5-2023

FDI and Environmental Externalities in Southeast Asia

Kevin Bloodworth
William & Mary

"FDI and Environmental Externalities in Southeast Asia"

A thesis submitted in partial fulfillment of the requirement
for the degree of Bachelor of Arts in Economics from
William & Mary

by

Kevin L. Bloodworth II

Accepted for Honors

Ariel BenYishay
____
Advisor: Ariel BenYishay

____
Advisor: Luis Baldomero-Quintana

R Sayers
____
Dr. Rachel Sayers

Williamsburg, VA
May 11, 2023

FDI and Environmental Externalities in Southeast Asia

Kevin L. Bloodworth II

April 21, 2023

Abstract

In this paper I explore the relationship between foreign direct investment (FDI) and deforestation in Cambodia. Through an event study framework, I show that economic land concessions have a negative relationship with tree cover, over time, having stronger and stronger negative effects. This relationship is more pronounced in foreign economic land concessions when compared to domestic economic land concessions. Through the use of a difference in differences research design I examine the relationship between foreign and domestic concessions through the implementation of a ELC concession ban. The ban only led to worsening levels of deforestation within the borders of foreign economic land concessions. This paper provides evidence that not only is foreign direct investment is a significant driver of deforestation but that also attempts to reduce or stop foreign direct investment can exacerbate levels of deforestation present in a nation already.

Introduction

Tropical deforestation is a large environmental challenge with significant economic policy implications. The UN Food and Agriculture Organization estimates that around 420 million hectares of forest were lost between 1990 and 2020 (FAO, 2022). Land use change, mainly deforestation, contributes to 12-20 percent of global greenhouse emissions (Watson, 2020). In this paper I examine the relationship between foreign direct investment and the environment, looking at the impact foreign direct investment has on forest cover within Cambodia. I measure this impact by spatially examining economic land concessions and taking advantage of a policy change within Cambodia.

In the first chapter I employ a differences in differences event study in order to estimate the impact that the establishment of economic land concessions have on the forest cover within their borders. I show that economic land concessions have a negative relationship with tree cover, over time having stronger and stronger negative effects. This relationship is more pronounced in foreign economic land concessions when compared to domestic economic land concessions. In the second chapter, through the use of a difference in differences research design, I examine the relationship between foreign and domestic concessions through the implementation of a ELC concession ban. The ban only led to worsening levels of deforestation within the borders of foreign economic land concessions.

Although most of the literature on environmental externalities focuses on pollution this paper joins a larger literature consisting of economic analyses of deforestation in tropical regions. Examples include Ferraro and Simorangkir (2020), Berazneva and Byker (2017), Austin et al. (2019), Carlson et al. (2018), Burgess et al. (2019), Leijten et al. (2021), and Pfaff (1999). There is evidence suggesting that due to by policy distortions and subsidies, deforestation throughout Southeast Asia might not be optimal but excessive (Barbier, 1993). Deforestation in Cambodia has increased in recent years. Cambodia is one of the world's most forested countries that was not historically deforested. As of 2015, Cambodia has one of the highest rates of deforestation in the world. Cambodia's primary forest cover fell from over 70 percent in 1970 at the end of the Vietnam War to just 3.1 percent in 2007, with less than 3,220 square kilometers of primary forest remained (Department, 2007). Nearly 75 percent of forest loss in the country has occurred since the end of the 1990s.

The Cambodian government has played an outsized role in shaping the use of Cambodia's forest. The World Bank (1996), considered the forest to be "one of the few publicly owned resources in Cambodia that have strong potential for making a significant contribution to badly needed growth in Government revenues." This role often takes the form of granting economic land concessions or ELCs to various companies. A land concession is a grant of rights over an area of land for specific purpose. In Cambodia there are various types of land concessions. An economic land concession, or ELC, allows a concessionaire to clear land in order to develop industrial-scale agriculture. Social land concessions allow concessionaires to build residences or cultivate the land for subsistence farming. There are other forms of concessions as well, such as tourism concessions, but the framework for these concessions is undeveloped.

Literature Review

The relationship between economic growth and the environment has been studied extensively within economics. With increased output and consumption, we're likely to see various cost imposed on the environment. The environmental impact of economic growth includes the consumption of non-renewable resources, higher levels of pollution, global warming, and the potential loss of environmental habitats. A prominent theory examined in Grossman and Krueger (1995) is that economic growth initially brings an initial phase of deterioration followed by a subsequent phase of improvement. Commonly known as the environmental Kuznets Curve, there is some disputes on whether environmental improvement continues indefinitely as the phase of improvement advances.

The primary theory relating trade openness to negative environmental outcomes is the "pollution haven" hypothesis. The pollution haven hypothesis is examined in the context of international competition for foreign direct investment (FDI). With increased competition for FDI, polluting industries in developed countries would tend to move to developing countries due to strict regulations and the rising cost of pollution abatement in developed countries. Though empirically, Kearsley and Riddel (2010), find little evidence that pollution havens play a significant role in shaping the environmental Kuznets curve. Support for the pollution haven hypothesis come mainly from papers that examine the relationship free trade has on the environment. Levinson and Taylor (2008) find that pollution costs have a statistically significant positive relationship with net imports and use this as justification for the pollution haven hypothesis. Ederington et al. (2005) use data on pollution abatement cost and trade flows finding that environmental regulations have stronger effects on trade between industrialized and developing economies.

The theory relating trade openness to positive environmental outcomes is known as the "Porter Hypothesis." This theory argues that well-designed environmental regulations increase productivity by kickstarting innovation and reducing agency cost (Ambec and Barla, 2002). Further support for this comes from Antweiler et al. (2001). They find that international trade creates relatively small changes in pollution concentration. Through the combination of their various estimates, they find that free trade appears to be good for the environment.

The relationship between trade openness and the environment has also been examined within the context of deforestation. Angelsen and Kaimowitz (1999), synthesize the results of more than 140 economic models examining the causes of tropical deforestation. They find that more roads, higher agricultural prices, lower wages, and off-farm employment shortages generally lead to more deforestation. Due to remote sensing, our ability to detect what's happening in forest represent an enormous step forward in the ability to monitor and analyze changes in forest use. Leblois et al. (2017) take advantage of the geospatial dataset on forest cover constructed by Hansen et al. (2013) to look at the determinants of deforestation. They find that economic development, agricultural activity, and population pressure are important drivers of deforestation at a national level. They also show that trade plays a crucial role in driving deforestation as an increase in agricultural exports decreases the proportion of forest area in a country.

Regarding deforestation in more specific Southeast Asia, Barbier (1993) finds that forest clearing for agriculture is the main source of tropical deforestation in the region. He also finds that timber production has indirect effects on deforestation through opening up and improving access to forest for land clearing activities. Institutional policies common in Southeast Asia create the conditions incentivizing short-term tree-harvesting and even subsidize harvesting at inefficient levels. The result reached in the paper is that without certain policies, Southeast Asian countries will fail to manage the natural capital in their tropical forest. Leading to an economic asset that is too quickly depleted, inefficiently extracted, and sub-optimally invested.

Data

This paper's empirical analysis uses two datasets. One uses a 2001 through 2021 land concession-by-year panel dataset. The second uses a 2001-2021 pixel-by-year panel dataset. Both are entirely built from publicly available data. The first sample includes all of the land concessions within Cambodia and the yearly tree cover measured within each land concession over the duration of the period. The second sample splits the land concessions into a more "granular" form. With the yearly tree cover being contained to a 5-arcsecond pixel which is approximately 150 square meters at Cambodia's latitude.

Land Concession Data

The main independent variable, land concessions, are long term leases that allow a concessionaire to clear land in order to develop industrial-scale agriculture and can be granted for activities including large scale plantations, raising animals, and building factories to process agricultural products. The dataset, hosed by Open Development Cambodia, contains a geospatial shapefile containing the name, region, ownership, primary crop, and size of the various concessions in Cambodia. The list contains concessions with known contract dates from 1996-2014.

The key observations of interest within this dataset are the physical geospatial boundaries of the land concessions, their year of establishment, and their ownership. By having the boundaries and establishment dates of the various economic land concessions I can estimate what effect land concessions have on the levels of forest cover within their borders prior and post the establishment of the land concession. By having access to what companies lease each concession I can compare the effects foreign and domestic land concessions have on forest cover within their boundaries.

Deforestation Data

The main dependent variable, forest cover, was generated from a time-series analysis of Landsat images measuring global forest extent and change from 2000 through 2021 (Hansen et al., 2013). Each image contains measures of forest cover with a spatial resolution of 1 arc-second per pixel, which is equivalent to about 30 meters at the equator. The base year is the tree cover in the year 2000. Which is defined as the canopy closure for all vegetation taller than 5 meters in height. These values represent what percentage of the pixel is covered by vegetation taller than 5 meters in height, in the range 0-100. I measure the rates of deforestation by comparing the tree cover in 2000 to the measured forest loss during the period 2000-2021. Forest loss is defined as the year a pixel went from a forested state to a non-forested state. These values are encoded as 0 (representing no loss) or a value in the range 1-21, representing loss detected primarily in the years 2001-2021. These images were then overlayed a map of all the economic land concessions in Cambodia.

To construct the panel dataset, I extracted the values of the pixels within each of the economic land concessions. I then gave each pixel a unique ID. To convert from a percent value to square meters I multiplied the percentage by 30 square meters (as 1 arc-second is approximately 30 meters at Cambodia's latitude.). From each pixel I created year dummy variables. These dummy variables had a value of "1" prior to their year of forest loss and a value of "0" afterwards. Those dummy variables with the value of "1" were then multiplied by the forest cover in meters. This wide dataset was then reshaped into a long format in order to construct the panel dataset. The dependent variable, forest cover, is defined as the logarithm of the forest cover in each year.

In the first sample these converted pixels are aggregated all the way up to the land concession level with each year representing the average level of tree cover for a 1-arc second pixel within each land concession each year. In the second sample the original 1-arc second pixels are aggregated to 5-arc seconds maintaining their year 2000 forest cover until the year the loss occurs in which the 5-arc second pixel is coded as 0 for the rest of the period. To represent the change in forest cover, in the first sample, the log of the forest cover is taken. In the second sample the log(n+1) of the forest cover is taken.

Controls

The main set of controls are agricultural commodity prices. Specifically, the global price of rubber, palm oil, sugar, and corn. by including commodity price controls, I can isolate the effect commodity price changes have on forest cover. For example, it was found that the price of rubber is highly correlated with deforestation in Cambodia (Grogan et al., 2019). The second control is an independently generated dummy variable to capture the effects of an order/decree by the Cambodian government. In 2008, the Cambodian government started allowing companies to lease economic land concession in protected forested areas around Cambodia. I include province level fixed effects in order to capture any unobserved factors that vary across provinces such as geography, governmental structure, or various policy measures that don't vary over time. I also include pixel level fixed effects to control for similar time-invariant unobserved factors that vary across pixels. Finally, through the inclusion of time fixed effects I can control for factors that impact all land concessions in Cambodia in a given year such as national economic shocks or global markets.

Summary Statistics

In table 1, I show the summary statistics for economic land concessions overall. In table 2, I show the summary statistics for domestic and foreign leased economic land concessions in the years 2001, 2012, and 2019. In table 1, we can see that the mean logarithm of the forest cover is decreasing over these three periods. I want to specifically draw attention to the fact that the median pixel value in the year 2012 is zero for panel B. Indicating that at that point in time, about half if not more of the forest cover in the entire sample had been removed or cut down at that point in time.

Table 1: Log Forest Cover for all ELCs

Year	Mean	SD	p10	Median	p90
Panel A. *ELC Level Aggregation*					
2001	5.67	1.41	4.22	6.07	6.69
2012	5.17	1.50	3.55	5.65	6.42
2019	4.69	1.45	3.04	5.14	5.97
Panel B. *5 Arc-Second Pixel Aggregation*					
2001	7.70	3.32	0.00	9.14	9.97
2012	4.24	4.49	0.00	0.00	9.91
2019	3.02	4.17	0.00	0.00	9.55

In table 2 we can see that foreign land concessions generally start off with more forest cover within their borders when compared to domestic economic land concessions. Reasons for this could be because (1) foreign ELCs could be located on better tracks of land or because (2) foreign land concessions overall might just be larger than domestic concessions.

Table 2: Log Forest Cover Domestic v. Foreign ELCs

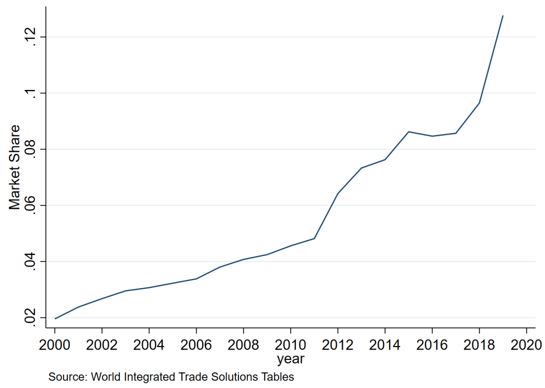
Year	Mean	SD	p10	Median	p90
Panel A. *ELC Level Aggregation*					
Domestic ELCs					
2001	5.50	1.65	2.94	6.09	6.69
2012	4.94	1.78	2.23	5.62	6.51
2019	4.46	1.71	1.95	4.94	6.06
Foreign ELCs					
2001	5.80	1.19	4.62	6.06	6.68
2012	5.34	1.23	3.97	5.68	6.34
2019	4.86	1.21	3.59	5.21	5.92
Panel B. *5 Arc-Second Pixel Aggregation*					
Domestic ELCs					
2001	6.96	3.84	0.00	8.89	9.96
2012	3.91	4.47	0.00	0.00	9.92
2019	2.89	4.15	0.00	0.00	9.78
Foreign ELCs					
2001	8.21	2.80	4.99	9.25	9.98
2012	4.47	4.49	0.00	4.78	9.90
2019	3.10	4.18	0.00	0.00	9.41

Motivating Facts

This section describes five empirical facts about Cambodia that motivates the empirical framework. First, Cambodia's position in the global rubber market is growing as rubber is becoming increasingly making up a larger number of Cambodian exports. Second, most if not all of Cambodian rubber is exported. Third, FDI (foreign direct investment) inflows into Cambodia are growing. Fourth, 55.7 percent of all current economic land concessions in Cambodia are foreign owned. Finally, it can be observed that forest loss is occurring more rapidly in foreign leased economic land concessions.

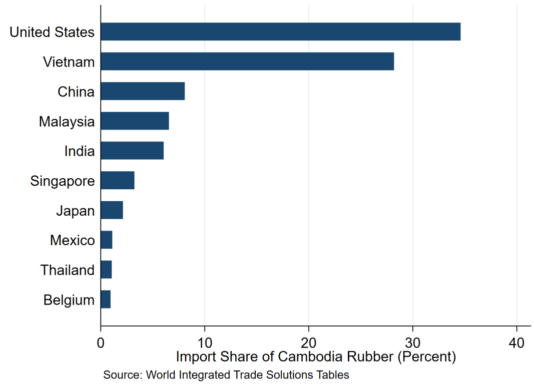
Fact 1, Cambodia's importance in the global rubber market is growing. Figure 1 shows that Cambodia's share of total global rubber exports has grown from 2 percent in the year 2000 to over 12 percent in the year 2019, with a significant increase around the 2012-2014 period. Between 2019 and 2020 rubber exports grew the fastest in Cambodia, signifying Cambodia's growing importance in the global rubber market. The rubber industry was identified by the diagnostic trade integration study 2007 as one of the top five sectors with high export potential and medium-high contribution to human development (WTO, 2017).

Figure 1: Cambodia's Global Rubber Market Share



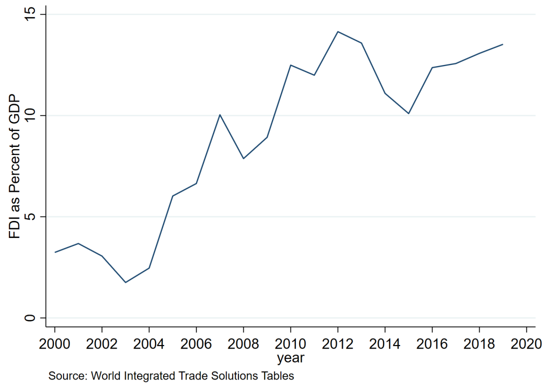
Fact 2, the destination of Cambodia's rubber exports. The rubber sector present in Cambodia is mainly export-oriented. Most if not all of Cambodian rubber is exported, due to Cambodia's lack of manufacturing facilities (WTO, 2017). Cambodia mainly exports rubber to the United States, Vietnam, China, India, and Malaysia alongside many other nations predominately in South and Southeast Asia. As demonstrated in figure 2 the United States is currently the largest importer of Cambodian rubber and has progressively become a larger and larger importer of Cambodian rubber overtaking Vietnam in 2018 importing 34 percent of Cambodia's exported rubber. Vietnam was previously Cambodia's largest importer of rubber.

Figure 2: Major Cambodian Rubber Export Destinations



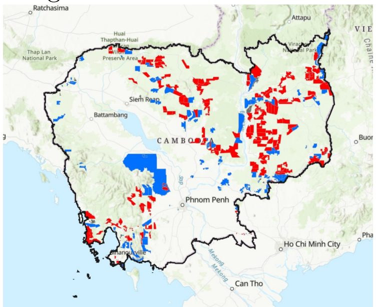
Fact 3, foreign direct investment flows into Cambodia are growing. Foreign nations have steadily begun to invest more into Cambodia. Foreign direct investment has begun to make up a higher percentage of Cambodia's gross domestic product each year. As demonstrated in figure 3, in 2000, foreign direct investment inflows present in Cambodia made up approximately 3 percent of the nation's GDP, in 2019 foreign direct investment inflows represented approximately 13 percent of Cambodian GDP. Cambodia's annual average FDI inflow growth is larger than the average annual FDI inflow growth for Asia and the Pacific (Asi, 2018).

Figure 3: FDI Inflows into Cambodia



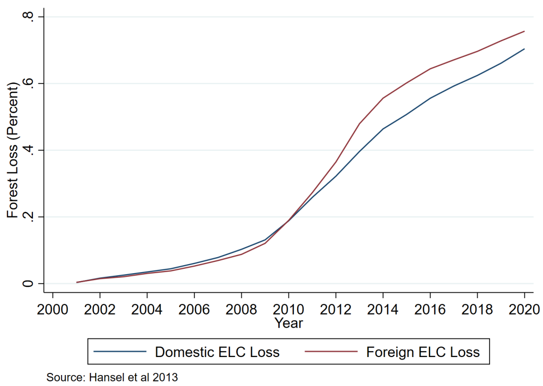
Fact 4, 55.7 percent of all current economic land concessions in Cambodia are foreign owned. As of the most recent data collected by Global Forest Watch, a majority of the current economic land concessions in Cambodia are owned by foreign companies, represented by the color red, as shown in figure 4. Rubber makes up a large percent of the economic land concessions in Cambodia, 43 percent of the total land dedicated to economic land concessions are used for rubber cultivation and rubber related agribusiness. Grogan et al. (2019) found that annual forest-to-rubber conversion rates closely followed the global price of rubber. The Cambodian government requires that all agribusinesses present in an economic land concession utilize all the land they were granted and this finding could partially explain the heavy deforestation rates seen across most land concessions.

Figure 4: ELCs in Cambodia



Fact 5, deforestation is occurring more rapidly in foreign leased economic land concessions. Using the data collected by Global Forest Watch, it can be seen that while all economic land concessions, regardless of ownership, have extremely high levels of deforestation over time as demonstrated in figure 5. Deforestation is more prominent in ELCs that are leased to foreign companies. The baseline used to calculate this figure was the total forest cover within Cambodian ELCs in the year 2000. Foreign ELC deforestation rates begin to overtake domestic deforestation rates in 2010 and begin to overtake domestic ELCs noticeably in 2012. The decline in forestry stocks in Cambodia poses concerns as forest are an important part of the lives of the rural poor in Cambodia. Which depend on the forest for food, medicinal herbs, fuel, and wood for artisanal purposes.

Figure 5: Forest Loss in Domestic and Foreign ELCs



Chapter 1 - Event Study

In first chapter of this paper, I examine the relationship foreign direct investment has on environmental externalities within a nation. This is done by estimating the impact that the establishment of economic land concessions have on forest cover in Cambodia. The ELC-year panel dataset was constructed by taking the average tree cover for all one arc-second pixels contained within a land concession over time. Through the implementation of the robust estimators introduced by Callaway and Sant'Anna (2018) I find that over over tree cover progressively decreases after the establishment of an economic land concession. This result suggest that foreign direct investment has a negative relationship with the environment.

Empirical Model and Identification

In this section I will discuss the empirical framework I use to estimate the causal impact that the establishment of economic land concessions have on deforestation in Cambodia. I employ a two-way fixed effects model. I estimate the following econometric model:

$$\ln\left(Forest\ Cover_{it}\right) = \alpha_i + \delta_t + \beta_1 ELC_{it} + \sum_{j=1}^{k} \gamma_j X_{ijt} + \epsilon_{it} \tag{1}$$

where $ln\left(Forest\ Cover_{it}\right)$ is the logarithm of the average level of forest cover within a one arc-second pixel in an ELC i in year t. α_i and δ_t represent ELC and time-based fixed effects respectively. The treatment variable, ELC_{it} is a binary variable that takes the value "1" the year the land concession was established. The control variables are represented by X_{ijt}. These control variables include province level fixed effects and commodity price controls. Finally, ϵ_{it} represents the error term, containing unobserved factors affecting deforestation that are not accounted for by the other variables and parameters in the model.

Researchers tend to use TWFE for staggered treatment research designs. The main issue with TWFE is that it only delivers consistent estimates under relatively strong assumptions about homogeneity in treatment effects. Since the treatment effect estimate in the traditional TWFE model is a weighted average of all comparisons between groups, the estimator is only consistent when there is a single treatment period. Since the treatment, the establishment of an economic land concession, appears in certain areas at different times, the TWFE estimator cannot deliver consistent estimates for the average treatment effect.

To address the reliability of the TWFE estimator I use the robust estimator introduced by Callaway and Sant'Anna (2018). By addressing the comparisons between the treated groups and the not yet treated groups, the estimators deliver consistent estimates when there's different treatment periods across groups. To accurately identify the effects ELCs have on forest cover various assumptions that need to be satisfied. First, the treatment must only turn on; it cannot turn off and then turn on again. Second, I also assume parallel trends between the not yet treated control group and the treated group. This change is represented by the following equation:

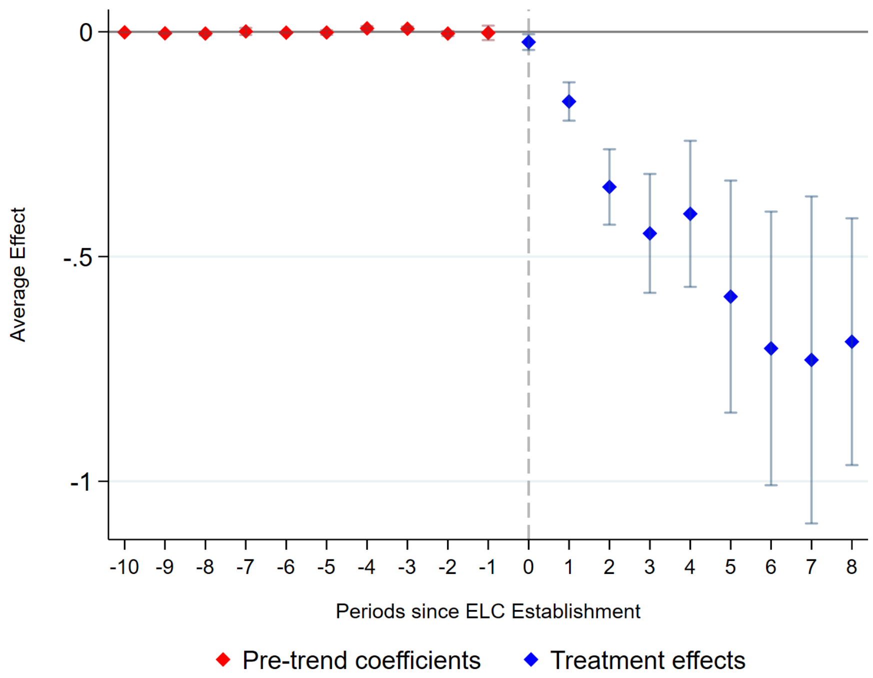
$$ln\,(Forest\ Cover_{it}) = \alpha_i + \delta_t + \sum_{j=2001}^{2021} \beta_j ELC_{it} + \sum_{j=1}^{k} \gamma_j X_{ijt} + \epsilon_{it} \qquad (2)$$

In this setup the treatment variable is again represented by ELC_{it}. The parameter β_j measures the change in deforestation associated with the treatment in the j-th year after the establishment of the economic land concession.

Results

In this section I present the main results. I show that the establishment of economic land concessions impacted the rate of deforestation within their borders. I show in figure 6 that prior to the establishment of an economic land concession, the coefficients are essentially zero and there's a very small if not nonexistent effect on forest cover. Once an economic land concession established, we can observe that for each post-treatment period we see a further decrease in forest cover. This decrease in treatment effects over time could be explained by the fact that the Cambodian government requires that all agribusinesses present fully utilize the land they were granted (Fox et al., 2018).

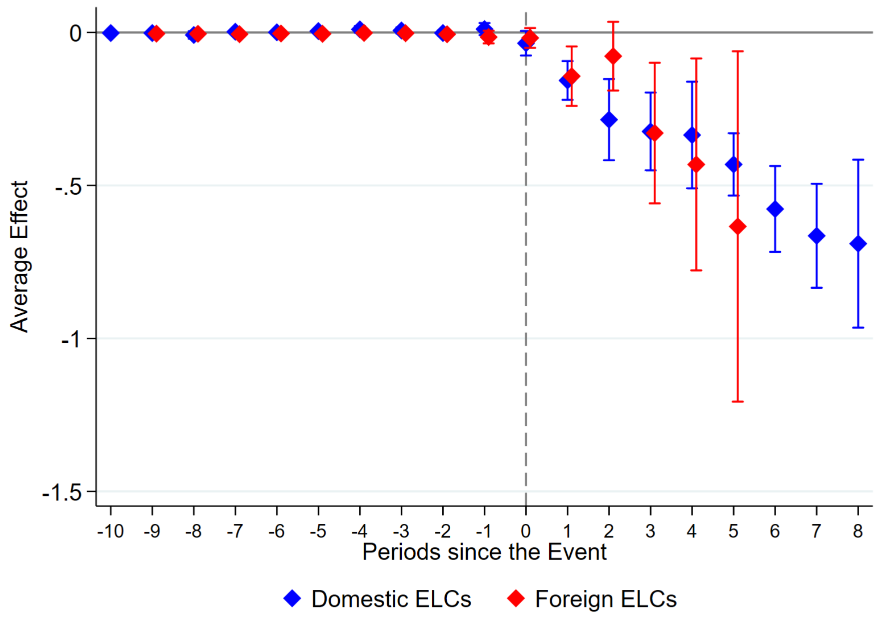
Figure 6: Initial Event Study Results



Then I proceed to split the sample in two sub-samples. I create a sub-sample with land concessions to domestic companies, and a second sub-sample for those concessions given to foreign multinationals. I display the results in figure 7. While all economic land concessions have high levels of deforestation over time, foreign-owned economic land concessions experience stronger deforestation. Noticeably, the estimates for domestically owned land concessions are smaller than the estimates for foreign ones.

Granted, there is more variability for foreign concessions and more certainty for domestic concessions. We can observe this by looking at the confidence intervals of the estimates. A potential explanation for the variability could be that foreign land concessions generally have later establishment dates . We can see this in figure 7 as foreign concession have a smaller number of periods post treatment. This implies that foreign economic land concessions have a larger effect on the levels of forest cover within their borders, but the impact is more uncertain due to either the sample size or the number of post-treatment periods.

Figure 7: Event Study: Foreign vs. Domestic ELC's



Regardless of this variability we can also see that the foreign concessions have larger coefficients post-treatment when compared to the estimates of the domestic land concessions. This indicates that there are potentially faster rates of deforestation within foreign concession relative to domestic concessions. Reasons for this could include (i) protest against deforestation by domestic groups are more successful in domestically owned concession versus foreign owned concessions (ii) foreign concessions are more likely to grow crops that take advantage of current price fluctuations (iii) foreign concessions are more likely to use mono-culture cultivation versus more indigenous slash-and-burn agricultural styles.

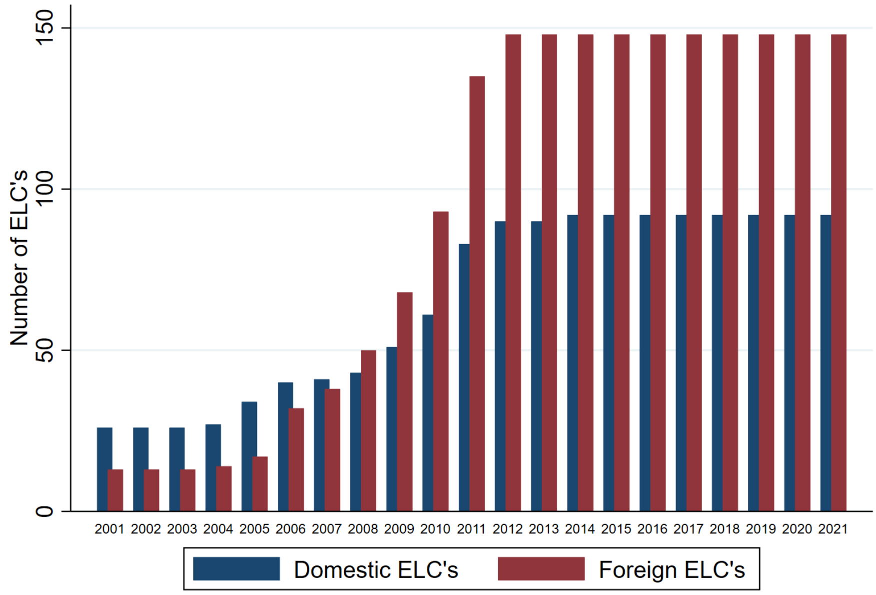
Chapter 2 - Policy Evaluation

In the second chapter of this paper, I explore how the implementation of a ban on economic land concession affected forest cover. This pixel-year panel dataset was created by aggregating the one arc-second pixels to five arc-second pixels and calculating their average forest cover each year. Through the use of a traditional difference in differences I can examine to what extent does preventing or stopping further foreign direct investment has on environmental outcomes within a nation. Through the implementation of this research design I find that the establishment of the ban had a significant negative effect on forest cover. This result suggest that preventing or stopping foreign direct investment will only further exacerbate environmental issues.

Empirical Model and Identification

In this section I discuss the empirical framework to estimate the impact that order 01 , enacted in 2012, has on deforestation in Cambodia. "Order 01 on the Measures Strengthening and Increasing Effectiveness of the Economic Land Concessions Management," froze the issuing of new ELCs and ordered a review of existing concessions. In practice we observe that the Cambodian government still allowed the establishment of economic land concessions leased by domestic companies and that the freeze seemingly only applies to economic land concessions leased to foreign companies. This is demonstrated in figure 8. We can see that after 2012 there were no more foreign economic land concessions established. We can see above this does not hold for domestic economic land concessions as there was an additional domestic concession established in 2014.

Figure 8: Impact of Order 01 on Number of ELCs



Source: Global Forest Watch

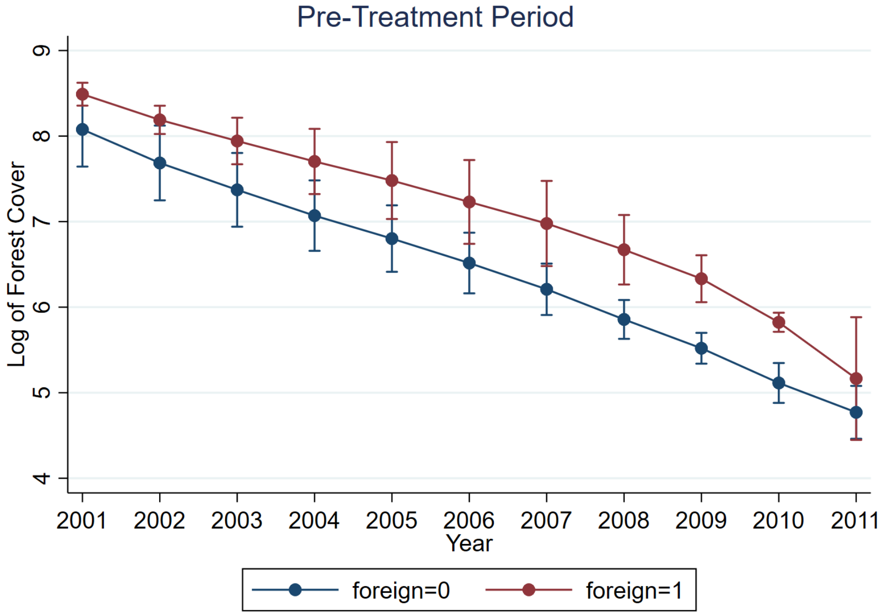
To capture the effects of the policy change, I employ a two-way fixed effects model. In my empirical approach I use a TWFE estimator in order to execute the difference in differences research design. By comparing the forest cover in domestic ELCs and the forest cover in foreign ELCs after the implementation of Order 01 I estimate the average treatment effect Order 01 had on the forest cover in foreign owned ELCs. I estimate the following model:

$$ln\left(Forest\ Cover_{it}\right) = \beta_0 + \beta_1 \left(Foreign\right)_i \cdot \left(Ban\right)_t + \sum_{j=1}^{k} \gamma_j X_{ijt} + \delta_i + \omega_t + \epsilon_{it} \quad (3)$$

where subscripts i and t represent the pixel (my unit of observation) and the year, respectively. The outcome variable of interest $ln\left(Forest\ Cover_{it}\right)$ is the logarithm of the average forest cover in year within pixel p. The explanatory variable of focus is the interaction of $Foreign_i$, which represents the pixels that fall inside the borders of a foreign owned economic land concession, and Ban_t, which is an indicator variable for the years at and after 2012, the year in which the ban was enacted. The set of variables X_{ijt}, control for all the additional years post economic land concession establishment and controls for foreign economic land concession that Cambodia established in protected wildlife areas post-2008.

To accurately estimate the impact of order 01 on deforestation within economic land concessions in Cambodia using a difference in differences framework, I need to observe that the parallel trends assumption is satisfied. In figure 9 below we can see that the graph comparing tree cover between foreign and domestic land concessions prior to the implementation of Order 01 moves in a parallel fashion. In 2008 the Cambodian government started allowing the establishment of economic land concessions in protected areas.To address the slight deviation starting in 2008 I include a control and assume parallel trends conditioned on this occurrence.

Figure 9: Demonstration of Parallel Trends



According to Garcia and Heilmayr (2022)), the use of TWFE regressions with pixel unit fixed effects is potentially biased due to the binary nature of the forest cover measurement. Their advice is to add fixed effects that aggregate pixels e.g., agricultural land districts. I implement this suggestion in one of their alternative model specifications. Instead of just using pixel based fixed effects, I include specifications that include both spatially aggregated province and spatially aggregated ELC based fixed effects.

Results

In this section I present the results from analyzing the impact Order 01 had on forest cover within economic land concessions. I demonstrate that the establishment of Order 01 had a negative, statistically significant relationship with forest cover and ultimately worked to exacerbate deforestation in the area. The results of equation 3 are shown in table 3.

Table 3: Regression Results - Impact of Order 01 on Forest Cover

VARIABLES	(1) Model 1	(2) Model 2	(3) Model 3	(4) Model 4	(5) Model 5	(6) Model 6
Order 01	-0.488	-1.610**	-1.610**	-1.092**	-1.092**	-1.055**
	(0.761)	(0.639)	(0.639)	(0.415)	(0.415)	(0.400)
Post ELC Establish.	-2.835***	-0.691*	-0.691*	-0.265	-0.265	-0.686***
	(0.367)	(0.358)	(0.358)	(0.197)	(0.197)	(0.173)
Protect. Areas	-0.452	-1.890***	-1.890***	1.013**	1.013**	0.652
	(0.363)	(0.549)	(0.549)	(0.472)	(0.472)	(0.432)
Constant	6.599***	4.269***	4.269***	5.540***	5.540***	5.755***
	(0.446)	(0.293)	(0.293)	(0.156)	(0.156)	(0.290)
Observations	27,183,681	27,183,681	27,183,681	15,806,070	15,806,070	15,806,070
R-squared	0.089	0.795	0.795	0.685	0.288	0.224
Pixel FE	NO	YES	YES	YES	NO	NO
Time FE	NO	YES	YES	YES	YES	YES
Province FE	NO	NO	YES	YES	YES	YES
Commodity FE	NO	NO	NO	YES	YES	YES
ELC FE	NO	NO	NO	NO	YES	NO

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

To estimate these results I include weights, giving more importance to larger economic land concessions and clustered the standard errors around both the year and the economic land concession. Model 1 includes no fixed effects and finds an ambiguous relationship regarding the impact Order 01 had on forest cover within foreign leased economic land concessions. Through the inclusion of pixel and year based fixed effects to control for unobserved heterogeneity both model 2 and model 3 found that the beta value of Order 01 has a statistically significant negative relationship with the logarithm of forest cover with a value of -1.610. This corresponds to an approximately 80 percent decrease in forest cover.

The preferred model 4 includes commodity fixed effects in order to control the role commodity prices and global market shocks play in affecting tree cover in Cambodia. Here it can be seen that the beta value of Order 01 again has a statistically significant negative relationship with the logarithm of forest cover with a value of -1.092. This corresponds to an approximately 66 percent decrease in forest cover. Both model 5 and model 6 incorporate the specifications suggested by Garcia and Heilmayr (2022). By not including pixel fixed effects and instead using spatially aggregated fixed effects to help address potential bias. Both find a statistically significant negative relationship between the logarithm of forest cover and the enactment of Order 01.

From these results as a whole I conclude that Order 01 exacerbated the issue of deforestation within foreign economic land concessions. The coefficient estimates presented in Table 3 indicate the importance governmental policies play in alleviating or exacerbating environmental issues. By preventing foreign companies, the opportunity to expand outwards we can see that the implementation of this ban only caused foreign firms to further intensify destructive practices within their respective economic land concession.

Conclusion

Following various papers examining the relationship between foreign direct investment and environmental outcomes I explore the relationship between foreign direct investment and deforestation in Cambodia. Through the use of open-source data detailing various land concession through Cambodia from Open Development Cambodia and global forest change data hosted from the University of Maryland. Through the use of an event study framework, I examine the impact economic land concessions had on forest cover within Cambodia. I show that economic land concessions have a negative relationship with tree cover, over time having stronger and stronger negative effects. This relationship is more pronounced in foreign economic land concessions when compared to domestic economic land concessions.

I further examine the relationship between foreign and domestic leased concessions by looking at the implementation of a ELC concession ban that in practice, only affected foreign economic land concessions. Through the use of a difference in differences research design I estimate that the impact of Order 01, a ban on the further establishment of economic land concessions, only led to worsening levels of deforestation within the borders of foreign economic land concessions.

In conclusion the results of this paper provide evidence that not only is foreign direct investment is a significant driver of deforestation but that also attempts to reduce or stop foreign direct investment can exacerbate levels of deforestation present in a nation already.

References

Cambodia - forest policy assessment. https://documents.worldbank.org/pt/publication/documents-reports/documentdetail/103791468743779984/cambodia-forest-policy-assessment, 1996. [Online; Accessed April 12, 2023].

Trade policy: Review report by the secretariat - cambodia. https://www.wto.org/english/tratop_e/tpr_e/s364_e.pdf, 2017. [Online; Accessed April 12, 2023].

Asia-pacific trade briefs 2018: Cambodia. https://www.unescap.org/resources/aptir-2018-country-briefs-cambodia, 2018. [Online; Accessed April 12, 2023].

S. Ambec and P. Barla. A theoretical foundation of the porter hypothesis. *Economics Letters*, 75(3):355–360, 2002. URL https://EconPapers.repec.org/RePEc:eee:ecolet:v:75:y:2002:i:3:p:355-360.

A. Angelsen and D. Kaimowitz. Rethinking the causes of deforestation: Lessons from economic models. *The World Bank research observer*, 14(1):73–98, 1999. ISSN 0257-3032.

W. Antweiler, B. R. Copeland, and M. S. Taylor. Is free trade good for the environment? *The American economic review*, 91(4):877–908, 2001. ISSN 0002-8282.

K. G. Austin, A. Schwantes, Y. Gu, and P. S. Kasibhatla. What causes deforestation in indonesia? *Environmental research letters*, 14(2):24007–, 2019. ISSN 1748-9318.

E. B. Barbier. Economic aspects of tropical deforestation in southeast asia. *Global ecology and biogeography letters*, 3(4/6):215–234, 1993. ISSN 0960-7447.

J. Berazneva and T. S. Byker. Does forest loss increase human disease? evidence from nigeria. *The American economic review*, 107(5):516–521, 2017. ISSN 0002-8282.

R. Burgess, F. J. M. Costa, and B. Olken. The brazilian amazon's double reversal of fortune. *IDEAS Working Paper Series from RePEc*, 2019.

B. Callaway and P. H. C. Sant'Anna. Difference-in-differences with multiple time periods. 2018.

K. M. Carlson, R. Heilmayr, H. K. Gibbs, P. Noojipady, D. N. Burns, D. C. Morton, N. F. Walker, G. D. Paoli, and C. Kremen. Effect of oil palm sustainability certification on deforestation and fire in indonesia. *Proceedings of the National Academy of Sciences - PNAS*, 115(1):121–126, 2018. ISSN 0027-8424.

F. Department. Brief on national forest inventory nfi, cambodia. https://www.fao.org/3/ap183e/ap183e.pdf, 2007. [Online; Accessed April 12, 2023].

J. Ederington, A. Levinson, and J. Minier. Footloose and pollution-free. *The review of economics and statistics*, 87(1):92–99, 2005. ISSN 0034-6535.

FAO. The state of the world's forest 2022. `https://www.fao.org/3/cb9360en/online/cb9360en.html`, 2022. [Online; Accessed April 13, 2023].

P. J. Ferraro and R. Simorangkir. Conditional cash transfers to alleviate poverty also reduced deforestation in indonesia. *Science advances*, 6(24):eaaz1298–, 2020. ISSN 2375-2548.

J. Fox, T. Nghiem, H. Kimkong, K. Hurni, and I. Baird. Large-scale land concessions, migration, and land use: The paradox of industrial estates in the red river delta of vietnam and rubber plantations of northeast cambodia. *Land (Basel)*, 7(2):77–, 2018. ISSN 2073-445X.

A. Garcia and R. Heilmayr. Conservation impact evaluation using remotely sensed data. 2022.

K. Grogan, D. Pflugmacher, P. Hostert, O. Mertz, and R. Fensholt. Unravelling the link between global rubber price and tropical deforestation in cambodia. *Nature plants*, 5(1):47–53, 2019. ISSN 2055-0278.

G. M. Grossman and A. B. Krueger. Economic growth and the environment. *The Quarterly journal of economics*, 110(2):353–377, 1995. ISSN 0033-5533.

M. C. Hansen, P. V. Potapov, R. Moore, M. Hancher, S. A. Turubanova, A. Tyukavina, D. Thau, S. V. Stehman, S. J. Goetz, T. R. Loveland, A. Kommareddy, A. Egorov, L. Chini, C. O. Justice, and J. R. G. Townshend. High-resolution global maps of 21st-century forest cover change. *Science (American Association for the Advancement of Science)*, 342(6160):850–853, 2013. ISSN 0036-8075.

A. Kearsley and M. Riddel. A further inquiry into the pollution haven hypothesis and the environmental kuznets curve. *Ecological economics*, 69(4):905–919, 2010. ISSN 0921-8009.

A. Leblois, O. Damette, and J. Wolfersberger. What has driven deforestation in developing countries since the 2000s? evidence from new remote-sensing data. *World development*, 92:82–102, 2017. ISSN 0305-750X.

F. Leijten, S. Sim, H. King, and P. H. Verburg. Local deforestation spillovers induced by forest moratoria: Evidence from indonesia. *Land Use Policy*, 109: 105690, 2021. ISSN 0264-8377. doi: https://doi.org/10.1016/j.landusepol.2021.105690. URL `https://www.sciencedirect.com/science/article/pii/S0264837721004130`.

A. Levinson and M. S. Taylor. Unmasking the pollution haven effect. *International economic review (Philadelphia)*, 49(1):223–254, 2008. ISSN 0020-6598.

A. S. Pfaff. What drives deforestation in the brazilian amazon?: Evidence from satellite and socioeconomic data. *Journal of environmental economics and management*, 37(1):26–43, 1999. ISSN 0095-0696.

C. . L. S. Watson. Climate finance thematic briefing: Redd+ finance. https://climatefundsupdate.org/wp-content/uploads/2020/03/CFF5-2019-ENG-DIGITAL.pdf, 2020. [Online; Accessed April 12, 2023].