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Deforestation in Indonesia: The Politics of Land Use Change Post Suharto

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Deforestation in Indonesia: The Politics of Land Use Change Post Suharto

by

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Abstract

Over the past 25 years over 130 million hectares of natural forest land on our planet has been lost accelerating climate change and threatening the world's most diverse ecosystems. Although the annual rate of global deforestation is half of what it was in the early 1990s it remains problematic in several regions of the world. Indonesia, for example, currently accounts for nearly 25% of global deforestation annually and has shown no signs of improvement. This thesis explores some of the key drivers of deforestation in Indonesia by making use of a rich dataset that tracks forest loss across eight years when Indonesia was undergoing political restructuring following the collapse of the Suharto dictatorship. Previous literature has pointed to the expansion in the number of political jurisdictions as a vehicle for increased political corruption which in turn could cause deforestation. The hypothesis is that when a new district is created there is increased competition for the sale of logging permits within a provincial wood market. This may incentivize district governments to issue more than the legal quota of permits consistent with Cournot-style competition. However, the data does not seem to line up with this argument. Instead, forest loss in Indonesia appears to be related to widespread forest fires caused by landowners for the purposes of clearing land primarily for palm oil plantations. The results from this thesis lay the groundwork for future research to focus on the determinants of growing demand for palm oil such as international trade.

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i. Global and Local Effects of Deforestation

Addressing the deteriorating state of the planet's forests is arguably one of the biggest challenges policy makers around the world face today. Forests provide important ecosystem services that all living species around the world, including humans, rely on every day. The destruction of forests jeopardizes these ecosystem services and affects our quality of life. On a global scale, the most important ecosystem service delivered by forests is the sequestration of carbon dioxide which not only cleans the air that we breathe but also helps mitigate the effects of global climate change. It is estimated that the world's forests in 2015 stored up to 296 gigatonnes of carbon dioxide equivalent with the higher density forests in tropical regions storing roughly 120 tonnes per hectare (Food and Agriculture Organization of the United Nations, 2016). This is a considerable carbon store given that total greenhouse gas emissions globally in 2015 were estimated to be 35.5 gigatonnes (Quiere et al., 2018).

Deforestation has two effects on greenhouse gas emissions. Not only does deforestation reduce the amount of carbon that can be sequestered in forests, it also releases carbon that was stored in the trees that are burned or cut. It is estimated that between 1990-2015 the changes in carbon stock[1] from deforestation contributed 1.6 gigatonnes of carbon dioxide equivalent emissions per year which is equivalent to 15-20% of annual global greenhouse gas emissions.[2]

[1] Over this time period there was a reduction in the carbon store of 11.1 gigatonnes (billion tonnes) or 442 million tonnes annually.

[2] Forests can act as a carbon sink or as a carbon source. They are a carbon source if they release more carbon than they absorb. Conversely, they are a carbon sink if they absorb more carbon than they release. The change in carbon stock between 1990-2015 have made the world's forest a net carbon source emitting 1.6 gigatonnes of carbon dioxide annually on average.

For perspective, this level of emissions is greater than the entire world's transportation sector and the second largest contributor to global greenhouse gas emissions after fossil fuel combustion.

Apart from carbon storage there are also important ecosystem services that are provided by forests at a local level. Forests play a key role in regulating the water cycle and preventing soil erosion. Following precipitation, the water cycle is characterized either by surface run off, which ends up in streams, rivers, and lakes and evaporates back into the atmosphere or by plant uptake where water vapors eventually transpire back into the atmosphere. Since tree roots typically penetrate deeper than the roots of alternative types of vegetation[3] the loss of trees reduces plant uptake and the transpiration of water vapor into the atmosphere. This disruption of the water cycle has three effects on local environments. First, precipitation patterns may change, and in the most extreme cases desertification can occur. This affects agricultural productivity and is especially consequential for local communities that depend on subsistence agriculture (Lawrence & Vandecar, 2015). Second, surface temperatures become more extreme since there is a reduction in evapotranspiration which has a cooling effect on the local environment. It is estimated that a single tree that transpires up to 100 liters of water every day has the equivalent cooling capacity of two central air conditioning units (Wolosin & Harris, 2018). Finally, without trees there may be greater surface run off which ends up in streams, rivers, and lakes adversely affecting those ecosystems. Soil erosion occurs when soil that was anchored by forest land can no longer be anchored by alternative uses of land.[4] This fertile soil is washed away, and this leads to problems with vegetation growth. World Wildlife Fund estimates that a third of the

[3] Alternative types of vegetation that forests are presumed to be replaced by such as crop plantations.
[4] For example, consider agricultural expansion - the roots of palm oil, soy, coffee, cotton etc. plants can not anchor down soil as effectively as the roots of a fully mature tree.

world's arable land has been lost through soil erosion caused by deforestation since 1960 (World Wildlife Fund, 2017).

Forests are also home to much of the biodiversity that exists on our planet. Loss of habitat due to deforestation can lead to species extinction which harms the planet's biodiversity. Preserving biodiversity is important in protecting ecosystems and the services that they provide us since greater biodiversity provides greater insurance to an ecosystem. When an ecosystem is more diverse it is better suited to adapt to disturbances versus ecosystems that are less diverse. This is because the species in diverse ecosystems can occupy an array of different ecological niches while the species in less diverse ecosystems are competing for the same niche (Naeem & Li, 1997). For instance, if a bird species goes extinct then a forest ecosystem that has 50 different types of bird species is likely to adapt better than a forest ecosystem that only has 5 different types of species since the species in the more diverse ecosystem occupy many different niches. Biodiversity is key in maintaining ecosystems.

Biodiversity is also important in some of the ecosystem services that we rely on. About 75% of our food supply comes from just 12 different plant species but these species are in turn dependent on hundreds of other species occupying their niches in an ecosystem (Mclendon, 2016). For example, these plant species depend on bees for pollination, they depend on bats for eating pests, they depend on earthworms for maintaining soil fertility. Finally, biodiversity is important for medical research. Many medical discoveries begin by researching the genetics and biology of plant and animal species but with reduced biodiversity these discoveries are limited. Every time a species goes extinct there is a lost opportunity in discovering a new drug.

ii. Global Deforestation Statistics

Given some of the global and local consequences associated with deforestation understanding the extent and spatial patterns of forest loss is important. However, measuring deforestation depends on how forests are defined. The Food and Agriculture Organization of the United Nations (UN FAO) defines a forest as land spanning more than 0.5 hectares with trees higher than 5 meters and a canopy cover[5] of more than 10%. This definition does not include land that is predominantly under agricultural or urban land use (Food and Agriculture Organization of the United Nations, 2016). The FAO definition of forests is not only determined by the biophysical presence of trees but also accounts for land use by excluding tree stands in agricultural production systems such as fruit tree plantations, oil palm plantations, and orchards. In contrast, areas of land that have been recently logged or burned and are temporarily devoid of trees would still be considered as forest land as long as they are expected to regenerate and reach the height and canopy cover thresholds under the FAO definition within 5 years. Therefore, according to the FAO definition deforestation is the conversion of a forest to other land uses or the permanent reduction of the tree canopy cover. Alternative definitions will also be discussed in greater detail shortly.

Since the 1990s the global rates of deforestation have been slowing down, mostly due to better forest management,[6] but forest loss on a global scale is still concerning and unsustainable. The UN FAO in the latest Forest Resource Assessment (FRA) report estimates that global forest cover in 1990 was 4,128 million hectares but dropped to 3,999 million hectares by 2015. This is

[5] Canopy cover defined by the UN FAO is the percentage of ground covered by a vertical projection of the outermost perimeter of the natural spread of the foliage of plants. It cannot exceed 100%.
[6] Better forest management practices include designating more land to permanent forests (including forests designated for conservation of biodiversity), better assessments, monitoring, reporting, as well as stronger legal frameworks.

a net loss[7] of 129 million hectares over a 25-year period implying a decrease in forest area of -3.13% or an average annual loss of -0.13%. Although this average annual loss seems very small, in absolute terms this is the equivalent to losing forest area roughly equal to the total land area of South Africa over a 25-year period. Table 1 shows the changes in global forest area between 1990-2015 estimated[8] by the FAO in each of their past Forest Resource Assessment reports. In the period from 1990-2000 the average annual forest loss rate was estimated to be -0.18% (-7.267 million hectares in absolute terms) while the average annual forest loss rate in the period from 2010-2015 was estimated to be -0.08% (-3.308 million hectares in absolute terms). This is a slowing down of more than 50% within a 20-year period.

Table 1 - Global Forest Area Change 1990-2015

Global Forest Area Change 1990-2015				
Year	**Forest (million ha)**	**Period**	**Area (million ha)**	**Annual Rate (%)**
1990	4,128			
2000	4,056	1990-2000	-7.267	-0.18
2005	4,033	2000-2005	-4.572	-0.11
2010	4,016	2005-2010	-3.414	-0.08
2015	3,999	2010-2015	-3.308	-0.08

Source: Food and Agriculture Organization of the United Nations. (2016). *Global Forest Resource Assessments 2015*.

While these statistics provide some optimism, higher rates of deforestation continue to persist in certain regions of the world with no clear indication of slowing down. This is particularly true in tropical regions such as South America, Africa, and parts of Southeast Asia. Table 2 shows the top ten countries experiencing the greatest average annual forest loss between 2010-2015. It also compares the rate of forest loss during this time period to the rates of forest loss experienced

[7] Net of any forest gains during the same period (i.e. net forest loss is the difference between forest area that is permanently lost to conversion to agriculture for example and permanently gained through afforestation).
[8] The FRA uses a combination of remote sensing satellite data as well as self-reported surveys from each country's government.

between 1990-2000. All ten of these countries are either from South America, Africa, or Southeast Asia.

Table 2 - Forest area Change in Selected Countries

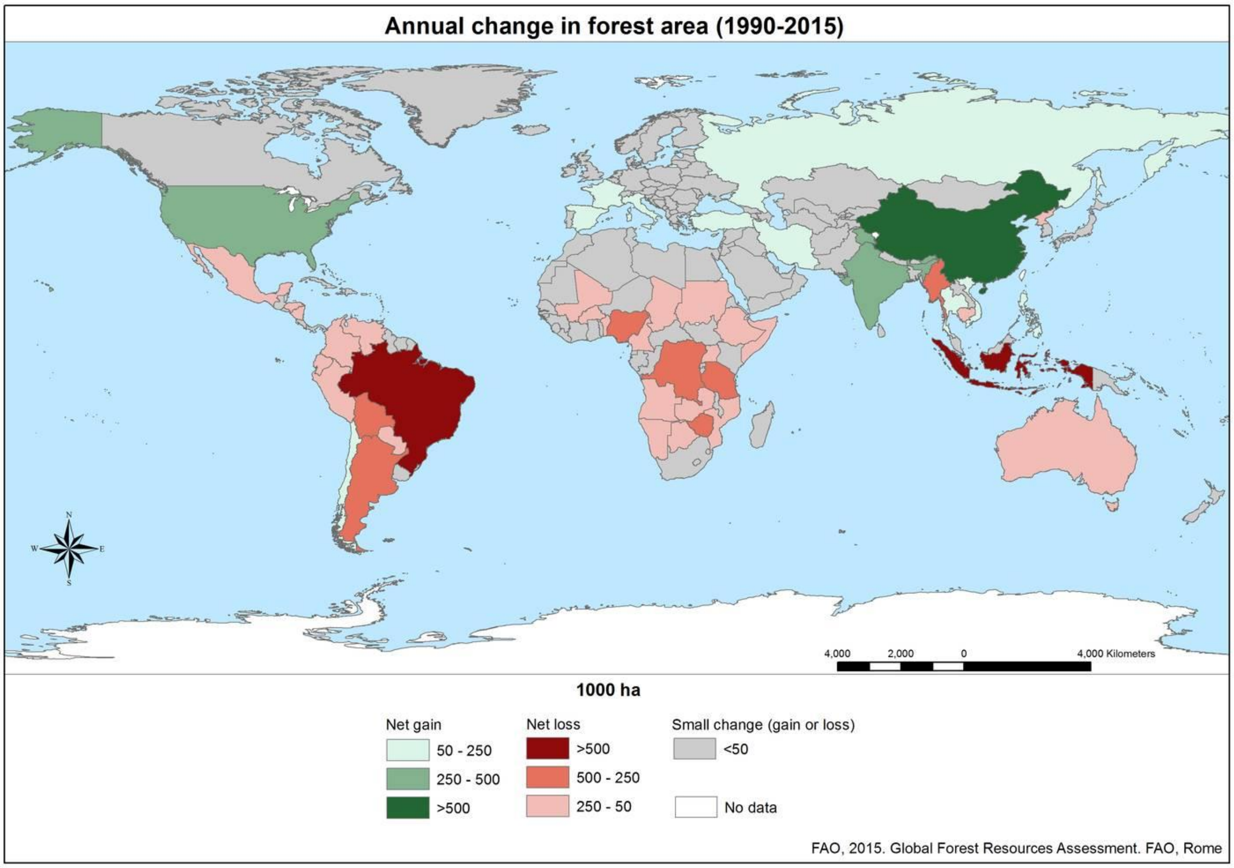
	Forest Area (million ha)					1990-2000		2000-2005		2005-2010		2010-2015	
	1990	2000	2005	2010	2015	Annual Forest Area Loss	Annual Rate	Annual Forest Area Loss	Annual Rate	Annual Forest Area Loss	Annual Rate	Annual Forest Area Loss	Annual Rate
Brazil	546.71	521.27	506.73	498.46	493.54	-2.543	-0.48%	-2.908	-0.56%	-1.654	-0.33%	-0.984	-0.20%
Indonesia	118.55	99.41	97.86	94.93	91.01	-1.914	-1.61%	-0.310	-0.31%	-0.586	-0.60%	-0.684	-0.72%
Mynmar	39.22	34.87	33.32	31.77	29.04	-0.435	-1.17%	-0.310	-0.89%	-0.310	-0.93%	-0.546	-1.78%
Nigeria	17.23	13.14	11.09	9.04	6.99	-0.409	-2.68%	-0.410	-3.12%	-0.410	-3.70%	-0.410	-5.01%
Tanzania	55.92	51.92	49.92	47.92	46.06	-0.400	-0.74%	-0.400	-0.77%	-0.400	-0.80%	-0.372	-0.79%
Paraguay	21.16	19.37	18.48	16.95	15.32	-0.179	-0.88%	-0.178	-0.92%	-0.306	-1.66%	-0.325	-2.00%
Zimbabwe	22.16	18.89	17.26	15.62	14.06	-0.327	-1.58%	-0.326	-1.73%	-0.328	-1.90%	-0.312	-2.08%
Congo	160.36	157.25	155.69	154.14	152.58	-0.311	-0.20%	-0.312	-0.20%	-0.310	-0.20%	-0.311	-0.20%
Argentina	34.79	31.86	30.19	28.6	27.11	-0.293	-0.88%	-0.334	-1.05%	-0.318	-1.05%	-0.297	-1.06%
Bolivia	62.8	60.09	58.73	56.21	54.76	-0.271	-0.44%	-0.272	-0.45%	-0.504	-0.86%	-0.289	-0.52%

Source: Food and Agriculture Organization of the United Nations. (2016). *Global Forest Resource Assessments 2015.*

Although Brazil and Indonesia have slowed down their average annual deforestation rates by more than 50% during the 2010-2015 period relative to the 1990-2000 period, they still experience the most absolute forest loss in the world. Aside from Brazil and Indonesia all the other countries presented in Table 2 have increased their average annual rate of deforestation between 2010-2015 relative to the 1990-2000 period. Nigeria has gone from an average annual rate of deforestation of -2.68% between 1990-2000 to a rate of -5.01% between 2010-2015 which is the highest of any country between 2010-2015. Paraguay more than doubled their average annual rate of deforestation from -0.88% between 1990-2000 to -2.00% between 2010-2015. These countries show no signs of slowing deforestation.

To get a better view of the spatial distribution of global deforestation between 1990-2015, Figure 1 maps the average annual change in forest area between 1990-2015.

Figure 1 - Annual Change in Forest Area Globally 1990-2015



Source: Food and Agriculture Organization of the United Nations. (2016). *Global Forest Resource Assessments 2015.*

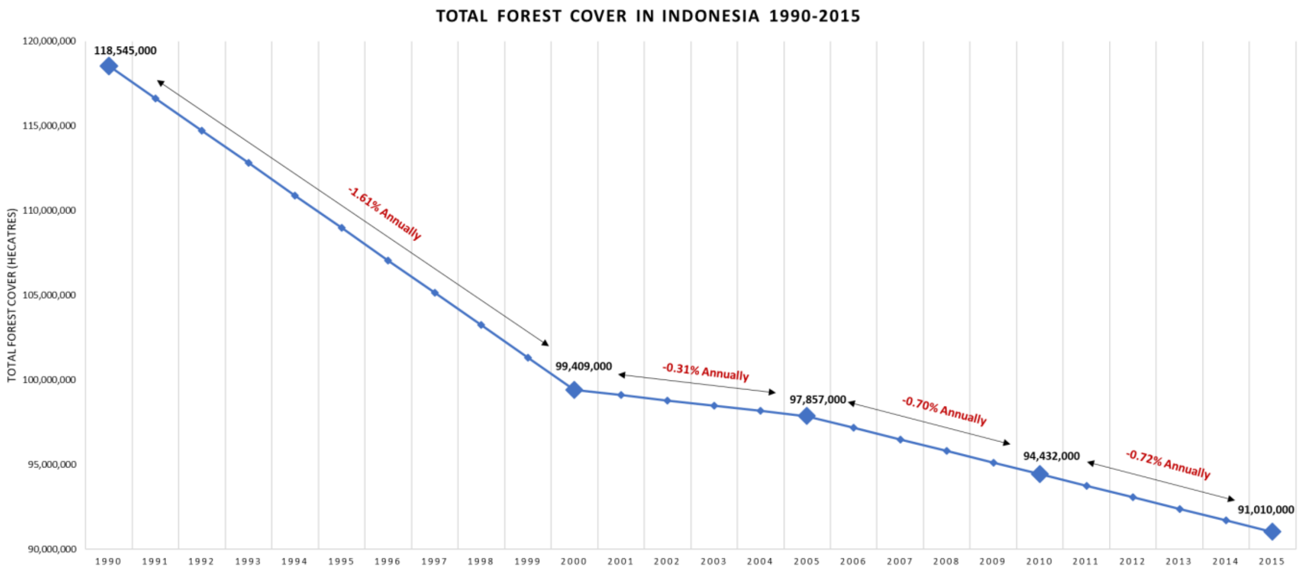
Not surprisingly the countries with the largest average annual change in forest area between 1990-2015 are in tropical regions of South America, Central Africa, and Southeast Asia. Of the countries that experienced a net loss in forest area, Indonesia and Brazil are the only two countries that have lost more 0.5 million hectares of forest area each year between 1990-2015 on average. Over this 25-year period Brazil and Indonesia experienced average annual forest loss of -2.13 million hectares and -1.10 million hectares respectively. Together this is the equivalent of losing forest area roughly equal to the total land area of the Netherlands every year for 25 years. The next highest is Nigeria who experienced an average annual forest loss of -0.41 million hectares between 1990-2015 which is not even half of what Indonesia lost.

Understanding the patterns of deforestation across time and in different regions of the world is crucial in identifying where to focus efforts in mitigating global forest loss. Following the statistics presented above it appears that over the 25-year period between 1990-2015 Brazil and Indonesia are still major hotspots for deforestation despite clear improvements over time. While they both seem to have reduced their annual rates of deforestation by more than 50% the improvements made in Indonesia are less significant than those made in Brazil. Indonesia appears to have an average annual rate of forest loss that is nearly 4 times the average annual rate of forest loss in Brazil. Therefore, understanding deforestation in Indonesia is central in addressing deforestation on a global scale and deforestation in Indonesia will be the focus for the remainder of this thesis.

iii. Deforestation in Indonesia

Indonesia is the largest archipelago in the world consisting of 17,508 islands stretching 5,150 kilometers west to east between the Indian Ocean and Pacific Ocean (Embassy of The Republic of Indonesia in Washington D.C, 2018). The entire archipelago contains land that is very fertile and without human occupation would be largely covered by tropical rainforests. The total change in forest area in Indonesia between 1990-2015 is shown in Figure 2.

Figure 2 - Forest Area in Indonesia 1990-2015 (UN FAO)



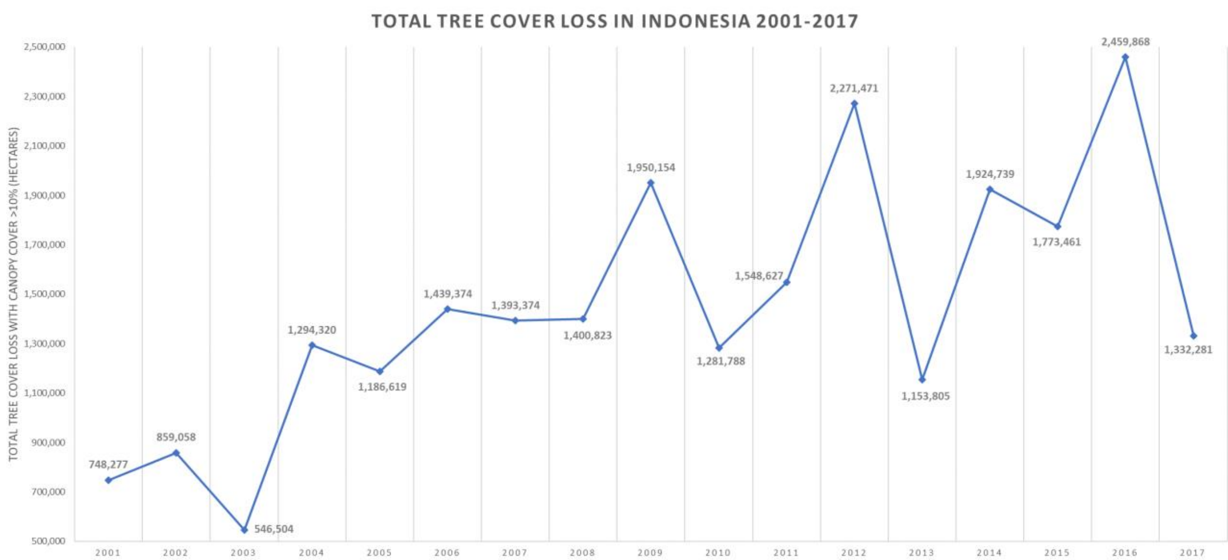
Source: Food and Agriculture Organization of the United Nations. (2016). *Global Forest Resource Assessments 2015.*

Since the FAO only conducts their Forest Resource Assessment at five-year intervals the annual forest area data shown in Figure 2 is calculated by the FAO by linearly interpolating in between each interval. They apply the average annual forest loss rates shown in Table 2 to all the years intermediate to five-year intervals. This provides us with an idea of how total forest area trends over time but does not say much about deforestation patterns within each interval. Total forest area in Indonesia between 1990-2015 decreased by 27.5 million hectares which accounts for more than 20% of global deforestation during this period.

To get a more granular view of how deforestation has changed over time and in different regions across Indonesia it is useful to consider data from Global Forest Watch (GFW) which uses remote sensing satellite technology to monitor global forest loss (Global Forest Watch, 2018). This data is updated annually and since it is collected at a very detailed level (i.e. 30m x 30m pixels) it can be used to analyze changes in forest area in a particular geographic region of interest such as an Indonesian island for example. However, GFW uses a different definition of deforestation than the FAO Forest Resource Assessment which makes it hard to compare between the two. GFW uses the term "tree cover" instead of forest and defines it as all vegetation greater than 5 meters in height with a canopy cover of more than 10% in all different land uses. This definition is based entirely on the biophysical presence of trees and does not distinguish between tree cover in different land uses like the FAO definition does. GFW detects and reports all instances of tree cover loss regardless if the loss is permanent (e.g. for the establishment of plantations or shifting agriculture) or if the loss is temporary (e.g areas that are cleared possibly from non-human causes such as natural fires but are expected to regrow).[9]

The data from GFW is useful in helping us understand the patterns of deforestation in Indonesia across time and different regions. Figure 3 shows total tree cover loss in Indonesia annually between 2001-2017.[10]

Figure 3 - Tree Cover Loss in Indonesia 2001-2017



Source: Global Forest Watch

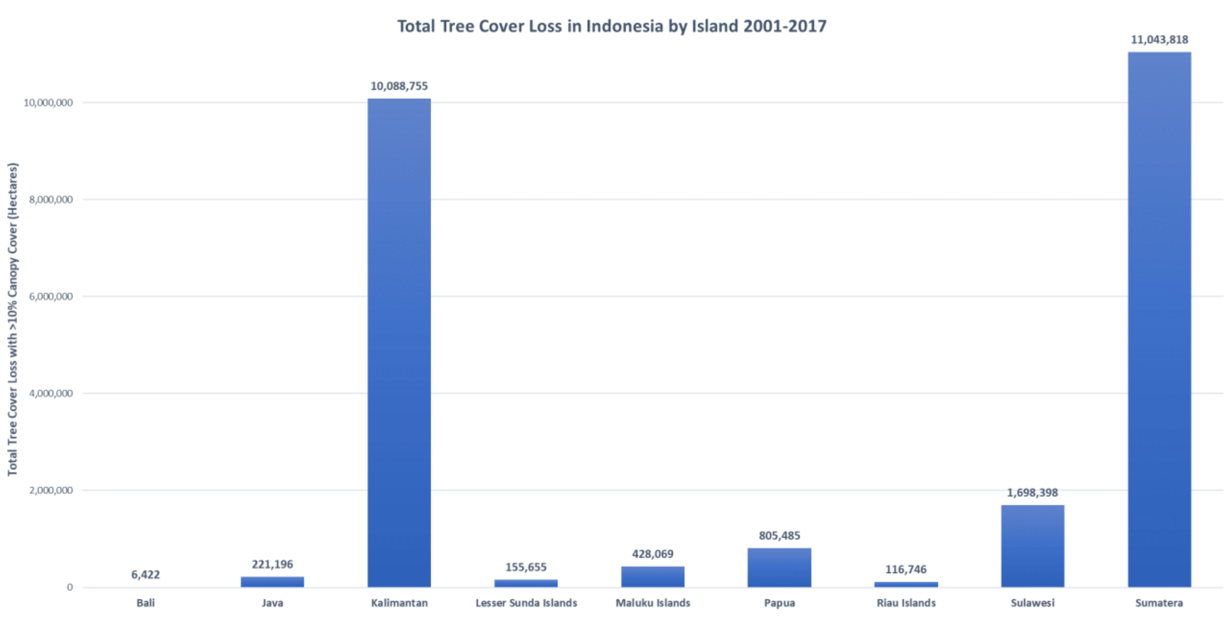
[9] See summary of differences between FAO and GFW for more details: https://www.wri.org/blog/2016/08/insider-global-forest-watch-and-forest-resources-assessment-explained-5-graphics.

[10] GFW reports total tree cover in 2000 and in 2010. Due to variation in research methodologies and date of content annual forest extent the authors advise against simply subtracting forest loss each year to get annual extent. Therefore Figure 3 shows annual loss rather than annual extent as in Figure 2.

From Figure 3 it appears that tree cover loss across time in Indonesia is volatile with large increases in deforestation in certain years followed by a sharp decline the following year. For example, between 2008-2009 there was an increase in tree cover loss of 39% followed by a decline between 2009-2010 of -34%. Similarly, between 2011-2012 there was an increase in tree cover loss of 47% followed by a decrease in tree cover loss of -49% between 2012-2013. The volatility of tree cover loss in Indonesia over time is interesting and makes one wonder what is occurring in Indonesia in that may be driving this pattern.

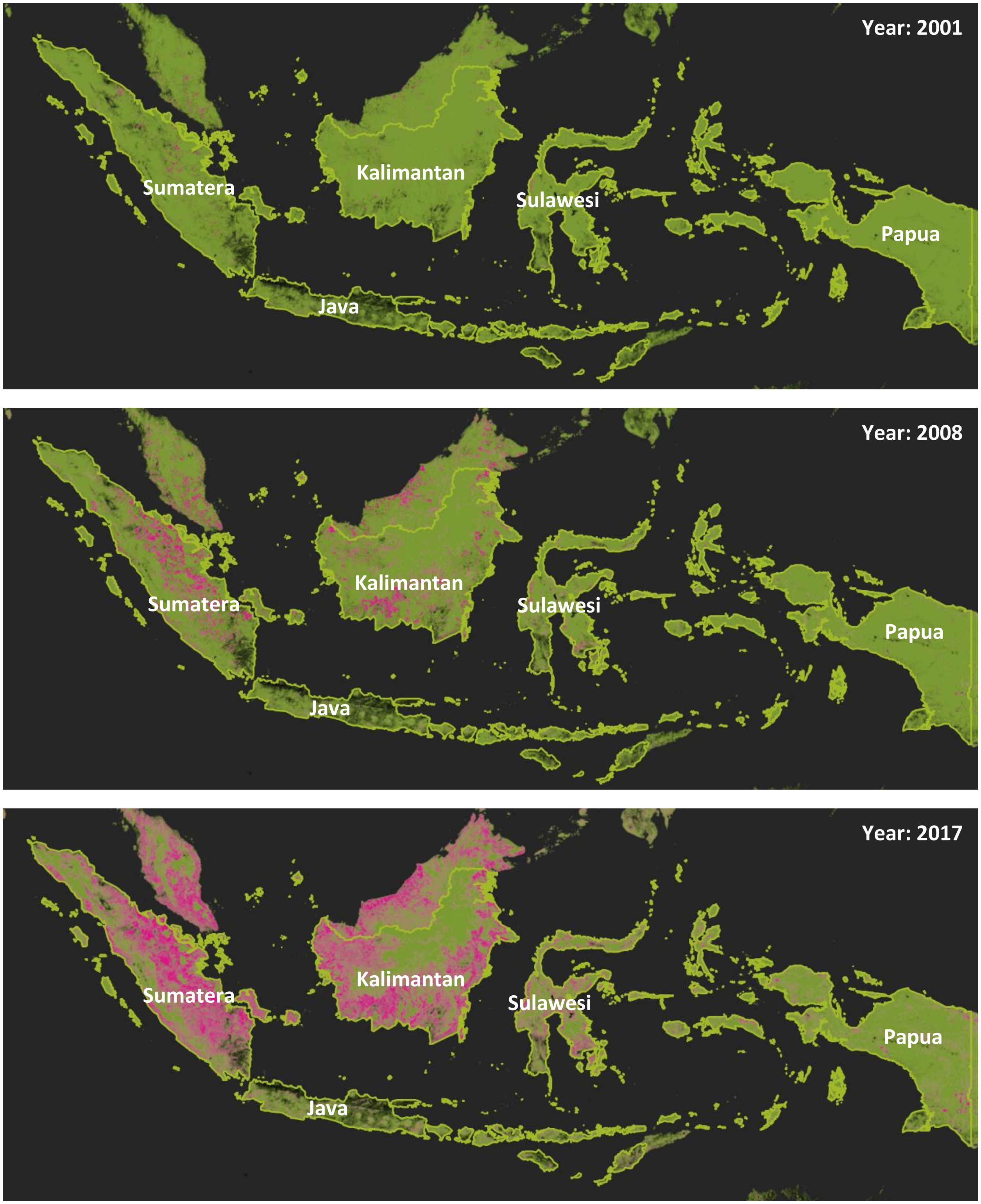
The spatial distribution of tree cover loss in Indonesia between 2001-2017 is also interesting. Figure 4 shows the total tree cover loss during this time period by the main Indonesian islands and island groups in a chart. Figure 5 geographically illustrates total tree cover loss across Indonesia by 2001, 2008, and 2017.

Figure 4 - Total Tree Cover Loss in Indonesia by Indonesian Islands 2001-2017



Source: Global Forest Watch

Figure 5 - Tree Cover Loss Between 2001-2017



Source: Hansen/UMD/Google/USGS/NASA, accessed through Global Forest Watch

From Figure 4 and Figure 5 it is clear that practically all of the tree cover loss that has occurred in Indonesia between 2001-2017 has occurred on two islands: Sumatera and Kalimantan (Indonesian part of Borneo). In the maps shown in Figure 5 the green areas represent the total extent of tree cover in Indonesia in the year 2000 which was 165 million hectares across the entire country while the red areas show the total loss accumulated by each year indicated. By 2017 the total tree cover loss estimated by Global Forest Watch was 24.5 million hectares with 11.0 million hectares lost on Sumatera and 10.1 million hectares lost on Kalimantan. Together this accounts for 86% of all tree cover loss that occurred in Indonesia between 2001-2017. These figures illustrate that the vast majority of tree cover loss that has occurred in Indonesia is spatially concentrated on two islands.

Forests are one of the world's most important resources. On a global scale they are central in the fight against climate change by sequestering nearly 2 billion tonnes of carbon dioxide equivalent from the atmosphere each year. On a local scale they provide important ecosystem services that we rely on every day such as regulating the water cycle, preventing soil erosion, and promoting biodiversity by providing a habitat for many of the planet's plant and animal species. Although it appears that deforestation has slowed down by more than 50% between 1990-2015 there are certain regions where it continues to be a problem. Total deforestation in Indonesia over this 25-year period according to the UN FAO amounted to 27.5 million hectares or an annual average of more than 1.1 million hectares a year. This is approximately one fifth of all deforestation that occurred worldwide during this period. Although Brazil experienced greater absolute forest loss the rate of deforestation in Indonesia is still nearly four times higher than the rate of forest loss in Brazil. Therefore, understanding the driving forces of deforestation in Indonesia is likely central in addressing deforestation on a global scale. This is the goal of this thesis.

The remainder of this thesis is organized as follows. Chapter 2 provides a comprehensive review of the expanding deforestation literature. This review categorizes the literature based on each study's scope of analysis (e.g. cross-country studies and within country studies). Chapter 3 presents the theoretical framework. In this chapter the data and summary statistics that are used in the empirical model are presented. Chapter 4 presents the empirical model and key results. Chapter 5 concludes.

Chapter 2: Literature Review

The literature on deforestation is quite broad and continuously growing. Decades of research has resulted in a collection of published journal articles that are scattered in their scope of analysis, theories, and empirical strategies with no consensus on the direction research should take. However, much of the empirical and theoretical knowledge on deforestation currently is contained in the handful of studies presented in this section. This literature review categorizes these articles by their scope of analysis: cross-country studies and single country case studies.

This review begins with cross country studies. All of these studies acknowledge the importance of property rights as a determinant of deforestation and in the case of Erhardt (2018) overfishing. Ferreira (2004) and Erhardt (2018) also consider the role that international trade may have on the overexploitation of natural resources. However, these cross-country studies struggle with incorporating measures of trade and property rights into an empirical model in way that convincingly avoids endogeneity problems. Measures of insecure property rights and international trade, which will be discussed in further detail, should not be thought of as truly exogenous since they will likely depend on some other factor that is also correlated with deforestation. For instance, insecure property rights which is often proxied by political unrest (e.g. riots, guerilla warfare, revolutions, etc.) may be determined by a country’s income or population growth which is also likely to be correlated with deforestation. Therefore, unravelling the chain of causation requires special attention for any meaningful conclusion to be reached. Another limitation of these cross-country studies is that none of them utilize remote sensing satellite data for forest cover. At the time these studies were published remote sensing technology was fairly new and the remote sensing data on forest cover that was available was limited in geographic coverage. This made it difficult to construct a dataset that had a long enough time series and covered a cross section of countries. Instead, these studies rely on each government's self reported forest inventories and surveys which may be misreported. Satellite data is likely more precise since it can capture all types of deforestation without any objectivity.

The next part of this review discusses within country case studies. Unlike the cross-country studies, the case studies identified in this part of the literature review largely ignore the effect that international trade may have on deforestation except for Lopez (1997). These studies do a better job of avoiding endogeneity problems and are more convincing in identifying causal effects of deforestation than the cross-country studies. This is in part because these studies focus on individual countries where it is easier to find exogenous variation that affects regions within a country rather than variation that affects a cross section of countries. For example, Southgate, Sierra, Brown (1991) uses institutional and demographic variation across 11 cantons in Eastern Ecuador to test the effect that insecure property rights have on agricultural expansion. Also, the set of possibly excluded variables in a country case study may be smaller since it is likely easier to control for these variables across regions within a single country rather than controlling for them across many different countries. This is explored in greater detail below. Another improvement these case studies make is that all of them make use of remote sensing satellite data. Lopez (1997) was among the first to make use of remote sensing satellite data to study deforestation.

i. Cross-Country Studies

The review of cross-country studies begins with Deacon (1994) which examines the relationship between deforestation and three possible causes: population growth, income growth, and insecure property rights. This study makes use of forest cover data from UN Food and Agricultural Organization (FAO) *Interim Report on the State of Forest Resources in Developing*

Countries which contains total forest cover[11] for 129 countries in 1980 and 84 countries in 1985. The author fills in the missing data in 1985 by estimating a statistical relationship for the 84 countries where data did exist and then used this relationship to predict total forest cover for the missing observations.[12] Data on population and political/legal indicators are from Banks (1990) *Cross National Time-Series Data Archive* while data on gross domestic product are from Summers and Heston (1991) *The Penn World Table*. Political stability indicators include major constitutional changes, guerilla warfare, and attempts at revolution.[13] The author also includes indicators of political representation such as type of government executive (e.g. military executive, elected executive, monarch) and whether or not the executive is a premier.[14] Data for population, GDP, and political indicators is collected for the time period between 1970-1985. The sample of countries excludes countries with a population of less than 500,000 people or countries that have less than 1% of their land area covered by forests so that the total number of countries in this sample is 120. Only twenty of these countries are classified as high-income countries by the World Bank.

[11] Total forest cover includes land area covered by both open and closed forest - closed forests is a forest with a tree canopy cover of greater than 20% while open forest consists of a canopy cover of at least 10%.

[12] A second order Taylor approximation around 1980 values: $T_1 = T_0 + T'(w_1 - w_0) + (T''/2)(w_1 - w_0)^2$ where 0 and 1 denote values in 1980 and 1985 respectively. T is total forest while w is forest and woodland area which is reported annually for most countries in the *FAO's Production Yearbook.* Forest woodland area is defined as land under natural or planted stands of trees plus logged over area that will be re-planted (a closely related measure of forest cover from the *FAO Interim Report on the State of Forest Resources* for which there is missing data in 1985).

[13] Specifically, *guerrilla warfare* is defined as the presence of any armed activity, sabotage, or bombings carried on by independent bands of citizens aimed to overthrow a regime; *revolution* is defined an attempted illegal or forced change in top government elite; *constitutional change* reports the number of basic alterations in a state's constitutional structure (e.g. altering the functions of different branches of government).

[14] Specifically, military executive indicates that the individual who exercises primary influence in shaping a country's internal and external affairs is in armed services; executive who is not a premier indicates that the executive is not drawn from the legislature of a parliamentary democracy.

To test for a relationship between deforestation and population growth, income growth, and insecure property rights the author estimates the following three regressions by ordinary least squares (OLS):

$$Deforest_{i,t} = \beta + \delta ln\Delta Pop_{i,t-q} + \varepsilon \tag{1}$$

$$Deforest_{i,t} = \beta + \delta ln\Delta GDPCapita_{i,t-q} + \alpha ln\Delta GDP_{i,t-q} + \varepsilon \tag{2}$$

$$\begin{aligned} Deforest_{i,t} = \ & \beta + \delta GuerWar_{i,t-q} + \alpha Revolutions_{i,t-q} + \vartheta ConstChange_{i,t-q} \\ & + \tau MillitaryExec_{i,t-q} + \gamma ExecPremier_{i,t-q} + \varepsilon \end{aligned} \tag{3}$$

In each of the OLS regressions above the i subscript refers to a country while the t subscript refers to the time period 1980-1985. The q subscript refers to the number of lag periods and can take the value 0,1, or 2. Each variable is measured between five-year intervals so a lag of 0 indicates the period between 1980-1985, a lag of 1 indicates the period between 1975-1980, and a lag of 2 indicates the period between 1970-1975. In all the dependent variables in each regression there is two lags. For example, in equation (1) the dependent variable the deforestation rate in country i between 1980-1985 and the independent variables are the log change in population between 1980-1985 in country i, log change in population between 1975-1980 in country i, and the log change in population between 1970-1975 in country i.

The results suggest that there is a positive relationship between population growth and deforestation (more prevalent with a lag), negative relationship between GDP growth and deforestation, and a positive relationship between insecure property rights and deforestation. However, there are important limitations in this study that should be addressed. First, the political indicators used to measure the effect that insecure property rights have on deforestation are endogenous. For example, the frequency of constitutional changes, guerilla warfare, and attempts at revolution likely depend on a country's income or rapid population growth. Wealthier developed countries likely experience less political unrest than poor developing countries. However, income is also determined endogenously since a country's income may depend on other factors that also affect deforestation such as their openness to trade. For these reasons it is difficult to identify effects of insecure property rights, income, and population on deforestation, but this study is useful in introducing potentially important determinants for deforestation in a cross section of countries.

Ferreira (2004) improves on Deacon (1994) by exploring the interaction between international trade and institutional factors and its effect on deforestation in a cross section of countries. This study uses forest cover data between 1990-2000 from the UN FAO *Forest Resource Assessment (FRA) 2000* which includes changes in forest area for every country in the world. An important limitation of the FRA data before 2000 is that it relies entirely on each government's self-reported forest inventories which are likely not as precise or consistent across countries as remote sensing satellite data. An index for trade openness which is just total exports plus imports as a fraction of GDP is obtained from the World Bank *World Development Indicators 2002 (WDI)* for the year 1990. To purge the effect that the size of each country has on its trade openness the author regresses the trade to GDP ratio on land area, total population, and income and uses the residuals as a measure of trade openness. The author uses five proxies for institutional quality from the Political Risk Services' *International Country Risk Guide* including: government repudiation of contracts, risk of expropriation, corruption, rule of law, and quality of the bureaucracy.[15] Averages for these indicators for each country between 1990-1997 are used. In addition to forest cover data, trade openness, and institutional quality this study also incorporates data on each country's population density in 1990 from the WDI, wood price in each country in 1990 from the FAO, length of coastline from the Central Intelligence Agency *World Factbook 2000*, and kilometers of road from the WDI.

The empirical model allows for an interaction term between trade openness and institutional quality. This term captures the heterogenous effects of trade openness in countries with different levels of institutional quality. All five of the proxies for institutional quality are included in the empirical model separately. The model specification is as follows:

$$Deforest_i = \alpha + \beta Openness_i + \delta' InstQuality_i + \rho' Openness_i * InstQuality_i + \gamma' Z_i + \varepsilon_i \quad (4)$$

Z_i is a vector of control variables in country i such as population density, wood price, length of coastline, and kilometers of road. $Openness_i$ is each country's openness to trade measured by their total trade flows (e.g. exports + imports) as a fraction of their GDP in 1990. $InstQuality_i$ is a vector of the five proxies for institutional quality. $Deforest_i$ is the deforestation rate in each country between 1990-2000. The empirical estimation strategy follows a general-to-specific technique where the most general form is estimated with all regressors included and regressors are iteratively removed according to statistical significance until a final specification is reached

[15] Specifically, *government repudiation (scale 0-10)* with low scores indicating risk of modification in contracts such as repudiation (e.g. rejection), postponement, or scaling down; *risk of expropriation (scale 0-10)* with low scores indicating possibility of confiscation and forced nationalization; *corruption (scale 0-6)* with low scores indicating likely dishonest and fraudulent behavior of government officials; *rule of law (scale 0-6)* with low scores indicating weak political institutions, weak courts, and not very orderly succession of political power; *bureaucratic quality (scale 0-6)* with low scores indicating inefficiency in the provision of government services.

(Hendry, 1995). The results suggest that a country's openness to trade has a statistically significant effect on deforestation (e.g. greater openness to trade results in greater deforestation) but only when interacted with the indicators for institutional quality. This implies that the effect that trade openness has on deforestation acts through institutional quality which is proxied by government repudiation of contracts, risk of expropriation, and quality of bureaucracy.

The improvement made in this study compared to Deacon (1994) is that it attempts to incorporate the effect that international trade may have on deforestation in a cross section of countries. However, there are still important endogeneity issues which make the results questionable. For example, there are likely important variables that are excluded from the model. One omitted variable may be the size of a country's agricultural sector relative to other sectors of the economy. Countries that are more agriculturally intensive will likely experience rapid land conversion from forest land to agricultural land (e.g. land for livestock to graze or land for plantations). Another omitted variable may be a country's total land area. It is likely harder to monitor and enforce illegal deforestation in larger countries compared to smaller countries.

Another issue in Ferreira (2004) is the possibility of reverse causation between deforestation and openness to trade since a reduction in forest area may also affect a country's ability to export forestry products. Suppose there is some exogenous shock to a forest stock such as a fire a disease. This shock would reduce a country's openness to trade since the ability to harvest and export forestry products is reduced. Reverse causation will result in biased estimators which will affect the validity of the results.

Erhardt (2018) extends the Ferreira (2004) study by investigating the effect that international trade and institutional quality have on the extraction of a different renewable resource: fish. The dataset used in this study is an unbalanced panel on 80 developed and developing countries across five time periods.[16] Data for overfishing comes from the University of British Columbia's *Sea Around Us* project. It contains data on the number of species fisheries that have collapsed, are overexploited, exploited, developed, or recovering in each country's exclusive economic zones (EEZs). A collapsed fishery is defined as a fishery where the catch in a particular year is less than 10% of the catch in the previous year. An overexploited fishery is a fishery where the catch in a particular year is 10-50% of the catch in the previous year. The author uses two different measures for the extent of overfishing: (i) collapsed share, which is the share of collapsed fish species in the total number of assessed species per EEZ; (ii) overused share, which is the share of overexploited fish species in the total number of assessed species per EEZ. The author uses two different measures for openness to trade. First, total trade flows as a fraction of GDP which is the same measure used in Ferreira (2004). Data for this comes from the World Bank. Second, KOF Index of Economic Globalization which reflects trade restrictions (e.g tariffs and barriers to investment) and actual flows (e.g. foreign direct investment and trade in goods). A measure of the quality of governance is obtained from the Political Risk Services' *International Country Risk Guide.* This measure is an average of corruption, law and order, and bureaucratic quality indexed between 0-1 with 0 being weak governance and 1 being strong governance (see footnote 15 for definitions).

This study examines two competing hypotheses of renewable resource extraction and international trade. The resource haven hypothesis which says countries that have weakly defined property rights will have a comparative advantage[17] in the resource industry and with the

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[16] Data in five-year intervals from 1986-2006. Data for governance is only available for the five time periods. between 1986-2006 but in specifications with lagged dependent variables and instruments additional data from 1981 and 1976 (two lagged periods) are also used.

[17] Comparative advantage occurs when a country can produce a good relatively cheaper (in terms of opportunity cost) than another country.

introduction of liberal trade policies the resources will be overexploited. This was the result in Ferreira (2004). The severe overuse hypothesis which says when a resource is subject to severe overuse in a country with weakly defined property rights the cost of harvesting the resource is relatively high and the introduction of liberal trade policies will lead to specialization away from the resource good. When a resource is subject to severe overuse the cost of harvesting the resource is relatively high since it requires more effort. For example, harvesting the last fish in a sea is more costly (i.e. requires more effort) than harvesting fish in a sea with plenty of fish. The severe overuse hypothesis suggests opening up to trade may cause the overused resource stock to replenish. Although this study was done in the context of fish stocks these two competing hypotheses can be extended to any renewable resources such as forests.

To empirically evaluate these competing hypotheses the author estimates the following dynamic fixed effects model:

$$\begin{aligned} Overuse_{i,t} = {} & \beta_1 Overuse_{i,t-1} + \beta_2 Openness_{i,t} + \beta_3 Openness_{i,t} * Governance_{i,t} \\ & + \beta_4 Governance_{i,t} + \mu_i + \delta_t + \varepsilon_{i,t} \end{aligned} \tag{5}$$

where the i and t subscripts denote the country and time. μ_i and δ_t are country and time fixed effects. The lagged dependent variable, $Overuse_{i,t-1}$, is the effect that overfishing last period has on overfishing in the current period. The interaction term, $Openness_{i,t} * Governance_{i,t}$, is similar to the interaction term in Ferreira (2004). It captures the effect that openness to trade has on overfishing in countries with different levels of governance quality. To examine the competing hypotheses the coefficient of interest is β_3. If β_3 is negative this would suggest that greater openness leads to greater overuse in countries with weak property rights in favor of the resource haven hypothesis. Conversely, if β_3 is positive this would suggest that greater openness to trade leads to less overuse in countries with weak property rights in favor of the severe overuse hypothesis. Upon estimating (5) the author finds the coefficient β_3 to be positive and statistically significant which is evidence for the severe overuse hypothesis.

Interestingly, this is the opposite conclusion to Ferreira (2004). Recall in that study the author finds that openness to trade in countries that had weakly defined property rights lead to greater deforestation. The result in Ferreira (2004) provides support for the resource haven hypothesis. The most obvious differences between the two studies is the estimation strategy. Ferreira (2004) estimates an OLS model with cross sectional data whereas Erhadt (2018) estimates a fixed effects model with panel data. Another difference is that they examine the effect that openness to trade has on two different resources. In a fishery, stock depletion raises the cost of harvesting. More effort is required to harvest a fish in a sea that is nearly depleted versus harvesting a fish in a sea filled with fish. However, this may not necessarily be true in a forest. The cost of harvesting trees in a forest may not change as much as the forest stock is depleted. The amount of effort required to harvest the last tree in a forest likely does not require much more effort than harvesting the first tree in a forest. Therefore, the introduction of liberal trade policies may not lead to specialization away from the resource good like the severe overuse hypothesis suggests since a country may still have a comparative advantage in the resource good. The differences in the effort and costs associated with harvesting a nearly depleted fish stock versus a nearly depleted forest stock is likely responsible for the different results in Erhardt (2018) and Ferreira (2004).

The final cross-country study is Bohn and Deacon (2000). This study examines the effect that ownership risk has on capital investment, oil production, oil discovery, and deforestation.

Ownership risk in all of these cases is modelled by some probability of expropriation. Expropriation is defined as any event that eliminates an investor's claim to the earnings of an investment. For example, this could include the government directly taking property away from the investor or theft by private parties (e.g. think about terrorist groups taking over oil fields in the Middle East[18]). Expropriation is an all or nothing event. There is some probability, π_t, that in period $t+1$ expropriation occurs indicated by 0-1 variable ε_t. If expropriation occurs ($\varepsilon_t = 1$) then an investor loses all of his/her claims to investment projects at the start of $t+1$ and in all periods that follow. This implies that for all types of projects (e.g. capital investments, oil production, oil drilling, forest extraction) the investor's value function will depend on π_t and ε_t and they will maximize current period profits, PR_t, plus the discounted value of future payoffs. This value function takes the form:[19][20]

$$V_t(\pi_t, \varepsilon_t, \dots) = \max\left\{PR_t + \frac{1}{1+r}\int V_{t+1}(\pi_{t+1}, \varepsilon_{t+1}, \dots)dG(\pi_{t+1}, \varepsilon_{t+1}|\pi_t, \varepsilon_t)\right\} \qquad (6)$$

For each specific type of project there are additional state variables indicted by the (...). For example, capital investment also depends on physical capital, labour, productivity, and factors that affect productivity growth (e.g. international trade[21]). Oil production and oil discovery also depends on known reserves not yet extracted, unknown reserves, capital specific to oil extraction (e.g. pumps, pipes, etc.), total amount of oil in the ground, and the price of oil. Forest extraction

[18] See report by OECD: *Terrorism, Corruption, and the Criminal Exploitation of Natural Resources* (OECD, 2017).
[19] $dG(\pi_{t+1}, \varepsilon_{t+1}|\pi_t, \varepsilon_t)$ is a transition function for the bivariate Markov process of (π, ε) - stochastic process where the probability of an event occurring depends on the event occurring previously.
[20] This is only if $\varepsilon_t = 0$ if $\varepsilon_t = 1$ then obviously $V_t(\pi_t, \varepsilon_t, \dots) = 0$.
[21] International trade is justified to effect productivity growth because interaction with more developed countries enhances learning and exchange of ideas.

also depends on current period forest biomass, level of forest biomass that would exist in a region absent any extraction (reference level of forest biomass), and the price of wood. The authors then use dynamic programming techniques to maximize the four value functions (i.e. there is one value function for each type of specific project that takes the form of equation (6) with project specific state variables mentioned above) and obtain optimal policy functions that can be estimated:

Capital Investment:	investment/output ratio = f(output/worker, human capital, expropriation risk, factors that affect productivity growth)
Oil Production:	oil production/reserve ratio = f(oil price, ownership risk)
Oil Discovery:	oil drilling rate = f(oil price, ownership risk, remaining reserves not yet discovered)
Forest Extraction:	deforestation rate = f(current period biomass, reference level biomass, price of wood, ownership risk)

The first part of the empirical estimation involves estimating a relationship between the probability of expropriation and capital investment to create an ownership risk index. Probability of expropriation is proxied by indicators of political instability that were used in Deacon (1994) including major constitutional changes, guerilla warfare, frequency of political assassinations, attempts at revolution, and type of political regime (see footnote 13 and 14 for definitions). This relationship is estimated with an OLS regression of the investment-output ratio in a country on the measures of political instability, output per worker, secondary school enrollment (proxy for human capital), and openness to trade (proxy for productivity growth). The ownership risk index is then created by multiplying together the coefficients on the political instability variables. This ownership risk index is then inserted into the OLS regressions for oil discovery, oil production, and forest extraction. For example, to estimate the effect that ownership risk has on oil production the authors regress the oil production to reserves ratio in a country on oil price and ownership risk. To estimate the effect of ownership risk on oil discovery the authors regress the number of wells drilled per a year in a country on oil price, geological abundance, and ownership risk. Finally, to estimate the effect that ownership risk has on deforestation the authors regress the change in forest stock on ownership risk, the price of wood, and initial forest area.

Data for the measures of political instability mentioned above are from Banks (1990) *Cross National Time-Series Data Archive* and contains data for the period 1950-1989 for 125 countries. Data on the investment/output ratio and output/worker ratio are both from the *Penn World Table 1996* and contains data on 125 countries between 1955-1988. A proxy for human capital, ratio of secondary school enrollment to population, was obtained from Banks (1990) *Cross National Time-Series Data Archive*. Data for a country's openness, which is used as a proxy for productivity growth, comes from the *Penn World Table 1996* and is measured by a country's imports plus exports as a fraction of their GDP. Forest cover data is similar to the data used in Deacon (1994). That is, the forest cover data is from two different FAO sources. The primary source is the UN FAO *Forest Resource Assessment 1988* which includes forest cover data between 1980-1985. This source reports forest cover data for 129 countries in 1980 but only 84 countries in 1985. To fill the missing data the authors used the UN FAO *Production Yearbook 1986* which provides data from 1980-1985 on "forest and woodland" area, a closely related measure of land use (see footnote 12). All petroleum data (discovery and production) is from the *Oil and Gas Journal Database 1993.*

The key conclusion reached in this study is that a greater degree of ownership risk results in a greater degree of current period consumption of forest stock but not necessarily oil production. Specifically, the effect ownership risk has on natural resource use depends on the capital intensity required to extract the resource. If natural resource extraction requires a large amount of capital (e.g. petroleum) then increased ownership risk will have a minimal effect on extraction since landowners will not have an incentive to invest the capital required to exploit the resource. Conversely, if natural resource extraction requires less capital (e.g. forest) then increased ownership risk will have a greater effect on extraction since landowners will discount future consumption more heavily.

A major difficulty with Bohn and Deacon (2000) is the way in which the authors incorporate a country's openness to trade into the model. Openness to trade is included in the capital investment model that is used to create the ownership risk index and it is used as a proxy for productivity growth. The rationale for proxying productivity growth with openness to trade is that when less developed countries interact with more developed countries this may enhance learning. However, incorporating openness to trade in this way may result in the same endogeneity problems seen in the previous cross-country studies. For example, in the capital investment model it may be the case that the investment to output ratio (i.e. dependent variable) and a country's openness to trade (i.e. independent variable) are simultaneously determined. A country's openness to trade may lead to greater investment (e.g. foreign direct investment) but at the same time a country's trade policies may also be influenced by investment. This endogeneity will bias the ownership risk index and consequently bias the effect that ownership risk has oil production, oil discovery, and forest extraction.

ii. Individual Country Case Studies

The review of country case studies begins with Lopez (1997) which estimates the value environmental resources such as biomass and forests as factors of agricultural production in

Ghana. The data for this study comes from two sources: (i) World Bank *Living Standards Survey (LSS)* conducted in Ghana in 1988 and 1989; (ii) satellite imagery conducted by Earth Satellite Corporation (EarthSat) in 12 villages[22] in the west region of Ghana in 1988 and 1989. The LSS data is a panel that includes 139 households across 12 villages in 1988 and 1989 and contains data on consumption and production at the household level, labour force activity, individual characteristics (e.g. education, age, family size, ethnic background, etc.), as well as wages. The EarthSat data contains data on total forest area, agricultural land, land under fallow, and biomass density in each village.

There are two important characteristics of traditional Ghana agriculture that are key in this study. First, agriculture in Ghana follows a system of shifting cultivation where land is intensively cultivated for 1-2 years and then left fallow for 4-10 years to regenerate natural nutrients (i.e. biomass) which can then be used as fertilizer during the next cultivation period. Biomass is therefore an important factor to agricultural production and its depletion via the shortening of the fallow periods is likely to have a negative effect on agricultural production. Second, property rights in Ghana are not well defined. A large portion of land available in a village is exclusively for communal use by the villagers in that village. This land is open access within a village but closed to outsiders. Additionally, a farmer has exclusive rights to land that is under cultivation but once the land is left fallow it is available for use by other villagers.

Weak property rights along traditional agricultural practices of shifting cultivation may lead to the overexploitation of natural resources. To protect their land rights farmers will have an incentive to either shorten their fallow periods, which results in less biomass nutrients and lower

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[22] Satellite imagery used in this study was conducted as a special project by Earth Satellite Corp. It was one of the first studies to use satellite imagery to study deforestation. The 12 villages in the sample include New Bansakrom, Yankye, Akantamwa, Tanoso, Sireso, Bibiani, Asunsu, Doduoso, Susuanso, Dormaa, Apronsie, and Boasi.

agricultural productivity, or expand the cultivation area, which leads to deforestation. The author suggests that there is an optimal fraction of land that should be cultivated in order to maximize social income in a village. If the land under cultivation is above or below the optimum, then village income is reduced. This study solves for the optimum amount of land that should be cultivated to maximize village income and uses the data from Ghana to test whether land is allocated efficiently.

The author develops a general equilibrium model where farmers choose the level of land they wish to cultivate to maximize their income subject to a fixed stock of biomass in a village. The choice made by each farmer is summed up to get an expression for aggregate village wealth:

$$\max_{x_i L_i} \int_0^\infty \left(\sum_{i=1}^{N} pF^i(L_i, x_i, K_i, \theta) - wL_i - cx_i \right) e^{-rt} dt$$
$$\text{s.t} \qquad \theta = \eta \left(\bar{x} - \sum_{j=1}^{N} x_j \right) \tag{7}$$

where x_i is the level of land cultivated by farmer i, L_i is the labour input used by farmer i, p is the output price (all farmers are price takers in output markets), K_i are fixed factors used to produce output (e.g. tools, machines, etc.), θ is the total biomass in a village, $F^i(\cdot)$ is the production function which depends on biomass, w is the wage rate, c is the private cost to clear land, and r is the discount rate. Total biomass in a village is expressed as the total fallow area, $\bar{x} - \sum_{j=1}^{N} x_j$, times the average biomass density per acre of fallow land, η. The first order conditions from this maximization are the following:

$$\frac{\partial Y}{\partial L_i} = pF^i(\cdot) - w = 0, i = 1, \dots, N \tag{8}$$

$$\frac{\partial Y}{\partial x_i} = pF^i(\cdot) - c - \eta \sum_j pF^j(\cdot) - \frac{\mu\eta}{\bar{x}} = 0, i = 1, \dots, N \tag{9}$$

$$\dot{\mu} = \left(r + \frac{\sum x_j}{\bar{x}}\right)\mu - \left(x - \sum x_j\right) \sum_j pF^j(\cdot) \tag{10}$$

where μ is the Lagrange multiplier (e.g. the shadow value of biomass). Equation (8) is the usual profit maximizing condition for labour which says a farmer will choose labour so that the marginal product of labour is equal to the wage rate. Equation (9) is the equation that is of interest to examine the optimal land under cultivation. It says that a farmer will adjust the level of land under cultivation until the marginal effect of x_i on Y (income) is zero. In the steady state $\dot{\mu} = 0$ and once solving for μ^*, substituting into equation (9), and taking logs the author obtains the following expression which can be estimated:

$$\frac{\partial \ln Y}{\partial \ln x} = N \frac{\partial \ln Y}{\partial x_i} = \frac{1}{1 - S_L - \epsilon} \left[\frac{\partial \ln F}{\partial \ln x} - \epsilon - \frac{z}{1 - z} \ \frac{1 + r}{r + z} \ \frac{\partial \ln F}{\partial \ln \theta}\right] \tag{11}$$

where S_L is the share of labour in the total value of output, ϵ is the share of land clearing costs in the total value of output, and z is the proportion of the total village land that is cultivated (e.g. $z \equiv \sum_j x_j / \bar{x}$).

Testing whether or not land cultivation is efficient in Ghana requires the marginal effect of total land under cultivation on total income to be zero (e.g. $\frac{\partial \ln Y}{\partial \ln x} = 0$). From equation (11) all that it is needed to do this is an estimation for the production function, F. The author assumes a Cobb-Douglas functional form for the production function and estimates it using OLS with a log-log specification:

$$\ln Q_{ijt} = \beta_0 + \beta_x \ln x_{ijt} + \beta_L \ln L_{ijt} + \beta_\theta \ln \theta_{jt} + \beta_k \ln K_{ijt} + \varepsilon_{ijt} \tag{12}$$

where Q_{ijt} is output of farmer i in village j at time t and everything else is as defined before. Equation (12) is estimated and the coefficients β_x, β_L, and β_θ are substituted into equation (11) as constants (e.g. $\beta_x = \frac{\partial \ln F}{\partial \ln x}$, $\beta_\theta = \frac{\partial \ln F}{\partial \ln \theta}$, and $\beta_L = S_L = \frac{\partial \ln F}{\partial \ln L}$). The two key conclusions reached are: (i) farmers in Ghana internalize a small amount of the social cost of biomass in their land allocation decision and cultivate more than the efficient amount required to maximize income; (ii) biomass is an important contributor to agricultural revenues accounting for ~15% of revenues in Ghana.

Lopez (1997) further extends his study to consider the effect that liberal trade policies in the agriculture sector may have on national income. Ghana trade policy imposes a 20% export tax on agricultural products and trade liberalization would be a reduction or complete elimination of this tax. The idea is that trade liberalization has two effects on national income: (i) it reduces the inefficiencies of resource allocation caused by the initial export tax (positive for national income) and (ii) it may magnify the environmental distortion associated with inefficient land allocation (negative for national income). The author conducts a trade simulation exercise[23] to find the net effect of trade policies on national income. The total differentiation of the system of equations in the general equilibrium model noted in footnote 23 suggests that if the environmental externality is fully internalized by individual farmers then trade liberalization will unambiguously increase income. On the other hand, if the environmental externality is not internalized then the effect of trade liberalization on national income is ambiguous. The empirical estimation suggests that complete trade liberalization (i.e. no agricultural export tax) will decrease national income by about 10% which implies the magnification of the environmental distortion outweighs the reduction in the trade distortion.

One of the most important weaknesses of this study is that the theoretical model assumes all farmers in a village are identical and that the market is perfectly competitive in outputs and inputs. However, this seems unlikely. These villages in Western Ghana are likely very small with very few farmers. Therefore, instead of these farmers competing against each other in a perfectly competitive market it seems more reasonable to think that there would be some strategic interaction between farmers in a village. That is, each farmer's output decisions would depend on the output decisions of all other farmers in the village. Maximizing equation (7) for each farmer's choice of land cultivation will also depend on some expectation of other farmers choice of land cultivation and this may lead to even greater overexploitation of biomass.

[23] This is done with a two-sector (agricultural good and industrial good) general equilibrium model: (i) national income depends on world price of agricultural good, agricultural production function (which depends on cost of clearing land, stock of biomass, total cultivated land, and fixed factors), world price of industrial good, and production function of industrial good (depends on labour and capital); (ii) labour allocation in each sector which depends on export tax on agricultural goods and import tax on industrial goods as well as the world price in each sector; (iii) total labour market clearing.

Southgate, Sierra, Brown (1991) investigate the role that agricultural expansion and insecure property rights play in deforestation in Ecuador. They make use of multiple sources of data primarily from official government records. The model presented in this paper is static and data was obtained for the year 1982. Forest loss data comes from the National Institute for the Colonization of the Ecuadorian Amazon (INCRAE) and the Center for Integrated Inventory of Natural Resources (CLIRSEN) who have used satellite images and aerial photographs to assess the extent of tropical deforestation in 11 of eastern Ecuador's 20 cantons between 1977 and 1985. Data for each canton's agricultural labour force and urban population are obtained from a census conducted in 1982 by the National Institute for Statistics and the Census (INEC). A measure of total area in each canton with good agricultural potential was assessed through soil maps prepared by the National Program for Agrarian Regionalization (PRONAREG). Each region's soil quality was classified according to drainage and fertility. It was determined that 5.64% of Eastern Ecuador was free of serious drainage and fertility problems which is consistent with the United Nations Environmental Program (UNEP) assessment of the area which made use of the same soil maps. INEC also prepared road maps that were used to determine how many kilometers of all-weathered roads existed in each canton in 1982. Lastly, total land adjudication determined by the Ecuadorian Institute for Agrarian Reform and Colonization (IERAC) as well as land use data from INCRAE were used to create an index for tenure security.[24]

With this data, the authors present two empirical models to test the effect that agricultural colonization and tenure security have on deforestation Ecuador. They estimate the following system of two regressions using ordinary least squares:

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[24] Tenure security index, TENSEC, is just simply the ratio of adjudicated percentage of a canton's agricultural land to the adjudicated percentage of total agricultural land in the study (TENSEC$=\frac{\text{adjudicated \% of a canton's agricultural land}}{\text{adjudicated \% of agricultural land in study area}}$)

$$AGPOP = \beta_0 + \beta_1 URBPOP + \beta_2 SOILS + \beta_3 ROADS \tag{13}$$

$$DEFOR = \delta_0 + \delta_1 AGPOP + \delta_2 TENSEC \tag{14}$$

The first regression estimates a canton's agricultural labour force, which is a proxy for agricultural rents. Agricultural labour force is dependent on the canton's urban population, soil quality, and kilometers of all-weathered roads. All of the regressors in this regression were found to have a significantly positive impact on agricultural rents. The second regression estimates the extent of land clearing in a canton and is dependent on agricultural rents from the first regression and tenure security. Tenure security index was shown to have a negative effect on deforestation since enhancing tenure security would imply there is reduced need to exercise informal land claims. The key conclusion from this study is that settlement in forest hinterlands is driven by the prospect of collecting agricultural rents and deforestation is a consequence of demographic pressures as well as colonists attempt to protect their tenuous legal hold on land.

Alston, Libecap, Schneider (1996) explore the determinants of supply and demand for land titles as well as well as the impact land titles have on land value and agricultural investment in two agricultural frontier regions in Brazil: in the southern state of Parana and in the Amazon state of Para. This study makes use of two different datasets: (i) household survey data conducted by the authors at four different sites in the state of Para near the communities of Altamira, Tucuma, Sao Felix, and Tailandia in 1992 and in 1993; (ii) Brazilian Agriculture Census in Parana from 1940-1970 (four census periods in 10-year intervals) and in Para from 1970-1985 (four census periods in 5-year intervals). The sites of the household survey are scattered around Para and provide some degree of variation since the mix of sites allows the authors to analyze the effects of different agency jurisdictions and title administration processes. In total, there are 206 landholders that are surveyed across the four different sites. The surveys contained data on land characteristics (e.g. percentage of farmers with title, value per hectare, total distance to market, percentage of area cleared, etc.) as well as data on landholder characteristics (e.g. education, time on plot, age, wealth). Survey data allows the authors to examine the determinants of land title, investment, and land value at the individual level. In contrast, the census data is at the county level and provides a much longer time series. There are 79 counties in Para for four census periods while, in Parana, there are initially 49 counties in 1940 and grows to 288 in 1970. This provides the authors with ample cross sectional and time variation within the states of Para and Parana. The census data contains information on land value per hectare, distance between the county capital and the state capital (i.e. distance to the central market), proportion of farmers within the county with title, average soil quality, population density, and average investment per hectare.

Land title is defined as a formal document issued by the Brazilian federal government that signifies and legitimizes the government's recognition of an individual's property rights to land.[25] Land with title is closely monitored and policed by the government. Title reduces private enforcement costs, provides security for long term investment, and promotes development of land. It mitigates the risk of land expropriation and it is clear that title increases the value of land.

[25] The authors note that title applications are usually processed within 2-5 years (this involves land assessments, site visits, boundary demarcations, and other administrative work) but government policy in Para and Parana differ which may cause additional delays. There are three key differences: (i) in Para both the federal and state governments are involved in the titling process - in counties where most of the land is owned by the state the state government is responsible for issuing title and since the state government faces more local political pressure title applications are processed quicker and more complete than applications by the federal government; (ii) in Para migration was stimulated by federal government in infrastructure (e.g. roads, subsidized colonies, etc.) - these infrastructure programs brought settlers to Para before land values had risen to a level that would have otherwise attracted migrants; (iii) In Para there has been much more violence and more land disputes between small landholders and ranchers.

However, what is not immediately obvious is the relationship between the value that title adds to land and the distance to central markets. The authors suggest that at a location close to the market center land with title will be valued more than land without title, but the further you move away from the market center (i.e. towards the frontier) land value with and without title will converge. Contribution of title is the greatest closer to the market center. This is because potentially high valued land close to the market center but without title will be subject to intense competition that will make private enforcement costs high. However, with title, the government enforces land rights. The added value of title decreases as distance to the market center increases since the further you move away the higher transportation costs will be and there will be less competition for that land. Using this relationship, the authors are able to create a demand curve where the difference in value of land between titled and non-titled land is decreasing as distance from market center increases.

The empirical model in this study is simple. The authors estimate three equations using ordinary least squares: (i) land value, (ii) demand for title, and (iii) land specific investment. The specification for each regression is as follows:

$$\begin{aligned} lnValue = {} & \alpha_1 + \alpha_2 lnDistance + \alpha_3 lnTitle \cdot Distance + \alpha_4 lnSoil + \alpha_5 lnClear \\ & + \alpha_6 lnInvestment + \alpha_7 lnDensity + \alpha_8 Title + \alpha_9 Jurisdiction \\ & + \alpha_{10} Conflict + \varepsilon \end{aligned} \tag{15}$$

$$\begin{aligned} Title = {} & \beta_1 + \beta_2 ChangeInValue + \beta_3 Size + \beta_4 Jurisdiction + \beta_5 Conflict \\ & + \beta_6 Distance + \beta_7 Charactaristics + e \end{aligned} \tag{16}$$

$$\begin{aligned} lnInvestment = {} & \delta_1 + \delta_2 lnDistance + \delta_3 Title + \delta_4 lnSoil + \delta_5 lnCharacteristics \\ & + \delta_6 Jurisdiction + \delta_7 Conflict + \varepsilon \end{aligned} \tag{17}$$

$Value$ is the value of agricultural land per hectare in each county (using the survey data it is the reported per-hectare value of a farmer's land). $Title$ is the percentage of farmers in a county that have title on their land (using the survey data it is 1-0 indicator variable of whether a household has title on their land). $Distance$ is the distance from each county capital to the state capital (using survey data this is the distance from each site to the closest market town[26]). $Soil$ is the average soil quality in each county (this data does not exist for the survey data, so the authors include dummy indicators for each site to account for soil quality and other site-specific variables). $Clear$ is the percentage of agricultural land that is cleared of forest in each county or for each household in the survey data. $Investment$ is land-specific investment per hectare of agricultural land in each county or for each household in the survey data. $Density$ is the population density in each county. $Jurisdiction$ and $Conflict$ indicate whether a county is in a state where the administration of land title is contested between the state and federal government or whether the county experienced land conflicts (see footnote 25 for more details). Finally, $Charactaristics$ include individual characteristics of the landowners. For the census data this includes average age, income, and education of all landowners in each county. For the survey data this includes each landowner's time on plot, age, education, and wealth.

Based on the theory it is expected that having land title increases the value of land (i.e. $\alpha_8 > 0$ in equation (15). The increase in land value from having title should also affect the demand for title which is captured by the β_2 coefficient in equation (16). However, since the $ChangeInValue$ variable is not directly observable in either of the datasets the authors introduce a constructed variable for the expected change in value for having title. This is done by calculating the difference in equation (15) for when title equals one and when title equals zero.

[26] The three market towns include Altamira, Tucuma, and Tailandia.

The resulting expression is the change in land value as a function of investment and exogenous factors. Because of the possible simultaneity between investment and title the authors estimate these variables using a two-stage approach. Specifically, predicted investment is used to calculate the change in value variable and predicted title is used to estimate investment in equation (17).

The key conclusion upon estimating these three equations is: land title and investment contribute to land value and title induces agriculture specific investment in Brazil. Additionally, as distance from the market center increases land value for titled and non-titled land decrease with a larger effect for titled land as predicted by the theory. This confirms that demand for title is determined by distance to the market center.

Foster and Rozenweig (2003) examine the effect that increasing income and population has on the growth of forests in India. The authors construct a village level panel data set in 250 villages from 1971-1999 containing census data, household surveys, and satellite imagery.[27] Census and survey data contains information on household demographics, land use, incomes, agricultural output, and prices and is matched with satellite data for changes in forest density. Satellite images are based on light frequencies that enable the construction of indices that measure vegetation for small geographic regions. The index the authors use is called the normalized differentiated vegetation index (NDVI) which measures differences in reflectance between red light and infrared light. This index correlates well with plant matter since vegetation reflects infrared light and absorbs red light. The output of this index is a measure between -1 and

[27] Data comes from six sources: (i) The National Council of Applied Economic Research (NCAER) Additional Rural Income Survey 1970-1971, (ii) NCAER Rural Economic Development Survey 1981-1982, (iii) Indian Census 1991, (iv) NCAER Village Rural Economic Development Survey, (v) National Climate Data Center monthly global surface data, (vi) satellite spectral images for India from 1972-1980, 1992, 1999.

1 where any value above 0.2 indicates vegetation associated with trees. This data was then geocoded to match the household survey and census data in the 250 villages. Finally, to construct a measure for agricultural productivity, surveys for crop output, land usage per crop, type of land, and seed type (high yielding HYV or not) were used to create a Laspeyres index[28] of HYV crop yields using corn, rice, sorghum, and wheat.

The theoretical model presented in this case study is a general equilibrium model with three sectors including forestry, agriculture, and manufacturing all with two factors of production land and labour. In all sectors land is immobile and in the forestry sector labour is also immobile while it is mobile in the manufacturing and agricultural sector. There are three sources of growth in this model: (i) agricultural technology; which, for instance, could mean the adoption of HYV crops; (ii) factors that affect labour productivity in manufacturing, which mainly includes infrastructure; (iii) population growth. Further, it is assumed in this model that India is a closed economy since there are high import tariffs on wood products and domestic demand must be met by domestic supply. It is also assumed that property rights are well defined and enforced in India. Households maximize utility by choice of land allocations to forest and agricultural production, labour allocations to manufacturing, forest harvesting, and agriculture, as well as consumption for local and imported forest and non-forest goods. First order conditions from this maximization yield predictions of how opportunity costs in the form of rent and wages change with growth in agricultural technology, infrastructure, and population. Particularly, as agricultural technology increases rent and wages both increases, as population increases rent increases, but wages fall, and as infrastructure increases wages increase but the effect on rent is ambiguous depending on land intensity of manufacturing. This theoretical model can't say anything about how agricultural

[28] Uses constant 1971 prices.

technology, infrastructure, or population affect forests since forest area is connected to local demand for forest products which depends on income and price: two endogenous variables. The theory can be used to create an estimable equation that relates technology, infrastructure, population, wages, and income to forest allocation.

The empirical part of this study begins by estimating equations relating variation in agricultural productivity, population size, and infrastructure (e.g. roads and electricity) to village wage, agricultural land price, and household income. Specifically, the empirical model takes the form:

$$Z_t = \beta_{zt} + \beta_{z\theta}\theta_t + \beta_{zl}l_t + \beta_{zN}N_t + \beta_{z\eta}\eta_t + \beta_{ze}e_t + \beta_{zv}v + \beta_{zt}t_t + \varepsilon_{zt} \quad (18)$$

where Z is either the log of the average price of land in the village (r), the log of the village male agricultural wage rate (w), or log of average household income in the village (y). θ_t is th index of agricultural productivity described above, η_t is industrial infrastructure and it is measured by dummy variables that indicate whether or not a village was electrified and had a paved road, e_t represents weather conditions and is measure by the amount of rainfall at the nearest weather station, l_t is log of average household size in a village, and N_t is log of population in the village. t_t and v are time and village fixed effects respectively.

This is estimated three different ways. First, simple ordinary least squares. Second, fixed effects controlling for village specific agroclimatic conditions as well as yearly fixed effects. Third, the authors use the same fixed effects, but they use instruments to predict village specific changes in crop productivity. To do this they make use of three characteristics of the green revolution in India: (i) climate conditions make some areas of India more suitable for growing certain crops; (ii) advances in productivity vary by crop; (iii) a variable indicating whether a certain village was located in an Intensive Agricultural District Program district. The outcome of these estimations confirms the theory in the general equilibrium model. That is, agricultural productivity, infrastructure, and population all have their expected effects on inputs. Increasing agricultural productivity increases land price and wages, increasing infrastructure increases wages, and increasing population increases land price but decreases wages. It is also shown that agricultural productivity, population, and infrastructure all increase household income.

The next part considers if advances in agricultural productivity and the associated wage and income increases can account for the growth of forests India. The estimation strategy is the same except now the dependent variable is forest cover and the instrument set has changed. They now use exogenous variables that affect technology and infrastructure. Particularly, initial period crop production interacted with time, electrification, and road building. This model takes the form:

$$A_t = \alpha_t + \alpha_\theta \theta_t + \alpha_w w_t + \alpha_l l_t + \alpha_N N_t + \alpha_y y_t + \alpha_e e_t + \alpha_v v + \alpha_t t_t + \xi_t \tag{19}$$

where A_t is forest cover in a village, w_t is the wage rate, y_t is income, and everything else is the same as equation (18). The result from this estimation is that increases in crop productivity are associated with a significant reduction in forest area. This implies that increases in land and labour input costs are not factors leading to forest growth. Instead, the main conclusion of this study is that the increase in demand associated with greater income is what is driving afforestation in India. This is important for policy since it implies that policies that attempt to reduce demand for forestry products do not necessarily save forests.

Burgess et al. (2012) explore how political corruption affects deforestation in Indonesia. This study makes use of very rich remote sensing data as well as institutional changes that resulted from the collapse of the Suharto regime in 1998. Burgess et al. (2012) argue that because much of the logging that takes place in Indonesia is done illegally, official production statistics are unreliable. Therefore, it is crucial to develop good remote sensing satellite data that encompasses both illegal and legal logging. This is done using the Moderate Resolution Imaging Spectrometer (MODIS) satellite to create an annual measure of forest cover change between 2001-2008. The biggest benefit of using MODIS instead of other satellites that are traditionally used for remote sensing (e.g. LANDSAT) is the frequency in which MODIS revisits an area. In a humid and cloudy region like Indonesia it is beneficial to have a satellite that passes over the same area every 1-2 days (versus 1-2 weeks for LANDSAT) to maximize the likelihood of obtaining cloud free images. However, the spatial resolution of MODIS is considerably coarser at 250m x 250m (versus 30m x 30m for LANDSAT).[29] To create the forest cover data used in this study the authors start by using MODIS 32-day composite images as raw inputs.[30] The time-sequential 32-day inputs were transformed into annual metrics that capture noticeable changes vegetation growth without specific reference to a time of year. The next step is to take the composited images and create an algorithm that discriminates between forest and non-forest. The authors do this using a decision tree bagging algorithm.[31] The final output is 34.6 million 250m x

[29] A single LANDSAT pixel covers an area of (30m x 30m = 900m^2) versus a MODIS pixel which covers an area of (250m x 250m = 62,500m^2) which means there are (62,500/900 ≈ 70) LANDSAT pixels in a single MODIS pixel

[30] These composite images include data from MODIS land bands: RGB bands (red, green, blue), near infrared, and mid infrared. The composite images also include data on surface temperatures.

[31] Specifically, the authors begin with higher resolution LANDSAT images (this consists of the best available cloud free images) and classify each pixel (30m x 30m for LANDSAT) as experienced forest loss or not. These

250m pixels between 2001-2008 across all of Indonesia that are estimated to be forested or non-forested. As a final step, each pixel in each year is summed up by Indonesian districts where a deforested pixel is indicated by a -1.

Burgess et al. (2012) also make use of institutional changes that were occurring in Indonesia during the early 2000s that resulted from the fall of the authoritarian Suharto regime in 1998. Following this political change, forest management in Indonesia was decentralized and the authority, monitoring, and enforcement of forestry rights became the responsibility of each district's forestry office.[32] Also, following the collapse of the Suharto regime there was an increase in the number of districts from 146 prior to decentralization in 1998 to 312 in 2008. The number of new political jurisdictions[33] as well as the differential timing of the establishment of these jurisdictions between 2000-2008 is the source of exogenous variation that the authors exploit in this study. The splitting of districts in Indonesia was dictated by three factors: (i) geographic area of each district, since it is more likely that larger districts will split to ease administration; (ii) the degree of ethnic clustering geographically, particularly off the island of Java there has been ethnic tensions and certain districts are more likely to split because of it; (iii) size of government sector in a district (Fitrani, Hofman, & Kaiser, 2005). However, the variation exploited by the authors isn't whether a split has occurred, but rather the timing of a split. The authors argue that the timing of splits is random due to idiosyncratic factors such as the long administrative process that is required for a split to occur. The authors also note that the

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classifications are then related to the MODIS data using the decision tree algorithm - hierarchical algorithm used to recursively partition a dataset into subsets with less variation of forest loss. Finally, a derived set of partitioning rules from this algorithm is used to extrapolate across the entire MODIS data set and to predict for each pixel in each year the probability that a pixel is deforested. A pixel is coded as clear if the probability of deforestation is greater than 90%.

[32] A district (kabupaten) in Indonesia is the third level of governance behind the national government (level 1) and the provincial governments (level 2).

[33] The number of new districts created at the margin not whether a district was created

administrative process is not the same for every district split. In some cases it may take a longer for a split to occur while in other cases the split may occur quicker.

The theoretical model used in Burgess et al. (2012) is a modified Cournot model that makes use of the institutional changes that occurred during the post Suharto era discussed above to predict the effect that an increase on political jurisdictions has on deforestation. As mentioned, district governments are responsible for regulating and monitoring logging rights in their district so that if a firm wishes to log in a district, they must obtain a permit (legal or illegal) at some cost from that district's forestry office. This Cournot model assumes that the logging industry is perfectly competitive with many firms that are free to choose where to log contingent on obtaining a permit.[34] District officials then choose how many permits to issue given the number of permits issued by neighboring districts. Districts are Cournot competitors with each other within a provincial market[35] for the sale of permits. This model also allows for the possibility that a district forestry office can issue more permits than its legal quota[36] if bribed. However, there is a probability that this illegal behavior will be detected. If caught, the district government loses all future rents since they will be forced out of office (including alternative sources of resource rents such as oil and gas). This theoretical framework predicts, just as any Cournot model, as the number of districts increases, and the sale of logging permits becomes more competitive the number of permits issued increases (forest loss increases) and the prices of logs decreases. The theory also predicts that there may be some substitution between illegal logging

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[34] It is assumed that it does not matter where the firms choose to log, they operate at equal constant marginal cost.

[35] The authors justify provincial boundaries as the relevant market since exporting raw logs is illegal in Indonesia which means logs would have to be transported to sawmills to be processed which is costly. Provincial boundaries often coincide with rivers and mountains (means of transporting logs that are costly).

[36] This legal quota is determined jointly between the National Ministry of Forestry and each district forestry office each year.

and other sources of resource rents (e.g. oil and gas revenues[37]). As the number of illegal permits issued by a district government increases the probability of being detected and losing all future rents also increases. Therefore, higher rents in oil and gas will induce substitution away from logging.

The empirical model makes use of the remote sensing satellite data for forest cover and institutional changes that occurred in Indonesia between 2000-2008 to evaluate the predictions from the theoretical model. The empirical specification for the effect that number of districts has on deforestation is presented in the paper as follows:

$$E\left(Y_{pit}\right) = \mu_{pi} e^{\beta X_{pit} + \varphi_{it}} \tag{20}$$

Where Y_{pit} is the number of pixels deforested in province p on island i in year t, X_{pit} is the number of number of districts in a given province at a point in time, μ_{pi} is a province fixed effect, and φ_{it} is an island fixed effect. To estimate the effect of increasing districts on wood prices the authors specify the following:

$$\log\left(\rho_{wpit}\right) = \beta X_{pit} + \mu_{wpi} + \varphi_{wit} + \varepsilon_{wpit} \tag{21}$$

[37] Indonesian national law requires that oil and gas revenues be shared among districts within a province. 15% of all national oil revenues and 30% of all national gas revenues gets redistributed back to the provinces where the producing district gets 50% of the redistributed revenues and the remaining 50% is shared equally among all other districts. Each district's oil and gas revenue can be determined by:

$$R_{dp} = 0.075 o_{dp} + 0.15 g_{dp} + \frac{0.075}{N_p - 1} \sum_{j \neq i} o_{jp} + \frac{0.15}{N_p - 1} \sum_{j \neq i} g_{jp}$$

where there are N_p districts in province p and each district d produces o_d oil revenues and g_d gas revenues.

Where ρ_{wpit} indicates the price of wood and the additional w subscript indicates the species of wood harvested. In these two models the primary focus is on the β which represents the semi-elasticity of deforestation with respect to the number of districts. Finally, to test the effect that oil and gas rents have on logging the authors specify the following district (d) level regression:

$$E(Y_{dit}) = \mu_{di} e^{\beta X_{dit} + \gamma Z_{dit} + \varphi_{it}} \qquad (22)$$

Where Z_{dit} indicates per capital oil and gas revenues received by a district and γ is the semi elasticity of deforestation with respect to oil and gas rents. In the estimation the authors include lags in an effort to capture medium to long run effects. Upon estimating these three equations the authors find that: (i) the semi elasticity of quantity logged with respect to new districts in all forests (legal and illegal) is 0.0385 in the short run and 0.0822 in medium run; (ii) the price elasticity of demand in the short and medium run is -2.27; (iii) for each additional dollar of oil and gas revenues received by the district logging falls by 0.3% in the short run. This substitution effect is reduced in the medium to long run.

The shortcomings in Burgess et al. (2012) will be discussed in much greater detail in Chapter 3 but there are some issues that should be addressed. First, the theoretical Cournot model presented by the authors does not seem realistic for modelling deforestation. Burgess et al. (2012) suggests that a growing number of districts is a vehicle for increased corruption since there will be greater intraprovincial competition for the sale of logging permits. District governments will, in turn, have an incentive to issue more than the legal number of permits consistent with Cournot-style competition. However, the authors do a poor job of thinking about other possible explanations that a growing number of districts may have on deforestation. For example, it may be the case that each district's forestry office is efficiently managing their resources. If a district government can anticipate a split occurring in the near future they will want to extract as much resources as they can immediately. This explanation as well as other possible explanations are explored in greater detail in Chapter 3.

Chapter 3: The Indonesian Context and Data

Following the collapse of the Suharto dictatorship in 1998, which has been regarded as one of the most politically corrupt regimes of all time (Transparency International, 2004), Indonesia began the process of democratization. During this process, the management of the forestry sector was decentralized to local district[38] governments where these district governments were able to enact their own regulations and were responsible for monitoring and enforcing these regulations with some passive oversight from the national government. District government leaders, called bupatis, had practically full autonomy[39] in issuing land rights[40] to whoever they wished and through a series of investigative case studies conducted by The Gecko Project and Mongabay, which are detailed below, it is shown that certain corrupt bupatis were motivated by bribes and political support from large multinational palm oil corporations who seek land rights to develop plantations (The Gecko Project & Mongabay, 2017). The first part of this chapter explores two case studies that highlight the relationship between political corruption, land rights, and deforestation. The next part of this chapter presents the data in Burgess et al (2012) and points to inconsistencies between the data and their arguments. Burgess et al. (2012) propose a very specific hypothesis that links an expansion in the number of political jurisdictions (i.e districts) to greater corruption which in turn drives forest loss across Indonesia. I argue that this

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[38] In Indonesia the district (also known as a regency or kabupaten in Indonesia) is the third level of government below the national government and provincial government - Indonesia is made up of a total of 34 provinces today which all contain a varying number of districts.

[39] Each year the district forestry offices negotiate their annual workplans which outlines number of permits to be issued and total area that the permits cover with the national Ministry of Forestry to ensure that total forest area being cut does not exceed some predetermined level. The national Ministry of Forestry rarely declines these workplans and is very weak in enforcing/monitoring district forestry offices.

[40] Land rights in this context refers to the government transferring the rights to the resources on the land. For example, this could include the harvesting of trees (logging permit) or the clearing of trees for plantation (plantation permit) but it does not involve direct ownership of the land - any activity conducted on the land not outlined in the permit is illegal. Permits last anywhere between 1 year (typically for logging) to 35 years (typically for plantations)

hypothesis does not appear to be consistent with the data. The final part of this chapter presents additional data and suggestive evidence of an alternative story explaining deforestation in Indonesia.

i. Corruption Case Studies

Indonesia for Sale is a series of investigative case studies done jointly by The Gecko Project and Mongabay that attempts to shed light on the political corruption behind Indonesia's land rights and deforestation issues (The Gecko Project & Mongabay, 2017). The first case study focuses on the corrupt behavior of Darwan Ali who was the first elected bupati of the district of Seruyan in the province of Central Kalimantan (The Gecko Project & Mongabay, 2017). During the Suharto era and into the early 2000s the local economy of Seruyan was largely dependent on logging but following the election of Darwan in 2003 the logging industry was starting to stagnate,[41] and the district's economy was shifting to an agriculture-based economy (Casson, 2001). This gave rise to the expansion of palm oil[42][43] and natural rubber plantations in Seruyan starting in about 2005 (Gaveau, et al., 2016). Since Darwan had full autonomy in issuing plantation licenses to whoever he wanted to, with very few checks and balances in place, this expansion in plantations was largely in Darwan's hands and resulted in widespread deforestation and greenhouse emissions. Greenhouse gas emissions and forest loss data will be discussed in more detail shortly but 2006 was a record year in Central Kalimantan with close 280 Mt of CO^2 equivalent being released into the atmosphere from 380,000 hectares of forest being burned

[41] Logging was stagnating mostly because of poor management - harvest levels were beyond what was legally permitted and sustainable.
[42] Palm oil is produced from processing palm fruit grown on a palm tree (which takes 2-4 years to mature from the time a tree is planted to when it starts producing fruit) - the seed is extracted from the fruit and the oil produced.
[43] Palm oil is a cash crop (crop that are grown for the purposes of selling and earning a profit) that is used in variety of products such as soaps, detergents, cosmetics, pharmaceuticals, food, biofuel and is widely demanded globally.

down (Indonesia Ministry of Enviornment and Forestry , 2015). For context this is about 2.5% of the total land area of the province of Central Kalimantan or roughly equivalent to the size of Los Angeles.

Not surprisingly, Darwan did not issue licenses to everyone that was looking to obtain a license, but instead he was very strategic and manipulative in issuing licenses in an attempt to mask corrupt behavior for financial and political gain. Between 1998 and 2003 there were only three plantation licenses issued to plantation companies in Seruyan. Between 2004 and 2005 Darwan had issued 37 plantation licenses covering an area of nearly 500,000 hectares which is about one third of the entire district. The most troubling part, however, is the way in which these licenses were issued. The investigative report by The Gecko Project and Mongabay followed a paper trail left by Darwan and pieced together a story that reveals an elaborate and coordinated scheme to make millions in profits. Evidence suggests that Darwan would have shell companies set up under the names of his relatives and closest friends to which he would issue plantation licenses for thousands of hectares and then these shell companies would get sold for millions of dollars to the region’s largest conglomerates. Figure 6 shows a map of the district of Seruyan and all the plantation concessions. The areas in red show licenses that were issued to shell companies that were owned by Darwan’s family and friends.

Figure 6 - Plantation Concessions and Shell Companies in Seruyan

Source: The Gecko Project & Mongabay. (2017). The Palm Oil Fiefdom.

In total there were 18 companies that were connected to Darwan through his wife, his daughters, his son, his brothers, and his nieces and nephews. Although none of these companies were directly connected to Darwan's it is likely that he was central in coordinating these shell companies. Some of the plantation firms that these shell companies were sold to include Wilmar International and Triputra Agro Persada, which are two of the largest plantation firms in Indonesia and among the largest in the world. These companies were willing to pay hundreds of thousands of dollars for the shell companies that were endowed with massive land concessions to fund Darwan's political campaigns and ensure he remains in power. In 2008, Darwan was re-elected as Seruyan's bupati for another five-year term. After the resignation of Suharto in 1998 there was optimism across Indonesia that graft was on the decline and that the decentralization of authority would shift accountability for political decisions close to the people affected by them (see the series of interviews of locals in Seruyan conducted as part of the Indonesia for Sale Project: The Gecko Project & Mongabay, 2017). However, it was becoming increasingly clear through cases like Darwan Ali that the political corruption had just simply moved down through the system to local governments.

The second case study explores corrupt behavior of Akil Mochtar, the highest-ranking judge of Indonesia's Constitutional Court (The Gecko Project & Mongabay, 2018). Following district elections, candidates who have felt that they have been cheated out of victory with illegal measures such as bribes or vote tampering can challenge the election result in Akil's court. This meant that Indonesia's top court has the final say in determining the governing bupati in each district and the highest-ranking judge holds all this power since he can either overturn or uphold an election result at his discretion. There have been cases in Indonesia where candidates will directly pay off Akil to ensure that an election results in their favor such as the case of Hambit Binth explored in more detail below. There have been other instances where successful candidates will bribe Akil to ensure a winning election result gets upheld if challenged by other candidates.[44] The KPK (Komisi Pemberantasan Korupsi), which is Indonesia's anti-graft agency, found that Akil made up to $4 million by accepting bribes and perverting both the justice system and democracy simultaneously (The Gecko Project & Mongabay, 2018). It was to the surprise of Indonesians across the entire archipelago that the highest-ranking judge was part of a system that he was supposed to be policing.

[44] For example see article on Akil's bribery record: http://www.thejakartapost.com/news/2014/02/22/court-reveals-akil-s-bribery-record.html.

This case study focuses on the 2013 district election in Gunung Mas in the province of Central Kalimantan and two politicians from the same political party: Hambit Bintih and Cornelis Nalau Antun. At the time Hambit was the ruling bupati seeking re-election and Cornelis was the party's treasurer. The plan was for Hambit to negotiate a bribe with Akil to ensure that he would get re-elected in the 2013 election while Cornelis would not only deliver the bribe to Akil but also source the funds of the bribe. Hambit and Cornelis had a pact that if they were successful in the election then the outgoing bupati in 2018, Hambit, would appoint Cornelis as his successor. This was contingent on Hambit winning the election which relied on the flow of money to fund his campaign and bribe Akil. With the possibility of being becoming Hambit's successor in 2018 as motivation, Cornelis set up shell companies as a vehicle to sell plantation licenses. These shell companies were similar to Darwan Ali's shell companies where Cornelis would set them up under the name of close relatives and friends, endow them with plantation licenses, and sell them to large plantation firms. Over the course of nine months in 2012, leading up to the election, Cornelis sold four shell companies that had licenses of nearly 6,000 hectares of land all to a Malaysian plantation firm called CB Industrial Product (CBIP). Much of this concession area overlapped with villages and smallholding plantations that were in some cases bulldozed without compensation from neither CBIP nor by Hambit's government. Before the election, Cornelis sold a fifth shell company to CBIP and made a total of $9.2 million. The election was held on September 2013 and it is no surprise that Hambit was declared the winner. Claims to challenge the election result from opposing candidates where unsuccessful and shortly after the election the KPK brought this case to Indonesia's top court where it was tried without Akil as chief justice. Hambit was subsequently sentenced to four years in prison while Cornelis was sentenced to three years in prison. Akil was not imprisoned, but one of the lawmakers who was working for Akil and facilitating the bribes on his behalf was sentenced to four years. Akil was removed from his position as chief justice. Hambit's party remained in power even with him behind bars and his running mate, Arton Dohong, was inaugurated as the bupati of Gunung Mas.

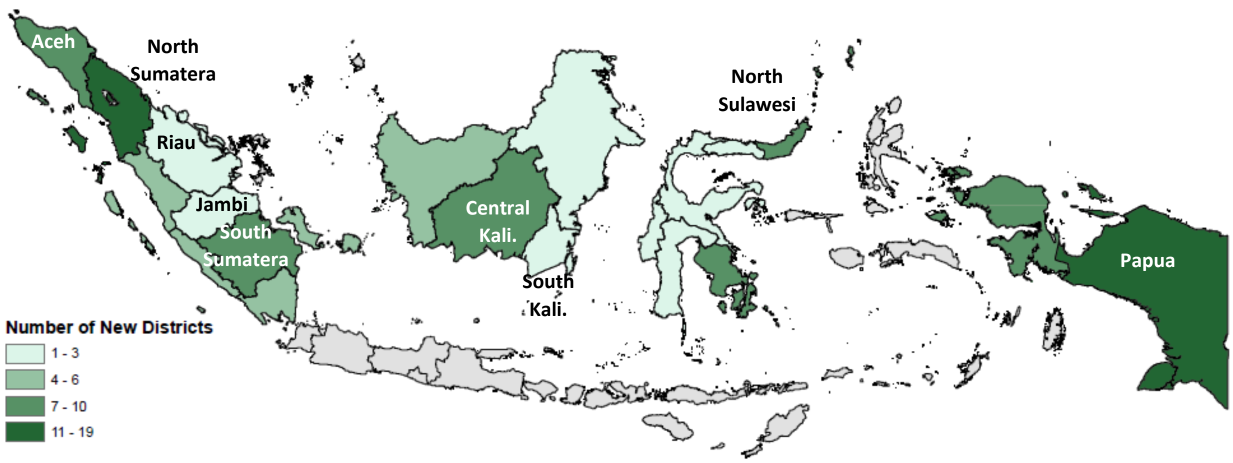
The main purpose of the investigations by The Gecko Project and Mongabay was to shed light on the role that political corruption has on deforestation in Indonesia. The cases of political corruption in Seruyan and Gunung Mas highlighted in the investigative reports show how certain politicians are willing to trade-off environmental degradation for the prospect of making a profit or advancing their own political agenda. It was shown that politicians such as Darwan Ali, Hambit Bintih, and Cornelis Nalau Antun have the interests of large plantation companies, that burn down large areas of forest land to make way for their plantations, as a top priority as long as these plantation firms pay significant bribe money.

ii. Re-examination of Political Corruption

The focus now shifts to the quantitative evidence and the apparent inconsistencies in Burgess et al. (2012) model of political corruption in Indonesia. Recall from Chapter 2 the Cournot framework that the authors use as a model for corruption. They suggest that within each provincial wood market each district competes with their neighboring district for the sale of logging permits. Under this framework each district allocates some number of permits to logging firms to maximize their expected payoff taking the number of permits allocated by their neighbors as given. A bribe in this framework is just the price paid for a permit beyond a legal quota and upon maximizing each district's payoff function it is not surprising to find that as the number of districts within a province increases the number of logging permits allocated (i.e. deforestation) increases and the price paid for a permit decreases just like in any Cournot model. This is a very specific hypothesis for how political corruption affects deforestation and the purpose of this section is to evaluate how well it holds up to the same dataset used in Burgess et al. (2012).

Following this hypothesis, one should expect that as the number of districts within a province increases between 2000-2008 the rate of deforestation within that province should also grow. Figure 7 maps the total district growth that occurs across all provinces in the sample.[45]

Figure 7 - District Growth Across Indonesia Between 2000-2008



Source: Created using data from Burgess et al. (2012)

Between 2000-2008 every province had at least one new district created and overall there was 123 new districts created during this period taking the total number of districts from 189 in 2000 to 312 in 2008. As shown in the map the distribution of new districts varies across provinces and the timing of creation, which the authors suggest is their primary source of exogenous variation, also varies. Table 3 summarizes the timing of splits.

[45] There are 21 provinces in the sample - the dataset excludes provinces on Java since there is little forest loss on Java during the sample period.

Table 3 - District Growth Across Indonesia Between 2000-2008

Number of Districts by Province										
Province	2000	2001	2002	2003	2004	2005	2006	2007	2008	Total New Districts
Riau	11	11	11	11	11	11	11	11	12	**1**
Jambi	10	10	10	10	10	10	10	10	11	**1**
South Kalimantan	11	11	11	13	13	13	13	13	13	**2**
East Kalimantan	12	12	13	13	13	13	13	14	14	**2**
Bengkulu	4	4	4	9	9	9	9	9	10	**6**
South Sumatera	7	10	11	14	14	14	14	15	15	**8**
Lampung	10	10	10	10	10	10	10	11	14	**4**
Central Kalimantan	6	6	14	14	14	14	14	14	14	**8**
West Kalimanatan	9	10	10	12	12	12	12	14	14	**5**
Southeast Sulawesi	5	6	6	10	10	10	10	12	12	**7**
North Sulawesi	5	5	6	9	9	9	9	13	15	**10**
Central Sulawesi	8	8	9	10	10	10	10	10	11	**3**
West Papua	4	4	9	9	9	9	9	9	11	**7**
Gorontolo	3	3	3	5	5	5	5	6	6	**3**
West Sulawesi	3	3	4	5	5	5	5	5	5	**2**
Bengka Belitung	3	3	3	7	7	7	7	7	7	**4**
Aceh	13	15	20	21	21	21	21	23	23	**10**
North Sumatera	19	20	20	25	25	25	25	28	33	**14**
West Sumatera	15	15	16	19	19	19	19	19	19	**4**
South Sulawesi	21	21	22	23	23	23	23	23	24	**3**
Papua	10	10	19	20	20	20	20	21	29	**19**
Total	**189**	**197**	**231**	**269**	**269**	**269**	**269**	**287**	**312**	**123**

Source: Burgess et al. (2012)

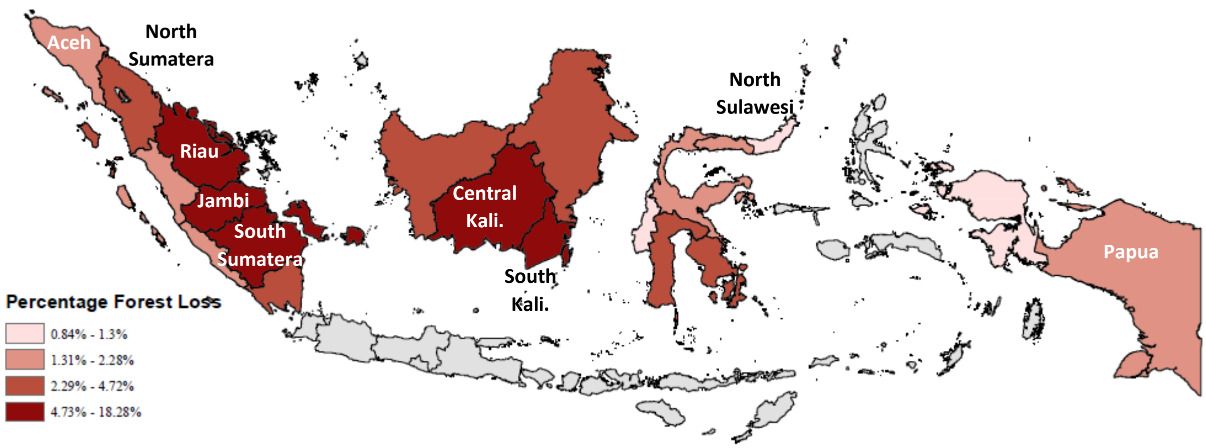
As mentioned in Chapter 2 the creation of new districts is dictated primarily by three things: (i) the geographic area of a district, (ii) the degree of ethnic clustering within a district, and (iii) the size of the government sector in a district (Fitrani, Hofman, & Kaiser, 2005).[46] However, the timing of the splits is argued to be random in Burgess et al. (2012) due to idiosyncratic factors such as the long administrative process involved in creating a new district.

If the theory presented in Burgess et al. (2012) is consistent with the data, then it would be expected that provinces such Papua, North Sumatera, Aceh, and North Sulawesi would have the greatest rate of forest loss between 2000-2008 while provinces such as Riau, Jambi, East Kalimantan, and South Kalimantan would have the lowest rate of forest loss. This does not

[46] (i) Geographic size is an important determinant since partitioning a larger district into smaller jurisdictions would ease administration; (ii) ethnic clustering is an important determinant since districts off Java, all of which included in this sample, were subject to ethnic tensions and violence; (iii) size of government sector is an important determinant for financial reasons - each district receives a block grant from the national government which means partitioning into smaller districts resulted in more financial support.

appear to be the case. Figure 8 shows a map of the percentage of total forest loss between 2001-2008 as a fraction of total forest area of each province in 2000.[47]

Figure 8 - Forest loss as a Percentage of Initial Forest Area in 2000



Source: Created from data from Burgess et al. (2012)

The patterns shown in the map in Figure 8 appear to be the opposite of the patterns shown in the map in Figure 7 which suggests that the theory presented in Burgess et al. (2012) does not hold. Those provinces with the fewest number of new districts created such as Riau, Jambi, Central Kalimantan, and South Kalimantan appear to have the highest rate of deforestation while those provinces with lots of new districts created such as Papua, Aceh, and North Sumatera do not appear to have any extraordinary rates of forest loss. However, these maps only look at the percentage of forest loss between 2001-2008 as a fraction of forest area in 2000 and do not say anything about the certain patterns that are occurring between 2001-2008. Similarly, the map in Figure 7 is restricted by not showing the changes over time but instead only shows the total change in the number of districts between 2000-2008.

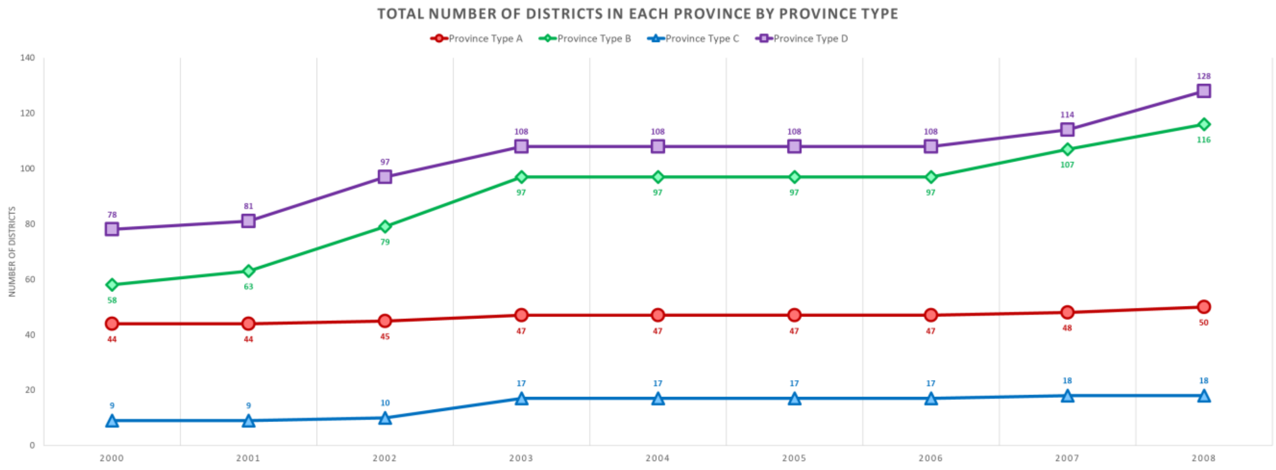
[47] Also refer to Figure 5 in Chapter 1 that shows tree cover loss at the pixel level between 2001-2017 - Figure 5 is from a different data source which is at a finer granularity but still consistent with Figure 8.

Therefore, the next step in this analysis is to divide each province into four different groupings so that yearly rates of deforestation for each province can be compared against provinces that share similar characteristics. The way in which the provinces have been divided is by common characteristics of district growth. There are four distinct types of provinces groups identified:

1. Province Type A - provinces that have a high number of districts in 2000 (>10) but there are very few new districts created between 2000-2008 (<5)
2. Province Type B - provinces that have a low number of districts in 2000 (<10) but experience considerable growth in the number of districts between 2000-2008 (>5)
3. Province Type C - provinces that have a low number of districts in 2000 (<10) but there are very few new districts created between 2000-2008 (<5)
4. Province Type D - provinces that have a high number of districts in 2000 (>10) but experience considerable growth in the number of districts created between 2000-2008 (>5)

With these province type definitions in mind Figure 9 plots the evolution of district growth in each grouping.

Figure 9 - Growth in the Number of Districts in Each Province Grouping

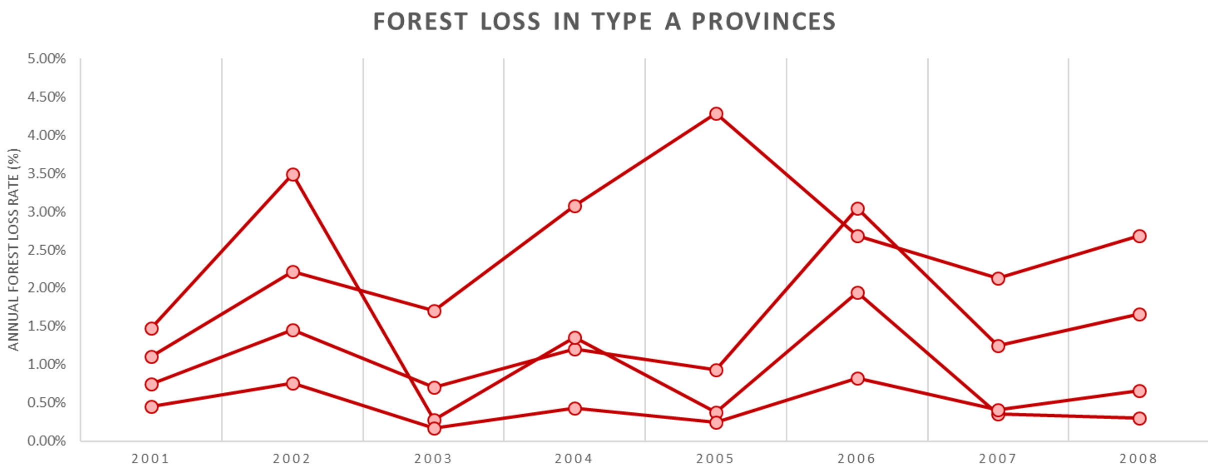


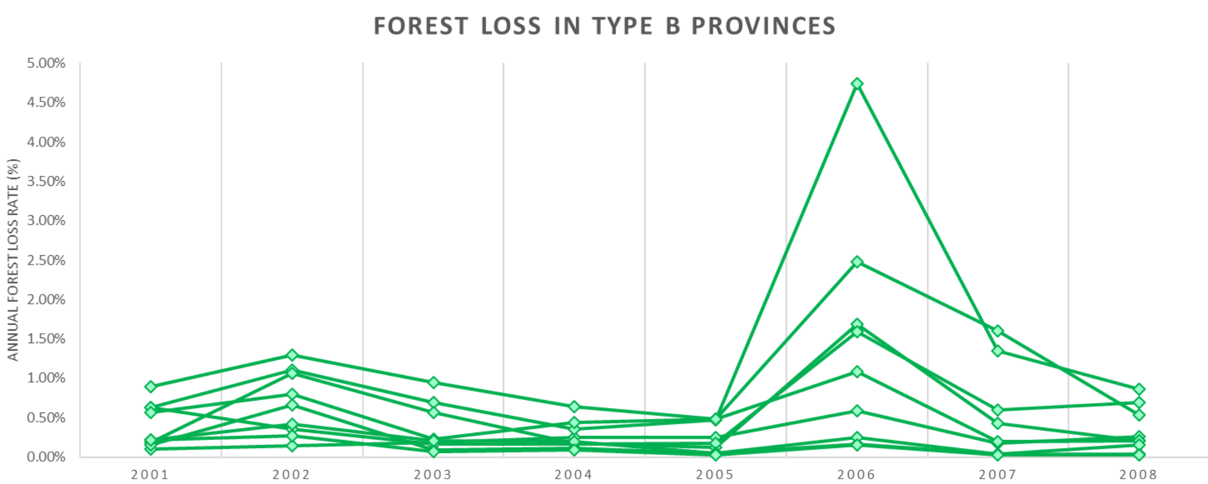
Source: Created with data from Burgess et al. (2012)

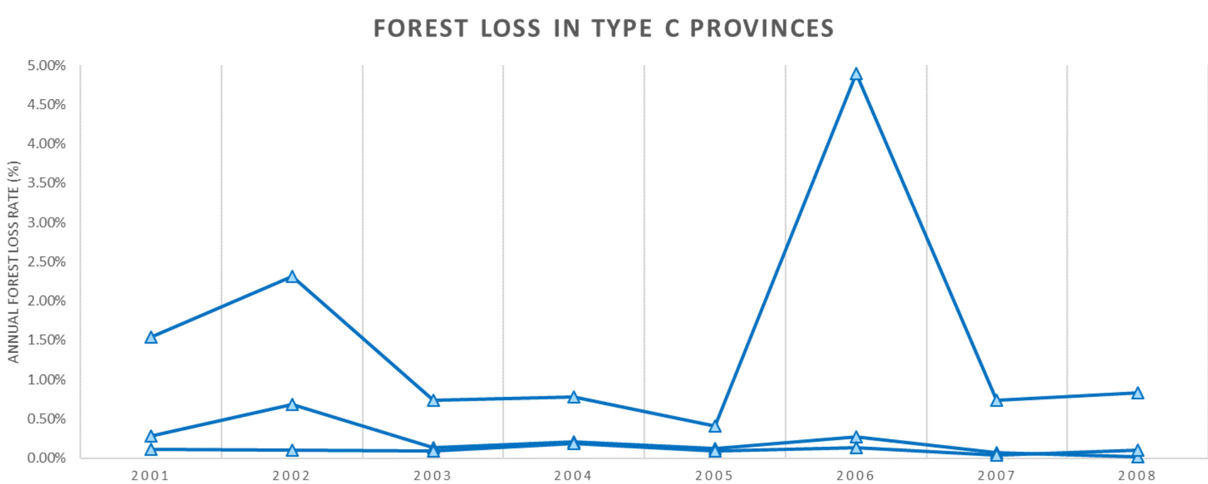
An important note about Figure 9 is that there are 4 provinces characterized as Type A provinces, 9 provinces characterized as Type B provinces, 3 provinces characterized as Type C provinces, and 5 provinces characterized as Type D provinces so while it appears that Type B provinces have more districts than Type A provinces in 2000 this is simply because Type B provinces are summed across 5 more provinces. For any individual province in the Type B grouping it will contain less districts than any given district in the Type A grouping in 2000. It is also important to note that there was a national moratorium on the creation of new districts between 2004-2006 which is apparent in all provinces in Figure 9.

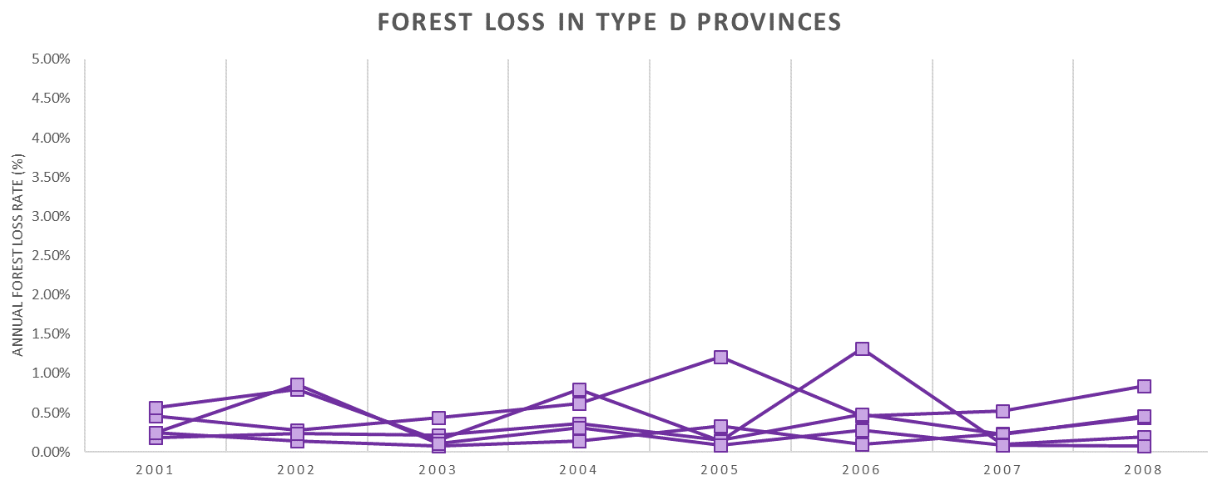
Using these province group definitions to test the theory in Burgess et al. (2012) it would be expected that the province groups that have a growing number of districts between 2000-2008 would have the highest rates of deforestation. From Figure 9 these are characterized as types B and D. Figure 10 shows the annual rate of deforestation for all 21 provinces in the sample split into their respective province groupings. Table 4 shows the annual percentage change in forest area in a table for every province in a table.

Figure 10 - Annual Rate of Deforestation by Province Groups (Graphs)









Source: Created with data from Burgess et al. (2012)

Table 4 - Annual Rate of Deforestation by Province Groups (Table)

Annual Rate of Forest Area Loss

	Province	2001	2002	2003	2004	2005	2006	2007	2008
Type A	Riau	1.11%	2.21%	1.70%	3.07%	4.29%	2.69%	2.13%	2.69%
	Jambi	0.75%	1.46%	0.70%	1.21%	0.93%	3.04%	1.25%	1.66%
	South Kalimantan	1.48%	3.49%	0.28%	1.36%	0.38%	1.94%	0.35%	0.30%
	East Kalimantan	0.45%	0.76%	0.18%	0.43%	0.24%	0.83%	0.41%	0.66%
Type B	Bengkulu	0.11%	0.15%	0.19%	0.25%	0.25%	0.59%	0.18%	0.26%
	South Sumatera	0.63%	1.10%	0.69%	0.36%	0.47%	4.74%	1.35%	0.87%
	Lampung	0.18%	1.06%	0.57%	0.18%	0.13%	1.68%	0.43%	0.20%
	Central Kalimantan	0.89%	1.29%	0.95%	0.64%	0.48%	2.47%	1.60%	0.54%
	West Kalimanatan	0.63%	0.36%	0.17%	0.16%	0.17%	1.59%	0.60%	0.69%
	Southeast Sulawesi	0.56%	0.80%	0.23%	0.44%	0.48%	1.08%	0.19%	0.20%
	North Sulawesi	0.16%	0.66%	0.09%	0.11%	0.05%	0.16%	0.04%	0.03%
	Central Sulawesi	0.21%	0.42%	0.21%	0.20%	0.05%	0.25%	0.04%	0.15%
	West Papua	0.22%	0.27%	0.06%	0.09%	0.03%	0.16%	0.03%	0.03%
Type C	Gorontolo	0.28%	0.69%	0.14%	0.21%	0.13%	0.27%	0.07%	0.02%
	West Sulawesi	0.11%	0.10%	0.09%	0.18%	0.09%	0.13%	0.04%	0.10%
	Bengka Belitung	1.54%	2.32%	0.74%	0.77%	0.40%	4.89%	0.73%	0.84%
Type D	Aceh	0.25%	0.13%	0.08%	0.14%	0.33%	0.10%	0.24%	0.43%
	North Sumatera	0.46%	0.27%	0.44%	0.61%	1.21%	0.46%	0.52%	0.84%
	West Sumatera	0.18%	0.24%	0.21%	0.36%	0.15%	0.48%	0.23%	0.46%
	South Sulawesi	0.56%	0.80%	0.15%	0.80%	0.14%	1.32%	0.09%	0.19%
	Papua	0.24%	0.86%	0.11%	0.31%	0.09%	0.27%	0.09%	0.07%
	All 21 Provinces	**0.50%**	**0.86%**	**0.37%**	**0.54%**	**0.49%**	**1.22%**	**0.56%**	**0.54%**

Source: Created with data from Burgess et al. (2012)

Based on the graphs in Figure 10 there does not appear to be any sort of connection between district growth and forest loss like Burgess et al. (2012) suggests. Consider the province of Riau for instance. Between 2000-2008 Riau had one new district created in 2008 yet experienced significant forest loss (see appendix Figure A.1 and Table B.1 for absolute deforestation). The most deforestation in all of Indonesia. Conversely, Papua had 19 new districts created during this period, 9 of which before the moratorium and 10 after the moratorium but did not see extraordinary rates of forest loss. Even in the provinces that did see growth in new districts created and considerable forest loss there doesn't appear to be any connection. For example, consider the province of South Sumatera. South Sumatera is classified as Type B province that had a low number of districts in 2000 but saw significant growth in the number of districts by 2008. South Sumatera is also one of the provinces that experienced the highest rates of deforestation between 2000-2008. However, if you look at the timing of the creation of new districts created it does not correspond to the years that had the greatest rates of forest loss. There were three new districts created in 2001, one new district created in 2002, three new districts created in 2003, and one new district created in 2007 yet the two spikes in deforestation rates occurred first in 2002 and again, at a much larger scale, in 2006. Central Kalimantan is another Type B province that exhibits this behavior. All 8 of the new districts created in Central Kalimantan between 2000-2008 were created in 2002, but the highest rates of deforestation occurred in 2006. This evidence should make one concerned about theory and hypothesis of deforestation in Indonesia proposed by Burgess et al. (2012).

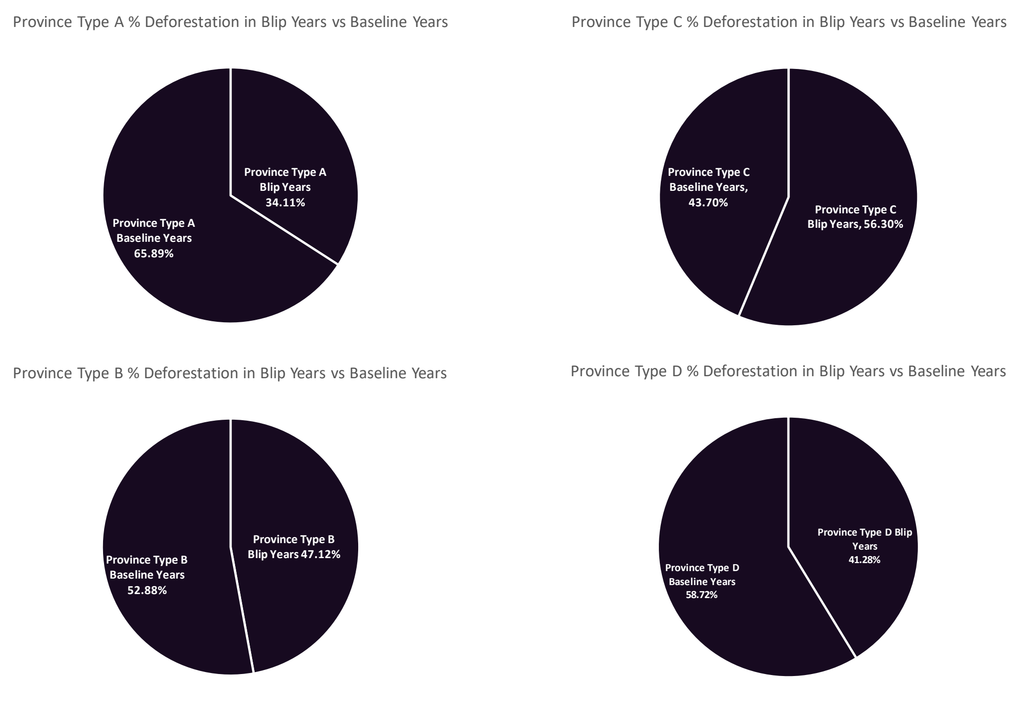
An important limiting feature in the theoretical model proposed by Burgess et al. (2012) is that it is an entirely static model. Each district's government officials issue permits each period based on some expectation of the behavior of their neighboring districts in that same period. If there are district splits occurring within a province in a given year then their model suggests that the number of permits, legal and illegal, issued by all districts within that province will increase immediately that year and there will be an immediate effect on deforestation. First, this is completely inconsistent with the data seen in Table 3 which shows the timing of district splits and Table 4 which shows rates of deforestation in each province. Additionally, it is unlikely that any forestry office would behave like this in reality. Instead, it may be the case that each district forestry office is efficiently managing their resources when faced with insecure property rights. Much of the literature reviewed in Chapter 2 suggests that when property rights are insecure then there is a high discount rate and the optimal decision is to extract more resources today rather than in the future (see: Deacon 1994, Bohn & Deacon 2000, Lopez 1997, Southgate, Sierra, Brown 1991). In the context of Indonesia during the post-Suharto era if a district government can anticipate being split in the future with some probability, therefore losing some of their forest resource, then that district is likely going to extract as much resource as it can today.

The purpose of this section was not to suggest that political corruption is not an important factor in Indonesia's deforestation problem, but instead to shed light on the apparent inconsistencies between the theory and data presented in Burgess et al. (2012). It was shown that there is a clear disconnect in every province between the creation of new districts and the rate of deforestation across Indonesia. The authors limit themselves by describing a very specific model for which political corruption affects deforestation in Indonesia and, given the data, we should be concerned about the conclusions reached in that study.

iii. Alternative Story of Deforestation in Indonesia

If the alarming rates of deforestation seen in the previous subsection are not caused by political corruption in the way that Burgess et al. (2012) suggest this begs the question: what is really happening to Indonesian forests? The graphs in Figure 10 show a strikingly interesting pattern that is consistent among nearly all provinces in the sample. In all four of the different province groups each individual province appears to have a peak in deforestation rates in 2002 followed by a much more prominent peak in 2006. The one important exception to this is the province of Riau which peaks in 2005 at a rate of deforestation of 4.29%. Figure 11 shows the split between the total amount of deforestation that occurs in the blip years (e.g. 2002 and 2006) and the baseline years (e.g. all other years in the sample) by each province grouping.[48]

Figure 11 - Percentage of Deforestation in Blips and Baseline Years by Province Groupings



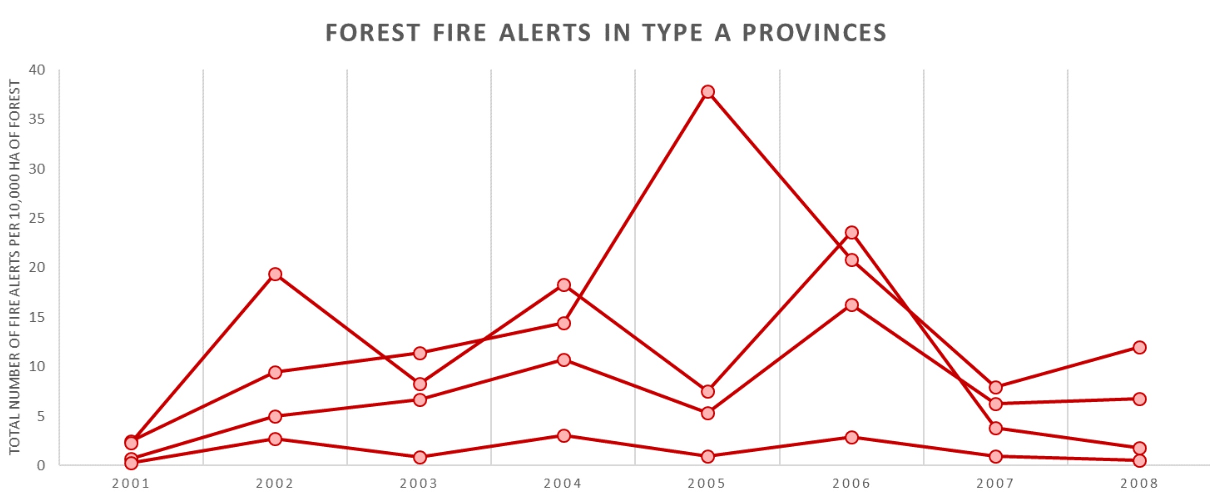
Source: Created with data from Burgess et al. (2012)

[48] The percentage of deforestation in blip years for Province Type A has been adjusted to include Riau's blip in 2005 and 2006 is a baseline year in Riau.

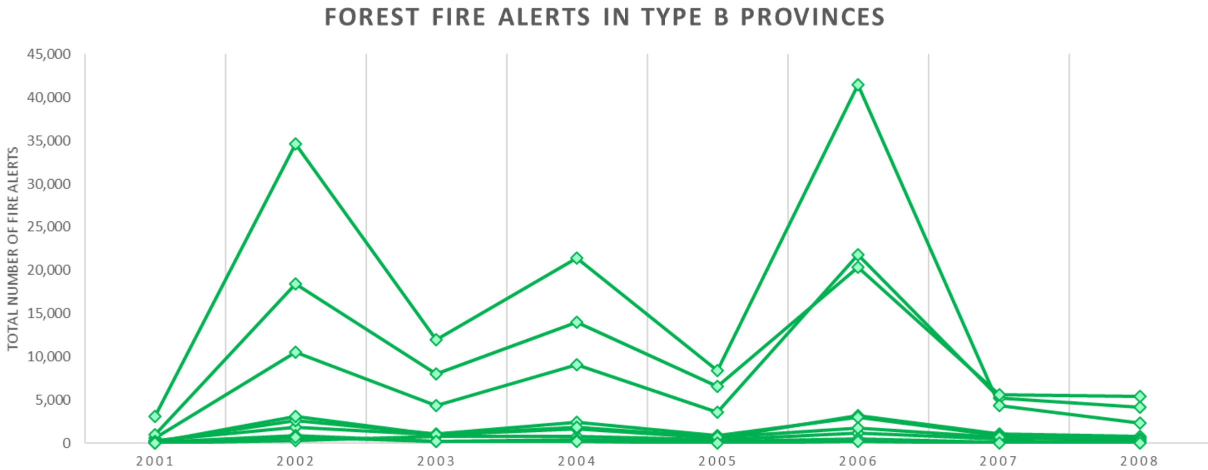
From Figure 11 it is appears that the deforestation that occurred in 2002 and 2006 comprises a significant portion of total deforestation that occurred between 2001-2008. For all province groups it is anywhere between one third to two thirds of all deforestation during this period and given the importance of deforestation in 2002 and 2006 these two years will be the focus for what follows.

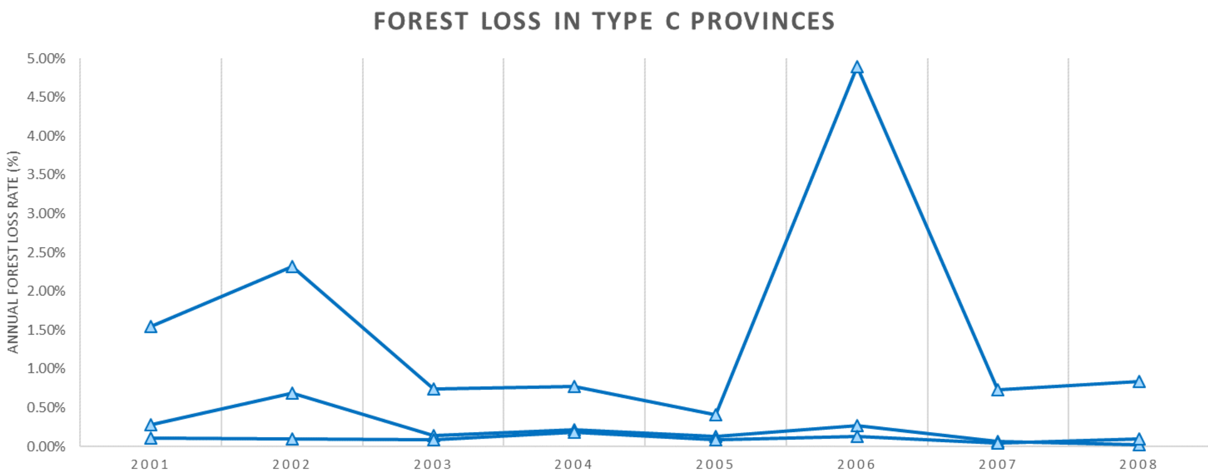
Indonesian forest and peat fires in 2006 were among the most destructive and widespread in Indonesia's history.[49] Air quality in Indonesia plunged to "very unhealthy" levels across the entire country and into other parts of Southeast Asia including nearby Malaysia. The haze from the fires in 2006 were so extreme that a blanket of smoke could be seen spewing from the islands of Sumatera and Kalimantan from space (NASA, 2018). This was a record setting year for the number of forest fires in Indonesia. Figure 12 shows the total number of fire alerts per 10,000 hectares of forest area in Indonesia between 2001-2008 for each province categorized in their respective groupings (see appendix Table B.2 for data table).

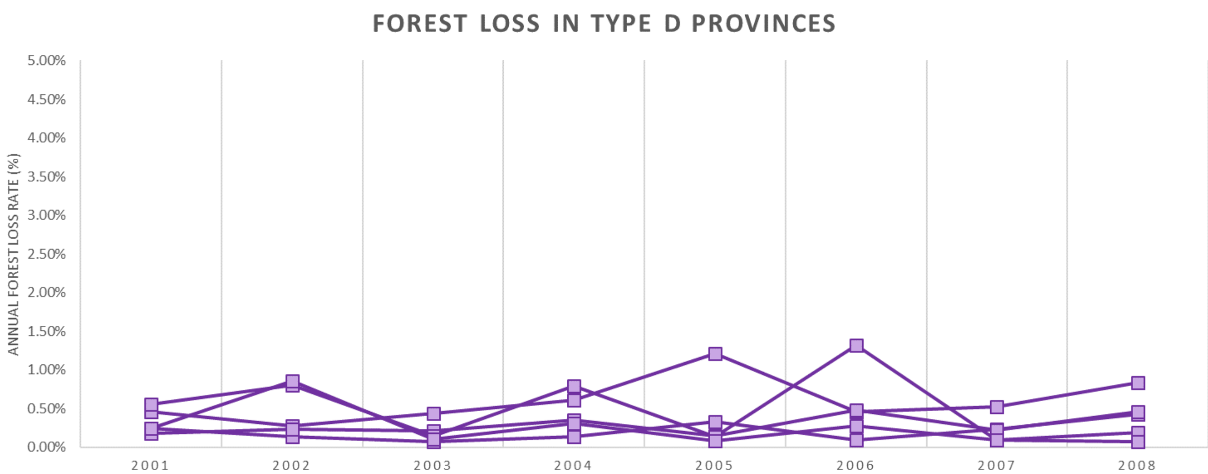
Figure 12 - Fire Alerts in Indonesia 2001-2008 (Graphs)



[49] For example see https://news.mongabay.com/2007/03/2006-indonesian-forest-fires-worst-since-1998/ and https://www.theguardian.com/environment/2006/oct/06/indonesia.pollution.





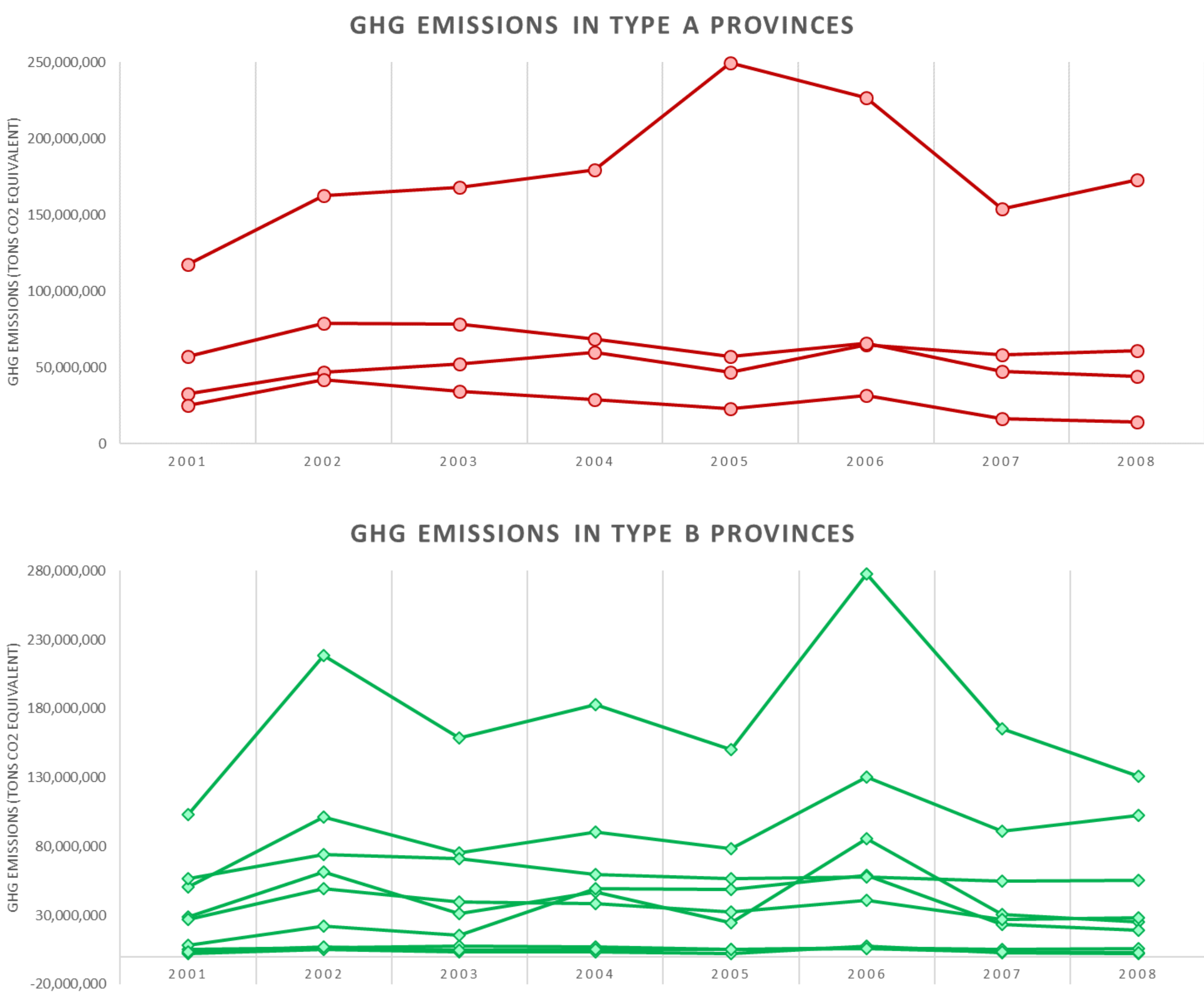


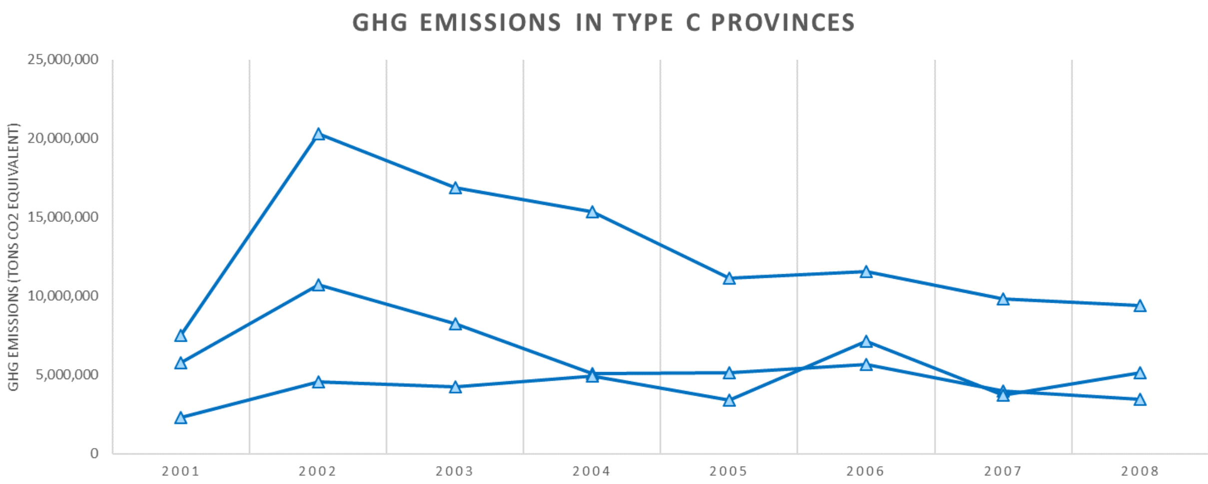
Source: NASA Fire Information for Resource Management (FIRMS) Active Fire Data

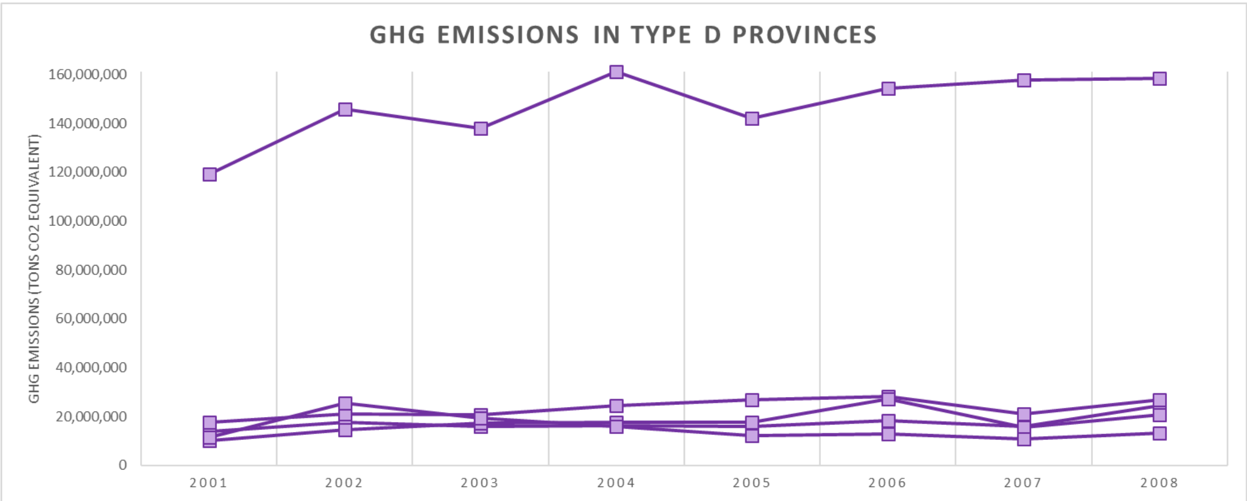
The data on fire alerts comes from NASA Fire Information for Resource Management System (FIRMS) which uses the MODIS satellite to map fire locations. The sensors on the satellite can detect heat signatures from fires and when a fire is detected the system indicates the area where the fire occurred with an alert in near real time (National Aeronautics and Space Administration (NASA), 2018). Between 2001-2008 there was a total of 553,347 fire alerts across all 21 provinces in the sample with 108,796 in 2002 (~20%) and 142,904 in 2006 (~26%). Out of the total number of fire alerts 167,765 (~30%) were from Type A provinces, 307,135 (~56%) were from Type B provinces, 13,399 (~2%) were from Type C provinces, and 65,048 (~12%) were from Type D provinces. However, the most interesting part of these fire alerts is that the timing in which the fires occurred appear to line up with the blips in deforestation rates seen in Figure 10. In 2005 Riau saw its highest rate of deforestation of 4.29% and largest number of fire alerts of nearly 30,000. South Sumatera and Central Kalimantan, which are both Type B provinces, had two major blips in deforestation rates in 2002 and 2006 which appear to be consistent with the fire alerts. South Sumatera had a deforestation rate of 1.10% and 4.74% in 2002 and 2006 respectively while Central Kalimantan had a deforestation rate of 1.29% and 2.47% in 2002 and 2006 respectively. South Sumatera had 10,498 and 21,831 fire alerts in 2002 and 2006 respectively while Central Kalimantan had 34,622 and 41,424 fire alerts in 2002 and 2006 respectively. This suggests that the trees that are lost in Indonesia during this period are likely being burned in forest fires.

Given the blips in the number of forest fires it should come as no surprise that the total greenhouse gas emissions from Indonesian forests also appear to line up nicely with deforestation rates in Indonesia between 2001-2008 which supports the idea that the trees that are being lost are being burned. Figure 13 shows total greenhouse gas emissions in tons of carbon dioxide equivalent by province type between 2001-2008 from the Indonesian National Carbon Accounting System (See appendix Figure A.2 for annual percentage change). In the Type A provinces, the blip in deforestation rates in Riau in 2005 appear to be consistent with greenhouse gas emissions. At a peak deforestation rate of 4.29% in 2005 in Riau there is an associated peak of greenhouse gas emissions of 250 million tons of carbon dioxide equivalent which is among the highest in any given year in any province in Indonesia. Along with large peaks in greenhouse gas emissions in 2006 there also appears to be a slightly less prominent peak in 2002 for nearly all provinces.

Figure 13 - Total Greenhouse Gas Emissions from Indonesian Forests 2001-2008





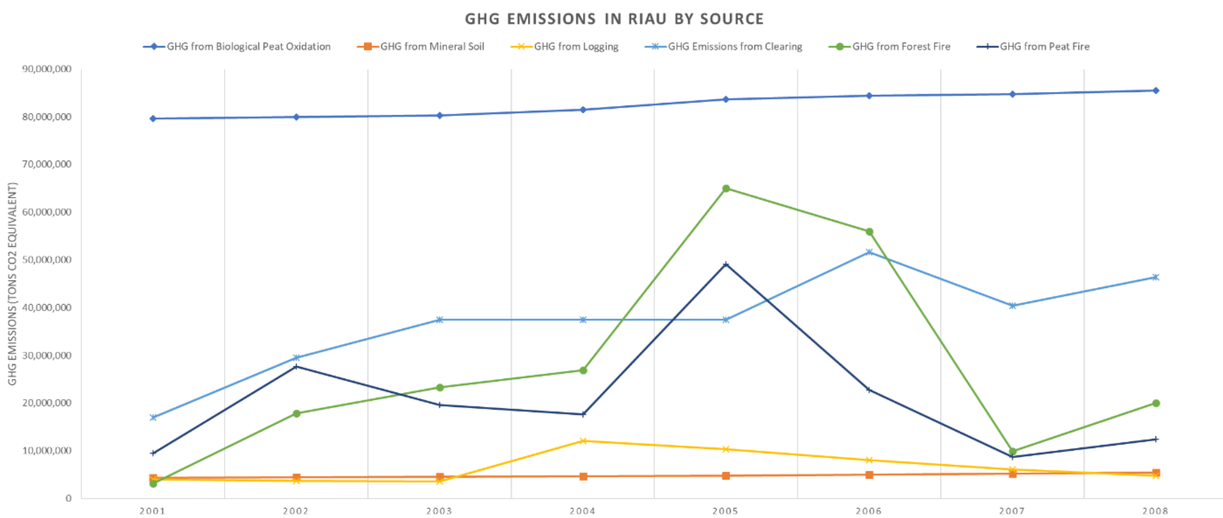


Source: Indonesia National Carbon Accounting System (INCAS) (Indonesia Ministry of Enviornment and Forestry , 2015)

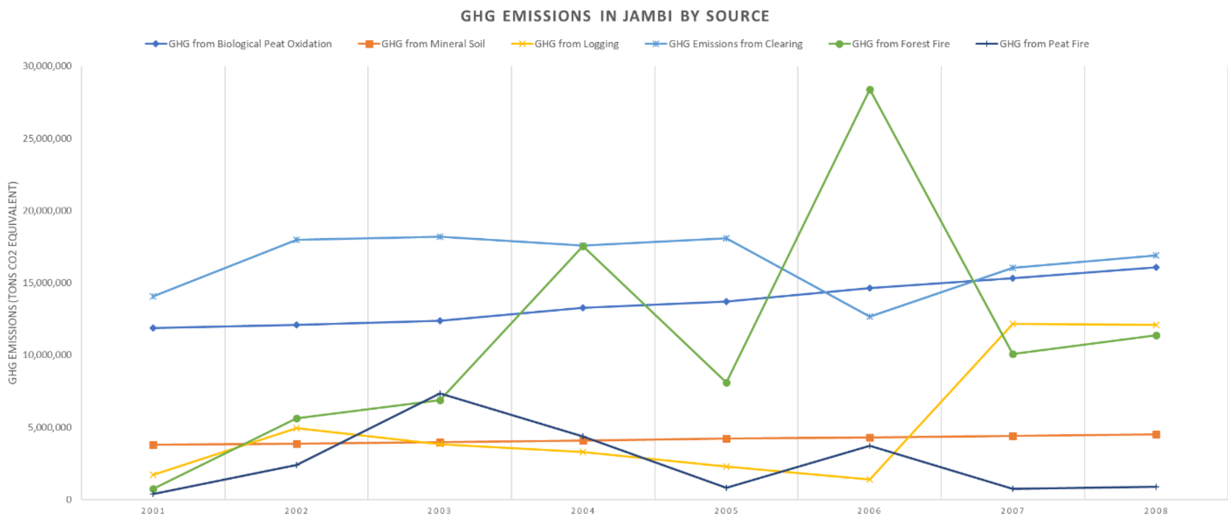
When a natural forest is cleared there are many ways in which this contributes to greenhouse gas emissions. First, there is a reduction in the carbon store and greenhouse gasses that are already in the atmosphere will not be absorbed. Second, when a tree is cut down or burned it releases all the carbon dioxide it was storing. However, the most impactful and intense contribution to greenhouse gas emissions are when peatlands are burned (Center for International Forestry Research, 2018). Peat is a thick layer of debris and decomposed organic matter that is extremely carbon rich. Many of Indonesia's natural forests, particularly on the islands of Sumatera and Kalimantan, sit on peat and when these forests are burned the peat is also burned. Peat can release up to ten times as much carbon dioxide into the atmosphere. Peat fires are also very difficult to put out and they can smolder for years.

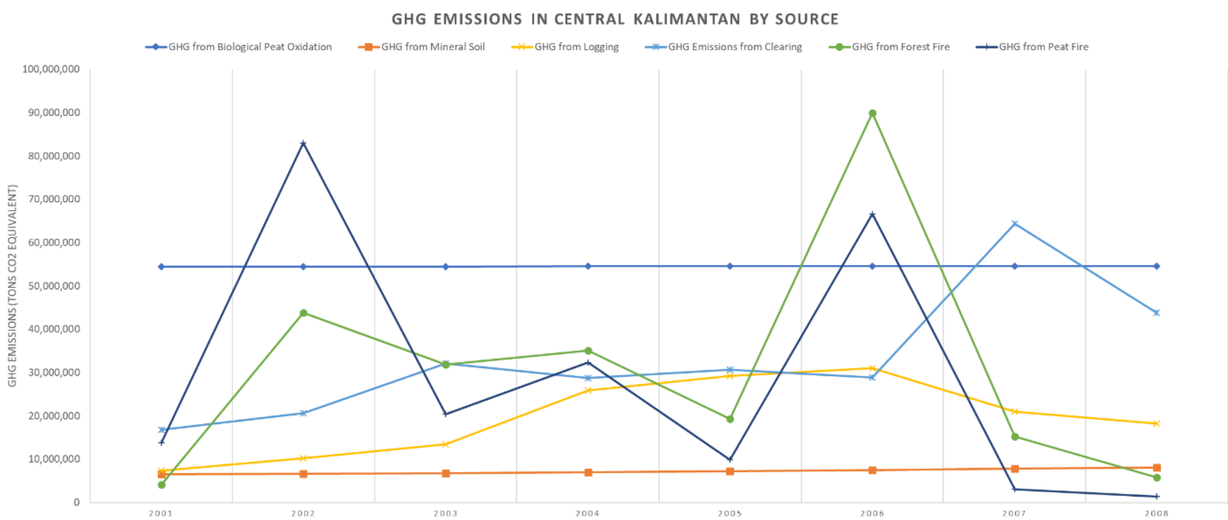
To get a closer look at greenhouse gas emissions, Figure 14 graphs emissions by source for a select few provinces.[50] These selected provinces include Riau and Jambi (Type A Provinces on Sumatera) and Central Kalimantan and West Kalimantan (Type B Provinces on Kalimantan) which are four provinces with the highest level of deforestation. These graphs illustrate that in all four of these provinces GHG emissions from forest fires and peat fires (green and dark blue lines respectively) are not only significant but are also correspond with the patterns of deforestation in each province seen in Figure 10. In Jambi, Central Kalimantan, and West Kalimantan there appears to be a sharp peak in emissions from forest fires and peat fires in 2002 and 2006 which is consistent with the rates of deforestation each of these provinces shown in Figure 10. As expected, Riau experiences its peak one year earlier in 2005 which also consistent with its pattern of deforestation.

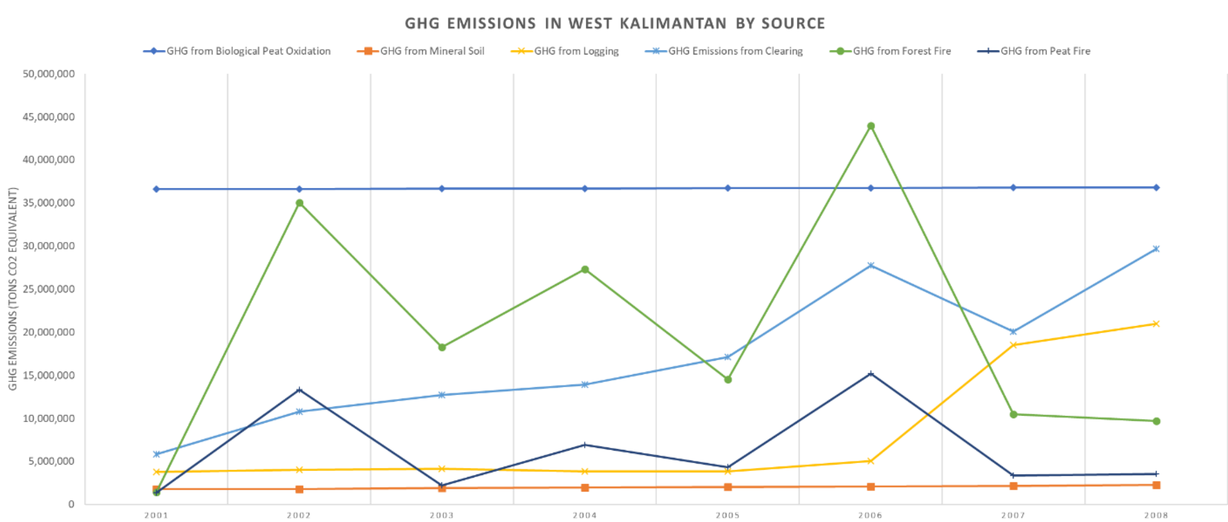
Figure 14 - GHG Emissions by Source in Select Provinces 2001-2008



[50] Clearing is defined as a conversion of forest area of either primary or secondary forests into other land uses and a conversion of natural forest into timber plantations. This event removes all aboveground biomass from the site.







Source: Indonesia National Carbon Accounting System (INCAS) (Indonesia Ministry of Enviornment and Forestry , 2015)

In all four of these provinces, greenhouse gas emissions from peat oxidation and mineral soil are relatively constant but still make up a significant portion of emissions which suggests there is a considerable amount of peat in these provinces. Greenhouse gas emissions from logging in these four provinces appear to be relatively negligible during this time period.

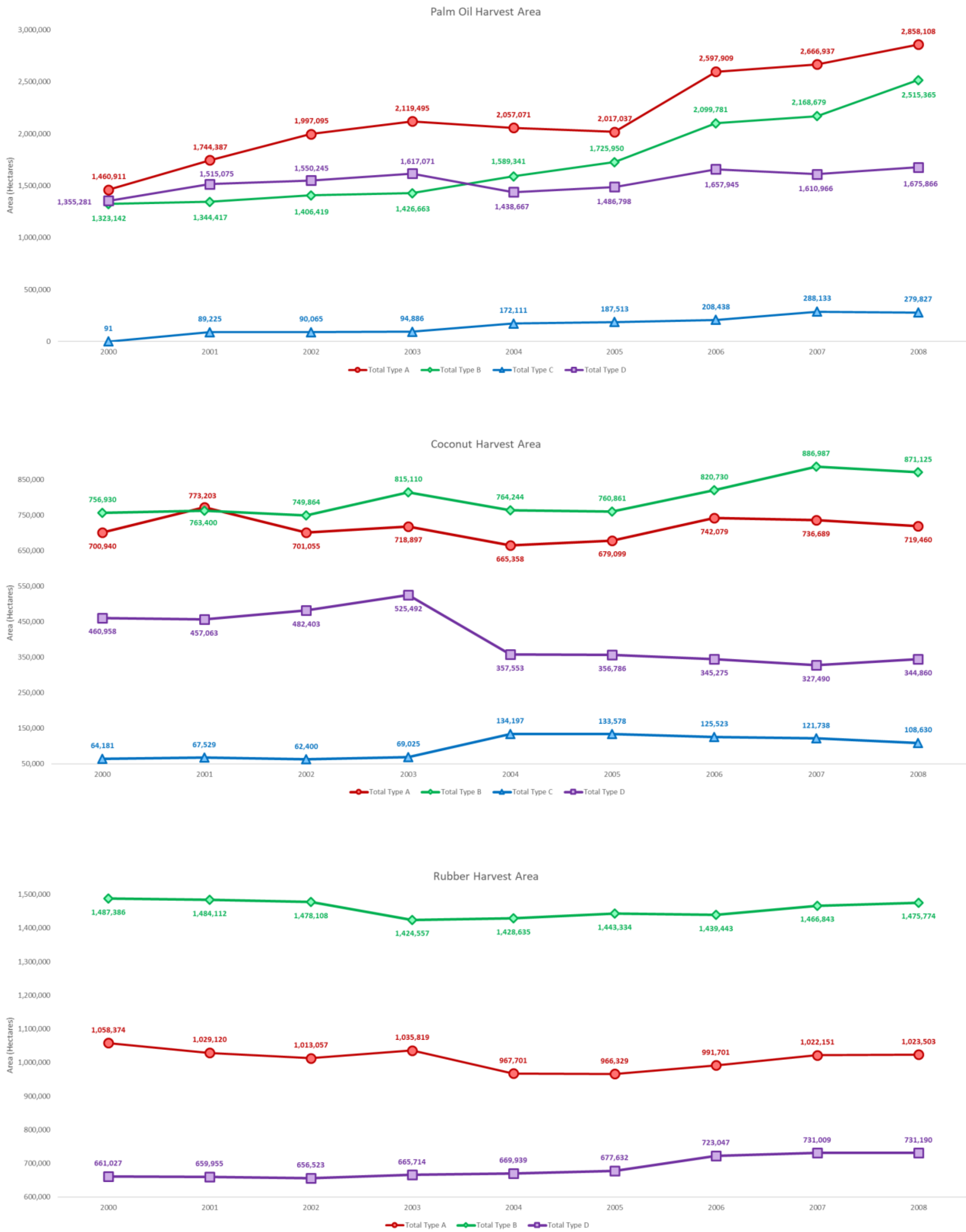
The next question becomes: why are the forests being burned? Based on qualitative evidence presented in the Mongabay and The Gecko Project case studies as well as other news stories[51] one may be inclined to think the expansion of plantations, particularly palm oil plantations, are to blame. Typically, the process of creating a palm oil plantation begins by digging out trenches to drain out an area of land. Once excess water is drained, the land owner will employ the use of fire to clear the plot covered by forest to make the land accessible and prepare the land for planting (Schreval, 2008). The harvest area from plantations that are subject to this kind of slash and burning agriculture is extensive. Figure 15 shows harvest area for palm oil plantations, coconut plantation, and rubber plantations, which are the three largest estate crops in terms of total production between 2000-2008,[52] by each province group[53] (see appendix Figure A.3 for palm oil plantation areas as annual percentage change). This data comes from the Indonesian Ministry of Agriculture (Indonesian Ministry of Agriculture , 2018).

[51] See: https://news.mongabay.com/2006/10/forest-fires-result-from-government-failure-in-indonesia/ and http://www.thejakartapost.com/news/2015/10/22/indonesias-carbon-emissions-set-cross-2006-crisis-level.html and https://www.straitstimes.com/opinion/fix-indonesias-land-use-crisis-to-tackle-the-haze and https://www.theaustralian.com.au/news/world/indonesias-deforestation-accelerating-study/news-story/cdb970d1fecc1fb2dca924e7f3a96caf and https://www.theguardian.com/world/2006/oct/07/indonesia.pollution and https://www.rainforest-alliance.org/articles/relationship-between-deforestation-greenhouse-gas-emissions .

[52] Between 2000-2008 there was a total of 110 million tons of palm oil production, 28 million tons of coconut, and 19 million tons of natural rubber.

[53] Type C provinces are omitted from rubber harvest area since they are relatively small.

Figure 15 - Plantation Harvest Areas by Province Grouping 2000-2008



Source: Indonesia Ministry of Agriculture (Agricultural Statistics Database)

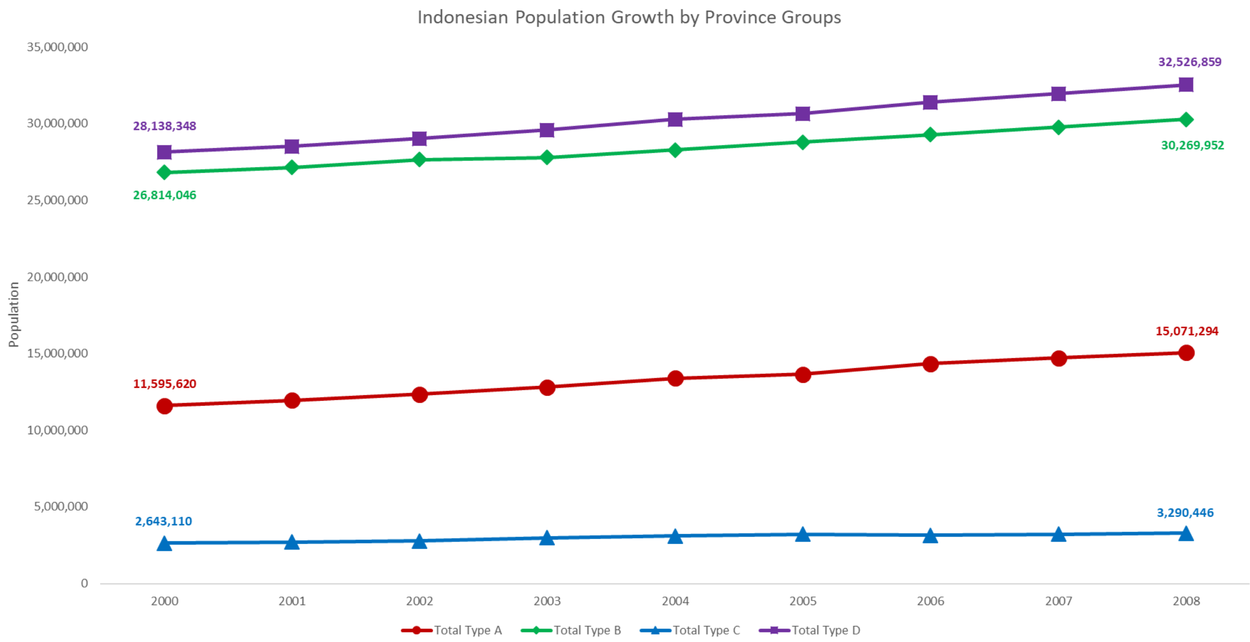
From the graphs in Figure 15 it appears that the only type of estate crop that is growing in harvest area over time is palm oil. In Type A provinces the total palm oil plantation area nearly doubled from 1.46 million hectares to 2.86 million hectares between 2000-2008 while in Type B provinces the total palm oil plantation area also nearly doubled from 1.32 million hectares to 2.52 million hectares. An important observation about the palm oil graph shown in Figure 15 is that there appears to be a jump in harvest area from 2005 to 2006 in all province groups. From 2005 to 2006 there is a 28.8% increase in palm oil plantation area in Type A provinces while there is a 21.66% increase in Type B provinces. The absolute increase in palm oil plantation harvest area in Type A provinces is about 580,000 hectares while the increase is about 375,000 hectares in Type B provinces.

Some caution should be exercised when looking at the expansion palm oil harvest areas to draw conclusions about deforestation. It is difficult to disentangle the relationship between expanding harvest areas and deforestation since it is unlikely that they occur immediately subsequent to each other. The data presented on plantation harvest areas in Figure 15 represents the total area planted by the end of each year, but it may not be the case that a forest is cleared to make way for planting that same year. For example, if a forest is burned to make way for a plantation in late in 2006 and the plantation is actually planted in 2007 or even 2008 then the reported deforestation and associated expansion in harvest area will show up in different years. There may be a lag in harvest area expansion. A recent report by the Center for International Forestry Research suggests that this delay in planting a plantation after clearing a forest is a means to avoid direct deforestation (Gaveau, et al., 2016). The idea is that the plantations that are planted immediately after a forest is cleared are directly responsible for that clearance, but the longer the delay in the establishment of a plantation the more likely that plantation will avoid direct deforestation. Instead, these plantations are considered to be established on land that has already been degraded and it will appear as though the plantation did not cause any forest loss. In any case, summing up the total change in plantation harvest area (i.e. palm oil, coconut, and rubber) between 2000-2008 and dividing it by the total change in forest area between 2000-2008 in Type A and Type B provinces suggests that 41.23% and 39.33% of deforestation may be accounted by these plantation expansions respectively.

The final part of this section explores possible drivers for the rapid increase in plantations. The discussion begins with possible explanations domestically such as population growth and gross regional domestic product (GRDP). These two factors are motivated by Foster & Rozenweig (2003) who found that an increased demand for forestry products in India from an increase in population and income led to afforestation. Then international drivers such as increasing international demand for palm oil and shocks to Indonesian exchange rates are explored. Between 2001-2008 about 70% of total Indonesian palm oil production was exported so having a better understanding of the global demand for palm oil is likely important.

One might be inclined to believe that rapid population growth in a developing country like Indonesia may increase domestic demand for palm oil and other estate crops which in turn results in forests being cut down to make way for expanding plantation areas. Figure 16 graphs the population growth across Indonesia by province groups between 2000-2008. The Indonesian Bureau of Statistics completes their population census every five years with all intermediate years based on estimates and interpolations based on expected population growth rates (Indonesian Bureau of Statistics, 2018).

Figure 16 - Population growth in Indonesia 2000-2008

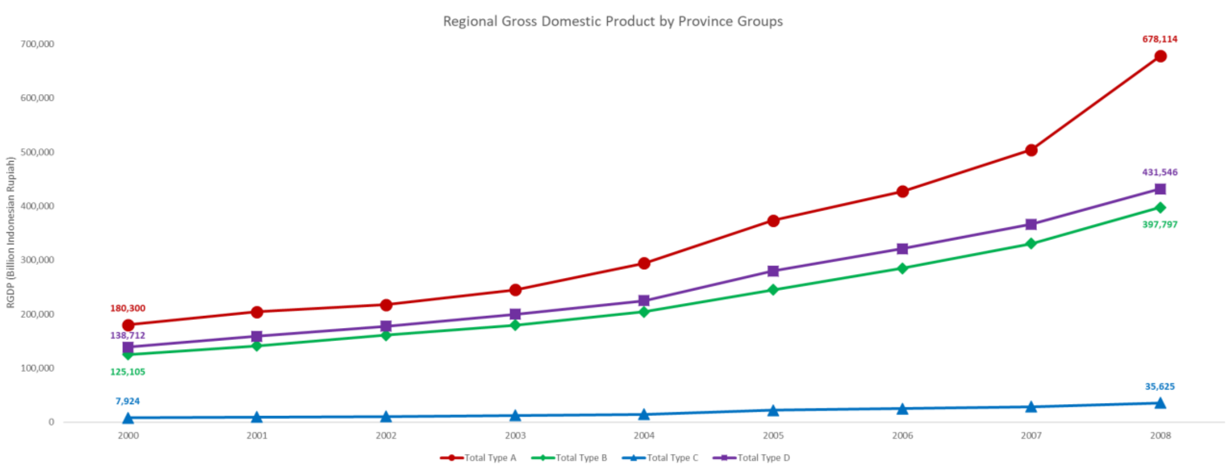


Source: Indonesian Bureau of Statistics

Total population in Indonesia grew from 205.1 million people in 2000 to 231.6 million people in 2008 which is an increase of about 13% over an eight-year period. However, the island Java, which is the most populated island in Indonesia, is not included in our sample since there is little forest loss on the highly urbanized island. Between 2000-2008 Type D provinces had a population growth rate of 15.6%, Type B provinces had a population growth rate of 12.9%, Type A provinces had a population growth rate of 29.9%, and Type C provinces had a population growth rate of 24.5%. From Figure 16 there does not appear to be any strikingly obvious peaks or major deviations from Indonesia's natural rate of population growth in any given year in any province grouping. This suggests that population growth is not likely a contributing factor to the major blips in deforestation rates in in 2002 and 2006 seen in Figure 10 but it may instead be a contributor to the baseline rate of deforestation seen in all other years.

The next possible domestic explanation for increased deforestation in Indonesia is the growth in gross regional domestic product (GRDP). Increased income may have two different effects on the demand for palm oil and other estate crops which work in opposite directions. On one hand, with increased income people will demand more palm oil but on the other hand people may substitute away from palm oil and towards more expensive alternatives. Foster & Rozenweig (2003) found that higher incomes in India resulted in greater demand for forestry products which led to afforestation in India. There is practically no afforestation occurring in Indonesia between 2000-2008 so it is unlikely that the Foster & Rozenweig (2003) story holds for Indonesia but increased income still may have some effect on forests. Figure 17 graphs gross regional domestic product by province groups between 2000-2008. These GRDP figures are calculated by the Indonesian Bureau of Statistics using a value-added based approach using current market prices (i.e. nominal).

Figure 17 - Gross Regional Product in Indonesia by Province Groups 2000-2008



Source: Indonesian Bureau of Statistics

Total Indonesia GDP grew from 1,389,770 billion rupiah in 2000 to 4,948,688 billion rupiah in 2008 which is an increase of more 250% over an 8-year period. Again, it is important to remember that the sample of provinces included here does not include any provinces on Java which is substantial portion of Indonesia's economy. Jakarta, which is Indonesia's capital and economic epicenter is located on Java. The 21 provinces included in the sample make up only about one third of total Indonesian GDP. Type C provinces saw the largest growth in GRDP of 350% although relatively small in magnitude. Type A provinces experienced the next largest growth of 276% followed by Type D and Type B provinces that experienced growth of 211% and 218% respectively between 2000-2008. However, just like the population growth graph in Figure 16 there does not appear to be anything unusual about this growth particularly around 2002 or 2006 which is the primary focus. This suggests that if growth in RGDP indeed contributes to forest loss it most likely contributes to the baseline rate of deforestation rather than the blips seen in 2002 and 2006.

The focus now shifts to possible international factors that may be driving deforestation in Indonesia. Palm oil is a very versatile and productive crop that is used many products such as soaps, detergents, candles, ice cream, cosmetics, processed foods, biofuels, candy, chocolate and cakes. Because of its productivity (i.e. greater yield at lower cost of production relative to other vegetable oils) the global demand for palm oil has skyrocketed and continues to grow. Between 2000-2008 Indonesia has supplied more than half of the world's palm oil market surpassing Malaysia in 2006 as the world leader (Worldwatch Institute, 2009). Figure 18 graphs total global palm oil exports from Indonesia between 2000-2008.

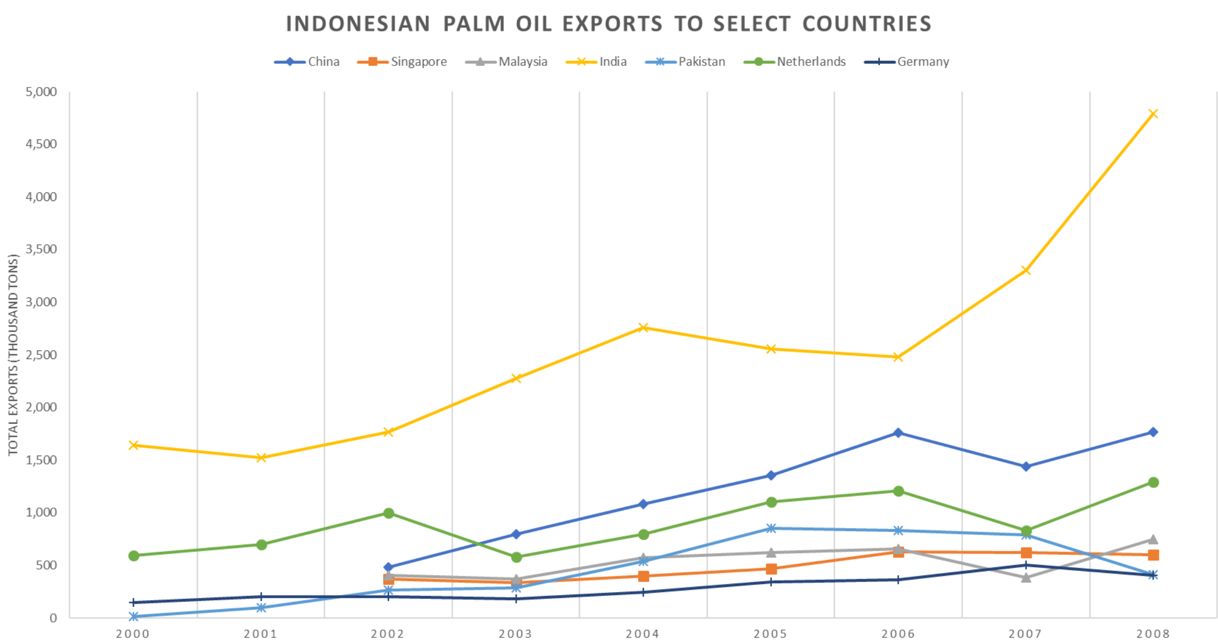
Figure 18 - Total Global Palm Oil Exports from Indonesia 2000-2008

Source: Indonesian Bureau of Statistics

Total exports of Indonesian palm oil between 2000-2008 were over 79 million tons worldwide. During this period, total palm oil exports from Indonesia grew from 4,110,000 tons in 2000 to 14,291,000 tons in 2008 which represents growth of nearly 250% over eight years. It is important to note that once a palm oil plantation is planted it typically takes 2-4 years for the plantation to fully mature and bear fruits but it can produce fruits for up to 30 years (Food and Agricultural Organization of the United Nations, 1990). This makes it difficult to directly connect deforestation to increasing palm oil exports since there is a lag involved from the time of clearing a forest to when palm oil can be produced. However, it may be reasonable to suggest that 2-4 years after clearing a forest Indonesian palm oil can be sold on the world market assuming the plantation gets planted immediately after being cleared. For example, if large areas of land are cleared in 2002 which is what is shown in Figure 10 and a plantation is planted immediately then palm oil will be ready to be exported anywhere between 2004-2006 and this appears to be the case in Figure 18 where these three years saw the highest growth of palm oil exports between 2000-2008. There is also what seems to be a large increase in exports in 2008 of 20% which may be from plantations that were cleared in 2006 and matured early.

Figure 19 shows palm oil exports to selected destinations between 2000-2008. India is by far the largest importer of Indonesian palm oil with total imports between 2000-2008 being over 23 million tons. Imports grew in India from 1.6 million tons in 2000 to 2.7 million tons in 2004 to 4.7 million tons by 2008 which represents a total growth in palm oil imports of nearly 200% over the eight-year period. China is the next largest importer with total imports between 2002-2008[54] being 8.7 million tons peaking in 2006 at 1.8 million tons.

Figure 19 - Palm Oil Exports to Selected Countries 2000-2008



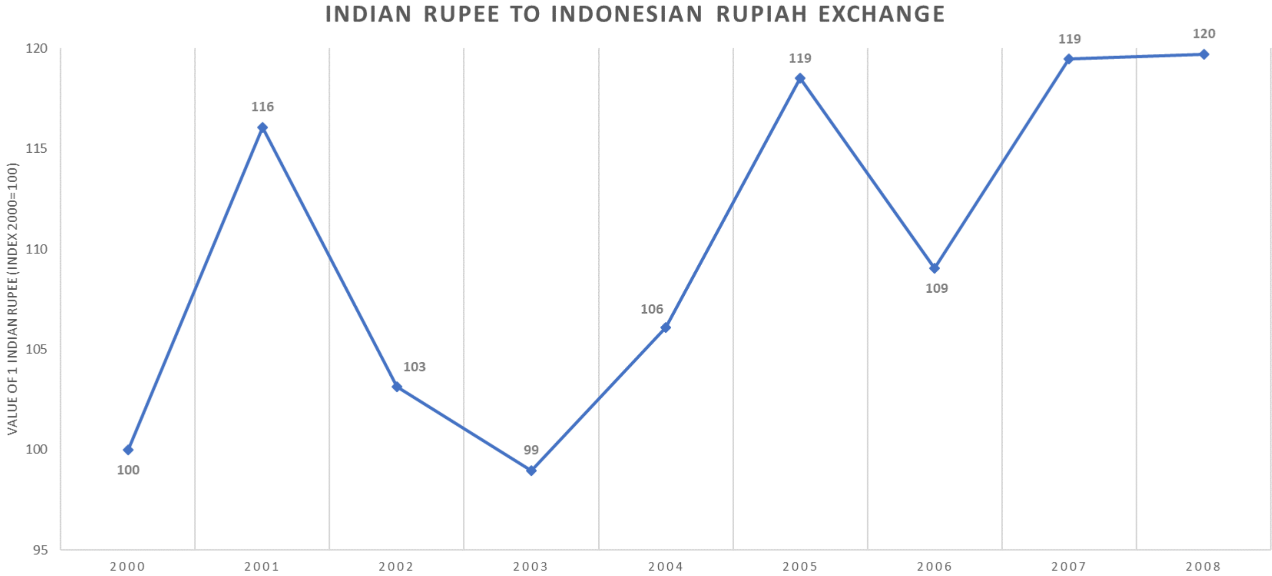
Source: Indonesian Bureau of Statistics

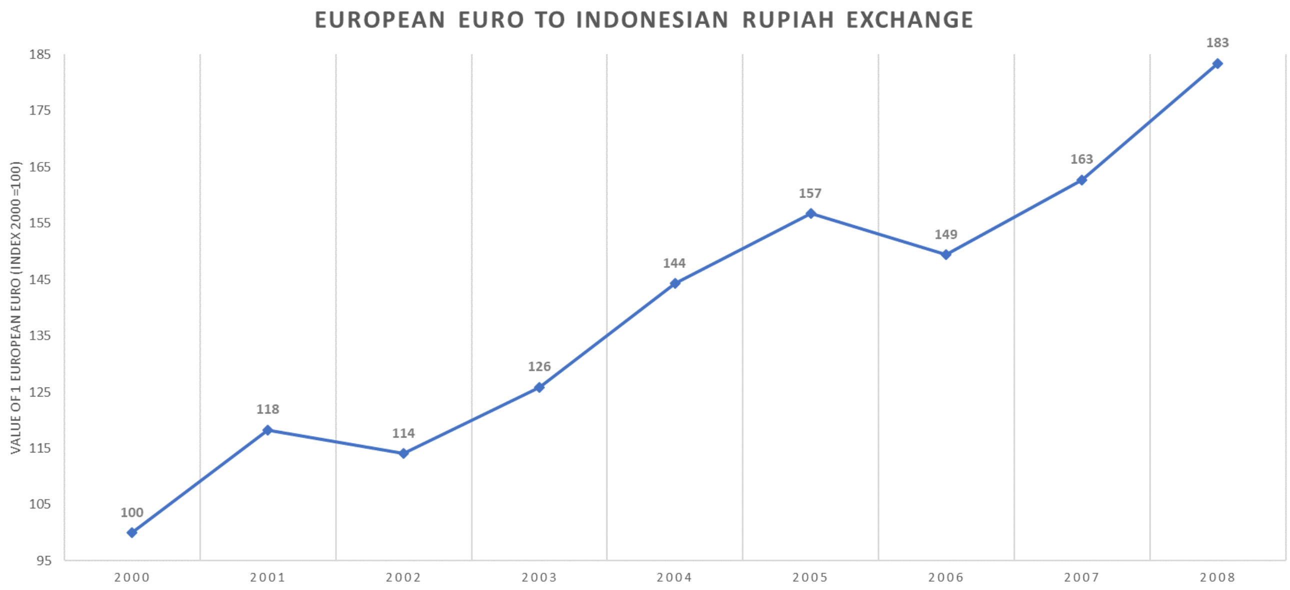
[54] Palm oil import data comes from the Indonesian Bureau of Statistics who do not report export data in China in 2000 or 2001.

Over this period China experienced growth in Indonesian palm oil imports of 266% from 483 thousand tons in 2002 to 1.7 million tons by 2008. The third largest importer of Indonesian palm oil is the Netherlands. Total imports of Indonesian palm oil to the Netherlands between 2000-2008 is slightly over 8 million tons with total growth of 120% over the eight-year period. Aside from India most other major destinations appear to peak in exports in 2006 which is consistent with plantations that were planted in 2002 and grew to full maturity by 2006. India was perhaps able to benefit from plantations that matured earlier which what is seen in 2004. Most destinations appear to be on the upswing in 2008 which may be the result of production from plantations that were planted in 2006.

Given the importance Indonesian palm oil exports to India, China, and the Netherlands the next step is to examine macro-economic trends in Indonesia during this period. Figure 20 graphs the exchange rates between the Indonesian Rupiah and the Indian Rupee, Chinese Yuan, and the European Euro. These graphs show the value of annual average exchange rate between these currencies. They show the value of the one Indian Rupee, Chinese Yuan, and European Euro in terms of Indonesian Rupiahs. Therefore, higher values imply a weaker Indonesian Rupiah relative to the other currencies.

Figure 20 - Exchange Rate Between Indonesia Rupiah and Indian Rupee, Chinese Yuan, European Euro 2000-2008





Source: Pacific Exchange Rate Service

The two biggest financial shocks that occurred in Indonesia in recent times most likely did not influence these exchange rates since they occurred before the sample time period and towards the very end of the sample time period. These two shocks are the Asian financial crisis that occurred in 1997-1998 and the global financial crisis in 2007-2008. Indonesia was mostly recovered from the Asian financial crisis, which was the real trigger behind the fall of the Suharto regime, by the start of the millennium (International Monetary Fund, 2000). In 1996 the value of one Euro was 2,917 Indonesian Rupiah. In the midst of the financial crisis in 1998 this exchange rate jumped to 11,307 Indonesian Rupiah per Euro but by 2000 it fell back down to 7,704 Rupiah per Euro. This is the most valuable the Rupiah has been against the Euro since 1996 which suggests that by the start of 2000 the Indonesian economy had largely recovered. The global financial crisis shows up in Figure 20 towards the end of the sample period in 2007-2008 where the Indonesian Rupiah again drops in value this time even lower than during the Asian financial crisis. One Euro in 2008 was worth 14,133 Indonesian Rupiah.

However, the key observation from the graphs in Figure 20 are the periods of Rupiah devaluation intermediate to the Asian financial crisis in 1998 and the global financial crisis in 2008. For all three different currencies the Rupiah is compared against in Figure 20 there appears to be a significant devaluation in 2001 and 2005. These devaluations are most likely attributed to the normal business cycles that occur in the Indonesian economy. More interestingly, these devaluations occurred one year before the blips in deforestation rates and greenhouse gas emissions seen in Figure 10 and Figure 13 respectively. The relatively weak Indonesian Rupiah in 2001 and 2005 may have led to an anticipatory increase in exports to countries with stronger currencies such as India, China, and the Netherlands. From the perspective of a country that has a relatively stronger currency it is cheaper to import more palm oil from Indonesia who has a relatively weak currency. Thus, these foreign countries become net importers of palm oil while Indonesia becomes a net exporter of palm oil. Anticipating this, landowners may have seen an opportunity to expand their plantation harvest areas to satisfy increasing global demand which would in turn influence deforestation rates and greenhouse gas emissions.

The purpose of this chapter was to lay the groundwork for further empirical work in Chapter 4. This was done first by qualitatively examining Indonesia’s corruption problem in the forestry and agricultural sectors through two different case studies. It was shown that politicians in Indonesia often have their own political agendas above environmental degradation. Large conglomerates can easily obtain land rights by bribing and promoting a corrupt politician into power. Although political corruption is clearly an important issue in Indonesia the story told by Burgess et al. (2012) does not seem to agree with the data. The authors of this study suggest that the increase in the number political jurisdictions across in Indonesia following the collapse of the Suharto regime results in more corruption and more deforestation. However, there does not seem to be any sort of link between the number of districts and deforestation in the data. There does seem to be strikingly interesting blips in the deforestation rates in 2002 and 2006. These blips appear to also line up with greenhouse gas emissions particularly emissions from peat and forest fires which suggests that there was widespread slash and burn agriculture occurring in 2002 and 2006. This was most likely to make way for plantations particularly palm oil plantations since the demand for palm oil on the global market has been steadily increasing and Indonesia supplies more than half of this market.

Chapter 4: Empirical Methodology

Does political corruption cause deforestation in Indonesia? Recall Burgess et al. (2012) hypothesizes that the increase in political jurisdictions across Indonesia is associated with greater corruption which leads to an increase in deforestation through illegal logging. Their theory suggests that as the number of districts within a provincial wood market increases, each district's government officials have an incentive to issue more than the legal quota of logging permits consistent with Cournot-style competition. To test this theory their empirical identification strategy makes use of the seemingly random timing in the creation of new district splits as a source of exogenous variation in governance quality. This chapter presents three different models that exploit a similar identification strategy as Burgess et al. (2012) but rather than estimating the effect that the number of districts has on deforestation directly these models estimate the effect that the number of districts has on forest fires. Following the suggestive evidence presented in Chapter 3 it appears that forest fires facilitate the expansion of palm oil plantations since plantation firms use fire to clear land. These firms obtain land rights from the bupati of the district that they operate in and from the investigative case studies presented in Chapter 3 it is shown that issuance of land rights can be politically motivated. The objective of this chapter is to formally evaluate the link between governance quality and forest fires in Indonesia between 2001-2008.

The approach is similar to Macdonald and Toth (2018) which also leverages the random timing in the creation of new districts as a source of exogenous variation for studying the effect of governance quality on forest fires. Macdonald and Toth (2018) hypothesize that there are two different channels for which governance quality may affect fire activity. First, the corruption channel where district governments are willing to allow greater fire activity, presumably for the purposes of clearing land for plantations, in return for some bribe. The rationale for this channel follows from the Burgess et al. (2012) Cournot framework. If there is a provincial market for land conversion permits, then the creation of an additional district in that province will induce greater competition among districts which will lead to additional permits being issued beyond the legal limit. If this is the case, then the authors suggest that there will be a persistent increase in the number of forest fires and the effect will be similar in newly formed districts (e.g. child districts) and originating districts (e.g. parent districts).[55]

The second channel is the weakened enforcement capacity channel where newly formed districts initially lack the capacity to police fires despite the government's best intentions to stop the fires. Unlike the corruption channel, the authors suggest that the increase in fire activity will be short lived and mostly concentrated in the newly formed districts rather than the originating districts. However, one potential problem with this hypothesis is that the authors do not consider that it is likely easier to manage or police a smaller district.

Macdonald and Toth (2018) use fires as their outcome variable rather than deforestation like Burgess et al. (2012) because they believe governance may have a different effect on forest fires since forest fires are supposedly more publicly visible than illegal logging. The idea is that if the public can observe smoke plumes from forest fires then they may be more likely to hold the government more accountable. On the other hand, illegal logging occurs in forests where local citizens may not necessarily know whether that particular forest is designated for illegal or legal logging. It is concealed. The authors suggest that the public visibility of forest fires is one force that may oppose the corruption channel. However, this theory does not seem very plausible

[55] Recall permits do not give the permit holder ownership over the land but it does give the owner the right to carry out what ever activity the permit is intended for (i.e logging or land conversion). If the permit is a land conversion permit, then the permit holder will use fire to clear the land for their plantation.

since there are likely forest fires that are naturally occurring all the time across Indonesia. The occurrence of natural fires may make it difficult for the public to distinguish between fires that are anthropogenic and fires that are natural. Forest fires may be just as invisible, if not more invisible, than illegal logging.

The models presented here do not attempt to explain which channel is more likely, but instead are primarily interested in studying whether an increase in the number of political jurisdictions has a causal effect on the number of forest fires and the extent of this effect. The first model is the baseline model and it is similar to the baseline models in Macdonald and Toth (2018)[56] and Burgess et al. (2012).[57] The specification is as follows:

$$lnFires_{pt} = \beta_0 + \beta_1 NumDist_{pt} + Y_t + P_p + \varepsilon_{pt} \qquad (23)$$

where the p subscript indexes provinces and the t subscript indexes the year between 2001-2008. $lnFires_{pt}$ is the natural logarithm of the number of fires that occur in province p at time t. $NumDist_{pt}$ is the total number of districts in province p at time t. Y_t and P_p are time and province fixed effects respectively. As discussed in Chapter 3, the data for number of fires comes from NASA Fire Information for Resource Management Systems (FIRMS) which uses MODIS satellite to map fire locations based on the heat and light signatures of a fire. Although the detection of fires is not perfect since cloud cover and smoke plumes may interfere with the sensors this data is likely to be more reliable than official government records or public crowd

[56] The baseline model in Macdonald and Toth (2018) is shown by equation (1) in their paper.
[57] The baseline model in Burgess et al. (2012) is shown by equation (5) in their paper or by equation (20) in the literature review in this thesis.

sourced data. The data provided by NASA FIRMS provides a measure of confidence for each fire detected and only fires that are detected with greater than 80% confidence are used. Data for the number of districts in each province is taken directly from Burgess et al. (2012). The official date that the national parliament approved the formation of a new district is what dictates the timing of district splits.

The baseline model in equation (23) as well as all other models that follow are estimated using fixed effects. Fixed effects models are useful since they control for, or partial out, time invariant variables that may be unobserved and potentially correlated with other explanatory variables in the model. For example, as noted in footnote 46 and in the discussion on Burgess et al. (2012) in the literature review, Fitrani et al. (2005) suggest there are three main factors driving district splits: geographic size of districts (e.g. area), ethnic clustering within districts, and the size of a district government. These factors are largely time invariant and would get partialled out of a fixed effects model. The estimator, β_1, in equation (23) which estimates the effect that the number of districts in a province has on the number of forest fires will still be consistent despite omitted variables that are correlated with the number of districts (e.g. district size, ethnic clustering, size of government, etc.). However, one of the biggest negatives about fixed effects models is that in some cases it may be important to have time invariant controls included in the model which cannot be estimated. This problem and a possible workaround are described in the models that follow. To test the robustness of each model they are also estimated using random effects and negative binomial.

The results for the baseline model (equation 23) are reported below in Table 5. This model is estimated for the full sample of provinces as well as for two different subsamples. The first subsample groups together Type A and Type C provinces together. Recall Type A provinces are provinces that had a high number of districts in 2000 and did not experience much growth in districts between 2000-2008. Type C provinces are provinces that had a low number of districts in 2000 and did not experience much growth in districts between 2000-2008. Therefore grouping Type A and Type C provinces together results in a sub sample of provinces that did not experience much growth in the number of districts and will be referred to as low growth provinces. The second sub sample groups together Type B and Type D provinces together. Recall Type B provinces are provinces that had a low number of provinces in 2000 but experienced significant growth in districts between 2000-2008. Type D provinces are provinces that had a high number of districts in 2000 and experienced significant growth in districts between 2000-2008. Therefore, grouping Type B and Type D provinces together results is a sub sample of provinces that experienced significant growth in the number of districts and will be referred to as high growth provinces.

Table 5 - Results from Estimating Baseline Model

Fixed Effects (Dependent Variable = lnFires)			
	All Provinces	Low Growth Provinces	High Growth Provinces
Number of Districts	-0.0074	0.0424	0.0020
	(0.0379)	(0.2670)	(0.0414)
Constant	4.0650***	3.4696	4.0782***
	(0.3911)	(2.2848)	(0.4776)
R-squared	0.6611	0.6995	0.6538
Province FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
P-Value on Number of Districts	0.848	0.879	0.963
Total Observations	168	56	112
Total Provinces	21	7	14

All estimates from a fixed effects model. Dependent variable is the natural log of the number of fires per province per year. Standard errors clustered by provinces in parentheses. Column 1 includes the full sample of 21 provinces across Sumatera, Kalimantan, Sulawesi, and Papua. Column 2 and 3 are sub samples that contain Type A plus Type C provinces and Type B plus Type D provinces respectively (see Chapter 3 for details).

* p<0.10; ** p<0.05; *** p<0.01

The coefficient on the number of districts is negative for the full sample while it is positive for both sub samples. The standard errors are reported in parentheses. The point estimates imply that for each additional district within a province there is a 0.7 percent decrease in fire activity for the full sample while there is a 4.2 percent increase and a 0.2 percent increase in fire activity for each sub sample respectively. However, all these coefficients are statistically insignificant which suggests that, in this simple baseline model, the number of districts in a province likely does not have a significant effect on fire activity in that province. The results of the random effects estimation of the baseline model are reported in Table 6 and are similar to the results from the fixed effects estimation: the effect that an additional district has on fire activity is statistically insignificant.

Table 6 - Baseline Model Estimated by Random Effects

Random Effects (Dependent Variable = lnFires)

	All Provinces	Low Growth Provinces	High Growth Provinces
Number of Districts	0.0224	0.2510***	0.0223
	(0.0347)	(0.0645)	(0.0388)
Constant	3.7860***	1.8903***	3.8687***
	(0.5309)	(0.6369)	(0.6331)
R-squared	0.6594	0.6870	0.6528
P-Value on Number of Districts	0.520	0.000	0.565
Total Observations	168	56	112
Total Provinces	21	7	14

All estimates from a random effects model. Dependent variable is the natural log of the number of fires per province per year. Standard errors clustered by provinces in parentheses. Column 1 includes the full sample of 21 provinces across Sumatera, Kalimantan, Sulawesi, and Papua. Column 2 and 3 are sub samples that contain Type A plus Type C provinces and Type B plus Type D provinces respectively (see Chapter 3 for details).

* $p<0.10$; ** $p<0.05$; *** $p<0.01$

This contradicts the result found in Macdonald and Toth (2018) which finds that an additional district in a province results in a statistically significant increase of 3% to 11.7% in fire activity. One possible explanation for this difference is that Macdonald and Toth (2018) use a nonlinear negative binomial count model to estimate their baseline equation whereas the baseline equation here is estimated with a linear fixed effects model. To get a fairer comparison equation 23 was also estimated using a negative binomial model and the results are reported in Table 7. The results from this estimation suggest that an additional district in a province increases fire activity by 2.3 percent for the full sample of provinces which is still quite different than the result found in Macdonald and Toth (2018). The coefficient on the number of districts is still statistically insignificant but has more statistical power relative to the fixed effects and random effects model (see p-value). Another possible explanation for this difference is that Macdonald and Toth (2018) use a longer time series from 2002-2015 while the time series used here is from 2001-2008 and they include more provinces in their sample (34 in total).[58]

Table 7 - Baseline Model Estimated Using Negative Binomial Model

Negative Binomial Model (Dependent Variable = Fires)			
	All Provinces	Low Growth Provinces	High Growth Provinces
Number of Districts	0.0228	0.0160	0.0289
	(0.0176)	(0.0609)	(0.0206)
Constant	-0.2552	-0.3287	-0.2400
	(0.2463)	(0.5631)	(0.3078)
Time Fixed Effects	Yes	Yes	Yes
Province Fixed Effects	Yes	Yes	Yes
P-Value on Number of Districts	0.195	0.793	0.161
Total Observations	168	56	112
Total Provinces	21	7	14

All estimates from a negative binomial count model. Dependent variable is the number of fires per province per year. Standard errors clustered by provinces in parentheses. Column 1 includes the full sample of 21 provinces across Sumatera, Kalimantan, Sulawesi, and Papua. Column 2 and 3 are sub samples that contain Type A plus Type C provinces and Type B plus Type D provinces respectively (see Chapter 3 for details).

* p<0.10; ** p<0.05; *** p<0.01

[58] The authors include the islands of Java, Sunda Islands, and Maluku Islands in their sample. These islands do not contain much forest area and therefore are less likely to be subject to forest fires. These islands are also highly urbanized and the fires that do occur are likely not for land conversion but rather fires that occur naturally. The rates of deforestation on these islands are very low.

The second model is an extension to the baseline model which includes additional controls that may have important effects on the number of fires in province such as climatic conditions, demographic characteristics, and economic factors. The added controls are both time invariant and variant. The specification is as follows:

$$lnFires_{pt} = \beta_0 + \beta_1 NumDist_{pt} + \gamma' X_p * T + \delta' Z_{pt} + Y_t + P_p + \varepsilon_{pt} \qquad (24)$$

where X_p is vector of time invariant controls which includes the suitability for palm oil cultivation in province p and the total forest area in 2000 in province p. Z_{pt} is a vector of time variant controls which includes total annual rainfall, total population, and GDP in province p at time t. In this model the time invariant controls (i.e. suitability and forest area in 2000) are interacted with yearly time dummies, T, to capture effect that these controls have each year.[59] Interacting the time invariant controls with a yearly time dummy will ensure that these controls do not get partialled out in a fixed effects model. All independent variables in equation (24) except for the number of districts are in natural logarithmic form.

Data for palm oil suitability come from the UN Global Agro-Ecological Zones (GAEZ) database. Palm oil suitability is an index created by UN GAEZ which is based on factors such as soil quality, terrain, climate, and input levels (data used here assumes high input levels for the purposes of commercial production) over a 30-year period from 1961-1990. This index is at a pixel level (900m resolution) and spatially averaged by province. Data for total rainfall comes from the National Oceanic and Atmospheric Administration's Precipitation Reconstruction Over

[59] The interaction term captures the effect that the time invariant controls have each year relative to the base period which is arbitrarily chosen to be 2001.

Land (NOAA PRECL) database. This data is based on gauge observations which are spatially averaged by province. Population and GDP data are from the Indonesia Bureau of Statistics and described in Chapter 3. Data for total forest area in 2000 is taken from Burgess et. al (2012).

The results for the first extension model (equation 24) are reported below in Table 8. Just like the baseline model, the coefficient on the number of districts is negative and statistically insignificant for the full sample of provinces. This suggests that even when additional controls are added into the model, the number of districts in a province is not likely to have a significant effect on fire activity in that province. In province types that did not experience much growth in the number of districts the coefficient on the number of districts is positive while it is negative for the provinces that experienced considerable growth in the number of districts. Both coefficients are also statistically insignificant. The only coefficient that seems to be significant in this model is the coefficient for total rainfall. In the full sample of provinces, a 1 percent increase in total rainfall leads to a 3.12 percent decrease in fire activity which is consistent with the findings in Macdonald and Toth (2018).

Table 8 - Results from Estimating Extension Model 1

Fixed Effects (Dependent Variable = lnFires)			
	All Provinces	Low Growth Provinces	High Growth Provinces
Number of Districts	-0.0077	0.2313	-0.0226
	(0.0317)	(0.2867)	(0.0504)
ln(Palm Oil Suitability) * 2002	0.7148	0.6932	0.4013
	(0.6335)	(1.7146)	(0.6264)
ln(Palm Oil Suitability) * 2003	1.5726*	2.1205	0.9132
	(0.7802)	(1.5704)	(0.7074)
ln(Palm Oil Suitability) * 2004	1.3739*	1.5823	0.8606
	(0.7089)	(1.6819)	(0.6967)
ln(Palm Oil Suitability) * 2005	1.7006***	2.3588**	1.0400
	(0.5298)	(0.8502)	(0.6086)
ln(Palm Oil Suitability) * 2006	1.5890**	1.7493	1.3917
	(0.6176)	(1.0006)	(0.8154)
ln(Palm Oil Suitability) * 2007	1.3707*	1.7456	1.1215
	(0.7004)	(1.3903)	(0.8091)
ln(Palm Oil Suitability) * 2008	1.5274**	2.6724*	1.0511
	(0.7189)	(1.2947)	(0.6255)
ln(Forest Area 2000) * 2002	0.1024	-0.4945	0.5307
	(0.2846)	(0.5548)	(0.3151)
ln(Forest Area 2000) * 2003	0.0292	-0.0200	0.3687
	(0.3306)	(0.2969)	(0.4460)
ln(Forest Area 2000) * 2004	0.1047	0.0143	0.3983
	(0.2718)	(0.3224)	(0.3543)
ln(Forest Area 2000) * 2005	-0.2223	-0.0929	0.0331
	(0.2469)	(0.3306)	(0.3398)
ln(Forest Area 2000) * 2006	-0.0751	0.0699	0.1099
	(0.2282)	(0.3819)	(0.3460)
ln(Forest Area 2000) * 2007	-0.2483	-0.1194	-0.1195
	(0.3278)	(0.4192)	(0.4338)
ln(Forest Area 2000) * 2008	-0.0044	-0.1101	0.1037
	(0.3874)	(0.5220)	(0.5158)
ln(Population)	-2.0309	-2.2461	-2.2523
	(2.2019)	(5.4331)	(3.8371)
ln(GDP)	0.6465	2.5586	-0.4953
	(1.1009)	(2.7227)	(1.1393)
ln(Total Rainfall)	-3.1169***	-4.0645	-2.2846**
	(0.7701)	(2.9954)	(0.9344)
Constant	52.2923	41.6999	60.8198
	(31.3465)	(97.2399)	(51.6472)
R-squared	0.7525	0.8806	0.7560
P-Value on Number of Districts	0.810	0.451	0.662
Province FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Total Observations	163	52	111
Total Provinces	21	7	14

All estimates from a fixed effects model. Dependent variable is the natural log of the number of fires per province per year. Standard errors clustered by provinces in parentheses. Column 1 includes the full sample of 21 provinces across Sumatera, Kalimantan, Sulawesi, and Papua. Column 2 and 3 are sub samples that contain Type A plus Type C provinces and Type B plus Type D provinces respectively (see Chapter 3 for details).

* $p<0.10$; ** $p<0.05$; *** $p<0.01$

Three different robustness tests are conducted to verify these results. First, equation 24 is estimated using random effects rather than fixed effects and the results are shown in Table 9. Again, the main coefficient of interest, number of districts, is negative and statistically insignificant for the full sample of provinces. Total rainfall and palm oil suitability are both statistically significant in the random effects model. Specifically, for a 1 percent increase to a province's palm oil suitability there is an increase of 1.65 percent in fire activity. Conversely, a 1 percent increase in rainfall leads to a 2.22 percent decrease in fires which is similar to the main fixed effects estimation. The second robustness test involves removing the interaction terms between the time dummies and time invariant effects and estimating equation (24) without the time invariant factors (i.e. total forest area in 2000 and palm oil suitability). The results are shown in Table 10. Just as before, the coefficient on the number of districts is statistically insignificant across all samples while total rainfall appears to be the only important control.

Table 9 - Extension Model 1 Estimated by Random Effects

Random Effects (Dependent Variable = lnFires)			
	All Provinces	Low Growth Provinces	High Growth Provinces
Number of Districts	-0.0044	-0.1225	0.0162
	(0.0321)	(0.0758)	(0.0384)
ln(Palm Oil Suitability)	1.6478***	2.0334***	1.7325***
	(0.3642)	(0.3513)	(0.5532)
ln(Forest Area in 2000)	0.6535**	1.1201***	0.6417**
	(0.2995)	(0.1725)	(0.3091)
ln(Population)	0.3306	0.7951*	0.2391
	(0.4177)	(0.4465)	(0.6256)
ln(GDP)	0.2836	-0.0449	0.2134
	(0.3513)	(0.1058)	(0.6432)
ln(Total Rainfall)	-2.2178***	-3.2506**	-1.9338**
	(0.7316)	(1.3809)	(0.9131)
Constant	-1.2225	-3.9279	-1.6019
	(7.7724)	(13.3186)	(9.6530)
R-squared	0.6807	0.7601	0.6570
P-Value on Number of Districts	0.891	0.106	0.674
Total Observations	163	52	111
Total Provinces	21	7	14

All estimates from a random effects model. Dependent variable is the natural log of the number of fires per province per year. Standard errors clustered by provinces in parentheses. Column 1 includes the full sample of 21 provinces across Sumatera, Kalimantan, Sulawesi, and Papua. Column 2 and 3 are sub samples that contain Type A plus Type C provinces and Type B plus Type D provinces respectively (see Chapter 3 for details).

* p<0.10; ** p<0.05; *** p<0.01

Table 10 - Extension Model 1 Estimated by Fixed Effects Without Time Invariant Controls

Fixed Effects (Dependent Variable = lnFires)			
	All Provinces	Low Growth Provinces	High Growth Provinces
Number of Districts	-0.0195	0.0119	0.0162
	(0.0323)	(0.2142)	(0.0384)
ln(Population)	-2.2369	-3.8040	-4.4433
	(1.6809)	(2.3467)	(2.6061)
ln(GDP)	0.4124	2.2072	-0.8554
	(1.0599)	(1.3226)	(0.9908)
ln(Total Rainfall)	-2.2267***	-4.3135**	-1.5334**
	(0.7112)	(1.5162)	(0.6980)
Constant	50.7055*	71.1260	90.7461**
	(24.9625)	(48.0469)	(35.6691)
R-squared	0.6893	0.7943	0.6962
P-Value on Number of Districts	0.553	0.957	0.679
Province FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Total Observations	163	52	111
Total Provinces	21	7	14

All estimates from a fixed effects model. Dependent variable is the natural log of the number of fires per province per year. Standard errors clustered by provinces in parentheses. Column 1 includes the full sample of 21 provinces across Sumatera, Kalimantan, Sulawesi, and Papua. Column 2 and 3 are sub samples that contain Type A plus Type C provinces and Type B plus Type D provinces respectively (see Chapter 3 for details).

* p<0.10; ** p<0.05; *** p<0.01

As a final robustness test equation (24) was estimated using a negative binomial model. The results are shown below in Table 11. The coefficient on the number of districts is positive but still statistically insignificant. However, just like in the baseline model, the p-value for the coefficient on the number of districts is considerably lower than in the fixed effects and random effects estimations suggesting that the number of districts is more likely to influence fire activity. The results from this estimation suggests that an additional district in a province increases fire activity by 3.5 percent for the full sample of provinces which is similar to the baseline negative binomial model.

Table 11 - Extension Model 1 Estimated Using Negative Binomial Model

Negative Binomial Model (Dependent Variable = Fires)			
	All Provinces	Low Growth Provinces	High Growth Provinces
Number of Districts	0.0351	0.0393	0.0735**
	(0.0246)	(0.1304)	(0.0311)
ln(Palm Oil Suitability)	0.1682	-1.2977	0.7652
	(0.3345)	(1.6365)	(0.4698)
ln(Forest Area in 2000)	0.0484	2.2817*	0.1049
	(0.1706)	(1.1852)	(0.2261)
ln(Population)	-0.1665	-3.2552***	-0.1107
	(0.2654)	(1.1392)	(0.3332)
ln(GDP)	0.0571	0.4118	-0.3819
	(0.2465)	(0.8000)	(0.4191)
ln(Total Rainfall)	-1.8627***	-1.1716	-2.5400***
	(0.4916)	(0.8288)	(0.6023)
Constant	14.9013***	26.5695**	20.5288***
	(4.8699)	(12.0404)	(5.9144)
P-Value on Number of Districts	0.153	0.763	0.018
Total Observations	163	52	111
Total Provinces	21	7	14

All estimates from a negative binomial count model. Dependent variable is the number of fires per province per year. Standard errors clustered by provinces in parentheses. Column 1 includes the full sample of 21 provinces across Sumatera, Kalimantan, Sulawesi, and Papua. Column 2 and 3 are sub samples that contain Type A plus Type C provinces and Type B plus Type D provinces respectively (see Chapter 3 for details).

* p<0.10; ** p<0.05; *** p<0.01

The third and final model includes the effect that the number of district splits per a province per a year has on the number of fires rather than just the level number of districts in a province. Also, rather than including total forest area in 2000 as a time invariant control, this model includes the percentage of forest area in 2000 that is designated as legal or illegal forest zones. The specification for this model is as follows:

$$lnFires_{pt} = \beta_0 + \beta_1 NumDist_{pt} + \beta_2 Splits_{pt} + \gamma' X_p * T + \delta' Z_{pt} + Y_t + P_p + \varepsilon_{pt} \qquad (25)$$

where $Splits_{pt}$ is the number of district splits that occur in province p at time t.[60] X_p is the vector of time invariant controls but now includes the share of forest area in 2000 in each province that is designated as illegal or legal forest zones rather than just the total forest area in 2000.

Forest resources in Indonesia are categorized into four different zones: conversion zones, productions zones, conservation zones, and protection zones. In conversion and production zones some deforestation is legally permitted for the purposes of land use change (e.g. converting natural forest land to palm oil plantations) or for logging. In conservation and protection zones there should be no deforestation occurring since it is illegal in these zones. Rather than just including the total forest area in a province it may be more insightful to categorize the forest area according to legality. Provinces that have a greater share of their total forest area in legal zones would be expected to have more forest fires. If not, illegal deforestation which may be the result of poor governance may be occurring. The share total 2000 forest area in legal and illegal zones is time invariant and therefore interacted with a yearly time dummy just as before.

The inclusion of the number of district splits follows from Macdonald and Toth (2018). The authors include the number of district splits to gain a better understanding of the time dynamics for the effect that new districts have on the number of fires in a province. In doing so, they also include two-year lags on district splits. The idea is that if the effect that a new district has on the number of fires in a province is short term (e.g. one period lag is significant) then this would provide evidence for the weakened enforcement capacity channel but if the effect is long

[60] District splits refers to the number of new districts that are created in a given year in a province whereas the total number of districts is the total number of districts in a given province at a given point in time. For example, in 2007 North Sumatera had 28 total districts but 3 new districts created from the previous year. District splits can be thought of a flow variable whereas total number of districts is a stock.

term (e.g. two period lag is significant) then this is evidence in favor of the corruption channel. However, the inclusion of two lags is arbitrary since the authors do not formally test the lag structure. It is also unclear that just a two-period lag is long enough to suggest that the effect that a new district has on fires is persistent. To address these problems equation (25) is also estimated with lags and tested for the appropriate lag structure. The initial estimation includes five lags[61] which are jointly tested for significance using an F-test. If they are jointly insignificant then the model is re-estimated with four lags. This testing down method continues until a lag specification is reached where all lags are jointly significant. The results are presented below in Table 12:

Table 12 - Testing for the Optimal Lag Structure

	Fixed Effects (Dependent Variable = lnFires)				
	5 Lags	4 Lags	3 Lags	2 Lags	1 Lag
Number of Districts	-0.0667	-0.1012	-0.0242	-0.0297	-0.0382
	(0.1177)	(0.0786)	(0.0895)	(0.0707)	(0.0424)
Number of Splits	0.1113	0.0806	0.0218	0.0694	0.1204**
	(0.1412)	(0.0803)	(0.0920)	(0.0707)	(0.0499)
ln(Population)	2.6760	-2.2647	-1.5681	-0.9602	-2.9562
	(11.2239)	(3.0766)	(1.9026)	(1.7778)	(1.7511)
ln(GDP)	-3.5821*	-3.0523***	-1.0872	-0.6769	0.0083
	(1.7771)	(0.8885)	(0.8827)	(1.0614)	(0.9545)
ln(Total Rainfall)	-5.6007***	-5.8207***	-4.6582***	-3.3626***	-3.8794***
	(1.5712)	(0.9453)	(1.1376)	(0.8193)	(0.8312)
Number of Splits T-1			-0.0242	0.0096	0.0140
			(0.0463)	(0.0394)	(0.0411)
Number of Splits T-2		0.1155	0.0395	0.0232	
		(0.0954)	(0.0403)	(0.0501)	
Number of Splits T-3	0.1436	0.0276	-0.0311		
	(0.1119)	(0.0503)	(0.0414)		
Number of Splits T-4	0.1530**	0.0664*			
	(0.0719)	(0.0384)			
Number of Splits T-5	0.0785				
	(0.0631)				
Constant	47.9336	116.9249**	76.9531**	53.3434*	80.2717***
	(166.7016)	(44.2535)	(29.3679)	(25.7169)	(26.7264)
Joint Significance of Lags (F Test p-value)	0.1206	0.2697	0.6618	0.8964	0.7366
Time Interaction with Suitability	Yes	Yes	Yes	Yes	Yes
Time Interaction with Forest Area	Yes	Yes	Yes	Yes	Yes
Total Observations	63	84	104	124	144
Total Provinces	21	21	21	21	21

All estimates from a fixed effects model. Dependent variable is the natural log of the number of fires per province per year. Standard errors clustered by provinces in parentheses. Each column indicates the number of lags included in the model. When 5 lags and 4 lags are included in the model some lags are not estimated because of collinearity - since there are only 8 years in the full sample including 5 or 4 lags results in a substantial loss of observations. * p<0.10; ** p<0.05; *** p<0.01

[61] Since there are only 8 time periods in our sample (e.g. 2001-2008) the inclusion of more than five lags will result in a loss of too many degrees of freedom.

Each column in Table 12 indicates the number of lags included in the estimation. The p-value for the F-test that tests the joint significance of lags is reported below the table. In all cases the lags are not jointly significant even at a 10% level of significance. Interestingly, the inclusion of two lags, which is what Macdonald and Toth (2018) include, has the highest p-value for the joint significance test which suggests this is worst possible specification. Overall, the results Table 12 suggests that including no lags for this model is optimal.

Given the insignificance of lags on new district splits, equation (25) is estimated without any lags. The results are shown below in Table 13. For the full sample of provinces, the main coefficient of interest, the number of districts, has a negative effect on fire activity which is consistent with the baseline model and extension model 1. For each extra district in a province there is decrease in fire activity of 2.7 percent on average. The two sub samples also show similar results to the previous models. In low growth provinces an additional district leads to a slight increase of 1.8 percent in fire activity while in high growth provinces an additional district leads to a slight decrease of 1.7 percent in fire activity. All these results are again statistically insignificant which suggests the number of districts in a province is not likely to have an effect on fire activity. In fact, for the full sample of provinces not many of the variables included appear to be statistically significant including the new district splits and share of illegal or legal forest zones. Like extension model 1 the only variable that does appear to be significant is total rainfall where a 1 percent increase in total rainfall leads to a 2.2 percent decrease in fire activity which is consistent with the findings in Macdonald and Toth (2018).

Table 13 - Results from Estimating Extension Model 2

Fixed Effects (Dependent Variable = lnFires)			
	All Provinces	Low Growth Provinces	High Growth Provinces
Number of Districts	-0.0266	0.0182	-0.0171
	(0.0383)	(0.0798)	(0.0673)
Number of Splits	0.0522	-0.0944	-0.0061
	(0.0359)	(0.0877)	(0.0697)
ln(Palm Oil Suitability) * 2002	0.1804	-9.0697***	0.2422
	(0.8339)	(1.4303)	(0.8616)
ln(Palm Oil Suitability) * 2003	1.2464	-6.1712***	1.0871
	(1.2366)	(1.3237)	(1.2736)
ln(Palm Oil Suitability) * 2004	1.1939	-3.9356***	0.9221
	(1.0691)	(1.0498)	(1.0949)
ln(Palm Oil Suitability) * 2005	1.1998*	-1.1292	0.8197
	(0.6652)	(2.6465)	(0.7698)
ln(Palm Oil Suitability) * 2006	1.2085	-1.8120	1.2194
	(0.8332)	(2.9652)	(0.9898)
ln(Palm Oil Suitability) * 2007	0.8620	-6.3667***	0.8713
	(0.9461)	(0.9092)	(1.0653)
ln(Palm Oil Suitability) * 2008	1.7780*	-5.5898**	1.6467
	(1.0183)	(1.8629)	(1.1241)
Share Legal Forest Area * 2002	-0.7847	-2.7946***	1.5910
	(1.8229)	(0.5824)	(2.1029)
Share Legal Forest Area * 2003	-1.1992	-3.7075***	0.7083
	(1.6975)	(0.4743)	(2.7761)
Share Legal Forest Area * 2004	-1.4406	-3.2751***	0.4699
	(1.7044)	(0.4486)	(2.5241)
Share Legal Forest Area * 2005	-1.7999	-0.3920	-0.9971
	(1.3555)	(0.9974)	(2.1305)
Share Legal Forest Area * 2006	-2.2477*	-3.7703***	-0.7526
	(1.2376)	(0.7348)	(2.4192)
Share Legal Forest Area * 2007	-3.6748**	-5.0136***	-2.1833
	(1.3844)	(0.3801)	(2.5962)
Share Legal Forest Area * 2008	-3.2845*	-5.4827***	-1.0451
	(1.6603)	(0.8821)	(2.7778)
Share Illegal forest Area * 2002	-3.0803	-38.5268***	-0.8355
	(3.3629)	(6.3188)	(3.3991)
Share Illegal forest Area * 2003	-2.2707	-34.8019***	1.1442
	(4.5259)	(5.5242)	(5.4637)
Share Illegal forest Area * 2004	-1.6353	-21.8405***	1.0059
	(3.9937)	(4.1495)	(4.8804)
Share Illegal forest Area * 2005	-2.9151	-13.0959	-0.9910
	(2.5376)	(11.1012)	(3.3265)
Share Illegal forest Area * 2006	-3.0217	-15.9261	-1.2631
	(2.8532)	(11.5444)	(4.5649)
Share Illegal forest Area * 2007	-4.3784	-34.8034***	-1.6450
	(3.5146)	(3.5885)	(4.9051)
Share Illegal forest Area * 2008	-1.2607	-38.4790***	3.2976
	(4.4437)	(7.8565)	(5.2574)
ln(Population)	-0.8013	-0.8773	-2.7256
	(0.9773)	(1.1514)	(1.9811)
ln(GDP)	0.8521	5.0325***	-0.2113
	(1.1618)	(0.5294)	(0.8915)
ln(Total Rainfall)	-2.2420**	-0.9738	-0.9623
	(0.9100)	(1.1037)	(1.2171)
Constant	25.4357*	-24.3175	54.6496*
	(14.4663)	(17.8240)	(26.2825)
R-squared	0.7929	0.9746	0.7993
P-Value on Number of Districts	0.495	0.827	0.803
P-Value on Number of Splits	0.161	0.323	0.931
Province FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Total Observations	163	52	111
Total Provinces	21	7	14

One result that is strange however is the signs on the coefficients for the share of legal forest area. Recall legal forest zones are a combination of both production forests as well as conversion forest. Therefore, if land conversions are occurring and fire is being used to facilitate the conversion, which from Chapter 3 seems to be the case (see Figure 12 and Figure 15), it would be expected that provinces with a greater share of legal forests would also experience greater fire activity. However, the results in Table 13 show the opposite. The sign on the coefficients are negative suggesting that provinces with a greater share of legal forest area have less fire activity. The signs on the coefficients for the share of illegal forest area are also negative which is expected. One possible explanation for this result is that the majority of the legal forest area in all provinces is designated as production forests for logging rather than conversion forests. This is shown in Table B.3. Even in the provinces with the greatest amount of land conversions like Riau and Central Kalimantan much of the legal forests are production forests. In Central Kalimantan 71% of legal forests are production forests while 52% of the legal forests in Riau are production forests. Across all provinces 76% of legal forests in Indonesia are production forests. This suggests that even though a province may have a greater share of legal forest area it may not result in greater fire activity since much of that legal forest area is designated as production forest rather than conversion forest.

The same three robustness tests used to validate the results in extension model 1 are used to validate these results and are shown below in Table 14-16. The first test estimates equation (25) using a random effects model. Recall one of the benefits of using random effects estimation is that it allows for time invariant characteristics to be estimated directly. Thus, there is no need to interact the time invariant characteristics such as palm oil suitability and share of forest area that is legal or illegal with yearly time dummies like in the fixed effects estimation. The results are reported in Table 14. For the full sample of provinces, the coefficient on the number of districts is again statistically insignificant and negative. The results from the random effects estimation suggest that an additional district in a province leads to a 0.27 percent decrease in fire activity consistent with the fixed effects estimation. However, unlike the fixed effects estimation, the coefficient on the share of legal forest area is positive which may be more in line with what would be expected. The second robustness test estimates equation (25) using a fixed effects model but removes the time invariant characteristics altogether. The results are reported in Table 15. The story remains the same: an additional district in a province leads to a negative and statistically insignificant effect on fire activity in that province.

Table 14 - Extension Model 2 Estimated by Random Effects

Random Effects (Dependent Variable = lnFires)			
	All Provinces	Low Growth Provinces	High Growth Provinces
Number of Districts	-0.0027	-0.0350	0.0396
	(0.0332)	(0.1762)	(0.0458)
Number of Splits	0.0429	0.0539	-0.0038
	(0.0383)	(0.1301)	(0.0475)
ln(Palm Oil Suitability)	1.2739***	22.4081***	1.3984***
	(0.4426)	(6.3936)	(0.4946)
Share Legal Forest Area in 2000	1.8158	1.7931	1.1923
	(1.4053)	(1.4699)	(1.9666)
Share Illegal Forest Area in 2000	-0.7648	86.3263***	-3.3523
	(2.2712)	(24.5872)	(3.3743)
ln(Population)	0.3109	-5.0889**	0.1607
	(0.4005)	(2.5506)	(0.4798)
ln(GDP)	0.5481**	2.8227***	0.4332
	(0.2571)	(0.5439)	(0.4019)
ln(Total Rainfall)	-1.8611**	-4.2118***	-1.5818
	(0.8004)	(1.5224)	(1.1193)
Constant	3.4642	-24.8623**	5.2504
	(7.6239)	(11.6351)	(9.4339)
R-squared	0.6825	0.7923	0.6516
P-Value on Number of Districts	0.936	0.842	0.388
P-Value on Number of Splits	0.263	0.679	0.937
Total Observations	163	52	111
Total Provinces	21	7	14

All estimates from a random effects model. Dependent variable is the natural log of the number of fires per province per year. Standard errors clustered by provinces in parentheses. Column 1 includes the full sample of 21 provinces across Sumatera, Kalimantan, Sulawesi, and Papua. Column 2 and 3 are sub samples that contain Type A plus Type C provinces and Type B plus Type D provinces respectively (see Chapter 3 for details).

* p<0.10; ** p<0.05; *** p<0.01

Table 15 - Extension Model 2 Estimated by Fixed Effects Without Time Invariant Controls

Fixed Effects (Dependent Variable = lnFires)			
	All Provinces	Low Growth Provinces	High Growth Provinces
Number of Districts	-0.0617	-0.0066	-0.0034
	(0.0374)	(0.2553)	(0.0395)
Number of Splits	0.0855**	0.0600	0.0330
	(0.0408)	(0.1269)	(0.0443)
ln(Population)	-2.5484	-3.8143	-4.3891
	(1.5912)	(2.3666)	(2.6204)
ln(GDP)	0.2605	2.0628	-0.8680
	(1.0879)	(1.3722)	(1.0299)
ln(Total Rainfall)	-2.3264***	-4.2050**	-1.5805**
	(0.7397)	(1.6001)	(0.7200)
Constant	57.9395**	71.9570	90.6154**
	(24.4022)	(48.5684)	(35.9131)
R-squared	0.6984	0.7950	0.6980
P-Value on Number of Districts	0.115	0.980	0.932
P-Value on Number of Splits	0.049	0.653	0.469
Province FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Total Observations	163	52	111
Total Provinces	21	7	14

All estimates from a fixed effects model. Dependent variable is the natural log of the number of fires per province per year. Standard errors clustered by provinces in parentheses. Column 1 includes the full sample of 21 provinces across Sumatera, Kalimantan, Sulawesi, and Papua. Column 2 and 3 are sub samples that contain Type A plus Type C provinces and Type B plus Type D provinces respectively (see Chapter 3 for details).

* $p<0.10$; ** $p<0.05$; *** $p<0.01$

The final robustness test involves estimating equation (25) using a negative binomial model. The results are shown below in Table 16. Just like previous negative binomial model estimations the coefficient on the number of districts is positive and statistically insignificant. However, this time the p-value on the number of districts is much higher suggesting that the number of districts is highly insignificant in this particular specification. The results from the negative binomial estimation suggest that an additional district results in 0.3 percent decrease in fire activity.

Table 16 - Extension Model 2 Estimated Using Negative Binomial Model

Negative Binomial Model (Dependent Variable = Fires)			
	All Provinces	Low Growth Provinces	High Growth Provinces
Number of Districts	0.0026	0.0290	0.0569
	(0.0271)	(0.0889)	(0.0430)
Number of Splits	0.0574*	0.1087	0.0265
	(0.0307)	(0.0780)	(0.0347)
ln(Palm Oil Suitability)	0.7132*	-11.1148	1.0220**
	(0.4213)	(6.8629)	(0.5064)
Share Legal Forest Area in 2000	-1.3353*	-8.3462***	-0.3970
	(0.7876)	(1.9347)	(1.3139)
Share Illegal Forest Area in 2000	1.0029	-28.4321	0.6064
	(1.4522)	(26.9290)	(2.1858)
ln(Population)	-0.4592	0.4007	-0.1949
	(0.2792)	(1.8603)	(0.3585)
ln(GDP)	0.3478	2.0831***	-0.2575
	(0.2414)	(0.5841)	(0.4200)
ln(Total Rainfall)	-1.8494***	-1.9580*	-2.3942***
	(0.4875)	(1.0447)	(0.6133)
Constant	15.3537***	43.8256**	19.9538***
	(4.5667)	(17.0171)	(6.3985)
P-Value on Number of Districts	0.924	0.745	0.185
P-Value on Number of Splits	0.062	0.163	0.445
Total Observations	163	52	111
Total Provinces	21	7	14

All estimates from a negative binomial count model. Dependent variable is the number of fires per province per year. Standard errors clustered by provinces in parentheses. Column 1 includes the full sample of 21 provinces across Sumatera, Kalimantan, Sulawesi, and Papua. Column 2 and 3 are sub samples that contain Type A plus Type C provinces and Type B plus Type D provinces respectively (see Chapter 3 for details).

* p<0.10; ** p<0.05; *** p<0.01

The purpose of this chapter was to formally evaluate the link between governance quality and forest fires in Indonesia. This was achieved by using a similar identification strategy as Burgess et al. (2012) where the seemingly random timing in district splits that were occurring in Indonesia between 2000-2008 is used as a source of exogenous variation in governance quality. Three different fixed effects models were estimated. The first model is the baseline model and it estimates the effect that the number of districts has on the number of fires in a province without any additional controls. The second model is an extension which includes additional time invariant characteristics of a province such as the initial forest area in 2000 and palm oil suitability as well as time variant characteristics of a province such as total rainfall, population, and GDP. The third model is another extension which also includes the number of district splits in a given year rather than just the number of districts in a province. All three models included province fixed effects and time fixed effects. The results from all three models suggest that the effect that the number of districts has on fire activity is negative and not statistically significant. This contradicts the results found in Macdonald and Toth (2018) and Burgess et al. (2012) which both find that the number of districts has a positive effect on fire activity and deforestation more generally.

Chapter 5: Conclusion

The purpose of this thesis was to gain a better understanding of the causes of deforestation in Indonesia. Global deforestation has slowed down by more than 50% between 1990-2015 but there are still regions of the world where it remains a problem. The UN FAO has estimated that during this period Brazil and Indonesia are the only two countries who have lost over a million hectares of forest land every year on average. However, between 2010-2015 Indonesia's annual rate of forest loss was nearly four times greater than Brazil's therefore understanding the patterns and causes of deforestation in Indonesia is likely central in combatting deforestation globally.

Previous literature on deforestation is scattered with no clear consensus on the direction of research. Fortunately, much of the empirical and theoretical knowledge on deforestation is contained within a smaller set of studies which can be categorized by their scope of analysis. On one hand, cross-country studies stress the importance of property rights and international trade as determinants of deforestation but struggle with incorporating measures of property rights and international trade in an empirical model in such a way that avoids endogeneity. On the other hand, individual country case studies do a better job of using theory as a guide for empirical analysis and are more convincing in identifying causality but are limited in geographic scope.

The most influential study specific to Indonesia is Burgess et al. (2012) which makes use of a rich dataset that tracks annual forest loss between 2000-2008 as well as institutional changes that were occurring following the collapse of the Suharto regime. Post Suharto, the regulation of the forestry industry was decentralized to local district governments and between 2000-2008 the number of districts more than doubled across the archipelago. The authors abstract that within a provincial wood market each district's government engages in Cournot-style competition where their choice of how many logging permits to issue depends on the choice of their neighboring districts. This leads to the hypothesis that as the number of districts within a province increases the number of permits issued (i.e. deforestation) increases beyond the legal limit. All permits that are issued beyond the legal limit are obtained via a bribe from the logging firms. Therefore, the basic idea presented by Burgess et al. (2012) is that political corruption is the key driver of deforestation in Indonesia. However, this specific hypothesis of how political corruption effects deforestation appears to be inconsistent with the data. Simple exploratory analysis shows that there is not much of a link between district growth and deforestation in Indonesia between 2000-2008. Certain provinces that experienced widespread deforestation did not see much growth in the number of districts while other provinces that experienced little deforestation saw a large increase of new districts.

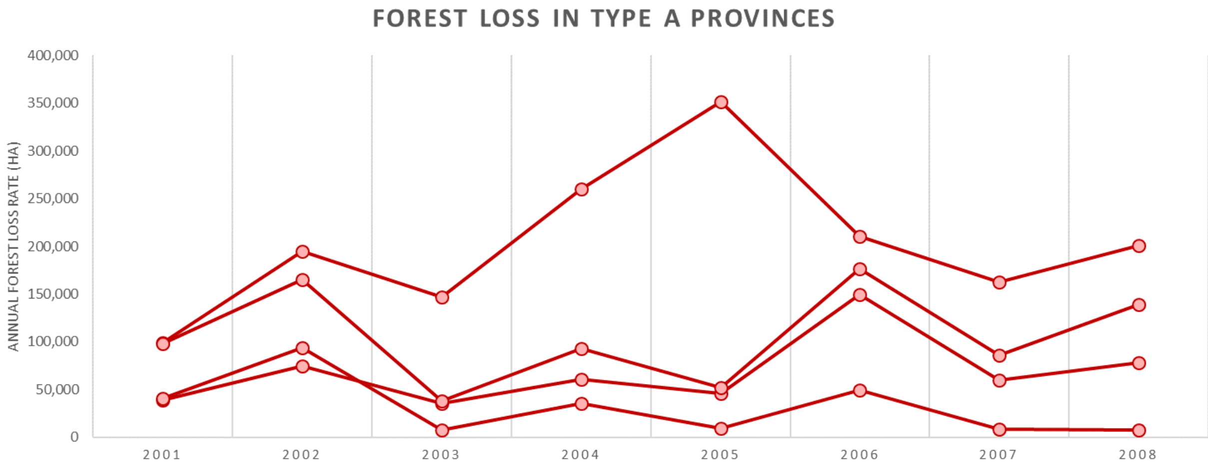
The exploratory analysis also pointed to interesting blips in deforestation rates in practically every province in 2002 and 2006. These blips appear to line up nicely with the forest fires, greenhouse gas emissions, and palm oil plantation harvest areas in each province which suggests that deforestation is likely the result of land conversions from natural forests to plantations facilitated by fires rather than illegal logging. To compliment the data, there is strong qualitative evidence that also points to the expansion of plantations as the primary cause of deforestation. Two cases studies highlighted the role that corrupt government officials have in allowing large multinational plantation firms expand their operations at the expense of local communities. These case studies did not mention anything about political corruption being the result of an increased number of neighboring districts like the Burgess et al. (2012) hypothesis suggests.

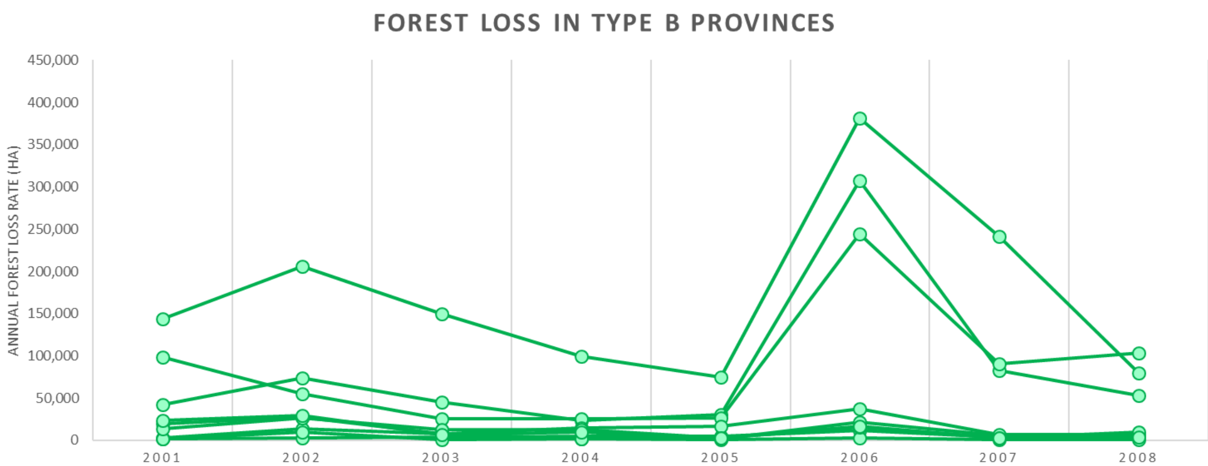
To formally evaluate the link between governance quality and fire activity the empirical models in this thesis leverage a similar identification strategy used in Burgess et al. (2012) where the seemingly random timing of district splits is used as a source of exogenous variation in governance quality. Three separate fixed effects models were estimated: (i) baseline model, which estimated the effect that the number of districts has on fire activity in a province directly; (ii) extension model 1, which estimated the effect that the number of districts has on fire activity in province while controlling for time invariant characteristics such as palm oil suitability and initial forest area as well as time variant characteristics such as population, GDP, and annual rainfall; (iii) extension model 2, which added to extension model 1 by also including number of district splits that occurred in a given year in a province. The results from estimating all three of these equations suggest that the number of districts likely does not have effect on fire activity which contradicts previous literature.

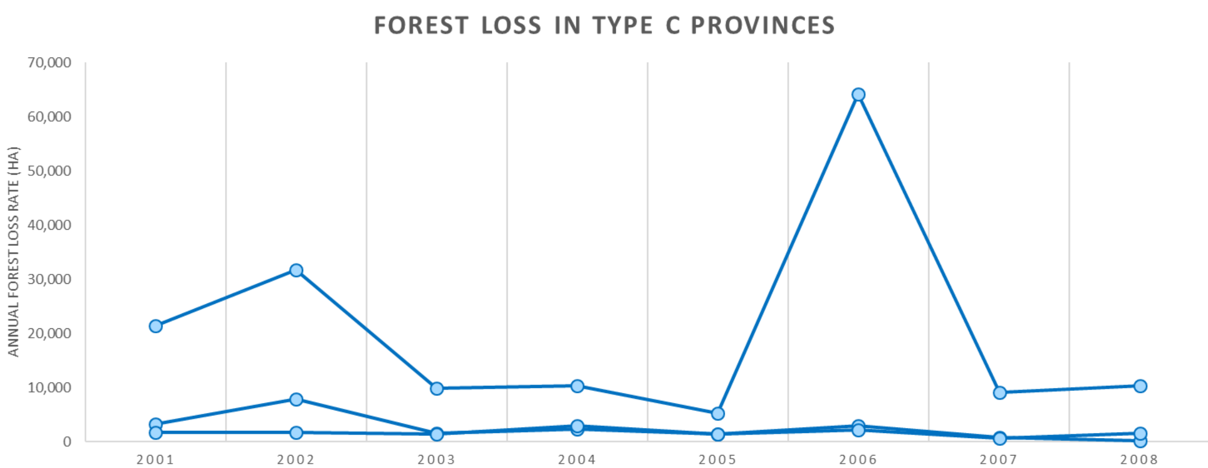
Admittedly there are some shortcomings and gaps in this analysis that future research may be able to fill in. First, the validity of the identification strategy adopted from Burgess et. al (2012) is questionable. They suggest that the timing of district splits is random due to idiosyncratic factors but do not detail these factors or how they could be random. For example, they point to the long administrative process involved in creating a district split as being one of these idiosyncratic factors but do not detail or show how the process would be different for any given split. The administrative process is likely the same across all of Indonesia for any district that wishes to split. Second, the empirical models did not explain what is actually causing deforestation instead they just showed that the number of districts in a province likely does not have any effect. However, this thesis did provide very informative suggestive evidence that may be useful for future research. This suggestive evidence showed that deforestation in Indonesia has a volatile pattern that appears to line up nicely with forest fires, greenhouse gas emissions, and plantation expansions. The suggestive evidence also showed how growing international demand for Indonesian palm oil may also play a role in deforestation which may be interesting to investigate further.

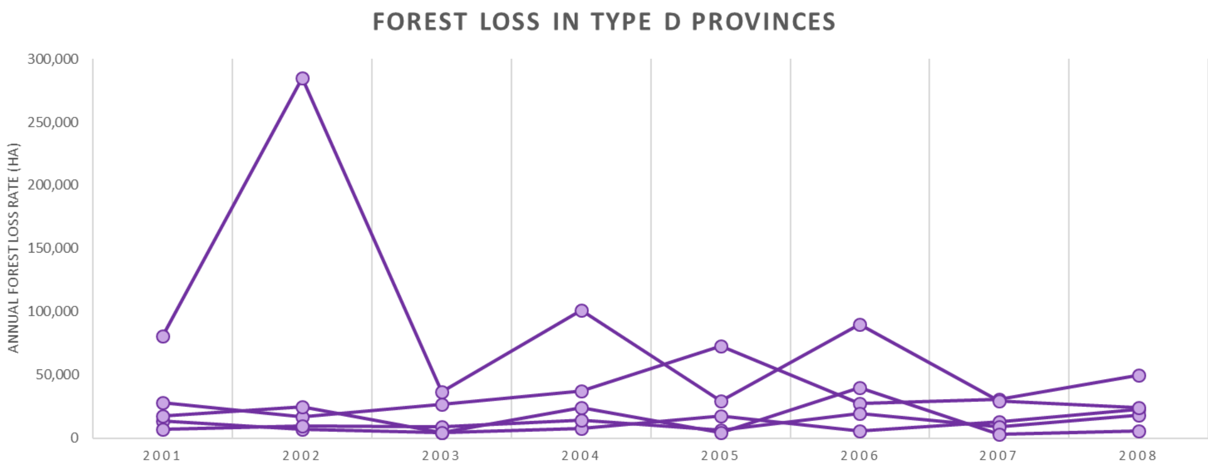
Appendix A - Supplementary Figures

Figure A.1 - Annual Absolute Deforestation by Province Groups (Graphs)



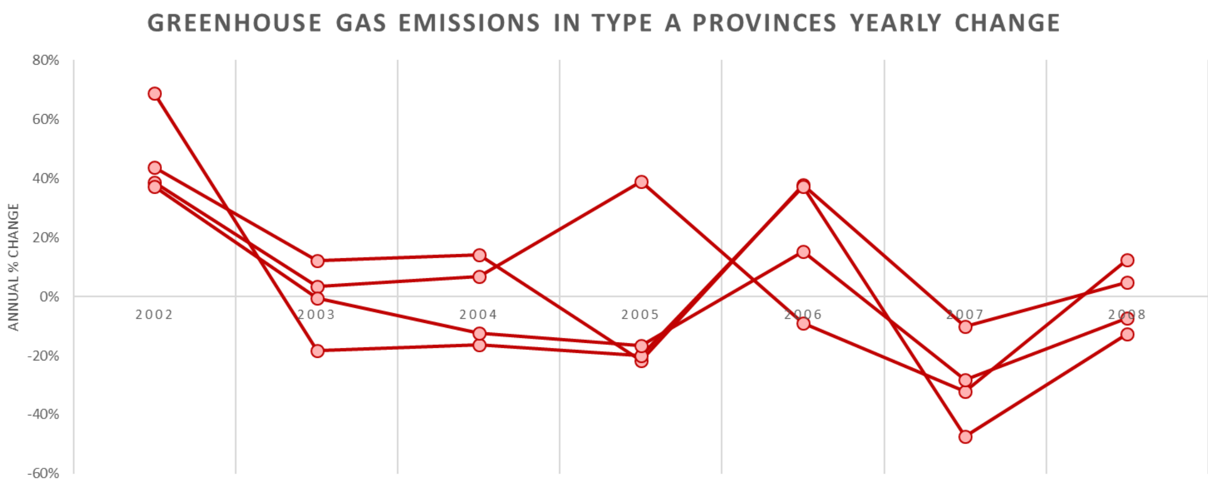


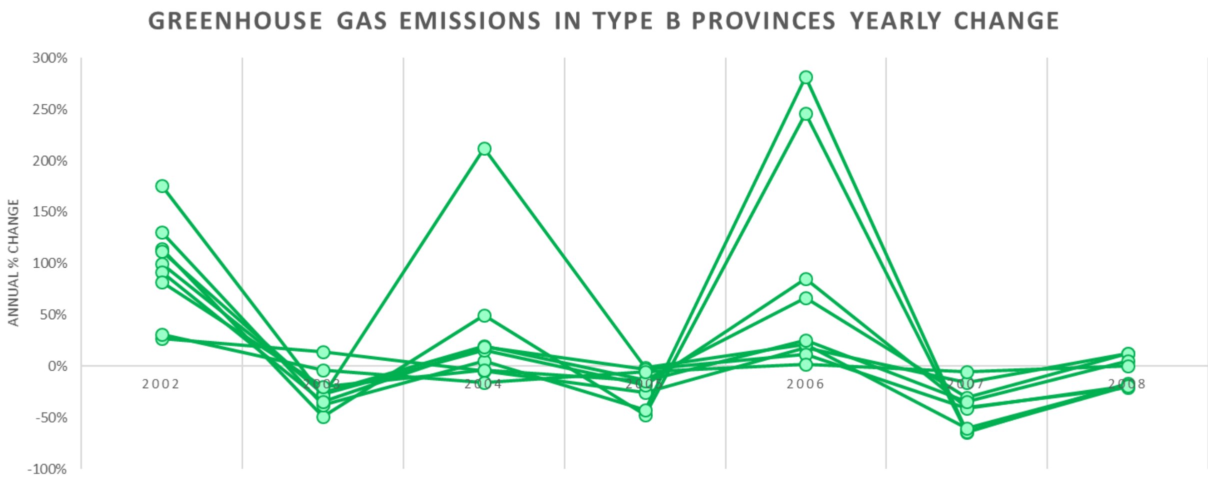


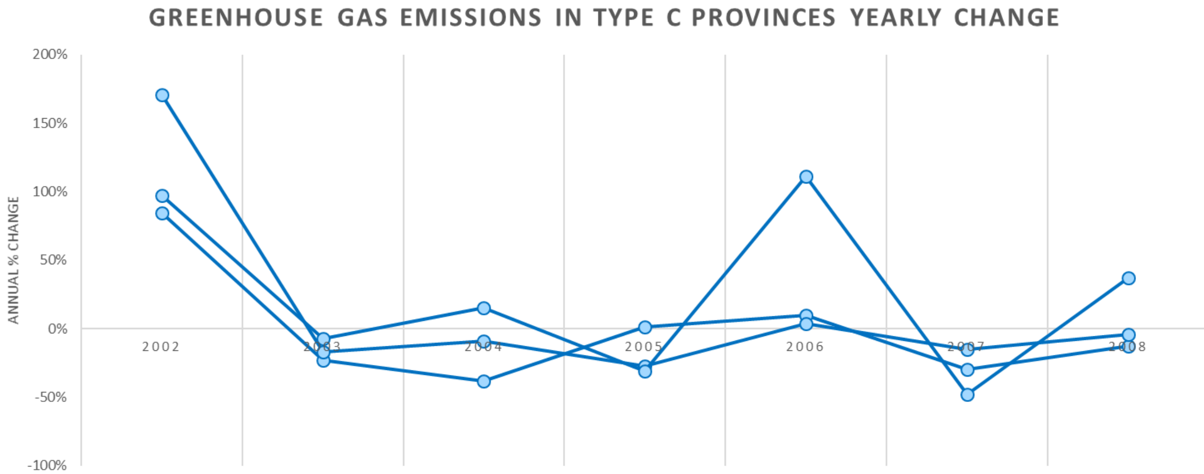


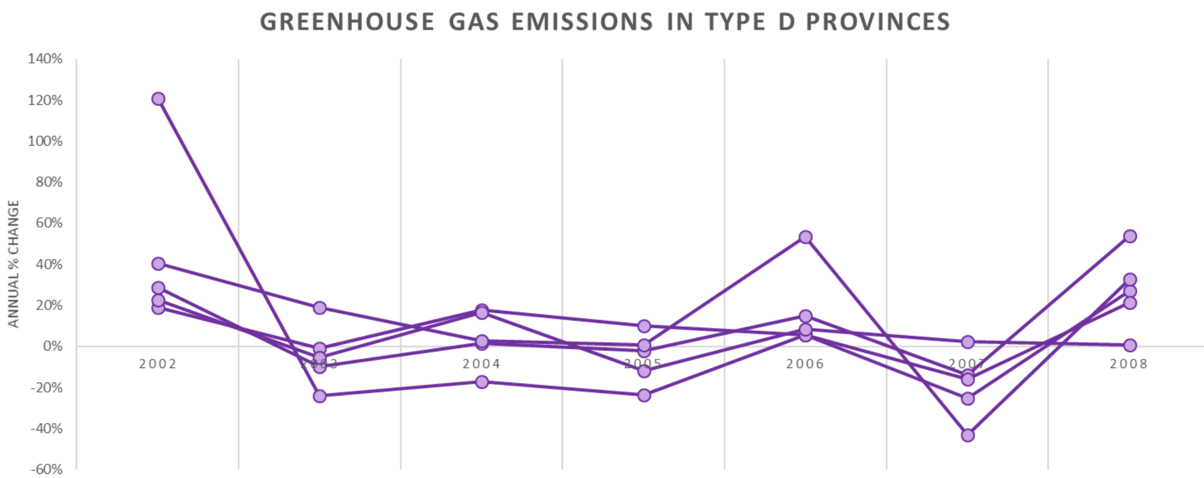
Source: Created with data from Burgess et al. (2012)

Figure A.2 - Greenhouse Gas Emissions from Indonesian Forests 2001-2008 Annual Percentage Change



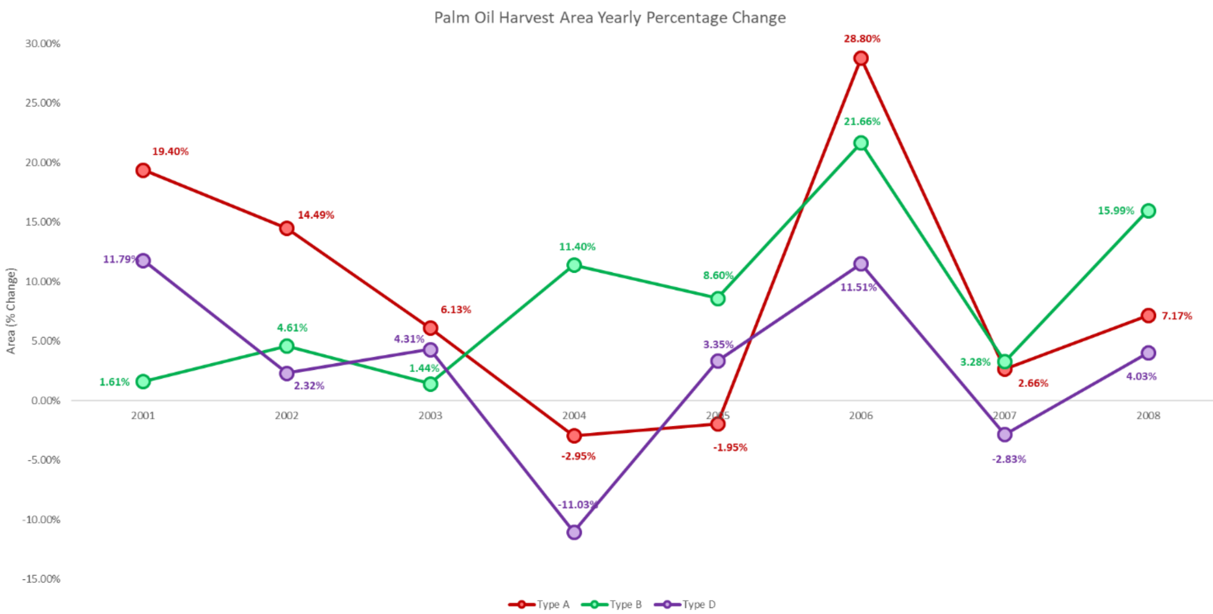






Source: Indonesia National Carbon Accounting System (INCAS) (Indonesia Ministry of Enviornment and Forestry , 2015)

Figure A.3 - - Palm Oil Plantation Harvest Areas by Province Grouping (Annual Percentage Change)



Source: Indonesia Ministry of Agriculture (Agricultural Statistics Database)

Appendix B - Supplementary Data Tables

Table B.1 - Annual Absolute Deforestation by Province Groups (Table)

	Change in Forest Area (Ha)							
	2001	**2002**	**2003**	**2004**	**2005**	**2006**	**2007**	**2008**
Riau	98,631	194,713	146,600	259,744	351,438	210,656	162,650	200,900
Jambi	38,594	74,844	35,425	60,600	46,131	149,694	59,650	78,281
South Kalimantan	40,250	93,900	7,188	35,088	9,650	49,344	8,713	7,500
East Kalimantan	97,919	164,988	37,675	93,113	52,238	176,163	85,700	138,888
Total Type A	**275,394**	**528,444**	**226,888**	**448,544**	**459,456**	**585,856**	**316,713**	**425,569**
Bengkulu	2,194	3,056	3,844	5,125	5,075	12,038	3,631	5,238
South Sumatera	42,419	73,406	45,419	23,294	30,600	307,575	83,163	52,844
Lampung	2,419	13,919	7,406	2,313	1,625	21,681	5,406	2,575
Central Kalimantan	143,938	206,106	149,350	99,831	74,556	381,806	241,144	79,400
West Kalimanatan	98,531	54,963	25,488	25,206	26,731	243,900	90,288	103,613
Southeast Sulawesi	19,631	27,806	7,938	15,050	16,375	36,869	6,494	6,863
North Sulawesi	2,300	9,769	1,306	1,681	738	2,350	588	506
Central Sulawesi	13,513	26,381	12,950	12,369	2,956	15,650	2,594	9,444
West Papua	23,488	29,363	6,963	9,481	2,794	16,913	2,713	3,431
Total Type B	**348,431**	**444,769**	**260,663**	**194,350**	**161,450**	**1,038,781**	**436,019**	**263,913**
Gorontolo	3,219	7,813	1,556	2,394	1,413	2,988	731	200
West Sulawesi	1,769	1,675	1,438	2,994	1,425	2,181	631	1,631
Bengka Belitung	21,463	31,763	9,881	10,275	5,338	64,219	9,144	10,369
Total Type C	**26,450**	**41,250**	**12,875**	**15,663**	**8,175**	**69,388**	**10,506**	**12,200**
Aceh	13,313	7,219	4,156	7,425	17,688	5,413	12,744	23,019
North Sumatera	28,075	16,669	26,500	37,113	72,694	27,344	30,825	49,488
West Sumatera	7,263	9,594	8,663	14,438	6,088	19,206	9,038	18,194
South Sulawesi	17,338	24,688	4,606	24,375	4,150	39,919	2,819	5,788
Papua	80,431	285,138	36,363	101,044	29,206	89,869	29,694	24,219
Total Type D	**146,419**	**343,306**	**80,288**	**184,394**	**129,825**	**181,750**	**85,119**	**120,706**

Source: Created with data from Burgess et al. (2012)

Table B.2 - Fire Alerts in Indonesia 2001-2008 (Table)

Total Number of Fire Alerts								
	2001	**2002**	**2003**	**2004**	**2005**	**2006**	**2007**	**2008**
Riau	2,143	8,105	9,628	11,840	29,698	15,924	5,921	8,717
Jambi	346	2,538	3,359	5,317	2,606	7,774	2,931	3,138
South Kalimantan	620	5,040	2,137	4,669	1,901	5,884	947	441
East Kalimantan	658	5,838	1,793	6,565	2,087	6,074	1,944	1,182
Total Type A	**3,767**	**21,521**	**16,917**	**28,391**	**36,292**	**35,656**	**11,743**	**13,478**
Bengkulu	71	319	809	805	432	1,183	489	566
South Sumatera	623	10,498	4,366	9,080	3,636	21,831	5,261	4,164
Lampung	272	1,897	1,008	1,634	639	3,174	1,063	803
Central Kalimantan	3,126	34,622	12,015	21,381	8,371	41,424	4,368	2,347
West Kalimanatan	1,020	18,401	8,041	14,043	6,543	20,347	5,597	5,445
Southeast Sulawesi	268	2,647	1,048	2,462	890	2,983	910	505
North Sulawesi	152	882	217	373	241	483	148	80
Central Sulawesi	160	3,146	1,007	1,899	691	1,716	691	323
West Papua	41	741	189	186	50	176	70	46
Total Type B	**5,733**	**73,153**	**28,700**	**51,863**	**21,493**	**93,317**	**18,597**	**14,279**
Gorontolo	47	1,085	208	392	245	563	172	66
West Sulawesi	136	1,143	247	653	313	559	238	105
Bengka Belitung	51	1,295	1,147	1,134	400	1,616	715	869
Total Type C	**234**	**3,523**	**1,602**	**2,179**	**958**	**2,738**	**1,125**	**1,040**
Aceh	253	696	493	763	799	885	678	965
North Sumatera	774	1,713	2,405	3,149	4,337	2,674	1,631	1,362
West Sumatera	189	463	1,143	1,326	542	2,195	723	1,411
South Sulawesi	466	2,519	1,132	2,294	1,044	1,558	938	671
Papua	691	5,208	2,564	6,855	1,563	3,881	844	1,251
Total Type D	**2,373**	**10,599**	**7,737**	**14,387**	**8,285**	**11,193**	**4,814**	**5,660**

Source: NASA Fire Information for Resource Management (FIRMS) Active Fire Data

Table B.3 - Total 2000 Forest Area in Each Province by Forest Zone

Province	Total 2000 Forest Area in Conversion Zones	Total 2000 Forest Area in Production Zones
Aceh	0	124,622
Bengka Belitung	0	67,708
Bengkulu	0	38,284
Central Kalimantan	671,793	1,629,262
Central Sulawesi	44,267	341,711
East Kalimantan	0	1,785,268
Gorontolo	3,027	81,505
Jambi	279	255,907
Lampung	0	12,531
North Sulawesi	2,836	52,241
North Sumatera	52,823	328,350
Papua	1,032,882	1,776,250
Riau	609,395	651,864
South Kalimantan	20,269	164,337
South Sulawesi	4,313	100,936
South Sumatera	74,025	293,359
Southeast Sulawesi	29,305	173,227
West Kalimantan	89,257	832,254
West Papua	412,038	674,113
West Sulawesi	13,248	70,600
West Sumatera	29,032	111,081
Grand Total	**3,088,789**	**9,565,410**

Source: Burgess et al. (2012)

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