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

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March 21, 2025

Abstract

Focusing on the 2017 European Union resolution to phase out palm oil in all biofuels to limit deforestation in supplier countries, I consider how heterogeneity among upstream oil palm farmers interacts with coarse environmental policy. Upstream oil palm producers include both small farms for which oil palm has played a historically important role in poverty reduction and large estates owned by publicly traded corporations. Producer countries initially protested that the resolution failed to distinguish between these different types of farmers. Leveraging Malaysian government data on aggregate regional land use by farm type from 2006 to 2019 and a dynamic model of oil palm cultivation decisions, I find that distributional consequences coincide with policy inefficiency in terms of farmer losses relative to reduced deforestation across types. I then explore targeted taxes and supplier quantity coordination as counterfactual policies that could better align producer (country) interests with forest conservation goals. I find that targeted taxes on large estates creating a reduction in deforestation equivalent to the E.U. policy help reduce the burden on smallholders but are still potentially politically infeasible due to the costs to large estates. Supplier coordination, in the form of jointly restricting quantity, could both increase total payoffs to all farmers and further reduce deforestation.

*Contact: audreytiew@nyu.edu. Previously titled "E.U. Trade Restrictions and Heterogeneity among Malaysian Oil Palm Farmers." Results reported are preliminary. I thank Robin Lee, Myrto Kalouptsidi, and Ariel Pakes for their continued guidance and support. I am also grateful to Paul Scott, Allan Hsiao, Tomás Domingo-Iino, and Jun Ishii, as well as the participants in the Harvard IO workshop, Berkeley development and trade workshops, Stanford IOFest 2023, Northwestern Industrial Organization seminar, Boston University Applied Micro seminar, and U. Wisconsin-Madison Industrial Organization seminar for their helpful comments.

1 Introduction

In recent years, the European Union has begun using trade policies restricting palm oil imports to combat global deforestation and climate change. Unsurprisingly, these policies have led to opposition from both Malaysia and Indonesia on the grounds of being protectionist at the cost of Malaysian and Indonesian farmers and especially hurting their historically poorer smallholder farmers (Tan, 2019; Jaiswal, 2023; Christina, 2024). Heterogeneity among upstream producers in affected countries such as Indonesia and Malaysia implies that these policies could have distributional consequences as well as be mistargeted in terms of maximizing protected forest. As such, this paper examines potential counterfactual policies that could be more favorable to supplier countries and be 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 restricting quantity.

A targeted tax is of interest because it distinguishes between heterogeneous types of upstream producer, smallholders and large estates. Allowing producer countries to target taxes at large estates addresses the distributional concerns that smallholders could bear a disproportionate burden of the policy in terms of facing a higher fraction of total losses relative to their share of oil palm land expansion and deforestation. Moreover, targeting taxes at large estates may actually reduce deforestation by more than the E.U. policy. Large estates have access to better land-clearing technologies than smallholders and consequently may deforest more when expanding.

However, large estates still have incentives to block a targeted tax. Even though a targeted tax could improve long-run payoffs to smallholders, large estates experience losses under this policy. Furthermore, the tax revenues collected may not be sufficient to offset large estate losses, and large estates may not trust their governments to redistribute any taxes collected. As such, in the spirit of Asker et al. (2024) finding that one benefit of OPEC's market power was a reduction in carbon emissions, I explore to what extent allowing Malaysian oil palm farmers to form a trade organization that restricts quantity can limit deforestation. 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). Such a policy could be more attractive to all incumbent farmers by allowing them to jointly maintain

higher prices. Potential entrants are much less likely to be sufficiently organized to block a policy.

In this project, I specifically focus on evaluating the European Union's 2017 resolution to restrict palm oil imports on Malaysia's upstream oil palm industry and comparing it to a targeted tax and supplier coordination. 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 of palm oil. Moreover, Malaysia's oil palm farmers are heterogeneous, with small farms of, on average, 10 acres (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). The government has created multiple programs to help rural farmers gain access to the crop. The E.U. policy is cause for concern because it correlates with observed slowdowns in land area expansions and sometimes even contractions across regions. These slowdowns and contractions imply that small farms in particular may have to accept lower value outside options post policy than they would have otherwise. 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 E.U. 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 (e.g., 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 the 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, and 2) dynamic oil palm industry entry and exit decisions. 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 distinguish between losses to farms remaining in the market and the forgone profits of farmers exiting or choosing not to enter due to the policy.

I use a simulated method of moments to estimate parameters that rationalize observed land flows by farmer type across region. 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 E.U. policy, (ii) a targeted tax on large estates, and (iii) supplier quantity coordination.

This structural framework is useful because the treatment effects of trade policies targeting commodities are non-randomly assigned and all related markets are either directly or indirectly affected. The immediate short-run impacts of the EU trade policy on land use and inequality directly correlate with the pre-existing distribution of farm sizes, which varies substantially across regions. This is because this distribution affects treatment intensity via initial decreases in equilibrium prices. Moreover, the policy's initial effect on prices and the initial distribution of farms interact to determine the long-run evolution of regional equilibrium prices, total land utilization, and farm composition. Since this occurs across all producing regions, there is no control group for how land use and equilibrium prices would have evolved absent the E.U. policy (or under different policies).

Consistent with large farms having access to better (cheaper) land clearing technology, I estimate that large estates face entry costs that are on average roughly half the entry costs faced by smallholders. Moreover, I also estimate that large estates have higher value alternative uses of their farmland, as reflected in higher scrap values. These differences translate into smallholders experiencing proportionately larger losses in longer run discounted flow payoffs. In particular, on the external margin evaluated from 2017 to 2019, smallholders account for 52.6% of the reduction in oil palm land expansion but make up 65.8% of the losses in discounted long-run payoffs. This indicates that external margin smallholders bear a larger faction of the initial policy cost. Similarly, on the internal margin, smallholders account for 14.2% of land that continues to be farmed regardless of the policy's status but account for 21.2% of the long-run discounted losses.

Examining alternative policies that could appeal more to producers, I find that roughly a

5.7% per unit tax targeted at only large estates could reduce deforestation the same amount as under the E.U. trade policy. Moreover, a targeted tax also leads to higher long-run equilibrium prices for smallholders, generating an increase of almost $50 Million USD in incumbent long-run discounted flow payoffs. However, unsurprisingly, large estates face even greater log-run losses under the targeted tax than under the E.U. trade restriction. Consequently, such a targeted tax may be politically infeasible, as large estates have substantial economic incentives to block such policies. 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 the total long-run payouts to Malaysian farmers, net over the internal and external margins, as well as decrease deforestation by more than the E.U. trade restriction does.

This paper connects and extends the literatures on using economic policy as a means of addressing deforestation and the implications of firm (farm) heterogeneity for productive efficiency and inequality. While larger firms (farms) may be more cost-efficient in terms of long-run production (which includes land-clearing costs), they may also produce larger negative environmental externalities in the form of more deforestation. Thus, this paper adds to the existing literature on the correlation between farm sizes and productivity by accounting for an environmental externality also correlated with a notion of firm productivity. More specifically, beyond considering how endogenizing the farm size distribution impacts productivity (see for example: 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.

Furthermore, the link between heterogeneous farm sizes and differences in productivity also corresponds to the literature on agricultural inequality in developing economies (e.g., 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 work on how households smooth short-run consumption shocks from global commodities price fluctuations by temporarily engaging in enterprise ownership.

Most directly, this paper ties into the recent literature on optimal policies for managing deforestation and climate change. I contribute to this literature an exploration of possible policies that could lead to greater supplier incentive with environmental goals and how these policies interact act with farmer heterogeneity. Souza-Rodrigues (2019) and Assuno et al. (2023), for instance, explore the efficiency of domestic policies, both command-and-control as well as as economic, 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.[1] Domínguez-Iino (2022) provides a counterpart to Souza-Rodrigues (2019) by looking at geographic variation in policy impacts and finds that poorer regions do in fact bear the brunt of the cost of the policy. This project further adds to the discussion of heterogeneity by looking at the policy cost burden on different types of farmers within the same geographic region(s).

Farmer heterogeneity within region is important, because the differences in oil palm land utilization decisions between small and large/corporate farms correlate not only with a potentially unequally distributed cost burden but also inefficient policy implementation. With respect to distributional equity, a policymaker might hope to mitigate the cost burden on smaller, traditionally poorer farms. Income inequality is already, on average, worse in developing countries than it is in Europe and the U.S.[2] By explicitly modeling land use decisions, my model captures how the long run expected payoffs to produce palm oil could change differentially across groups post trade policy and how targeted taxes could be used to redistribute payoffs. Targeted taxes are potentially effective because within-region heterogeneity in this context implies that both types face the same equilibrium prices and are thus directly affected by each other's entry and exit decisions. This contrasts with cross-region heterogeneity where farmers within each region are similar but different geographic regions face different prices.

[1]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 E.U.'s policy against deforestation targets a broad class of imported goods associated with deforestation, including but not limited to cocoa, coffee, palm oil, and rubber. While the E.U. 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).

[2]`https://www.stlouisfed.org/on-the-economy/2017/october/how-us-income-inequality-compare-worldwide`

In terms of efficiency, some evidence suggests that large firms may contribute more to deforestation. 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, contrasting the 10.7% attributed to smallholdings. Moreover, large enterprises convert 16.7 times more peat swamp forests, which release more carbon than other types of land, 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. As such, understanding the heterogeneity across groups in oil palm land expansion choices is important, as policymakers may prefer to more heavily restrict expansion by groups whose agricultural activities correlate with more deforestation.

Concerns about distributional equity and mistargeting are linked together in this setting because different types of farms have access to different resources and technologies for clearing the land in terms of getting rid of old trees or preparing new land for planting. In particular, large estates (and organized smallholders) can more cheaply clear and plant large swaths of land at the same time (Kailany, 2011). Accordingly, I estimate that large estates face lower average entry costs than small farms and that smallholders face lower scrap values for their land. This implies that it is easier for large estates to (re)enter the oil palm market and benefit from higher prices if prices increase again in the future. This has consequences for equity because a low scrap value can also imply a low outside option. Thus, under low scrap values, smallholders who exit or fail to enter due to a negative demand shock are worse off in the sense that they will be "stuck with" their lower outside options for longer relative to large estates. That large estates have access to better land clearing resources and technologies also makes it easier for them to deforest. Accordingly, Gutirrez-Vlez et al. (2011) find that large farms prefer large concessions in forested regions whereas smallholders prefer already cleared land. Lee et al. (2014) note that large estates have capital and expertise to drain and cultivate peat swamps that independent smallholders might not have access to.

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 model in detail. Section 4 discusses the data used. Section 5 discusses estimation and identification. Section 6 presents estimation results. Section 7 discusses counterfactuals eliminating the trade policy and taxing large estates.

Section 8 concludes with a brief discussion.

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 globally the second largest 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).

Palm oil originates from the fresh fruit bunches (FFB) growing on an oil palm tree. 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. As a result, the initial processing of oil palm into crude palm oil (CPO) must be done locally. All harvesting of FFB must be done by hand. Downstream, palm oil can be found in biofuels, retail foods and snacks, as well as cosmetics. The World Wide Fund for Nature notes that "it's in close to 50% of the packaged products we find in supermarkets."

Heterogeneous Producers Given its large downstream demand, palm oil has come to play an important role in poverty alleviation for Malaysia 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 to be all farms under 40 hectares.[3] However, most smallholdings are far from this cutoff, with the average size being 3.9 hectares, which is less than 10% of the cutoff (Ahmad et al., 2023). There are two types of smallholders in Malaysia, independent smallholders and organized smallholders who are part of government programs (e.g., FELDA, FELCRA). Independent smallholders manage approximately 17% of total oil palm area cultivation in Malaysia. Whereas 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 that of

[3](https://www.mpoc.org.my/oil-palm-has-closest-resemblance-to-forest-than-other-major-oil-crops/).

other vegetable crops (Voora et al., 2020). This implies that it is a relatively efficient use of land for small farms.

As such, in addition to growing demand, palm oil's efficiency has made it a historically important means of poverty alleviation in Malaysia. The president of Malaysia's National Association of Smallholders described the importance of palm oil as

> 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).

Organized smallholders originated from early land resettlement schemes to reduce poverty by the Malaysian government. The Federal Land Development Authority (FELDA) was one of the earliest programs of this kind and formed in the late 1950s. Some estimate the program to have reduced poverty among its participants from 50% in the 1960s to 5% in the present day (Rahman, 2020).

Large estates produce the other 60% of Malaysian palm oil. Unlike smallholders which are often individual family units, large estates are often publicly traded companies with often more than 2000 acres of land on average. The largest company associated with a large estate is Sime Darby, which owns roughly 5% of oil palm land in Malaysia (743,854 acres of land) (*Sime Darby Annual Report*, n.d.). Notably, while large estates are hundreds of times larger than smallholdings, no individual large estate produces the majority of market share.

The differences in scale between large estates and smallholdings generate differences in entry costs and outside options between the two groups. For independent smallholders, replanting takes place on a small scale. This implies that access to technology for clearing the land in terms of getting rid of old trees or preparing new land for planting is different from other groups (i.e., organized smallholders, large estates) who can clear and plant large swaths of land at the same time (Kailany, 2011). This leads to differences in the entry cost of clearing each acre of land between independent smallholders and other farmers.

Furthermore, differences in landholdings mean that large estates (and organized smallholders making collective decisions) have different alternative uses of land even though the oil palm production process is relatively homogenous across farm sizes. Given that oil palm has yields

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 who often consist of individual family groups would be to switch to subsistence or sell the land and leave for urban areas to find 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).

Regional Variation Both smallholders and large estates exist across Malaysia. As shown in Figure 1, Malaysia spreads across two main land masses: Peninsular Malaysia and Malaysian Borneo. Peninsular Malaysia is divided into 10 administrative regions (i.e., Johor, Kedah, Kelantan, Melaka, Negeri Sembilan, Pahang, Perak, Pulau Pinang, Selangor, and Terengganu), and Malaysian Borneo includes two regions (i.e., Sabah, Sarawak). Dispersion in FFB prices shown in Figure 2 across administrative regions comes from the high cost of transporting FFB across regional boundaries, which restricts price arbitrage. As such, I define each of the administrative regions as a separate market.

Variation in prices across regions and time is driven, in part, by differences in aggregate supply and demand. Figure 4 displays how the evolution of total oil palm producing land differs by region, with some regions, especially Sarawak and Sabah in Borneo, experiencing much greater expansion than others. Figure 5 shows how the composition of farm types (i.e., large estate vs. smallholder) evolves differently across regions over time. In particular, there is both regional variation in the fraction of land farmed by independent smallholders in 2006 and how this fraction changes over 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.

2017 E.U. Palm Oil Resolution Malaysia exported between 67% and 76% of its palm oil in 2017.[4]. Through 2019, the E.U. was generally one of the two largest importers of Malaysian

[4]Range is based off of government data and a crude palm oil refinement rate of 0.88 (`https://www.edibleoilrefinerymachine.com/FAQ/improve_the_crude_palm_oil_refining_to_edible_oil_conversion_rate_695.html`)

palm oil, accounting for between 9% and 12% of all exports (Chu, 2023; Tan, 2019). As a result of its large imports of palm oil, the E.U. resolved to introduce a single certifications scheme for palm oil entering the E.U. and phase out the use of palm biodiesel by 2020 (Keong, 2017). The European Parliament cites concerns about the illegal deforestation of rainforests and concerns about climate change as the main reason behind its import restrictions (E.U., 2017).

As the world's two largest exporters of palm oil, Malaysia and Indonesia interpreted the resolution with alarm. Skeptical observers worried that these policies were protectionism framed as environmentalism and noted that the resolution "indrectly favored Europe's homegrown products like rapeseed and sunflower oils." Malaysia and Indonesia have filed separate suits with the World Trade Organization against the E.U. (Tan, 2019). Discussions of Malaysia and Indonesia jointly banning all palm oil exports to the E.U. have been on the table from 2017 through 2023 (Chu, 2023). The reaction of crude palm oil futures profits in contrast to that of soybean oil prices around the time of the announcement captures these concerns that the policy would result in a large negative palm oil demand shock. Soybean oil is one of palm oil's closest and main substitutes. Figure 3 shows that palm oil and soybean oil futures prices generally move together but diverged around the time of the E.U. 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 6 and Table 1 provide evidence that upstream FFB prices responded to the EU resolution. In particular, Table 1 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 look at 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 a couple of exchanges. I find that post-2017 CPO prices are significantly decreasing over time while pre-2017 CPO prices are significantly increasing.

I find evidence 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.[5] Table 2 attempts to quantify the change in trends after 2017

[5]I distinguish between Peninsular Malaysia and Sabah/ Sarawak (Borneo) because the expansion patterns

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 few 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.

Notably, the E.U. resolution is not the only policy to address deforestation and sustainability concerns in the oil palm industry. Starting in 2004, sustainability certifications have been available to oil palm farmers such as the Roundtable on Sustainable Palm Oil (RSPO), Indonesian Sustainable Palm Oil (ISPO), and Malaysian Sustainable Palm Oil. The ISPO was launched in 2011 by the Indonesian government and the MSPO in 2013 by the Malaysian government. The roll-out and uptake of these certifications have been gradual and sometimes coupled with government assistance, making assessing their direct implications on farmer profits difficult. I abstract away from these existing schemes in my model and analysis.

3 Model

In this section I describe a model rationalizing farm decisions 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, plausibly 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 be evolve given the current state of the world.

across the two land masses are especially different, as shown in Figure 4.

3.1 Environment

Agents and Actions Agents in this model include FFB farm(er)s and FFB buyers. In each period t, a mass of farmers of type f equal to the amount of land τ_t^f 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 $\tau_{f,t}^e$ 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.

Market State Space I assume that the state space is discrete. The market state space captures variables that determine per period equilibrium farmer payoffs and are informative about next period profits. The market state in a given period t is $s_t = (p_t^{soy}, r_t, \tau_t, \tau_t^{small}, \tau_t^{large}, a_t, d_t, eu_t)$ where:

- $p_t^{soy} \in \{p^{soy,1}, \ldots, p^{soy,L^{soy}}\}$ are soy prices
- $r_t \in \{r^1, \ldots, r^{L^r}\}$ is rainfall
- $a_t \in \{a^1, \ldots, a^{L^a}\}$ are common marginal cost (supply) shocks
- $d_t \in \{d_{pre}^1, \ldots, d_{post}^1, \ldots, d^{L^d}\}$ are common demand shocks. This would include the effects of a trade policy cutting international demand (i,e., the evolution of demand shocks will be allowed to differ before and after the official announcement of the trade policy).
- $\tau_t \in \{\tau^1, \ldots, \tau^{L^{total,\tau}}\}$ is the total land area devoted to palm oil.
- $\tau_t^{small} \in \{\tau^{small,1}, \ldots, \tau^{L^{small,\tau}}\}$ is the total smallholder land area devoted to palm oil.
- $\tau_t^{large} \in \{\tau^{large,1}, \ldots, \tau^{L^{large,\tau}}\}$ is the total large estate land area devoted to palm oil.
- $eu_t \in \{0, 1\}$ is an indicator for whether the 2017 EU trade policy to phase out palm oil is in effect.

I separately specify total land τ_t, smallholder land τ_t^{small}, and large estate land τ_t^{large} because τ_t helps determine equilibrium payoffs and $\tau_t^{small}, \tau_t^{large}$ help determine how τ_t evolves. Additionally, it must hold that $\tau_t \geq \tau_t^{small} + \tau_t^{large}$.[6] Let L^τ be the total number of unique combinations of $\tau_t, \tau_t^{small}, \tau_t^{large}$ that satisfy $\tau_t \geq \tau_t^{small} + \tau_t^{large}$. Then there a total of $L^{soy} \times L^r \times L^\tau \times L^a \times L^d \times 2$ possible market states.

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 E.U. trade policy, and 3) an endogenous process depending on agent actions. I distinguish between exogenous processes that do and do not depend on the E.U. 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 E.U. policy:

$$s_{AR(1)} = \{p^{soy}, r, a\}$$

I will assume that this process is an AR(1). Since the E.U. trade policy ultimately affects FFB demand, I assume the demand shock d_t evolves according to an exogenous process that does depend on the E.U. policy:

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

where ν_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 τ_t^f belonging to farm type f evolves such that:

$$\tau_{t+1}^f(s_t) = \underbrace{Pr(\delta\phi_{it}^f \leq VC_t^f(s_t)) \times \tau_t^f}_{\text{incumbents remaining}} + \underbrace{Pr(\kappa_{jt}^f \leq VC_t^f(s_t)) \times \tau_{f,t}^e}_{\text{entrants}} \tag{2}$$

where ϕ_{it}^f is a farm type specific random scrap value, κ_{jt}^f a farm type specific random entry cost,

[6] I write this as an inequality to account for how a small fraction of land belongs to organized smallholders not included in either τ_t^{small} or τ_t^{large}. I will assume that the land farmed by organized smallholders is constant over time. This is consistent with the data and how the related land was allocated.

and VC_t^f 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 following first-order Markov process:

$$\begin{aligned} F(s_{t+1}|s_t) =& F_{soy}(p_{t+1}^{soy}|p_t^{soy}) \times F_r(r_{t+1}|r_t) \times F_a(a_{t+1}|a_t) \\ & \times F_d(d_{t+1}|d_t, eu_t) \times F_\tau^{small}(\tau_{t+1}^{small}|s_t) \times F_\tau^{large}(\tau_{t+1}^{large}|s_t) \end{aligned} \tag{3}$$

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

3.2 Static Farmer Payoffs

Each farmer's payoffs in a given period are a function of state variables s_t. Since farmers are price takers, I first express the individual farmer's payoffs as a function of costs, effort, and observed prices. 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 implied production to derive aggregate supply. I then model aggregate demand for FFB, which, combined with aggregate supply, gives an expression for equilibrium prices as a function of s_t. I discuss how aggregate supply and demand determine equilibrium prices static farmer profits below and leave the details of the microfoundation to Appendix A.

Per Period Equilibrium Prices The per-period equilibrium prices are determined by the intersection of aggregate supply and demand:

$$\text{Supply: } ln(Q_t) = \alpha_1 ln(p_t) + \beta_1 X_{1t} + \frac{a_t}{b} \tag{4}$$

$$\text{Demand: } ln(Q_t) = \alpha_2 ln(p_t) + X_{2t}' \boldsymbol{\beta_2} + d_t \tag{5}$$

where p_t is the price of FFB, $X_{2t} = \ln(p_t^{soy})$ is the log price of soy, and $X_{1t}' = [\ln(\tau_t), \ln(r_t)]$ contains log rainfall and log total land area in t. $\frac{a_t}{b}$ captures shifts due to changes in marginal costs, and d_t captures shifts in demand. The equilibrium price and total quantity as a function

of the state variables s_t are:

$$p_t^* = exp(\frac{X_{2t}'\boldsymbol{\beta_2} + d_t - \beta_1 X_{1t} - \frac{a_t}{b}}{\alpha_1 - \alpha_2})$$
$$Q_t^* = exp(\frac{\alpha_1}{\alpha_1 - \alpha_2}(X_{2t}'\boldsymbol{\beta_2} + d_t) - \frac{\alpha_2}{\alpha_1 - \alpha_2}(\beta_1 X_{1t} + \frac{a_t}{b}))$$

Substituting p_t^* into equation 15 yields equilbrium farmer payoffs for a given state of the world s_t. Thus, for each farmer j static per period profits are:

$$\pi_{jt}(p_t^*) = p_t^* q_t(e(p_t^*)) - TC_{jt}(e(p_t^*)) \tag{6}$$

where $e(p_t^*)$ is the farmer's endogenous amount of effort as a function of the equilbrium prices they face, $q_t(e(p_t^*)) = r_t^{\beta_r} e(p_t^*)$ is quantity as a function of farmer effort and rainfall, and $TC_{jt}(e(p_t^*))$ is the total cost function. Functional form details for $e(p_t^*)$ and $TC_{jt}(e(p_t^*))$ are in Appendix A.

3.3 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 6 and the corresponding expected discounted flow payoffs. This implies that they need not observe and form expectations over all market state variables in s_t. In particular, I assume that farmers only observe and form beliefs about equilibrium prices p_t, cost shocks a_t, and rainfall r_t. Farmer beliefs about equilibrium prices change with the E.U. policy, but they experience the policy as an unforecasted shock. I assume that farmer fixed costs FC_{jt} are fixed by farmer type over time. As a result, Variables a_t, r_t, p_t alone are sufficient to determine each farmer's optimal quantity in equation 19 and payoffs in equation 15. In addition to a_t, r_t, p_t, farmers condition their expectations of future payoffs on eu_t, as the policy state could imply a different evolution of equilibrium prices.

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

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

2. All incumbents and potential entrants observe state variables $\tilde{s}_t = \{p_t, a_t, r_t, eu_t\}$, where p_t is the equilibrium price implied by the market state s_t.

3. Incumbents j choose quantities to supply and collect current period profits π_{jt}.

4. Potential entrants and incumbents make the following decisions simultaneously:[7]

   (a) Mass $\tau^e_{f,t}$ 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 τ^f_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.

Farmer Beliefs I assume that farmers have rational beliefs about the evolution of a_t, r_t, and p_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 $F_a(a_{t+1}|a_t)$ and $F_r(r_{t+1}|r_t)$. 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

[7] 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.

with marginal costs and rainfall as follows:

$$p_{t+1} = \lambda_1 p_t + \lambda_2 eu_t \times p_t + \lambda_3 a_{t+1} + \lambda_4 r_{t+1} + \eta_t \tag{7}$$

where η_t is an iid random variable with mean zero and with a variance reflecting uncertainty in agent beliefs. The variance of η_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). Including the E.U. indicator eu_t allows the mean of expected prices to differ pre- and post- E.U. trade policy.

$E[p_{t+1}] = \lambda_1 p_t + \lambda_2 eu_t \times p_t + \lambda_3 a_{t+1} + \lambda_4 r_{t+1}$ 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 E.U. 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_t, r_t, p_t, farmers believe that their payoff-relevant variables $\tilde{s_t} = \{p_t, eu_t, a_t\}$ evolve as follows:

$$F_{\tilde{s}}(\tilde{s}_{t+1}|\tilde{s}_t) = F_r(r_{t+1}|r_t) \times F_a(a_{t+1}|a_t) \times F_\eta(p_{t+1}|p_t, eu_t, r_t, a_t) \tag{8}$$

Farmer Value Function Since $\tilde{s_t}$ determines farmer payoffs and farmers hold beliefs over only variables in $\tilde{s_t}$, I define an incumbent type f farmer's expected discounted flow payoffs as a function of $\tilde{s_t}$:

$$V^f(\tilde{s_t}) = \pi_{it}(\tilde{s_t}) + \mathbb{E}_\phi \left[max \left\{ \delta \phi_{it}^f, VC^f(\tilde{s_t}) \right\} \right] \tag{9}$$

where δ is the discount rate and the continuation value $VC^f(s_t)$ is:

$$VC^f(\tilde{s_t}) = \delta \sum_{\tilde{s}_{t+1}} V^f(\tilde{s}_{t+1}) P(\tilde{s}_{t+1}|\tilde{s}_t) \tag{10}$$

Similarly, since a potential entrant enters if $VC^f(\tilde{s}_t) \geq \kappa^f_{jt}$, the entrant's discounted flow payoff is:

$$max\{VC^f(\tilde{s}_t) - \kappa^f_{jt}, 0\} \tag{11}$$

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 supersript f:

1. Farmers are playing optimal entry and exit strategies given their beliefs over the evolution of $\tilde{s}_t$. In particular, incumbent i chooses exit if $max\{\delta\phi_{it}, VC(\tilde{s}_t)\} = \delta\phi_{it}$ and to stay in the market if $max\{\delta\phi_{it}, VC(\tilde{s}_t)\} = VC(\tilde{s}_t)$ where VC is defined as in equation 10. Entrant j chooses entry if $max\{VC(\tilde{s}_t) - \kappa_{jt}, 0\} = VC(\tilde{s}_t) - \kappa_{jt}$ and not to enter otherwise.

2. Farmer beliefs over the evolution of $\tilde{s}_t$ are 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.

4 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 4 displays aggregate land flows by region over time, and Figure 5 shows changes in land use composition with respect to what 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 change of types of farmers growing oil palm unlike work focusing primarily on the external margin of land use (Hsiao, 2020; Domínguez-Iino, 2022). All additional data are similarly collected for 2006 to 2019, since my main goal is to rationalize changes in the composition of farm types underlying external 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.[8] I combine yield and land area data to calculate monthly quantities of FFB for each administrative region. Figure 2 shows the range of FFB prices across administrative regions over time. While there is variance in the range of prices, there does not appear to be consistent upward or downward trends over time.

Lastly, I collect data on key palm oil supply and demand shifters. 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 soy bean 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 commodities exchanges but are highly correlated. Given how closely soy bean and palm oil prices move together, as shown in Figure 3, I also collect monthly rainfall in major soybean oil producing countries (i.e., Brazil and the U.S.) as plausibly exogenous demand shifters.

5 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 distribution. I rely

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

on panel variation in my data across over region and over time to identify my key parameters.

5.1 Static Payoffs

I modify the market-specific aggregate supply in equation 4 and aggregate demand in equation 5 to generate estimation equations that allows me to use panel variation to identify $\alpha_1, \alpha_2, \beta_1, \boldsymbol{\beta_2}$ as follows:

$$\text{Supply: } ln(Q_{mt}) = \alpha_1 ln(p_{mt}) + \beta_1 X_{1,mt} + \boldsymbol{\gamma}_{1,t} + \boldsymbol{I}_{1,m} + \epsilon_{1,mt} \tag{12}$$

$$\text{Demand: } ln(Q_{mt}) = \alpha_2 ln(p_{mt}) + X'_{2,mt}\boldsymbol{\beta_2} + +\boldsymbol{\gamma}_{2,t} + \boldsymbol{I}_{2,m} + \epsilon_{2,mt} \tag{13}$$

Equation 12 assumes that prices, rainfall, and total oil palm land have the same effect on quantity supplied across regions and months but that there are different average cost shocks by month and region. Similarly, equation 13 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 15 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, I use instrumental variables to identify the price coefficients in equations 12 and 13. In the supply equation 12, I use rainfall in large soybean producing countries (i.e., U.S. and Brazil) as instruments. Rainfall in the U.S. 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.

In demand equation 13, 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 regional Malaysian rainfall as an additional instrument to identify the palm oil price coefficient and U.S. and Brazilian rainfall to identify the soybean oil price coefficient. Rainfall serves as a supply shifter independent of demand for both types of oils.

5.2 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.

Similarly 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 7, 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 land totals to those observed in the 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 to 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 2 shows that prices generally fluctuate within the same range even when land and supply are generally expanding in most regions (Figures 4 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 enough 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 decrease in payoffs. These instruments are plausibly uncorrelated with land-use decisions other than through affecting static profits.

6 Results

6.1 Aggregate Supply and Demand

Table 3 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, increasing in the amount of rainfall, and increasing in the total oil palm land area. The estimated price coefficients indicate that 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 picked FFB (instead of transporting and selling them to a mill) can be costly. That the coefficient of total land area is < 1 reflects how most but not all of the land dedicated to oil palm produces yield.

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 13 and 12, respectively. Examining the residuals confirms 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 as compared to Peninsular Malaysia. This helps rationalize why, as shown in Figures 4 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 E.U. 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[9] 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 3, and corresponding higher equilibrium prices after the E.U. policy. Increasing marginal costs (negative supply shocks) would similarly have decreased supply, also increasing prices.

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 up with 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 \$130.46 USD per month in Sabah/Sarawak and by \$45.10 USD per month in Peninsular Malaysia. These amounts are potentially nontrivial relative to Malaysia's mean income (\$11,142 USD) and poverty line (\$6,094). \$130.46 USD per month aggregated over 12 months is 14.05% of annual mean income and 25.69% of the povety line. \$45.10 USD per month aggregated over 12 months is 4.86% of mean annual income and 8.88% of the poverty line.

[9]For years affected by the pandemic

6.2 Entry Costs and Scrap Values

Table 4 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 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 the oil palm land being relative 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 land 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 implied the E.U. trade policy, I can calculate how much the policy impacted continuation values.

The first row of Table 5 shows the average change in continuation value (ΔVC) per hectare of oil palm land by farm type pre and post the E.U. policy. Consistent with smallholders having worse outside options, as reflected in a lower scrap value distribution mean, they experience a greater decrease in continuation value relative to large estates.

Appendix D 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.

7 Counterfactuals

Explicitly modeling entry and exit decisions enables me to predict changes in farm profits that are consistent with long-run changes in the external margins of oil palm land cultivation. Moreover, persistent changes to static profits also impact farmers in the long run and influence their decisions whether to remain in the oil palm industry. As such, the negative demand shocks implied by the E.U. trade policy leads to both: (a) lost potential profits for farmers who would have entered otherwise and for those who would not have exited otherwise, and (b) lower equilibrium prices offset by farm exit for farmers choosing to remain in the market.

Heterogeneous scrap value and entry cost distributions across types of farmers implies that both (a) and (b) are also associated with distributional and efficiency consequences. Consequently, I use my estimates and model to explore the following counterfactuals: (i) the E.U. policy's effects across different farm types, and (ii) how the E.U. policy compares to a more targeted policy. The targeted policy addresses supplier concerns about the losses the E.U. policy imposes on smallholders, making it potentially more palatable to producers than an externally imposed trade restriction that potentially hurts small farmers the most.

However, a targeted tax may also be politically infeasible, and there may be practical reasons why such a tax has not been implemented domestically (and what we do observe is a form of externally imposed policy). One possible reason for this is that large estates still have incentives to block taxes targeted at them, since they still face losses under these taxes. Consequently, I explore a third counterfactual that could make reducing deforestation incentive compatible for all producers. In particular, I predict the relative long-run payoffs and reductions in deforestation under a policy allowing Malaysian oil palm farmers to form a trade organization

limiting total quantities produced. Since it is infeasible to monitor and control quantities on incumbent farms[10], I assume that the trade organization limits quantity by limiting new entry.

Impact of EU Trade Restriction Table 5 describes the impacts of the E.U. policy on total oil palm land and long-run discounted payoffs on the internal and external margins. With respect to total land, I find that the E.U. policy decreased the expansion of oil palm land by 3.69 thousand hectares from 2017 to 2019. Smallholders make up for 1.94 thousand hectares or 52.6% of the reduction. Large estates make up for 1.75 thousand hectares or 47.4% of the reduction.[11] These decreases in external margin oil palm land also correspond to lost discounted flow payoffs on the external margin. These external margin losses account for lower prices, lower expected entry costs conditional on entry, and farm(er)s accepting lower scrap values on average as a result of lower profits from continuing to cultivate oil palm. I calculate that, in total on the external margin, smallholders experienced a loss in discounted flow payoffs of $4.25 million USD, and large estates experienced a loss of $2.21 million USD. Notably, because smallholders and large estates draw from different entry cost and scrap value distributions, decreases in flow payoffs are not proportional to decreases in external margin oil palm land expansion. Smallholder losses account for 65.8% of all losses. This is proportionately higher than the smallholder reduction in land expansion, reflecting that, from 2017 to 2019, smallholders bore a disproportionately higher cost of the E.U. policy per unit decrease in oil palm land expansion.

The counterpart to external margin losses is internal margin losses which capture aggregate discounted long run losses in payoffs to smallholders and large estates who would have entered and/or continued to produce oil palm in 2017 with or without the E.U. trade policy. These losses reflect changes in equilibrium prices from both the E.U. policy's demand reduction and the decrease in supply expansion (on the external margin) as well as changes in the expected scrap value accepted. Table 5's counterfactual indicates that smallholders accounted for 21.2% and large estates 78.8% of the $38.55 million USD in internal margin losses. Again, smallholders' fraction of losses is larger than their fraction of land farmed, which is 14.2%. This reflects the lower scrap values smallholders face.

Since the primary stated motivation of the EU policy is to limit deforestation, I also use these

[10] Yield is influenced by many unobservable factors such as farmer effort.

[11] Appendix E discusses how smallholder and large estate shares of land evolves over a longer time horizon.

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 farmers' outside options include other forms of agriculture such as rubber farming that could also require clearing primary forest. 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 mis-classify 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 releases carbon and limiting future carbon storage relative to the clearing of secondary forest.

In order to conduct this exercise, I project changes in primary forest cover by region onto changes in the total oil palm area farmed by large estates and smallholders. Table 6 displays the different specifications I try. The changes in primary forest reported in Table 5 utilize specification (1). 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 the expansion in large estate land. Note, the different specifications in Table 6 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 and large estates may be more likely to clear forest.

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

Targeted Policy Comparison One possible policy alternative to address farm(er) heterogeneity is a targeted policy that treats different types of farmers differently. In the years since the original E.U. resolution, criticisms have arisen highlighting the harmful effects coarse poli-

cies[12] could have on smallholders (see, for example, Hancock 2023). In light of recent policy discussions regarding targeting sustainability certification schemes at large estates, I explore the possible implications of a per unit targeted tax at large estates. If certification is such that large estates need to certify (through some independent external agency) the origins of their FFB and this certification costs some fraction of market price per unit FFB, the certification scheme would be equivalent to a targeted task (minus collected tax revenues).

Lacking a good estimate of the potential cost of certification to large estates, I explore a targeted tax that reduces deforestation the same amount as the negative demand shocks correlated with the E.U. resolution. I find that a 5.7% tax on only large estates reduces total oil palm land expansion the same amount as the E.U. policy (from 2017-2019) and compare the potential impacts of the two policies in Figure 13. Panel 13a shows that the tax leads large estates to make up a greater fraction of decreased external margin expansion than smallholdings, in contrast to the E.U. policy which led to a roughly equal decrease across both groups. Panel 13b projects these counterfactual land flows onto changes in primary forest area. Since large estate land expansion correlates with more loss of primary forest, the targeted tax preserves more primary forest. Appendix F discusses the projections for the other two specifications in Table 6.

Panels 13c and 13d illustrate the losses in discounted flow payoffs from the targeted tax relative to the E.U. policy on the external and internal margins, respectively. The tax is indirectly "redistributive" in favor of smallholders, relative to the E.U. policy, on both the external and internal margins. On the external margin, smallholders as a group benefit from increased participation and higher equilibrium prices from decreased aggregate supply, leading them to experience a small increase in continuation values aggregated on the external margin. Similarly, smallholders on the internal margin benefit from higher equilibrium prices from decreased aggregate supply, also increasing continuation values aggregated on the internal margin .

Large estates on the external margin lose proportionately more (relative to land reduction and losses under the E.U. policy) in long-run discounted payoffs because, under taxes, they have less net entry and their long-run discounted payoffs conditional on entry are lower than under the E.U. policy. On one hand, this means that the average farm who exits under the

[12]The latest iteration as of the end of 2023 includes a ban on all imports related to deforestation by the end of 2024

targeted policy accepts a lower expected scrap value than under the E.U. policy. On the other hand, it also means that the difference between the discounted flow payoff and the expected entry cost conditional on entry paid by a "lost" entrant goes up.[13] In other words, large estates are being pushed towards lower average outside options, and more efficient entry, in terms of average entry costs, is being deterred.

Quantity Coordination I also consider a policy counterfactual in which the government can act as a monopolist in setting prices for each region. One possible motivation behind the E.U. policy is that it is not incentive compatible for the palm oil producer countries to independently curb deforestation, and, as a result, the E.U. needs to exert external pressure in the form of trade restrictions. However, allowing for more market power among upstream producers could theoretically address the incentive compatibility concern. Allowing suppliers to act like monopolists gives them incentives to curb quantity in order to increase prices. 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 the Malaysian Sustainable Palm Oil organization (MSPO) acts as a trade organization that controls how much additional 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 hectors 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 E.U.'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 MSPO was "in favor" of forming a body similar to OPEC for palm oil Tan 2019.

For this counterfactual, 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

[13]Expected entry costs conditional on entering absent the tax and not entering under the tax are lower than expected entry costs conditional on entering absent the E.U. policy and not entering under the E.U. policy because the former eliminates more potential entrants with lower entry cost draws.

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 RISDA, FELDA, and FELCRA. In particular, the MSPO chooses potential entry area $\Delta\tau_t^{MSPO}$ to maximize the total expected flow payoffs, excluding scrap values, of all active farmers in the organization $VC^{MSPO}(\tau|\tilde{s}_t)$:

$$\Delta\tau_t^{MSPO} = \underset{\Delta\tau}{argmax} \boldsymbol{E}\left[VC^{MSPO}(\Delta\tau, s_t) + \omega_{\Delta\tau,t}\right] \tag{14}$$

where the expectation is taken over independent farmer entry and exit decisions at the MSPO price, realizations of $\omega_{\Delta\tau,t}$ corresponding to total areas of entry permits made available, and the evolution of the state s_t, conditional on the total amount of land they choose to add. $\omega_{\Delta\tau,t}$ 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, 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:

$$\begin{aligned} V^{MSPO}(s_t) =& \pi(s_t) + \underset{\Delta\tau}{max} \boldsymbol{E}\left[VC^{MSPO}(\Delta\tau, s_t) + \omega_{\Delta\tau,t}\right] \\ VC^{MSPO}(\Delta\tau, s_t) =& \delta \sum_{s_{t+1}} V^{MSPO}(s_t) P(s_{t+1}|s_t, \Delta\tau) \end{aligned}$$

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 7. 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.

Table 7 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

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 demand from Malaysia versus Indonesia constant. This is somewhat plausible for smaller deviations in Malaysia's equilibrium price from the observed competitive equilibrium, as Indonesian producers are less likely to respond differently to these changes (relative to how they respond under Malaysia's perfectly competitive equilbirium). However, under larger deviations in long run prices from the observed competitive equilibrium, such as under switching to a monopolist-like entity, 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 discounted flow payoffs across both types of farmers. Moreover, gains on the internal margin exceed losses on the external margin, leading to a net positive increase in flow payoffs across incumbents and potential entrants. Since the fraction of imports of palm oil going to each consumer region (e.g., China, India, E.U.) is very stable from 2006 to 2017, I use these to take the weighted average of the regional elasticities Hsiao (2020) estimates. I then plug this elasticity in to 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, netting across incumbents and potential entrants, across both types of farmers. These results support the potential of allowing for an OPEC-like organization to be supported by incumbent Malaysian farmers and palatable to excluded entrants under some feasible set of transfers.

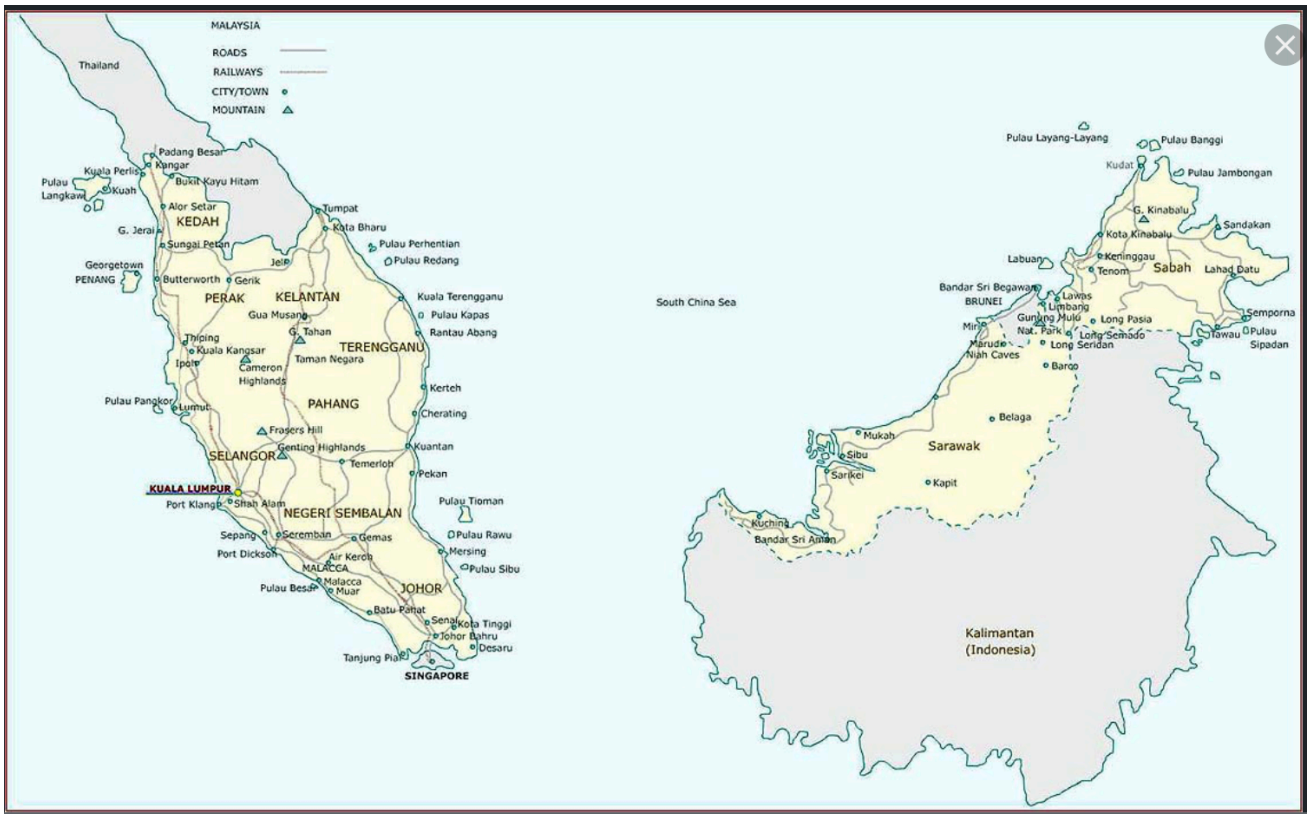
8 Discussion

Deforestation and climate change are undeniably pressing issues that need to be addressed, and there are many policy tools, both domestic and international, to consider. Tariffs and trade restrictions are generally coarse policies that impact entire industries or whole regions. This paper explores how heterogeneity might affect the implications of these policies for distributional equity and efficiency in preserving primary forests. I then use counterfactual exercises to explore alternative policies that could be more favorable to producers.

My counterfactuals suggest that a targeted policy could be more distributionally favorable towards smallholders and reduce primary forest more successfully than a coarse demand reduction. This would help address one aspect of the complaints that exporter countries have raised about the E.U. trade policy. However, a targeted tax still imposes large long-run losses on large-estates, which may have more resources to yield political influence, making the targeted tax potentially political infeasible. Political infeasibility is a possible explanation for why we have not yet observed such a policy implemented in producer countries. I find that allowing for producers to form an OPEC-like trade organization that controls quantities by limiting entry could be an alternative policy that increases payoffs to farmers and decreases deforestation. Counter to the general intuition that firms use market power to circumvent complying with environmental directives (e.g., Ziady, 2021), this suggests that allowing for market-power in this scenario could actually help align supplier incentives with environmental goals.

9 Figures

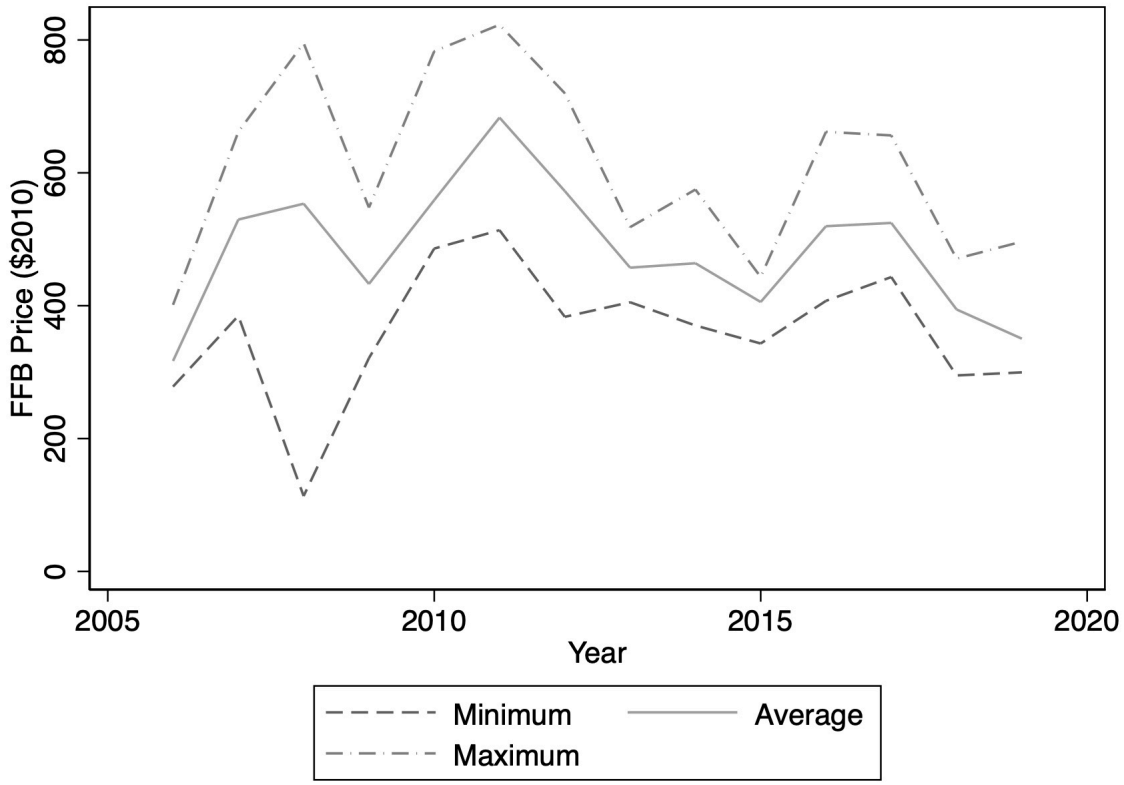
Figure 1: Map of Malaysia



Source:`https://www.orangesmile.com/travelguide/malaysia/country-maps.htm`

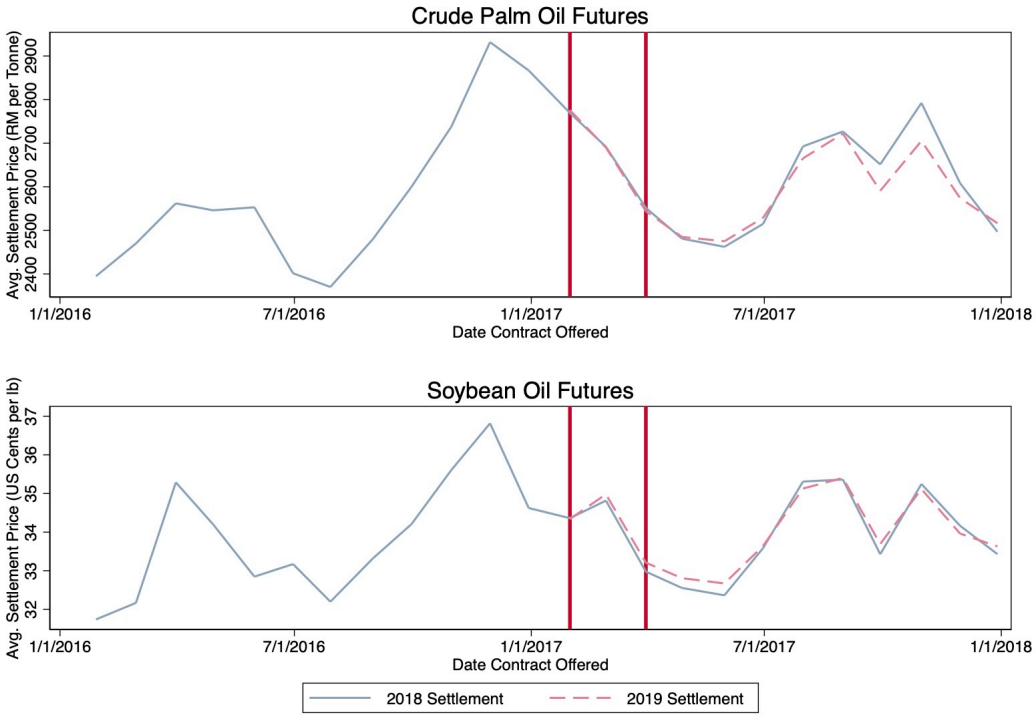
Note: Peninsular Malaysia is the land mass to the left.

Figure 2: Dispersion in FFB Prices Over Time



Note: Minimum price is the minimum regional FFB price reported by the MPOC for the year, and maximum is the maximum. Average is the average price across all regions. Prices are in RM.

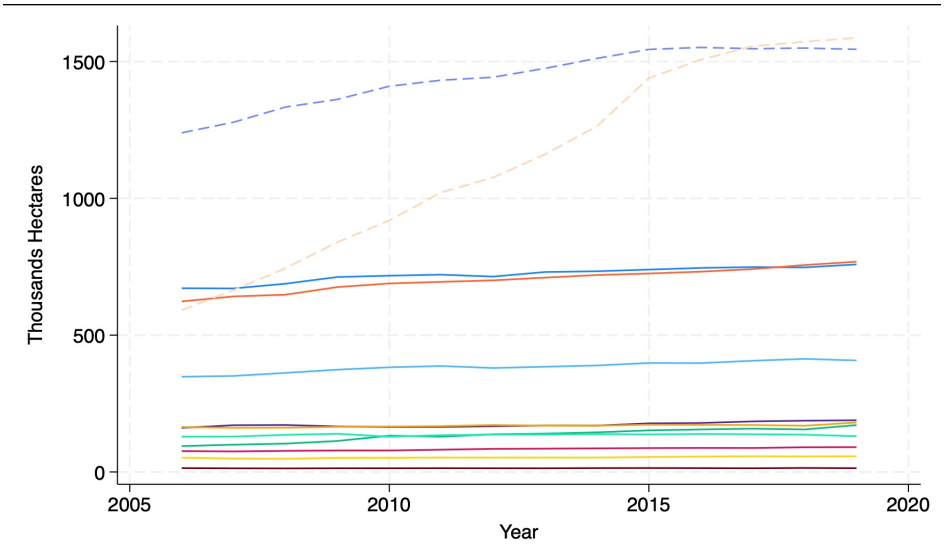
Figure 3: Palm Oil vs. Soybean Oil Futures Prices, 2006 to 2019



Source: Datastream

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.

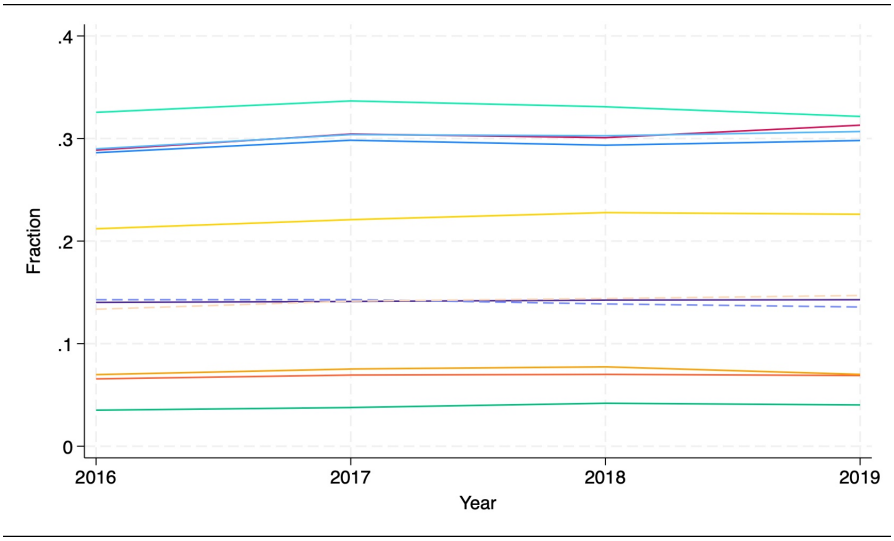
Figure 4: Total Oil Palm Land by Region, 2006 to 2019



Note: Each line corresponds to a separate region. Solid lines are regions in Peninsular Malaysia, and dashed lines are regions in Borneo.

Source: Malaysian Palm Oil Council

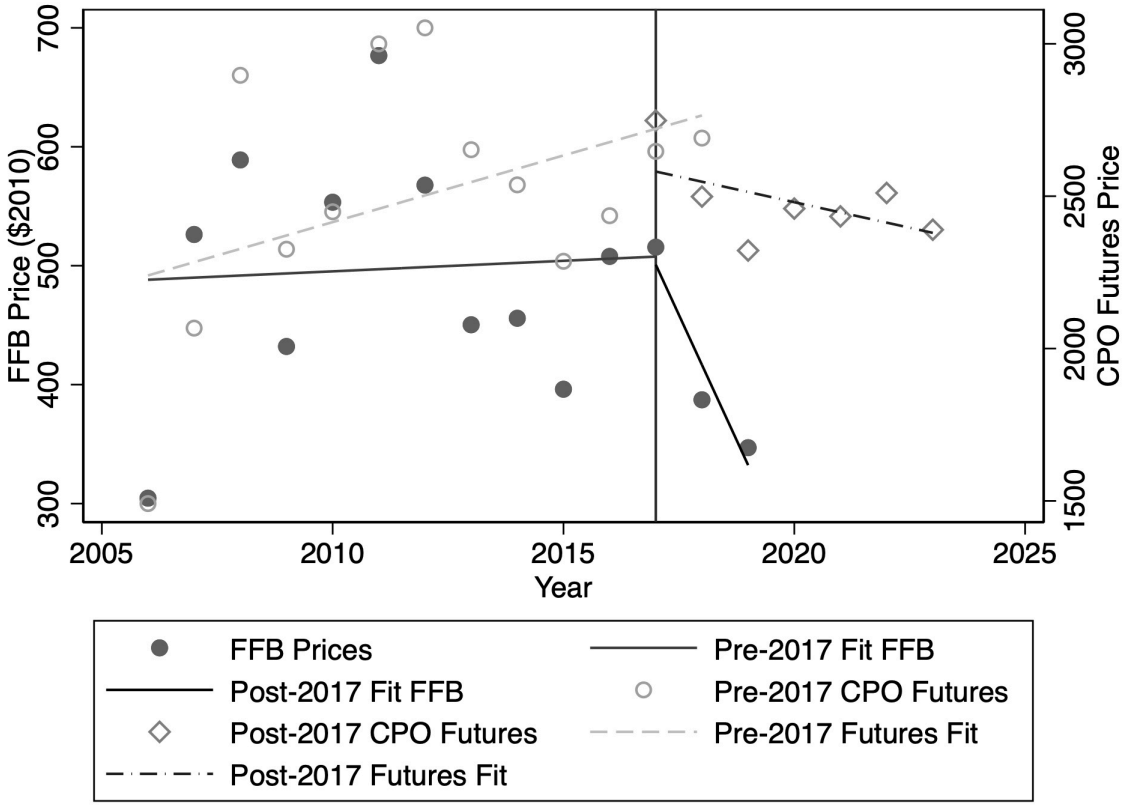
Figure 5: Change in Smallholder Land Shares by Region, 2006 to 2019



Source: Malaysian Palm Oil Council

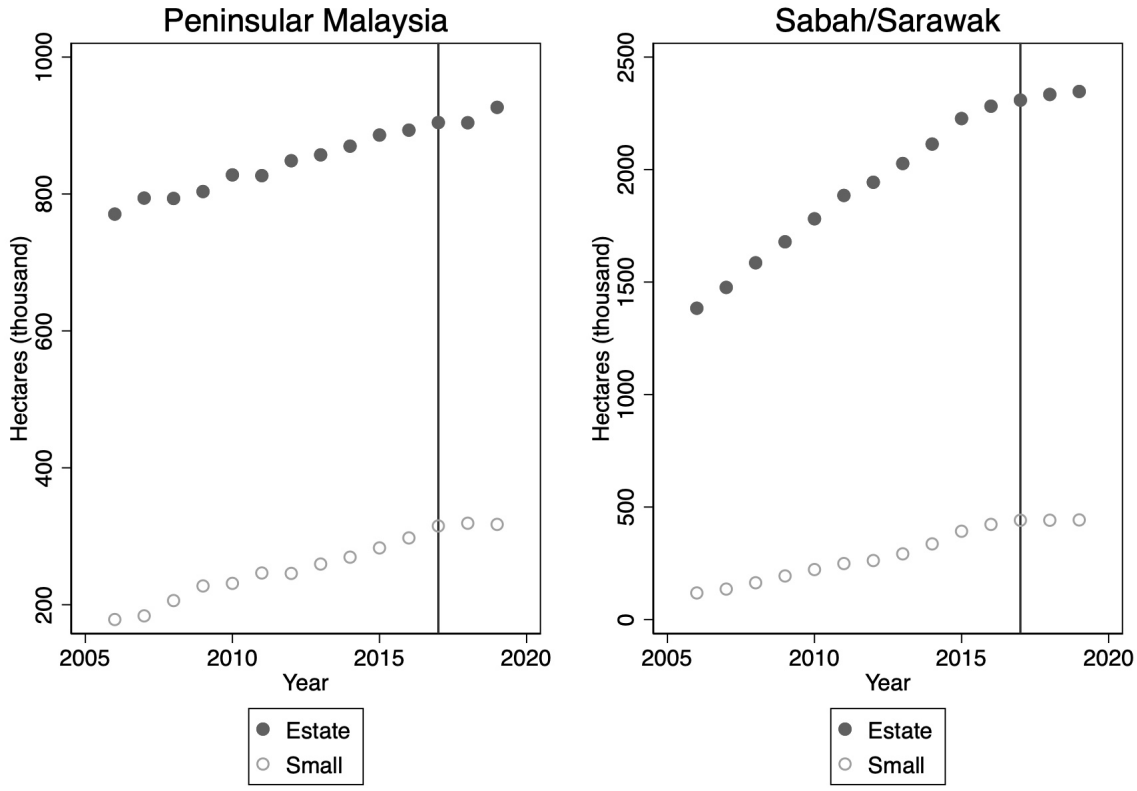
Note: "Smallholder" includes only independent smallholders. Denominator out of which total land is calculated does not include government programs (e.g., FELDA, RISDA). Each line corresponds to a separate region. Solid lines are regions in Peninsular Malaysia, and dashed lines are regions in Borneo.

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



Note: Prices are in RM.

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

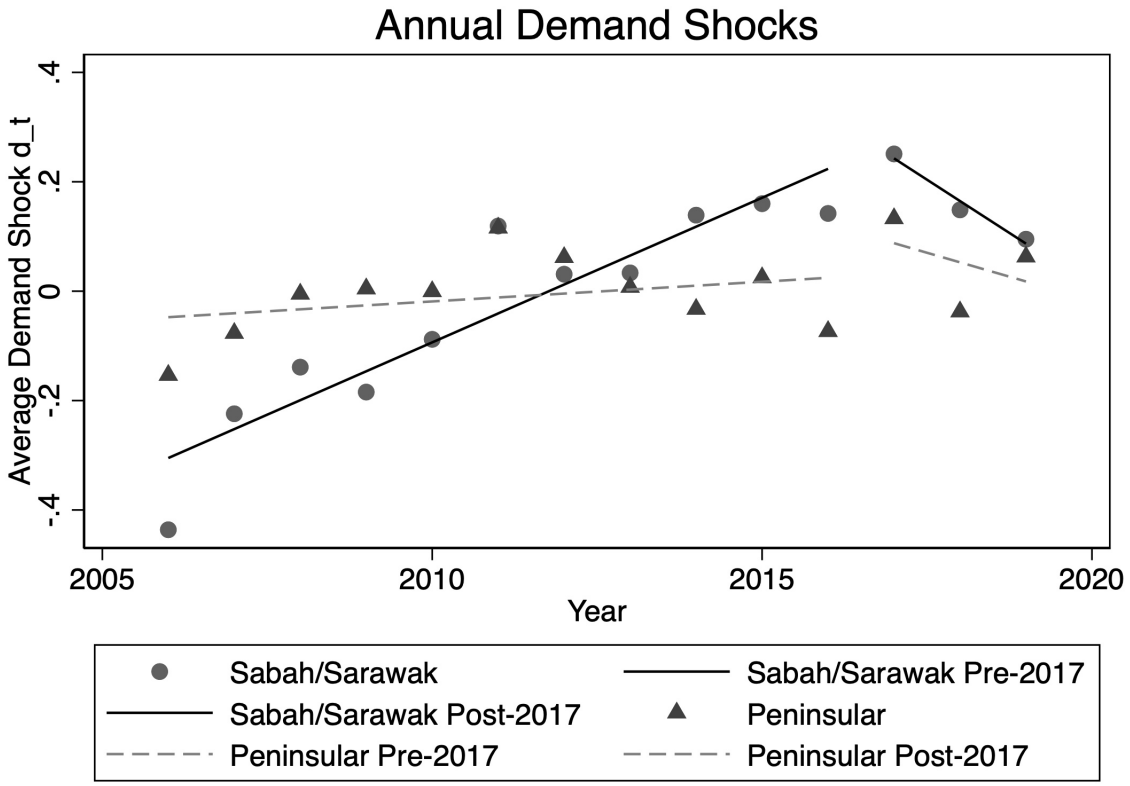


Figure 9: Average Values of All State Variables, All Regions

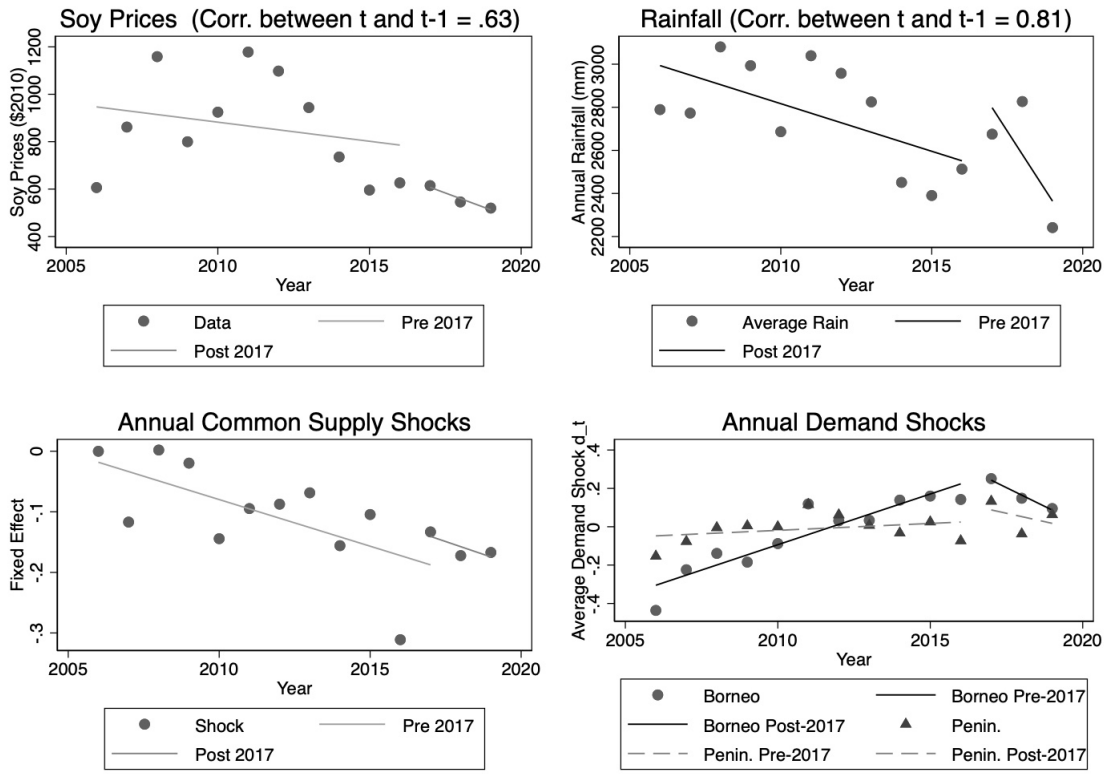
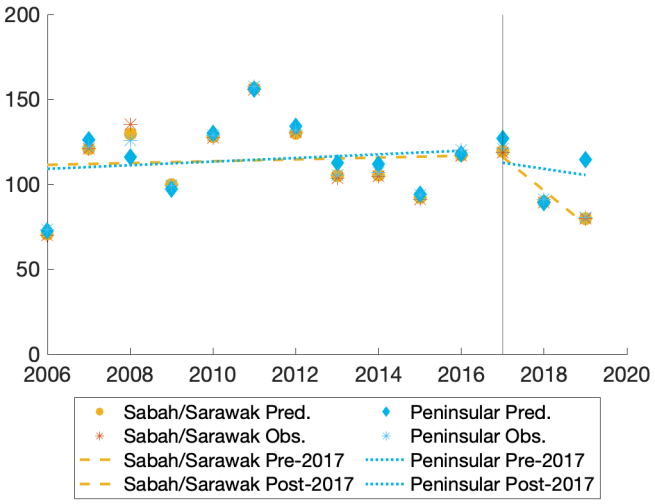
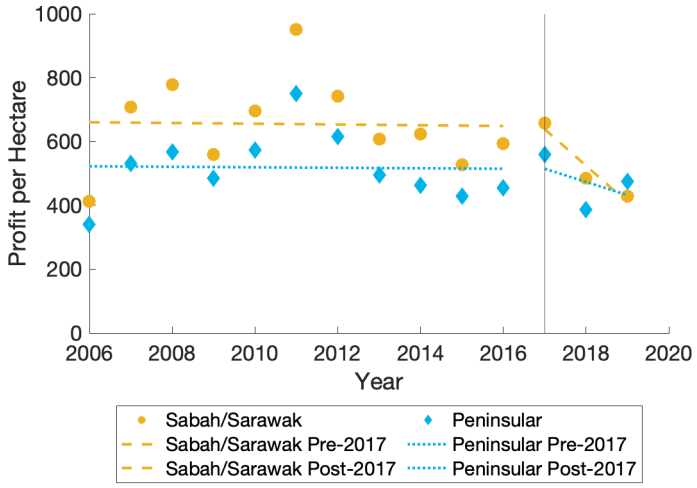


Figure 10: Predicted Prices



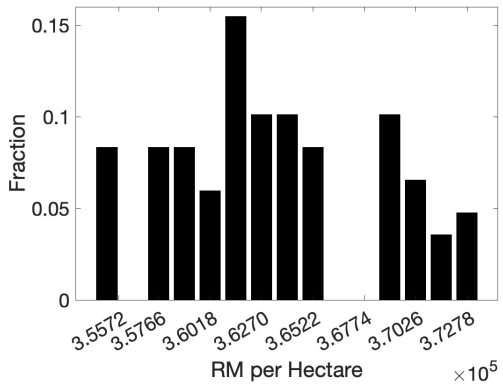
Note: Equilibrium prices calculated using parameter estimates and recovered supply and demand residuals. Prices are given in USD. 1 RM = 0.23 USD.

Figure 11: Predicted Monthly Profits

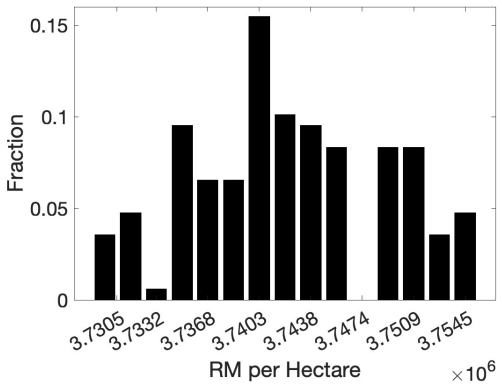


Note: Predicted profits using parameter estimates. Pre-2017 mean is \$654.41 (USD) for Sabah/Sarawak and \$518.44 for Peninsular Malaysia. Post-2017 mean is \$523.95 for Saba/Sarawak and \$473.33 for Peninsular Malaysia.

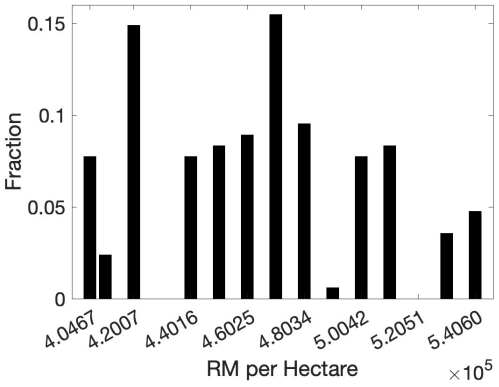
Figure 12: Conditional Expected Values of Estimated Parameters



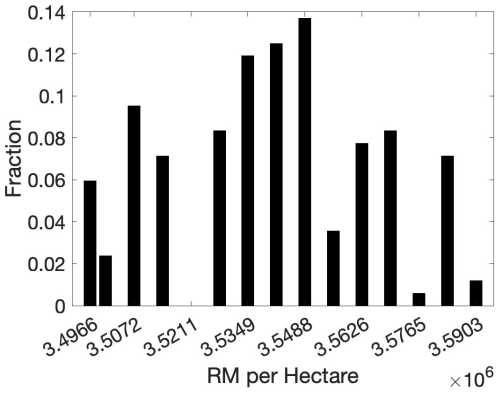
(a) Smallholder Scrap Value



(b) Large Estate Scrap Value



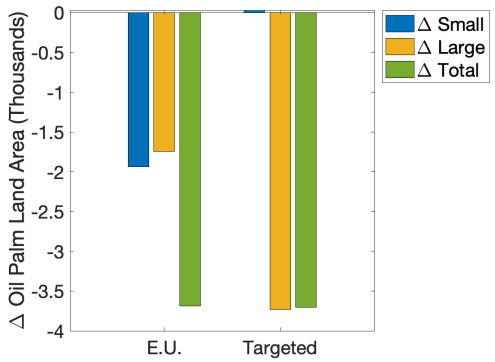
(c) Smallholder Entry Cost



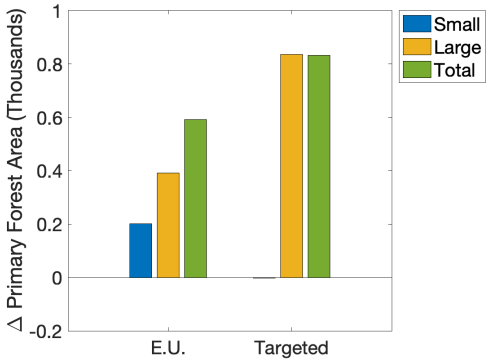
(d) Larger Estate Entry Cost

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.

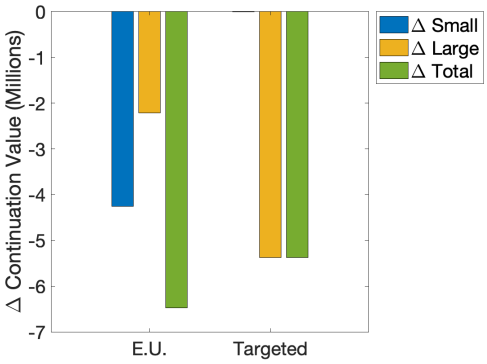
Figure 13: Comparing E.U. Trade Restriction to a Targeted Policy



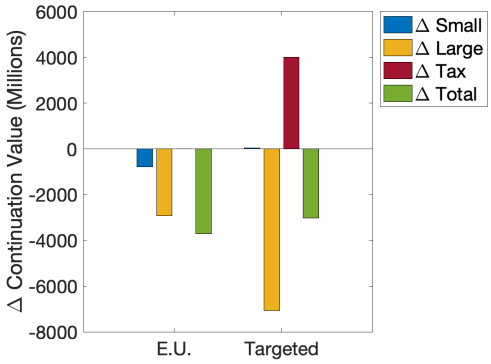
(a) Δ Total Oil Palm Area



(b) Δ Primary Forest



(c) Δ Total External Margin VC



(d) Δ Internal Margin VC

Note: The targeted policy here is a 5.7% per unit tax on only FFB sold by large estates. Land areas are reported in hectares and continuation values are reported in USD. Changes in continuation values reported are scaled up (multiplied) by relevant land area. Continuation value is calculated as the continuation value of continuing to farm oil palm on a hectare of land.

10 Tables

Table 1: 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 2: 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 3: Short Run Aggregate Supply and Demand Estimates

	(1)	(2)
	Demand	Supply
ln_price_ffb	-0.359**	0.0140
	(0.110)	(0.0647)
ln_price_soy	0.145**	
	(0.0538)	
ln_rainfall_mm_annual		0.360**
		(0.0623)
ln_hectares_TOTAL		0.894**
		(0.0297)
_cons	15.05**	-1.169*
	(0.404)	(0.567)
month_fe	X	X
state_fe	X	X
year_fe		
additional_instrument	X	X
N	1944	2016
r2	0.978	0.984
fs	16.45	35.26

Standard errors in parentheses

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

Table 4: Entry Cost and Scrap Value Parameter Estimates

$\hat{\theta}$	*Smallholders*	*Large Estates*
Entry Cost $\hat{\mu}_\kappa$	720 Mil. RM/hectare	329 Mil. RM/hectare
	(166 Mil. USD/hectare)	(75.7 Mil. USD/hectare)
Scrap Value $\hat{\mu}_\phi$	0.34 Mil. RM/hectare	3.4 Mil. RM/hectare
	(0.08 Mil. USD/hectare)	(0.77 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 5: E.U. Trade Restriction and Farm Heterogeneity

		EU Policy				
		Small		*Large*		*Total*
Margin		#	% Total	#	% Total	
Avg. ΔVC per hectare (Not in Millions)		-1,915		-1,177		
External (2017-2019)	ΔLand	-1.94	52.6%	-1.75	47.4%	-3.69
	ΔPayoffs	-4.25	65.8%	-2.21	34.2 %	-6.46
Internal (2017)	Land	411	14.2%	2,482	85.8 %	2,893
	ΔPayoffs	-787	21.2%	-2,921	78.8%	-38.55
Δ Primary Forest		0.20	33.9%	0.39	66.1%	0.59

Note: ΔLand is in thousands of hectares. ΔPayoffs is in millions of USD. External margin is lost entry/ extra exit each year from 2017 to 2019, inclusive. Comparison is no EU policy counterfactual.

Table 6: Predicting 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: Regression includes region and year fixed effects. Location refers to an indicator for whether a region is in Peninsular Malaysia or Borneo.

Table 7: Producer Coordination Counterfactual

		MSPO Coordination						**EU**
Demand Elasticity		(Estimated) **-0.359**			(Hsiao 2024) **-0.819**			(Estimated) **-0.359**
		Small	*Large*	*Total*	*Small*	*Large*	*Total*	*Total*
Avg. ΔVC per hectare (Thousands)		282	179		0.9	1.1		
External (2017-2019)	ΔLand	-52.3	-96.9	-149.2	-52.3	-96.9	-149.2	-3.69
	ΔPayoffs	-58.4	-51.0	-109.4	-0.24	-0.45	-0.69	-.006
Internal (2017)	Land	411	2,482	2,893	411	2,482	2,893	2,893
	ΔPayoffs	115.7	444.0	559.7	0.37	2.75	3.12	-.039
Net	Payoffs	57.3	393	450.3	0.13	2.30	2.43	-0.045

Note: Payoffs in Billions USD. Land in thousands 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.

A Individual Farm(er)'s Problem

Since all farmers are atomistic, they take FFB prices p_t in each period t as given. Thus, for each farmer j static per period profits are:

$$\pi_{jt}(q) = p_t q_t(e) - TC_{jt}(e) \tag{15}$$

where e is the farmer's endogenous amount of effort, $q_t(e) = r_t^{\beta_r} e$ is quantity as a function of farmer effort and rainfall, and $TC_{jt}(\cdot)$ 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:

$$TC_{jt}(e) = \frac{1}{1+b} \exp^{a_t + (1+b)\ln(e)} + FC_{jt} \tag{16}$$

where a_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_{jt}. This total cost implies the following marginal cost:

$$MC_{jt} = MC_t = \exp^{a_t + b\ln(e)} \tag{17}$$

Since the short-run production technologies (i.e., harvesting methods) are similar across different types of farm, I currently assume that marginal costs across different types of farms are the same.[14] Taking the FOC of the profit function $p_t r_t^{\beta_r} = MC_t$, this parametrization implies that each farmer will exert the same amount of effort each in equilibrium.

$$\begin{aligned} p_t r_t^{\beta_r} &= \exp^{a_t + b\ln(e)} \\ \ln p_t + \beta_r \ln r_t &= a_t + b \ln e \\ e^* &= \exp(\frac{1}{b}(\ln(p_t) + \beta_r \ln r_t - a_t)) \end{aligned} \tag{18}$$

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

$$q(e^*) = r_t^{\beta_r} \exp(\frac{1}{b}(\ln(p_t) + \beta_r \ln r_t - a_t)) \tag{19}$$

[14] I plan to relax this assumption in the future, since there is some evidence of productivity differences.

Aggregate Supply In any given period, the total amount of land devoted to palm oil is τ_t but only a fraction of that land $\tau_t^{\beta_\tau}$, $0 \leq \beta_\tau \leq 1$ actually contributes to FFB yield. This could be due to patterns of replanting and tree aging, for instance. Palm trees need to be replanted roughly every 30 years and young trees take a few years to begin producing FFB. Taking into account that not all land always contributes to yield, the aggregate supply curve is:

$$Q_t = \tau_t^{\beta_\tau} q(e^*) = \tau_t^{\beta_\tau} r_t^{\beta_r} \exp(\frac{1}{b}(\ln(p_t) + \beta_r \ln r_t - a_t)) \tag{20}$$

$$\ln Q_t = \underbrace{\frac{1}{b}}_{=\alpha_1} \ln p_t + \underbrace{\beta_\tau}_{=\beta_{11}} \ln \tau_t + \underbrace{\frac{2\beta_r}{b}}_{=\beta_{12}} \ln r_t + \underbrace{\frac{a_t}{b}}_{=\gamma_{1t}} \tag{21}$$

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

$$ln(Q_t) = \alpha_2 ln(p_t) + \beta_2 p_t^{soy} + d_t \tag{22}$$

where p_t^{soy} is the price of soy oil, the main downstream substitute for palm oil products, and d_t represents aggregate demand shocks such as an overall reduction in palm oil imports to the E.U.

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:

$$\tau_{t+1}(s_t) = \underbrace{(1 - P_x^l(p_t(s_t), eu_t, a_t)) \times \tau_t}_{\text{incumbents remaining}} + \underbrace{P_e^l(p_t(s_t), eu_t, a_t) \times L_e}_{\text{entrants}} \tag{23}$$

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:

$$eu_{t+1} = max\{\mathbf{1}(\tau_{t+1} \geq \overline{\tau}_{eu}), eu_t\} \tag{24}$$

(d) The demand shock d_t evolves such that:

$$d_{t+1} = \varphi_0 + \varphi_1 d_t + \varphi_2 d_t eu_t + \nu_t \tag{25}$$

5. Calculate the distribution of equilibrium price transitions $p(s_t) \rightarrow p(s_{t+1})$ 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 7 (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:

$$\hat{\tau}_{t+1}(s_t) = \tau_{t+1}(s_t) + \zeta_{t+1} \tag{26}$$

   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 7 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

$$P_x(\hat{VC}(\theta)) = exp(-\frac{1}{\mu_\phi}\delta \hat{VC}(\theta)) \tag{27}$$

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 27 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.

$$P_e(\hat{VC}(\theta)) = 1 - exp(-\frac{1}{\mu_\kappa}\delta \hat{VC}(\theta)) \tag{28}$$

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 $\hat{VC}^f(\theta)$

$$\tau^f_{t+1} = \underbrace{Pr(\phi^f_{it} \leq VC^{f,l}_t) \times \tau_t}_{\text{incumbents remaining}} + \underbrace{Pr(\kappa^f_{jt} \leq VC^{f,l}_t) \times \tau^e_{f,t}}_{\text{entrants}} \tag{29}$$

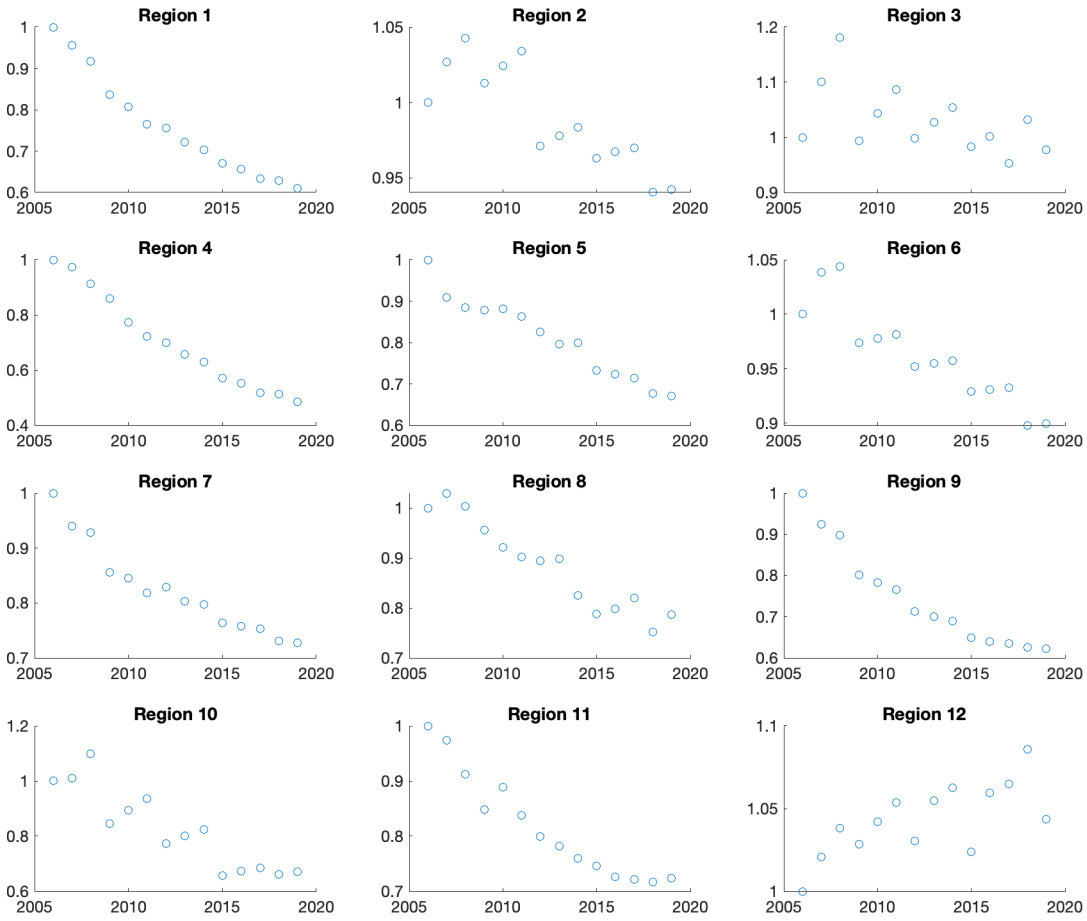
8. Use the objective function similar to the CCP one where $\hat{\boldsymbol{\tau}}^{\boldsymbol{f}}$ and $\boldsymbol{\tau}^{\boldsymbol{f}}(\hat{\boldsymbol{VC}}^{\boldsymbol{f}}(\boldsymbol{\theta}); \boldsymbol{\theta})$ are vectors of land areas flows observed in the data and predicted by the model,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

$$\hat{\theta} = \underset{\theta}{argmin} \left\| \begin{matrix} (\hat{\boldsymbol{\tau}}^{\boldsymbol{f}} - \boldsymbol{\tau}^{\boldsymbol{f}}(\hat{\boldsymbol{VC}}^{\boldsymbol{f}}(\boldsymbol{\theta}); \boldsymbol{\theta})) \\ (\boldsymbol{\Delta}\hat{\boldsymbol{\tau}}^{\boldsymbol{f}} - \boldsymbol{\Delta\tau}^{\boldsymbol{f}}(\hat{\boldsymbol{VC}}^{\boldsymbol{f}}(\boldsymbol{\theta}); \boldsymbol{\theta}))\boldsymbol{Z} \end{matrix} \right\| \tag{30}$$

D Model Fit

The following graph displays the ratio of model-predicted land flows by region for the estimated parameters to the observed total land flows. Differences in fit across regions come from assuming that all farms of the same type across all regions draw from the same scrap value and entry cost distributions but experience different static profits. Allowing for regional variation in these distributions would help improve fit. Fit gets worse over time, since errors are cumulative; error predicting land areas in time t also affect the predicted land area in period $t+1$.

Figure 14: Total Land Area Fit



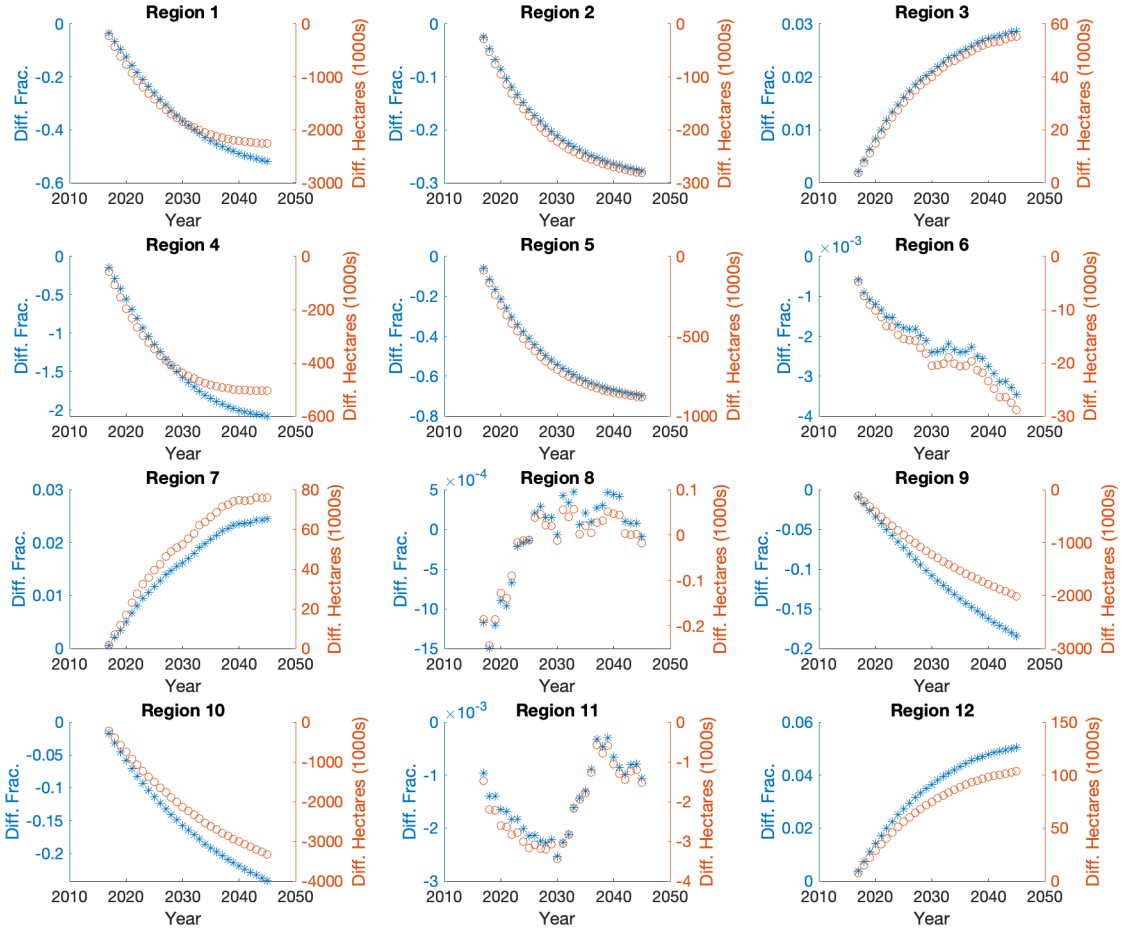
Note: This graph displays the ratio of model-predicted land flows by region for the estimated parameters to the observed land flows.

E 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.

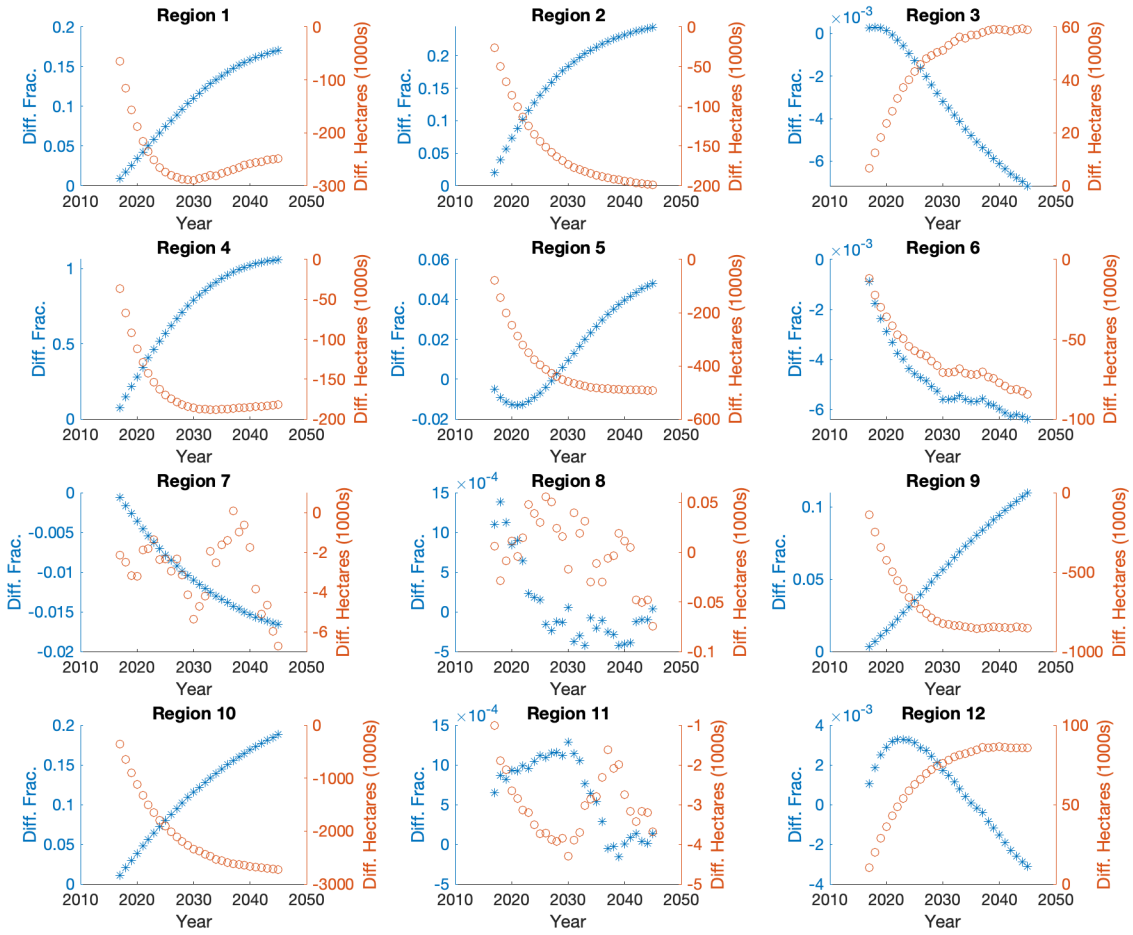
Heterogeneity in this setting potentially comes from the trade shock affecting different regions differently, depending on how much they export to the E.U. relative to China and India (where demand continued expanding during the study period). Regional differences in initial land shares belonging to each farm type (as shown in Figure 5)) 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

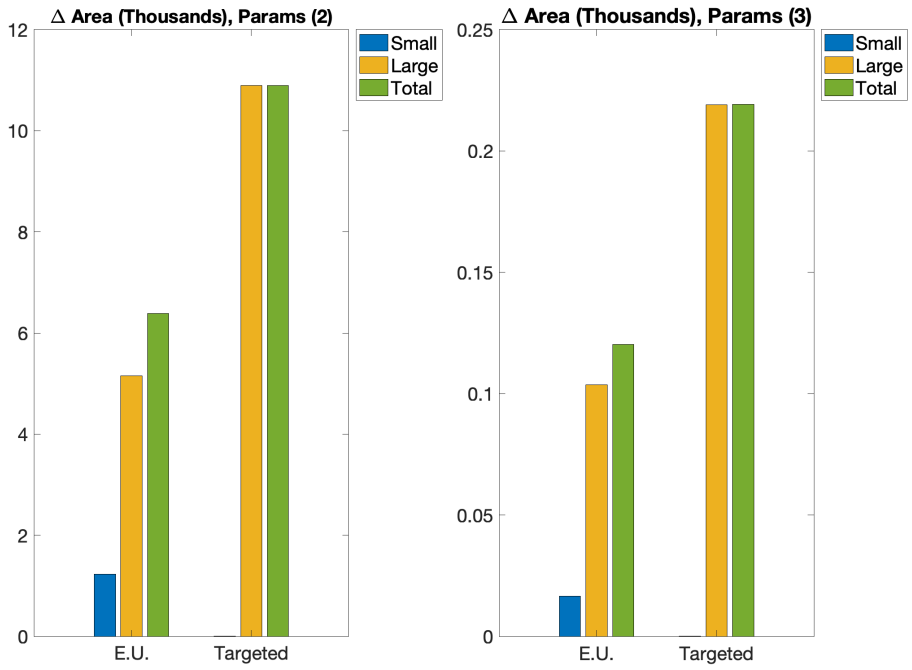


Note: This graph shows the difference between counterfactual predictions of smallholder and large estate land expansion with and without the negative demand shock resulting from the E.U. policy. The "*" markers correspond to the left y-axis, and the "o" markers to the right y-axis. "Diff. Frac." refers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

F 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 6. These are alternatives to Panel 13b. 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 Panel 13b.

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 6. Params (3) indicates that the prediction uses the specification from column (3) of Table 6.

G 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 18a 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 initially higher reduction in land expansion (relative to the counterfactual with homogeneous farmers and no trade shock). However, panel 18b shows that in the long run, the E.U. policy decreases land expansion by more when farmers are heterogeneous.

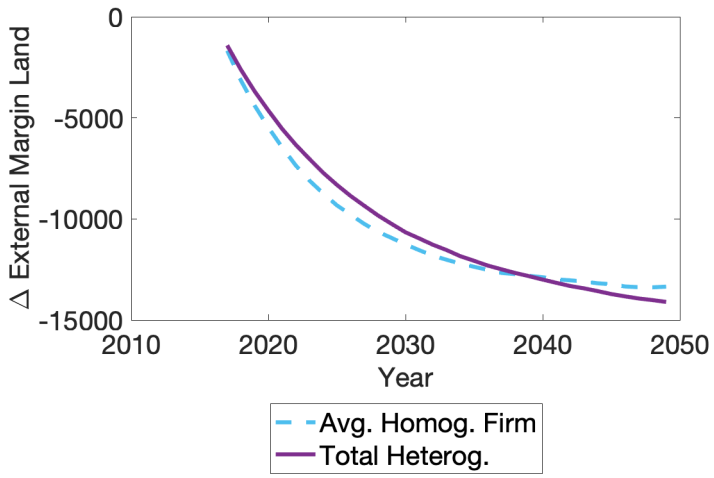
Underlying this difference is how the average farm compares to large estates and smallholdings, respectively. The average farm counterfactual yields a smaller change in continuation value, a decrease of \$2,225 as compared to a decrease of \$1,915 for smallholders and \$1,177 for large estates in the heterogeneous farm counterfactual. Furthermore, as compared to smallholdings, the average farm has higher exit percentages. These difference generate the initial greater decrease in net land expansion under the homogeneous firm assumption. However, in the long run, the average firm counterfactual predicts a smaller reduction because the average farm has lower entry and exit percentages compared to large estates. Thus, the model will predict that the E.U. policy will eventually decrease entry probabilities by less and increases exit probabilities by less under homogeneous firms. This limits the decrease in fraction of possible entrants entering and incumbents exiting and consequently also limits the decrease in total land expansion (i.e., a smaller percentage of the same constants are possible immediately after the policy).

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."[15] Figure 18 indicates that whether farms are homogeneous or heterogeneous could be important for how fast a proposed policy slows deforestation.

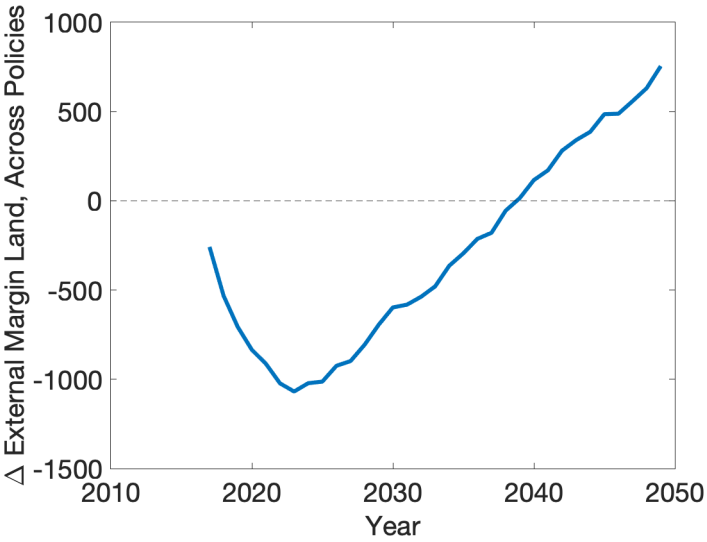
[15]See: President Bidens Actions to Tackle the Climate Crisis

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

(a) Reduced 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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