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

Audrey Tiew*

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Abstract

Focusing on the 2017 European Union resolution to phase out palm oil in all biofuels, I consider the implications of heterogeneity among upstream farmers for equitable and efficient environmental policy. Oil palm producers include both small farms for which oil palm has played a historical role in poverty reduction and large estates owned by publicly traded corporations. With respect to equity, differences in production technologies may lead to a persistent shift in the farm size distribution towards more large estates after a negative demand shock such as the E.U.'s palm oil import restriction. This shift also has negative implications for policy efficiency, as evidence suggests that large farms deforest relatively more. Leveraging data on aggregate regional land use by farmer type from 2006 to 2019 obtained from the Malaysian government and estimating a dynamic model of land use, I predict counterfactual differences in oil palm production entry and exit decisions between small and large farms in response to the E.U. policy and find that smallholders lose $47.9 million USD from lost entry. Using counterfactuals, I also find that domestic taxes and subsidies can be used to mitigate small farm losses and limit large farm deforestation.

*Contact: audreytiew@g.harvard.edu.Results reported are preliminary and/or incomplete.

1 Introduction

In recent years, the European Union has begun using trade policies restricting imports to combat global deforestation and climate change. Failing to adequately address heterogeneity among upstream producers in these policies has possible implications for (i) equity in terms of how the policy's economic cost is distributed and (ii) efficiency in terms of how much deforestation is reduced relative to the policy's total economic cost. With respect to equity, these trade policies could increase inequality within impacted exporter countries such as Brazil, Indonesia, and Malaysia, which export large quantities of agricultural goods such as palm oil, cocoa, and rubber to the E.U. In particular, upstream producers of crops such as oil palm are heterogeneous. Large plantations are often owned by large multinational corporations, and smallholdings tend to be run by historically rural poor individual families. Additionally, large plantations have access to better land clearing technologies than small farms, which can generate disparities in crop entry and exit behavior between small and large farms and decrease the total share of small farms after the initial negative demand shock. With respect to efficiency, having access to better technology may also mean that large farms engage in more deforestation and that a policy with relatively greater restrictions on large farms could be more efficient.

Using Malaysian data on upstream palm oil production, I develop a dynamic structural model capturing the heterogeneity in farm decisions to enter and exit oil palm production by farm size. Consistent with large farms having access to better (cheaper) land clearing technology, I estimate that large farm entry costs are on average 5 times lower than those of small farms. This translates into potentially large external margin losses to small farms. Accordingly, I find that the decreased downstream demand resulting from the 2017 iteration of the E.U.'s trade restrictions on palm oil could substantially decrease the long run discounted expected flow payoffs of not only small farms remaining in the industry regardless of the import policy but also the small farms that would have entered absent the policy ("missing entrants"). I estimate the decrease in long run discounted flow payoffs of the remaining farms to be 2.9 billion USD and the decrease for the missing entrants to be 47.9 million USD in 2017. These decreased payoffs account for not only the immediate fall in prices faced by farmers due to the decrease in demand but also long run changes in prices due to shifts in aggregate supply.

The current discussion about policies to address deforestation and climate change 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).

Similarly, the economics literature focuses on broader policy implementation with a limited focus on how heterogeneity affects who bears the cost of the policy as well as optimal policy implementation. Souza-Rodrigues (2019), for instance, explores the efficiency of domestic policies preventing deforestation in the Amazon and the general social benefits from resulting reduced carbon emissions. Hsiao (2020) examines the efficacy of trade policy as environmental policy, finding that international cooperation is needed to optimize efficacy. 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 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.[1] 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 domestic taxes and subsidies could be used to redistribute payoffs.

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, Gutiérrez-Vélez et al. (2011) find that, in Peru, 75% of oil palm

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

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 responsible for more deforestation.

Equity and efficiency 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 both groups face low 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, Gutiérrez-Vélez 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.

In this project, I study the implications heterogeneity has for equity and efficiency in the context of the European Union's 2017 resolution to restrict palm oil imports on the Malaysia's upstream oil palm industry. Malaysia is the second largest global exporter of palm oil after Indonesia, and the European Union has consistently ranked among Malaysia's top three importers of palm oil. Moreover, Malaysia's oil palm farmers are heterogeneous, with small farms of 10 or fewer 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 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 estimate that the discounted stream payoffs from entry that would have occurred absent the policy could have provided the annual income for 26,362 mean income Malaysian families or 35,455 median income families. Furthermore, large estates recover their former market shares more quickly than independent smallholders post policy, indicating that: (i) there is a sense in which smallholders bear more of the burden of the policy in that more smallholders are now "stuck with" a lower bound outside option due to facing higher entry cost frictions, and (ii) the policy as implemented was inefficient in that it slowed the entry of the farms associated with more deforestation by less.

To examine how domestic policy might be used to improve equity and efficiency, I calculate a counterfactual in which the trade policy still occurs but is now coupled with a lump sum per hectare tax targeted at large estates. I find that the resulting tax revenues at tax rates of 1,000RM (approx. 230 USD) and 2,000RM could more than compensate independent smallholders for their losses under the trade policy. The losses to incumbent large estates are roughly 50% higher under the 1,000RM tax than they would have been under the trade policy. Moreover, such a policy significantly reduces entry by large estates, thus targeting the farms associated with higher rates of deforestation.

While the discussion of optimal environmental regulation and its implications for inequality in the presence of firm heterogeneity is relatively novel, the literature on firm heterogeneity and endogenous industry composition is well established. Some of the earlier literature is theoretical. Hopenhayn (1992) lays a theoretical foundation for equilbirium existence in models with firm exit and entry. Caves (1998) provides a summary of early theoretical mechanisms underlying industry turnover. There is also a strand of literature focused on firm innovation and productivity as endogenous determinants of industry composition (Luttmer, 2007; Melitz, 2003). This project also contributes to this literature by empirically studying endogenous firm composition in a specific industry.

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 presents estimation results. Section 6 discusses counterfactuals eliminating the trade policy and taxing large estates. Section 7 concludes.

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 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 owning 10 or fewer acres produce about 40% of Malaysian palm oil (Ellis-Petersen, 2018). 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 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 (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. Figure 3 displays how the evolution of total oil palm producing land differs by region. Figure 4 shows how the composition of farm types (i.e., large estate vs. smallholder) evolves differently across regions 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.[2]. Through 2019, the E.U. was generally one of the two largest importers of Malaysian palm oil, accounting for between 9% and 12% of all exports (Chu, 2023; Tan, 2019). 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 5 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.

[2]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)

Oil palm farmers also plausibly took note of the decline in demand implied by the resolution. In figure 3, a noticeable slowdown in oil palm land expansion starts around 2017 in Sabah and Sarawak. Moreover, in keeping with the heterogeneity in entry costs and outside options across farm types, independent smallholders and large estates appear to have reacted differently to the negative shock. Figure 6 shows that the probability that a unit of land being used to produce oil palm being no longer owned by a smallholder increased by more as compared to the probability that a unit of land being no longer owned by a large estate after the resolution. This reflects that smallholders experienced a larger decline in relative benefit (compared to outside options or costs of entry) to farming oil palm than did large estates.

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.

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 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.

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 farmed by that farmer type makes decisions about how much FFB to sell, taking prices as given 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 $\tau_t \geq \tau_t^{small} + \tau_t^{large}$.[3] Let L^{τ} be the total number of 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:

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

[3] 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.

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

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

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.

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:

$$\pi_{jt}(q) = p_t q_t(e) - TC_{jt}(e) \tag{4}$$

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:

$$TC_{jt}(e) = \frac{1}{1+b} \exp^{a_t + (1+b)\ln(e)} + FC_{jt} \tag{5}$$

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:

$$MC_{jt} = MC_t = \exp^{a_t + b\ln(e)} \tag{6}$$

Since the production technologies are similar across different types of farm, I currently assume that marginal costs across different types of farms are the same.[4] 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.

$$p_t r_t^{\beta_r} = \exp^{a_t + b\ln(e)}$$

$$\ln p_t + \beta_r \ln r_t = a_t + b \ln e$$

$$e^* = \exp(\frac{1}{b}(\ln(p_t) + \beta_r \ln r_t - a_t)) \tag{7}$$

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

$$q(e^*) = r_t^{\beta_r} \exp(\frac{1}{b}(\ln(p_t) + \beta_r \ln r_t - a_t)) \tag{8}$$

Aggregate Supply In any given period, the total amount of land devoted to palm oil is τ_t but that 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:

$$Q_t = \tau_t^{\beta_\tau} q(e^*) = \tau_t^{\beta_\tau} r_t^{\beta_r} \exp(\frac{1}{b}(\ln(p_t) + \beta_r \ln r_t - a_t)) \tag{9}$$

$$\ln Q_t = \underbrace{\frac{1}{b}}_{=\alpha_1} \ln p_t + \underbrace{\beta_\tau}_{=\beta_{11}} \ln \tau_t + \underbrace{\frac{2\beta_r}{b}}_{=\beta_{12}} \ln r_t + \underbrace{\frac{a_t}{b}}_{=\gamma_{1t}} \tag{10}$$

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

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

$$ln(Q_t) = \alpha_2 ln(p_t) + \beta_2 p_t^{soy} + d_t \tag{11}$$

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 EU.

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

$$\text{Supply: } ln(Q_t) = \alpha_1 ln(p_t) + \beta_1 X_{1t} + \frac{a_t}{b} \tag{12}$$

$$\text{Demand: } ln(Q_t) = \alpha_2 ln(p_t) + X_{2t}' \boldsymbol{\beta_2} + d_t \tag{13}$$

where $X_{2t} = \ln(p_t^{soy})$ 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. Then equilibrium price and total quantity as a function of the state variables s_t are:

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

Substituting p_t^* into equation 4 yields equilbrium farmer payoffs for a given state of the world s_t.

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 directly informative about their static payoffs described in equation 4 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 8 and payoffs in equation 4. 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^f_{it-1}.
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:[5]
   (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.

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

[5] 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.

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 with marginal costs and rainfall as follows:

$$p_{t+1} = \lambda_1 p_t + \lambda_2 eu_t \times p_t + \lambda_3 a_{t+1} + \lambda_4 r_{t+1} + \eta_t \tag{14}$$

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:

$$F_{\tilde{s}}(\tilde{s}_{t+1}|\tilde{s}_t) = F_r(r_{t+1}|r_t) \times F_a(a_{t+1}|a_t) \times F_\eta(p_{t+1}|p_t, eu_t, r_{t+1}, a_{t+1}) \tag{15}$$

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 $\tilde{s}_t$:

$$V^f(\tilde{s}_t) = \pi_{it}(\tilde{s}_t) + \mathbb{E}_\phi\left[max\left\{\delta\phi_{it}^f, VC^f(\tilde{s}_t)\right\}\right] \tag{16}$$

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

$$VC^f(\tilde{s}_t) = \delta \sum_{\tilde{s}_{t+1}} V^f(\tilde{s}_{t+1}) P(\tilde{s}_{t+1}|\tilde{s}_t) \tag{17}$$

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

$$max\{VC^f(\tilde{s}_t) - \kappa^f_{jt}, 0\} \tag{18}$$

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 17. 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 A.

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 3 displays aggregate land flows by region over time, and Figure 6 shows changes in land use by farm type. 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 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 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.[6] 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 5, 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

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

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 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 12 and aggregate demand in equation 13 to generate estimation equations that allows me to use panel variation to identify $\alpha_1, \alpha_2, \beta_1, \boldsymbol{\beta_2}$ as follows:

$$\text{Supply: } ln(Q_{mt}) = \alpha_1 ln(p_{mt}) + \beta_1 X_{1,mt} + \boldsymbol{\gamma}_{1,t} + \boldsymbol{I}_{1,m} + \epsilon_{1,mt} \tag{19}$$

$$\text{Demand: } ln(Q_{mt}) = \alpha_2 ln(p_{mt}) + X'_{2,mt}\boldsymbol{\beta_2} + +\boldsymbol{\gamma}_{2,t} + \boldsymbol{I}_{2,m} + \epsilon_{2,mt} \tag{20}$$

Equation 19 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 20 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 4 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 19 and 20. In the supply equation 19, 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 20, 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 14, 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 B 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 (Figure 3)

Identification Parameters $\boldsymbol{\theta}$ are identified by variation in land flows by farm type across regions over time. Specifically, 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, as shown in Figure 6, I observe both net decreases and net increases across regions for each farm type. The variation from negative to positive values of percentage net land changes identifies the difference between the means of the distributions. Intuitively, the difference in scrap value and entry cost means acts as a variance term for the dispersion in 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, 3) soy price and other demand shocks, and 4) land in use at start of the period. The last three correlate with variation in static payoffs by state and emphasize changes in land flows due to either increases or decrease in payoffs.

6 Results

6.1 Aggregate Supply and Demand

Table 1 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 20 and 19, respectively. Examining the residuals confirms inward shifts of the demand curve correlate with the slowdown in land expansion across regions. Figure 7 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 Figure 3, the slowdown in land expansion in Sabah/Sarawak post policy was much more pronounced.

Furthermore, contrasting the evolution of demand shocks with the other state variables helps motivate contractions in demand from the E.U. policy as a main reason behind the slowdown in land expansion. Figure 8 displays trends in observed FFB prices and highly correlated CPO realized and future prices[7] 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 state variables shown in Figure 9 imply offsetting effects. The continued decrease in soybean oil prices would have caused decreases in equilibrium prices even prior to 2017. Decreasing average annual rainfall would imply decreasing yields over time and a contraction in supply and corresponding equilibrium prices before the E.U. policy. Increasing marginal costs would similarly have decreased supply.

Payoffs Table 2 displays the means and ranges of equilibrium prices and variable profits across market states for each region. Variable profits are annual and per hectare of oil palm land. The ranges of prices predicted are slightly larger than those observed in the data (see Figure 2) but are generally of similar magnitudes. The prices and profits show that the estimates yield regional variation in static payoffs.

6.2 Entry Costs and Scrap Values

Table 3 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 such parameters are usually large in the literature. That the mean of the smallholder entry cost distribution is approximately five times that of the large

[7] For years affected by the pandemic

estate distribution reflects how independent smallholders have much 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.

I solve the dynamic model using these estimated parameters and estimated AR(1) proceses of the exogenous state variables to recover farm continuation values by type. 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. Table 4 shows the changes in continuation value for smallholders in the market states observed each region right before the policy realization. There is a range of effects across regions with losses as high as $20,610 USD. A rationale for why some regions experience increases in continuation values is that they are exposed to positive demand shocks from China and India that more than offset decreased E.U. demand. Appendix C discusses model fit at the estimated parameters.

7 Counterfactuals

The benefit of explicitly modeling entry and exit decisions is being able to estimate changes in farm profits from changes in the external margins of oil palm land cultivation. In particular, persistent changes to static profits can 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 lead to losses not only for farmers choosing to remain in the market but also for those who would have entered otherwise and for those who would not have exited otherwise. A policymaker might be concerned that a decrease in profits pushes farmers to accept outside options lower than they would otherwise. Since scrap values and entry costs also theoretically capture opportunity costs, estimates of these parameter distributions facilitate calculating farm long run relative decreases in payoffs from lost profit opportunities from the E.U. trade restriction.

Table 5 describes aggregate discounted long run losses in payoffs to smallholders and large estates who would have continued to produce oil palm with and without the E.U. trade policy. 653 thousand hectares of land would continue to be cultivated by smallholders and 3.42 million hectares by large estates regardless of E.U. policy status. These smallholders in aggregate experience losses of 2.9 Billion USD, and large estates experience total loses of 10.7 Billion USD. Absent a model of entry and exit decisions, I would not be able to calculate the number of farmers choosing to remain in the industry.

Similarly, I would not be able to estimate counterfactual entry and exit as shown in table 6. I find that reductions in land expansion by smallholders is due primarily to reduced entry instead of increased exit. Right after the policy implementation in 2017, 18,700 fewer hectares of land were converted to smallholder oil palm cultivation due to the trade policy. Notably, the reduction in smallholder entry is persistent; there were 800 fewer new hectares cultivated in 2018 and 700 fewer new hectares cultivated in 2019. The large initial slowdown in smallholder expansion coincides with a small initial decrease in land exit of 19 hectares before exit increases (relative to what is would have been otherwise) in 2018 and 2019.

Entrants who would have entered absent the trade policy but do not under the policy experience a decrease in discounted flow payoffs of 47.9 Million USD in 2017, 6.4 Million USD in 2018, and 6.3 Million USD in 2019. These values net out the expected entry costs of this group of potential entrants. I focus on estimating smallholder losses over large estates because the parties receiving profits across these two groups differ. On one hand, since smallholdings are usually owned by family groups, smallholding profits go to the families owning them. On the other hand, large estates are more often owned by large corporations whose primary beneficiaries are shareholders, and plausibly much less of the profits contribute family incomes of median income households. With respect to Malaysian median incomes, these external margin losses are potentially nontrivial. In 2019, Malaysia's Department of Statistics reports that the mean income was 7,901 RM (1,817 USD) and the median income was 5,873 RM (1,351 USD) (Mahidin, 2020). Consequently, lost payoffs from entry in 2017 could have provided one year's worth of income for 26,362 mean income Malaysian families or 35,455 median income families.

Figure 10 indicates that the trade shock could also lead to compositional change, as large estates begin to recover their pre-policy share of total land areas more quickly than do smallholdings. In turn, this implies that smallholders as a group could suffer persistent lost entry beyond 2019 as large estates reenter the industry more quickly.

One potential domestic policy intervention to help both ameliorate losses to smallholders and decrease large estate expansion would be to charge large estates a lump sum tax per hectare of oil palm land owned. These taxes would be sunk at the beginning of each year before supply decisions are made, and consequently should not distort short-run supply decisions. The resulting tax revenues could then be redistributed as lump-sum transfers to low and median income family groups independent of oil palm industry participation. The main concern about smallholders is that they potentially represent individuals and families on the lower end of the Malaysian income distribution. Such a redistribution method targets the relevant segment of Malaysia's population without directly distorting oil palm production behavior by that group.

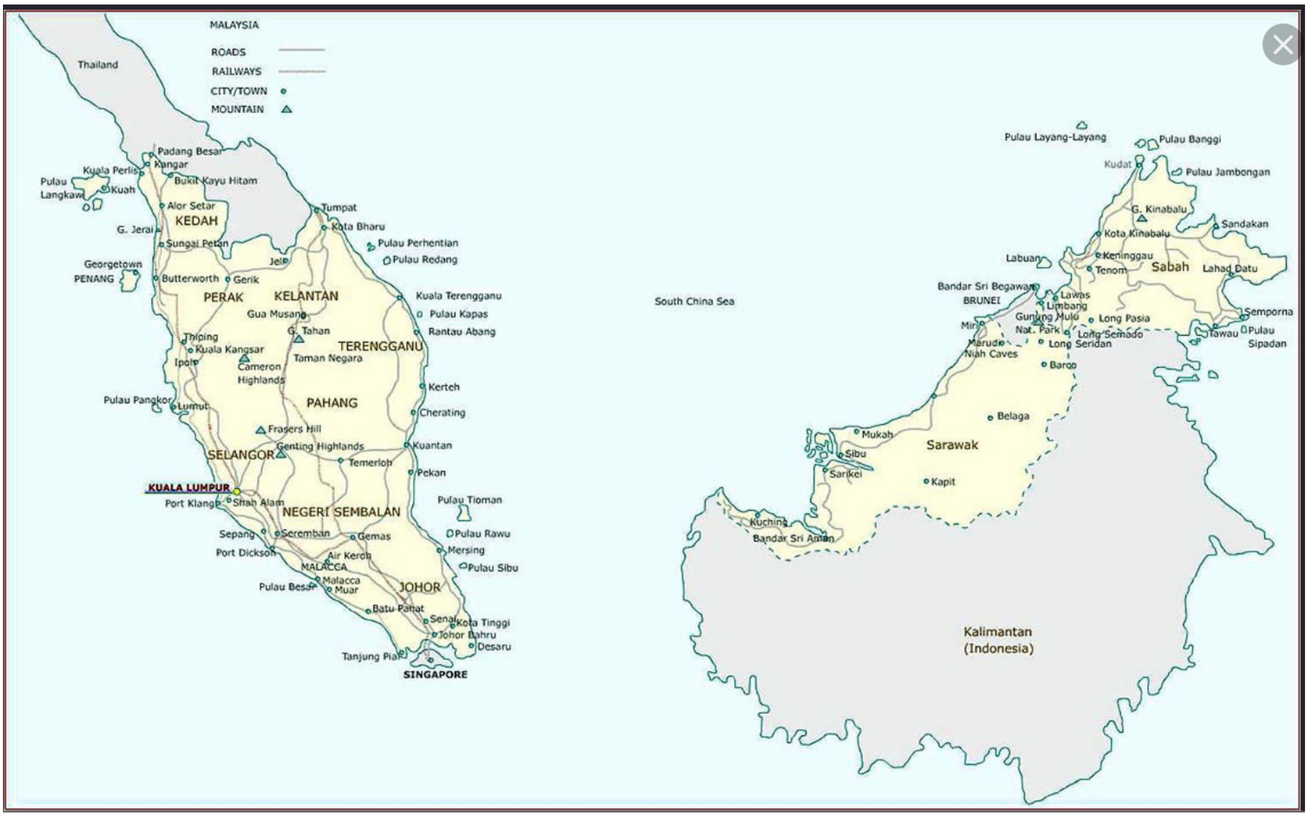
Table 7 displays the effects of 1,000 RM per hectare and 2,000 RM per hectare annual taxes on large estates. Notably, this tax benefits the smallholder demographic through increased prices in addition to through redistributed tax revenues. Increased prices occur through the supply reduction from decreased large estate entry. Both tax amounts yield sufficient revenues to compensate smallholders for their losses under the E.U. Trade policy. They are also sufficient to completely deter larger estate land area expansion. In particular, taxes of these magnitudes lead to a reduction in large estate plantation area that is large enough to offset expansions by small estates.

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. International trade policy has tended to focus on entire industries or whole regions. This paper explores (i) how heterogeneity might affect the implications of these policies for equity and efficiency, and (ii) how a combination of domestic and international policy could be used to address environmental concerns in the presence of upstream producer heterogeneity. Further research considering the interaction between climate policy and global inequality would be useful going forward in order to prevent inefficient policies fir which the agricultural poor in developing nations bear the brunt of the cost.

9 Figures

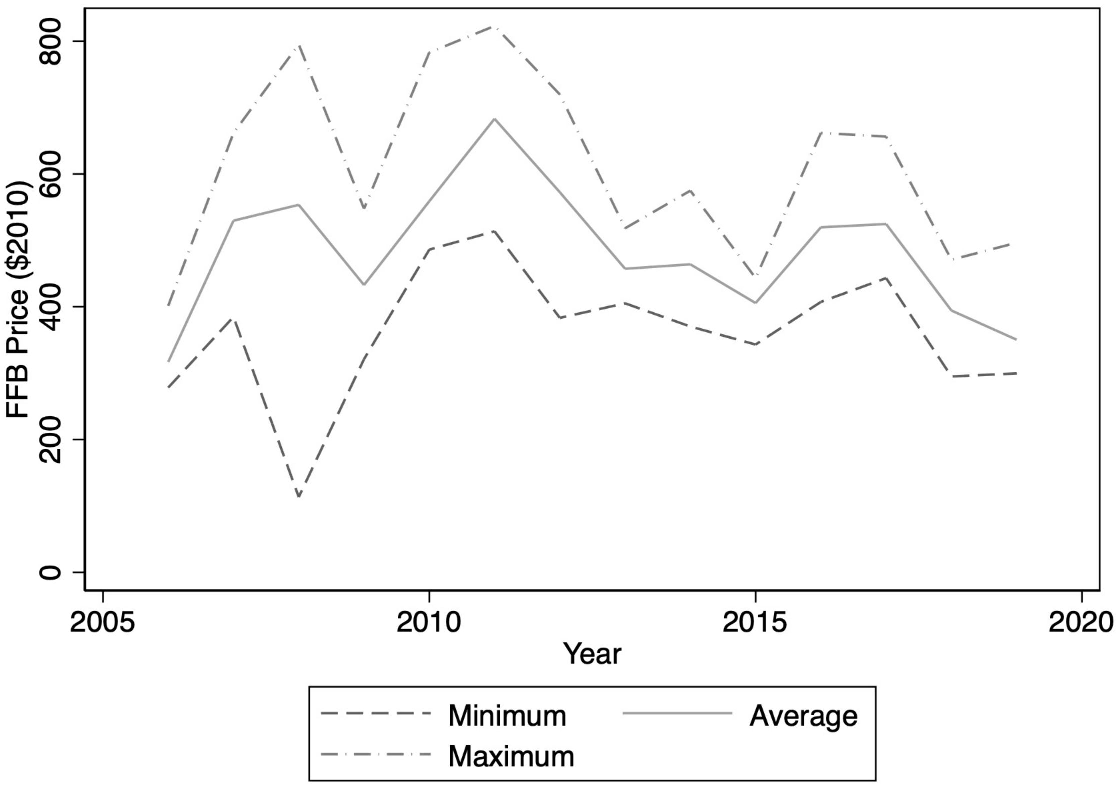
Figure 1: Map of Malaysia



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

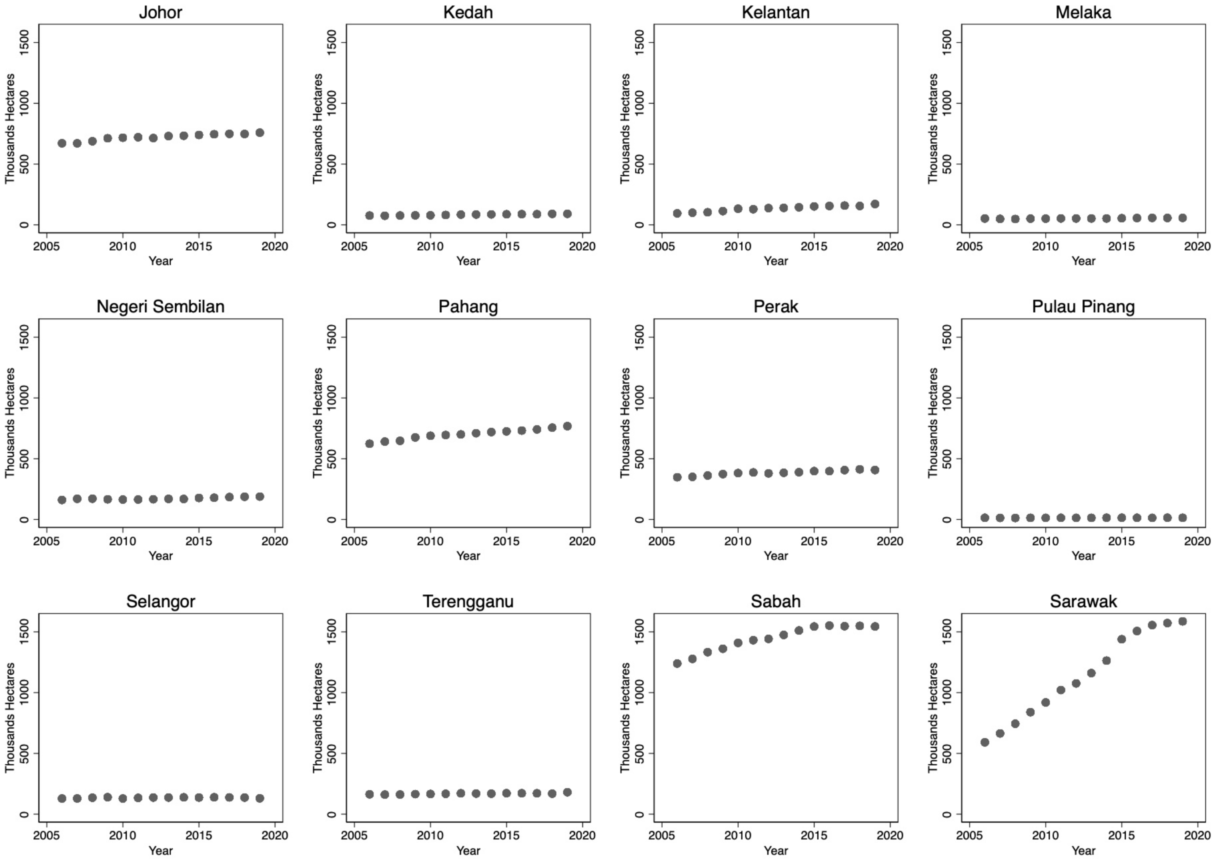
Note: Peninsular Malaysia is the land mass to the left.

Figure 2: Dispersion in FFB Prices Over Time



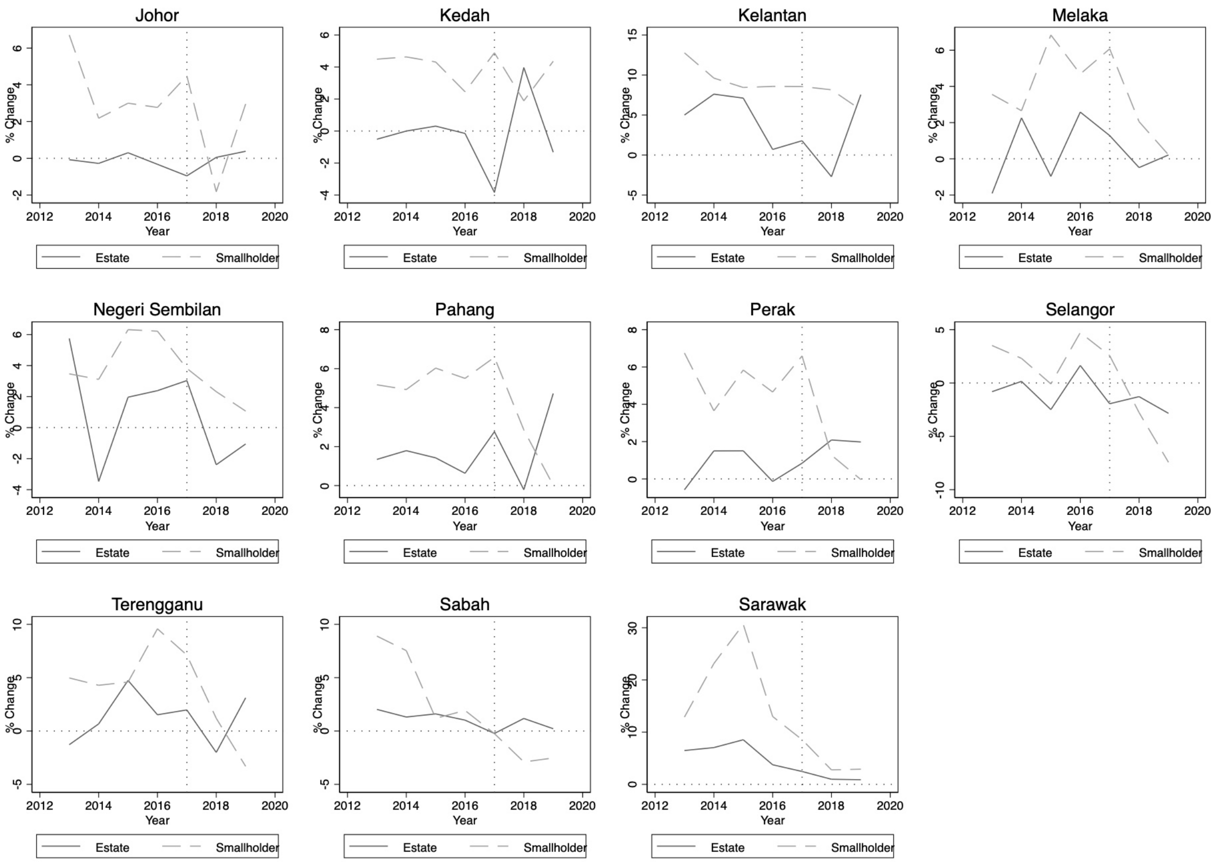
Note: Minimum price is the minimum regional FFB price reported by the MPOC for the year, and maximum is the maximum. Average is the average price across all regions.

Figure 3: Oil Palm Land by Region, 2006 to 2019



Source: Malaysian Palm Oil Council

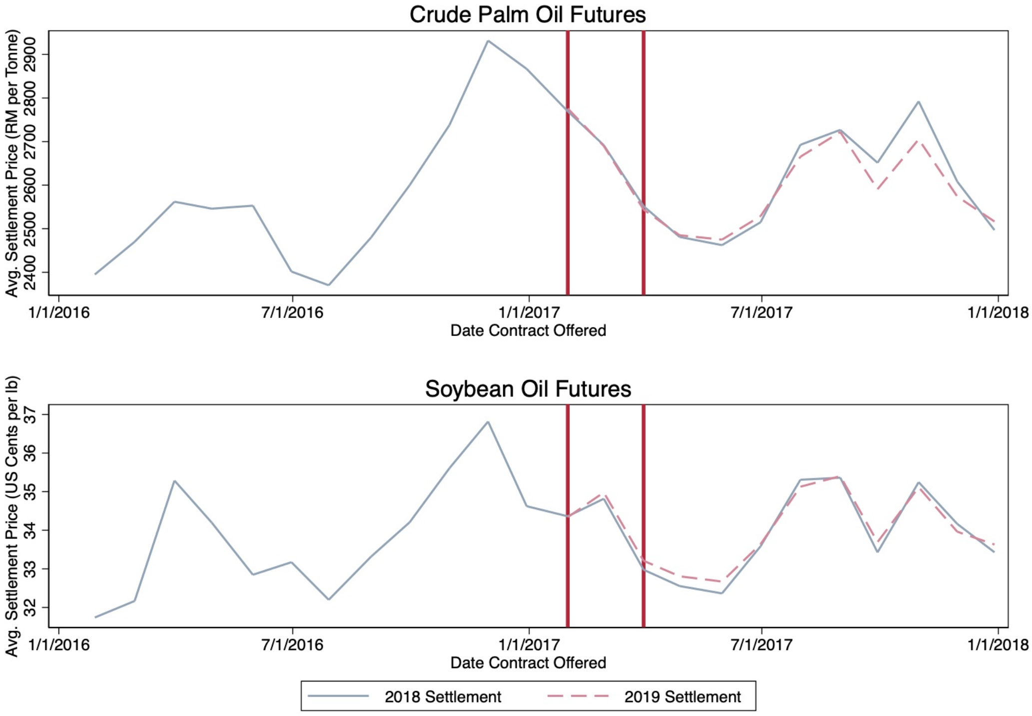
Figure 4: Change in Oil Palm Land by Farmer Type Region, 2006 to 2019



Source: Malaysian Palm Oil Council

Note: “Smallholder” includes only independent smallholders.

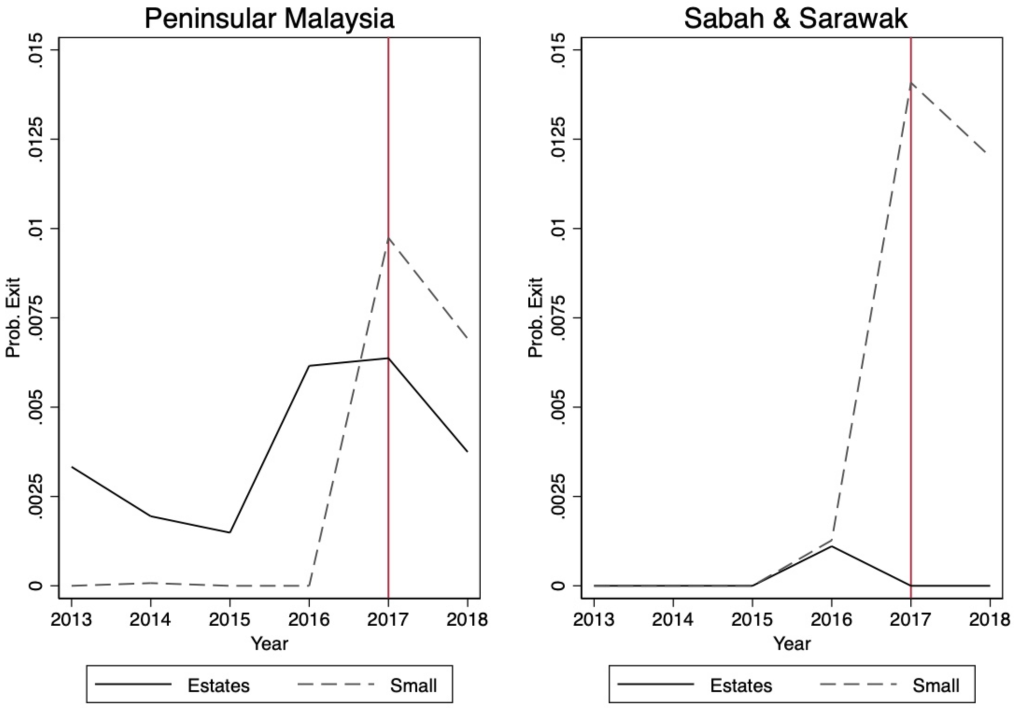
Figure 5: Palm Oil vs. Soybean Oil Futures Prices, 2006 to 2019



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 6: Change in Land Use by Farm Type



Source: Malaysian Institute of Plantation Industries

Note: Exit in this graph is the probability that a unit of land is no longer a part of a given type of farm (i.e., smallholder, large estate).

Figure 7: Average Aggregate Demand Shocks d_t, Peninsular Malaysia and Sabah/Sarawak

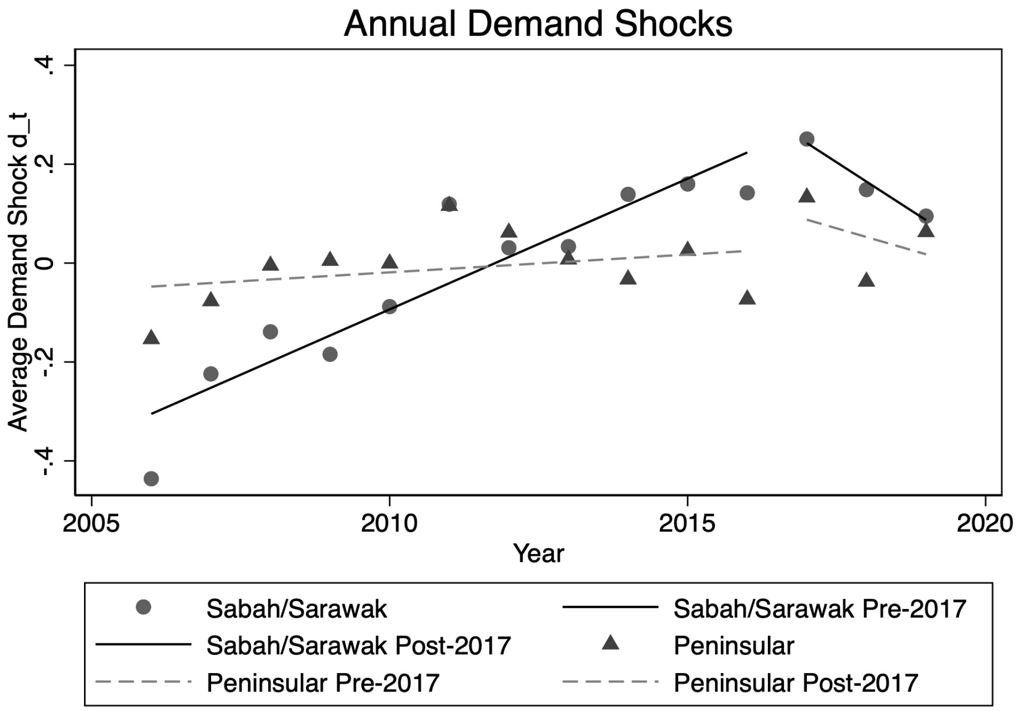


Figure 8: Average FFB and CPO Futures Prices, All Regions

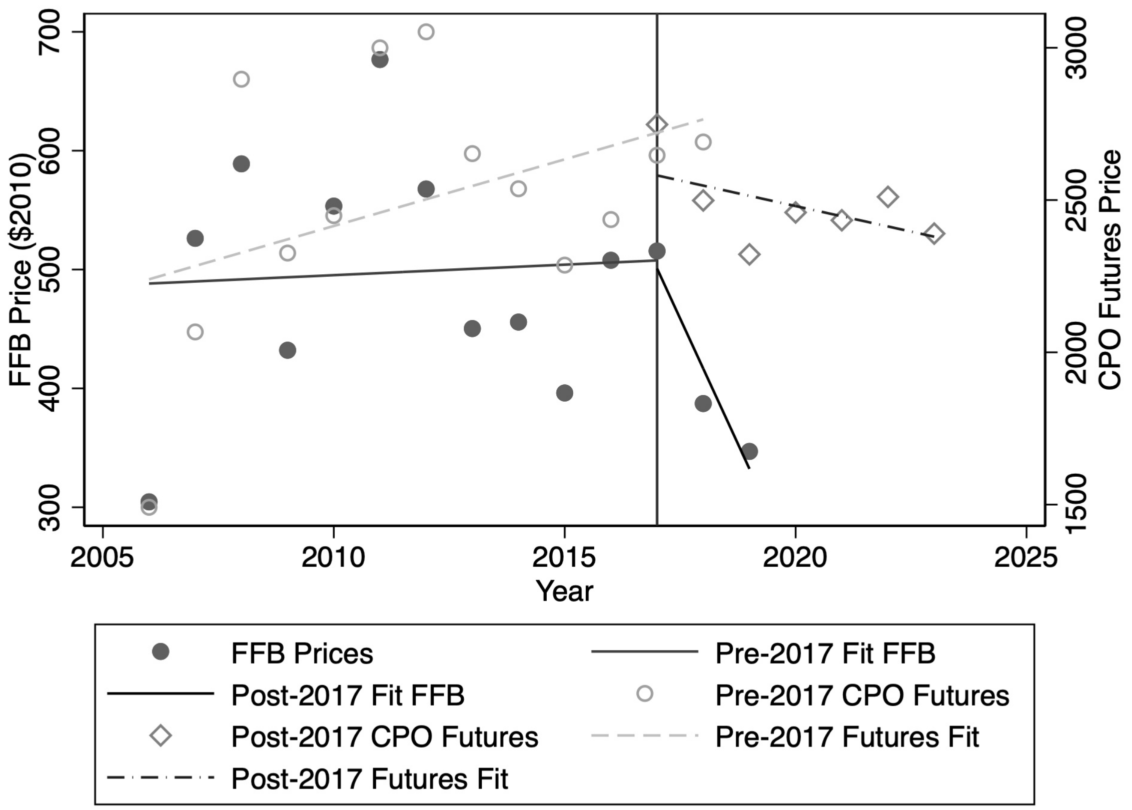
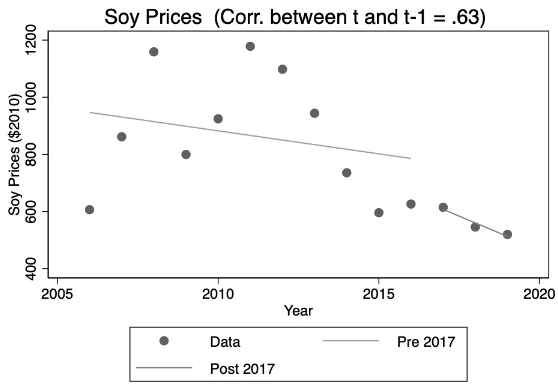
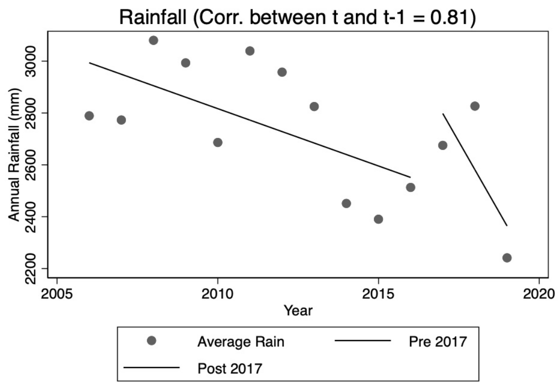


Figure 9: Average Values of Other State Variables, All Regions





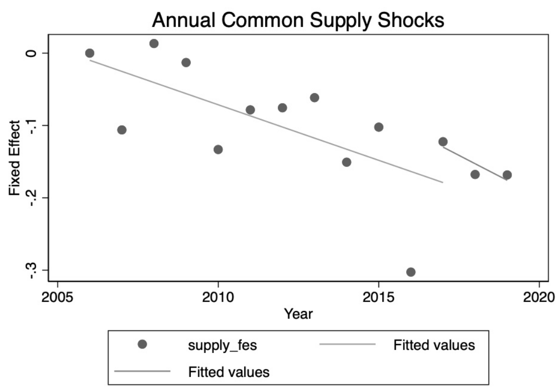
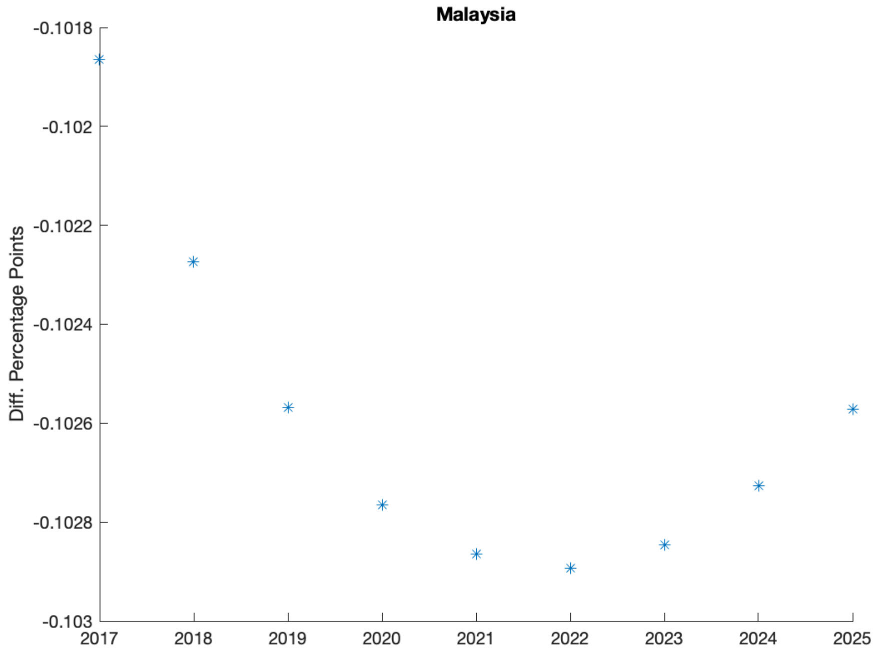
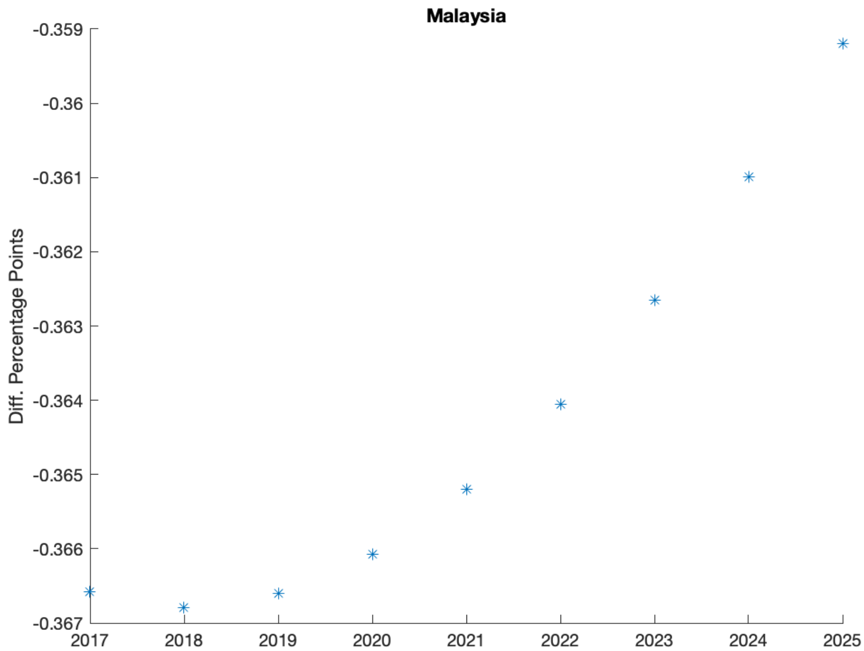


Figure 10: Change in Land Expansion from E.U. Policy, by Farm Type



(a) Smallholder



(b) Large Estate

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.

10 Tables

Table 1: Short Run Aggregate Supply and Demand Estimates

	(1) Demand Q_t	(2) Supply Q_t
$\ln p_t$	-0.359**	0.00425
	(0.110)	(0.0638)
$\ln p_t^{soy}$	0.145**	
	(0.0538)	
$\ln r_t$		0.370**
		(0.0618)
$\ln \tau_t$		0.895**
		(0.0298)
_cons	8.145**	-1.903**
	(0.404)	(0.412)
month_fe	X	X
state_fe	X	X
year_fe		
instrument	supply shifters	demand shifters
N	1944	2016
r2	0.978	0.984
fs	16.45	37.49

Standard errors in parentheses

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

Table 2: Static Prices and Variable Profits (2010 RM)

	Prices			Variable Profits		
Region	Mean	Min	Max	Mean	Min	Max
Johor	469	145	1,255	9,046	2,968	23,155
Kedah	464	130	1,316	8,949	2,654	44,712
Kelantan	552	104	2,410	10,694	2,136	44,712
Melaka	392	113	1,070	7,563	2,301	19,726
Negeri Sembilan	389	110	1,029	7,509	2,236	18,979
Pahang	519	146	1,498	10,014	2,975	27,661
Perak	527	155	1,479	10,180	3,160	27,294
Pinang	496	151	1,258	9,602	3,085	23,269
Selangor	479	153	1,222	9,237	3,133	22,558
Terengganu	510	157.76	1,286	9,868	3,133	23,774
Sabah	559	160	1,691	10,792	3,275	31,215
Sarawak	885	93	5,177	17,155	1,905	96,189

Note: Summary statistics are calculated over the distribution of states. Variable profits are annual.

Table 3: Entry Cost and Scrap Value Parameter Estimates

$\hat{\theta}$	*Smallholders*	*Large Estates*
Entry Cost $\hat{\mu}_\kappa$	107,910,000 RM/hectare (24,819,000 USD/hectare)	22,595,000 RM/hectare (5,196,000 USD/hectare)
Scrap Value $\hat{\mu}_\phi$	6,581 RM/hectare (1,514 USD/hectare)	3,082 RM/hectare (709 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 4: Changes in Smallholder Continuation Values with E.U. Trade Policy

Region	Continuation Value Before (RM)	Policy Δ (RM)	Policy Δ (USD)
Johor	181,160	2,404	553
Kedah	485,750	-19,724	-4,537
Kelantan	892,400	-2,274	-523
Melaka	394,360	-60,878	-14,002
Negeri Sembilan	379,560	-316	-73
Pahang	179,990	5,116	1177
Perak	537,250	-89,609.00	-20,610
Pinang	465,290	-355	-82
Selangor	451,150	-18,507	-4,257
Terengganu	475,000	-19,581	-4,507
Sabah	65,510	-5	-1
Sarawak	55,290	-6,600	-1,518

Note: Continuation values are reported for market state right before policy was announced (i.e., in 2016). Continuation values are per hectare of land.

Table 5: Losses in Discounted Flow Payoffs to Farms by Farm Type, Internal Margin

Counterfactual	Units	*Smallholders*	*Large Estates*
No Trade Policy	(Billion RM)	12.5	46.6
	(Billion USD)	2.9	10.7

Note: The internal margin of farms in this setting are the farms who remain in the oil palm industry both with and without the E.U. trade policy. Numbers are changes relative to the base case of the trade policy being implemented. Conversions assume $1RM = 0.23USD$.

Table 6: Losses in Discounted Flow Payoffs to Smallholders, 2017-2019 External Margin

	Units	2017	2018	2019
Δ Total Land Area	(1,000 Hectares)	18.7	19.4	20.2
Δ Entry Land Area	(1,000 Hectares)	18.7	0.8	0.7
Δ Exit Land Area	(1,000 Hectares)	.019	-.014	-.015
Δ Entrant Payoffs	(Million RM)	208.3	27.8	27.4
	(Million USD)	47.9	6.4	6.3
Δ Exit Payoffs	(Million RM)	-.04	.04	.04
	(Million USD)	-.008	.009	.009

Note: This table compares under the trade policy to a counterfactual under which the trade policy did not occur, and reports how much land expansion and payoffs would have increased absent the trade shock (Δ = no E.U. policy value - E.U. policy value). Δ Entrant Payoffs nets expected entry costs from expected values of entry; these capture the discounted payoffs of the net number of entrants that would have entered absent the trade policy and their continuation values. Δ Exit Payoffs nets expected continuation values from scrap values; these capture the net number of incumbents who would not have exited absent the trade policy and their continuation values. Regions with positive changes in either of these groups net out from those with negative changes.

Table 7: Large Estate Land Tax Counterfactual

	Units	Smallholder	Large Estate
1,000RM per Hectare Large Estate Tax			
Δ Total Land Area	(1,000 Hectares)	.02	-9.80
Δ Entrant Land Area	(1,000 Hectares)	.02	-9.75
Δ Exit Land Area	(1,000 Hectares)	.001	-.05
Δ 2017 Entrant Payoffs	(Million RM)	.004	-96
	(Million USD)	.001	-22
Δ 2017 Exit Payoffs	(Million RM)	.0002	-.27
	(Million USD)	.00004	-.06
Δ 2017 Incumbent Payoffs	(Million RM)	146	-67,700
	(Million USD)	33	-15,600
Tax Revenue*	(Million RM)	-	86,313
	(Million USD)	-	19,852
2,000RM per Hectare Large Estate Tax			
Δ Total Land Area	(1,000 Hectares)	0.12	-30.90
Δ Entrant Land Area	(1,000 Hectares)	0.11	-18.92
Δ Exit Land Area	(1,000 Hectares)	.007	-11.98
Δ 2017 Entrant Payoffs	(Million RM)	0.097	-363.32
	(Million USD)	.022	83.6
Δ 2017 Exit Payoffs	(Million RM)	.007	-77.74
	(Million USD)	.002	-17.88
Δ 2017 Incumbent Payoffs	(Million RM)	358	-136,010
	(Million USD)	83	-31,282
Tax Revenue*	(Million RM)	-	161,060
	(Million USD)	-	37,044

*Tax revenue takes into account land expansion and an increasing number of large estates over time. I calculate this using siumlated land.

Note: Δ Entrant Payoffs nets expected entry costs from expected values of entry. This compares how much adding a dixed per hectare tax on large estates to the trade policy shock would have changed welfare by farm type relative to just the policy shock alone (tax and policy value - policy value). Annual tax revenues are assumed to be redistributed elsewhere. Tax revenues exceed large estate entrant and incumbent losses, because entrant losses are only for farms that could have entered in 2017 but did not and tax revenue allows for continued large estate land area expansion into the future.

A 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:

$$\tau_{t+1}(s_t) = \underbrace{(1 - P_x^l(p_t(s_t), eu_t, a_t)) \times \tau_t}_{\text{incumbents remaining}} + \underbrace{P_e^l(p_t(s_t), eu_t, a_t) \times L_e}_{\text{entrants}} \tag{21}$$

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:

$$eu_{t+1} = max\{\mathbf{1}(\tau_{t+1} \geq \overline{\tau}_{eu}), eu_t\} \tag{22}$$

(d) The demand shock d_t evolves such that:

$$d_{t+1} = \varphi_0 + \varphi_1 d_t + \varphi_2 d_t eu_t + \nu_t \tag{23}$$

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 14 (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.

B Estimation Steps

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

$$\hat{\tau}_{t+1}(s_t) = \tau_{t+1}(s_t) + \zeta_{t+1} \tag{24}$$

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 14 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:

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

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

$$P_x(V\hat{C}(\theta)) = exp(-\frac{1}{\mu_\phi}\delta V\hat{C}(\theta)) \tag{25}$$

   Note, I cannot calculate $P_x(V\hat{C}(\theta))$ from the data, since I only observe *net* flows. However, using the contraction mapping theorem (appendix claim 1), equation 25 identifies a unique $V\hat{C}$ 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.

$$P_e(V\hat{C}(\theta)) = 1 - exp(-\frac{1}{\mu_\kappa}\delta V\hat{C}(\theta)) \tag{26}$$

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

$$\tau_{t+1}^{f} = \underbrace{Pr(\phi_{it}^{f} \leq VC_{t}^{f,l}) \times \tau_{t}}_{\text{incumbents remaining}} + \underbrace{Pr(\kappa_{jt}^{f} \leq VC_{t}^{f,l}) \times \tau_{f,t}^{e}}_{\text{entrants}} \quad (27)$$

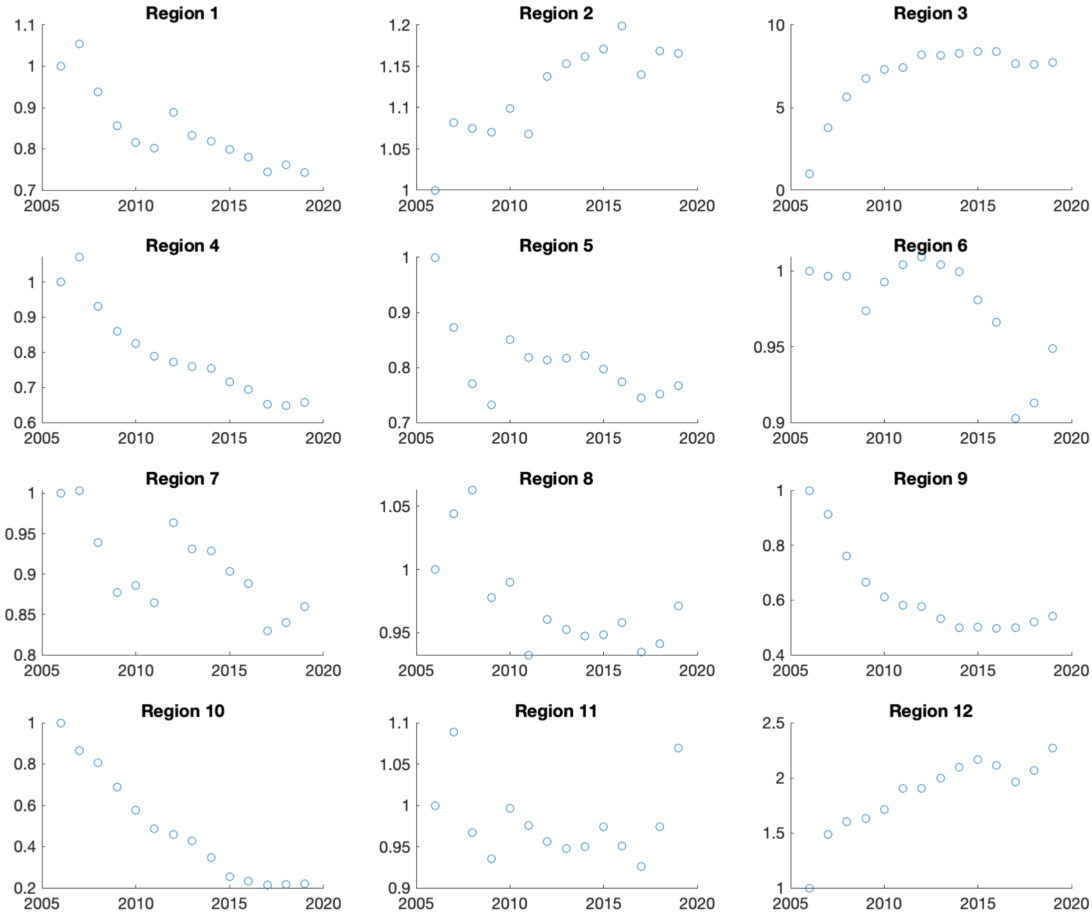
8. Use the objective function similar to the CCP one where $\boldsymbol{\hat{\tau}^{f}}$ and $\boldsymbol{\tau^{f}(\hat{VC}^{f}(\theta);\theta)}$ are vectors of type-specific land flows observed in the data and predicted by the model, respectively and $\boldsymbol{Z}$ are the current period state variables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

$$\hat{\theta} = \underset{\theta}{argmin}||(\boldsymbol{\hat{\tau}^{f}} - \boldsymbol{\tau^{f}(\hat{VC}^{f}(\theta);\theta)})\boldsymbol{Z}|| \quad (28)$$

C Model Fit

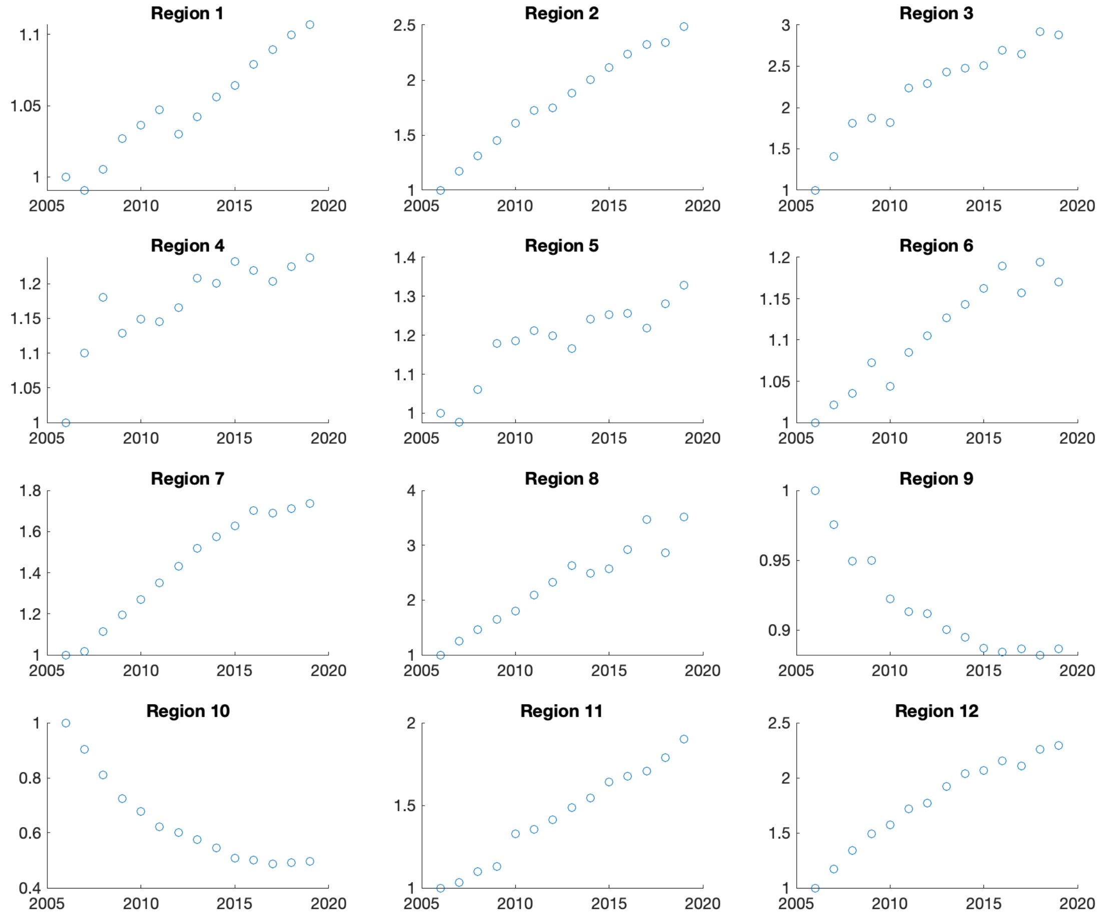
The following graphs display the ratio of model-predicted land flows by region for the estimated parameters to the observed land flows for each type of farm. The ratios are generally bounded between 0.2 and 3. The fit is different by region and does not systematically over or underpredict land flows by region or farm type. 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 11: Smallholder 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.

Figure 12: Large Estate Land Area Fit

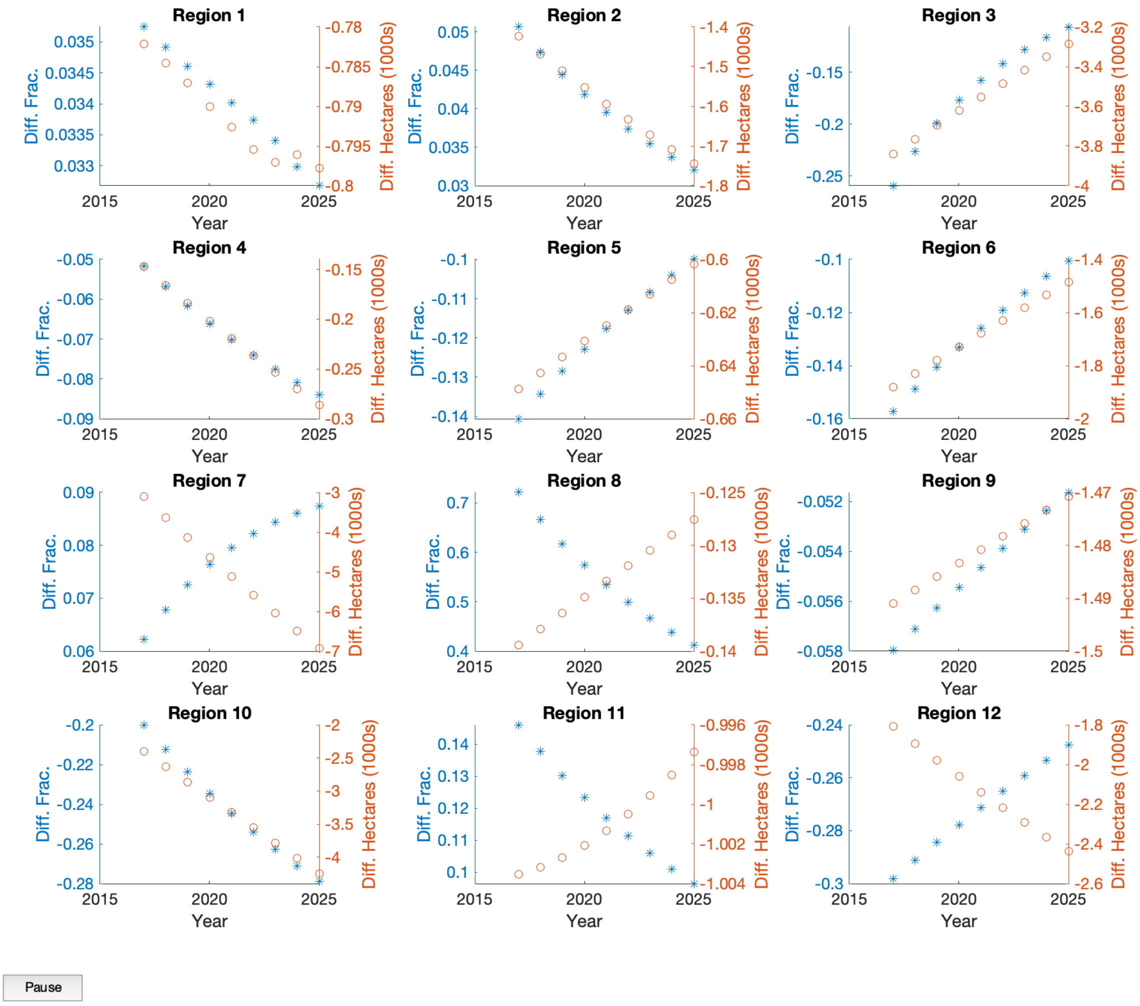


Note: This graph displays the ratio of model-predicted land flows by region for the estimated parameters to the observed land flows.

D Counterfactual Change in Land Flows by Region

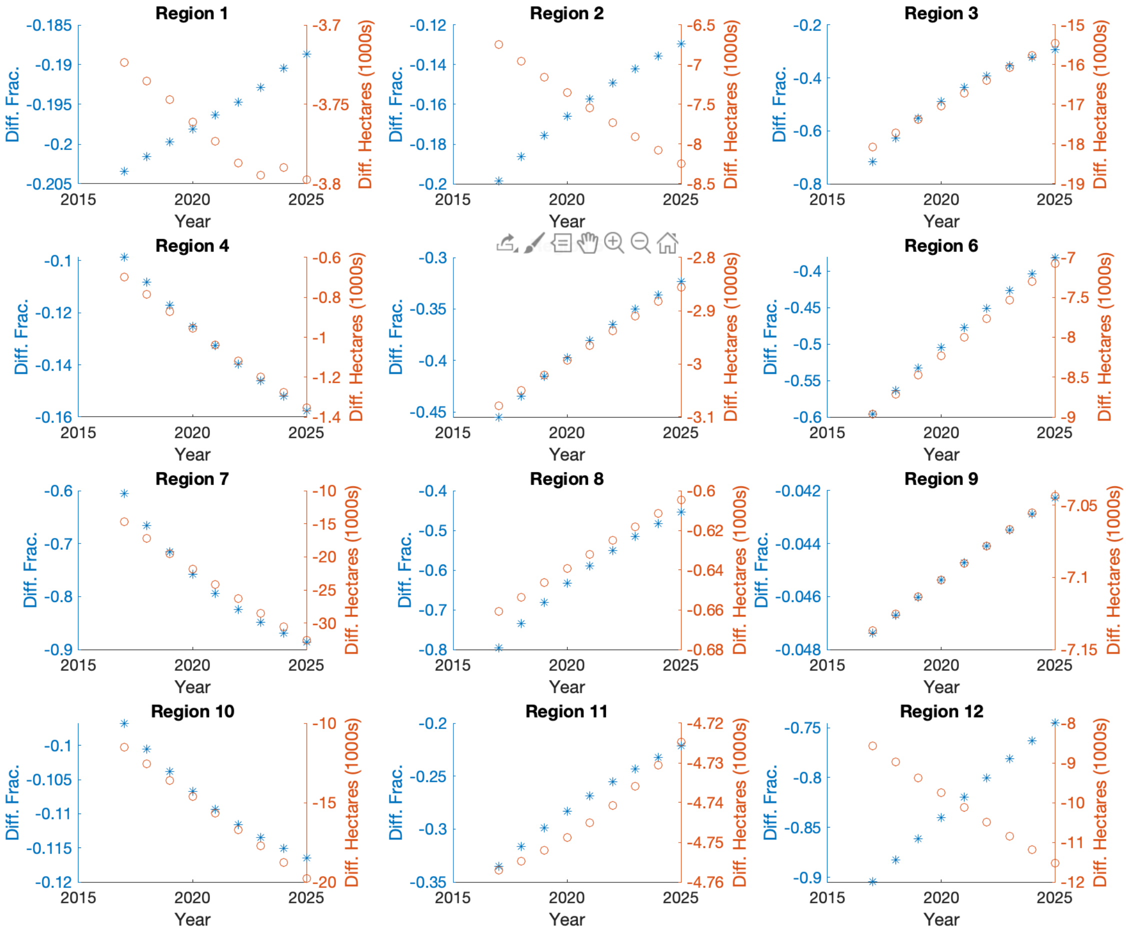
Figures 13 and 14 break down changes in fraction of total land and total land area by smallholders and large estates, respectively. These figures demonstrate regional heterogeneity in terms of compositional change. While large estates seem to regain their fraction of total oil palm land in more regions relative to smallholders, there are also regions in which both large estates and smallholders continue to lose share relative to organized smallholders (e.g., Region 10 - Sabah) and regions in which smallholders increase in their share of total land (e.g., Region 7 - Perak). 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).

Figure 13: 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 14: 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.

Table 8: Beliefs (Sabah and Sarawak) over change in land (thousand hectares)

	(1)	(2)
	delta_hectaresTOTAL	delta_hectaresTOTAL
annual_price	0.111**	0.111**
	(0.0183)	(0.0187)
annualxpolicy	-0.0948**	-0.0704
	(0.0205)	(0.0714)
policy		-11.25
		(32.66)
N	26	26
r2	0.642	0.642

Standard errors in parentheses

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

NOTE: Prices are a sufficent statistic without a constant term. Lack of significance in second specification is probably due to very small sample size...

Note, Sarawak prices are generally higher and correlated with there being less land as well as a higher growth rate at lower levels of land, which is consistent with farmers in both regions having the same beliefs.

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