Indonesia's Moratorium on Palm Oil Expansion from Natural Forests: Economy-Wide Impacts and the Role of International Transfers

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Indonesia has introduced a moratorium on the conversion of natural forests to land used for palm oil production. Using a dynamic, bottom-up, interregional computable general equilibrium model of the Indonesian economy, we assess several scenarios of the moratorium and discuss its impacts on the domestic economy as well as on regional economies within Indonesia. We find the moratorium reduces Indonesian economic growth and other macroeconomic indicators, but international transfers can more than compensate the welfare losses. The impacts also vary across regions. Sumatra, which is highly dependent on palm oil and is home to forests that no longer have a high carbon stock, receives fewer transfers and suffers the greatest economic loss. Kalimantan, which is relatively less dependent on palm oil and has forests with a relatively high carbon stock, receives more transfers and gets greater benefit. This implies that additional policy measures anticipating the unbalanced impacts of the moratorium are required if the trade-off between conservation and reducing interregional economic disparity is to be reconciled.

Keywords: carbon emissions, computable general equilibrium, Indonesia, palm oil
JEL codes: R10, R11, R13

I. Introduction

The United Nations Reduction of Emissions from Deforestation and Forest Degradation (REDD) program seeks to reduce carbon emissions resulting from deforestation and enhance carbon stocks in forests, while also contributing to national sustainable development (UN-REDD 2015). REDD supports developing countries in their efforts to mitigate climate change through the implementation of several activities. For example, financial mechanisms have been implemented

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to reduce deforestation and, therefore, carbon dioxide (CO_2) emissions by compensating countries and land owners for actions taken that prevent forest loss or degradation.

Deforestation and forest degradation have been estimated to contribute about 20% of global CO_2 emissions (Van der Werf et al. 2009). The main reason for deforestation is the conversion of forest to agricultural land for commercial and subsistence farming. Hosonuma et al. (2012) find that agricultural production contributes about 80% of deforestation worldwide, followed by mining and urban expansion. In Latin America, the main cause for deforestation is the expansion of cropland and pasture. From 2001 to 2013, it is estimated that 17% of new cropland and 57% of new pasture area was created by converting forest area (Graesser et al. 2015, De Sy et al. 2015). In sub-Saharan Africa, deforestation is mainly driven by the high demand for crop commodities such as cocoa and palm oil (Ordway, Asner, and Lambin 2017). Other determinants of the rates of deforestation in sub-Saharan Africa include population growth and the discovery of extractive resources such as oil and gas (Rudel 2013). In Southeast Asia, deforestation is driven by growth in the consumption of vegetable oil, such as palm oil, which is used in food and biodiesel. Within Southeast Asia, Indonesia contributes significantly to CO_2 emissions. Over the period 1990–2010, the forest cover in the peatlands of Peninsular Malaysia, Sumatra, and Borneo fell from 77% to 36%. Sumatra now only has 28% of its historical forested peatlands left after years of deforestation (Miettinen, Shi, and Liew 2012).

Several studies have been conducted to evaluate the economic viability of an incentive payment to reduce deforestation and CO_2 emissions. The viability and effectiveness of incentive payments depends on the profitability of alternative land uses (Butler, Koh, and Ghazoul 2009) and the price of CO_2 per ton (Sandker et al. 2010). For example, Sandker et al. (2010) developed a systems dynamics model for a cocoa agroforest landscape in southwestern Ghana to explore whether REDD payments are likely to promote forest conservation and what the economic implications would be. They find that in the short term, REDD payments are likely to be preferred by farmers, especially if there is a large annual up-front payment and when the policy only focuses on payments that end deforestation of old-growth forests. However, soon after the up-front payment, there may be an incentive to break the contract due to the higher rental returns from cocoa production. REDD payments may not be effective in avoiding deforestation of degraded forests since this is the type of land required for the expansion of cocoa production. If cocoa prices increase, the carbon prices should be even more than \$55 per ton of CO_2 to stop deforestation of old-growth forests (Sandker et al. 2010). Butler, Koh, and Ghazoul (2009) model and compare the profitability of converting forest to oil palm against conserving forests for a payment. They find that converting a hectare of forest to palm oil production is more profitable to land owners than preserving it for carbon credits. They suggest that giving REDD credits price parity with traded carbon credits would boost the profitability of avoiding deforestation (Butler, Koh, and Ghazoul 2009). Bellassen and Gitz (2008) calculate the breakeven price of carbon, which yields comparable revenue for preserving forests or shifting cultivation in Cameroon. They calculate that a breakeven price of \$2.85 per ton of CO_2 would generate similar revenue values. They suggest that at current CO_2 prices it could be more profitable to preserve the primary forest rather than converting it to crops (Bellassen and Gitz 2008). In general, it seems difficult to provide a framework for REDD, which is based on long-term contracts, given the fluctuation in agricultural commodity prices in the short term.

In this paper, we develop and apply a regional dynamic computable general equilibrium (CGE) model for Indonesia to investigate two scenarios regarding the moratorium placed on the conversion of managed and natural forest to oil palm plantations. In the first scenario, we model the moratorium in the absence of a once-off REDD payment. In the second scenario, we model the moratorium on land conversion and the role of a once-off REDD payment, while assuming a price of \$10 per ton of CO_2 emissions.

The rest of this paper is structured as follows. Section II provides a background on the palm oil sector in Indonesia. This section discusses both the general development of the sector as well as how it relates to Indonesia's carbon emissions. The methodology used in this paper is discussed in section III, which mainly describes the CGE model used in the analysis. The data used for the model are described separately in section IV, while section V provides a detailed description of the construction of scenarios simulated using the model. Section VI discusses the results of the simulations and section VII concludes.

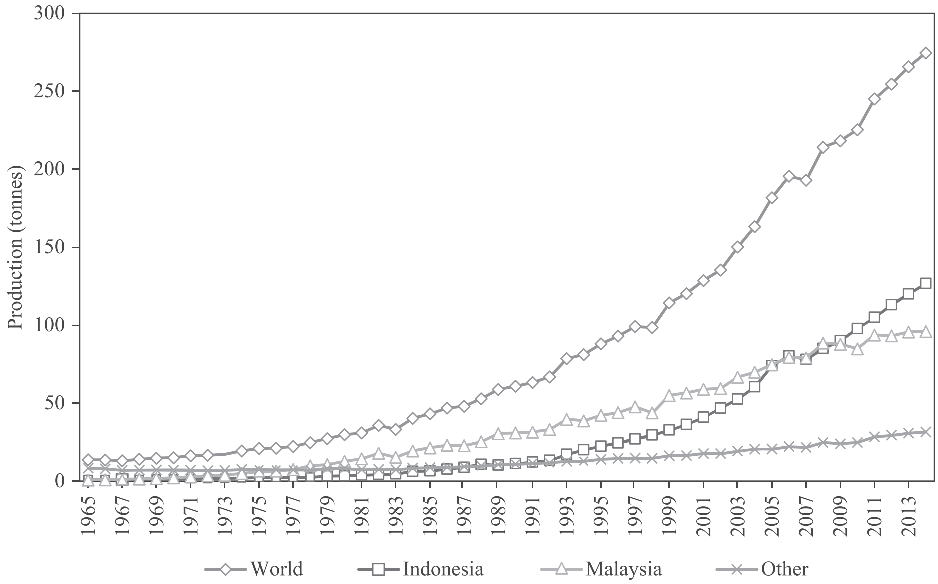
II. Palm Oil Sector in Indonesia

Indonesian economic growth has been highly dependent on its resource-based sectors.[1] In recent years, the palm oil sector has become one of the country's leading economic sectors and an important export-oriented industry. Palm oil is extracted from the bunches of plum-sized fruit borne by oil palm trees, which grow mostly in Malaysia and Indonesia.[2] Output has grown rapidly since the 1960s and it is now the world's highest-volume vegetable oil. It can be used for food, fuel, and other industrial purposes.

[1]Indonesia has significant natural resource reserves. It is a leading exporter of steam coal, tin, nickel, gold, bauxite, lead, copper, and zinc. In recent years, over 40% of Indonesian exports were mineral and petroleum products. Globally, Indonesia is also the largest palm oil producer and exporter, and the second-largest exporter of rubber, robusta coffee, and fish products (Dutu 2015).

[2]See Malaysian Palm Oil Board. Malaysian Palm Oil Industry. http://www.palmoilworld.org/about_malaysian-industry.html.

Figure 1. **Global Production of Palm Oil, 1965–2014**



Source: Food and Agriculture Organization of the United Nations (FAO). 2017. FAOSTAT Online Statistical Service. http://www.fao.org/faostat/en/#home (accessed July 15, 2015).

A. Development of the Palm Oil Sector in Indonesia

The development of the Indonesian palm oil sector dates to the early 1960s when 70,000 hectares were developed for harvesting. With an average productivity of 13.4 tons per hectare, Indonesia was able to produce approximately 936,000 tons of palm oil (Food and Agriculture Organization [FAO] 2017). Rapid developments in this sector occurred in 1980, when the government changed the plantation scheme. Before 1980, only the state-owned plantation company could operate. After 1980, however, both private plantations and smallholder plantations could also operate.

The immediate impact of this policy was an increase in plantation area to 204,000 hectares, with a production of 3.4 million tons, in 1980. In 2014, Indonesia was the world's largest producer of palm oil with a production capacity of 126.7 million tons on 7.4 million hectares of cultivated land (FAO 2017). Figure 1 shows global production of palm oil, which is dominated by Indonesia and Malaysia. Other producers include Cameroon, Colombia, Ghana, Nigeria, and Thailand, which collectively account for less than 15% of global production.

The increase in Indonesia's production of palm oil has partly been driven by transforming natural forests into plantation land. While FAO data show an increase in the area harvested from 204,000 hectares in 1980 to 7.4 million hectares in 2014, there was hardly any change in productivity during this period. The productivity from oil palm plantation in Indonesia increased from 11.1 tons per hectare in 1965 to an average of 17 tons per hectare in 2014. Over the last 2 decades, there has been little productivity improvement in Indonesia.

In contrast, Malaysia has a well-developed palm oil sector. Not only has Malaysia increased its production area, it also focused on increasing productivity. A contributing factor to Indonesia's low productivity is the involvement of small-scale palm oil producers. In 2010, 42% of total oil palm plantation holders were small-scale producers (Burke and Resosudarmo 2012). On one hand, the small-scale producers increase community involvement and provide economic benefits to rural communities, especially those in Sumatra and Kalimantan (Burke and Resosudarmo 2012). However, small-scale plantation owners typically have below-average levels of productivity (Burke and Resosudarmo 2012, Rudel et al. 2009).

Palm oil production is an important driver of Indonesian growth. Indonesia is also the world's largest exporter of palm oil (Burke and Resosudarmo 2012). In 2013, exports of Indonesian palm oil products reached 20.5 million tons and were valued at about $17 billion (FAO 2017).

Palm oil production in Indonesia is mainly located on the islands of Sumatra and Kalimantan. In 2012, Sumatra contributed approximately 73% to the national production of palm oil. Within Sumatra, Riau is the province with the greatest planted area and highest level of production. This province has 1.9 million hectares of palm plantations and produces 5.8 million tons of palm oil. Kalimantan (Borneo) contributes approximately 23% to the country's total palm oil production. Most recently, the government has also promoted palm oil production in the eastern part of Indonesia. Over the last 5 years, the area under cultivation in Central Sulawesi and Southeast Sulawesi increased annually by 17.8% and 15.4%, respectively.

B. Indonesia's Palm Oil Sector and Carbon Emissions

Indonesia contributes significantly to deforestation in Southeast Asia via the conversion of peat swamp forests for commercial use. Over the period 1990–2010, the proportion of forest cover in the peatlands of Malaysia and Indonesia (Sumatra and Borneo) fell from 77% to 36% (Miettinen, Shi, and Liew 2012). Miettinen et al. (2012) suggest that if current levels of peatland deforestation continue, then Southeast Asian peat swamp forests will disappear by 2030. This conversion has serious consequences for the environment by releasing greenhouse gases and damaging forest ecosystems and the communities that rely on forests for survival (Miettinen et al. 2012, Burke and Resosudarmo 2012, Carlson et al. 2013, Rudel et al. 2009).

Focusing on Indonesia, Miettinen et al. (2013) use historic analysis to show that 70% of all industrial plantations have been established since 2000, while only

4% of the current plantation area existed in 1990. They estimate that if future conversion rates are similar to historic conversion rates, 6–9 million hectares of peatland in insular Southeast Asia could be converted into plantations by 2020, leading to increased annual CO_2 emissions of 380–920 million tons by the same year. Miettinen et al. (2013) present a time series of peatland conversion and degradation in the Air Hitam Laut peatland in Jambi Province located in Sumatra. They use high-resolution satellite imagery to map land cover and degradation status between 1970 and 2009. They find that forest cover declined from 90% to 43% in the study area during the review period. Within the Berbak National Park, forest area fell from 95% to 73%; outside the national park, it fell from 86% to 25%. They also find that large-scale oil palm plantations and smallholder producers accounted for 21% and 8%, respectively, of the conversion (Miettinen et al. 2013).

Abood et al. (2015) compare the magnitude of forest and carbon loss, and forest and carbon stocks remaining, in four key industries: palm oil, logging, fiber, and coal mining. They find that the four industries accounted for 44.7% of forest loss in Kalimantan, Sumatra, Papua, Sulawesi, and Moluccas between 2000 and 2010. They rank third in the palm oil industry in terms of deforestation and second in terms of CO_2 emissions.

A recent study by Carlson et al. (2013) found that net cumulative greenhouse gas emissions from oil palm plantations in 2010–2020 are projected to reach 1.52 gigatons of CO_2. They also projected that during the same period, the carbon emissions from oil palm plantations in Kalimantan would rise by 284% and contribute 27% of Indonesia's projected land-based emissions in 2020. This undermines the government's efforts to reduce greenhouse gas emissions by 26% relative to the business-as-usual scenario by 2020. Considering the entirety of Indonesia's plantation area, the emissions from palm oil alone will prevent the country from reaching its 2020 target.

III. Modeling the Moratorium on Land Conversion in Return for a Payment

Capturing the regional impact of a moratorium on land conversion in return for a payment requires a detailed regional multisector model of Indonesia that accounts for changes in land availability and CO_2 emissions.[3] For this paper, we use INDOTERM, a multiregional, recursive dynamic general equilibrium model based on the well-known TERM model developed by Horridge (2012). This section provides a more detailed description of the INDOTERM model and the modeling of the land supply used in palm oil production.

[3]A more comprehensive discussion on the model's description can be read in the earlier and longer version of this paper in Yusuf, Roos, and Horridge (2017).

While the complete model is too large to describe in this paper, a comprehensive description is contained in Horridge (2012) and Horridge, Madden, and Wittwer (2005). The TERM model was created for Australia (Horridge, Madden, and Wittwer 2005; Wittwer 2012) and adopted for South Africa (Stofberg and Van Heerden 2016); Poland (Zawalinska, Giesecke, and Horridge 2013); Brazil (Ferreira Filho, dos Santos, and do Prado Lima 2010); the People's Republic of China (Horridge and Wittwer 2008); and Indonesia (Pambudi and Smyth 2008; Pambudi, McCaughey, and Smyth 2009; Pambudi 2005). As the theory of the TERM model and data structures are well documented, in this paper we provide an overview only.

INDOTERM consists of two interdependent modules. The first module describes the core model equations related to the region-specific behavior of producers, investors, households, governments, and exporters at a regional level. It also describes the dynamic mechanism in the model: capital accumulation and labor market adjustment. The second module describes the treatment of land-use change, emissions, and REDD payments.

The core model equations describe the behavior of producers, investors, households, governments, and exporters at a regional level. Producers in each region are assumed to minimize production costs subject to a nested constant returns to scale production technology. In this nested structure, each regional industry's inputs of primary factors are modeled as a constant elasticity of substitution (CES) aggregate of labor, capital, and land inputs. Commodity-specific intermediate inputs to each regional industry are modeled as CES composites of foreign and domestic varieties of the commodity. Labor inputs used by each regional industry are distinguished by occupation, with substitution possibilities over occupation-specific labor described via CES functions specific to each regional industry. In each region, the representative households are assumed to choose composite commodities to maximize a Klein–Rubin utility function. Households and firms consume composite commodities that are assumed to be CES aggregations of domestic and imported varieties of each commodity. The allocation of investment across regional industries is guided by relative rates of return on capital. For each region-specific industry, new units of physical capital are constructed from domestic and imported composite commodities in a cost-minimizing fashion, subject to constant returns to scale production technologies. Region-specific export demand for each commodity is modeled via constant elasticity demand schedules that link export volumes from each region to region-specific foreign currency export prices. Regional demand for commodities for public consumption purposes is modeled exogenously or linked to regional private consumption. For a detailed description of the input–output structure, see Horridge (2012).

As mentioned above, the core section includes equations determining the demand for factor inputs by industry. Typically, we model the demand for primary factors via the following optimization problem:

Each industry in all regions chooses $XPRIM_{(i,d)}$ to minimize total primary cost $\sum_i XPRIM_{(i,d)} * PPRIM_{(i,d)}$,[4] subject to

$$XPRIM_{(i,d)} = CES(LAB_{(i,d)}, CAP_{(i,d)}, LND_{(i,d)}) \tag{1}$$

where *LAB*, *CAP*, and *LND* are the overall labor, capital, and land demand, respectively. *PPRIM* and *XPRIM* are the primary factor price and quantity, respectively, in industry *i*. The percentage change form of the optimization problem yields the following demand equation for land:

$$xlnd_{(i,d)} = xprim_{(i,d)} - \sigma[plnd_{(i,d)} - pprim_{(i,d)}] \tag{2}$$

Equation (2) implies that in the absence of any price changes the demand for land moves in proportion to the overall demand for primary factors. The second term on the right-hand side shows the price-induced substitution effect between the primary factors. An increase in the price of land relative to the cost-weighted average of all three factors leads to substitution away from land in favor of the others. The magnitude of the change depends on the elasticity of substitution. It is common in CGE models to assume that the total quantity of land available for agricultural purposes are fixed.

The core model includes two dynamic mechanisms: capital accumulation and labor market adjustment. In each region, industry-specific capital is linked to industry-specific investment. Industry-specific investments are linked to changes in industry-specific rates of return. The labor market mechanism guides the labor market from a short-run environment (sticky real wages, flexible labor) to a long-run environment (flexible wage, fixed employment). Therefore, in the short run, positive (negative) outcomes are reflected in positive (negative) changes in employment (with no change in real wage), and in the long run are reflected as positive (negative) changes in real wage (with employment unchanged).

The second module describes the treatment of land-use change, emissions, and REDD payment. INDOTERM identifies five types of land use: crops, estate crops, oil palm plantation, managed forest, and natural forest. Below we specify a set of core equations that allow for the conversion of land use, emissions, and REDD payment. Specifically, we model (i) the conversion of natural forest to oil palm plantation; and (ii) the REDD payment, which is a once-off payment for the promise of not converting natural forest to oil palm plantations.

[4]In the INDOTERM database, Indonesia can be disaggregated regionally into 33 provinces. However, in this simulation we aggregate the provinces into 12 regions: West Sumatra (Aceh, Sumatra Utara, Sumatra Barat); East Sumatra (Riau, Kepulauan Riau, Jambi, Sumatra Selatan, Kep. Bangka Belitung, Bengkulu, Lampung); Northwest Java (DKI Jakarta, Jawa Barat, Banten); East Java (Jawa Tengah, DI Yogyakarta, Jawa Timur); West Kalimantan (Kalimantan Barat, Kalimantan Tengah); East Kalimantan (Kalimantan Selatan, Kalimantan Timur); North Sulawesi (Sulawesi Utara, Gorontalo, Sulawesi Tengah); South Sulawesi (Sulawesi Selatan, Sulawesi Barat, Sulawesi Tenggara); Bali Nusa Tenggara (Nusa Tenggara Barat, Nusa Tenggara Timur); Maluku (Maluku, Maluku Utara); and Papua (Papua Barat, Papua).

In this module, we do not explicitly model the supply of land available for agricultural purposes as a function of land rents. In other words, we do not model a supply curve. Instead, we take the quantity of total land available as exogenous and change the allocation of land between uses of land.

Our module begins with an equation that determines the change in land area, measured in thousands of hectares by industry and region as

$$\Delta AREA_{(i,d)} = \left[\frac{LNDAREA_{(i,d)}}{100}\right] * xlnd_{(i,d)} \text{ for } d \in REG, i \in \text{land using } IND \qquad (3)$$

where

- $\Delta AREA_{(i,d)}$ is the change in the amount of land available by industry i and region d,[5]
- $LNDAREA_{(i,d)}$ is the initial amount of the land available by industry i and region d, and
- $xlnd_{(i,d)}$ is the percentage change in the land rental value by industry i and region r (see equation 2).

Land may be used for either commercial purposes such as the cultivation of crops, estate crops, oil palm, managed forest, or classified as natural forest, which is defined as an undisturbed forest free of commercial activity.

Equation (4) determines the change in CO_2 emissions due to land-use change by region.[6] CO_2 intensity is measured as tons of CO_2 emissions per hectare. This equation states that the total change in CO_2 intensity by region is the sum of the product of the change in land area allocated to various land-using industries, including natural forest, and multiplied with the CO_2 intensity for each of these activities:

$$\Delta CO2_{(d)} = \sum_{i \in IND} CO2INT_{(i,d)} * \Delta AREA_{(i,d)} + CO2INTNF_{(d)} * \Delta NFAREA_{(d)} \qquad (4)$$

for $d \in REG$, $i \in$ land using IND
where

- $\Delta CO2_{(d)}$ is the total change in CO_2 emissions by region,

[5] A percentage change for the variable called x is defined as $x = \frac{\Delta X}{X} * 100$, where ΔX is the change in X and X is the initial value. The ordinary change in X can therefore be written as $\Delta X = (x * X) * 0.01$.

[6] As explained in section IV, converting land cover from one use (e.g., forest) to another (e.g., oil palm plantation) causes the volume of CO_2 stored in (or emitted from in the reverse case) the land cover to change. For example, natural forests store more CO_2 than plantations. If a natural forest is transformed into an oil palm plantation, which stores less CO_2 than a forest, more CO_2 is then emitted into the atmosphere.

- $CO2INT_{(i,d)}$ is the total CO_2 intensity measured as tons of emission per hectare for all industries using land,

- $CO2INTNF_{(d)}$ is the CO_2 intensity measured as tons of emissions per hectare of natural forest, and

- $\Delta NFAREA_{(d)}$ is the ordinary change in the natural forest area by region r.

Equations (5) and (6) allow us to impose two rules to simulate the different land conversion scenarios. The first rule (equation 5) states that half of the area allocated to oil palm plantations comes from managed forests. For example, if the land area for palm oil production increases by 2 hectares, 1 hectare of land will come from managed forest area. The remaining hectare comes from the conversion of natural forest to palm oil production. When this equation is operational in the business-as-usual scenario, we assume that both natural and managed forests contribute, in equal shares, to the oil palm plantation:

$$\Delta AREA_{(\text{"}Forestry\text{"},d)} = -0.5 * \Delta AREA_{(\text{"}OilPalm\text{"},d)} + f\_rule1_{(d)} \text{ for } d \in REG \tag{5}$$

The second rule is shown in equation (6). This equation states that an increase in the land allocated to palm oil production comes from only managed forests. When this rule is activated in the policy simulation, we place a moratorium on the areas converted from forest to palm oil production, allowing only the conversion from managed forests to palm oil production while conserving natural forests:

$$\Delta AREA_{(\text{"}Forestry\text{"},d)} = -\Delta AREA_{(\text{"}OilPalm\text{"},d)} + f\_rule2_{(d)} \text{ for } d \in REG \tag{6}$$

where

- $\Delta AREA$ is the change in the land area allocated to managed forestry and oil palm plantations by region, and

- f_rule1 and f_rule2 are shift variables used to activate or deactivate the respective equations.

Equation (7) calculates the change in the REDD payment by region as the difference between the REDD payment between 2 consecutive years:

$$\Delta REDD_{(d)} = REDD^{t}_{(d)} - REDD^{t-1}_{(d)} \text{ for } d \in REG \tag{7}$$

where

- $\Delta REDD$ is the change in the REDD payment between years t and $t-1$ by region d, and

- $REDD^{t}_{(d)}$ and $REDD^{t-1}_{(d)}$ are the REDD payments in 2 consecutive years by region d.

Equation (8) determines the REDD payment in year t as the carbon price per ton of CO_2 emissions multiplied by the fall in CO_2 emissions for that year. *BaseEmit* captures the base level of CO_2 emissions and is determined via equation (9). Equation (8) is activated in the policy simulation and states that if CO_2 emissions are above the base level of emissions, then the REDD payment will decline. Alternatively, if the CO_2 emissions fall in the policy simulation relative to the base level of emissions, then the REDD payment will increase. If the emissions in the policy simulation are fixed at the base level of emissions, the change in the REDD payment is zero:

$$REDD^{t}_{(d)} = CO2PRICE * \left[-\Delta CO2_{(d)} + BaseEmit_{(d)}\right] \text{ for } d \in REG \tag{8}$$

where

- *CO2PRICE* is the carbon price per ton of CO_2 emissions,
- $\Delta CO2$ is the change in CO_2 emissions from changing the use of land and is determined in equation (4), and
- *BaseEmit* is the level of CO_2 emissions in the baseline simulation and determined via equation (9).

Equation (9) is operational only in the baseline simulation and determines the base level of CO_2 emissions. Baseline emissions by region are determined by the ordinary change in CO_2 emissions in the business-as-usual simulation (determined in equation 4) and a shift variable:

$$BaseEmit_{(d)} = \Delta CO2_{(d)} + f\_BaseEmit_{(d)} \text{ for } d \in REG \tag{9}$$

where

- *BaseEmit* is the base level of CO_2 emissions by region, and
- *f_BaseEmit* is a shift variable used to activate or deactivate the equation.

In the baseline simulation, the shift variable is exogenous and *BaseEmit* is endogenous. In the policy simulation, this equation is inoperative with the shift variable set endogenously and *BaseEmit* set exogenously.

In our theory, the REDD payment is directly paid to households in each region. Equation (10) determines the value of household income by region as the sum of labor income and the REDD payment. This equation also includes two exogenous shift variables that allows for uniform or region-specific changes to household income to be imposed.

$$HOUTOT_{(d)} = WAGE_{(d)} + f\_HOU_{(d)} + f\_HOU\_D + \Delta REDD_{(d)} \text{ for } d \in REG \tag{10}$$

where

- $HOUTOT$ is the value of household income by region.
- $WAGE$ is the wage income by region,
- $\Delta REDD$ is the ordinary change in the REDD payment by regions as determined in equation (7), and
- f_HOU by region and f_HOU_D are naturally exogenous shift variables that can be used to impose uniform or region-specific changes to household income.

The REDD payment is a payment to Indonesian households from a foreign donor and therefore we include the REDD payment with other net transfers from the rest of the world.[7] The final equation shows that the share of the nominal change in the balance of trade (BOT) and REDD payment to gross domestic product (GDP):

$$SHRBOTGDP = \frac{[\Delta BOT + \Delta NTROW]}{GDP} \tag{11}$$

where

- $SHRBOTGDP$ is the share of the sum of BOT and $NTROW$ to GDP,
- ΔBOT is the nominal change in the balance of trade, which is defined as exports minus imports,
- $\Delta NTROW$ is the change in net transfers abroad which is the sum of net remittances and the REDD payment, and
- GDP is nominal GDP.

In the policy simulations, we hold the *SHRBOTGDP* exogenous. This captures the idea that on a national level, Indonesia faces an external balance

[7]Net transfers from the rest of the world include payments received such as remittances and aid, as well as payments from Indonesia to the rest of the world.

constraint. We also note that assuming there is no change in *GDP* or *SHRBOTGDP*, an increase in the *NTROW* implies a fall in the nominal *BOT*.

IV. Description of the Database

Two large databases form the initial solution to the INDOTERM model. The base year in each is 2005.

A. The Core Database

The core TERM database is calibrated using various sources. These sources include the following:

(i) Indonesian National Input–Output Table 2005,

(ii) Indonesian Interregional Input–Output Table 2005,

(iii) regional share of production for each commodity for various years, and

(iv) Indonesian Social Accounting Matrix 2005.

The process of the construction of the INDOTERM database can be found in Horridge (2012) and Horridge and Wittwer (2008). The regional database consists of a set of matrices, capturing the 2005 structure of the Indonesian economy. We begin by creating a USE matrix valued at producers' price. This matrix shows the flow of commodity c from source s to user u. Values at producers' price are the sum of the flows of commodity c from source s to user u at basic price and the associated indirect tax. We also have a matrix capturing the margins that facilitate the flow of commodities. Value-added matrices include labor payments by industry and occupation, capital, and land rentals by industry, and production taxes by industry. The database is balanced in that the costs equal sales for each sector. From the national database we create regional input–output data and interregional flows of commodities. Detailed regional data are not available in the required format. We use regional output shares to inform us on the regional distribution of inputs and outputs. We then construct interregional trade matrices that show the trade of commodities between regions. Our task is made easier by assuming that industry-specific technologies are similar across regions. Given these assumptions, we ensure that regional data are consistent with national data with regard to land use and the CO_2 database. For a detailed description of the TERM database, see Horridge (2012).

B. Land Use and Carbon Dioxide Database

In parameterizing the land-use module, we require data on

(i) land area, measured in hectares, used for commercial purposes by region;

(ii) land area, measured in hectares, identified as natural forest by region; and

(iii) the CO_2 intensities per hectare by land use and region.

As mentioned before, land is used for either commercial purpose (crops, estate crops, oil palm, and managed forests) or classified as natural forest, which is defined as an undisturbed forest free of commercial activity.

For this study, we need to know the initial carbon stock stored in different land-use activities (e.g., crops, oil palm, and natural forests). Drawing on literature, CO_2 is stored in plant biomass and soil. For example, Agus et al. (2009) describe the carbon stored in various biomass and soils. They note that the amount of carbon stored varies by region and growth stage (e.g., oil palm) and depends on climate conditions, soil fertility, elevation and drainage, and land use.

CO_2 emissions occur when there is a change in land use. The amount of CO_2 emissions depends on the carbon stock of the biomass of the initial land before conversion takes place. For example, converting peatland, which stores a high level of carbon, to oil palm plantations will increase greenhouse gas emissions in the atmosphere, especially CO_2.

We do not have data on the CO_2 intensities per hectare by land use and region. To infer the CO_2 intensities per hectare and region, we use the following data: (i) carbon stock map, and (ii) land-use map. We obtained these maps from Minnemeyer et al. (2009).

We estimate the carbon intensity (CO_2 per hectare) by land-using sector (agriculture) and natural forest (forest area that is not used by any of the industries). To do that using geographic information system software, we overlay the two maps and calculate the average of carbon intensity.[8]

V. Simulation Design: Business-as-Usual, Moratorium, and Reduction of Emissions from Deforestation and Forest Degradation Payment

We run three simulations with the INDOTERM model:

[8]Here, we do not distinguish between peatland or other types of land since whether the land is peat or non-peat has implicitly been accounted for in the carbon stock map.

(i) **SIM0—the baseline simulation.** This simulation shows the growth of the Indonesian economy in the absence of the moratorium and REDD scheme. We assume that oil palm lands grow between 3% and 8% per annum, depending on the region, until 2030. We use regional oil palm land data to come up with this scenario. Higher growth regions include provinces in Kalimantan and lower growth regions are in Sumatra. We assume that half the oil palm land originates from natural forest and the other half from managed forest. This is roughly based on Carlson et al. (2013).

(ii) **SIM1–moratorium without international transfers.** This simulation reproduces the growth path of (i) but without further conversion of natural forest to oil palm. We assume that oil palm land still grows but from the conversion from managed forest.

(iii) **SIM2–moratorium with international transfers.** This simulation reproduces the growth path of (ii) but with a REDD payment proportional to the emissions saved by (ii). Therefore, in this simulation we convert the avoided deforestation into avoided CO_2 emissions and translate it into international transfers by multiplying the avoided emissions with the price of carbon (see equations 4 and 8). We used \$10 per ton of CO_2 emissions and distribute the transfers to the regions according to their magnitude of emissions reduction.[9] The transfers are given directly to representative households who will spend the money received as consumption spending (equation 10).

SIM0: Baseline Simulation

The baseline simulation is designed to serve as a plausible business-as-usual scenario for the future path of the Indonesian economy in the absence of the REDD scheme, or the absence of additional efforts to curb deforestation and carbon emissions. This baseline is used as a benchmark against which the economic impacts of reduced forest clearing with and without a REDD payment are measured.

Our baseline forecast is driven by projected changes in population, labor force, productivity, and foreign demand that are roughly consistent with Indonesia's recent GDP growth rates of 6% per annum. We impose the following exogenous changes for each year of the baseline simulation:

[9]The choice of \$10 per ton of CO_2 emissions was chosen based on similar earlier work for Indonesia that uses economic modeling such as in Busch et al. (2012). To our knowledge, this is the best study published that we can use as a reference. Busch et al. (2012) estimate the impacts that alternative national and subnational economic incentive structures for reducing emissions from deforestation (REDD+) in Indonesia would have had on greenhouse gas emissions and national and local revenue if they had been in place from 2000 to 2005. Throughout the analysis, Busch et al. (2012) use the carbon price of \$10 per ton of CO_2 emissions.

(i) The labor force and population grow at 2.5% and 1.5% per annum, respectively, over the entire simulation period. The higher growth rate for the labor force reflects (a) Indonesia's relatively young population, and (b) the idea that over time workers will migrate from informal to formal sectors, becoming more productive.

(ii) There is a continued increase in foreign demand for Indonesian commodities, including edible oils.

(iii) Labor productivity improves for all service industries by 3% per annum and for nonservice industries by 6% per annum.

Of special importance in our simulations are our assumptions regarding natural resource endowment and productivity. Natural resources not only refer to land as defined in section IV, but also include ore bodies, fish stocks, and other water activities. We assume the following:

(i) Land productivity rises by 3% per annum in all agricultural sectors, including crops, estate crops, oil palm, and managed forests. Improved land productivity is another way of increasing output in, for example, the palm oil sector.

(ii) Land productivity in all extractive sectors, except for oil and gas, rises by 2% per annum. The assumption of no growth in land productivity in the oil and gas sector reflects our view that Indonesian oil reserves offer little scope for an output increase.

(iii) For all land-using sectors, except the palm oil sector, we assume that the land area under cultivation is fixed. Although current Indonesian policy is to not allocate more land to the palm oil sector, we increase the land allocated to this sector. This is because there are still substantial natural forest areas previously allocated for oil palm that have not actually yet been converted. This factor, and perhaps a flouting of the policy, could allow the area under cultivation to rise. We assume that the land area for oil palm increases on a per annum basis by 8% in Kalimantan and Papua, 4% in East Sumatra and Sulawesi, and 3% in West Sumatra.

All regions expand during the simulation period but at different growth rates. Regional performance is dependent on the type of economic activity that is dominant in that particular region. For example, palm oil production is mainly located in Sumatra (78.5%) and Kalimantan (17.5%). Therefore, any changes, such as a moratorium on the expansion of oil palm plantations, would affect the regional growth of Sumatra and Kalimantan. The extent of this impact depends on these regions dependence on palm oil production and related sectors such as the edible oils industry since palm oil is used as an input into the production of edible oils. Kalimantan's economy is less palm oil dependent, whereas Sumatra has a higher dependency on palm oil and related industries such as edible oils industry. Kalimantan, for example, has a higher share of mining (20%) and manufacturing other than edible oils (28%) as part of its economy.

Another difference between Sumatra and Kalimantan is the tons of CO_2 per hectare that is stored in their respective forests. As mentioned in section IV, the CO_2 stock stored in Kalimantan's forests is much higher than in Sumatra's. This does not have a direct impact on economic growth, but as we shall see in the policy simulations, it will affect the REDD payment to Sumatra and Kalimantan and alter welfare via changes in household income. We surmise that if Kalimantan converts fewer forests into oil palm plantations, more carbon would be stored in Kalimantan forests. With a higher carbon intensity, the level of CO_2 emissions would be lower and the transfer payments to Kalimantan households higher. Sumatran households would benefit from REDD transfers, but not at the same level as in Kalimantan since the carbon intensity of Sumatran forests are slightly lower.

Our baseline simulation results show that Java's output is more than 3 times larger in 2030 than in 2005, while Papua and Maluku double in size. Java has the highest growth rate over the period because it hosts the majority of Indonesia's manufacturing and service industries. These industries show strong growth over the simulation period, while Papua and Maluku, which grow at a lower rate, mainly produce output that does not benefit greatly from employment and productivity improvements.

In the baseline simulation, Kalimantan and Sumatra show the highest levels of land-use conversion from forests to oil palm plantations. Papua and Sulawesi show the lowest levels of land conversion. The increase in the land area designated for oil palm implies a loss of managed and natural forest area. With the change in land use, we expect a change in the level of CO_2 emissions. The change in CO_2 emissions follows a similar path to the change in oil palm land area. Based on the carbon stock of natural forests, the level of CO_2 emissions is the highest in Kalimantan and Sumatra. Regions with the lowest CO_2 emissions are Papua and Sulawesi.

The growth paths of economic indicators generated in SIM1 and SIM2, which are detailed in the next section, move away from the baseline, making it possible to evaluate the impact of the policy. Policy effects are reported as percentage deviations from the baseline forecast.

VI. Consequences of the Moratorium and Reduction of Emissions from Deforestation and Forest Degradation Payment

A. SIM1: Imposing a Land Moratorium in the Absence of REDD

In the first policy simulation, we simulate the economic impacts of the moratorium on converting natural forests to oil palm plantations in the absence of a once-off REDD payment. The features of the policy simulation are the same as the baseline but now we assume that from 2015 all land conversion from forest to oil palm plantation comes from managed forests only—no land will be allocated from natural forests. Following normal practice, we report policy results as differences from the baseline scenario.

Because land for oil palm is now sourced from managed forests only, the land area used for palm oil production grows half as fast as in the baseline simulation. Thus, the differences between the baseline and policy simulations include:

(i) there is 1 less hectare of land converted to oil palm;

(ii) the converted land only comes from managed forests;

(iii) no natural forest is converted to oil palm, avoiding deforestation and conserving this area;

(iv) there is a decline in CO_2 emissions; and

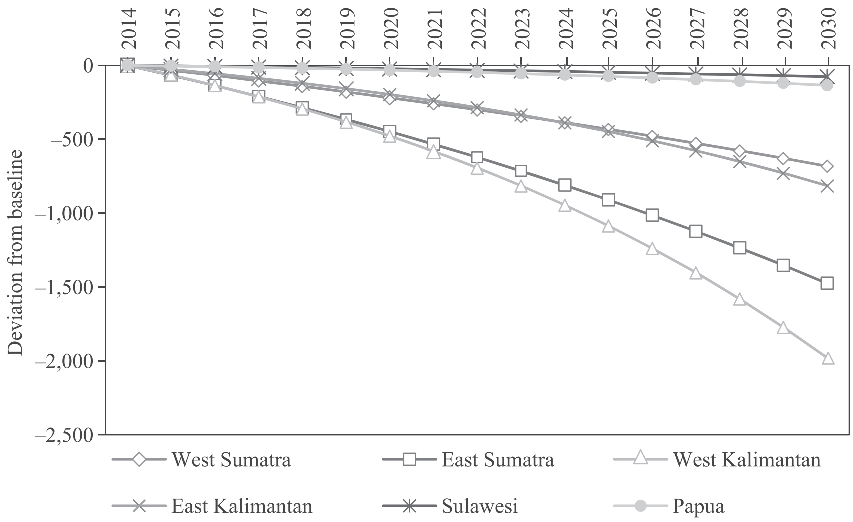
(v) there are varied regional economic impacts.

Figure 2 shows that the total area converted to oil palm is less than in the baseline simulation. The natural forest area, which is not converted to oil palm land, is higher in SIM1 than in the baseline. By the end of the simulation period, approximately 5 million hectares of forest have been conserved, with the bulk of this amount located in Kalimantan and Sumatra.

In the baseline, this land area grows to 18.6 million hectares in 2030, while in the policy simulation this area grows to 13.4 million hectares. The difference of 5.2 million hectares is the natural forest area that was conserved due to the moratorium. Therefore, instead of oil palm land area growing at an annual average of 4.9% as in the baseline simulation, oil palm land area grows at an average rate of 2.9% per annum.

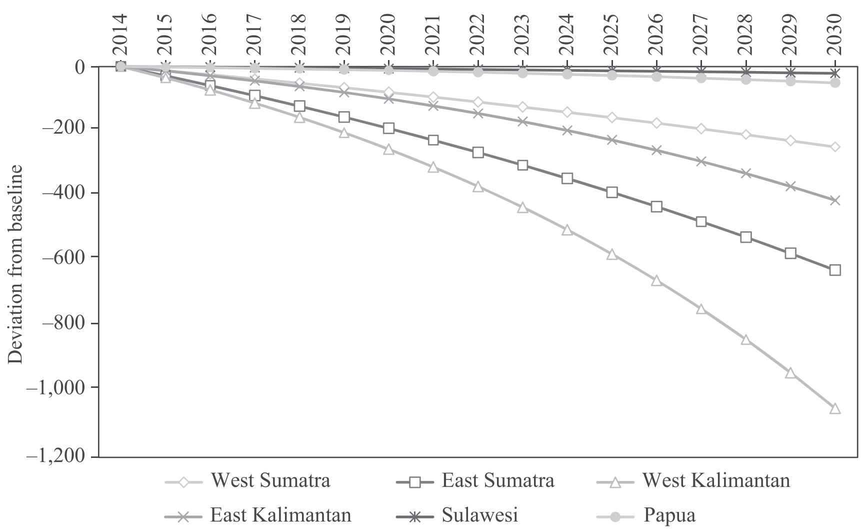
Due to the conservation of natural forests, CO_2 emissions fall relative to the baseline in all regions (although at different levels) (Figure 3). The change in the level of CO_2 emissions depends on the carbon stock intensity of each type of land

Figure 2. **Oil Palm Land Area by Region**



Source: Authors' calculations from model simulations.

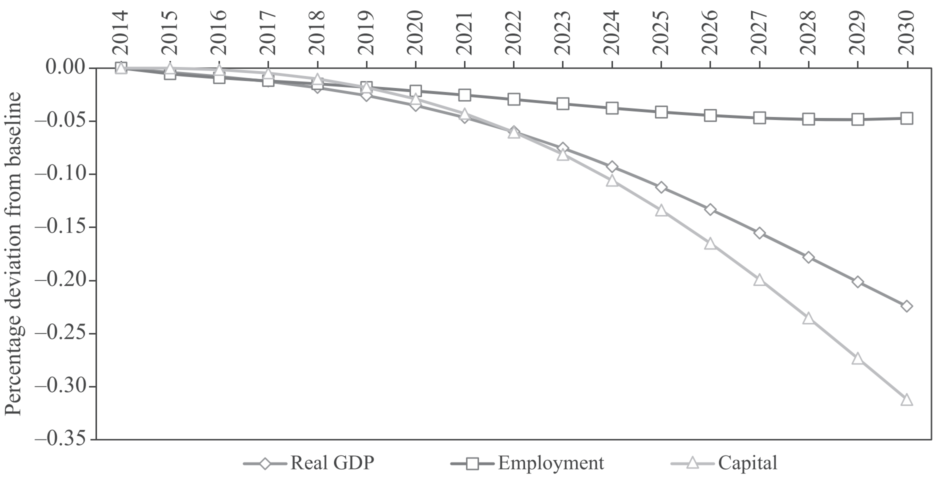
Figure 3. **Carbon Dioxide Emissions by Region**



Source: Authors' calculations from model simulations.

use (see section IV). This is because natural forests store more carbon stock than oil palm plantations. CO_2 emissions fall the most in West Kalimantan, followed by East Sumatra. These results are determined by the:

Figure 4. **Gross Domestic Product from the Income Side**



GDP = gross domestic product.
Source: Authors' calculations from model simulations.

(i) hectares of natural forests saved from deforestation, and

(ii) carbon stock stored in natural forests in different regions.

Our initial setting of CO_2 intensities show that the carbon stock stored in natural forests is highest for West Kalimantan at 800 tons per hectare.

On a macro level, the impacts of a moratorium on land conversion seem small. However, as we shall see, there are regional disparities that are significant, especially in Kalimantan and Sumatra. We next focus on the main macroeconomic variables before moving on to the regional impacts of the moratorium. Figure 4 shows the results for GDP components from the income side. The results show that capital and real GDP fall in the long run and are 0.3 and 0.23 percentage points below the baseline, respectively. Our assumption is that employment is fixed in the long run. With employment effectively unchanged and with no productivity improvements, capital adjusts given fixed rates of returns.

The percentage of GDP calculated as the share weighted sum of capital and oil palm land is

$$gdp = SHRlab * xlab + SHRcap * xcap + SHRlnd * xlnd + a \qquad (12)$$

where *gdp*, *xlab*, *xcap*, *xlnd,* and *a* are the percentage changes in real GDP, labor, capital, land, and productivity, respectively. These percentage change values are simulation results. *SHRlab*, *SHRcap*, and *SHRlnd* are the shares of labor, capital, and land in total primary factor costs, respectively. These numbers are calculated from the database values for the respective factors. With *xlab* and *a* fixed, the percentage change is dependent on the share capital and land and the percentage change in capital and land, specifically oil palm land.

$$gdp = SHRcap * xcap + SHRlnd * xlnd \tag{13}$$

$$gdp = 0.45 * -0.31 + 0.003 * -21 \tag{14}$$

$$gdp = -0.21 \tag{15}$$

We note that the percentage change in capital contributes the most to the change in GDP. For each $1 of land lost, $2 of capital is lost, given that capital is mobile and adjusts to fixed rates of return.

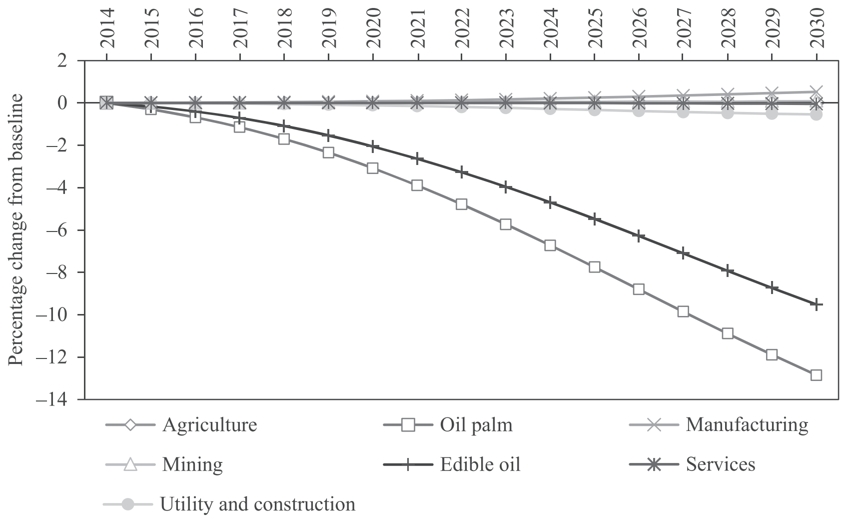
A point to note is that even though the long-run change in national employment is negligible, this does not mean that employment at the individual industry level remains close to baseline values. In most industries, there are permanent employment responses to the moratorium. In the long run, employment in the edible oils industry falls by 10% from the baseline. This result is explained by the underlying input–output linkage captured in the database, which shows that palm oil is mainly used as an input in the edible oils industry. With the change in aggregate employment negligible, the fall in employment in the edible oils and palm oil industries, implies an increase in employment in other industries such as manufacturing. In terms of regional employment, Sumatra shows the largest negative deviation due to the prominence of the palm oil and edible oils industries in this region.

Figure 5 shows the percentage deviation in output from the baseline for the main industries. Not surprisingly, the palm oil and edible oils industries show the largest declines in output. Regions that rely on palm oil production and related industries (such as the edible oils sector) for employment and economic growth show the strongest decline in regional employment and output.

In our simulation, wages adjust to hit the target employment rate while holding domestic employment fixed at base levels. Therefore, the loss of jobs in palm-oil producing areas means gains elsewhere. The regions making gains probably do not produce much palm oil, instead they produce, for example, other manufacturing commodities as is the case in Java. As mentioned before, most oil palm plantations and edible oils industries are located in Sumatra and Kalimantan. It is therefore not surprising that Sumatra's growth is below the baseline throughout the simulation period (Figure 6). Kalimantan, however, shows little change in regional growth. This is because Kalimantan is less dependent than Sumatra on palm oil production and more diversified in its productive activities. Therefore, it can better adjust to the land moratorium.

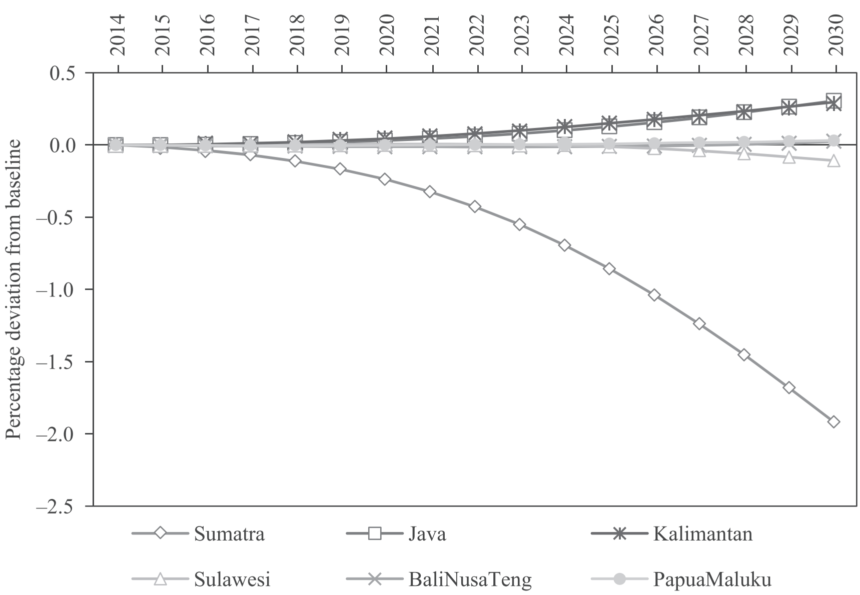
In the next simulation, we translate the moratorium on land conversion into a monetary reward to those regions with lower levels of CO_2 emissions.

Figure 5. **Output of Main Industries**



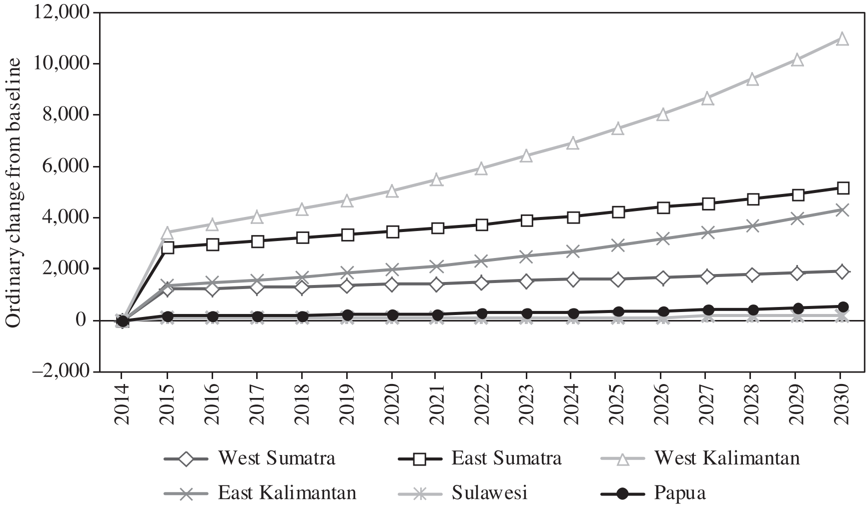
Source: Authors' calculations from model simulations.

Figure 6. **Gross Domestic Product by Region**



Source: Authors' calculations from model simulations.

Figure 7. **REDD Payments by Region**



REDD = Reduction of Emissions from Deforestation and Forest Degradation.
Source: Authors' calculations from model simulations.

B. SIM2: Imposing a Land Moratorium in Return for a REDD Payment

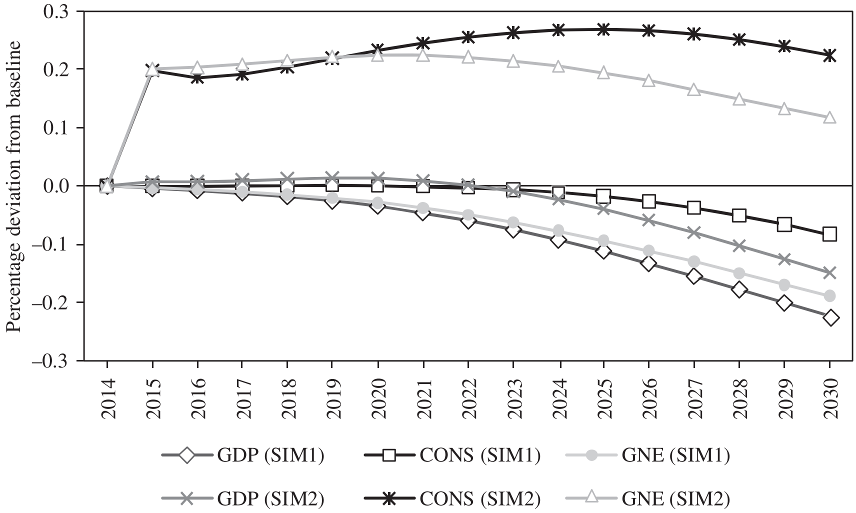
In this simulation, we evaluate the impact of a moratorium on the land used for palm oil production, which is similar to SIM1, but now it is accompanied with a gift of foreign exchange (REDD payment) in return for lower CO_2 emissions. The payment is directly awarded to households in region *r* (see equation 10).

As shown in Figure 3, West Kalimantan and East Sumatra shows the largest reductions in CO_2 emissions. Therefore, it is not surprising that the largest REDD payments are to West Kalimantan, followed by East Sumatra (Figure 7). West Kalimantan receives the most REDD payments because it has (i) a relatively high level of CO_2 emissions reduction, and (ii) the highest level of carbon storage per ton in natural forests among all regions (see section IV).

As shown in Figure 8, the moratorium reduces Indonesia's economic growth and negatively impacts other macroeconomic indicators such as gross national expenditure (GNE) and welfare.[10] International transfers ($10 per ton of CO_2 emissions avoided) can more than compensate for these welfare losses as measured by declines in consumption or GNE. However, the fall in GDP due to the moratorium cannot fully be compensated. In this context, GNE and consumption

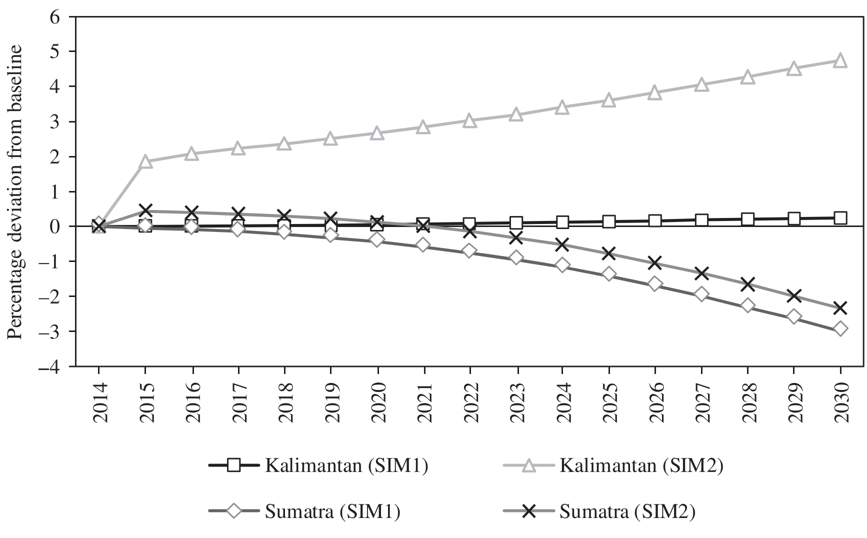
[10]GNE is the total value of private and public expenditure in the economy. It is different from GDP because GNE includes expenditures on imported commodities and excludes exports of commodities produced within a country. GDP is the total value of production within a country, which includes exports of commodities and excludes the imports of commodities.

Figure 8. **Gross Domestic Product, Gross National Expenditure, and Consumption**



Source: Authors' calculations from model simulations.

Figure 9. **Consumption in Sumatra and Kalimantan**



Source: Authors' calculations from model simulations.

are a better measure of welfare as the international transfers impact the current account deficit.

The impact of the moratorium with international transfers varies across regions; Kalimantan wins, Sumatra loses (Figures 8 and 9). Sumatra is highly dependent on palm oil and its economy is less broad based. The carbon stocks of its forests are no longer high compared to the past. Consequently, it receives a smaller amount of transfers than Kalimantan. Kalimantan, on the other hand, is not yet too dependent on palm oil as its economy is more broad based. In addition, the carbon stock of its forests is still high; therefore, it receives more transfers.

VII. Conclusion

The objectives of this paper are to (i) identify the macroeconomic effects on the Indonesian economy of a land moratorium, including how the effects are distributed across different regions in the country; and (ii) determine to what extent international transfers, which are payments for ecosystem services in which the international community pays for avoided deforestation and additional carbon storage services, can mitigate the effects of the moratorium.

We use the INDOTERM model—a bottom-up, multiregional CGE model of the Indonesian economy—to conduct three experiments. The first simulation is the business-as-usual simulation where we model the growth of the Indonesian economy in the absence of a moratorium and REDD payments. In the baseline simulation, we assume that both natural and managed forests are converted to oil palm plantations. We then use this model to evaluate alternative growth paths where we simulate a moratorium on converting forest area to oil palm plantation in the absence of REDD payments (SIM1), and in return for a REDD payment that is proportional to the fall in CO_2 emissions (SIM2).

Our results show that in the baseline simulation, 13.4 million hectares of forest land are converted to oil palm. Of the total land converted, half comes from managed forest and the other half from natural forest.

The results suggest that the moratorium reduces Indonesian economic growth and other macroeconomic indicators, but international transfers ($10 per ton of CO_2 emissions avoided) can more than compensate the welfare loss. However, the impact varies across regions. Sumatra, which is highly dependent on palm oil given that its economy is relatively less broad based than other regions and the carbon stock of its forests is no longer high, receives less transfers and suffers greater economic loss. Kalimantan, which is relatively less dependent on palm oil than Sumatra and has forests with a high carbon stock, receives more transfers, and enjoys greater benefits. This result suggests that additional policy measures anticipating the imbalanced impacts of the transfers are required if the trade-off between conservation and reducing interregional economic disparity is to be reconciled.

In the future, it may be useful to run several scenarios simulating different levels of REDD payments based on different prices for reducing CO_2 emissions. In the policy simulations in this paper, we also do not improve palm oil productivity over time. It would be interesting to see the regional and domestic impacts if productivity gains in the palm oil sector were to reach those in Malaysia.

References

Abood, Sinan A., Janice Ser Huay Lee, Zuzana Burivalova, John Garcia-Ulloa, and Lian Pin Koh. 2015. "Relative Contributions of the Logging, Fiber, Oil Palm, and Mining Industries to Forest Loss in Indonesia." *Conservation Letters* 8 (1): 58–67.

Agus, Fahmuddin, Eleonora Runtunuwu, Tania June, Erni Susanti, Herna Komara, Haris Syahbuddin, Irsal Las, and Meine van Noordwijk. 2009. "Carbon Dioxide Emission Assessment in Land Use Transitions to Plantation." *Journal Litbang Pertanian* 28 (4): 119–26.

Bellassen, Valentin, and Vincent Gitz. 2008. "Reducing Emissions from Deforestation and Degradation in Cameroon—Assessing Costs and Benefits." *Ecological Economics* 68 (1–2): 336–44.

Burke, Paul J., and Budy P. Resosudarmo. 2012. "Survey of Recent Developments." *Bulletin of Indonesian Economic Studies* 48 (3): 299–324.

Busch, Jonah, Ruben N. Lubowski, Fabiano Godoy, Marc Steininger, Arief A. Yusuf, Kemen Austin, Jenny Hewson, Daniel Juhn, Muhammad Farid, and Frederick Boltz. 2012. "Structuring Economic Incentives to Reduce Emissions from Deforestation within Indonesia." *Proceedings of the National Academy of Sciences* 109 (4): 1062–67.

Butler, Rhett A., Lian Pin Koh, and Jaboury Ghazoul. 2009. "REDD in the Red: Palm Oil Could Undermine Carbon Payment Schemes." *Conservation Letters* 2 (2): 67–73.

Carlson, Kimberly M., Lisa M. Curran, Gregory P. Asner, Alice McDonald Pittman, Simon N. Trigg, and J. Marion Adeney. 2013. "Carbon Emissions from Forest Conversion by Kalimantan Oil Palm Plantations." *Nature Climate Change* 3 (3): 283–87.

De Sy, Veronique, Martin Herold, Achard Frédéric, René Beuchle, J. G. P. W. Clevers, Erik Lindquist, and Louis Verchot. 2015. "Land Use Patterns and Related Carbon Losses Following Deforestation in South America." *Environmental Research Letters* 10 (12): 124004.

Dutu, Richard. 2015. "Making the Most of Natural Resources in Indonesia." OECD Economics Department Working Papers No. 1236.

Ferreira Filho, Joaquim, Carliton Vieira dos Santos, and Sandra Maria do Prado Lima. 2010. "Tax Reform, Income Distribution and Poverty in Brazil: An Applied General Equilibrium Analysis." *International Journal of Microsimulation* 3 (1): 43–59.

Food and Agriculture Organization of the United Nations (FAO). 2017. FAOSTAT Online Statistical Service. http://www.fao.org/faostat/en/#home.

Graesser, Jordan, T. Mitchell Aide, H. Ricardo Grau, and Navin Ramankutty. 2015. "Cropland/Pastureland Dynamics and the Slowdown of Deforestation in Latin America." *Environmental Research Letters* 10 (3): 034017.

Horridge, Mark. 2012. "The TERM Model and Its Database." In *Economic Modeling of Water: The Australian CGE Experience*, edited by Glyn Wittwer, 13–35. Dordrecht: Springer.

Horridge, Mark, John Madden, and Glyn Wittwer. 2005. "Using a Highly Disaggregated Multi-Regional Single-Country Model to Analyse the Impacts of the 2002-03 Drought on Australia." *Journal of Policy Modelling* 27: 285–308.

Horridge, Mark, and Glyn Wittwer. 2008. "SinoTERM, a Multi-Regional CGE Model of China." *China Economic Review* 19 (4): 628–34.

Hosonuma, Noriko, Martin Herold, Veronique De Sy, Ruth S. De Fries, Maria Brockhaus, Louis Verchot, Arild Angelsen, and Erika Romijn. 2012. "An Assessment of Deforestation and Forest Degradation Drivers in Developing Countries." *Environmental Research Letters* 7 (4): 044009.

Malaysian Palm Oil Board. Malaysian Palm Oil Industry. http://www.palmoilworld.org/about_malaysian-industry.html.

Miettinen, Jukka, Chenghua Shi, and Soo Chin Liew. 2012. "Two Decades of Destruction in Southeast Asia's Peat Swamp Forests." *Frontiers in Ecology and the Environment* 10 (3): 124–28.

Miettinen, Jukka, Aljosja Hooijer, Chenghua Shi, Daniel Tollenaar, Ronald Vernimmen, Soo Chin Liew, Chris Malins, and Susan E. Page. 2012. "Extent of Industrial Plantations on Southeast Asian Peatlands in 2010 with Analysis of Historical Expansion and Future Projections." *Gcb Bioenergy* 4 (6): 908–18.

Miettinen, Jukka, Jianjun Wang, Aljosja Hooijer, and Soo Chin Liew. 2013. "Peatland Conversion and Degradation Processes in Insular Southeast Asia: A Case Study in Jambi, Indonesia." *Land Degradation & Development* 24 (4): 334–41.

Minnemeyer, Susan, Lauriane Boisrobert, Fred Stolle, Y. I. Ketut Deddy Muliastra, Matthew Hansen, Belinda Arunarwati, Gitri Prawijiwuri, Judin Purwanto, and Rakhmat Awaliyan. 2009. "Interactive Atlas of Indonesia's Forests (CD-ROM)." Washington, DC: World Resources Institute.

Ordway, Elsa M., Gregory P. Asner, and Eric F. Lambin. 2017. "Deforestation Risk Due to Commodity Crop Expansion in Sub-Saharan Africa." *Environmental Research Letters* 12 (4): 044015.

Pambudi, Djauhari. 2005. "TABLO Programs and MS Word Files Underlying the EMERALD Model of Indonesia." *Centre of Policy Studies Archive, File TPMH0063*. http://www.copsmodels.com/archivep.htm (accessed December 7, 2017).

Pambudi, Djauhari, Nathalie McCaughey, and Russell Smyth. 2009. "Computable General Equilibrium Estimates of the Impact of the Bali Bombing on the Indonesian Economy." *Tourism Management* 30 (2): 232–39.

Pambudi, Djauhari, and Russell Smyth. 2008. "Making Indonesia More Attractive to Foreign Investors: A Computable General Equilibrium Analysis of Reducing the Risk Premium in Central Java." *Review of Urban & Regional Development Studies* 20 (3): 226–40.

Rudel, Thomas K., Ruth Defries, Gregory P. Asner, and William F. Laurance. 2009. "Changing Drivers of Deforestation and New Opportunities for Conservation." *Conservation Biology* 23 (6): 1396–405.

Rudel, Thomas K. 2013. "The National Determinants of Deforestation in Sub-Saharan Africa." *Phil. Trans. R. Soc. B* 368 (625): 20120405.

Sandker, Marieke, Samuel Kofi Nyame, Johannes Förster, Neil Collier, Gill Shepherd, Daniel Yeboah, Driss Ezzine-de Blas. 2010. "REDD Payments as Incentive for Reducing Forest Loss." *Conservation Letters* 3 (2): 114–21.

Stofberg, Francois Jacobus, and Jan Van Heerden. 2016. "The Short-Term Economic Impact of Levying E-Tolls on Industries." *South African Journal of Economics* 84 (4): 574–93.

United Nations-Reduction of Emissions from Deforestation and Forest Degradation (UN-REDD). 2015. UN-REDD Programme Strategic Framework 2016–2020. 2015. http://www.unredd.net/documents/foundation-documents-88/strategy-2016-2020-3619/14096-un-redd-pb14-2015-strategic-framework.html (accessed March 3, 2018).

Van der Werf, Guido, Douglas C. Morton, Ruth S. DeFries, J. G. J. Olivier, Prasad S. Kasibhatla, Robert B. Jackson, G. James Collatx, and James T. Randerson. 2009. "CO_2 Emissions from Forest Lost." *Nature Geoscience* 2: 737–38.

Wittwer, Glyn, ed. 2012. *Economic Modeling of Water: The Australian CGE Experience*, *Vol.* 3. Berline: Springer Science & Business Media.

Yusuf, Arief A., Elizabeth L. Roos, and Jonathan M. Horridge. 2017. "Indonesia's Moratorium on Palm Oil Expansion from Natural Forest: Economy-Wide Impact and the Role of International Transfers." *Centre for Policy Studies*, Victoria University Working Paper Number G-276.

Zawalinska, Katarzyna, James Giesecke, and Mark Horridge. 2013. "The Consequences of Less Favoured Area Support: A Multi-Regional CGE Analysis for Poland." *Agricultural and Food Science* 22 (2): 272–87.