The Effect of Trade Openness on Deforestation: Empirical Analysis for 142 Countries

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Abstract

This study explores the effect of trade openness on deforestation. Previous studies do not find a clear effect of trade openness on deforestation. We use updated data on the annual rate of deforestation for 142 countries from 1990 to 2003, treat trade and income as endogenous, and take into consideration an adjustment process by applying a dynamic model. We find that an increase in trade openness increases deforestation for non-OECD countries while slowing down deforestation for OECD countries. There is a possibility that both capital-labor and environmental-regulation effects have a negative impact on deforestation in developing countries, whereas the opposite holds in developed countries.

Key words Trade Openness; Environment; Comparative Advantage; Deforestation.

JEL Classifications: Q23, Q56, Q58

1. Introduction

The uptake of carbon in forests constitutes an important carbon sink, so that improved land-use management is essential to reduce greenhouse gases in the atmosphere. The maintenance of forests also plays an important role in preserving a wider diversity of livelihood options and buffers against extreme events such as floods and landslides (World Bank, 2010). The World Bank (2010) reports that the net global deforestation, however, averaged 7.3 million hectares a year from 2000 to 2005, contributing about 5.0 gigatons of carbon dioxide (CO_2) a year in emissions, or about a quarter of the global emission reduction needed. According to the Intergovernmental Panel on Climate Change (IPCC) (2007), emissions associated with land-use change and deforestation account for about 17 percent of total greenhouse gas emissions, which is larger than all the world's emissions via transportation and is comparable in size to the industrial sector. We also note that deforestation has been concentrated in developing countries, whereas forest cover in industrial countries is stable or even increasing slightly.

This study explores the determinants of deforestation, especially in terms of globalization, to clarify the effect of trade openness on deforestation. Fig. 1 shows a simple scatter plot of deforestation and trade openness. It indicates that there is no apparent correlation between deforestation and trade openness. Previous studies do not find a statistically significant effect of trade openness on deforestation (Frankel and Rose, 2005; Van and Azomahou, 2007). However, causality could be found if an improved estimation method is adopted. We use updated data on the annual rate of deforestation for 142 countries from 1990 to 2003, treat trade and income as endogenous, and take into consideration an adjustment process by applying a dynamic model. As a result, we obtain statistically significant results concerning trade that contradict previous studies.

The remainder of the paper is organized as follows. In Section 2, we review recent studies. In Section 3, we explain our research methods and data, and we discuss the trade elasticities in Section 4. In Section 5, we show the econometric results, and Section 6 concludes.

2. Background

In the literature, there are mainly four factors that cause deforestation: the desire to convert forest to pasture and cropland, increasing fuel wood demand, the harvesting of logs, and urbanization (e.g., road construction) (see Cropper and Griffiths, 1994; Van and Azomahou, 2007). Thus, economic growth, demographic factors, political institutions, and trade have been emphasized in previous studies as underlying causes of deforestation.[1] We now review these factors.

2.1 Economic growth

During the early stage of economic development, the requirement for economic growth and the expansion of income leads to an increase in the demand for logging or forest

[1] This study includes these key variables in the estimation.

clearing for agricultural activities and grazing. In contrast, a higher level of income causes changes in the composition of the demand for goods and services, as well as an increase in the demand for a better environment. This trend corresponds to the environmental Kuznets curve (EKC) hypothesis, which postulates that economic growth and environmental degradation follow an inverted U-curve (for a theoretical exploration of the EKC for deforestation, see Lopez, 1994).

Several empirical studies test this relationship. We summarize the estimation results in Table 1. As shown in Table 1, previous studies are inconclusive concerning the existence of the EKC. There is a discrepancy between the results from the early literature and those of the latest research. Cropper and Griffiths (1994) and Bhattarai and Hammig (2001) employ fixed effects estimation and confirm the existence of the EKC in Latin America and Africa. Furthermore, Frankel and Rose (2005) also find the EKC relationship using two-stage least squares. However, it is notable that Van and Azomahou (2007) and Arcand et al. (2008) do not find support for the EKC relationship, using more improved estimation techniques than did early studies. Van and Azomahou (2007) employ not only fixed effects estimation but also semi-parametric estimation, which is more flexible than popular parametric functional forms.[2] In contrast, Arcand et

[2] Recent empirical studies find that common EKC results are highly sensitive to changes in functional forms. The econometric applications have been criticized because of a lack of robust econometric methods (see Tsurumi and Managi (2010), for a review). This concern has inspired recent studies using semi-parametric or non-parametric techniques.

al. (2008) use difference GMM and system GMM.[3] These two latest works suggest that there is no robust EKC relationship for deforestation.

2.2 Demographic factors

Population growth or an increase in population density is often considered as a factor in deforestation. Allen and Barnes (1985) employ ordinary least squares (OLS) to explore the determinants of deforestation, using data from 1968-1978 in 39 countries in Africa, Latin America, and Asia. They find that deforestation is significantly related to an increase in the rate of population growth, which is indirectly related to agricultural expansion. Furthermore, the World Bank (2003) states that demographic growth has induced an increasing demand for goods, services, and basic provisions, which impacts the environment and exerts a pressure on natural resources. Cropper and Griffiths (1994), however, employ fixed effects estimations using the data from 1961-1988 in 64 developing countries in Africa, Latin America, and Asia, and find no statistically significant relations between the rate of population growth and deforestation. In addition, they find a statistically significant positive coefficient estimate for rural population density only for the sample in Africa. Furthermore, Bhattarai and Hammig (2001) find that the effect of demographic factors depends on the region, and recent literature has

[3] They prefer these GMM methods rather than fixed effects because fixed effects fail to account for the correlation between the transformed initial level of forest cover and the transformed disturbance term.

not obtained statistically significant results (see Table 1).[4] Thus, similar to economic growth, previous studies do not obtain robust results concerning demographic factors.

2.3 Political institution

The institutional variables allow for both non-income-driven environmental policy and the quality of policy-related institutions (Panayotou, 1997; Culas, 2007). Panayotou (1997) indicates that countries with the same level of income may consciously adopt different stringent environmental policies based on differences in educational level, quality of policy-related institutions, and rule of law, among others. He suggests that the EKC is flattened out by internalizing externalities and ensuring a clear definition and enforcement of property rights over natural resources.

Previous studies generally obtain statistically significant negative effects of political institution failure on deforestation.[5] However, it is notable that although Arcand et al. (2008) find statistically significant results in the fixed effects and their preferred specification, given by the common factor representation, they find no

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[4] Van and Azomahou (2007) find a statistically significant coefficient for population density, but the sign is negative, and hence it is difficult to interpret.

[5] Exceptions are the results obtained for Asia in Cropper and Griffiths (1994) and the results presented in Frankel and Rose (2005). Cropper and Griffiths (1994) find statistically significant positive coefficient estimates. According to Cropper and Griffiths (1994), a possible explanation for this finding concerns the importance of forest plantations in Asia. In contrast, Frankel and Rose (2005) obtain a statistically insignificant result. However, a relatively small sample size may affect this result.

statistically significant results in the difference GMM and system GMM. This implies that we need to interpret previous studies' results with caution.

2.4 Trade

More trade openness would increase the production share of the goods in which the countries have a comparative advantage. At the same time, more openness would increase production or per capita income, and thus may affect deforestation. Frankel and Rose (2005) consider trade openness and income as endogenous and explore the causal relationship between trade openness and deforestation, using cross-section data from 41 countries in 1990. However, they do not find statistically significant results. In contrast, Van and Azomahou (2007) employ fixed effects estimation and semi-parametric estimation. Similar to Frankel and Rose (2005), they find no statistically significant effects of trade. In summary, previous studies have not clarified the effects of trade on deforestation. Our goal in the present study is to clarify how trade openness affects deforestation.

3. Empirical strategy and data

3.1 Empirical strategy

As discussed in the previous section, previous studies do not find statistically significant effects of trade on deforestation, which may be due to their insufficient incorporation of the "composition effect". In the literature, the relative capital-labor ratio variables are not included in those models directly. The composition effect corresponds to the effect of the capital-labor ratio (the structure of the industry). In this study, by following Antweiler et al. (2001), we take into consideration the effect of factor endowment more directly than does the extant literature.

Antweiler et al. (2001) explore the determinants of environmental degradation to decompose them into scale, technique, and composition effects. In the case of deforestation, these three effects can be interpreted as follows. First, the scale effect refers to the effect of an increase in production (e.g., GDP) on deforestation. Second, the technique effect indicates the impact of income on deforestation. This refers to the effect of more stringent environmental regulations, which are put in place as additional income increases the demand for a better environment. Third, the composition effect explains how deforestation is affected by the composition of output (i.e., the structure of the industry), which is determined by the degree of trade openness as well as by the comparative advantage of the country. This effect could be positive or negative, depending on the country's resource abundance and the strength of its environmental policy. These are called the capital–labor (KLE) and environmental regulation effects (ERE), respectively (Managi et al., 2009).

Because trade openness could increase production and income, it may affect deforestation through the scale effect and the technique effect. Hereafter, we call these effects the trade-induced scale effect and the trade-induced technique effect. Antweiler et al. (2001) estimate how trade openness (increase in trade intensity) and GDP (or per capita income) affect pollution by using data on sulfur dioxide (SO_2) concentrations. They find that SO_2 concentrations increase as GDP rises (i.e., positive scale effect), decrease as per capita income rises (i.e., negative technique effect), and decrease as trade openness rises (i.e., negative composition effect).

Managi et al. (2009) consider the endogeneity problem in production (or income) and, thus, treat the effect of trade openness on production (or income) explicitly. Therefore, the effects of trade openness on emissions via income and production changes (i.e., the trade-induced scale and technique effects) can be compared to the composition effect induced by trade. As a result, we can infer the overall environmental consequences of trade as a summation of these effects. Furthermore, Managi et al. (2009) note that an increase in income (or production) associated with trade openness might affect the composition effect. For example, the composition effect resulting from the ERE might be larger under more stringent policies.

Managi et al. (2009) then estimate the overall impact of trade openness on the environment using the instrumental variables technique to extend Antweiler et al. (2001).[6] They analyze the causal effects of trade openness on SO_2, CO_2, and BOD

[6] To address potential simultaneous problems, they follow Frankel and Rose (2005). Frankel and Rose (2005) consider trade openness and income endogenously. They address the potential simultaneity of trade, environment, and income by applying instrumental variables estimations using a gravity model of bilateral trade and endogenous growth from neoclassical growth equations. We note that they do not consider the induced effects and the decomposed effects, such as the scale, technique, and composition effects.

emissions by using extensive annual data for OECD and non-OECD countries. They find that both the data coverage and the estimation method affect the estimation results, and thus they conclude that to obtain appropriate estimation results, it is important to address the endogeneity problems and to have more data coverage.

Following Managi et al. (2009), this study employs the following specification to analyze deforestation:

$$
\begin{aligned}
D_{it} &= c_1 + \alpha_1 D_{it-1} + \alpha_2 S_{it} + \alpha_3 S_{it}^2 + \alpha_4 (K/L)_{it} + \alpha_5 \{(K/L)_{it}\}^2 + \alpha_6 (K/L)_{it} S_{it} \\
&+ \alpha_7 T_{it} + \alpha_8 T_{it} (RK/L)_{it} + \alpha_9 T_{it} \{(RK/L)_{it}\}^2 + \alpha_{10} T_{it} RS_{it} + \alpha_{11} T_{it} RS_{it}^2 + \alpha_{12} T_{it} RS_{it} (RK/L)_{it} \\
&+ \alpha_{13} popd_{it} + \alpha_{14} popg_{it} + \alpha_{15} inst_{it} + \varepsilon_{1it}
\end{aligned}
$$

$$
\varepsilon_{1it} = \eta_{1i} + \lambda_{1t} + \nu_{1it} \qquad (1)
$$

where D_{it} denotes the annual rate of deforestation ($D_{it} \equiv (F_{it-1} - F_{it}) / F_{it-1}$, where F_{it} is the forest area) of country *i* in year *t*, and *S* is GDP per capita. GDP per capita and its quadratic are intended to capture the scale-technique effect. *K/L* denotes a country's capital–labor ratio; *RK/L* denotes a country's relative capital–labor ratio; *RS* is relative GDP per capita.[7] *T* is defined as the ratio of aggregate exports and imports to GDP, which, as in the growth literature, proxies trade openness (or trade intensity). As control variables, we include the variables often used by previous studies. They

[7] To show a country's comparative advantage, a country's capital–labor ratio and per capita income levels are expressed relative to the world average for each year.

are $popd$, $popg$, and $inst$, and they denote the rural population density, population growth, and political institutions, respectively. ε_1 is an error term and consists of an individual country effect η_1, a time-specific effect λ_1, and a random disturbance ν_1.

We also employ the following specification as an income equation:

$$
\begin{aligned}
S_{it} &= c_2 + \beta_1 S_{it-1} + \beta_2 T_{it} + \beta_3 \left(K / L\right)_{it} + \beta_4 pop_{it} + \beta_5 inv_{it} \\
&\quad + \beta_6 popg_{it} + \beta_7 sch1_{it} + \beta_8 sch2_{it} + \varepsilon_{2it} \\
\varepsilon_{2it} &= \eta_{2i} + \lambda_{2t} + \nu_{2it} \qquad (2)
\end{aligned}
$$

where *pop* is the population, *inv* is investment per worker, *popg* denotes population growth, *sch1* and *sch2* proxies human capital investment based on the gross enrollment ratio of primary school and secondary school, respectively, and ε_2 is an error term and consists of an individual country effect η_2, a time-specific effect λ_2, and a random disturbance ν_2.

3.2 Endogeneity

Following Frankel and Rose (2005), this study treats trade and income as endogenous. We construct an instrumental variable for trade openness by the following equation.

$$
\begin{aligned}
\ln(Trade_{ij} / GDP_i) &= c_3 + \gamma_1 \ln Dis_{ij} + \gamma_2 \ln P_j + \gamma_3 Lan_{ij} + \gamma_4 Bor_{ij} \\
&\quad + \gamma_5 \ln(Area_i \cdot Area_j) + \gamma_6 Landlocked_{ij} + \varepsilon_{3ij} \qquad (3)
\end{aligned}
$$

where $Trade_{ij}$ is the bilateral trade flows from country i to country j, GDP_i is the Gross Domestic Product of country i, Dis_{ij} is the distance between country i and country j, P_j is the population of country j, Lan_{ij} is a common language dummy that takes a value of 1 if two countries have the same language and 0 otherwise, Bor_{ij} is a common border dummy that takes a value of 1 if countries i and j share a border and 0 otherwise, *Area* is land area, and *Landlocked* is a dummy variable that takes a value of 1 if one country is landlocked, 2 if both countries are landlocked, and 0 otherwise, and ε_3 is an error term.

The results are presented in Table 2, and they are in line with the results in literature. We construct IV for openness as follows. A first-stage regression of the gravity equation is computed. Next, we take the exponential of the fitted values of bilateral trade and sum across bilateral trading partners as follows:

$$\sum_j Exp\left[Fitted\ \ln(Trade_{ij} / GDP_i)\right] \tag{4}$$

This fitted openness variable is added as an additional IV for the GMM.

3.3 Data

We obtain forest area data from FAOSTAT. This database is based on the FAO Global Forest Resources Assessment 2010 (FAO, 2010). FAO (2010) compile country reports and the numbers from remote sensing.[8] Compared with previous studies using the deforestation data before 1990 (such as Van and Azomahou, 2007), our data are more reliable in terms of data quality. For example, Rudel et al (2005) notes data weakness in the data before 1990, in particular its uneven quality and its inconsistent definitions across nations (also see Grainger, 2008, for more information). Per capita income, which is defined as GDP per capita, the capital-labor ratio, investment per worker, and population are taken from the *Extended Penn World Table 3.0*. The capital-labor ratio is available before 2004. Therefore, our data period covers 1990-2003. Trade openness, rural population density, population growth, and gross enrollment ratios come from the *World Development Indicators Online*. Political institution variables are from *Freedom House*.[9] We obtain data on bilateral trade flows from IFS *Direction of Trade* CD-ROM. Data on distances between the country pairs in question (physical distance and dummy variables indicating common borders, linguistic links, and landlocked status) come from the CIA *World Factbook* website. The list of countries is presented in Table A in Appendix A.

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[8] The data are based on the remote sensing survey conducted in 1990, 2000, and 2005. While data are provided by countries for years 1990, 2000, 2005, and 2010, data for intermediate years are estimated for FAO using linear interpolation and tabulation (FAO, 2010).

[9] Following Van and Azomahou (2007), we use two indices on political rights and civil liberties, the values of which vary from 1 (free) to 7 (not free), respectively. We aggregate these two variables to obtain an index of political institutions, scaling from 2 to 14.

4. *Trade elasticities*

We can decompose the terms in equation (1) into two groups as follows. One is the scale-technique effect (Y_{it}) and the other is the composition effect (C_{it}).

$$Y_{it} = \alpha_2 S_{it} + \alpha_3 \left[S_{it} \right]^2 \tag{5}$$

These terms reflect the effects of income and production on deforestation. From this, we expect to estimate the scale-technique effect (Managi et al., 2009).

$$\begin{aligned} C_{it} = {} & \alpha_4 (K/L)_{it} + \alpha_5 \left[(K/L)_{it} \right]^2 + \alpha_6 (K/L)_{it} \cdot S_{it} \\ & + \alpha_7 T_{it} + \alpha_8 (RK/L)_{it} \cdot T_{it} + \alpha_9 \left[(RK/L)_{it} \right]^2 T_{it} \\ & + \alpha_{10} RS_{it} \cdot T_{it} + \alpha_{11} \left[RS_{it} \right]^2 T_{it} + \alpha_{12} (RK/L)_{it} \cdot RS_{it} \cdot T_{it} \end{aligned} \tag{6}$$

These terms show the composition effects. A country's comparative advantage is a major factor influencing the composition effects. We consider factor endowment, stringency of environmental regulations, and trade openness as factors affecting the comparative advantage (Antweiler et al., 2001; Managi et al., 2009). A capital-abundant country will specialize in capital-intensive production, whereas a labor-abundant country has a comparative advantage in labor-intensive goods. Because forest products are relatively labor-intensive, in the case of forest industry, a country with a lower capital-labor ratio is expected to have a comparative advantage. At the same time, a country that has relatively lax regulations has a comparative advantage in goods with high environmental burden (i.e., forest products) because production would not be constrained by these regulations. Therefore, in countries that have a comparative advantage in forest products (i.e., a lower capital-labor ratio), the comparative advantage is strengthened by relatively lax regulations.

Equation (6) is divided into two parts: one without terms including T_{it}, and another one with terms including T_{it}, which captures the effect of trade openness on the composition effect through the KLE and/or the ERE.

The first part of Equation (6) is the indirect effect of trade, and the latter part is the direct effect of trade. We name the former the *Indirect Trade-Induced Composition Effect* (OC_{it})[10] and the latter the *Direct Trade-Induced Composition Effect* (TC_{it}). OC_{it} and TC_{it} are expressed as follows:

$$OC_{it} = \alpha_4 (K/L)_{it} + \alpha_5 \left[(K/L)_{it}\right]^2 + \alpha_6 (K/L)_{it} \cdot S_{it}. \tag{7}$$

$$\begin{aligned} TC_{it} = {} & \alpha_7 T_{it} + \alpha_8 (RK/L)_{it} \cdot T_{it} + \alpha_9 \left[(RK/L)_{it}\right]^2 T_{it} \\ & + \alpha_{10} RS_{it} \cdot T_{it} + \alpha_{11} \left[RS_{it}\right]^2 T_{it} + \alpha_{12} (RK/L)_{it} \cdot RS_{it} \cdot T_{it}, \end{aligned} \tag{8}$$

Here, we consider the effect of a one percent increase in trade intensity.

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[10] OC_{it} reflects the indirect effect of a trade-induced change in income on emissions.

$$\sigma_T^S = \frac{dD_{it}}{dT_{it}} = \left(\frac{dY_{it}}{dT_{it}} + \frac{dOC_{it}}{dT_{it}} + \frac{dTC_{it}}{dT_{it}} \right) = \frac{\partial Y_{it}}{\partial S_{it}} \frac{\partial S_{it}}{\partial T_{it}} + \frac{\partial OC_{it}}{\partial S_{it}} \frac{\partial S_{it}}{\partial T_{it}} + \frac{\partial TC_{it}}{\partial S_{it}} \frac{\partial S_{it}}{\partial T_{it}} + \frac{\partial TC_{it}}{\partial T_{it}} \quad (9)$$
$$= \sigma_{ST}^S + \sigma_{OC}^S + \sigma_{ITC}^S + \sigma_{DTC}^S .$$

σ_{ST}^S corresponds to the short-term trade elasticity of deforestation, driven by the scale-technique effect through trade-induced changes in income. σ_{OC}^S is the short-term trade elasticity of deforestation driven by the indirect composition effect through trade-induced changes in income. As we can see from equation (9), the effect of an increase in trade intensity on deforestation in (8) is decomposed into two parts: the indirect effect of trade intensity through changes in income, and the direct effect of trade intensity. We define these two effects as σ_{ITC}^S and σ_{DTC}^S, respectively. It should be noted that we use the short-term trade elasticity of income, which is calculated from equation (2) as $\frac{\partial S_{it}}{\partial T_{it}} = \beta_2$.

From these elasticities, the total short-term trade-induced composition effect, σ_C^S, is calculated as $\sigma_C^S = \sigma_{OC}^S + \sigma_{ITC}^S + \sigma_{DTC}^S$.

In summary, the short-term overall trade openness elasticity of deforestation, σ_T^S, is calculated as follows:

$$\sigma_T^S = \sigma_{ST}^S + \sigma_{OC}^S + \sigma_{ITC}^S + \sigma_{DTC}^S . \qquad (10)$$

In the same manner, considering the lagged term, D_{it-1}, and the long-term trade elasticity of income, which is calculated from equation (2) as $\beta_2/(1-\beta_1)$, the long-term trade elasticities of deforestation, σ_{ST}^L, σ_{OC}^L, σ_{ITC}^L, and σ_{DTC}^L, are defined. Thus, the long-term overall trade openness elasticity of emissions, σ_C^L, is defined as follows:

$$\sigma_T^L = \sigma_{ST}^L + \sigma_{OC}^L + \sigma_{ITC}^L + \sigma_{DTC}^L. \tag{11}$$

5. *Estimation results*

5.1 Estimation results of deforestation

Tables 3 and 4 present the estimation results of our deforestation model (equation (1)) and income model (equation (2)), respectively. In Table 3, we show two specifications: one includes control variables (columns 3 and 4), and the other does not include control variables (columns 1 and 2). Our preferred models are those including control variables because, as we show in section 2, these factors are often considered as essential factors of deforestation by previous studies. Table 5 reports the short-term and long-term trade elasticities of deforestation, which are evaluated using sample averages. For the computation, we adopt the parameter estimates in column 4 of Table 3 and the parameter estimates in column 2 of Table 4. This is because the Sargan test for over-identifying restrictions and the hypothesis of no second-order autocorrelation imply that the instruments used in the model are valid.[11]

In all of the specifications, almost all of the variables, including the endogenous variables such as trade openness, per capita income, and their interaction terms, have statistically significant effects. We thus obtain statistically significant results for all elasticities. It should be noted that in Table 3, concerning the terms related to scale, technique, and composition effect, we obtain similar parameter estimates between the specifications that include and do not include control variables. This implies that our computed elasticities in Table 5 are robust against these control variables.[12] As for the coefficient estimates for control variables, we do not obtain robust parameter estimates, which is in line with previous studies. More specifically, the coefficient estimates for rural population density are not statistically significant, whereas the coefficient estimate for population growth is statistically significant and positive only in system GMM. This result suggests that there is a possibility that an increase in population density leads to an increase in deforestation, but this hypothesis should be interpreted carefully because we do not obtain statistically significant results in the difference GMM. The coefficient estimate for political institution is statistically significant and positive only in the difference GMM. This implies that political institution failure leads to an increase

[11] The model of column 1 in Table 3 and the model of column 3 in Table 3 also clear the Sargan test. Thus, we also calculate the trade elasticities of deforestation using these parameter estimates. As a result, we obtain almost the same elasticities as Table 5 in both models.

[12] As we note in footnote 6, we obtain similar trade elasticities of deforestation among columns 1, 3, and 4 in Table 3.

in deforestation. However, for the same reason as population density, we should interpret this finding with caution.

From here, we interpret main coefficient estimates in Table 3. The lagged deforestation terms for all specifications are statistically significant, having a positive sign and values of less than one. These results imply that changes in explanatory variables, such as trade openness, at a specific point in time would also influence deforestation after the current period. This result indicates that there is an adjustment process and that the short- and long-term effects of trade on deforestation are different. This evidence confirms that we need to use a dynamic model, although previous studies do not. As shown in Table 5, we find that the long-term elasticities are larger than the short-term elasticities.

The signs of S are positive and statistically significant, whereas the signs of S^2 are negative and statistically significant in all estimates. These results indicate that a negative technique effect gradually dominates a positive scale effect as income increases, because higher income leads to a greater demand for less deforestation. To consider the effect of an increase of S on deforestation more precisely, we calculated the values of $\alpha_2 + 2\alpha_3 S$ and σ_{ST} using sample means of income in OECD and non-OECD countries. We find that both values are positive in both OECD countries and non-OECD countries. This implies that an increase in either production or income leads to an increase in deforestation. Thus, in both the average OECD and the non-OECD country, the scale effect dominates the technique effect. To consider whether the EKC hypothesis is supported or not, we calculate $\partial D_{it} / \partial S_{it}$ and $\partial D_{it}^2 / \partial^2 S_{it}$ using equation (1). We find that $\partial D_{it} / \partial S_{it}$ and $\partial D_{it}^2 / \partial^2 S_{it}$ are positive for both OECD countries and non-OECD countries, which implies that the EKC is not confirmed.

The signs of the cross product of *KL* and *S* are positive, with statistical significance in all estimates. An increase of income weakens the comparative advantages in forest industry because of stricter environmental policies, but it also strengthens these advantages because of technological changes caused by a larger production scale. The sign of this interaction term suggests that the latter dominates the former.

We find negative signs for *KL* and KL^2, with statistical significance in all cases. These results suggest that increases in the capital-labor ratio lead to decreases in deforestation with a diminishing marginal effect, implying that the forest industry is relatively labor-intensive.

Next, we consider the trade-induced composition effect. Table 5 shows that compared with the trade-induced scale-technique effect, the trade-induced composition effect is relatively large. In particular, we obtain relatively large elasticities for σ_{DTC}. We are able to determine how an increase in trade intensity affects composition effects through both the KLE and the ERE by evaluating the sign of σ_{DTC}, which is negative for OECD but positive for non-OECD countries. In the case of pollutants such as sulfur dioxide, with increases in trade intensity, a country that has a comparative advantage in capital-intensive products (i.e., pollution-intensive products) is likely to increase its emissions by specializing more in these products (see Managi et al., 2009). However, in the case of the forest industry, a country that is labor-intensive is likely to have a comparative advantage, and thus, with trade intensity increased, developing countries seem to accelerate deforestation by specializing more in such products (i.e., the KLE). At the same time, developing countries have relatively lax environmental policies (i.e., the ERE), which seems to explain why the signs of σ_{DTC} for non-OECD countries are positive. In the same manner, we can interpret the signs of σ_{DTC} for OECD countries.[13] Because the trade-induced composition effects dominate the trade-induced scale-technique effects for all cases in Table 5, the obtained signs of the overall trade-induced elasticities are all the same as those of trade-induced composition effects.

5.2 Robustness check

We have obtained statistically significant results concerning trade, a finding that is inconsistent with previous studies. To check the robustness of our results, we apply semi-parametric analysis. In this study, we use generalized additive models (see Hastie

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[13] Because the sample averages of *RS* and *RKL* are larger than 1 in OECD countries and are less than 1 in non-OECD countries, we see that developed countries have a comparative advantage in capital-intensive production and enforce relatively strict environmental policies. Meanwhile, developing countries have a comparative advantage in labor-intensive production and have relatively lax environmental policies.

and Tibshirani, 1990). We use a cubic spline smoothing[14] iteratively to minimize the partial residuals, which are the residuals after removing the influence of the other variables in the model. In this model, a Bayesian approach is used to derive standard errors and confidence intervals.[15] The model is as follows:

$$D_{it} = c_4 + f_1(predicted\ S_{it}) + f_2\left((K/L)_{it}\right) + f_3\left(predicted\ T_{it}\right) + \mu_{4i} + \nu_{4t} + \varepsilon_{4it}, \quad (12)$$

where $predicted\ S_{it}$ denotes predicted values of GDP per capita (constructed using equation (2)), and $predicted\ \mathrm{T}_{it}$ denotes predicted values of Trade openness (constructed from the gravity equation). We use predicted values to consider simultaneous problems. $f(\cdot)$ are generic flexible functional forms that allow potentially non-linear non-monotonic relationships.[16] μ_i is the country fixed effect, ν_t is the time fixed effect, and ε_{it} is the error term.[17]

Table 6 shows the results of the model fit test. We find that all terms are statistically significant. Fig. 2 shows the predicted contributions to the dependent

[14] When we used the loess function in place of the cubic spline function, the results were almost the same.

[15] Our estimation technique follows Wood (2004, 2008).

[16] We use the normal distribution for estimation. The link function is the identity.

[17] We include country dummy and year dummy to take into consideration individual and time fixed effects.

variable from each of the independent variables. As a result, the estimated slope of the predicted trade openness has an increasing trend. This suggests that deforestation tends to occur with increasing trade openness. Next, although the confidence interval is large, the slope of capital-labor ratio tends to be negative. This trend also corresponds to our parametric estimation results, supporting our hypothesis that the forest industry tends to be labor-intensive. Finally, we find a positive slope for GDP per capita, although the confidence interval is large. This trend also corresponds to our parametric estimation results for the scale-technique effect.

6. Conclusions and discussions

In this study, we explore whether an increase in trade intensity leads to deforestation by using updated data and by treating trade and income as endogenous. We obtain statistically significant results concerning trade, which is inconsistent with Frankel and Rose (2005) and Van and Azomahou (2007). Our results show that there is a sharp contrast between OECD and non-OECD countries. We find that an increase in trade openness slows down deforestation for developed countries but not for developing countries. The dominating impact of the composition effect implies that both capital-labor and environmental-regulation effects have a negative impact on deforestation in developing countries, whereas the opposite holds in developed countries.

Because a future increase in trade openness is expected in developing countries, additional policies are required to protect future deforestation. Reduced Emissions from Deforestation and forest Degradation (REDD) is one example, which reduces the speed for deforestation. We need additional incentives for protecting forest in developing countries.

Reflecting high quality data to future studies is also important to consider deforestation. FAO (2010) notes "countries use differing frequencies, classification systems and assessment methods when monitoring their forests, making it difficult to obtain consistent data". FAO therefore is now undertaking a global remote sensing survey to provide additional and more consistent information on deforestation for the period 1990-2005 (See Ridder, 2007, for more information). The initial results of this survey were released on 30th November 2011.[18] This survey is expected to improve future studies' reliability. In addition, Chen and Nordhaus (2011) also focus on grid-cell level data based on a global remote sensing. To improve the quality of socioeconomic data in developing countries, they examine luminosity (measures of night lights visible from space) as a proxy for standard measures of output (GDP) and compare luminosity and GDP at the country level and at the 1° latitude × 1° longitude grid-cell level. They find that luminosity has informational value for countries with low-quality statistical systems. To explore the determinants of deforestation it will be better to use more detailed and reliable data.

[18] Unfortunately, this survey has not yet been reflected to FAOSTAT at the present moment, so that our study use the data based on FAO (2010) released in 2010.

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Table 1. Previous studies concerning deforestation

	EKC	Coefficient for population growth	Coefficient for rural population density	Effect of Political institution failure on deforestation	Trade
Allen and Barnes (1985)		+			
Cropper and Griffiths (1994)	Latin America: confirmed Africa: confirmed Asia: not confirmed	insignificant	Latin America: insignificant Africa: + Asia: insignificant	Latin America: worsen Africa: worsen Asia: improve	
Bhattarai and Hammig (2001)	Latin America: Confirmed Africa: Confirmed Asia: not confirmed	Latin America: – Africa: – Asia: +	Latin America: + Africa: + Asia: –		
Frankel and Rose (2005)	Confirmed			insignificant	insignificant
Culas (2007)	Latin America: confirmed Africa: not confirmed Asia: not confirmed		insignificant	Worsen	
Van and Azomahou (2007)	Not confirmed	insignificant	–	Worsen	insignificant
Arcand et al. (2008)	Not confirmed	insignificant	insignificant	Worsen	

Table 2. Gravity Equation (1990-2003)

$\ln(Trade_{ij}/GDP_i)$	Parameter estimates
$\ln(Distance_{ij})$	−1.033*** (−157.09)
$\ln(Population_j)$	0.910*** (293.21)
$Language_{ij}$	0.566*** (43.16)
$Border_{ij}$	0.777*** (24.90)
$\ln(Area_iArea_j)$	−0.200*** (−110.76)
$Landlocked_{ij}$	−0.918*** (−91.97)
Constant	−1.503*** (−23.55)
Number of countries	196
Observations	190955
R squared	0.41

Note: Values in parentheses are t–values. *, ** and *** indicate "significant" at the 10% level, the 5% level and the 1% level, respectively. Time dummies are included.

Table 3. Deforestation equation (1990-2003)

Variable	Difference GMM +excluded IVs	System GMM +excluded IVs	Difference GMM +excluded IVs	System GMM +excluded IVs
column	1	2	3	4
D_{it-1}	0.143***	0.129***	0.098***	0.096***
	(3.52)	(4.26)	(4.98)	(13.55)
S	0.0000211***	0.0000231***	0.0000115***	0.0000149***
	(4.68)	(5.71)	(5.53)	(6.15)
S^2	-8.61×10^{-10}***	-1.05×10^{-9}***	-5.53×10^{-10}***	-8.17×10^{-10}***
	(−4.37)	(−5.81)	(−3.57)	(−9.50)
K/L	-5.00×10^{-6}***	-5.13×10^{-6}***	-3.43×10^{-6}***	-3.17×10^{-6}***
	(−3.98)	(−4.23)	(−3.70)	(−3.83)
$(K/L)^2$	-4.29×10^{-12}	-5.53×10^{-12}	-2.06×10^{-11}	-3.50×10^{-11}***
	(−0.26)	(−0.35)	(−1.19)	(−3.63)
$(K/L)S$	2.43×10^{-10}***	2.94×10^{-10}***	2.29×10^{-10}**	3.31×10^{-10}**
	(2.56)	(3.29)	(2.11)	(6.01)
T	0.000176**	0.000215**	0.000169***	0.000178***
	(1.85)	(2.39)	(3.86)	(3.92)
T relative S	−0.00209***	−0.00208***	−0.00131***	−0.00154***
	(−5.56)	(−6.41)	(−5.70)	(−9.18)
T relative S^2	0.00135***	0.00127***	0.00116***	0.00124***
	(8.28)	(8.32)	(6.44)	(15.68)
T relative *(K/L)*	0.00118***	0.00121***	0.000429*	0.000695***
	(3.72)	(4.09)	(1.91)	(4.35)
T relative $(K/L)^2$	0.000391***	0.000356***	0.000808***	0.000703***
	(4.64)	(4.36)	(5.60)	(8.37)
T rel S rel *(K/L)*	−0.00153***	−0.00144***	−0.00179***	−0.00179***
	(−7.18)	(−7.13)	(−5.49)	(−12.00)
popd			-1.77×10^{-6}	-1.51×10^{-6}
			(−0.95)	(−0.93)
popg			0.000129	0.000107*
			(1.55)	(1.80)
inst			0.000326*	0.000129
			(1.93)	(0.96)
Constant	−0.0138	−0.0229***	−0.00174	−0.0102*
	(−0.94)	(−3.15)	(−0.25)	(−1.90)
Observations	1394	1539	1082	1185
Number of countries	135	142	102	103
Sargan test: p-value	0.602	0.000***	0.521	0.372
AR(1): prob>chi2	0.340	0.309	0.315	0.329
AR(2): prob>chi2	0.570	0.454	0.453	0.523

Note: In column 1 and 3, instrumentation carried out using variables in levels lagged from t−3 to t−5; in columns 2 and 4, equation in levels is instrumented using variables in first-differences, lagged t−2 to t−4 periods; exogenous instruments used in columns 1 and 2 are: predicted value of T and S. (GMM procedures all use the one-step covariance matrix, z-statistics in parentheses)

*, ** and *** indicate "significant" at the 10% level, the 5% level and the 1% level, respectively. Time dummies are included in all specifications.

Table 4. Income Equation (1990-2003)

Variable	Difference GMM +excluded IV	System GMM +excluded IV
column	1	2
S_{it-1}	0.876***	0.871***
	(51.38)	(77.19)
T_{it}	3.033*	2.383**
	(1.87)	(2.37)
pop_{it}	-1.64×10^{-6}	-3.46×10^{-6}***
	(–0.78)	(–2.91)
inv_{it}	0.266***	0.260***
	(11.84)	(15.25)
$popg_{it}$	–8.910	–5.358
	(–0.65)	(–0.41)
$sch1_{it}$	8.104**	6.707**
	(2.34)	(2.15)
$sch2_{it}$	8.672***	9.883***
	(2.84)	(4.88)
Constant	–1160.771***	–552.392*
	(–3.38)	(–1.91)
Observations	1478	1617
Number of countries	134	135
Sargan test: p-value	0.000	0.9617
AR(1): prob>chi2	0.005***	0.004***
AR(2): prob>chi2	0.118	0.153

Note: Values in parentheses are t–values. *, ** and *** indicate "significant" at the 10% level, the 5% level and the 1% level, respectively. In column 1, instrumentation carried out using variables in levels lagged from t−3 to t−5; in columns 2, equation in levels is instrumented using variables in first-differences, lagged t−2 to t−4 periods; Trade openness is instrumented for using predicted openness (as an excluded IV). Time dummies are included in both specifications.

Table 5. Elasticity of trade openness on deforestation rate

Elasticity			Short Term		Long Term	
OECD	σ_{ST}		0.00708**		0.0607**	
	σ_C	σ_{OC}	−1.638**	−0.00905**	−1.880**	−0.0776**
		σ_{ITC}		-3.22×10^{-5}**		−0.00028**
		σ_{DTC}		−1.629***		−1.802***
	σ_T		−1.631**		−1.819**	
Non-OECD	σ_{ST}		0.00585**		0.0502**	
	σ_C	σ_{OC}	0.184**	0.00623**	0.249**	0.0534**
		σ_{ITC}		-7.10×10^{-5}**		−0.00061**
		σ_{DTC}		0.0988***		0.196***
	σ_T		0.189**		0.299**	
All data	σ_{ST}		0.000614**		0.0053**	
	σ_C	σ_{OC}	1.609**	0.0260**	1.974**	0.223**
		σ_{ITC}		-8.96×10^{-5}**		−0.00077**
		σ_{DTC}		1.583***		1.751***
	σ_T		1.610**		1.979**	

Note: *, ** and *** indicate “significant” at the 10% level, the 5% level and the 1% level, respectively. Elasticities are evaluated at sample means.

Table 6. Approximate significance of smooth terms of semi-parametric analysis of equation (12)

F statistics	F-value
$f_1(S_{it})$ or $f_1(predicted\ S_{it})$	4.251**
$f_2\left((K/L)_{it}\right)$	2.511*
$f_3\left(T_{it}\right)$ or $f_3\left(predicted\ T_{it}\right)$	18.118***
Deviance explained	58.6%
GCV score	0.000249
Number of Countries	123
Observations	1429

Note: *, ** and *** indicate "significant" at the 10% level, the 5% level and the 1% level, respectively.

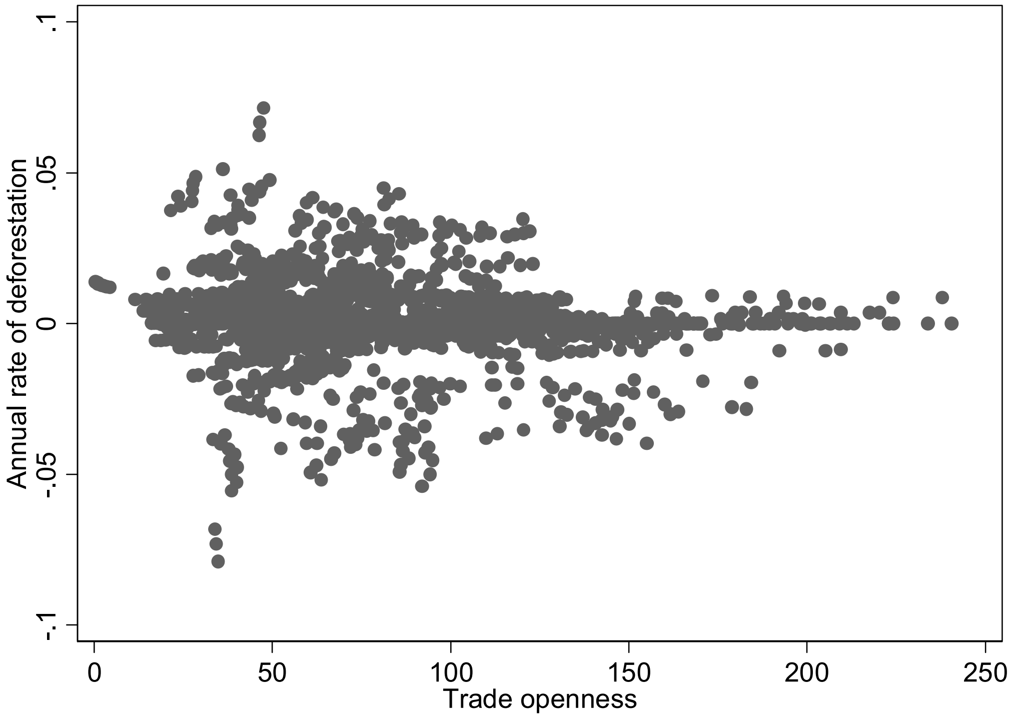

Fig. 1. Simple scatter plot of deforestation and trade openness

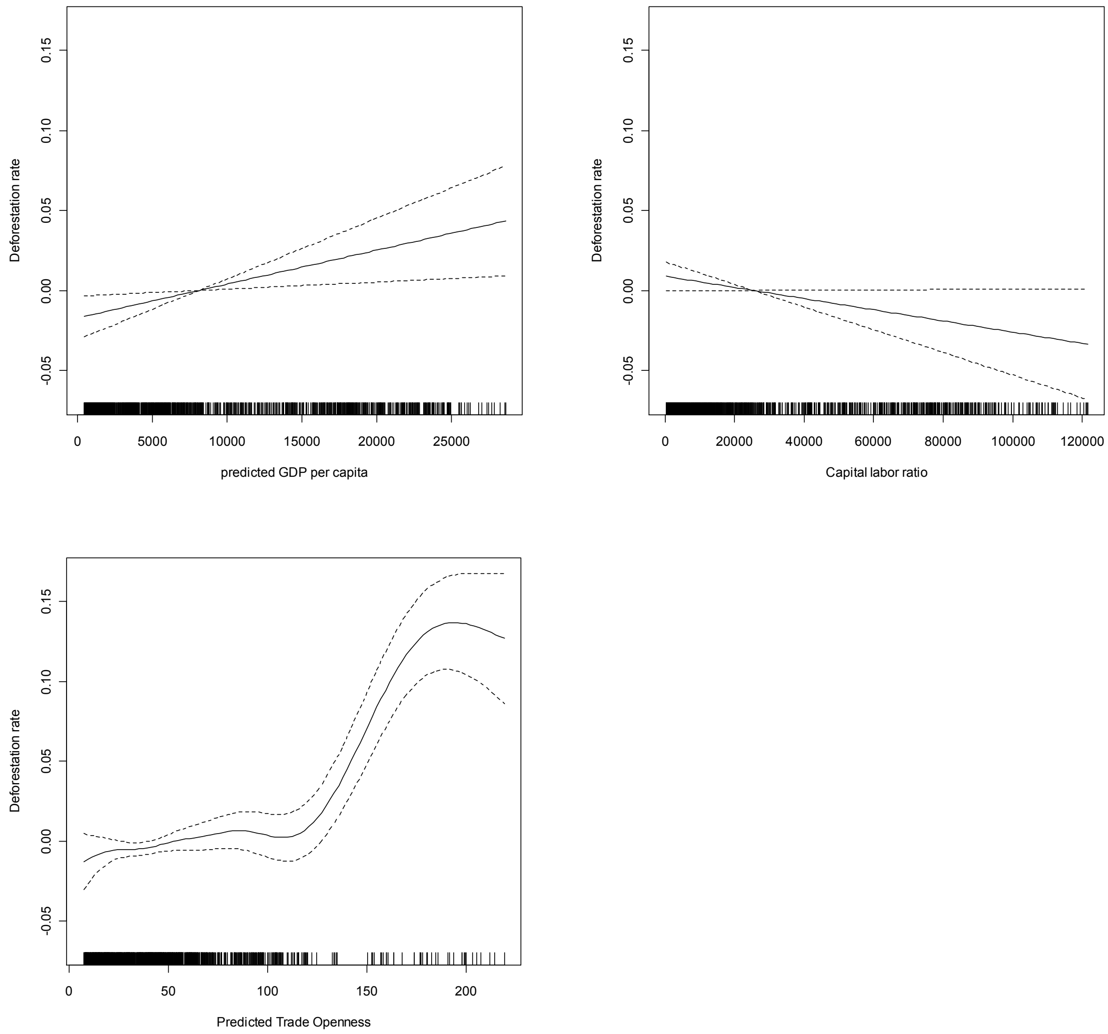

Fig. 2. Relationship between deforestation rate and three indices (predicted GDP per capita (left), capital labor ratio (center), and predicted trade openness (right))

Appendix A.

Table A. List of countries (142 countries)

Afghanistan (2.63)	Dominica (0.56)	Kuwait (–3.25)	Russia (0.00)
Albania (0.05)	Ecuador (1.57)	Kyrgyz Republic (–0.26)	Rwanda (–2.30)
Algeria (–1.68)	Egypt (–2.90)	Laos (0.46)	Samoa (–2.14)
Angola (0.21)	El Salvador (1.49)	Latvia (–0.39)	Senegal (0.50)
Argentina (0.43)	Equatorial Guinea (0.86)	Lebanon (–0.81)	Serbia & Montenegro (–0.34)
Armenia (1.32)	Estonia (–0.36)	Liberia (1.64)	Sierra Leone (0.66)
Australia (0.18)	Ethiopia (1.00)	Lithuania (–0.49)	Slovak Republic (–0.02)
Austria (–0.15)	Fiji (–0.16)	Madagascar (0.45)	Slovenia (–0.41)
Bahrain (–6.41)	Finland (–0.10)	Malawi (0.89)	Solomon Islands (1.58)
Bangladesh (0.05)	France (–0.48)	Malaysia (0.43)	Somalia (0.98)
Belarus (–0.48)	Gabon (0.05)	Mali (0.74)	Spain (–1.95)
Benin (2.22)	Gambia (–0.42)	Mauritania (2.80)	Sri Lanka (1.26)
Bolivia (0.44)	Georgia (–0.00)	Mauritius (0.32)	St. Vincent & Grens. (–0.77)
Brazil (0.55)	Germany (–0.24)	Mexico (0.49)	Sudan (0.81)
Brunei Darussalam (0.80)	Ghana (1.97)	Moldova (–0.21)	Sweden (–0.04)
Bulgaria (–0.45)	Greece (–0.87)	Mongolia (0.75)	Switzerland (–0.37)
Burkina Faso (0.34)	Grenada (0.18)	Morocco (–0.11)	Syrian Arab Republic (–1.46)
Burundi (3.98)	Guatemala (1.22)	Mozambique (0.25)	Tajikistan (–0.04)
Cambodia (1.32)	Guinea (0.66)	Myanmar (1.28)	Tanzania (1.06)
Cameroon (0.95)	Guinea-Bissau (0.45)	Nepal (1.92)	Thailand (0.67)
Cape Verde (–2.83)	Guyana (0.00)	Netherlands (–0.39)	Togo (3.59)
Central African Rep. (0.13)	Haiti (0.65)	New Zealand (–0.54)	Trinidad And Tobago (0.27)
Chad (0.63)	Honduras (3.01)	Nicaragua (1.56)	Tunisia (–3.60)
Chile (–0.37)	Hungary (–0.61)	Niger (3.10)	Turkey (–0.35)
China (–1.44)	Iceland (–4.22)	Nigeria (2.80)	Uganda (1.97)
Colombia (0.08)	India (–0.43)	Norway (–0.19)	Ukraine (–0.22)
Comoros (4.60)	Indonesia (1.78)	Pakistan (1.83)	United Arab Emirates (–1.86)
Congo, Dem. Rep. (0.35)	Iraq (–0.16)	Panama (0.14)	United Kingdom (–0.61)
Congo, Rep. (0.08)	Ireland (–2.97)	Papua New Guinea (0.45)	United States (–0.11)
Costa Rica (0.55)	Israel (–0.68)	Paraguay (0.89)	Uruguay (–3.80)
Cote D Ivoire (–0.11)	Italy (–1.18)	Peru Nuevos (0.14)	Uzbekistan (–0.53)
Croatia (–0.06)	Jamaica (0.12)	Philippines (2.63)	Venezuela (0.57)
Cuba (–1.82)	Japan (0.02)	Poland (–0.22)	Vietnam (–2.22)
Cyprus (–0.59)	Kazakhstan (0.17)	Portugal (–1.38)	Zambia (0.96)
Czech Republic (–0.04)	Kenya (0.34)	Romania (0.00)	Zimbabwe (1.54)
Denmark (–0.81)	Korea (0.11)		

Note: Numbers in the parentheses show the average rate of deforestation over our study period (%).