How does foreign direct investment impact deforestation in Indonesia?

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Abstract

Much work has been done in determining the drivers of deforestation, however, there has not been much recent focus on drivers of deforestation in developing nations. In this paper we concentrate on one potential determinant: manufacturing output. In particular, we are interested in how manufacturing output by foreign firms in Indonesia might impact deforestation. We use a robust new satellite data set on Global Forest Change, combined with micro data from the Indonesian Census of Manufacturing. Our definitions of foreign firms and deforestation follow from previous literature that works with these same data sets. Initially, we run our model using an OLS regression. Due to endogeneity concerns, we also attempt to instrument for output and foreign output. Our analysis does not enable us to conclude that foreign manufacturing output in Indonesia has any significant effect on deforestation.

1 Introduction

Tropical deforestation is a major environmental challenge with far-reaching economic policy implications. It not only accounts for almost a fifth of greenhouse gas emissions, but also results in a massive loss of biodiversity (Margono et. al., 2012). In light of this, understanding the underlying economic determinants of deforestation can serve to inform policy makers.

This paper will investigate the relationship between foreign direct investment and deforestation in Indonesia. Specifically, the question of interest is as follows: how does change in foreign direct investment impact forest loss? The question is pursued using highly dis-aggregated measures of deforestation at regency and year levels. Although the connections between deforestation and cattle ranching, agriculture, poorly defined property rights, road construction, and population growth have been well documented, there are few studies examining the relationship between deforestation and openness to trade in developing countries (Faria et. al., 2016). There have also been few studies considering the determinants of deforestation within the past two decades (Lebois et. al., 2017). Additionally, we have not encountered any studies focusing specifically on manufacturing as a potential determinant.

The effect of foreign direct investment (FDI) is not obvious, and existing literature has not come to a clear consensus on the issue. On one hand, FDI may increase pollution due to increased economic activity, and by providing incentive for polluting industries to locate where environmental standards are low. On the other hand, more stringent environmental regulation may arise as a result of income gains from trade (Copeland and Taylor, 1995). Although much of the literature focuses on pollution, similar effects can be expected for deforestation. While pollution is difficult to quantify, deforestation is one of the more concrete components contributing to it.

This paper focuses on Indonesia, where deforestation is a serious concern. Between 2000 and 2012, Indonesia surpassed Brazil in having the fastest rate of deforestation in the world (Margono et. al., 2014). Over the period of 2000 to 2012, Indonesia underwent the largest increase in forest loss of all countries (Hansen et. al., 2013). Although the Indonesian government has instated policy to curb practices that contribute to rapid deforestation, estimates of illegal logging in the country range from 60 percent to 80 percent. It should be noted that the dynamics of forest loss in Indonesia are unique in that most forest cover loss is quickly replanted by timber and palm concessions (Margono et. al., 2014).

In a similar time frame, Indonesia has received significant inflows of FDI (Arnold and Javorcik, 2009). There is evidence that foreign ownership of manufacturing firms in Indonesia has a significant impact on them in terms of efficiency gains (Arnold and Javorcik, 2009). This, combined with the fact that forests are crucial to both Indonesia's domestic and export economies, raises the question of how such foreign ownership may serve to influence deforestation.

Some additional motivation for this analysis can be found by looking at Brazil, which has experienced a dramatic policy-driven reduction in Amazon Basin deforestation (Hansel et. al. 2013). In its policy formulation and implementation, Brazil used data from the Landsat 7 satellite to document deforestation trends. Similar data will be used to measure deforestation in this paper. Although Brazilian gross forest loss remains the second highest, its percentage loss of forest cover is now lower than that of a number of other countries. The success observed in Brazil instills some hope that policy intervention could be successful in other countries, and specifically in Indonesia.

2 Literature Review

This paper follows the extensive literature focusing on the broad question of how globalization contributes to achieving the best trade-off between environmental and economic goals. We will first review literature pertaining to the relationship between trade and pollution in general, before focusing more specifically on the relationship between trade and deforestation. In this context, the novel contribution of this paper is its narrower focus on the impact that foreign direct investment in manufacturing has on deforestation, specifically focusing on this effect in Indonesia.

It general, empirical works are limited by the difficulty of measuring environmental quality. This issue arises both because it is hard to develop a single measure combining many important environmental factors, and because of the lack of data on such factors. For that reason, this paper focuses on one such factor, namely deforestation. The deforestation data used in this paper is significantly more robust than previous measures of deforestation, as well as other data used to quantify pollution.

Though this paper focuses on non-income channels, it is worth mentioning that some effects of trade occur through its effect on income and economic growth (Frankel, 2009). One common finding is the Environmental Kuznets Curve, which shows that growth causes environmental degradation where economic development is low. After income per capita reaches a certain level, further growth is thought to improve the environment as the economy moves from manufacturing to service sectors. However, there is some dispute about whether the improvement continues indefinitely.

Among non-income effects, three primary hypotheses are identified in the literature. Two of them posit that trade openness leads to negative environmental outcomes, while the third proposes a more positive scenario. On the negative side are the “race to the bottom” and “pollution haven” hypotheses. In the case of “race to the bottom”, countries that are more open have less stringent regulations as they fear that stringent regulation will make them less competitive.

Meanwhile, the “pollution haven” hypothesis proposes that trade openness may encourage firms in countries with less stringent environmental regulations to specialize in industries that are more polluting. Another possible effect is to encourage firms in countries with more stringent environmental regulation to relocate to developing countries. The response to regulation is therefore fleeing rather than innovation. The primary effect of globalization in this case is on the distribution of pollution, not the overall level of pollution (Frankel, 2009). Frequently, nations that become the recipients of these foreign firms are still developing. They then receive both increased investment and employment, but also a potentially negative environmental impact from the new firms.

A few papers find support for the pollution haven hypothesis, and maintain that free trade in fact has a negative effect on the environment. Among these are Levinson and Taylor (2006), Copeland and Taylor (1995), and Ederington et. al. (2005). In their study, Levinson and Taylor

(2006) challenge those that fail to find a pollution haven effect. They point out that it is unlikely that there is absolutely no effect of pollution abatement, though it be a small cost compared to other costs that firms are subjected to. They also take issue with the Porter hypothesis, which is used to justify findings that point to industries with high pollution abatement costs as being leading exporters. Meanwhile, Copeland and Taylor (1995) conclude that free trade serves to raise world pollution if incomes differ substantially across countries. The result is however, motivated by theory rather than empirical work. Additionally, Ederington et. al. (2005) question why previous research failed to produce robust relationships between environmental regulations and trade flows. They use data on pollution abatement costs and trade flows into and from the United States and determine that environmental regulations have stronger effects on trade between industrialized and developing economies.

A positive effect of trade openness can be see through the “gains from trade”, or Porter hypothesis, which argues that well-designed environmental regulations stimulate innovation and thus increase productivity (Ambec and Barla, 2002). Following this theory, environmental regulation is ultimately beneficial to firms.

In support of the idea that freer trade is good for the environment is a paper by Antweiler, Copeland and Taylor (1998). They come to their conclusion by dividing the impact of trade into scale, technique, and composition effects, and find that international trade creates relatively small changes in pollution concentrations when altering the composition of national output. They also find that the technique and scale effects of trade lead to a reduction in pollution. Unlike this paper, their explicit goal is to empirically verify some of the theoretical models surrounding trade openness and pollution. They seek to determine pollution directly by looking at sulfur dioxide concentration. This paper, however, does not attempt to tie deforestation to pollution, but is interested in deforestation as an issue in itself.

On that note, in their paper, Arild Angelsen and David Kaimowitz synthesized over 140 economic models investigating the causes of tropical deforestation (1999). They highlight the importance of distinguishing between different levels of analysis. Angelsen and Kaimowitz warn that mixing sources, immediate causes, and underlying causes of deforestation may confuse causal relationships and lead to misspecification. In their theoretical framework, trade is considered to be an underlying cause, for which macroeconomic models are used. However, since we are not investigating the policies associated with trade openness, but rather looking at direct measures of FDI, this paper is more akin to those investigating immediate causes than underlying causes.

Leblois et. al. (2017) provide an updated review of the determinants of deforestation, noting that few studies have examined such determinants since the 2000s. Similarly to this paper, they make use of a data set on deforestation put together by Hansen et. al. The paper finds that the same factors as mentioned by Angelsen and Kaimowitz, namely population density, economic development, and agricultural activity, explain national dynamics of deforestation. They also find that trade in forestry and agricultural commodities is an important factor in forest clearance, and that recent studies have identified trade as a potential driver of deforestation. Similarly, DeFries et. al. (2010) demonstrate that there is a positive relationship between trade and deforestation at a national level. They advocate for policies that reduce deforestation carried out through industrial-scale, export-oriented agricultural production.

In another recent paper on the topic, Faria et. al. investigated the drivers of deforestation in the Amazon (2016). They looked at the relationship between openness to trade and deforestation, where they defined trade openness as the total volume of foreign trade. This is a different specification than the one used to measure FDI in this paper. They considered openness to trade of all possible products, as well as only primary products. Faria et. al. also used satellite-based deforestation data, provided by the National Institute of Spatial Research (INPE). The INPE publishes annual rates of deforestation for all municipalities in the Amazon. In addition to openness to trade, they considered a variety of other explanatory variables, which are beyond the scope of this paper.

More directly related to this paper, a study by Lopez and Galinato (2004) concludes that trade openness has no significant effect on deforestation in Indonesia. It examines the economy-wide factors affecting deforestation by looking at their effect on the immediate causes of deforestation. These immediate causes are identified as poverty, agricultural expansion, and road building, as determined by other literature. Trade openness is examined as one of the economy-wide factors, and it is the one most relevant to this paper. According to the paper, the primary causes of deforestation in Indonesia have been agricultural expansion, government promotion of logging and timber, and transmigration into forested areas. Tree crops play a large role in deforestation, a fact that will be kept in mind when looking closely at a few specific industries. The data used by Lopez and Galinato (2004) is far less robust, as they matched statistical information on roads and crop area provided by Indonesia's statistical yearbook to the identified main forested regions. The claim from Burgess et. al. (2012) that government data regarding forest cover in Indonesia are unreliable highlights the importance of using more objective data, such as the satellite data used in this paper.

Although their work is of a different nature, Arnold and Javorcik (2009) provide motivation for looking at foreign involvement in Indonesia, as well as providing guidance on working with the manufacturing data, which they also use in their paper. They find that foreign ownership leads to significant productivity improvements. In fact, acquired plants experience a 13.5 percent higher productivity than the control group after 3 years. The paper also determines that better performing plants are more likely to be acquired, but also that foreign acquisition leads to higher productivity. It also supports the fact that foreign-owned firms are different enough from domestic ones to be worth investigating. Later, the definition of foreign-ownership follows directly from Arnold and Javorcik (2009).

Finally, Autor et. al. (2013) provides guidance for the instrumentation performed. This is performed in order to account for possible endogeneity between output and deforestation. During the 2000s, China experienced a marked growth in its economy. We will use this growth to determine a part of output produced by Indonesian industries that is not explained by amount of tree cover. The Autor (2013) paper instruments for US imports from China by using changes in Chinese imports by other high-income countries. Similarly, in this paper we use changes in Chinese imports of Malaysian goods to instrument for changes in output by Indonesian industries.

3 Data

The manufacturing data used in the paper were obtained from the annual Manufacturing Survey (*Survei Tahunan Perusahaan Industri Pengolahan*) administered by the Indonesian Central Bureau of Statistics. This census surveys all manufacturing firms employing more than 20 individuals. The data have a panel structure, with each set being indexed by the firm's unique code. Data is available over the course of the years 2000 to 2008. However, the data for the year 2001 is missing location identifiers, and as such cannot be merged in with the rest of the data directly. By constructing a dictionary between firm codes and location codes, it is evident that nearly 9000 firm codes appear to be unique to 2001. This signifies that there was likely a code shift between some of the earlier years, and as such this data could not be used to conduct the analysis. The data for years 2000 and 2001 is thus dropped.

The data for each year contains information on 20,000 to 30,000 firms. Individual year data is combined into a single manufacturing data frame for ease of merging with the deforestation data. Variables of interest include province and regency codes, as well as years, for identification. The data also contains information on the percent of foreign ownership and output in Indonesian rupiahs for each firm.

During the period examined here, Indonesia decentralized rapidly. In fact, the effect of this decentralization is itself the object of study for several papers (Burgess et al, 2012). Following the end of President Suharto's regime in 1998, decentralization laws were put into effect in 2001 (Burgess et al, 2012). During the period from 1998 to 2008, the total number of regencies increased from 292 to 483. If unaccounted for, this decentralization would pose an issue in the analysis conducted. Because some analysis is performed on a regency level, in later years the same geographic areas would be compared as if they were different locations. Fortunately, Samuel Bazzi of Boston University was kind to provide the necessary data in order to construct a dictionary of parent-child regency relationships between 2002 and 2008, using 2002 as the base year. Bazzi (2015) uses a similar parent-child analysis in his paper on the relationship between violent conflict and decentralization in Indonesia. Once the constructed dictionary is applied to the manufacturing data, we can be sure that we are only comparing distinct geographic areas to each other.

The manufacturing survey also reports the percent of capital owned by foreign firms. Based on the definition used in the Arnold and Javorick (2009) paper, we define a new binary variable, $foreign$, such that firms with greater than 20 percent foreign ownership are considered foreign acquisitions, while ones with less than 20 percent are domestic. The exact value of the threshold is not of great significance, as the majority of firms that do not qualify as foreign-owned have no foreign ownership. Arnold and Javorick (2009) find that more than 99% of cases have a foreign capital share of zero before they are acquired. Most firms under foreign ownership have a share of foreign ownership above 25%, and many above 50%. Firms characterized as foreign are found to be generally more productive than domestic ones.

This paper uses the Burgess et. al. (2012) paper for inspiration in measuring deforestation. According to Burgess et. al., rates of illegal logging are estimated to be high, at 60% to 80% of all logging in Indonesia. In 2006, up to 66% of Indonesia's forest sector production (about 60 million cubic meters per year) was based on non-legal sources.

The data used in Burgess et. al. (2012) was initially intended to provide the measure of deforestation. However, this data was discovered to not be usable in the context of this paper because the cell-level data is summed by regency and forest zone. Because this paper does not use forest zones for aggregation, there was no way to merge the deforestation data with the manufacturing data in a way that would yield meaningful interpretations of the coefficients.

Instead, Hansen et. al. (2013) provided the necessary deforestation data. The Global Forest Change data set became freely available in 2014, two years after the publication of the Burgess paper, of which Hansen is also one of the co-authors. Prior to the development of this data set spatially and temporally detailed information on global forest change did not exist, and this was a novel effort to quantify it. For the period from 2000 to 2012, the Hansen et. al. (2013) data set maps global tree cover extent, loss, and gain at a resolution of 30m by 30m, analyzing over 650,000 scenes from Landsat 7 Enhanced Thematic Mapper Plus (ETM+). Trees are defined as all vegetation taller than 5 meters, and forest loss is defined as the stand-replacement disturbance or complete removal of tree cover canopy. In the context of forest sciences, stand-level modeling involves modeling a forest as a collection of "stands". Stands are contiguous communities of trees which are somewhat uniform in characteristics such as composition, structure, age, and condition, among others. Additionally, in ecology, a disturbance can be any event that causes change in the structure and composition of a forest ecosystem. A pixel in the Landsat data is considered deforested when over 25% of the tree cover canopy has been disturbed or completely removed. Although later versions of the data allow for better detection of fires, selective logging, and clearing of short-cycle plantations, this update was not available for the period 2002 - 2008 at the writing of this paper.

According to Hansen et. al. (2013), of all countries globally, Indonesia exhibited the largest increase in forest loss. However, some advise that the data should be used carefully, as Hansen's forest loss estimate for Indonesia from 2009-2012 is triple the Indonesian Ministry of Forestry's national deforestation estimates (Center for International Forestry Research, 2013). Some of this can be attributed to different definitions of forest and deforestation. For instance, the Hansen data considers any conversion of natural forests, such as plantations or selective logging, as forest loss, while the Indonesian Ministry of Forestry considers plantations to be a type of forest (Center for International Forestry Research, 2013). However, since the updated detection of such processes only applies to the later period in the data, it is unclear how this impacts the deforestation estimates for 2000 - 2008. Nevertheless, one must be careful when looking at the magnitude of the coefficients.

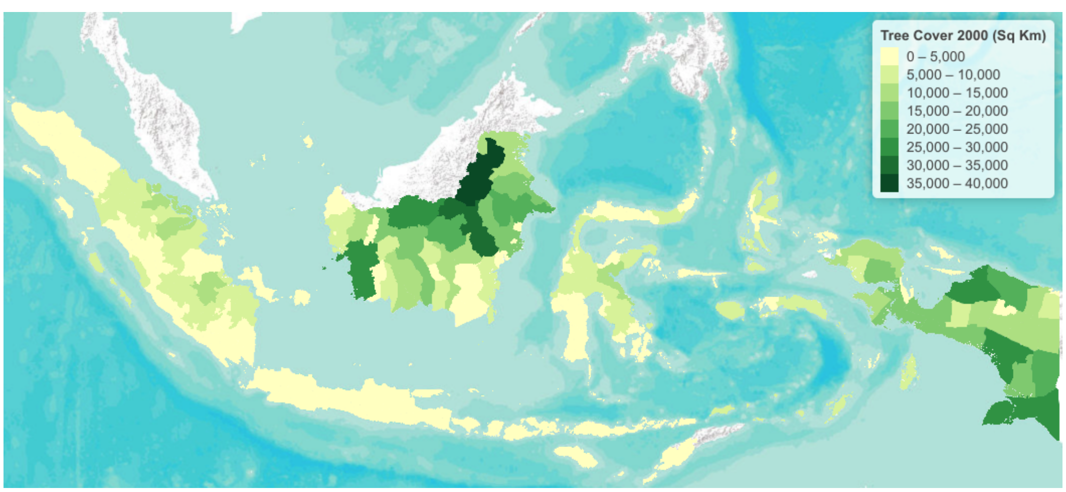

Figure 1: Base Year 2000 Tree Cover (in km^2)

In its original state, the Hansen data set consisted of about 1 Terabyte of data containing tree cover data for the entire planet. Seeing as most of the data was not necessary for the purpose of this paper, it was filtered to only cover Indonesia. Only the information on tree cover in the base year 2000, as well as yearly losses for the years 2001 to 2008, is required. Unfortunately, we cannot measure net loss for each year, as information on forest gain is only available in aggregate form for the entire period. We can, however, compute net loss for each regency for the entire 2000 - 2012 period. The correlation between gross loss over 2000 - 2008 and net loss over 2000 - 2012 comes out to be 0.846. Therefore, we can expect that the results obtained using gross loss will roughly apply to net loss as well.

In order to filter the data for Indonesia, and match data to Indonesian administrative regions, an additional data set was required. This was also necessary in order to conduct the merge with the manufacturing data. Indonesia is currently divided into 34 provinces, and 405 regencies, not including cities, a combination of which forms the primary location identifier used for data analysis in this paper (Kementerian Dalam Negeri - Republik Indonesia). A KML file from a spatial database containing the location of the world's administrative areas was used to add this dimension to the tree cover data. This information came from the Global Administrative Areas project, a collaboration between researchers at University of California, Berkeley and Davis. Once this information was added, the Hansen data was aggregated over the Indonesian regencies. The resulting data set contains tree cover in the year 2000 for each regency, as well as loss for each year. The base year tree cover by regency is mapped above. In **Figure 2**, we reproduce the plot by Leblois et. al. (2017) showing annual deforestation per year.

Three additional data sets are introduced to correct for possible endogeneity between output and deforestation. As mentioned, the Autor et. al. (2013) paper is used as inspiration for the instruments that we construct. We are instrumenting for the change in output in Indonesia resulting from the growth of China's economy by using Malaysian exports to China. Export data from Malaysia to China is acquired from the UN Comtrade Database for the period aligning with the rest of the data, namely 2002 to 2008. The value of trade in U.S. dollars is used to construct the instrumental variable. Data on HS to ISIC industry code concordance is imported

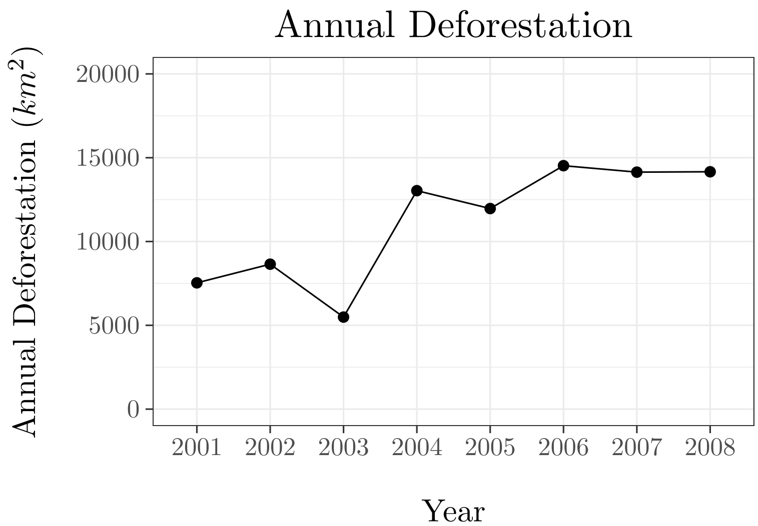

Figure 2: Deforestation in Indonesia from 2001 - 2008

from World Integrated Trade Solution. This is used to match industries in the manufacturing data, which use ISIC Revision 3 Product Code to the HS 1996 Product Codes used in the Comtrade data. Additionally, we use data on cost of distance to port to instrument for foreign output (Kasahara et. al., 2016).

3.1 Variable Descriptions

First, in order to aggregate individual firm output by location, we need to construct unique location codes for each firm. We do this by combining the province and regency codes into a single code, *kabkoda*. This is the same code used in the construction of the deforestation data. Second, in order to obtain the value of foreign output, we look for the firms that have their binary value for $foreign$ set to 1, and save the value of their output in a separate variable. We defined $foreign$ in the data description above. We aggregate all of our variables to be uniquely indexed by the *kabkoda* location code, and $year$.

The dependent variable used in the paper comes from the deforestation data set. We follow the construction of deforestation used in Lebois et. al. (2017), which in turn is based on a number of previous studies. They construct their deforestation indicator ($dfrst_{it}$), by looking at the yearly decrease in forest cover, $Loss_{it}$, divided by country area. Since our study is on a subnational level, we instead divide $Loss_{it}$ by regency $area_i$, measured in square kilometers. The variable $Loss_{it}$ is measured as square kilometers of forest loss for regency i in year t. Our resulting deforestation indicator is the proportion of a regency's total area that is loss in forest. Because this value is quite small, we multiply by 1000 for the purpose of displaying regression coefficients. [1] A positive coefficient on this indicator implies an increase in deforestation, while a negative one implies a decrease.

$$\frac{Loss_{it}}{area_i} \times 1000 \tag{1}$$

The two primary independent variables come from the manufacturing data. These variables are $Output_{it}$ and $ForeignOutput_{it}$, measured as the cumulative value of all income in Indonesian rupiah for regency i in year t.

The distribution of $ln(ForeignOutput)$ across different regencies appears random. There is no discernible pattern, even at the level of islands. Comparing the distribution of concentrations of foreign manufacturing output and deforestation seen in **Figure 3**, there is no strong reason to suspect that foreign firms are concentrated in areas with more tree cover. It should be noted, however, that the distribution of foreign output by tree-intensive industries may be different.

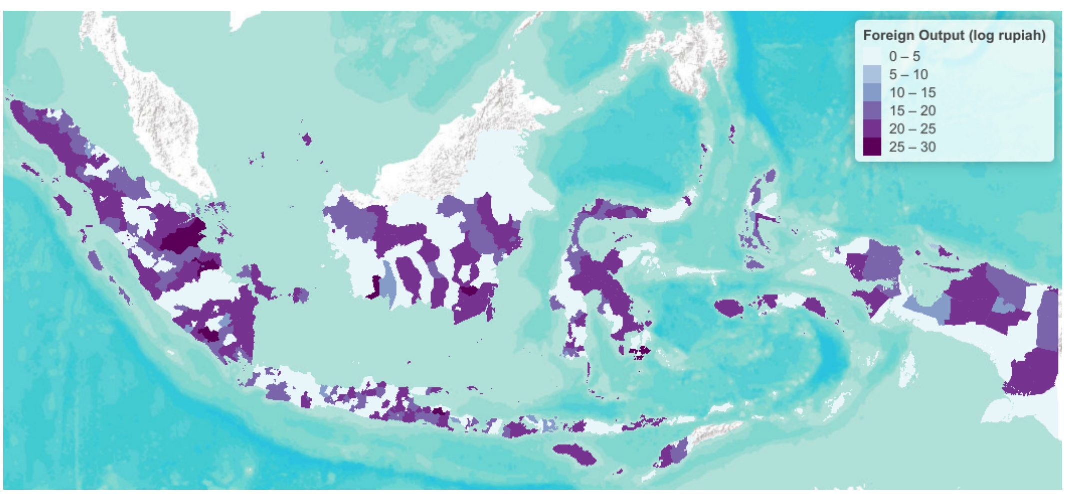

Figure 3: Foreign Output Concentrations

[1] This does not change the interpretation or significance of the coefficients.

We are interested in the percent change in output from year to year, so we take the log of $Output_{it}$ and $ForeignOutput_{it}$. As in the work of Leblois et. al. (2017), we lag $ln(Output)_{it}$ and $ln(ForeignOutput)_{it}$, as they are potentially endogenous to deforestation. The paper mentions the possibility of reverse causality, that is a bias resulting from the effects of the deforestation rate on the drivers of deforestation (Leblois et. al., 2017).

These specifications allow for a straightforward interpretation of coefficients once we run our regressions. Once we multiply $\beta_i X_i$ by $\frac{area_i}{1000}$, the coefficients on $ln(Output)_{it-1}$ and $ln(ForeignOutput)_{it-1}$ signify the mean change in forest loss in km^2 for each percentage change in $ln(Output)_{it-1}$ or $ln(ForeignOutput)_{it-1}$.

Additionally, we include the lag of deforestation, $dfrst_{it-1}$ as an explanatory variable. This is suggested by Leblois et. al. (2017) to check that deforestation is not stationary. Such a specification is also more robust in the context of time series analysis because it should help control for initial conditions across regencies. Because we find that $dfrst_{it-1}$ is highly persistent, it should also capture regency specific differences within a province to some extent.

Table 1: Variable Descriptions

$dfrst_{it}$	Primary dependent variable, proportion of forest lost out of area in regency, $Loss_{it}/\ area_i$
$dfrst_{it-1}$	The lag of loss in forest cover
$Loss_{it}$	Measures loss in forest cover in square kilometers for a given regency and year
$\ln(Output)_{it-1}$	The lag of log of output produced by firms in given regency and year, in Indonesian rupiah
$\ln(ForeignOutput)_{it-1}$	The lag of log of output produced by foreign firms in given regency and year, in Indonesian rupiah

By computing a few basic statistics on the key variables used we can see that the mean of $Loss_{it}$ is not trivial, though much smaller than the overall tree cover in 2000. The average loss of forest cover is a little over 32.36 square kilometers. We present the level values for output and foreign output, $Output_{it}$ and $ForeignOutput_{it}$, rather than $\ln(Output)_{it}$ and $\ln(ForeignOutput)_{it}$. For purposes of display we divide the outputs by 10,000,000.

We can see that most of our variables are quite spread out, with fairly large standard deviations.

Table 2: Descriptive Statistics for Key Variables

	Loss (km^2)	Tree Cover 2000 (km^2)	Foreign Output*	Output*
Mean	32.3642	2783.0986	113.9044	344.6369
Standard Deviation	77.3932	4587.2011	534.4676	997.2506
Minimum	0.0000	0.1306	0.0000	0.0004
Maximum	825.1359	27872.4791	11761.7381	14263.7619
Median	2.5165	691.5362	0.0000	36.8298

Notes: * 10000000s Indonesian rupiah

3.2 Empirical Patterns

We first construct a factor model to better understand deforestation averages across time and location. We regress our dependent variable, $dfrst_{it}$ on time and location fixed effects, Γ_t and Γ_k respectively.

$$dfrst_{it} = \Gamma_t + \Gamma_k + u_{it} \tag{2}$$

In this case, t is the year and k is the province. We use province codes instead of regency codes because there is very little variation from year to year in any given regency. By expanding the analysis to provinces, we compare each regency to itself in different years, but also to other regencies within the same province. The underlying assumption here is that persistent unobserved differences vary across provinces, but not within them.

The resulting coefficients on each year are as follows.

Table 3: Time Trends

Year	2002	2003	2004	2005	2006	2007	2008
Coefficients	1.2336	-0.2115	3.4278	2.8714	3.8348	3.3820	3.3660
Standard Errors	1.7110	1.7107	1.7104	1.7106	1.6821	1.6773	1.6774

Plotting these coefficients over the years of the analysis, we see the following result. We see that after 2003, the coefficients are positive, signifying that deforestation is occurring. The average level of deforestation between 2004 and 2008 seems to be roughly equal, and bigger than in was in 2002 or 2003.

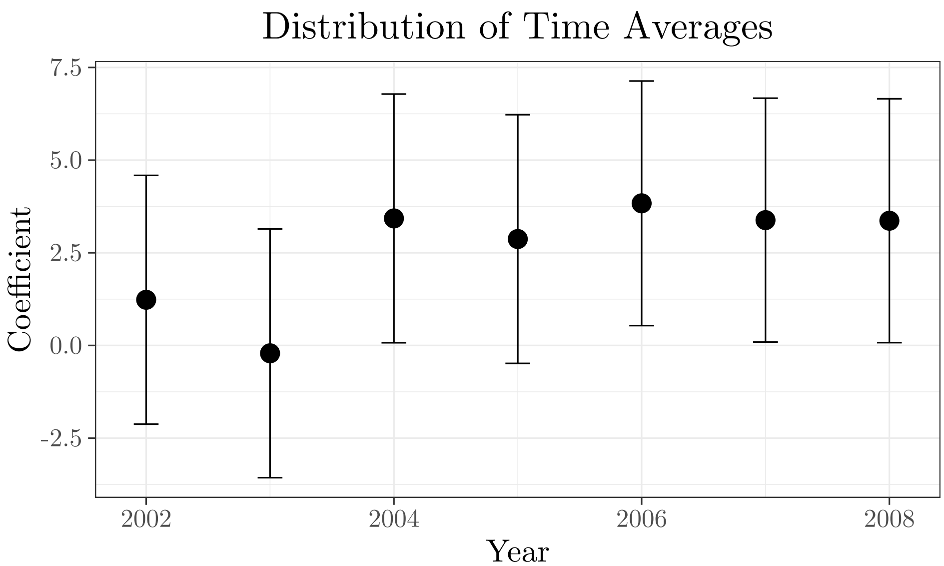

Figure 4: Average Deforestation per Year (with 95% confidence interval)

We additionally plot the coefficients for the location trends in the data, ordered by magnitude of the coefficient. There appears to be a large amount of heterogeneity across provinces.

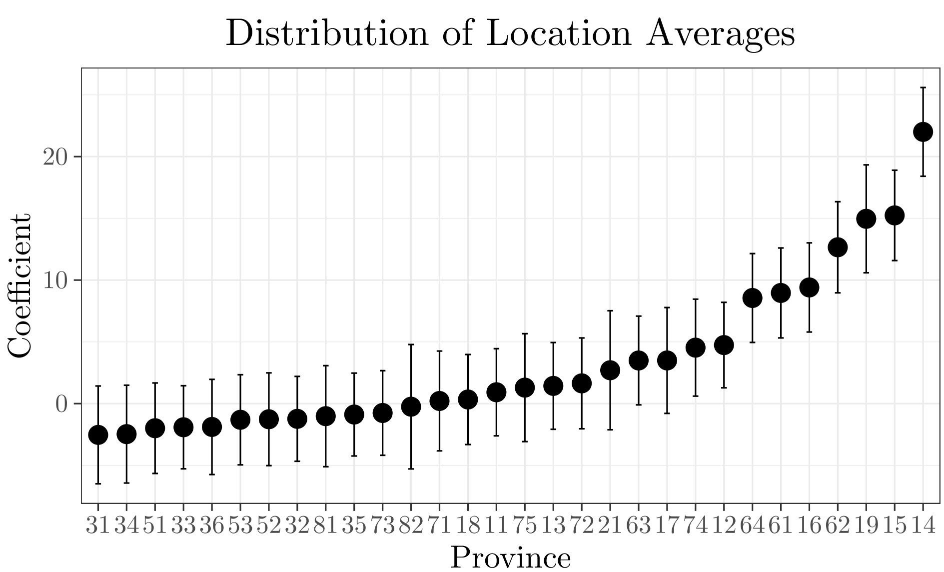

Figure 5: Distribution of Location Averages by Province

Below, the coefficients are mapped over their corresponding provinces. Sumutra and Java seem to be undergoing lower rates of deforestation, while Papau has the highest rates of deforestation.

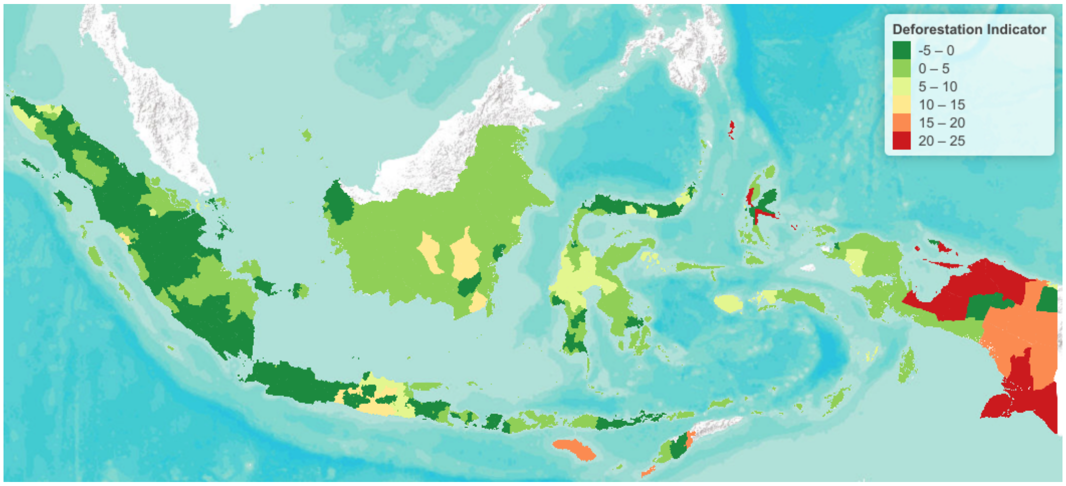

Figure 6: Distribution of Location Averages by Province

4 Empirical Model

We specify an econometric model to determine whether foreign direct investment has an impact on deforestation. In the below model, $dfrst_{it}$ represents the deforestation index constructed in the variable description. As defined earlier, the $\ln(ForeignOutput)_{it-1}$ variable is the log of total output produced by foreign firms in regency i and year t, lagged by one year (Leblois et. al., 2017). Similarly, $\ln(Output)_{it}$ is the log of total output produced by all firms in regency i and year t, also lagged by one year. Additionally, $dfrst_{it-1}$ is the lag of our dependent variable.

$$dfrst_{it} = \beta_0 + \beta_1 ln(Output)_{it-1} + \beta_2 ln(ForeignOutput)_{it-1} + \beta_3 dfrst_{it-1} + u_{it} \tag{3}$$

The first model is a multiple linear regression of deforestation on the lags of output, foreign output, and deforestation.

$$dfrst_{it} = \beta_0 + \beta_1 ln(Output)_{it-1} + \beta_2 ln(ForeignOutput)_{it-1} + \beta_3 dfrst_{it-1} + \Gamma_t + u_{it} \tag{4}$$

The second model introduces time fixed effects, Γ_t. This allows for the removal of trends from the data that are present both in the output variables and deforestation over time. Over the period represented by the data, both deforestation and foreign direct investment increased. Factors such as economic growth could have encouraged foreign firms to enter, but this same growth could also have increased deforestation in Indonesia. Including binary variables for years therefore allows to pull out differential variation over time. In the absence of these binaries, it is possible to mis-attribute deforestation to FDI even if this relationship does not exist.

$$dfrst_{it} = \beta_0 + \beta_1 ln(Output)_{it-1} + \beta_2 ln(ForeignOutput)_{it-1} + \beta_3 dfrst_{it-1} + \Gamma_t + \Gamma_k + u_{it} \quad (5)$$

The third model includes location fixed effects, Γ_k, for province k, in addition to the time fixed effects. Including location dummies allows the effect of foreign direct investment on deforestation to be isolated in the presence of persistent differences across provinces which may be correlated with deforestation and FDI. Without the use of a location fixed effect, such persistent differences would bias our results. It is possible that the province around Jakarta, Indonesia's capital, attracts a large number of foreign firms. It is also likely that deforestation around Jakarta is greater than in more remote regencies. This model therefore allows us to observe whether changes in foreign direct investment in a regency are correlated with changes in deforestation after variation in deforestation within provinces over time has been normalized.

4.1 Regression Results

As formulated in the model, FDI is measured in terms of change in output by foreign firms in a given regency i and year $t-1$. Unlike the output variables, the dependent variable of deforestation is in level form. Based on the earlier specification, we can interpret the effect of $ln(Output)_{it-1}$ and $ln(ForeignOutput)_{it-1}$ on $Loss_{it}$ in the following way: $Loss_{it} = \frac{\beta_i X_i \cdot area_i}{1000}$, where X_i is some independent variable. The result gives us the mean forest loss in km^2. The coefficient on $dfrst_{it-1}$ tells us the change in deforestation dependent on change in deforestation in the previous period.

In the regression equation without fixed effects, we implicitly assume that over the years

2002 to 2008, the number of foreign firms and the revenues generated by them was not driven by unobserved location-specific differences.

We can see that the regressions with and without year fixed effects yield very similar coefficients. All coefficients for the two regressions are statistically significant, and do not change much. This implies that there is not much variation occurring over time.

The positive coefficient on $\ln(Output)_{it-1}$ in the regression without fixed effects implies that a one percent increase in $\ln(Output)_{it-1}$ leads to an increase in the deforestation index by 0.000136 percentage points on average. We can find the range of forest loss for a median regency for a 1% change in output if we let $area_i$ be the median regency area, 1782 km^2. In this case, the average forest loss ranges from around 242,000 to 256,000 m^2 for the first two regressions.

The negative coefficient on foreign output suggests that though output is negatively impacting the environment, the effect of foreign output is somewhat less negative. To find the average forest loss occurring in a median regency due to a 1% change in foreign output, we must consider both the coefficient on output and on foreign output. Since foreign output is a part of output, its effect will be given by the sum of the coefficients. We find that the average forest loss for a 1% change in foreign output ranges from around 168,000 to 173,000 m^2 for the first two regressions. There are a variety of reasons why foreign firms may be causing less deforestation. For instance, in line with Antweiler, Copeland and Taylor (1998), trade may be changing the composition of national output if foreign manufacturing firms are less intensive in their use of trees.

The coefficients change in the final regression. In running this regression, we use province binary variables as the location fixed effects. Though a more dis-aggregated measure of location is available, there is very little variation from year to year in any given regency. We see here that the coefficients on $\ln(Output)_{it-1}$ and $\ln(ForeignOutput)_{it-1}$ are now much smaller, and not statistically significant. A 1% change in output now leads to 56,000 m^2 of forest loss on average. This same amount of change in foreign output implies an average 39,500 m^2 of forest lost. Once we account for variation across locations, we find that neither output nor foreign output have much explanatory power for deforestation. Meanwhile, the coefficient on $dfrst_{it-1}$ has fallen only slightly, and remains significant.

Table 4: OLS Regression Results

Dependent Variable: $dfrst_{it}$		Model	
	(1)	(2)	(3)
$ln(Output)_{it-1}$	.1360*	.1438**	.0314
	(.072)	(.070)	(.079)
$ln(ForeignOutput)_{it-1}$	-.0386*	-.0415**	-.0092
	(.020)	(.020)	(.019)
$dfrst_{it-1}$	.7732***	.7854***	.5660***
	(.017)	(.016)	(.021)
R^2	0.538	0.561	0.619
Year Fixed Effects	No	Yes	Yes
Province Fixed Effects	No	No	Yes
Number of Obs		1893	

Notes: Standard errors in parentheses. $*$, $**$, $***$ indicate statistical significance at the ten, five and one percent level, respectively.

4.2 Industries

A select number of industries were chosen to examine the link between changes in output, foreign output, and deforestation. The models used here are the same as those introduced earlier, with the distinction that the data is filtered to only include industries of interest. This is motivated by the possibility that deforestation in a regency may have more to do with the types of industries located there than with whether or not a firm is foreign-owned. It is also possible that there is correlation between industry and foreign ownership, either due to regulation or simply because foreign firms may prefer to invest in some industries over others.

From the manufacturing industries available in the data, of particular interest are palm oil, paper manufacture, and rubber manufacture. All of these are intensive in their use of trees, and there is evidence suggesting that they contribute to deforestation in Indonesia, as mentioned by Lopez and Galinato (2005). The first industry chosen falls under the ISIC code 1514, representing manufacture of vegetable and animal oils and fats. Although we cannot capture palm oil concessions in the manufacturing data, some production of palm oil is captured in this category. Additionally we look at the manufacture of pulp, paper and paperboard, corrugated paper and paperboard and of containers of paper and paperboard, noted under codes 2101 and 2102 respectively. Finally, codes 2511 and 2519 distinguish the manufacture

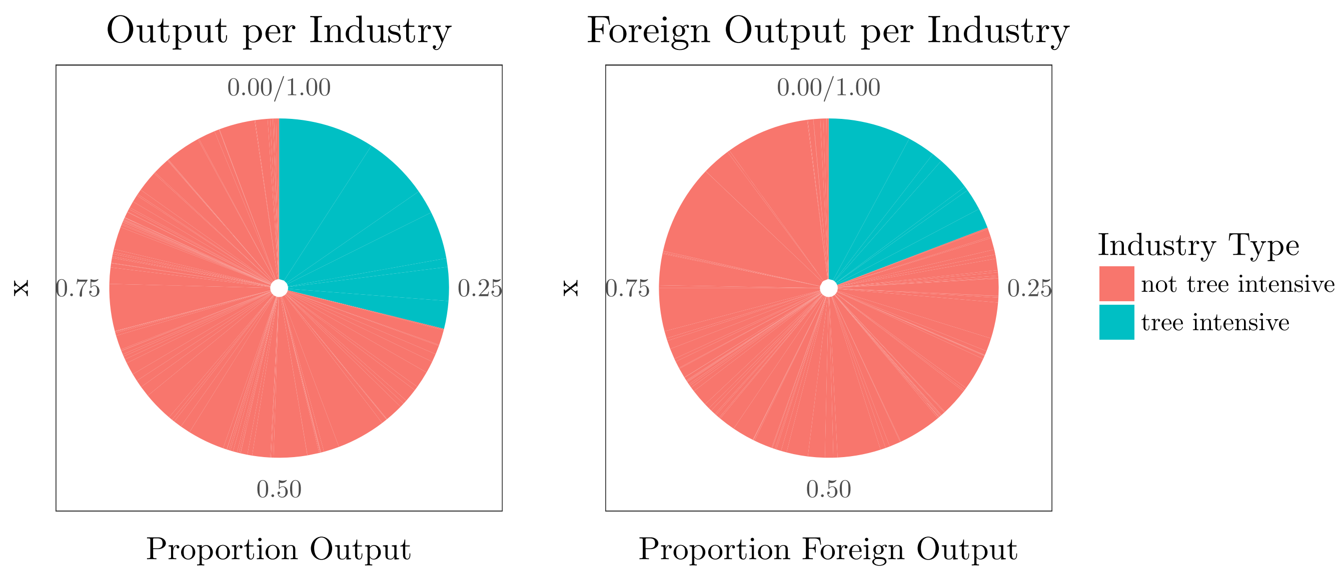

Figure 7: Output and Foreign Output per Industry

of rubber tires and tubes, retreading and rebuilding of rubber tires, and manufacture of other rubber products.

We label the industries specified above as *tree-intensive*, and check what proportion of output can be attributed to such industries. We then compare the proportion of output produced by tree intensive industries by foreign and domestic firms. It appears that a smaller proportion of foreign output is produced by industries that we call tree-intensive. As such, we may expect that foreign output would have less effect on deforestation than overall output due to industry composition.

When looking at industries related to oils and fats manufacturing, including palm oil, the significance on the output and foreign output variables fluctuates. Ultimately it appears that neither output nor foreign output have a significant effect once fixed effects are added. The coefficient on foreign output remains insignificant and close to zero in all three models. Meanwhile, the lag of deforestation is highly significant. We also see that the signs on the coefficients match those of the benchmark OLS regressions fairly closely.

For paper-related industries, we see fluctuation both in statistical significance and the sign of the coefficients. Though it is not significant in the first two regressions, foreign output becomes

Table 5: OLS Oils & Fats

Dependent Variable: $dfrst_{it}$			
		Model	
	(1)	(2)	(3)
$ln(Output)_{it-1}$	0.4439**	.3852**	.0660
	(.195)	(.186)	(.210)
$ln(ForeignOutput)_{it-1}$	-.0026	-.0004	.0164
	(.046)	(.044)	(.050)
$dfrst_{it-1}$	.7718***	.8006***	.6254***
	(.033)	(.032)	(.041)
R^2	0.572	0.619	0.660
Year Fixed Effects	No	Yes	Yes
Province Fixed Effects	No	No	Yes
Number of Obs		500	

Notes: Standard errors in parentheses. $*$, $**$, $***$ indicate statistical significance at the ten, five and one percent level, respectively.

marginally significant and changes sign in the last regression. This implies that there is some positive effect of foreign output on deforestation in paper-related industries. However, output and the lag of deforestation both lose significance. This is more so unusual in the case of lag deforestation, as this coefficient is significant in every other regression.

Table 6: OLS Paper-Related Industries

Dependent Variable: $dfrst_{it}$			
		Model	
	(1)	(2)	(3)
$ln(Output)_{it-1}$	.1405	.1479*	-.0371
	(.089)	(.089)	(.070)
$ln(ForeignOutput)_{it-1}$	0.0104	.0082	-.0404*
	(.030)	(.030)	(.023)
$dfrst_{it-1}$	.8730***	.8737***	.0024
	(.033)	(.034)	(.048)
R^2	0.605	0.609	0.820
Year Fixed Effects	No	Yes	Yes
Province Fixed Effects	No	No	Yes
Number of Obs		493	

Notes: Standard errors in parentheses. $*$, $**$, $***$ indicate statistical significance at the ten, five and one percent level, respectively.

For rubber-related industries, we see that output and foreign output are not significant in any of the regressions. The coefficients on those two variables also have signs that are opposite from the signs in other regressions, in particular the benchmark OLS regression. But since the coefficients are not statistically significant, and are close to zero, we cannot draw any conclusions about the impact that foreign output might have on deforestation.

Table 7: OLS Rubber-Related Industries

Dependent Variable: $dfrst_{it}$			
		Model	
	(1)	(2)	(3)
$ln(Output)_{it-1}$	-.0891	-.0819	-.1171
	(.072)	(.073)	(.076)
$ln(ForeignOutput)_{it-1}$	.0217	.0198	.0215
	(.020)	(.020)	(.020)
$dfrst_{it-1}$	.9395***	.9432***	.8395***
	(.030)	(.030)	(.040)
R^2	0.742	0.745	0.760
Year Fixed Effects	No	Yes	Yes
Province Fixed Effects	No	No	Yes
Number of Obs		352	

Notes: Standard errors in parentheses. $*$, $**$, $***$ indicate statistical significance at the ten, five and one percent level, respectively.

Among the three industries highlighted, rubber-related industries are the only category comprising a large portion of output in general, but not of foreign output. Even though rubber-related industries are dominated by domestic production, we still see no impact of domestic output on deforestation.

4.3 Regression in Changes

We recognize that there may be unobserved differences across regencies correlated with FDI and deforestation. As such, we attempt to control for these persistent differences by considering a regression in differences.

We accomplish this by taking the difference between the following equations,

$$dfrst_{it} = \beta_0 + \beta_1 ln(Output)_{it-1} + \beta_2 ln(ForeignOutput)_{it-1} + \beta_3 dfrst_{it-1} + \Gamma_t + \Gamma_k + u_{it} \quad (6)$$

$$dfrst_{it-1} = \beta_0 + \beta_1 ln(Output)_{it-2} + \beta_2 ln(ForeignOutput)_{it-2} + \beta_3 dfrst_{it-2} + \Gamma_{t-1} + \Gamma_k + u_{it-1} \tag{7}$$

for each province. This results in the following model:

$$\Delta dfrst_{it} = \beta_1 \Delta ln(Output)_{it-1} + \beta_2 \Delta ln(ForeignOutput)_{it-1} + \beta_3 \Delta dfrst_{it-1} + \Delta\Gamma_t + \Delta u_{it} \tag{8}$$

Since the values of $dfrst_{it}$ will be close to zero, the resulting coefficients are expected to be smaller.

Table 8: OLS Fixed Effects

Dependent Variable: $\Delta dfrst_{it}$	
$\Delta ln(Output)_{it-1}$	-.1092
	(.202)
$\Delta ln(ForeignOutput)_{it-1}$	-.0182
	(.029)
$\Delta dfrst_{it-1}$	-.4729***
	(.023)
R^2	0.254
Number of Obs	1540

Notes: Standard errors in parentheses. $*$, $**$, $***$ indicate statistical significance at the ten, five and one percent level, respectively.

The coefficients resulting from running this regression are all negative. The interpretation is that the change in output and foreign output has some positive effect on the change in deforestation, though this is not statistically significant. Here, $\Delta dfrst_{it-1}$ captures regency-specific differences in growth rates. The statistically significant negative coefficient on $\Delta dfrst_{it-1}$ is interesting, as it signifies that growth rate in deforestation is negatively correlated with the past growth rate. If we consider that some regencies have high levels of deforestation, while others have lower levels, then we find that if deforestation grows quickly we expect it to eventually slow down.

In any case, due to the nature of the relationship between output and deforestation, either of the models formulated may run into a problem arising from the endogeneity of the explanatory variables. This results from the likelihood that the relationship between deforestation and output in any given location is jointly determined. In order words, deforestation may be associated with greater output in a region. This increase in output may then drive further deforestation. On the other hand, locations with less deforestation may be less developed. Foreign firms may be less inclined to locate in such areas due to lack of infrastructure. The explanatory variable will be correlated with the error term in the model, leading us to underestimate the effects of output (Faria et. al., 2016). To handle this issue, will will attempt to instrument our explanatory variables.

5 Instrumentation

One way to deal with the possibility of endogeneity mentioned above is to develop a set of instrumental variables, z. Such variables must satisfy two conditions. They should be correlated with the endogenous explanatory variables, x, in this case $\ln(Output)_{it-1}$ and $\ln(ForeignOutput)_{it-1}$, while being uncorrelated with the error term. These conditions can be written as follows:

$$Cov(z, u) = 0 \tag{9}$$

$$Cov(z, x) \neq 0 \tag{10}$$

These variables can be used to extract the variation in the $\ln(Output)_{it-1}$ and $\ln(ForeignOutput)_{it-1}$ variables that is not correlated in any way with deforestation. The exogenous variation of the explanatory variables can then be used in our regression equation to find consistent estimators of β_0, β_1, and β_2.

We would like to isolate the variation in output driven by factors other than the supply of trees. In order to do this, we choose to isolate the part of demand driven by productivity growth in China during this period. So as not to confuse Indonesian output growth due to China's growth as opposed to internal factors, we instead look at Malaysian exports to China. Malaysia is similar to Indonesia in terms of geographic endowment but not subject to the same policy and other determinants of growth.

We construct an instrumental variable for $\ln(Output)_{it-1}$ as follows:

$$tvs_{it} = \sum_{j} s_{ijt=02} \cdot \tilde{z}_{jt} \tag{11}$$

Here, $\tilde{z}_{jt}$ represents Malaysian exports to China of industry j in year t, and $s_{ijt=02}$ is the share of regency i's output in year t. That is, $s_{ijt=02}$ is the output of an industry j in regency i, divided by the total output across all j in regency i. In this way, we use industry shares to connect the value of Malaysian exports to China to the value of Indonesian exports to China. Because our explanatory variable is lagged, we take tvs_{it-1}.

We use the first year of the data, 2002, to compute the share of output produced by each industry in each given regency. For any given regency, the sum of these shares should be 1. We then merge these share values into the data for each regency i and industry code j. Thus we have the break down of output shares of each industry j in regency i in the year 2002. Our instrument should therefore be orthogonal to any FDI that occurs in later periods. Changes in industrial composition that occur after 2002 due to FDI should not affect variation in the instrument.

The next step is to import the UN Comtrade Malaysian export data, and the data set on ISIC Revision 3 to HS 1996 concordance. The concordance data is then used to match the export data to the data containing shares of output by industry. This allows us to construct the trade value share variable, tvs_{it}, by multiplying the trade value in USD by the industry shares. Since our explanatory variables $\ln(Output)_{it-1}$ and $\ln(ForeignOutput)_{it-1}$ are lagged, we use the lag of trade value share, tvs_{it-1}, as the instrumental variable for output in the regression.

In order to find the variation in foreign output exogenous to variation in forest loss, we initially attempted to construct a variable containing the portion of trade value share determined by foreign-owned plants. However, this was too highly correlated with trade value share, and led to concerns that coefficient estimates may be inaccurate. Instead, we use the cost of shipping goods to the nearest port, $cdistport_i$ in each regency. Essentially, if it is more costly to get to a port, we expect there to be less foreign output in that regency. We claim that the cost of distance to a port in two neighboring regencies in the same province will be orthogonal to deforestation. The exogeneity assumption need not hold when comparing different provinces. Additionally, because the distance to a port does not vary over time, this variable cannot account for the time variation in foreign output.

Once we obtain these variables, we can run the first part of the two stage least squares regression. This involves regressing the endogenous variables on their respective instrumental variables. Because the F-statistic for both of these regressions is high, we satisfy the condition that $Cov(z, x) \neq 0$.

Table 9: First-Stage F-Statistics

	Model		
	(1)	(2)	(3)
$ln(Output)_{it-1}$	99.12	37.66	30.78
$ln(ForeignOutput)_{it-1}$	38.99	14.92	21.13
Year Fixed Effects	No	Yes	Yes
Province Fixed Effects	No	No	Yes
Number of Obs		1564	

One method of proceeding involves retrieving the fitted values from each of these regressions to obtain measures of output and foreign output that are now exogenous to $dfrst_{it}$. This would, however, result in an inaccurate measure of standard errors. Instead, we compute heteroskedasticity robust standard errors to account for the first stage error in the second stage least squares methodology.

Additionally, we check the validity of our use of two stage least square regression by running the Wu-Hausman test for endogeneity. This test compares the OLS estimate of the parameters with the two stage least squares estimate. The resulting p-value is very small, allowing us to reject the null hypothesis that the OLS and two stage least squares estimates are equally consistent. Although this would appear to support our use of the instrumental variable regression, it should be noted that the Wu-Hausman test depends on the assumption that the instrumental variables used are valid (Guo et. al., 2016). We should therefore treat this result with caution.

Table 10: Two Stage Least Squares

Dependent Variable: $dfrst_{it}$			
		Model	
	(1)	(2)	(3)
$\ln(Output)_{it-1}$	-0.07291**	-0.074366**	-0.01989
	(0.02685)	(.027951)	(0.02123)
$\ln(ForeignOutput)_{it-1}$	0.22673*	0.231545*	0.03983
	(0.08827)	(.09197)	(0.05379)
$dfrst_{it-1}$	0.72535***	0.738759***	0.53536***
	(0.04793)	(0.049175)	(0.02548)
Year Fixed Effects	No	Yes	Yes
Province Fixed Effects	No	No	Yes
Number of Obs		1564	

Notes: Standard errors in parentheses. $*$, $**$, $***$ indicate statistical significance at the ten, five and one percent level, respectively.

The two stage least squares coefficient estimates for $\ln(Output)_{it-1}$ and $\ln(ForeignOutput)_{it-1}$ are significant for the first two regressions. They also have signs opposite of the OLS estimate coefficients. One possible explanation for this could be that there is some mechanism whereby domestic firms internalize deforestation costs better than foreign firms. It is also important to note that agricultural production and agricultural trade have already been identified as primary drivers of deforestation (Leblois, 2017). Therefore, the negative coefficient on $\ln(Output)_{it-1}$ could be indicative of manufacturing growth in Indonesia taking the labor force out of non-manufacturing, and more specifically, agricultural industries. This in turn would contribute to the reduction of deforestation. Assuming that a shift to manufacturing is correlated with income growth in Indonesia, such an effect falls in line with the Environmental Kuznetz Curve (EKC) hypothesis. The EKC suggests an improvement in the environment as the economy moves from manufacturing to service sectors. In this case, it would instead be a decrease in deforestation due to shifts from agricultural to manufacturing sectors.

When we add the coefficients for output and foreign output, we find that the overall effect of foreign output seems to be positive. This implies that foreign firms, unlike domestic ones, drive deforestation. We could perhaps explain this by considering the findings of Arnold and Javorick (2009). Their results suggest that the foreign manufacturing firms considered in a similar set of data experience higher productivity than domestic firms. It is not implausible that the higher productivity by foreign firms leads them to be more deforesting.

6 Conclusions

Following a number of papers interested in the determinants of deforestation, we explore whether foreign direct investment in Indonesian manufacturing industries is a driver of deforestation. We do so with the help of the Global Forest Change data set compiled by Hansen et. al. (2013), which is the most accurate deforestation data set to date. We also make use of micro data from the Indonesian Census of Manufacturing. Our definitions of foreign firms and deforestation follow from previous literature that works with these same data sets.

We specify a model controlling for lagged output, lagged foreign output, and the lag of deforestation. Fixed effects for time and location are included in the model to normalize variation in deforestation across years and provinces. The OLS results show no significant effects for foreign output or output once both fixed effects are included in the model. It is important to note that the role of foreign firms implied by the OLS regression may be inaccurate due to the broader impacts that increases in manufacturing may have on the structure of the Indonesian economy. We also attempt to see whether trying to discern these effects within tree-intensive industries shows stronger results. This is not the case.

Due to endogeneity concerns, we construct instrumental variables for output and foreign output and run a two stage least squares regression. Though diagnostic tests show that our instruments appear to be strong, and that there is endogeneity in the the OLS model, it is likely that our instruments could be improved. The results of the instrumental variable regression imply that output has some negative impact on deforestation. This could be true if growth in manufacturing output has broader impacts on the Indonesian economy, such as taking the labor force out of agricultural industries. Since agriculture has been established as a driver of deforestation, this effect would work to decrease deforestation. In this context, foreign firms are worse for the environment than are domestic firms.

In conclusion, the results obtained in this paper do not provide the evidence to determine that foreign direct investment in Indonesian manufacturing is a significant driver of deforestation. The impact of foreign direct investment in manufacturing is likely small compared to primary drivers, such as agriculture. Additionally, it is still possible that we did not account completely for endogeneity, and as such the effect of FDI that we discern is not the true effect. Further research must be done to determine whether or not this is the case.

6.1 Further Research

It would be worth re-aggregating the Global Forest Change data set once it is updated for the 2000 - 2011 period. Currently, the data following 2011 is better at identifying deforestation occurring due to selective cutting, fire, and short cycle plantation. However, this is not yet available for the period of this study. As such, likely not all deforestation captured is the type of deforestation we are interested in examining.

Further, one of the primary areas in which the analysis could be improved is by finding better instruments for output and foreign output. For instance, it may be better to find a variable that varies across time, unlike the $cdistport_i$ variable.

Additionally, we could try to test for endogenity using a novel endogeneity test developed by Guo et. al. (2016). As mentioned above, one of the problems with using the Wu-Hausman test is that it assumes that our instruments are valid, which is not necessarily the case. Guo et. al. claim that their endogeniety test, two-stage hard thresholding (TSHT), is robust to invalid instruments, among other cases.

Finally, it would be interesting to extend the years of the study to match the available deforestation data. This may be possible by requesting additional Manufacturing Survey data from the Indonesian Statistical Bureau.

References

[1] Ambec, S. & Barla, P, 2002. "A theoretical foundation of the Porter hypothesis". Economic Letters, 75, 355-360.

[2] Angelsen, A. & Kaimowitz, D., 1999. "Rethinking the causes of deforestation : lessons from economic models (English)". The World Bank research observer. – Vol. 14, no. 1 (February 1999), pp. 73-98.

[3] Antweiler, W. & Copeland, B.R. & Taylor, M.S., 2001. "Is Free Trade Good for the Environment?". American Economic Review, 91(4), 877-908.

[4] Arnold, J. & Javorcik, B., 2009. "Gifted kids or pushy parents? Foreign direct investment and plant productivity in Indonesia". Journal of International Economics, 79, issue 1, 42-53.

[5] Autor, D. H. & Dorn, D. & Hanson, G., 2013. "The China Syndrome: Local Labor Market Effects of Import Competition in the United States". American Economic Review, 103(6): 2121-68.

[6] Bazzi, S. & Gudgeon, M., 2015. "Local Government Proliferation, Diversity, and Conict". HiCN Working Papers 205, Households in Conflict Network.

[7] Burgess, R. & Hansen, M. & Olken, B. & Potapov, P. & Sieber, S., 2012. "The Political Economy of Deforestation in the Tropics". The Quarterly Journal of Economics, 1707-754.

[8] Center for International Forestry Research, 2013. "Use Hansen High-Res Forest Cover Maps Wisely, Experts Say". CIFOR Forests News.

[9] Copeland, B.R. & Taylor, M.S., 1995. "Trade and Transboundary Pollution". American Economic Review, 85(4): 716-737.

[10] Ederington, J. & Levinson, A. & Minier, J., 2005. "Footloose and Pollution Free". Review of Economics and Statistics, 87, 92-99.

[11] Faria, W. R. & Almeida, A. N., 2016. "Relationship between openness to trade and deforestation: Empirical evidence from the Brazilian Amazon," Ecological Economics, Elsevier, vol. 121(C), pages 85-97.

[12] Frankel J., 2009. "Environmental Effects of International Trade, in Swedish Globalization Council". Stockholm, Sweden.

[13] Guo, Z. & Kang, H. & Cai, T. & Small, D., 2016. "Testing Endogeneity with Possibly Invalid Instruments and High Dimensional Covariates."

[14] Hansen, M. C. & Potapov, P. V. & Moore, R. & Hancher, M. & Turubanova, S. A. & Tyukavina, A. & Thau, D. & Stehman, S. V. & Goetz, S. J. & Loveland, T. R. & Kommareddy, A. & Egorov, A. & Chini, L. & Justice, C. O. & Townshend, J. R. G., 2013. "High-Resolution Global Maps of 21st-Century Forest Cover Change". American Association for the Advancement of Science, 342, 850-853.

[15] "Indonesia: Administrative Divisions". Permanent Committee on Geographical Names.

[16] Kasahara, H. & Y. Liang & J. Rodrigue. "Does Importing Intermediates Increase the Demand for Skilled Workers? Plant-Level Evidence, Journal of International Economics, 102, 2016, 242-261.

[17] Kode Dan Data Wilayah Administrasi Pemerintahan. Kementerian Dalam Negeri - Republik Indonesia.

[18] Leblois, A. & Damette, O. & Wolfersberger, J., 2017. "What has Driven Deforestation in Developing Countries Since the 2000s? Evidence from New Remote-Sensing Data," World Development, Elsevier, vol. 92(C), pages 82-102.

[19] Levinson, A., Taylor, M.S., 2008. "Unmasking the Pollution Haven Effect". International Economic Review, 49(1), 223-254.

[20] Lopez, R., Galinato, G.I., 2005. "Trade Policies, Economic Growth and the Direct Causes of Deforestation". Land Economics, 81(2), 145-169.

[21] Margono, B. A. & Potapov, P. V. & Turubanova, S. & Stolle, F. & Hansen, M. C, 2014. Primary Forest Cover Loss in Indonesia over 2000-2012, Nature Climate Change, 4.8, 730-35.

[22] The World Factbook: INDONESIA. Central Intelligence Agency, 2017.