at different stages of the domestic palm oil

supply chain.[7] I combine yield and land area data to calculate monthly quantities of FFB for each administrative region. Figure 3a shows the range of FFB prices across administrative regions over time. While there is variance in the range of prices, there do not appear to be consistent upward or downward trends in variance over time.

I also collect data on key palm oil supply and demand shifters to identify static supply and demand. From the World Bank, I collect monthly Malaysian rainfall data. Since FFB yields and quantities depend greatly on having the right amount of rainfall, these are important shifters of the FFB supply curve (and consequently the palm oil supply curve) in any given period. With respect to demand shifters, I collect monthly world soybean oil prices from the International Monetary Fund and MPIC. Soybean oil is one of the most common substitutes for palm oil (Hinrichsen, 2016). The two sources reflect different commodity exchanges but are highly correlated. Given how closely soybean and palm oil prices move together, as shown in Figure 4, I also collect monthly rainfall in major soybean oil producing countries (i.e., Brazil and the US) as plausibly exogenous demand shifters.

Lastly, I collect data on futures prices for crude palm oil and soybean oil from DataStream.

4 Descriptive Statistics

In this section, I provide descriptive evidence about the relationship between oil palm and deforestation, regional FFB markets being distinct, and the EU trade policy being correlated with a contraction in oil palm demand from Malaysia.

Deforestation and Heterogeneity Figure 1 graphs the total amount of industrial crop area in Malaysia separated by crop. It shows that oil palm makes up the majority of land expansion in agricultural land area while other crops, mainly rubber, have been decreasing over time, implying oil palm is likely the main contributor to agricultural deforestation in Malaysia. In Table 1, I examine the relationship between primary forest loss in Peninsular Malaysia, Sabah, and Sarawak and changes in total land area used to grow oil palm, rubber, cocoa, and pepper in each of those regions. In the first three specifications, the correlations between oil palm

[7] They also collect and report other industry characteristics such as conversion rates of FFB to crude palm oil and processing mill counts and capacities.

expansion and losses in primary forest are significantly positive.[8] The only other crop with a significant positive correlation with deforestation is rubber, and the magnitude of the oil palm coefficient, combined with greater expansions in land area per year as shown in Figure 1, supports that oil palm expansion is a much more important cause of deforestation in Malaysia than other crops.

Looking within palm oil and across farm types, large estate land expansion is much more correlated across regions and years with larger decreases in primary forest area, as shown in Table 2. Note that the different specifications in Table 2 imply quantitatively different results but still yield that smallholder land expansion results in proportionately less deforestation. This reflects how smallholders are more likely to convert already cleared land into oil palm land while large estates may be more likely to clear forest.

Regional Market Variation Variation in prices across regions and time is driven, in part, by differences in aggregate supply and demand. Figure 2 displays how the evolution of total oil palm producing land as a fraction of total land area differs by region, with some regions, especially Sarawak and Sabah in Borneo, experiencing much greater expansion than others. Furthermore, it displays how the degree to which smallholders are responsible for expanding oil palm land area differs by region over time, reflecting variation across geographies and time.

Paralleling regional heterogeneity in land cultivation, there are also differences in the number of processing mills and access to export ports. This implies that demand varies across regions, and that each region's exposure to international trade shocks may differ.

Figure 3 shows that there is persistent dispersion in regional FFB prices in panel 3a and in downstream CPO markets in panel 3b as a result of these differences in supply and demand. Dispersion in FFB prices shown in panel 3a across administrative regions comes from the high cost of transporting FFB across regional boundaries, which restricts price arbitrage. Dispersion in downstream prices comes from local restrictions on the exporting of crude or unprocessed oil. CPO, unlike processed palm oil, also has a relatively short shelf life, further limiting trade. As such, I define each of the administrative regions as a separate market for FFB.

[8]Specification (4) with both fixed effects has 19 fixed effects when the year and location fixed effects are combined, leaving little variation to identify the parameters of interest.

Reaction to Policy Figure 4 shows that palm oil and soybean oil futures prices generally move together but diverged around the time of the EU Resolution. In particular, in early 2017, soybean oil futures prices experienced a spike whereas palm oil futures prices dropped. These price changes are consistent with a projected decrease in demand for palm oil and increased demand for soybean oil as Europe shifts away from palm oil to other biofuels.

Figure 5 indicates that a decrease in Malaysian oil palm exports to the EU correlates with the 2017 policy. Levels of palm oil exports from Malaysia to the EU remained low after 2017, and the share of Malaysia's exports sent to the EU similarly declined. Figure 6 and Table 3 provide evidence that upstream FFB prices responded to the EU resolution. In particular, Table 3 indicates that the 2017 restriction correlates with a significant decrease in FFB price trends. Since I do not observe many years post-2017 unaffected by the pandemic in 2020, I also examine crude palm oil (CPO) futures prices for evidence of a potential effect on prices. CPO futures traded post-2017 extended into 2023. CPO is the immediate downstream product of FFB. Moreover, FFB futures are not traded, but CPO futures are traded on several exchanges. I find that post-2017 CPO futures prices are significantly decreasing over time while pre-2017 CPO futures prices are significantly increasing.

I also find evidence that the resolution and consequent change in prices correlate with a change in total oil palm land expansion for smallholders and large estates. Figure 7 displays aggregate land by farm type over time.[9] Table 4 attempts to quantify the change in trends after 2017 shown in Figure 7. I observe that the total land belonging to large estates increases faster than the total land belonging to smallholders both pre- and post-2017. However, the decrease in expansion rate after 2017 is larger for smallholders, though not significantly so due to the small number of observations I have for that period. As such, in keeping with the anecdotal heterogeneity in entry costs and outside options across farm types, independent smallholders and large estates appear to have reacted differently to the negative shock.

[9]I distinguish between Peninsular Malaysia and Sabah/Sarawak (Borneo) because the expansion patterns across the two land masses are especially different, as shown in Figure 2.

5 Model

In this section I describe a model rationalizing farm decisions about whether to enter or exit oil palm production within a regional market and how these decisions change with aggregate demand shocks. Oil palm is a commodity. Moreover, no market appears dominated by a single farm owner. For example, Sime Darby is the largest oil palm land owner in Malaysia and owned no more than 30% of total oil palm land in any state in 2019; the land in the region where Sime Darby holds the largest percentage of land (Selangor) is also spread across 23 separately managed estates (*Sime Darby Annual Report*, n.d.). Consequently, I assume that farms are atomistic price takers and cannot individually influence market prices.

Using this assumption about farmers, I model farm entry and exit as a single-agent dynamic problem similar to Rust (1987) and Scott (2014). While no individual farm has market power, aggregate behavior can still affect equilibrium FFB prices in any given period. As such, I adapt Lee (2013)'s parametrization of beliefs over how payoffs evolve to model farmer beliefs about how FFB prices will evolve given the current state of the world.

5.1 Environment

Agents and Actions Agents in this model include FFB farm(er)s and FFB buyers. In each market m, period t, a mass of farmers of type f equal to the amount of land $\tau^f_{m,t}$ currently farmed by that farmer type makes decisions, taking prices as given, about how much FFB to sell and whether or not to exit growing oil palm. I also allow for a mass of potential entrants $\tau^e_{f,m,t}$ making decisions about whether to enter growing oil palm. FFB buyers purchase FFB from sellers. They include intermediate FFB dealers and processing mills, as farmers sell directly to both. These buyers are upstream from palm oil exporters. I assume that buyers are also price takers, since there are many dealers and mills in each region according to the directory of FFB dealers released by the government. For a given price, buyers choose the quantity of FFB to purchase in a given period. I abstract away from the details of dealers and mills and assume that they only make static decisions to focus on farmer behavior.

Timing Farmer actions and payoffs occur in the following order in each period t:

1. Farmers who exited the previous period collect their previous period scrap values ϕ^f_{it-1}.

2. All incumbents and potential entrants observe state variables $\tilde{s}_{m,t} = \{p_{m,t}, a_{m,t}, r_{m,t}, eu_{m,t}\}$, where $p_{m,t}$ is the equilibrium price, $a_{m,t}$ are marginal cost shocks, $r_{m,t}$ is rainfall, and $eu_{m,t}$ indicates whether or not the E.U. trade restrictions are in place.

3. Incumbents j choose quantities to supply and collect current period profits $\pi_{j,m,t}$.

4. Potential entrants and incumbents make the following decisions simultaneously:[10]

   (a) Mass $\tau^e_{f,m,t}$ of each type of potential entrants observe a type-specific private entry cost $\kappa^f_{j,t}$ and decide whether or not to enter. If they enter, they pay the entry cost this period t but are not active until the next period $t+1$. If they decide not to enter, they disappear forever.

   (b) Mass $\tau^f_{m,t}$ of incumbent farmers of each type observe a type-specific private scrap value ϕ^f_{it} and choose whether to continue producing oil palm FFB or exit.

Assuming farmers make simultaneous entry and exit decisions is consistent with individual farmers having to make their own entry and exit decisions before observing other farmers' decisions. Given that land purchases, sales, and conversions to oil palm take time to process legally and publish publicly, this is a plausible assumption.

Furthermore, I assume that scrap values and entry costs are drawn i.i.d. within farm type each period. This implicitly assumes that smallholdings do not transition into large estates (i.e., that smallholdings do not "exit" by becoming larger estates), which is consistent with the average smallholding being a small fraction (1/10th) of the cutoff between the two groups.

5.2 Static Farmer Payoffs and Equilibrium Prices

Each farmer's payoffs in a given period are a function of regional market state variables $s_{m,t}$. Since farmers are price takers, I first express the individual farmer's payoffs as a function of costs, effort, and observed prices, where farmers endogenously choose effort. These individual payoffs also motivate the FFB quantity a farmer will produce for a given price, costs, and other exogenous determinants of yield (primarily rainfall). As such, I use the individual farmer's

[10] A practical reason I have entry/exit decisions occur simultaneously at the end of the period is because I only observe aggregate land flows per year. Thus, if I have farmers choose quantities after entry/exit decisions are made, I will not have the correct amount of land for aggregate supply. I will not be able to see how much palm oil land remains in the same period after exit decisions are made.

implied production to derive aggregate supply. I then model aggregate demand for FFB, which, combined with aggregate supply, gives an expression for equilibrium prices.

Individual Farmer's Problem Since all farmers are atomistic, they take FFB market prices $p_{m,t}$ in each period t as given. Thus, for each farmer j in market m static per period profits are:

$$\pi_{j,m,t}(e_{j,m,t}) = p_{m,t}q_{j,m,t}(e_{j,m,t}) - TC_{j,m,t}(e_{j,m,t}) \tag{1}$$

where $e_{j,m,t}$ is the farmer's endogenous amount of effort, $q_{j,m,t}(e_{j,m,t}) = r_{m,t}^{\beta_r} e_{j,m,t}$ is quantity as a function of farmer effort and rainfall, and $TC_{j,m,t}(\cdot)$ is the total cost function. I assume the following parametrization of total costs as a function of effort to reflect an upward sloping supply curve:

$$TC_{j,m,t}(e_{j,m,t}) = \frac{1}{1+b}\exp^{a_{m,t}+(1+b)\ln(e_{j,m,t})} + FC_{j,m,t} \tag{2}$$

where $a_{m,t}$ is a constant marginal cost shock faced by all farmers in period t, the supply elasticity is a constant b across all periods, and farmers are allowed to differ only in terms of per-period fixed costs $FC_{j,m,t}$. This total cost implies the following marginal cost:

$$MC_{j,m,t} = \exp^{a_{m,t}+b\ln(e_{j,m,t})} \tag{3}$$

Since the short-run production technologies (i.e., harvesting methods) are similar across different types of farms, I currently assume that marginal costs across different types of farms are the same.[11] Taking the FOC of the profit function $p_{m,t}r_{m,t}^{\beta_r} = MC_{j,m,t}$, this parametrization implies that each farmer in each market m and time period t will exert the same amount of effort in equilibrium.

$$\begin{aligned} p_{m,t}r_{m,t}^{\beta_r} &= \exp^{a_{m,t}+b\ln(e_{j,m,t})} \\ \ln p_{m,t} + \beta_r \ln r_{m,t} &= a_{m,t} + b\ln e_{j,m,t} \\ e_{m,t}^* = e_{j,m,t}^* &= \exp(\frac{1}{b}(\ln(p_{m,t}) + \beta_r \ln r_{m,t} - a_{m,t})) \end{aligned} \tag{4}$$

[11] I explore allowing for different marginal costs across types in Appendix A.

Then, in equilibrium each farmer (equivalent to a unit of land) produces:

$$q(e^*_{m,t}) = r^{\beta_r}_{m,t} \exp(\frac{1}{b}(\ln(p_{m,t}) + \beta_r \ln r_{m,t} - a_{m,t})) \tag{5}$$

Aggregate Supply In any given period, the total amount of land devoted to palm oil is $\tau_{m,t}$. Assuming that all units of land in each market are homogeneous, aggregate supply is:

$$Q_{m,t} = \tau_{m,t} q(e^*_{m,t}) = \tau_{m,t} r^{\beta_r}_{m,t} \exp(\frac{1}{b}(\ln(p_{m,t}) + \beta_r \ln r_{m,t} - a_{m,t})) \tag{6}$$

$$\ln(Q_{m,t}/\tau_{m,t}) = \underbrace{\frac{1}{b}}_{=\alpha_1} \ln p_{m,t} + \underbrace{\frac{2\beta_r}{b}}_{=\beta_1} \ln r_{m,t} - \underbrace{\frac{a_{m,t}}{b}}_{=\gamma_{1mt}} \tag{7}$$

Note that $q(e^*_{m,t})$ captures static intensive-margin supply in the form of yield per hectare.

Aggregate Demand Since FFB buyers are atomistic, I can express aggregate demand for FFB as the following:

$$ln(Q_{m,t}) = \alpha_2 ln(p_{m,t}) + \beta_2 \ln p^{soy}_t + d_{m,t} \tag{8}$$

where p^{soy}_t is the price of soy oil, the main downstream substitute for palm oil products, and $d_{m,t}$ represents regional market-specific aggregate demand shocks such as an overall reduction in palm oil imports to the EU. I allow for different markets to have different exposure to the shift in demand correlated with the EU trade shock because different regions may export different quantities to different export countries.

Per Period Equilibrium Prices The per-period equilibrium prices in each market are determined by the intersection of aggregate supply and demand. The equilibrium price and total quantity as a function of the state variables s_t are:

$$\begin{aligned} p^*_{m,t} =& exp(\frac{\beta_2 \ln p^{soy}_t + d_{m,t} - \ln \tau_{m,t} - \beta_1 \ln r_{m,t} + \frac{a_{m,t}}{b}}{\alpha_1 - \alpha_2}) \\ Q^*_{m,t} =& exp(\frac{\alpha_1}{\alpha_1 - \alpha_2}(\beta_2 \ln p^{soy}_t + d_{m,t}) - \frac{\alpha_2}{\alpha_1 - \alpha_2}(\ln \tau_{m,t} + \beta_1 \ln r_{m,t} - \frac{a_{m,t}}{b})) \end{aligned}$$

Substituting $p^*_{m,t}$ into equation 1 yields equilibrium farmer payoffs for a given state of the world $s_{m,t}$. Thus, for each farmer j static per period profits are:

$$\pi_{m,t}(p^*_{m,t}) = p^*_{m,t} q_{m,t}(e(p^*_{m,t})) - TC_{jmt}(e(p^*_{m,t})) \tag{9}$$

where $e(p^*_{m,t})$ is the farmer's endogenous amount of effort as a function of the equilibrium prices they face, $q_{m,t}(e(p^*_{m,t})) = r_t^{\beta_r} e(p^*_{m,t})$ is quantity as a function of farmer effort and rainfall, and $TC_{jmt}(e(p^*_{m,t}))$ is the total cost function.

5.3 Market State Space

I assume that the state space is discrete. The market state space

$$s_{m,t} = \{p_t^{soy}, r_{m,t}, a_{m,t}, d_{m,t}, \tau_{m,t}, \tau_{m,t}^{small}, \tau_{m,t}^{large}, eu_t\}$$

captures all variables that determine per period equilibrium farmer payoffs and are informative about next period profits.

Each market state variable evolves according to one of three processes: 1) an exogenous process fixed over time, 2) an exogenous process that changes after the EU trade policy, and 3) an endogenous process depending on agent actions. I distinguish between exogenous processes that do and do not depend on the EU trade policy to highlight how this policy affects farm composition through endogenous farmer entry and exit decisions that differ across farm types.

The following state variables evolve according to some exogenous process that does not depend on EU policy:

$$s_{AR(1),mt} = \{p_t^{soy}, r_{m,t}, a_{m,t}\}$$

I will assume that this process is an AR(1). Since the EU trade policy ultimately affects FFB demand, I assume the demand shock $d_{m,t}$ evolves according to an exogenous process that does depend on the EU policy:

$$d_{m,t+1} = \varphi_0 + \varphi_1 d_{m,t} + \varphi_2 d_{m,t} eu_t + \nu_{m,t} \tag{10}$$

where $\nu_{m,t}$ is mean zero and independent and $eu_t \in \{0, 1\}$ is an indicator variable denoting

whether the policy is in place ($eu_t = 1$) or not ($eu_t = 0$). This parametrization allows demand shocks to evolve according to a different AR(1) process after the EU trade policy is realized.

Land $\tau^f_{m,t}$ belonging to farm type f evolves such that:

$$\tau^f_{m,t+1}(s_t) = \underbrace{Pr(\delta\phi^f_{it} \leq VC^f_{m,t}(s_{m,t})) \times \tau^f_{m,t}}_{\text{incumbents remaining}} + \underbrace{Pr(\kappa^f_{jt} \leq VC^f_{m,t}(s_{m,t})) \times \tau^e_{f,m,t}}_{\text{entrants}} \tag{11}$$

where ϕ^f_{it} is a farm type specific random scrap value and κ^f_{jt} a farm type specific random entry cost. I omit the market subscript from these random variable draws because I assume that farms across all regional markets draw from the same distributions. $VC^f_{m,t}$ is the type specific discounted flow payoff from entering or remaining in the market (defined below). δ is the discount rate.

As a result of how the state variables evolve, the market state space evolves according to the following first-order Markov process:

$$\begin{aligned} F(s_{m,t+1}|s_{m,t}) =& F_{soy}(p^{soy}_{t+1}|p^{soy}_t) \times F_r(r_{m,t+1}|r_{m,t}) \times F_a(a_{m,t+1}|a_{m,t}) \\ & \times F_d(d_{m,t+1}|d_{m,t}, eu_t) \times F^{small}_\tau(\tau^{small}_{m,t+1}|s_{m,t}) \times F^{large}_\tau(\tau^{large}_{m,t+1}|s_{m,t}) \end{aligned} \tag{12}$$

Since the amount of land that does not belong to independent smallholders or large estates is fixed, how $\tau_{m,t}$ changes is completely determined by $\tau^{small}_{m,t+1}$ and $\tau^{large}_{m,t+1}$.

5.4 Single Agent Problem with Consistent Beliefs

Since farmers are atomistic, each farmer's problem is a single agent dynamic problem. Consequently, farmers need only observe variables that are directly informative about their static payoffs described in equation 9 and the corresponding expected discounted flow payoffs. This implies that they need not observe and form expectations over all market state variables in $s_{m,t}$. In particular, I assume that farmers only observe and form beliefs about equilibrium prices $p_{m,t}$, cost shocks $a_{m,t}$, and rainfall $r_{m,t}$. Farmer beliefs about equilibrium prices change with the EU policy, but they experience the policy as an unforecasted shock. I assume that farmer fixed costs FC_{jmt} are fixed by farmer type over time. As a result, variables $a_{m,t}, r_{m,t}, p_{m,t}$ alone are sufficient to determine each farmer's optimal quantity in equation 5 and payoffs in equation 1.

In addition to $a_{m,t}, r_{m,t}, p_{m,t}$, farmers condition their expectations of future payoffs on eu_t, as the policy state could imply a different evolution of equilibrium prices.

Farmer Beliefs I assume that farmers have rational beliefs about the evolution of $a_{m,t}, r_{m,t}$, and $p_{m,t}$ and experience a change in eu_t as an unforecasted shock. Farmers believe marginal cost shocks and rainfall evolve according to distinct AR(1) processes $F_a(a_{m,t+1}|a_{m,t})$ and $F_r(r_{m,t+1}|r_{m,t})$. These reflect, on average, the "true" evolutions of these state variables.

Following Lee (2013), I assume a parametric form for farmers' beliefs about how equilibrium prices evolve. In particular, farmers believe equilibrium prices evolve in a manner correlated with marginal costs and rainfall as follows:

$$p_{m,t+1} = \lambda_{1,m} p_{m,t} + \lambda_{2,m} eu_t \times p_{m,t} + \lambda_{3,m} a_{m,t+1} + \lambda_{4,m} r_{m,t+1} + \eta_{m,t} \tag{13}$$

where η_t is an iid random variable with mean zero and with a variance reflecting uncertainty in agent beliefs. The variance of $\eta_{m,t}$ captures some of the variation in equilibrium prices caused by variables in the market state variables s_t but not the farmer state variables $\tilde{s}_t$ (e.g., demand shifters $p_t^{soy}, d_{m,t}$). Including the EU indicator eu_t allows the mean of expected prices to differ pre- and post-EU trade policy. I include market subscripts in the belief parameters $\lambda_{1,m}, \lambda_{2,m}, \lambda_{3,m}, \lambda_{4,m}$ to reflect that they can differ across markets and equilibria.

$E[p_{m,t+1}] = \lambda_{1,m} p_{m,t} + \lambda_{2,m} eu_t \times p_{m,t} + \lambda_{3,m} a_{m,t+1} + \lambda_{4,m} r_{m,t+1}$ is the agents' expected next period price. These beliefs are consistent with the actual evolution of price but may not necessarily be consistent with the underlying static equilibrium model determining prices (the errors are not necessarily independent). They also reflect that farmers' realization that rainfall and costs will affect prices. Assuming that the EU policy occurs as a surprise to farmers means that they do not have expectations over its evolution and play different equilibria under $eu_t = 0$ and $eu_t = 1$.

Combining beliefs about $a_{m,t}, r_{m,t}, p_{m,t}$, farmers believe that their payoff-relevant variables $\tilde{s}_{m,t} = \{p_{m,t}, a_{m,t}, r_{m,t}, eu_{m,t}\}$ evolve as follows:

$$F_{\tilde{s}}(\tilde{s}_{m,t+1}|\tilde{s}_{m,t}) = F_r(r_{m,t+1}|r_{m,t}) \times F_a(a_{m,t+1}|a_{m,t}) \times F_\eta(p_{m,t+1}|p_{m,t}, eu_t, r_{m,t}, a_{m,t}) \tag{14}$$

Farmer Value Function Since $\tilde{s}_{m,t}$ determines farmer payoffs and farmers hold beliefs over only variables in $\tilde{s}_{m,t}$, I define an incumbent type f farmer's expected discounted flow payoffs as a function of $\tilde{s}_{m,t}$:

$$V^f(\tilde{s}_{m,t}) = \pi_{imt}(\tilde{s}_{m,t}) + \mathbb{E}_\phi\left[max\left\{\delta\phi^f_{it}, VC^f(\tilde{s}_{m,t})\right\}\right] \tag{15}$$

where δ is the discount rate and the continuation value $VC^f(\tilde{s}_{m,t})$ is:

$$VC^f(\tilde{s}_{m,t}) = \delta \sum_{\tilde{s}_{m,t+1}} V^f(\tilde{s}_{m,t+1})P(\tilde{s}_{m,t+1}|\tilde{s}_{m,t}) \tag{16}$$

Similarly, since a potential entrant enters if $VC^f(\tilde{s}_{m,t}) \geq \kappa^f_{jt}$, the entrant's discounted flow payoff is:

$$max\{VC^f(\tilde{s}_{m,t}) - \kappa^f_{jt}, 0\} \tag{17}$$

where κ^f is that entrant's idiosyncratic entry cost.

Equilibrium The relevant equilibrium concept is First Order Markov Perfect with additional restrictions on farmer beliefs. This means that in equilibrium, omitting the farm type superscript f:

1. Farmers are playing optimal entry and exit strategies given their beliefs over the evolution of $\tilde{s}_t$.

2. Farmer beliefs over the evolution of $\tilde{s}_t$ are on average consistent with the true first-order Markov evolution of s_t (i.e., on average correct about the evolution of prices, marginal cost, and rainfall implied by the evolution of the market state space).

Computing an equilibrium requires iterating between the policy functions implied by agent beliefs over the evolution of $\tilde{s}_t$ and the implied total palm oil land and equilibrium prices until beliefs about the evolution of prices are on average correct about the evolution of prices consistent with farmer entry and exit behavior. I provide a fixed-point algorithm for computing an equilibrium of this game in Appendix B.

6 Estimation and Identification

Estimating the key parameters of the model takes place in two stages. First, I estimate the parameters underlying aggregate supply and demand. These allow me to predict farmer payoffs in different states of the world. Second, using the payoffs recovered in stage 1, I use a method of simulated moments to estimate parameters of the scrap value and entry cost distributions. I rely on panel variation in my data across regions and over time to identify my key parameters.

6.1 Static Payoffs

I modify the market-specific aggregate supply in equation 7 and aggregate demand in equation 8 to generate estimation equations that allow me to use panel variation to identify $\alpha_1, \alpha_2, \beta_1, \beta_2$ as follows:

$$\text{Supply: } \ln(Q_{mt'}/\tau_{mt'}) = \alpha_1 \ln(p_{mt'}) + \beta_1 \ln r_{1,mt'} + \boldsymbol{\gamma}_{1,t'} + \boldsymbol{I}_{1,m} + \epsilon_{1,mt'} \tag{18}$$

$$\text{Demand: } \ln(Q_{mt'}) = \alpha_2 \ln(p_{mt'}) + \beta_2 \ln p^{soy}_{m,t'} + \boldsymbol{\gamma}_{2,t'} + \boldsymbol{I}_{2,m} + \epsilon_{2,mt'} \tag{19}$$

where m indexes the market or region, t' indexes months, $\boldsymbol{\gamma}_{1,t'}, \boldsymbol{\gamma}_{2,t'}$ are month fixed effects, and $\boldsymbol{I}_{1,m}, \boldsymbol{I}_{2,m}$ are region fixed effects. Equation 18 estimates output per hectare and assumes that prices and rainfall have the same effect on yield supplied across regions and months but that there are different average cost shocks by month and region. This comes from the modeling assumption that production on each hectare of land is the same in each region.

Similarly, equation 19 assumes that prices and soy prices have the same effect on quantity demanded across regions and months but that there are different average demand shocks by month and region. This reflects that global soy prices affect each region similarly. The month fixed effects in both equations control for seasonality. $\epsilon_{1,mt'}$ and $\epsilon_{2,mt'}$ capture the variance in cost and demand shocks, respectively.

Given estimates of the supply and demand parameters, I can calculate the equilibrium prices and quantities corresponding to each market state s_t by solving the system of equations. Substituting prices and quantities into the farmer payoff equation 1 yields farmer payoffs by month for each state s_t. I sum over months to calculate annual farmer payoffs $\pi(s_t)$ as a function of s_t.

Identification Since quantities and prices are jointly set in equilibrium each month, I use instrumental variables to identify the price coefficients in equations 18 and 19. In the supply equation 18, I use monthly rainfall in large soybean producing countries (i.e., US and Brazil) as instruments. Rainfall in the US and Brazil exogenously affects palm oil demand by shifting the price of palm oil's closest substitute. More rainfall, barring extremely heavy rain, correlates with more soy supply, lower soy prices, and less demand for palm oil.

Observing yields, prices, and rainfall at a monthly frequency helps me identify the short-run, intensive margin elasticity of production α_1 because only intensive margin effort $e_{j,m,t}$ can adjust in the monthly static game but total productive land $\tau_{m,t}$ is fixed. By instrumenting for prices with monthly rainfall in soybean producing countries, I identify α_1 using only variation in stochastic, monthly shifts of demand. This excludes variation in total quantity due to the extensive margin $\tau_{m,t}$ that adjusts over longer periods of time.

In demand equation 19, soybean oil prices are potentially endogenous in addition to palm oil prices because palm and soy being close substitutes means prices of both oils are highly correlated. Consequently, I use monthly regional Malaysian rainfall as an additional instrument to identify the palm oil price coefficient and US and Brazilian rainfall to identify the soybean oil price coefficient. Rainfall serves as a supply shifter independent of demand for both types of oils.

6.2 Dynamic Parameters

I use a 2-step method to estimate $\boldsymbol{\theta} = (\boldsymbol{\mu_\phi}, \boldsymbol{\mu_\kappa})$, where $\boldsymbol{\mu_\phi}$ is a vector of parameters characterizing distinct exponential distributions from which each type of incumbent farmer draws scrap values and $\boldsymbol{\mu_\kappa}$ is a vector of parameters characterizing distinct exponential distributions from which each type of potential entrant farmer draws entry costs. I currently assume that $\boldsymbol{\mu_\phi} = \{\mu_\phi^{large}, \mu_\phi^{small}\}$ where μ_ϕ^{large} and μ_ϕ^{small} are the mean parameters of the two different exponential distributions for each farmer type. Similarly, $\boldsymbol{\mu_\kappa} = \{\mu_\kappa^{large}, \mu_\kappa^{small}\}$ where the elements are again two mean parameters corresponding to different farmer types. This parametrization assumes that different farmer types have different entry costs and scrap values but that the unconditional distributions of possible entry costs and scrap values remain the same across markets and time periods. Under this assumption, the main rationalization for different rates

of entry and exit across markets comes from differences in static supply and demand conditions.

One justification for assuming stationary distributions over time would be that changes in the oil palm market have negligible effects on the overall value distributions of alternative palm oil land uses (by the same farmer or a potential purchaser) as well as land that can potentially be used to grow palm oil. Palm oil prices having negligible effects on these distributions is plausible if: (i) palm oil land plays a small role in overall land markets, and (ii) oil palm farmers interact with these broader markets and predominantly buy from and sell to agents who do not grow oil palm trees consistently pre- and post-EU policy. Point (i) is plausible given that oil palm plantations do not make up the majority of land area in any state in Malaysia. In most states (except Johor, Melaka, and Negeri Sembilan), the fraction of total land area dedicated to oil palm is consistently below 20%. As such, moderate changes in the value of oil palm land from changes in palm oil prices could be overwhelmed by random larger variation or uncertainty in land prices from year to year. Point (ii) is difficult to test directly without data on the universe of related land transactions. However, there is anecdotal evidence of oil palm farms increasingly being converted to coconut oil and fruit farms (e.g., durian for export to China). Data on other crops from the Malaysian Ministry of Primary Industries also indicate that the slowdown in palm oil expansion post-2017 coincides with expansions of coconut, flower, and fruit production across various regions. This is suggestive of the relevant outside options being to grow different crops on the same land or to sell to farmers growing other crops. Similarly, expansion of palm oil correlates with reductions in rubber plantation areas both before and after the policy, which suggests that other types of agricultural land are being converted into oil palm land.[12] I explore relaxing the stationary distributions assumption in Appendix D.

Similar to the CCP methods described in Hotz et al. (1994), I first calculate payoffs as a function of the farmer state space $\tilde{s}_t$ and estimate farmers' believed transition probabilities of $\tilde{s}_t$ using data. I specify that the transition probabilities are "farmers' believed transition probabilities" because I use equation 13, which parametrizes farmers' beliefs over the evolution of equilibrium prices, to calculate price transition probabilities. Taking the payoffs and transitions over $\tilde{s}_t$, I recover continuation values for guesses of $\boldsymbol{\theta}$, use these continuation values to simulate land totals by farmer type over time and for each region, and match these simulated

[12] I am also currently implementing a robustness test that will allow the distributions to shift post-policy to reflect how the changes in equilibrium prices may have shifted land prices.

land totals and changes to those observed in the data. This differs from Hotz et al. (1994) and Scott (2014) estimation techniques in its application to aggregate data. Appendix C fully details the estimation process.

The advantage of using the farmer state space over the market state space is that equilibrium prices are more likely to be bounded than total land and demand in a growing industry. In particular, increases in equilibrium prices resulting from increases in demand are likely to correlate with expansions in land which increases supply and limits the equilibrium price increase. The opposite also applies to decreases in demand and decreases in supply limiting the extent to which equilibrium prices will fall over time. With respect to palm oil, Figure 3a shows that prices generally fluctuate within the same range even when land and supply are generally expanding in most regions (Figures 2 and 7).

Identification Parameters $\boldsymbol{\theta}$ are identified by variation in land flows by farm type across regions over time and the functional form assumption restricting the supports of both the entry cost and scrap value distributions to be non-negative. The net land changes across all regions by farm type will identify either the mean of the relevant scrap value distribution or the mean of the relevant entry cost distribution. I can separately identify scrap value and entry cost means because I observe both net decreases and net increases across regions for each farm type. Intuitively, the difference in scrap value and entry cost means acts as a variance term for the dispersion in positive and negative net land changes observed across regions.

I use the following instruments to generate moments to identify the four parameters in $\boldsymbol{\theta}$: 1) constant, 2) marginal cost and rainfall supply shocks, and 3) regional demand shocks. The supply-side and demand shocks correlate with variation in static payoffs by state and emphasize changes in land flows due to either increases or decreases in payoffs. These instruments are plausibly uncorrelated with land-use decisions other than through affecting static profits.

7 Results

7.1 Aggregate Supply and Demand

Table 5 displays the estimated aggregate demand and supply parameters. Column 1 shows that short-run FFB demand slopes downward with respect to FFB prices and is increasing in the

price of soybean oil. The latter is consistent with soybean oil being a close substitute for palm oil. Column 2 shows that short-run FFB supply is upward sloping with respect to price and increasing in the amount of rainfall. The estimated price coefficients indicate that short-run supply is much more price-inelastic relative to demand. This is consistent with the observation that farmers have little short-run control over monthly yield. They can only pick FFB that are already ripe, as unripe FFB do not produce oil. Moreover, failing to pick ripe fruit harms the tree's ability to produce more fruit, and disposing of picked FFB (instead of transporting and selling them to a mill) can be costly.

State Variables Using the estimated supply and demand parameters, I recover the demand shocks and supply shocks implied by the residuals and fixed effects in equations 19 and 18, respectively. Examining the residuals confirms that inward shifts of the demand curve correlate with the slowdown in land expansion across regions. Figure 8 shows demand shocks averaged across all regions on Peninsular Malaysia and Sabah/Sarawak with linear trends for years up to 2016 (i.e., before the policy announcement) and 2017 onwards (i.e., after the policy announcement). These trends indicate that demand expanded on average prior to 2017 and contracted post-2017. Demand contracted more severely in Sabah/Sarawak compared to Peninsular Malaysia. This helps rationalize why, as shown in Figures 2 and 7, the relative slowdown in land expansion in Sabah/Sarawak post-policy was more pronounced.

Furthermore, contrasting the evolution of demand shocks with the other state variables helps motivate contractions in demand correlated with the EU policy as a main reason behind the slowdown in land expansion. Figure 6 displays trends in observed FFB prices and highly correlated CPO realized and future prices[13] pre- and post-2017. Notably, the break in trend for the demand shocks explains the break in equilibrium price trends; decreased demand would decrease equilibrium prices. Trends in the other exogenous state variables shown in Figure 9 imply potentially offsetting effects. The continued decrease in soybean oil prices would have caused decreases in equilibrium prices even prior to 2017 by decreasing downstream palm oil demand. Decreasing average annual rainfall would imply decreasing yields over time, a contraction in supply as reflected in the positive coefficient on rainfall in Table 5, and correspondingly higher equilibrium prices after the EU policy. Decreasing marginal costs (increasing supply

[13]For years affected by the pandemic

shocks) would have increased supply and decreased prices consistently both before and after 2017, failing to explain the trend break observed in the data.

Payoffs Using all the state variables (demand shocks, marginal cost supply shocks, rainfall, soy prices, and total land), I can predict equilibrium prices and profits over time. In Figure 10, I compare the average prices in Peninsular Malaysia and Sabah/Sarawak observed in my data to those implied by my parameter estimates. The predicted equilibrium prices generally match those observed. Figure 11 shows the equilibrium profits corresponding to the predicted equilibrium prices. Average predicted profits after 2017 are lower than those before 2017 in Peninsular Malaysia and Sabah/Sarawak. In particular, mean profits per hectare decrease by $34.58 USD per month in Sabah/Sarawak and by $8.85 USD per month in Peninsular Malaysia. These amounts are potentially nontrivial relative to Malaysia's mean monthly income ($929 USD) and monthly poverty line ($508), given that the average smallholding has about 4 hectares (10 acres) of land. I discuss how estimating different static marginal costs for smallholders and large estates would not change these much in Appendix A.

7.2 Entry Costs and Scrap Values

Table 6 shows the parameters defining the exponential distributions for entry costs and scrap values separately for each type of farm. These parameters represent the means of unconditional distributions. The magnitudes of entry cost mean parameters are usually large in the literature. That the mean of the smallholder entry cost distribution is larger than that of the large estate distribution reflects how independent smallholders have more limited access to land clearing and planting technology. They cannot afford the machines or services generally available to large estates. The scrap value means are much smaller than the entry cost means, which is consistent with the alternative uses for oil palm land being relatively limited across both types. Smallholders facing much lower scrap values than large estates reflects how there are fewer productive alternative uses (e.g., crops that are sufficiently high yield per acre) for small farms than large ones.

I solve the dynamic model using these estimated parameters and estimated AR(1) processes of the exogenous state variables to recover farm continuation values by type. Using the continuation values consistent with my estimated parameter values, I can recover the conditional

expected values of the scrap values and entry costs for both farm types in states of the world observed in my data. I call these conditional expected values because they are the expected values, conditional on a firm finding either market entry or market exit optimal. Figure 12 shows the conditional expected scrap and entry costs paid and received, respectively, for both types of farms. I obtain confidential oil palm land valuations from a company with land across multiple regions (Sabah, Negeri Sembilan, and Selangor) in Malaysia. Reported farm land valuations range from roughly 59,000 RM per hectare to 3.26 million RM per hectare. While I do not explicitly model land valuations, these are related to entry costs and scrap values in that buying or selling farm land are ways of "entering" or "exiting" the market. These valuations are similar in magnitude to the conditional expected values I recover but not perfectly overlapping because my estimates also (i) implicitly include discounted flows of annual fixed costs (which I cannot separately identify) and (ii) do not include standard deviations of the conditional means.

Since the market state space includes regimes with and without the negative demand shocks correlated with the EU trade policy, I can calculate how much the policy impacted continuation values. Table 7 shows the average change in continuation value (Avg. Δ Payoffs) per hectare of oil palm land by farm type pre- and post-EU policy, weighted by internal margin land use. Consistent with smallholders having worse outside options, as reflected in a lower scrap value distribution mean, they experience a greater average decrease in continuation value relative to large estates. In fact, the average change in ΔVC for large estates is positive because markets in which equilibrium prices increase from lower aggregate supply expansion have more large estates.

Appendix E discusses model fit at the estimated parameters. The parameters fit the evolution of land better in some regions than others since I currently assume that all farmers in all regions draw from common distributions.

8 Counterfactuals

Explicitly modeling entry and exit decisions enables me to predict farm profit evolution consistent with long-run changes in the extensive margins of oil palm cultivation. I use my estimates and model to explore three counterfactuals: (i) the EU policy's differential effects across farm

types, (ii) how the EU policy compares to more targeted alternatives, and (iii) how the EU policy compares to allowing supplier quantity coordination.

For targeted policies, I compare the EU policy to a per-unit fresh fruit bunch (FFB) tax on large estates only and to a farm type-specific Pigovian tax on extensive margin expansion. The targeted FFB tax that achieves the same extensive margin reduction as the EU policy preserves substantially more primary forest than the EU policy. However, both policies preserve far less primary forest than the Pigovian tax, while quantity coordination leads to even greater forest preservation than the Pigovian tax.

These policies also generate different distributions of winners and losers among farmers, pointing to distinct political economy tradeoffs. The EU trade restriction requires no cooperation from upstream exporters but yields the smallest deforestation reduction. The targeted per-unit and Pigovian taxes require Malaysian government support and enforcement as well as backing from different farm interest groups. Since these policies target larger estates more heavily—reflecting the higher correlation between large estate expansion and deforestation—they create incentives for large estates and potentially the Malaysian government to oppose implementation when losses are sufficiently large. Conversely, producer quantity coordination benefits both producer groups but may generate opposition from importing countries.

EU Trade Restriction Table 7 describes the impacts of the EU policy on total oil palm land and long-run discounted payoffs on the internal and external margins. I compare the change in the demand shock AR(1) process correlated with the start of the EU policy to a counterfactual in which there is no change in the AR(1) process in 2017. With respect to total land, I find that the EU policy decreased the expansion of oil palm land by 214 hectares from 2017 to 2019. Smallholders account for 345 hectares of the reduction. In contrast, large estates actually expanded in total land area (aggregated across all regional markets) relative to the counterfactual in which there is no EU policy.[14] This counterfactual increase exists due to decreased levels of smallholder land expansion being large enough to increase counterfactual equilibrium prices, and increased large estate expansion being consistent with entrants still benefiting from counterfactually higher equilibrium prices. Since large estates face much lower entry costs on average, entry can still be optimal for them under equilibrium prices that make

[14] Appendix F discusses how smallholder and large estate shares of land evolve over a longer time horizon.

entry non-optimal for smallholders. This drives the compositional shift toward having more large estates under the EU shocks relative to the counterfactual.

On both the extensive and intensive margins, smallholders face net losses while large estates experience net gains in discounted flow payoffs. Table 7 shows that smallholders faced $44.6 million USD in extensive margin losses and $73.6 million USD in intensive margin losses. Large estates gained $14.5 million USD from the extensive margin and $85.4 million from the intensive margin. These differences are driven by large estates benefiting from higher equilibrium prices under the EU policy shocks in some regions and large estates drawing from a higher scrap value distribution. The latter moderates how much decreases in equilibrium prices can decrease large estate expected flow payoffs, as the scrap value serves as a lower bound for flow payoffs. As such, the increases in discounted flow payoffs in regions with extensive margin expansion outweigh any decreases in regions with extensive margin contraction.

Since the primary stated motivation of the EU policy is to limit deforestation, I also use these counterfactual results to predict how much of the decrease in primary forest loss is associated with the decrease in oil palm land expansion. A decrease in oil palm land expansion does not translate one-to-one into primary forest preserved, because there are other secondary causes of deforestation, such as smaller-scale agriculture and industrial construction. Moreover, entry into oil palm can also include converting already-cleared land previously used for other purposes. I focus on primary forests, because the Landsat images (Hansen et al., 2013) underlying the Global Forest Watch data on forest cover that I use for this exercise sometimes misclassify tree crops as secondary forest (Sandker et al., 2021; Tropek et al., 2014). The Global Forest Watch defines primary forest as forest with little to no human interference and continuous tree cover. They are especially carbon-rich, and clearing these forests plays a greater role in releasing carbon and limiting future carbon storage relative to the clearing of secondary forest.

In order to conduct this exercise, I use the results in Table 2 to project changes in primary forest cover by region onto changes in the total oil palm area farmed by large estates and smallholders. The changes in primary forest reported in Table 7 utilize specification (1) of Table 2. Consistent with how large estates have access to more efficient land-clearing technologies, the projection indicates that expansion in smallholder land leads to (much) less primary forest loss than expansion in large estate land. As a result, the expansion of large estate oil palm land

area offsets most of the increase in primary forest area that decreased smallholder expansion generates.

I discuss in Appendix H in further detail how allowing for heterogeneous farmers, compared to assuming homogeneous farmers, changes predictions about the effectiveness of coarse trade policy in reducing deforestation beyond the distributional effects.

Targeted Taxes The ideal policy in this setting would be to impose a Pigovian tax on each type of farmer that internalizes their associated social cost of deforestation. I calculate the social cost of deforestation from oil palm land expansion as the social cost of carbon emissions correlated with extensive margin expansion by each farm type using data on carbon emissions associated with deforestation from Global Forest Watch (2025). I use a social cost of carbon from the Biden Presidential administration of $51 per metric ton (U.S. Interagency Working Group on Social Cost of Greenhouse Gases, 2021). I find that each hectare of large estate expansion releases on average 1,217 metric tons of CO2 and each hectare of smallholder expansion releases an average of 48.5 metric tons. I then add these costs to the entry costs faced by each farm type. The third panel of Table 7 shows the results of this exercise. Using this policy as the "first-best" benchmark, the EU trade restriction generates 0.2% of the socially optimal reduction in deforestation by allowing expansion by large estates with a higher propensity to deforest at the expense of smallholders.

While intensive margin farmers may support this tax if they do not wish to expand, large estates have a strong incentive to arbitrage land expansion with smallholders to avoid significantly higher taxes implied by this policy. If implementable, the targeted Pigovian tax would generate $34.7 million USD in tax revenue from smallholders and $1.697 billion USD in tax revenue from large estates from 2017 to 2019. In particular, large estates have incentives to pay smallholders to expand first and then purchase the cleared land from them to avoid the tax. They could even provide smallholders with better land-clearing technologies, potentially worsening the deforestation associated with smallholder expansion in the process.

An alternative targeted tax that may provide fewer opportunities for arbitrage would be a targeted per-unit FFB tax on large estates. Large estates, aggregating across hectares of land, produce much more than smallholders. They also aggregate outputs across their own properties into shipments to mills, unlike smallholders who rely on middlemen for aggregation.

These market characteristics make it more difficult for large estates to pool significant amounts of their FFB with those from smallholders to avoid the tax, making this tax potentially more enforceable than the Pigovian tax.[15] In panel 2 of Table 7, I show results from a 0.9% per-unit targeted tax on large estates. I chose this tax to approximately reduce extensive margin expansion by as much as the EU policy.

Reflecting large estates' greater propensities to deforest, I find that this tax also leads to much more primary forest preserved than the EU trade restrictions.[16] Contrasting with the EU policy, this tax is indirectly "redistributive" in favor of smallholders. Smallholders on the intensive margin benefit from higher equilibrium prices from decreased aggregate supply, also increasing continuation values aggregated on the intensive margin. On the extensive margin, smallholders as a group benefit from increased participation and slightly higher equilibrium prices from decreased aggregate supply, leading them to experience a $2.9 million USD increase in continuation values aggregated on the extensive margin and a $7.4 million increase on the intensive margin.

While the per-unit targeted tax may be easier to enforce and can help address exporter country distributional concerns, it still leads to total losses in discounted flow payoffs on both the external and internal margins. The targeted per-unit tax generates $193 million USD in discounted flow tax revenues, which is insufficient to offset large estate losses. Consequently, an exporter country may be unlikely to independently levy such a tax. One way foreign intervention can help achieve such a tax domestically is with the threat of a trade restriction. However, the EU policy shocks I estimate are not large enough to be a credible threat to incentivize the Malaysian government to adopt a domestic tax. Faced with the choice between a credibly large trade restriction and implementing a domestic targeted tax achieving the same reduction in deforestation, Malaysia may have incentives to implement the tax, since the tax leads to lower total industry-wide losses.

[15] Notably, I also consider a targeted domestic per-unit tax instead of targeted export or import restrictions because of the intermediate step in production between farming and exporting. Both smallholders and large estates sell to the same sets of mills, and this makes the exported oil a combination of oil palm from different types of farms. As a result, at the point of export, it is not possible to trace the upstream farm origins of the oil and accordingly enforce a penalty targeted at large estates. Since a tax would need to be levied on downstream firms, those firms have an incentive to lie about the origins of their inputs to avoid an import or export tax. This market structure also makes certification schemes imposed by the EU but directed at large estates difficult to implement because it is hard to credibly trace from which farms the oil comes.

[16] Appendix G discusses the projections for the other two specifications in Table 2.

Quantity Coordination Given the potential political economy limitations of targeted taxes, I also consider a policy counterfactual in which a trade organization acts as a monopolist in setting prices for each region. One possible motivation behind the EU policy is that it is not incentive compatible for palm oil producer countries to independently curb deforestation, and that the threat of environmentally motivated trade restrictions alone has not been sufficient to incentivize exporter countries to reduce deforestation by socially optimal amounts. Even if a targeted tax could increase total payoffs, groups or types (i.e., large estates) harmed by a targeted domestic policy still have strong incentives to block the policy from being implemented.

Allowing for more market power among upstream producers could theoretically address the incentive compatibility concern across all types of farmers. Allowing suppliers to act like monopolists gives them incentives to curb quantity to increase prices, and all farmers would benefit from higher equilibrium prices (holding all else constant). Limiting oil palm land expansion, which directly limits deforestation, is a direct way to restrict quantity. As such, I consider the counterfactual scenario under which a trade organization controls how much additional land, if any, to devote to oil palm. I limit my counterfactual to producers jointly limiting quantity via coordination on the external margin, because farmer effort is generally non-observable and non-contractible. Consequently, yield per hectare cannot be specified, but the number of hectares made available to farmers can be specified.

Notably, Indonesia and Malaysia have tried to start various trade organizations in the past. In 2015, they formed the Council of Palm Oil Producing Countries (CPOPC) with the original goal of "organizing and harmonizing stock management" (*Indonesia, Malaysia form OPEC-like palm oil council*, 2015). However, CPOPC's purpose evolved to mainly be countering the EU's trade restriction against palm oil, and there were renewed calls for an organization capable of stock management and price maintenance in 2019. At that time, the Malaysian Sustainable Palm Oil council (MSPO) was "in favor" of forming a body similar to OPEC for palm oil (Tan, 2019).

For this counterfactual, I use a stylized modification of my original model to examine what could have happened if CPOPC had succeeded in its original purpose. I call the Malaysian branch of this organization the MSPO. I assume that farmers can leave freely and make individual exit decisions. However, the MSPO decides how much potential entry to allow each

period and grants land rights to new entrants. I assume that the farmers granted entry face the entry cost distribution of large estates. This is realistic in that a trade organization could help provide cheaper entry technologies to smallholders as in the case of Federal Land Development Authority (FELDA), Federal Land Consolidation and Rehabilitation Authority (FELCRA), and the Rubber Industry Smallholders Development Authority (RISDA). In particular, the MSPO chooses potential entry area $\Delta\tau_{m,t}^{MSPO}$ to maximize the total expected flow payoffs in each regional market, excluding scrap values, of all active farmers:

$$\Delta\tau_{m,t}^{MSPO} = \underset{\Delta\tau}{argmax}\{\delta \sum_{s_{m,t+1}} V^{MSPO}(s_{m,t})P(s_{m,t+1}|s_{m,t}, \Delta\tau) + \omega_{\Delta\tau,m,t}\}_{\boldsymbol{\Delta_\tau}} \tag{20}$$

where $\boldsymbol{\Delta_\tau}$ is the set of all possible values of Δ_τ. $\omega_{\Delta\tau,m,t}$ is a random variable distributed Type I Extreme Value that is observed by the MSPO but not the econometrician. It can be interpreted as an exogenous shock or noise to flow payoffs that the MSPO privately observes. Following Rust, I assume the distribution is mean zero and normalize the variance to 1. Note that farmer decisions to enter and exit are still private and independent. I define the MSPO continuation value that it uses to determine how much land to open to potential entry as follows:

$$V^{MSPO}(s_{m,t}) = \tau_{m,t} \times \pi(s_{m,t}) + \underset{\Delta\tau}{max}\boldsymbol{E}\left[\delta \sum_{s_{m,t+1}} V^{MSPO}(s_{m,t})P(s_{mt+1}|s_{m,t}, \Delta\tau_{m,t}^{MSPO}) + \omega_{\Delta\tau,m,t}\right]$$

As members of the MSPO, individual farmers decide whether to exit or stay in each period simultaneously while farmers granted production rights by the MSPO decide on entry. They only keep track of state variables $\tilde{s}_t$. I assume that farmer beliefs over how $\tilde{s}_t$ evolves are still as in equation 13. I further assume that the MSPO forms beliefs over the evolution of all variables in the original state space s_t and conditions these beliefs on the current state and how much potential entry it chooses to allow each period.[17]

Table 8 displays the results of this counterfactual exercise for two different possible demand elasticities. I report results for both my estimated elasticity of demand and an elasticity of demand derived from those found in Hsiao (2020). For the MSPO counterfactual, I interpret the results using the estimated demand elasticity from this paper as an upper bound of possible

[17]I impose a maximum amount of total oil palm land that the MSPO is allowed to consider to address stationarity.

discounted long-run payoffs from production entry coordination. One way to interpret the elasticity I estimate in this paper is as holding the fractions of total global demand from Malaysia versus Indonesia and palm oil relative to other seed oils constant. Shares between Malaysia and Indonesia remaining constant is plausible if Malaysia successfully coordinates with Indonesia such that Indonesia also curbs expansion and they agree to keep their relative shares of global demand constant. It is also plausible for smaller deviations in Malaysia's equilibrium price from the observed competitive equilibrium, as Indonesian producers are less likely to react to these changes (relative to how they respond under Malaysia's perfectly competitive equilibrium). However, under larger deviations in long-run prices from the observed competitive equilibrium and continued competition with Indonesia, demand for Malaysian palm oil is likely to become more elastic as Indonesian farmers start to adjust their quantities (and prices) to respond to greatly restricted Malaysian supply and much higher Malaysian prices. I find under my estimated elasticity large increases in total long-run intensive margin discounted flow payoffs across both types of farmers relative to the EU trade restriction and the targeted tax policies I examine.

Since the fraction of imports of palm oil going to each consumer region (e.g., China, India, EU) is very stable from 2006 to 2017, I use these to take the weighted average of the regional elasticities Hsiao (2020) estimates to address concerns about substituting to other oils. I then plug this elasticity into my constant-elasticity demand function and recalculate my counterfactuals to see if the qualitative result I predict with my own estimated elasticity is robust under a much more elastic demand curve. Even allowing for a much higher elasticity of demand, I find positive gains, aggregated across the intensive margin, across both types of farmers. These gains are also higher than those in the EU trade restriction and the targeted tax policies I examine. While payoffs to Indonesia are outside the scope of this paper, this suggests that Indonesia could also receive large payoff increases from supply coordination, given the similarity in supply-side processes across both countries and the low world substitution from oil palm to other seed oils. As such, a counterfactual assuming shares between Malaysia and Indonesia remain constant is still potentially informative of gains to coordination.

The external margin shows that the decrease in deforestation is much higher because MSPO acting as a monopolist does not want any further land expansion post-2017 beyond 2017 levels.

Cutting off all future land expansion also explains the large external margin losses. These results support the potential of allowing for an OPEC-like organization to be supported by incumbent Malaysian farmers. Assuming that potential entrants are not a coherent group, which seems realistic given that there are no major firms trying to enter the oil palm industry, this support by incumbent farmers could translate into policy implementation. Notably, supply coordination achieves a much larger reduction in deforestation than what may be social optimal, indicating a drawback to this policy.

9 Discussion

Deforestation and climate change are pressing issues requiring careful consideration of policy design, particularly when market-level environmental policies face within-market leakage from firm heterogeneity. This paper demonstrates how competing producer types can undermine the effectiveness of broad-based policies like the EU palm oil trade restriction through equilibrium price effects that incentivize offsetting behavior.

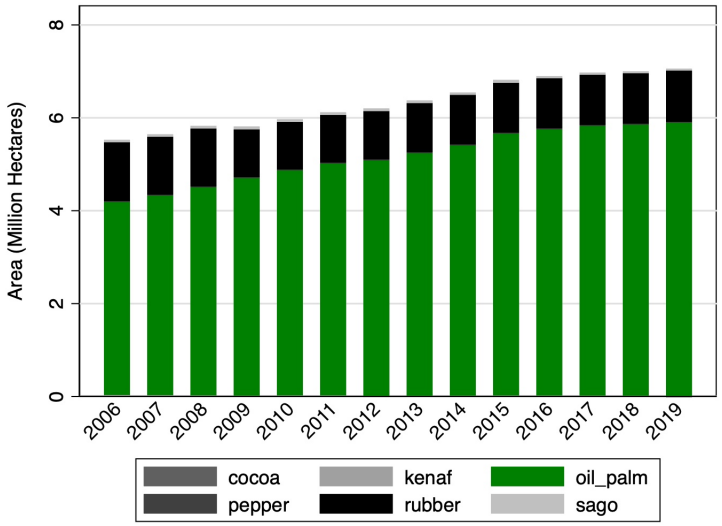
My analysis reveals that large estate expansion substantially offsets deforestation reductions achieved through decreased smallholder participation under the EU policy. Counterfactual exercises show that while targeted policies—such as per-unit taxes on large estates or Pigovian taxes on extensive margin expansion—would preserve significantly more primary forest than the EU restriction, they face substantial political economy constraints. These targeted policies impose large losses on large estates, which may have greater resources to wield political influence, potentially explaining why such policies have not been implemented in producer countries despite their superior environmental outcomes.

However, I find that sanctioning supplier quantity coordination emerges as a potentially superior alternative that aligns environmental and producer interests. Counter to the general intuition that firms use market power to circumvent environmental compliance (e.g., Ziady, 2021), allowing producers to form an OPEC-like organization that controls quantities by limiting entry could simultaneously reduce deforestation while increasing payoffs for both smallholders and large estates. This finding suggests that in markets with heterogeneous producers and environmental externalities, carefully designed coordination mechanisms may offer a path toward policies that are both environmentally effective and politically feasible—addressing the dual

challenges of within-market leakage and political opposition that plague current approaches.

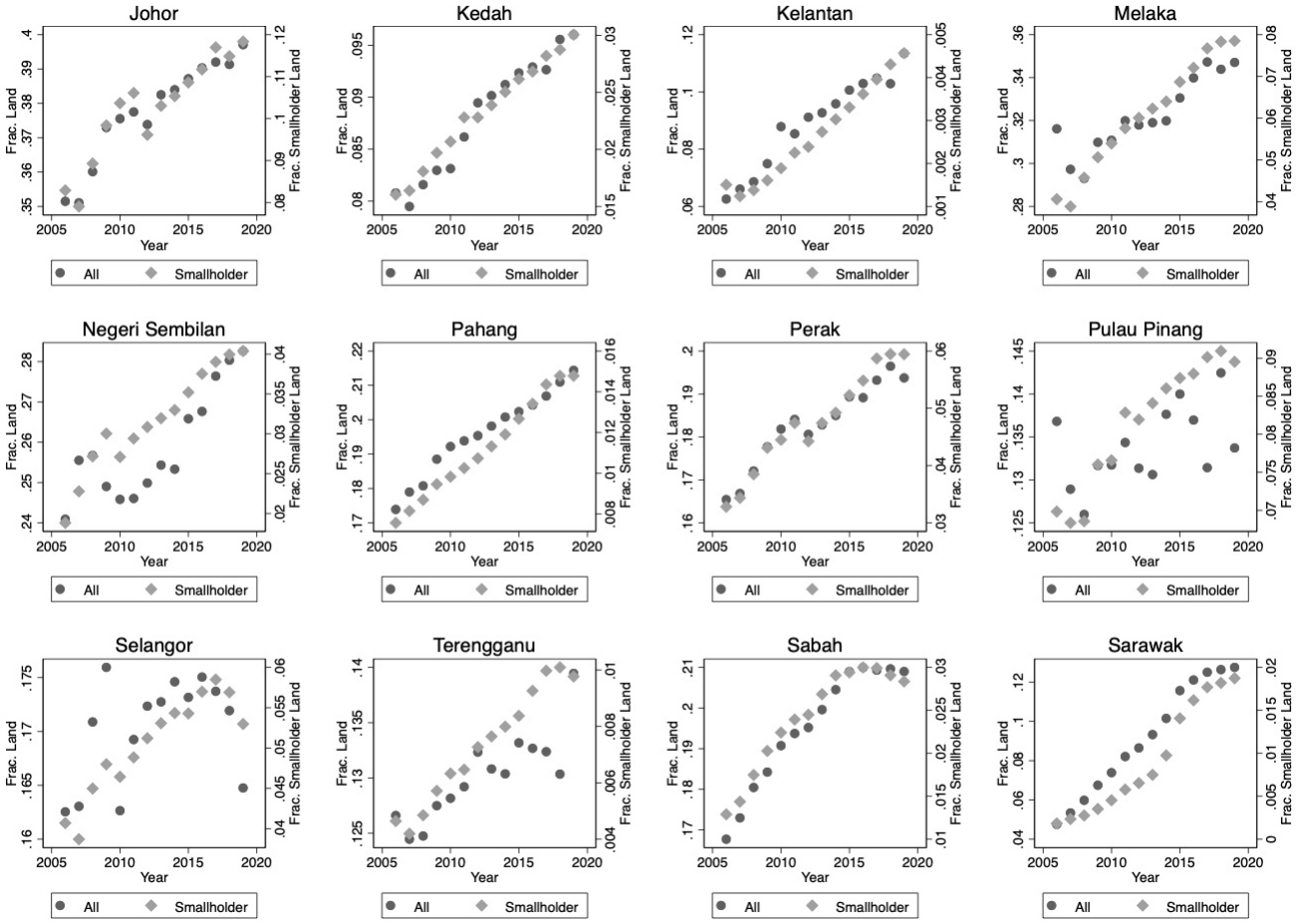
10 Figures

Figure 1: Malaysia's Main Commercial Crops



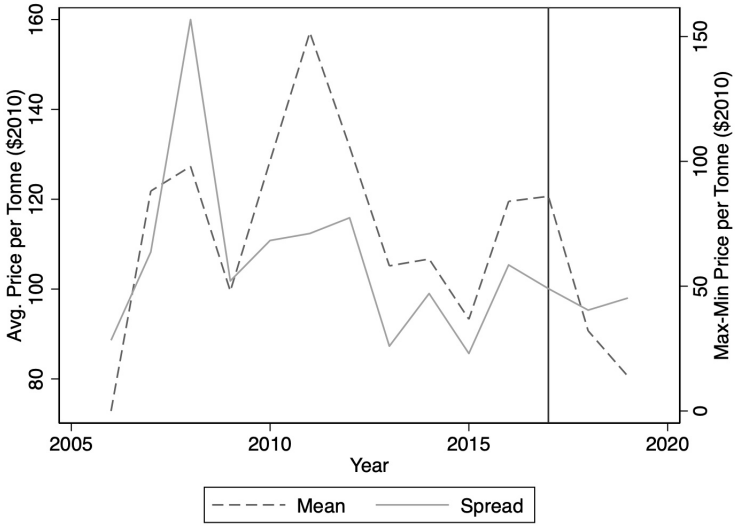
Note: Data are from DOSM, originally collected by the Ministry of Primary Industries.

Figure 2: Oil Palm Land by Region, 2006 to 2019

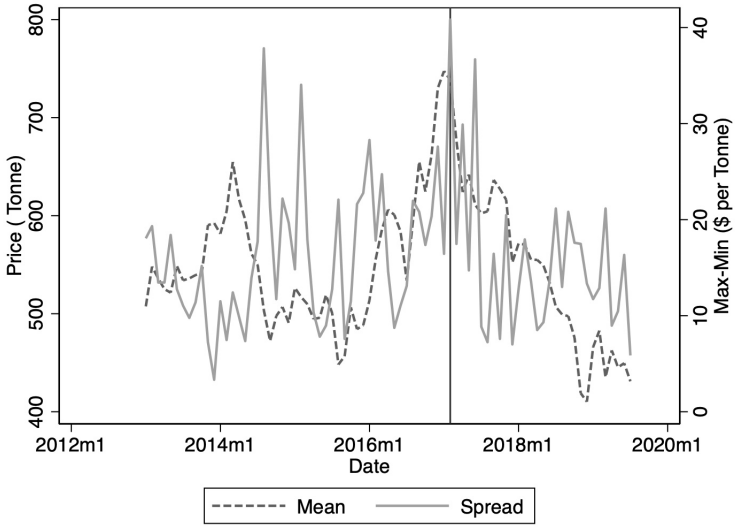


Note: Oil palm land areas are divided by the total areas of each region. Left y-axes are for fraction of oil palm land over total land. Right y-axes are for fraction of smallholder oil palm land over total land. Data are from Malaysian Palm Oil Council.

Figure 3: Price Dispersion Over Time



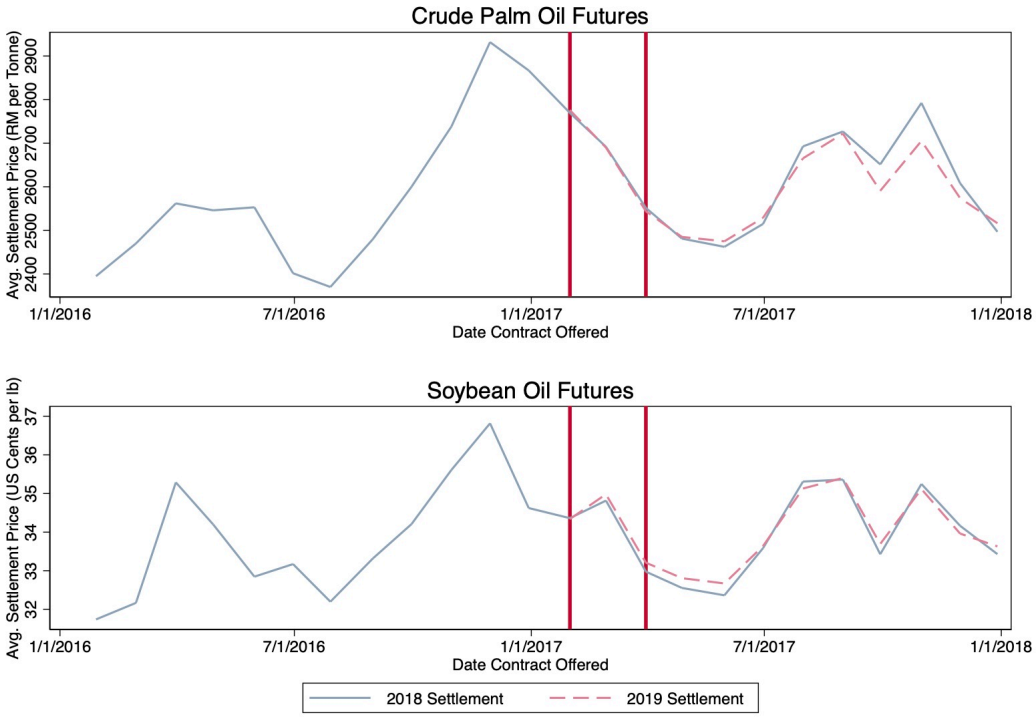
(a) Dispersion in FFB Prices Over Time



(b) Dispersion in CPO Prices Over Time

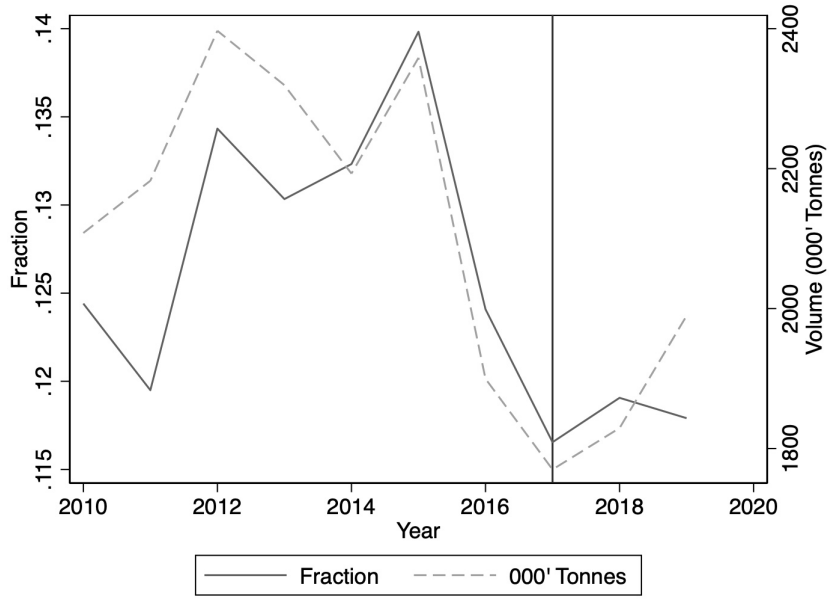
Note: Minimum FFB price is the minimum regional FFB price reported by the MPOC for the year, and maximum FFB price is the maximum. Average FFB price is the average price across all regions. Minimum CPO price is the minimum price across regions aggregated into central, eastern, northern, southern, Sabah, and Sarawak. Maximum CPO price is the maximum. Average CPO price is the average price. Prices are in USD. Data are from the Malaysian Palm Oil Board.

Figure 4: Palm Oil vs. Soybean Oil Futures Prices, 2006 to 2019



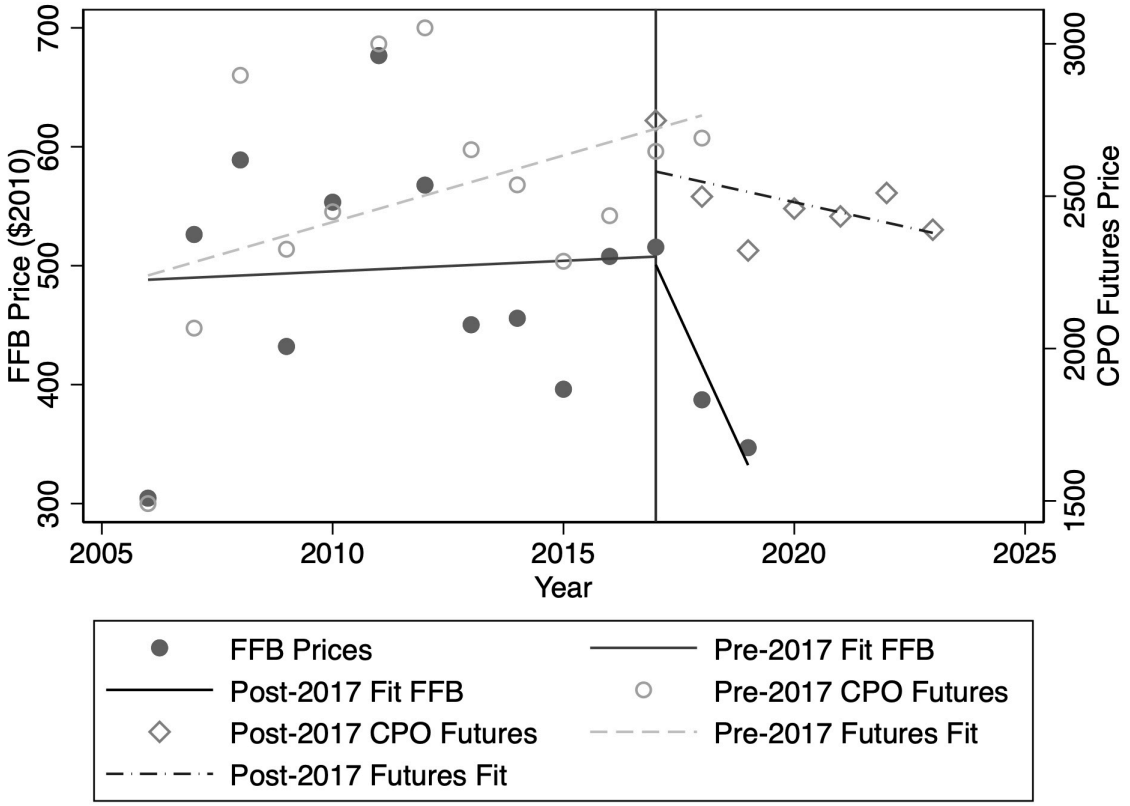
Note: 1 Tonne= 2205 lbs, 1 USD $\approx$ 4.15 RM. July 2016 coincides with announcement of EU Strategy for low-emission mobility. Futures prices are from DataStream.

Figure 5: Malaysian Palm Oil Exports to the E.U.



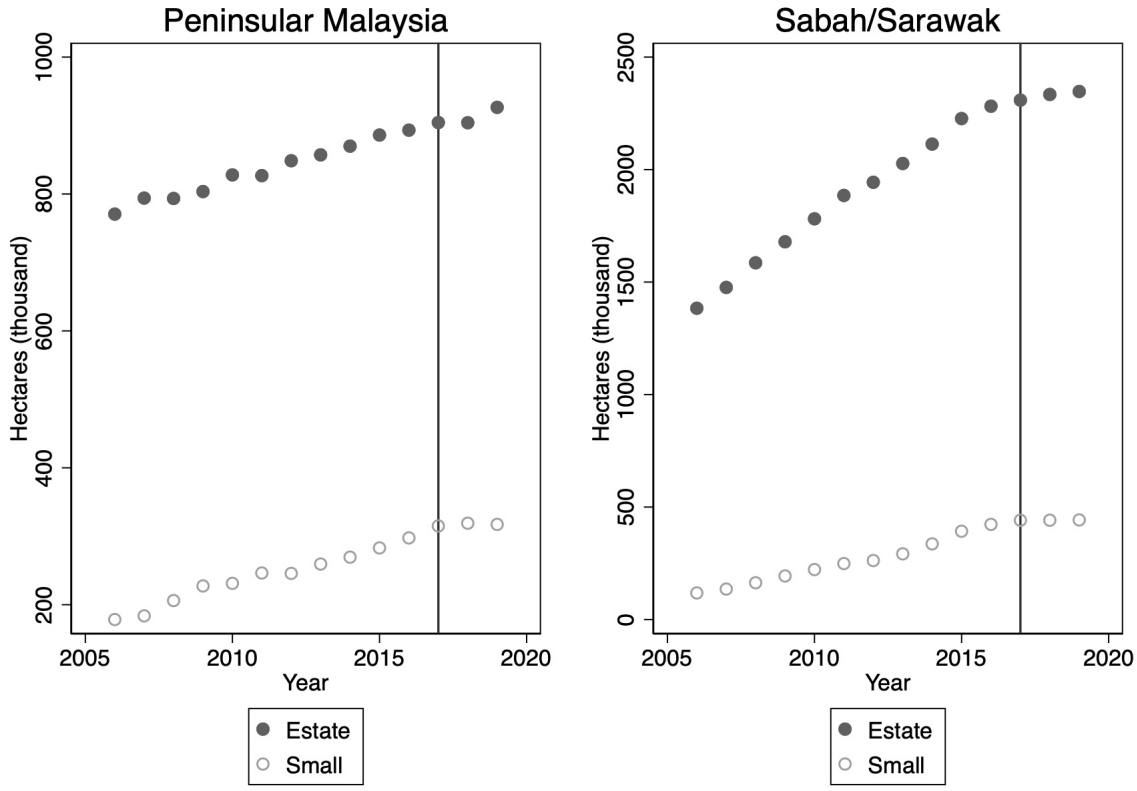
Note: Data are from DOSM (Department of Statistics Malaysia) and MPI (Ministery of Primary Industries). Vertical line represents year 2017.

Figure 6: Average FFB and CPO Futures Prices, All Regions



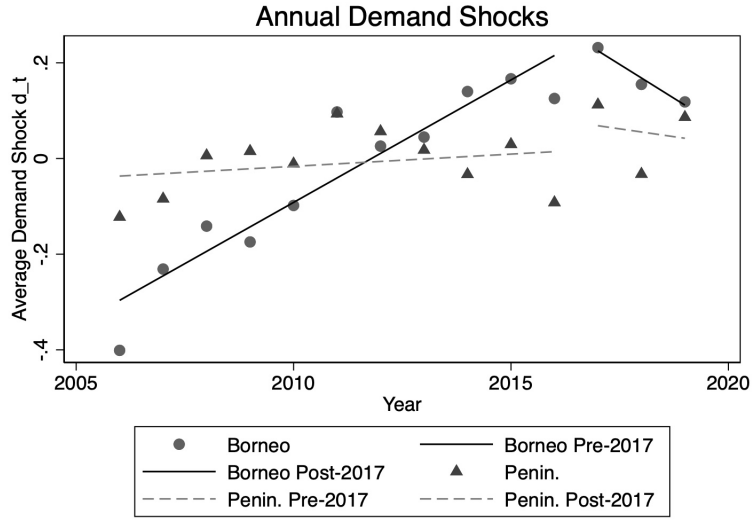
Note: Prices are in RM. For CPO futures prices, years on the x-axis correspond to futures expiration dates. I average across the prices of all futures with the same expiry date, separated by whether they are sold before or after 2017. The dashed line to the left corresponds to futures sold before 2017. The dashed-dot line to the right corresponds to futures sold after 2017.

Figure 7: Total Oil Palm Land, 2006 to 2019



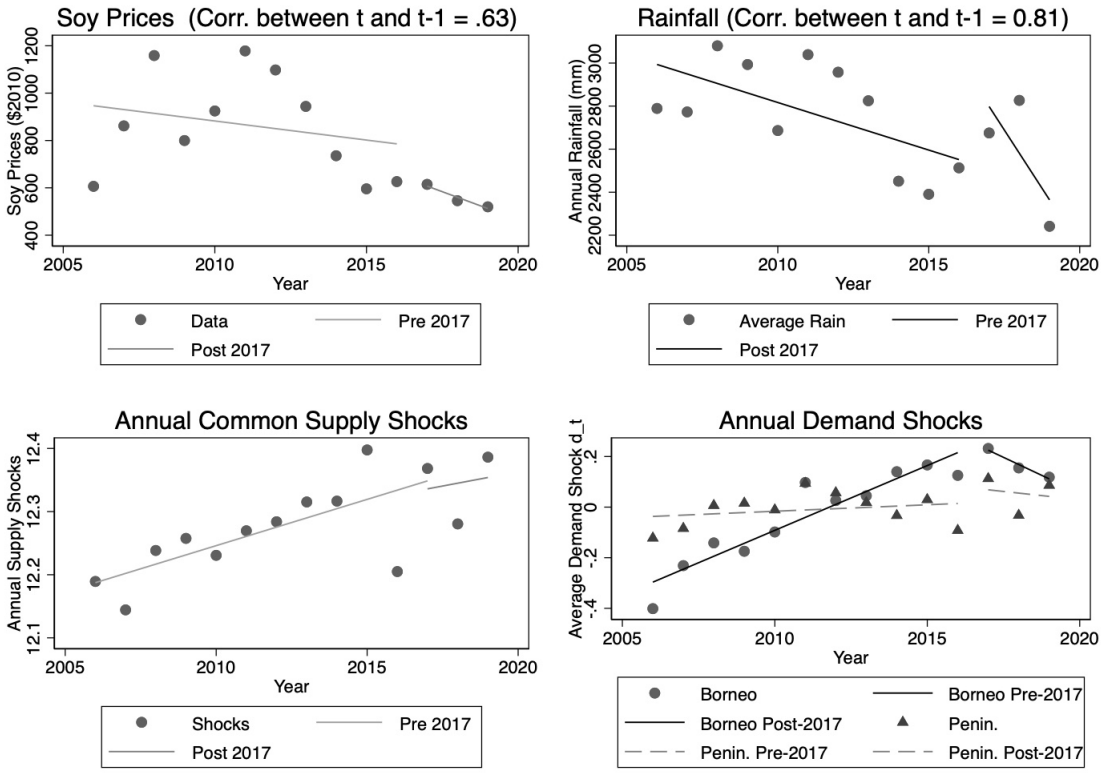
Source: Malaysian Palm Oil Council

Figure 8: Average Aggregate Demand Shocks d_t, Peninsular Malaysia and Sabah/Sarawak



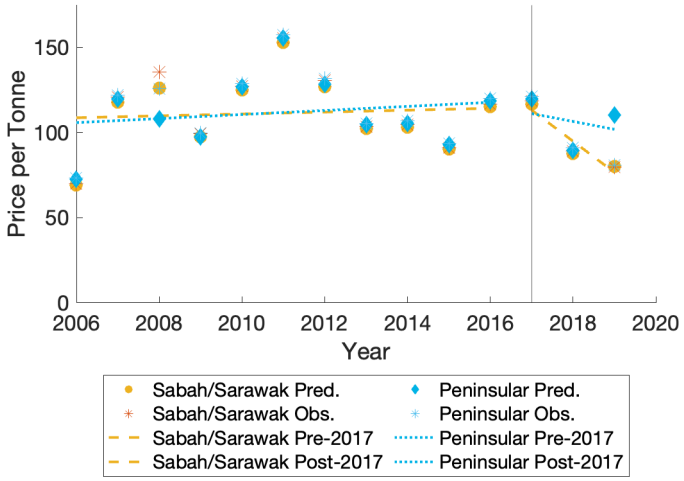
Note: Demand shocks are residuals recovered from estimating regional demand curves. In this figure I average across all regions in Peninsular Malaysia for one data series and Sabah and Sarawak in Borneo for the other data series.

Figure 9: Average Values of All State Variables, All Regions



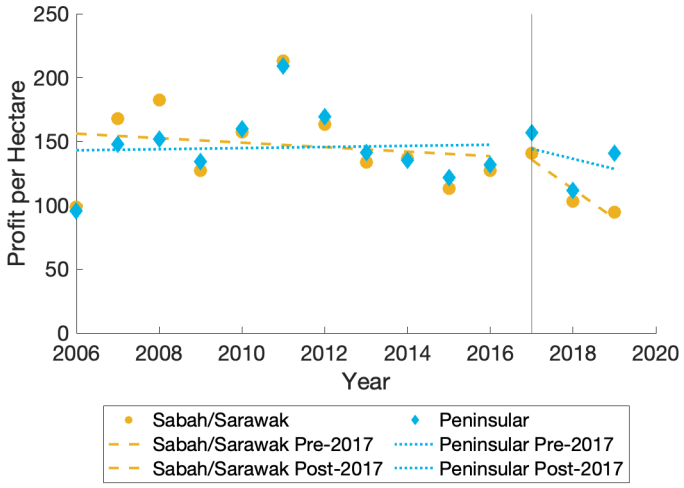
Note: Soy prices and rainfall series are averaged across all regions. Annual common supply shocks are the averages of all supply residuals across all regions. The demand shocks are the same as shown in Figure 8.

Figure 10: Predicted Prices



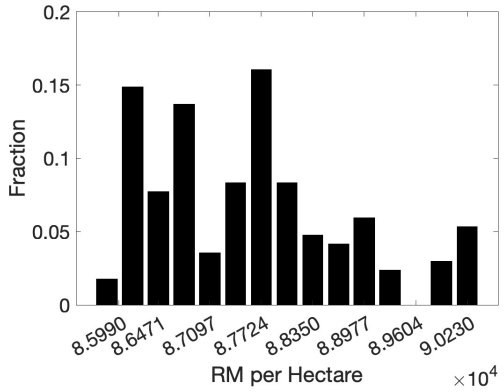
Note: Equilibrium prices calculated using parameter estimates and recovered supply and demand residuals. Prices are given in USD. 1 RM = 0.23 USD.

Figure 11: Predicted Monthly Profits

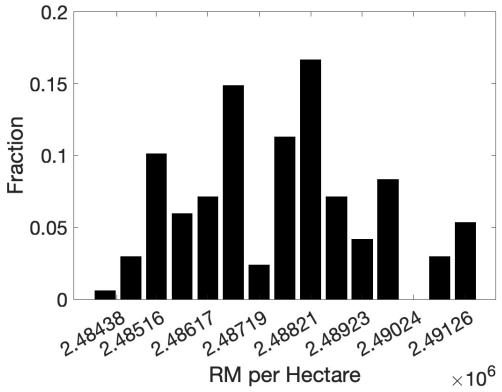


Note: Predicted profits using parameter estimates. Pre-2017 mean is \$147.33 (USD) for Sabah/Sarawak and \$145.26 for Peninsular Malaysia. Post-2017 mean is \$112.75 for Saba/Sarawak and \$136.41 for Peninsular Malaysia.

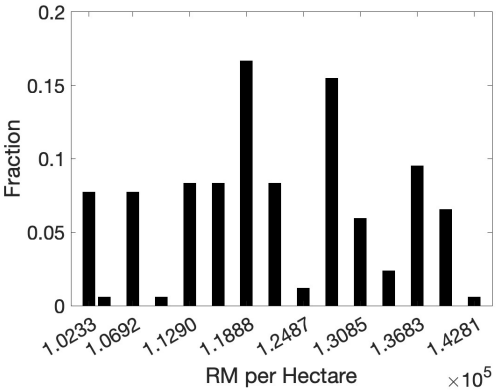
Figure 12: Conditional Expected Values of Estimated Parameters



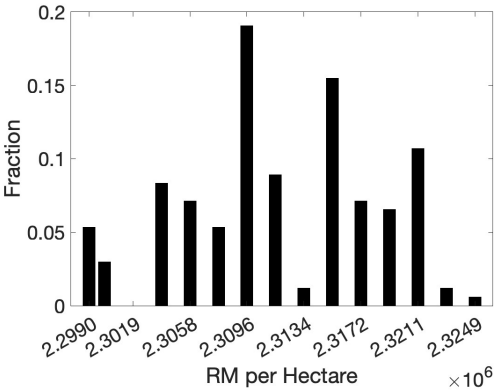
(a) Smallholder Scrap Value



(b) Large Estate Scrap Value



(c) Smallholder Entry Cost



(d) Larger Estate Entry Cost

Note: Conditional expected values are calculated for each observed state. The displayed distributions are across observed states. These values are means and do not capture the standard deviations of possible outcomes in each state.

11 Tables

Table 1: Relationship of Industrial Crops to Deforestation

	(1)	(2)	(3)	(4)
	Δ Primary Forest	Δ Primary Forest	Δ Primary Forest	Δ Primary Forest
Δ Oil Palm	0.790**	0.985**	0.201*	0.181
	(0.141)	(0.177)	(0.0963)	(0.134)
Δ Rubber	0.250**	0.191**	0.129**	0.109*
	(0.0563)	(0.0461)	(0.0357)	(0.0495)
Δ Cocoa	0.358	0.725	0.825	-0.896
	(3.515)	(2.999)	(1.198)	(1.181)
Δ Pepper	-4.402**	-3.101*	0.388	1.664
	(0.851)	(1.407)	(1.396)	(1.545)
Constant	19743.9**	11266.0	46215.0**	46045.4**
	(6211.1)	(8112.5)	(6023.4)	(7165.1)
year_fe		X		X
location_fe			X	X
N	39	39	39	39
r2	0.496	0.680	0.761	0.875

Standard errors in parentheses

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Note: Observations are at the location-year level. Locations include Peninsular Malaysia, Sabah, and Sarawak. Years are from 2006 to 2019. I do not include sago and kenaf, since they are only available at the level of the entire country, and a regression at the country-year levels does not have sufficient observations to detect any significant correlations.

Table 2: Loss in Primary Forest from Smallholder and Large Estate Oil Palm Expansion

	(1)	(2)	(3)
Δ Large Estate Land	0.224***	1.391***	0.0280
	(0.0377)	(0.0290)	(0.0309)
Δ Smallholder Land	0.104	0.306***	0.00413
	(0.0627)	(0.0595)	(0.0375)
_cons	12.94***	2.835***	14.89***
	(0.372)	(0.409)	(0.335)
Mean	15.13	15.13	15.13
N	1668	1668	1668
Region FE	X		X
Year FE	X		
Location x Year FE		X	X

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: Outcome variable is primary forest area. Observations are at the region-year level. Regression includes region and year fixed effects. Location refers to an indicator for whether a region is in Peninsular Malaysia or Borneo.

Table 3: Price Trends, Pre- and Post-2017

	(1)	(2)	(3)
	FFB Prices	Pre-2017 CPO Futures	Post-2017 CPO Futures
Slope	2.835**	43.61**	-128.2**
	(0.990)	(3.039)	(13.45)
Δ Slope, Post 2017	-89.94**		
	(3.454)		
Constant	-5202.0**	-85237.8**	261276.2**
	(1993.0)	(6119.6)	(27152.7)
N	2016	1752	445
r2	0.135	0.116	0.372

Standard errors in parentheses

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Note: Allows for different intercept (constant) post 2017 (inclusive).

Table 4: Oil Palm Land Expansion Rate, Pre- and Post-2017

	(1)	(2)
	Large Estates	Smallholders
Slope, Pre-2017	40.03**	14.28**
	(7.739)	(1.745)
Δ Slope, Post 2017	-2.298	-3.300
	(16.52)	(6.750)
Δ Slope, Peninsular	-37.79**	-12.98**
	(7.286)	(1.656)
_cons	-79590.1**	-28593.1**
	(15591.6)	(3515.1)
N	167	168
r2	0.942	0.732

Standard errors in parentheses

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Note: Units are in thousands of hectares. Time is per year. Allows for different intercept (constant) post 2017 (inclusive) and for regions in Peninsular Malaysia.

Table 5: Short Run Aggregate Supply and Demand Estimates

	(1)	(2)
	Demand	Supply
ln_price_ffb	-0.254**	0.0335
	(0.0897)	(0.0758)
ln_price_soy	0.105*	
	(0.0482)	
ln_rainfall_mm_annual		0.385**
		(0.0643)
_cons	14.67**	-2.908**
	(0.327)	(0.317)
month_fe	X	X
state_fe	X	X
IV	X	X
N	1944	2016
r2	0.979	0.578
fs	15.59	25.08

Standard errors in parentheses

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Note: Instrumental variables for demand include rainfall in major soy growing regions of the world (Brazil, Indiana, Illinois, and Minnesota) and regional rainfall within Malaysia. Instrumental variables for supply includes rainfall in major soy growing regions of the world as demand shifters.

Table 6: Entry Cost and Scrap Value Parameter Estimates

$\hat{\theta}$	*Smallholders*	*Large Estates*
Entry Cost $\hat{\mu}_\kappa$	221 Mil. RM/hectare	206 Mil. RM/hectare
	(51 Mil. USD/hectare)	(47 Mil. USD/hectare)
Scrap Value $\hat{\mu}_\phi$	0.084 Mil. RM/hectare	2.23 Mil. RM/hectare
	(0.019 Mil. USD/hectare)	(0.51 Mil. USD/hectare)

Note: Estimates assume that total possible land area devoted to oil palm is 88% of total land area. The percentage estimate is taken from Shevade and Loboda (2019).

Table 7: EU Trade Restriction and Targeted Taxes

		EU Policy				
		Small		*Large*		*Total*
Margin		#	% Total	#	% Total	
External	ΔLand	-345	161.3%	131	-61.3%	-214
(2017-2019)	ΔPayoffs	-44.6	148.0%	14.5	-48.0 %	-30.2
Internal	Land (1000's)	422	14.5%	2,489	85.5 %	2,911
(2017)	Total Δ Payoffs	-73.6	-624.0%	85.4	724.0%	11.8
	Avg. Δ Payoffs	-174(*)	-	34(*)	-	-
Δ Primary Forest		35.8	559%	-29.4	-459.0%	6.4
		0.9% Large Estate Targeted Tax				
External	ΔLand	45	-20.9%	-263	120.9%	- 217
(2017-2019)	ΔPayoffs	2.9	-6.1%	-50.3	106.1 %	-47.4
Internal	Land (1000's)	423	14.5%	2,489	85.5 %	2,911
(2017)	Total Δ Payoffs	7.4	-2.3%	-325.3	102.3%	-317.9
	Avg. Δ Payoffs	17(*)	-	131(*)	-	-
Δ Primary Forest		-4.7	-8.5%	58.8	108.5%	54.1
		Pigovian Land Tax				
External	ΔLand	-209	2.0%	-10,503	89.0%	- 10,712
(2017-2019)	ΔPayoffs	-24.5	0.04%	-55,043.0	99.96 %	-55,067.0
Internal	Land (1000's)	402	14.0%	2,470	86.0 %	2,872
(2017)	Total Δ Payoffs	28.3	18.5%	124.7	81.5%	152.9
	Avg. Δ Payoffs	70(*)	-	50(*)	-	-
Δ Primary Forest		21.7	0.9%	2,353.1	99.1%	2,375.8

Note: ΔLand is in hectares. ΔPayoffs is in millions of USD. (*) Payoffs are in USD. External margin is lost entry/ extra exit each year from 2017 to 2019, inclusive. Comparisons are to a no EU policy counterfactual. The targeted tax is a per unit FFB tax directed at large estates. The Pigovian land taxes are per hectare of land cleared and calculated using a $51 social cost of carbon and the average amount of carbon release correlated with oil palm land expansion by farm type. (1,217 Mt for large estates and 48.5 metric tons for smallholders).

Table 8: Producer Coordination Counterfactual

		MSPO Coordination						**EU**
Demand Elasticity		(Est.) **-0.254**			(Hsiao 2024) **-0.819**			(Est.) **-0.359**
		Small	*Large*	*Total*	*Small*	*Large*	*Total*	*Total*
Avg. ΔVC per hectare		183	619		137	165		
External	ΔLand	-52.3	-96.9	-149.2	-52.3	-96.9	-149.2	-0.2
(2017-2019)	ΔPayoffs	-18,711	-655,970	-674,680	-716	-110,060	-110,770	-30.2
Internal	Land (1000's)	411	2,482	2,893	411	2,482	2,893	2,911
(2017)	ΔPayoffs	77.2	1,541	1,619	58	411	469	11.8

Note: Payoffs in millions USD. Land in thousands of hectares. External margin is no net entry. Comparison is no EU Policy. Alternative demand elasticity is a weighted average of regional elasticities from Hsiao (2024) using average country trade shares. The concern is that larger prices in equilibrium prices could lead to aggregate responses from other countries, implying a more elastic demand curve. Both counterfactual and non-counterfactual equilibrium profits are calculated with the new elasticity and the resulting continuation values are compared. Since the MSPO policy stops all entry, I assume that the lost payoffs to farms on the external margin are the discounted flow payoffs in the counterfactual world with neither the E.U. trade nor the MSPO policy.

A Allowing for Different Static Cost Shocks Across Types

Now assume that smallholders and large estates face different static cost shocks a_t^S, a_t^E, respectively. Define γ_t^S and γ_t^E as the shares of total oil palm land belonging to each type:

$$\gamma_t^S = \frac{\tau_t^S}{\tau_t}, \qquad \gamma_t^E = \frac{\tau_t^E}{\tau_t}$$

Then total quantity supplied becomes:

$$Q^t = r_t^{\beta_r}\tau_t exp\big(\frac{1}{b}(\ln p_t + \beta_r \ln r_t)\big) \times \big((\gamma_t^S)^{\beta_\tau} exp(\frac{-a_t^S}{b}) + (\gamma_t^E)^{\beta_\tau} exp(\frac{-a_t^E}{b})\big) \tag{21}$$

If $a_t^S = a_t^E$, this equation reduces to the original case with both types of farms facing the same static marginal costs.

For the purposes of estimation, I can still use the same specification to estimate β_r, β_τ, and b:

$$\ln Q_t = (\beta_r + \frac{\beta_r}{b})\ln r_t + \ln \tau_t + \frac{1}{b}\ln p_t + \tilde{a}_t \tag{22}$$

where

$$\tilde{a}_t = \ln\big(\gamma_t^S exp(\frac{-a_t^S}{b}) + \gamma_t^E exp(\frac{-a_t^E}{b})\big) \tag{23}$$

Further assume that both types of firms have different average static costs but face the same per-period shocks $a_t^S = \bar{a}_t^S + \epsilon_t^a$ and $a_t^E = \bar{a}_t^E + \epsilon_t^a$. I make this assumption because I cannot identify separate stochastic processes across farm types. Then:

$$\tilde{a}_t = \frac{\epsilon_t^a}{b} + \ln\big((\gamma_t^S)^{\beta_\tau} exp(\frac{-\bar{a}^S}{b}) + (\gamma_t^E)^{\beta_\tau} exp(\frac{-\bar{a}^E}{b})\big) \tag{24}$$

Estimation Under this modification, $\tilde{a}_t$ can be as type of weighted average of type-specific cost shocks that are drawn from distributions with different means but the same variances. Note that these are shocks per land-unit. Since the cost shock distributions are stationary over time and the ϵ_t^a shocks are exogenous by construction, γ_t^S and γ_t^E affect $\tilde{a}_t$ only through the relative

means of each type distribution, I estimate $\bar{a}^S, \bar{a}^E$ using the following moment condition:

$$\boldsymbol{E}[\tilde{a}_t \Gamma_t] = 0 \tag{25}$$

where Γ_t are the type-specific land shares. I find that the mean of the smallholder supply shock distribution is 0.7247, and that the mean of the large estate distribution is -0.1749.

For smallholders, these parameters imply pre-trade policy average profits of \$147.33 in Borneo and \$145.26 in Peninsular Malaysia. The changes after the trade policy are \$34.58 and \$8.84, respectively. For large estates, these parameters imply pre-trade policy average profits of \$146.88 in Borneo and \$146.82 in Peninsular Malaysia. The changes after the trade policy are \$34.00 and \$9.07, respectively. These values are very similar to my main specification of assuming both types face the same static marginal cost, indicating that relaxing this assumption would not change my results much.

B Equilibrium Algorithm

The following fixed-point algorithm will solve for an equilibrium:

1. Choose some starting distributions for farmer beliefs over price transitions $G_p^0(p_{t+1}|\tilde{s}_t)$ and beliefs over the evolution of the trade policy $G_{eu}^0(eu_{t+1}|\tilde{s}_t)$. Using these transition probabilities, calculate a Markov transition matrix M^0 giving the transitions over farmers' sufficient state variables $\tilde{s}_t$.

2. Take M^l (where l is the algorithm iteration number) as fixed in the following value function iteration

   (a) Update continuation value:

   $$VC^{l,k+1} = M^l(\pi + \delta P_x^{l,k}\mu_\phi + \delta VC^{l,k})$$

   (b) Calculate the new policy function (probability of exit).

   $$P_x^{l,k+1} = 1 - (1 - exp(-\frac{1}{\mu_\phi}VC^{l,k+1})) = exp(-\frac{1}{\mu_\phi}VC^{l,k+1})$$

(c) Update the value function.

$$V^{l,k+1} = \pi + \delta(P_x^{l,k+1}\mu_\phi + VC^{l,k+1})$$

(d) STOP when $||V^{l,k+1} - V^{l,k}|| < \epsilon_k$.

(e) Call the $V^{l,k+1}$ that satisfies this condition V^l and the corresponding continuation value and exit policy function VC^l,P_x^l, respectively.

3. Calculate the implied entry policy function P_e^l.

4. Using the farmers' entry and exit policy functions, calculate the resulting conditional state transition probabilities $F^l(s_{t+1}|s_t)$.

(a) $s_{AR(1)} = \{p^{soy}, r, a\}$ evolve according to exogenous AR(1) processes.

(b) Land will evolve as follows:

$$\tau_{t+1}(s_t) = \underbrace{(1 - P_x^l(p_t(s_t), eu_t, a_t)) \times \tau_t}_{\text{incumbents remaining}} + \underbrace{P_e^l(p_t(s_t), eu_t, a_t) \times L_e}_{\text{entrants}} \tag{26}$$

Note that for each state s_t, we can calculate a unique equilibrium price $p(s_t)$. Thus, all states with the same equilibrium price, EU policy, and marginal cost will have the same land transition probabilities.

(c) The EU policy eu_t evolves such that:

$$eu_{t+1} = max\{\mathbf{1}(\tau_{t+1} \geq \overline{\tau}_{eu}), eu_t\} \tag{27}$$

(d) The demand shock d_t evolves such that:

$$d_{t+1} = \varphi_0 + \varphi_1 d_t + \varphi_2 d_t eu_t + \nu_t \tag{28}$$

5. Calculate the distribution of equilibrium price transitions $p(s_t) \to p(s_{t+1})$ that correspond to the transitions of the actual state variables.

6. Recover farmer beliefs over price evolution $G_p^l(p_{t+1}|\tilde{s}_t)$ consistent with the actual evolution of prices using equation 13 (and beliefs $G_{eu}^l(eu_{t+1}|\tilde{s}_t)$ over EU policy evolution).

7. Repeat steps 2-6.

8. STOP when *implied policy functions* converge according to some tolerance.

C Estimation Steps

1. Define observed next period land for a given state s_t as:

$$\hat{\tau}_{t+1}(s_t) = \tau_{t+1}(s_t) + \zeta_{t+1} \tag{29}$$

   where ζ_{t+1} is some mean-zero measurement error.

2. Calculate equilibrium prices for each market state s_t and use these prices to relabel each state according to the farmer state variables $\tilde{s_t}$.

3. Calculate farmer static profits $\pi(\tilde{s_t})$ for each $\tilde{s_t}$.

4. Estimate the farmer's Markov transition matrix (this will also be held constant while searching over dynamic parameters) from the data:

$$F_{\tilde{s}}(\tilde{s}_{t+1}|\tilde{s}_t) = F_r(r_{t+1}|r_t) \times F_a(a_{t+1}|a_t) \times F_\eta(p_{t+1}|p_t, r_{t+1}, a_{t+1})$$

   (a) Using the data, estimate te AR(1) processes underlying $F_r(r_{t+1}|r_t)$ and $F_a(a_{t+1}|a_t)$.

   (b) Using data, estimate the belief parameters λ in equation 13 and the variance σ_η^2 of the random in certainty in beliefs $\eta + t \sim \mathcal{N}(0, \sigma_\eta^2)$.

   (c) Calculate $F_\eta(p_{t+1}|p_t, r_{t+1}, a_{t+1})$ using (λ, σ_η^2).

   Call the resulting Markov transition matrix $\hat{M}$.

5. Estimate the continuation value using $\hat{M}$ and fixed-point iteration for a guess of parameters θ:

$$\hat{VC}(\theta) = \hat{M}(\pi + \delta P_x(\hat{VC}(\theta))\mu_\phi + \delta \hat{VC}(\theta))$$

where π is a vector of state-specific payoffs calculated from the static portion of the model and

$$P_x(\hat{VC}(\theta)) = exp(-\frac{1}{\mu_\phi}\delta\hat{VC}(\theta)) \tag{30}$$

Note, I cannot calculate $P_x(\hat{VC}(\theta))$ from the data, since I only observe *net* flows. However, using the contraction mapping theorem (appendix claim 1), equation 30 identifies a unique $\hat{VC}$ for a given θ. The contraction mapping will also provide a percentage of available land that enters which is the following under an exponential distribution.

$$P_e(\hat{VC}(\theta)) = 1 - exp(-\frac{1}{\mu_\kappa}\delta\hat{VC}(\theta)) \tag{31}$$

6. If estimating parameters for multiple types, repeat the previous step to recover $\hat{VC}^f(\theta)$ for each type.

7. Calculating the model-implied land transitions using $\hat{VC}^f(\theta)$

$$\tau^f_{t+1} = \underbrace{Pr(\phi^f_{it} \leq VC^{f,l}_t) \times \tau_t}_{\text{incumbents remaining}} + \underbrace{Pr(\kappa^f_{jt} \leq VC^{f,l}_t) \times \tau^e_{f,t}}_{\text{entrants}} \tag{32}$$

8. Use the objective function similar to the CCP one where $\hat{\boldsymbol{\tau}}^{\boldsymbol{f}}$ and $\boldsymbol{\tau^f(\hat{VC}^f(\theta);\theta)}$ are vectors of land areas flows observed in the data and predicted by the model, $\boldsymbol{\Delta\hat{\tau}^f}$ and $\boldsymbol{\Delta\tau^f(\hat{VC}^f(\theta);\theta)}$ are changes in land areas in the data and model, and $\boldsymbol{Z}$ are the current period state variables used as instruments:

$$\hat{\theta} = \underset{\theta}{argmin} \left\| \begin{matrix} (\hat{\boldsymbol{\tau}}^{\boldsymbol{f}} - \boldsymbol{\tau^f(\hat{VC}^f(\theta);\theta)}) \\ (\boldsymbol{\Delta\hat{\tau}^f} - \boldsymbol{\Delta\tau^f(\hat{VC}^f(\theta);\theta)})\boldsymbol{Z} \end{matrix} \right\| \tag{33}$$

C.1 Claim 1: Equation 30 is a contraction mapping for $\hat{VC}(\theta)$ if $\delta < 1$

Recall that equation 30 is:

$$\hat{VC}(\theta) = \hat{M}(\pi + \delta(exp(-\frac{1}{\mu_\phi}\hat{VC}(\theta))\mu_\phi + \hat{VC}(\theta)))$$

Proof using Contraction Mapping Theorem

- Take $\delta < 1$ (i.e., the agent is not infinitely patent)
- Define $B(f)$ as the following operator

$$B(f) = \hat{M}(\pi + \delta(exp(-\frac{1}{\mu_\phi}f)\mu_\phi + f))$$

- Since $\hat{M}$ is a Markov matrix (following proof step in footnote 8 of POB),

$$||B(f) - B(g)|| \leq ||\delta(exp(-\frac{1}{\mu_\phi}f)\mu_\phi + f) - \delta(exp(-\frac{1}{\mu_\phi}g)\mu_\phi + g)||$$

- Since for each element v_i of f (or g)

$$\begin{aligned} h(v_i) =& exp(-\frac{1}{\mu_\phi}v_i)\mu_\phi + v_i \\ \frac{\partial h}{\partial v_i} =& - exp(-\frac{1}{\mu_\phi}v_i) + 1 \in [0, 1] \end{aligned}$$

  and the support of the exponential distribution is $[0, \infty)$, it follows that for $\beta = \delta < 1$

$$||\delta(exp(-\frac{1}{\mu_\phi}f)\mu_\phi + f) - \delta(exp(-\frac{1}{\mu_\phi}g)\mu_\phi + g)|| \leq \delta||f - g||$$

- Therefore $B(f)$ is a contraction mapping
- Since the Euclidean space with the sup metric (the Euclidean metric also works) is a complete metric space, B has an unique fixed point.

D Entry Cost and Scrap Value Parametrization

The main specification of entry costs and scrap values in the paper assume that the distributions of entry costs and scrap values for both types of farmers are the same across all market states. Assuming fixed distributions is reasonable if the prices of palm oil do not affect the value of land in broader land markets. However, given palm oil's dominant role in Malaysian agriculture as

show in in Figure 1, it is difficult to rule out entry and costs and scrap values being uncorrelated with prices.

To explore how allowing the scrap value and entry cost distributions to shift with equilibrium prices could affect my results, I parameterize the mean parameters of the scrap value and entry cost exponential distributions as follows:

$$\mu_{\phi}^{large} = \beta_{\mu,0}^{large} + \beta_{\mu,1}^{large} p_{m,t}$$
$$\mu_{\phi}^{small} = \beta_{\mu,0}^{small} + \beta_{\mu,1}^{small} p_{m,t}$$
$$\mu_{\kappa}^{large} = \beta_{\kappa,0}^{large} + \beta_{\kappa,1}^{large} p_{m,t}$$
$$\mu_{\kappa}^{small} = \beta_{\kappa,0}^{small} + \beta_{\kappa,1}^{small} p_{m,t}$$

where $p_{m,t}$ is the equilibrium FFB price in market m and period t.

For estimation, I use the same moments given by equation 33 with additional instruments in order to help identify the additional parameters. In particular, I interact the moments formed with land area changes and the constant and supply shocks with indicators for whether the land area I am matching is for smallholders or large estates. I also interact the moments matching land area levels with the same indicators for smallholding vs. large estate. Lastly, I restrict $\beta_{\mu,1}^{large} = \beta_{\mu,1}^{small}$. This is because, as shown in Figure 2, I have trouble identifying them separately due to there being relatively few periods of land area decreases across smallholdings and large estates. This yields an over-identified system of equations with 8 moments and 7 parameters.

I estimate the following values (in RM) for the components of the distribution means that do not vary with equilibrium FFB prices: $\hat{\beta}_{\mu,0}^{small} = 0.084$Mil., $\hat{\beta}_{\mu,0}^{large} = 2.23$Mil., $\hat{\beta}_{\kappa,0}^{small} = 221$Mil., $\hat{\beta}_{\kappa,0}^{large} = 206$Mil.. These are almost the same as those in Table 6. For the parameters that capture how the distributions vary with equilibrium FFB prices, I estimate: $\beta_{\mu,1}^{large} = \beta_{\mu,1}^{small} = 45.56$, $\beta_{\kappa,1}^{small} = 52.83$, and $\beta_{\kappa,1}^{large} = 65.30$. Qualitatively, these estimates imply that the scrap value and entry cost distributions are increasing in equilibrium prices. This is consistent with incumbent farmers asking for and receiving higher prices to sell their land to potential entrants when oil palm is more profitable of a crop.

Allowing the distributions to adjust with prices using my estimated parameters decreases the calculated counterfactual effectiveness of the E.U. policy relative to the results in Table 7.

Having the scrap value distributions to also shift down when equilibrium prices decrease offsets the increase farmer exit after the policy. Similarly, allowing the entry cost distributions to also shift down with equilibrium price decreases offsets the decrease in farmer entry after the initial demand shock. In some simulations, I find that the entry cost and scrap value distributions decrease so much with equilibrium prices that the E.U. policy actually generates an increase in land expansion because land is cheaper.

Regarding the changes in continuation values for incumbent farmers, I find smaller average losses (and larger average gains). Average decreases in smallholder continuation values across regions are smaller because there are regions in which there is still a net decrease in land expansion that increases equilibrium prices for farmers on the internal margin. These higher equilibrium prices translate into higher scrap value distributions for those farmers. As such, the increase in continuation values in these regions can be larger than when assuming fixed scrap value distributions. They offset the decreases in continuation values in regions with greater decreases in equilibrium prices. Internal margin large estates experience a larger increase in average continuation value for similar reasons. Despite these quantitative changes, the qualitative results of the model remain similar, because large estates still have on average higher scrap values and lower entry costs even with the distribution adjustments. As such, the equity results implying that smallholders are disproportionately hurt (in terms of decreased flow payoffs) relative to their role in oil palm land expansion and deforestation still holds.

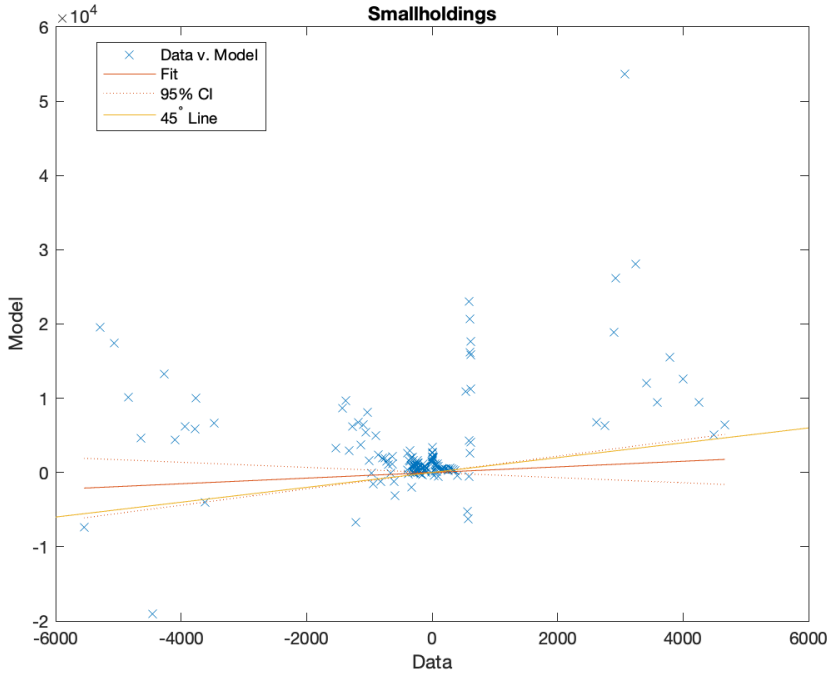
With respect to the other counterfactuals, allowing these distribution shifts likely increases their effectiveness relative to the E.U. trade policy. The targeted tax increases the path of equilibrium prices which would generate higher entry cost cost and scrap value distributions over time. This would decrease the amount of entry and increase exit under the tax even more so than when the distributions are stationary. As such, a targeted tax would be more likely to generate a decrease in deforestation. Since a monopolist only considers aggregate discounted flow profits across all farmers, it would still prefer to stop all land expansion.

E Model Fit

The next graphs show how well the model matches percentage changes in land area, since this is how the entry cost and scrap value distributions affect land area over time to normalize for

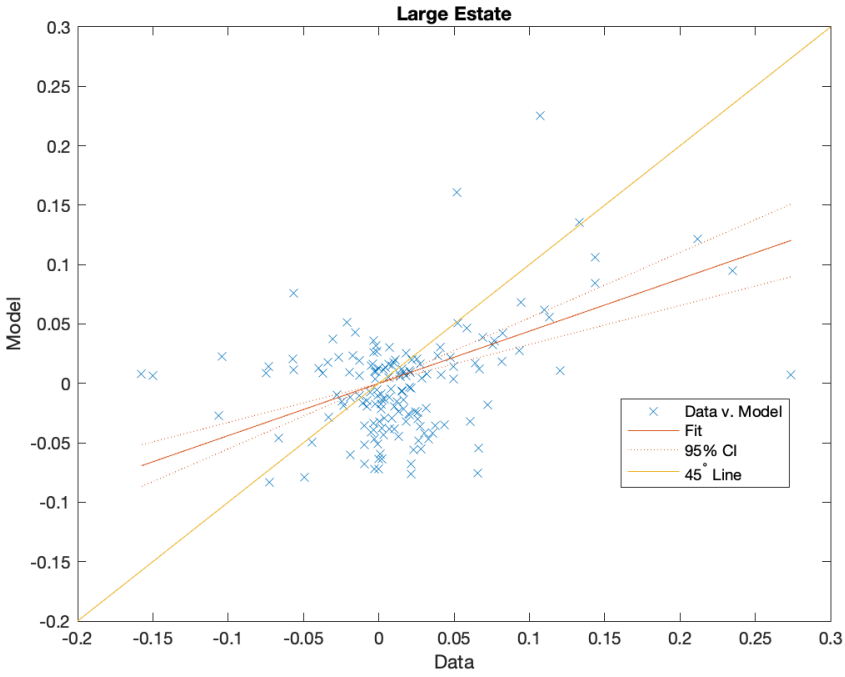
how different regions have different starting land areas tau_t and potential entry areas $\tau^e_{f,t}$ as in equation 32. We are primarily interested in how well we capture changes. The fit for smallholdings is noisy but matches the data on average. The model for large estates underestimates the increases in land areas. As a result, my counterfactual exercises likely understate the degree to which large estates expand more under the trade restriction than smallholdings.

Figure 13: Percentage Land Area Change: Smallholdings



Note: Best fit line is weighted by previous period land area. Confidence interval does not currently account for estimation or simulation error used to generate the model-predicted values.

Figure 14: Percentage Land Area Change: Large Estate



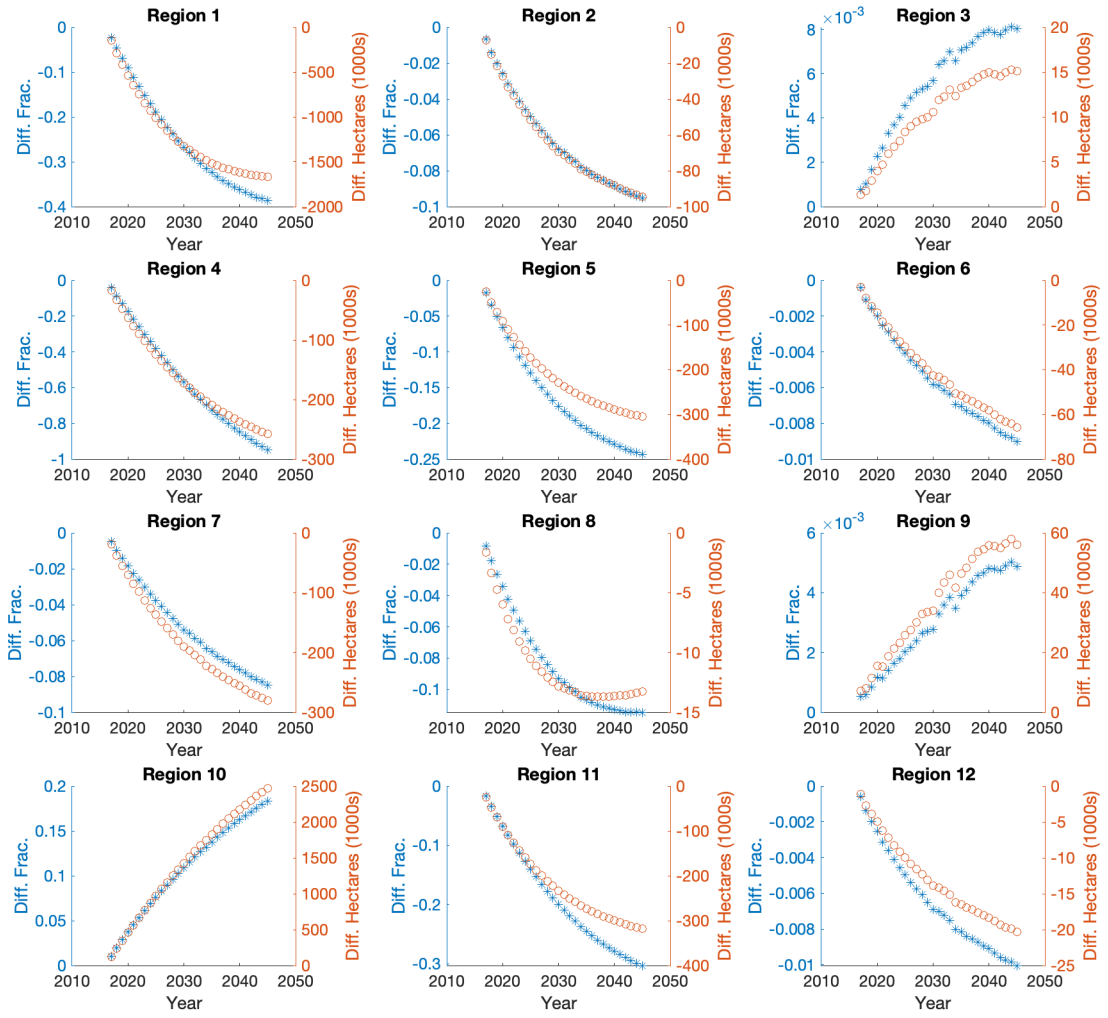
Note: Best fit line is weighted by previous period land area. Confidence interval does not currently account for estimation or simulation error used to generate the model-predicted values.

F Counterfactual Change in Land Flows by Region

Figures 15 and 16 break down changes in fraction of total land and total land area by smallholders and large estates, respectively. These figures demonstrate regional heterogeneity in terms of compositional change. I find the composition of farms shift away from smallholders towards large estates in most regions but not all.

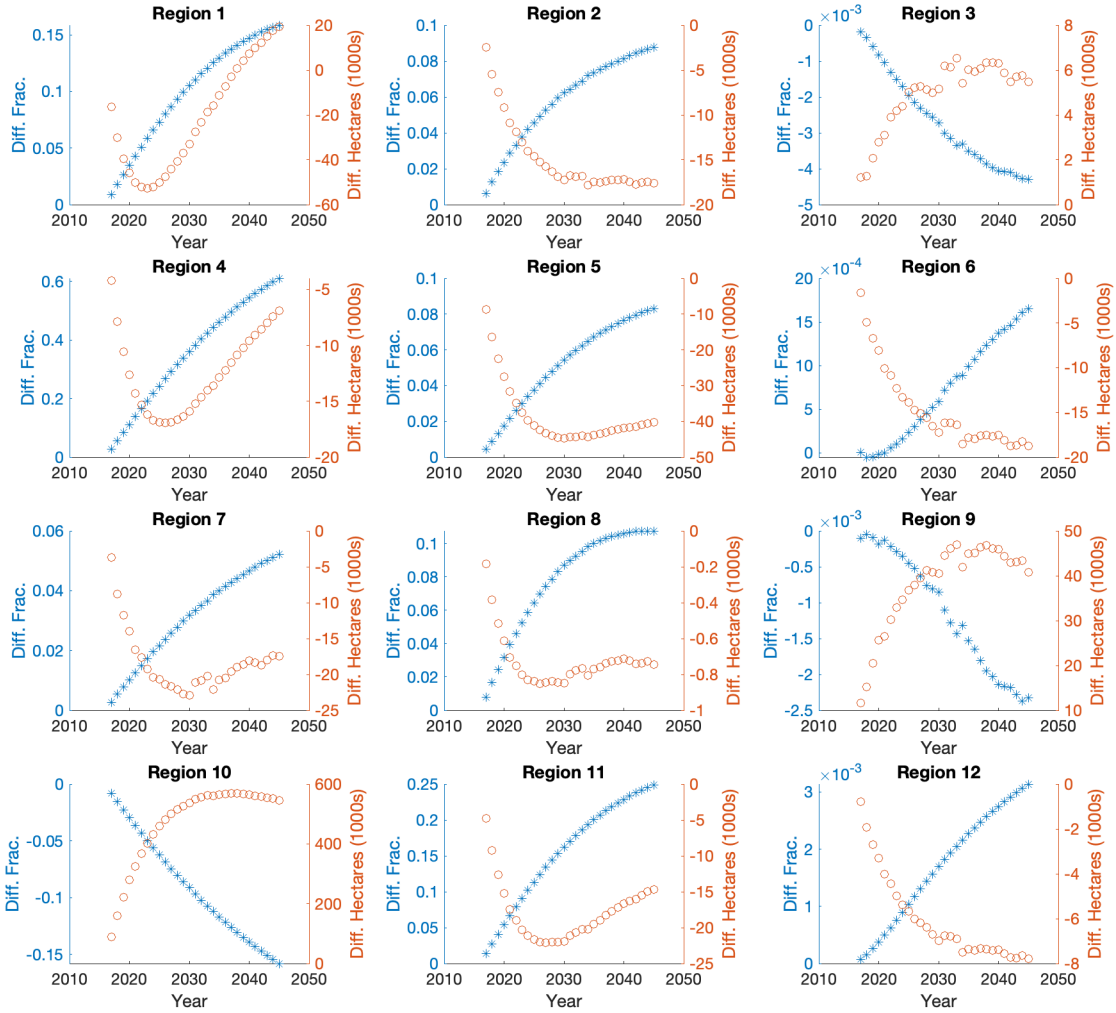
Heterogeneity in this setting potentially comes from the trade shock affecting different regions differently, depending on how much they export to the E.U. relative to China and India (where demand continued expanding during the study period). Regional differences in initial land shares belonging to each farm type (as indicated by Figure 2)) likely also influences the evolution of land shares over time.

Figure 15: Change in Smallholder Land Expansion from E.U. Policy, by Region



Note: This graph shows the difference between counterfactual predictions of smallholder and large estate land expansion with and without the negative demand shock resulting from the E.U. policy. The "*" markers correspond to the left y-axis, and the "o" markers to the right y-axis. "Diff. Frac." refers to the difference in how much of total oil palm land each type consists of.

Figure 16: Change in Large Estate Land Expansion from E.U. Policy, by Region

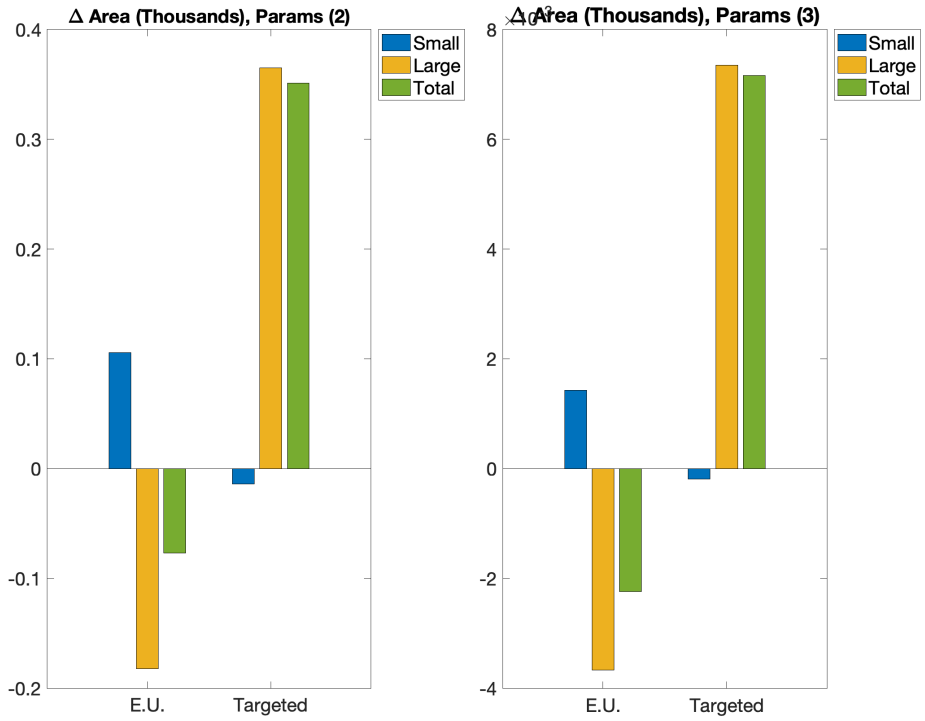


Note: This graph shows the difference between counterfactual predictions of smallholder and large estate land expansion with and without the negative demand shock resulting from the E.U. policy. The "*" markers correspond to the left y-axis, and the "o" markers to the right y-axis. "Diff. Frac." refers to the difference in how much of total oil palm land each type consists of.

G Alternative Projections onto Primary Forest Change

In Figure 16, I show the projected increases in primary forest preserved from specifications (2) and (3) of Table 2. Even though these specifications predict very different levels of overall primary forest protection, the qualitative differences between the E.U. policy and the targeted tax are similar to Table 7.

Figure 17: Alternative Projections onto Primary Forest Change



Note: Area is measured in hectares. Params (2) indicates that the prediction uses the specification from column (2) of Table 2. Params (3) indicates that the prediction uses the specification from column (3) of Table 2.

H Comparison to Homogeneous Farms

Lastly, I explore the implications of within-region (i.e., within-market) heterogeneity for evaluating the impact of the E.U. trade policy. I model all farms in each region as the "average" farm in that region instead of separately as smallholders and large estates. In particular, I average across both smallholder and large estate entry cost and scrap value distributions by assuming that the average farm draws from each distribution type with probabilities corresponding to that type's share of land in that period. I assume that these probabilities evolve exogenously following the observed empirical evolution of shares. One can think of this evolution as exogenous unanticipated shocks to land-clearing technologies over time.

Figure 18 displays the results of this exercise for relative changes in the external land margin. In this counterfactual, there are no longer ex ante distributional concerns. Notably, the long-run path for total external margin differences depends on whether I assume farms are

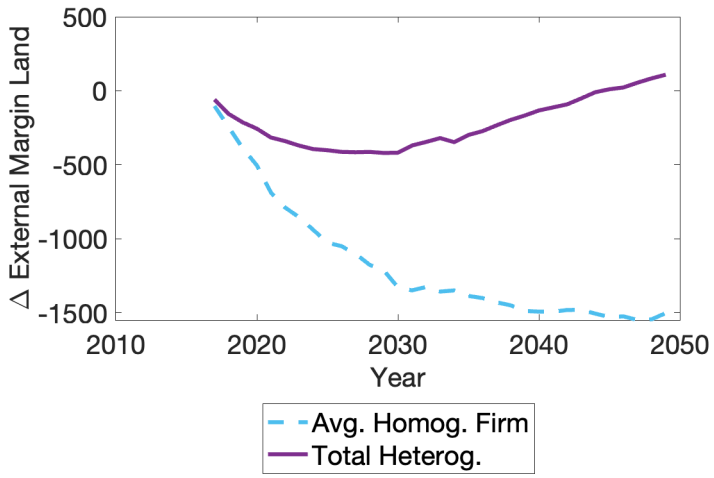
heterogeneous or homogeneous. Panel 18 shows how the total reduction in external land for a counterfactual with no E.U. trade shock evolves under both assumptions. Under homogeneous farms equivalent to the average farm in a given period, the E.U. policy leads to a persistently higher reduction in land expansion (relative to the counterfactual with homogeneous farmers and no trade shock). Underlying this difference is how the average farm compares to large estates and smallholdings, respectively. Without heterogeneity, all farms experience a decrease in continuation value. Since many more farms face a decrease in continuation value, this leads to greater decreases in expansion.

This counterfactual is potentially useful to policymakers if they care about the rate at which deforestation is slowed down or meeting policy targets by certain deadlines. Policymakers are plausibly concerned about the rate at which effects are realized because many climate goals are stated in terms of time cutoffs. For example the U.S., White House has the goal of "Reducing U.S. greenhouse gas emissions 50-52% below 2005 levels in 2030" and "Reaching 100% carbon pollution-free electricity by 2035."[18] Figure 18 indicates that whether farms are homogeneous or heterogeneous could be important for how fast a proposed policy slows deforestation.

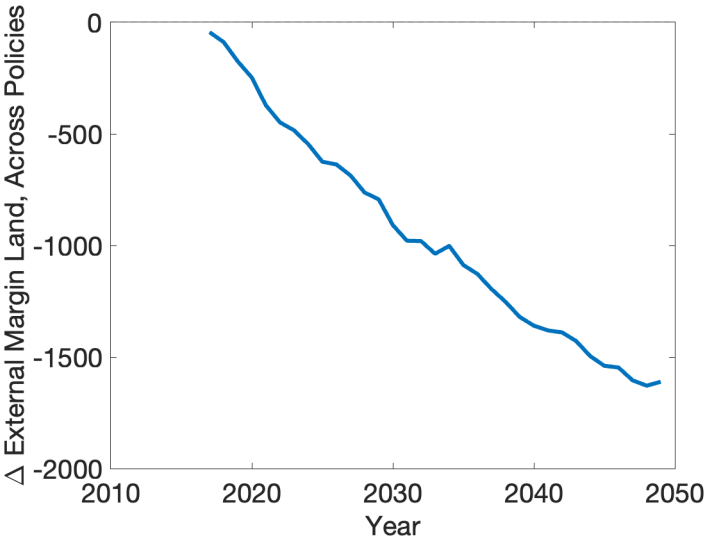
[18]See: President Bidens Actions to Tackle the Climate Crisis

Figure 18: E.U. Trade Restriction, Comparison to Homogeneous Farm(er)s

(a) Change in Land Expansion from Different Policies



(b) Difference in Reduction between Policies



Note: Reductions in external margin land expansion are cumulative. Land units are in thousands of hectares.

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