What has driven deforestation in developing countries since the 2000s? Evidence from new remote-sensing data*

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Abstract

Using newly-released and globally available high resolution remote sensing data on forest loss, we update the assessment of the cross-country determinants of deforestation in developing countries.

We validate most of the major determinants found in the previous literature, generally based on earlier time-periods, except for the role of institutional quality. Agricultural trade, hitherto relatively neglected, is found to be one of the main factors causing deforestation. Focusing on the effect of international trade, we show that countries with different levels of relative forest cover react differently to a shock in agricultural exports value. We also emphasize that taking countries' development into account may be critical in assessing global deforestation trends. The impact of trade is high in countries still endowed with a large proportion of forest cover while it is lower in countries with smaller remaining forest cover.

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We finally estimate, through a simple calibration exercise, the requirements for a cost-effective REDD+ policy for compensating trade losses in an open economy exporting agricultural commodities and endowed with tropical forests. We conclude that, in a world with increasing global demand, it might be costly to compensate totally and thus to offer the right incentives for developing countries to limit deforestation.

Keywords: deforestation; development; international trade.

Contents

1 Introduction

Deforestation in the tropics remains an important environmental issue in the context of global climate change and biodiversity losses. For example, the International Panel for Climate Change (IPCC, 2014) states that "the Agriculture, Forests and Other Land Uses"(AFOLU) sector currently represents a quarter of world greenhouse gas emissions.

Economists have been studying the drivers of deforestation for a long time, and at different scales (Angelsen & Kaimowitz, 1999). Analyzing its underlying causes has highlighted economic development, population pressure and institutions as important determinants of forest loss in the tropics[1]. However, as we explain in Section 2.2, only a few studies have looked at determinants of deforestation since the 2000s.

The purpose of our paper is to provide an update of the recently-observed determinants of deforestation in tropical countries by using a new data-set based on time-series analysis of satellite images, offering a unique level of precision concerning forest losses (Hansen et al., 2013).

The contribution of this paper lies in testing competing determinants of recent deforestation and in the use of new data of a unique quality. To the best of our knowledge, it is the first study that has used this dataset in order to statistically assess the underlying causes of deforestation in a cross-country panel[2] framework. Although some studies at the sub-national level were already based on such data (Burgess et al., 2012; Alesina et al., 2014; Lubowski et al., 2014; Blankespoor et al., 2014; Busch et al., 2015), they have still never been used in a cross-country panel framework. Indeed, so far, macroeconomic empirical analysis has been based on the widely criticized data provided by the FAO[3], and focused on periods prior to the 2000s.

Different data sources lead to different assessments of global forest resources. According to the last Forest Resource Assessment from FAO (2015), deforestation has been slowing down: from an annual average rate of 0.18% in the early 1900s to 0.08% during the period 2010-2015. This decreasing trend is at odds with another study, Kim et al. (2015), showing that deforestation increased by 62% in the 2000s relatively to the previous decade, using very similar data to the Hansen et al. (2013) dataset, also uniquely based on land cover imagery processing. Moreover, as explained in Li et al.

[1]See for instance Angelsen & Kaimowitz (1999); Cropper & Griffiths (1994); Bohn & Deacon (2000).

[2] A panel is a dataset in which entities (countries in the case of our study) are observed across time.

[3] For the criticisms, see DeFries et al. (2002); Czaplewski (2003); Grainger (2008); Furukawa et al. (2015) and Kim et al. (2015)

(2016), a different canopy fraction is adopted in the forest definition in the two methodologies: over 10% in the FAO assessment against a threshold of 25% in Hansen et al. (2013).

We conducted our panel analysis for the period 2001-2010, using the usual explanatory variables present in the literature. Our analysis suggests that (i) usual drivers of deforestation (population density, economic development and agricultural activity) tend to explain the dynamics of deforestation at the national level in the 2000s as was the case during previous decades. However, we do not find evidence that institutional quality (measured by governance and freedom indices) influence deforestation. More importantly, we found evidence that (ii) trade in forestry and agricultural commodities, a factor which has been quite neglected in previous literature, is an important factor in forest clearance and that (iii) the impact of trade is predominant in countries still endowed with a large proportion of forest cover.

The paper is organized as follows. The second section presents a literature review of the determinants of deforestation. Section 3 describes the data and the recent trends in forest land cover and losses at the national level. Section 4 presents the results of the analysis of the standard determinants of deforestation and section 5 investigates the effect of trade. Section 6 concludes.

2 Determinants of deforestation: a review

2.1 Trade as one of the main channels identified in recent studies

Recent studies have highlighted trade as a potential driver of deforestation. Faria & Almeida (2016) show empirical evidence that between 2000 and 2007, when Brazilian municipalities of the *Amazonia Legal* opened to international trade, deforestation increased. This is also the case of studies emphasizing the role of industrial production oriented towards international trade. DeFries et al. (2010) show the same relationship at the national level for the period 2000-2005, arguing that policies should focus on reducing deforestation that is carried out for industrial-scale, export-oriented agricultural production. In the same vein, Hosonuma et al. (2012) shows that commercial agriculture is the first determinant, followed by subsistence agriculture. Finally, Gaveau et al. (2016) examined the effect of industrial plantation in Borneo since the 1970s. These authors find that it has been the main cause of deforestation of old-growth forests in the Malaysian part, and to a lesser extent in the Indonesian part too. However, the limited availability of aggregated data at the national level about the type of agriculture (subsistence vs. commercial) prevents the use of robust quantitative methods.

Schmitz et al. (2015) show that further liberalization would lead to an expansion of deforestation in Amazonia due to the comparative advantages of agriculture in South America. Globally, they estimate, using a spatially explicit economic land-use model coupled to a biophysical vegetation model, that an additional area of between 30 and 60 million ha (5-10%) of tropical rainforests would be cleared, leading to 2040 Gt of additional CO2 emissions by 2050.

Facing such pressure, conservation is put forward as one of the main solutions for a policy-oriented response (Schmitz et al., 2015). Lavelle et al. (2016) investigate the sustainability of deforested land in the Brazilian Amazon using socioeconomic and environmental data. While sustainability, as defined by their own index, decreases over time, they find that agroforestry practices can be used to achieve environmental and social goals in the region.

The effectiveness of protected areas in preventing deforestation in the tropics has already been thoroughly examined. For instance, Haruna et al. (2014) discuss the importance of forward-looking plans when implementing those protected areas in Panama, Robalino et al. (2015) study the optimal spatial distribution of these policies in Costa Rica. Finally, this subject has been looked at by two other research teams (Blankespoor et al., 2014; Maher et al., 2013) working with the same dataset that we use in this article. However, Pfaff et al. (2015) find that protected areas tend to be located on land facing less pressure which would reduce the efficiency of such policies. This is consistent with Ferretti-Gallon & Busch (2014) and Heino et al. (2015) results showing limited impact of protected areas on deforestation at the national level and high heterogeneity across countries.

Amin et al. (2015) nevertheless found that, if leakage reduces the amplitudes of reduction in deforestation, it does not annihilate it. Moreover Nolte et al. (2013) has found that lands under sustainable use, strict protection as well as indigenous land, efficiently reduced deforestation in the 2000's decade, in an empirical estimation on 264 Amazonian municipalities. Barber et al. (2014) found it is true even when properly controlling for access to transportation (different types of roads and navigable rivers).

This result validates the ones of Nelson & Chomitz (2009, 2011) who showed that strict protected areas were more efficient in reducing deforestation than multi-use protected areas, although endogeneity may exist in the localisation of multi-use areas, generally located in zone of higher deforestation pressure. However spatial leakage is not controlled in those analysis. And such result does not seem very robust since Nelson & Chomitz (2011); Ferraro et al. (2013) show the very high heterogeneity in the positive relation between strictness of protection and performance in terms of deforestation reduction across within and across countries and continents. Pfaff et al. (2014) also investigated the efficiency of governance in managing protected areas (PAs) in one specific state of the Brazilian Amazon. They found that the beneficial effect of PAs was actually driven by location: PAs with a strict-blocking governance were assigned to areas with low pressure (weak development and poor population density), i.e. in areas where deforestation was less likely to take place even in absence of public policies. For this reason, they claim that sustainable use areas helped reducing more significantly deforestation. To do that, the authors used spatial data only available at the state-scale. Moreover, Rasolofoson et al. (2015) has showed that community forests are not always reducing deforestation, they are efficient only if they do not allow commercial use of the forest. As well, Bottazzi & Dao (2013) studied the impact of political processes on forest harvesting in the Bolivian Amazon. Authors also took into account some spatial impacts only visible at the state level. They found that collective property rights were attributed to remote areas with little or no pressure on forests, and that this was explaining the fact that this regime of land rights exhibited less deforestation.

2.2 Statistical determinants: a review of cross-country panel studies

In this section we review the determinants of deforestation found in the economic literature more systematically. Geist & Lambin (2002) distinguish biophysical, economic or technological, demographic or institutional and cultural factors leading to deforestation. We will focus on economic, demographic and institutional factors. Many of them are found in a recent meta-analysis (Ferretti-Gallon & Busch, 2014) including microeconometric studies and thus incorporating additional variables such as road network density, commodity prices, protected areas and payment for ecosystem services among others.

The famous stylized fact revealed by Simon Kuznets in the 1950's, the so-called Kuznet curve: an inverse U-shaped relationship between income and inequalities, was then extended to the consumption of natural resources and emission of pollutants. It is known as the Environmental Kuznets Curve (EKC), the first determinant we will discuss.

Empirical studies describe an inverted U-shaped relationship between environmental quality and income per capita. The main insight of such theory is that GDP and environmental degradation grow together during the first steps of a countrys development, and, once a given threshold of income (unique to each country) is reached, environmental degradation starts decreasing while

GDP per capita keeps increasing.

This has then been applied specifically to deforestation issues, as described in the geography literature (Rudel et al., 2005) or in environmental economics (Wolfersberger et al., 2015) literature. To describe the link between deforestation and income, the authors used the forest transition theory and talk about the economic development path, whose impact on forest conservation seems to be ambiguous.

First, early development steps are characterized by agricultural expansion and forest clearance. In the short term, an increase in the global income may raise the total demand for agricultural products, leading to agricultural land expansion and in turn promoting deforestation (Angelsen & Kaimowitz, 1999). For instance, over the period 1980-2000, more than 80% of new croplands were created at the expense of previously forested lands (Gibbs et al., 2010).

Then, when enough capital has been accumulated from land clearance, the industrial sector develops and commands higher rents than agriculture. Some farmers leave their land to move to the cities, where they can take manufacturing jobs with higher wages. Along with this urbanization pattern, agricultural intensification occurs as a result of the increase in physical capital (*e.g.* machines, fertilizers) per worker. In the meantime, the demand pattern changes and the population consumes more non-agricultural based products. The combination of all these macro-trends can lead, in certain cases, to the end of deforestation in a country.

Since the 1990's, many studies have tested the existence of an EKC for deforestation, defined by the underlying forces described above. However, there is no evidence that such a stylized fact is always verified (Choumert et al., 2013). Indeed, depending on data sources or the analysis period, results vary. Also, empirical evidence shows that urbanization can occur without a slowdown in deforestation rates. For example, the urban population (as a percentage of total population) in Indonesia increased from about 30% in 1990 to almost 50% in 2010 (World Bank data). However, over this period, deforestation also increased, notably for exports. This is why stylized facts must be interpreted cautiously, as must the time lapse of analysis.

As a complement to these economic mechanisms, it is important to consider the potential impact of pro-environmental policies. As Lambin & Meyfroidt (2011) highlight, the "international environmental nongovernmental organizations, multilateral environmental conventions, and aid agencies also globalize sustainable development objectives and related forest management practices". This globalization of an environmental consciousness has contributed to more environmentally-friendly education and can, eventually, lower the threshold above which deforestation decreases.

Population density is often mentioned as a major factor putting pressure on natural resources, including forests. In developing countries endowed with forest resources, rural populations migrate when access to land is improved, and convert forests into croplands, harvest trees for fuelwood, timber and other forest products. Meanwhile, demographic expansion supplies a large number of workers, maintaining the wages of the agricultural sector at a low level (Angelsen & Kaimowitz, 1999). As a result, agricultural rents are high and land conversion proceeds. Since the seminal work of Cropper & Griffiths (1994), several econometric analyses have found evidence that population is positively correlated with deforestation in developing countries.

Institutional quality has been found to be critical in the deforestation process (Bohn & Deacon, 2000; Barbier & Burgess, 2001; Bhattarai & Hammig, 2001; Culas, 2007; Nguyen-Van & Azomahou, 2007). Because of corruption and high tenure costs, landowners are encouraged to turn their land over to agriculture, in order to define property rights[4]. More broadly, weak governance in developing countries with forests often leads to higher rates of deforestation (Barbier et al., 2005).

The impact of international trade[5] on land conversion remains unexplored in the field of deforestation. First, economic principles from early trade theory suggest that a country with a substantial amount of natural resources might develop a system that uses those resources intensively. This is why countries with large areas of forest and arable land export timber and agricultural products. While about 80% of current global deforestation is supposedly due to agricultural production (FAO, 2015), most of it is traded internationally: few empirical works identified a significant relationship between trade and deforestation. Among these, Barbier et al. (2005) found that policies improving the terms of trade (i.e. the relative price of exports in terms of imports, corresponding to price competitiveness) in a country with forests increases producers' prices, and thus promotes deforestation. Arcand et al. (2008) have shown that a depreciation of the real exchange rate can increase the exports of commodities in countries from the South, and then increase deforestation.

Finally, recent empirical studies using cross-country panel data focus on the forest transition hypothesis to explain deforestation dynamics (Culas, 2012; Wolfersberger et al., 2015). The forest transition (Mather, 1992) describes changes in the forest stock in a country, in relation to its level of development. It states that forest cover first declines, then stagnates and

[4] On the productive use of land, see for example Araujo et al. (2009) for a study from Brazil.

[5] Defined as the flows of exports and imports of agricultural and timber products between countries.

may finally even experience an increase concomitant with the development of other economic sectors such as industry. The latter phase of forest increase may be more or less pronounced, depending on the country. Some developed countries, such as France or the USA, have experienced a substantial increase (Mather, 1992). However, if empirical evidence indicates that the same pattern is seen in emerging economies such as India (Foster & Rosenzweig, 2003) or Vietnam (Meyfroidt et al., 2013), it may take a long time or even never be triggered in some other developing countries.

Total accumulated deforestation differs in the Democratic Republic of Congo, where the forest transition has not yet started and land is still largely covered by forests, or in Vietnam, where the large phase of deforestation is over. It is thus reasonable to assume that forest policy and economic incentives related to land use also differ at distinct stages of development. Wolfersberger et al. (2015) found that determinants of land-use changes differ depending on whether a country is before the turning point or has already reached it.

Table 1 summarizes previous studies that have developed an econometric methodology to identify the macroeconomic drivers of deforestation. For each study, we give the period studied, the source of the dependent variable, the type of model estimated, and the macroeconomic variables that are found significant.

Studies presented in Table 1 were carried out over time-periods prior to the 2000s (with the exception of Combes-Motel et al. (2009) that goes up to 2005). Also, studies listed in Table 1 use the FAO data, which was the only dataset available for a long time. In contrast, we use recent and more accurate data, outlined in the section below.

Table 1: Main results of the literature composed of cross-country analyses

Authors	**Time-period**	**Model**	**Data** (dependent variable)	**Developmt**	**Populat**^{o}	**Institut**^{o}	**Trade**	**Comments**
Cropper & Griffiths (1994)	1961-1991	FE	FAO	X	X	∅	∅	By continent.
Rudel & Roper (1997)	1975-1990	OLS	Deforestation - FAO, IUCN & others	X	X			Also tested: debt, roads & wood products per forest area.
Barbier & Burgess (2001)	1961-1994	OLS, FE and RE	Agricultural expansion - FAO				X^{3}	All countries and by continent. Also tested: cereal yields & arable land per capita.
Bhattarai & Hammig (2001)	1972-1991	FGLS	Deforestation rate - FAO	X	X	X	∅	By continent. Also tested: cereal yields & debt level.
Barbier (2004)	1960-1999	RE	Agricultural expansion - FAO	X		X	X^{1,3}	Also tested: cereal yields & growth in agricultural value added.
Barbier et al. (2005)	1961-1999	RE	Agricultural expansion - FAO	X		X	X^{1,3}	Also tested: cereal yields.
Mahapatr & Kant (2005)	1980-1995	OLS and logistic models	Deforestation rate - FAO		X		∅	
Scriecu (2007)	1980-1997	OLS, FE	Deforestation rate - FAO	X	X	∅	X^{1}	
Culas (2007)	1972-1994	OLS, FE and RE	Deforestation rate - FAO	X		X		Also tested: debt, agricultural production and wood price.
Nguyen-Van & Azomahou (2007)	1972-1994	FE & non parametric	Deforestation rate - FAO		X	X		
Arcand et al. (2008)	1961-1988	OLS, FE and GMM	Deforestation rate - FAO	X		X	X^{2}	Also tested: timber price.
Combes-Motel et al. (2009)	1970-2005	FE (5 and 10 years av., only natural forest area)	Deforestation rate - FAO	X	X	∅	∅	All countries. No test for trade.
Damette & Delacote (2011)	1972-1994	FE (1 and 5 years average)	Deforestation rate - FAO	X	X	X	X^{1}	Also tested: timber price, harvesting & certification.
Culas (2012)	1972-1994	FE and RE	Deforestation rate - FAO	X		∅		Also tested: debt, agricultural production, wood price & export index price.
Damette & Delacote (2012)	1972-1994	FE and Quantiles (pooled and FE)	Deforestation rate - FAO	X^{4}	X^{4}	X^{4}	X^{2,4}	Also tested: timber price.

Notes: OLS: ordinary least squares; FGLS: feasible weighted least squares; FE: fixed effects model; RE: random effects model, GMM: generalized method of moments.
X: the variable was found to have a significant role in deforestation
∅: the variable was not tested
For studies containing regressions both on all countries and per continent, we have reported the results of the regression on all countries
[1]: terms of trade, export or timber prices
[2]: real exchange rate
[3]: agricultural exports
[4]: only FE and higher quantiles of pooled quantiles regressions are significant, not FE quantiles regressions

3 Data and recent trends in deforestation

3.1 Data

We use new high-resolution data (Hansen et al., 2013) that provides a 1 arc second (about 30m at the equator) grid of a land cover estimate, corresponding to the percentage of the pixel size with vegetation taller than 5 meters in height, in 2000. It also estimates, at the same resolution, for every year from 2001 to 2012 whether forested cells were cleared, or if other land uses were turned into forest. The 2011-2013 data were updated in February 2015, and 2014 data were made available in 2016, but since we only have macroeconomic variables up to 2010, we do not use this second (v1.2) version of the data. Both estimates allow us to compute the deforestation rates and cover for each year of the considered period (2001-2010)[6].

We first average the forest cover of every pixel (i) of 1 arc-second in year 2000, for every country (j, with N pixels inside its borders) area. In accordance with (Lubowski et al., 2014) and given the way the data were computed from satellite imagery (Landsat 7 ETM+), we only consider grid cells (i) with more than 25% of forest cover as forests[7].

$$
\begin{aligned}
&Fcover_j = \frac{1}{N}\sum_{i=1}^{N} Fcover_i^{1''},\\
&\quad if \quad (Fcover_i^{1''} > .25 \quad \& \quad AverageCoord(Fcover_i^{1''}) \in Country_j)
\end{aligned}
$$

Then, we average the forest land cover ($Fcover_j^{30''}$) for every 30 arc-second (0.05^o, about 900m at the equator) pixels, reducing resolution in order to meet computing time constraints. We also computed the annual weighted average of deforestation for 1 arc second [8]) by their percentage of forest cover ($Defor_j^{30''}$).

$$
Defor_j^{30''} = \frac{1}{N}\sum_{i=1}^{N} Fcover_i^{1''} \times Defor_i^{1''}, \quad if \quad Pix_i^{1''} \in Pix_j^{30''}
$$

Using both new resolution (30 arc-second) grids, we finally multiply the forest cover and deforestation ratios by the surface area of each cell in square

[6] Online material, i.e. the Matlab© code, used for allocating and averaging 1 arc-second pixels of publicly available data on forest cover and deforestation into country averages, is available at the following link.

[7] Unlike (Lubowski et al., 2014) we do not use a count model, but a finer estimation by averaging the cover of every 1 arc-second / 30 meters at the equator pixels.

[8] Dummy variable provided by Hansen et al. (2013) at the following link.

km and sum all the cells that have their barycentres inside a given country border, for a given year (y).

$$Defor_{y,j} = \sum_{i=1}^{N} Defor_i^{30''} \times Area_i^{30''},$$
$$if \quad AverageCoord(Defor_i^{30''}) \in Country_j$$

The major drawback of this data is that forest gains and losses can not be merged, which prevents us from looking at net deforestation. However, we only consider developing countries in our study, where intensive forest harvesting (i.e. with short rotation periods) and/or harvest-plantations are scarce, reducing the potential bias. As showed in Hansen et al. (2013), pixels where both losses and gains are experienced during the considered period (purple color locations in Figure 1) are largely concentrated in richer countries. Considering only primary forests would have been another way of dealing with such bias, however, we cannot consider only primary forests without drastically reducing our sample size[9].

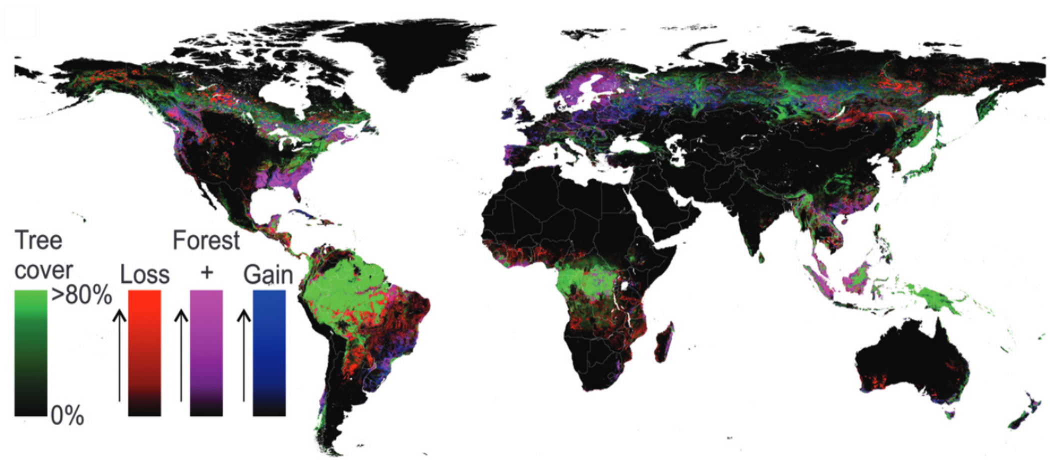

Figure 1: Deforestation (losses), afforestation (gains) and net afforestation between 2000 and 2012, source: Hansen et al. (2013).

Moreover, when looking at rich countries, round-wood production played a great and significant role in deforestation, while this was not true when running the same regressions in our final sample of 128 developing countries (cf. Table 6 in Appendix A.1), studied from section 4 onwards.

[9] 64 countries had intact forest landscapes (IFL) in 2013. Most of the world's IFL area is concentrated in a small number of countries - 11 countries contain 90% of the total IFL area (with 65% in three countries).

Following previous studies (Damette & Delacote, 2011; Culas, 2007; Scriecu, 2007; Arcand et al., 2008; Combes-Motel et al., 2009; Choumert et al., 2013; Culas, 2012), our deforestation indicator ($dfrst$) is the yearly decrease in forest cover ($Defor_t - Defor_{t-1}$), divided by the the country area ($land_t$). Using the annual deforested area relative to the country size as the dependent variable allows us to standardize country level deforestation and control for the high heterogeneity in country size and their proportion of forest land cover in our sample. A large deforested surface area has a different meaning in a small than in a large country, dividing by the country size thus normalizes our dependent variable. Moreover, from the statistical point of view, such normalization also avoids heteroscedasticity issues by reducing the variance of the variable and its variability between countries.

3.2 Recent trends in forest losses

In this section we describe (i) recent global deforestation trends, (ii) the specific trends in our final sample of developing countries analyzed in the results section and (iii) specific graphical evidence in countries with the largest levels of deforestation.

(i) World

First, we investigate the global dimension of deforestation. To assess global trends in different types of forests, we classify them, using the mean latitude, into boreal (43 countries), temperate (40 countries) and tropical forests (85 countries).

The three climate zones are characterized by the same trend of increasing deforestation (see Figure 2), meaning that the objective of stopping deforestation at a global level has not been reached. Moreover, they showed the same pattern until the 2008 financial crisis. After that period, a divergence is observed among the three types of forests[10]. Figure 2 also shows that tropical deforestation represents almost half of overall global forest clearance.

(ii) Developing countries

As mentioned above (end of section 3.1), we restrict our sample to 128 countries, with an average GDP per capita (2000-2010) of below US$ 12,746 (in line with the World Bank threshold of the low and middle income countries categories for the 2015 fiscal year).

When looking at those with more than 5% of forest cover in 2000, we see

[10] Note that losses in temperate and boreal forest may be due to sustainable harvesting and deforestation compensated by plantations. Anecdotal observation from Hansen data on-line, shows that the increase in boreal deforestation after 2009 probably corresponds to tar sand exploitation in Canada and increased deforestation in Russia.

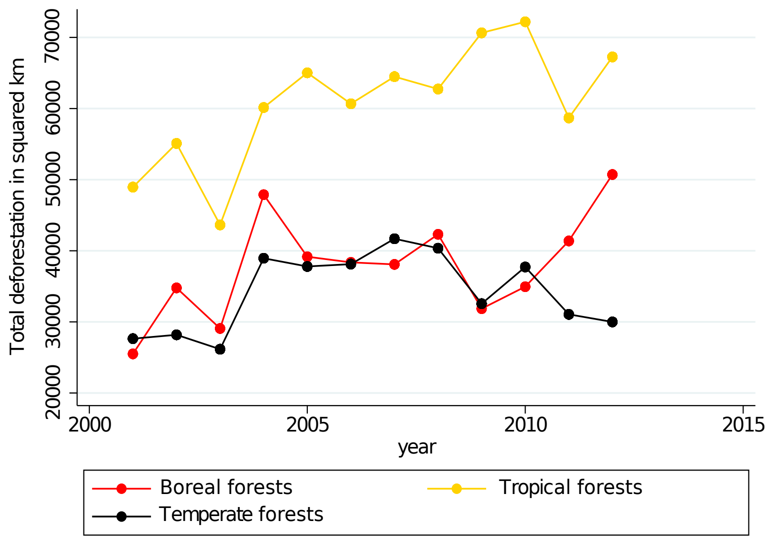

Figure 2: Sum of country-level deforestation (sq. km) under different climates.

that they are characterized by two kinds of trends (Fig 3). Some countries (region names in red) exhibit some positive trends while on the contrary other countries (in green) exhibit volatile but similar paths. In the latter, changes seem to be subject to more erratic variations, which suggests the presence of common factors such as the impact of world demand and business cycles driving the deforestation patterns in this kind of country. In both cases, the change in the trend after the financial crisis is distinguishable, however no strong effect was detected through fixed effects regressions and will thus not form part of our empirical analysis in the following sections.

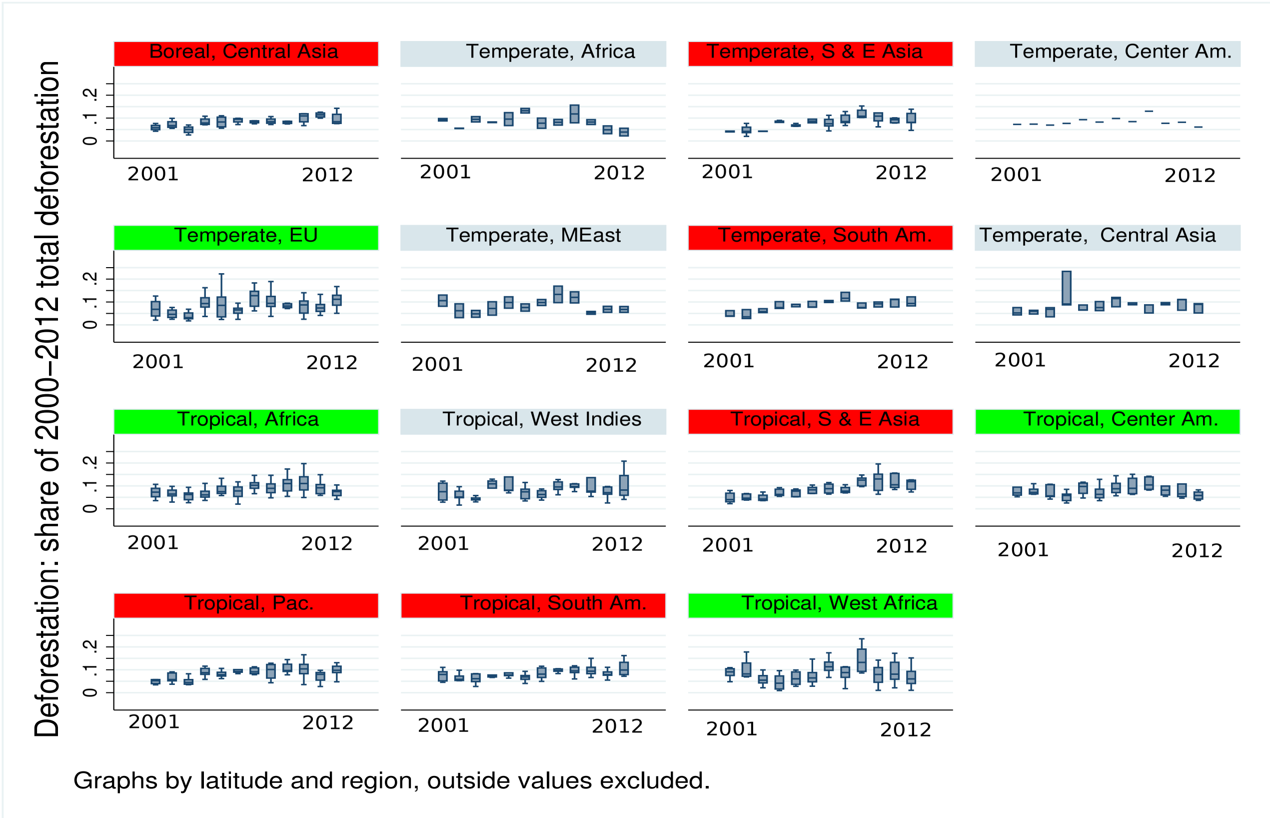

Figure 3: Annual percentage of study period deforestation, by country (with more than 5% of forest in the country area and an average GDP per capita inferior to US$ 10,000) over the period considered. Lower and upper bound respectively corresponding to the lowest and highest values and box limits to 25 and 75 percentiles, median line corresponding to the median of the distribution.

(iii) Country level deforestation

In this section we consider the 30 countries with the largest level of deforestation from our final sample[11], i.e. countries with more than 6,000 km^2 of deforestation over the period 2001-2012, in order to look at national trends.

We first focus on the 6 countries with the highest level of deforestation, above 40,000 km^2 over the period considered. Figure 4 shows the changes in deforestation levels over the period studied for the 6 biggest countries in terms of absolute forest clearance, and Figure 5 shows changes in deforestation in the next 24 countries.

We can see that if, from 2005 onwards, deforestation was reduced in Brazil[12] thanks to stringent national policies, it may have simply leaked across into neighbouring countries such as Bolivia, Paraguay and Peru. Moreover, considering that global demand may be sustained and geographically widely distributed through international trade, this potential leakage effect could also be tested in other tropical countries. However, given the limited time span of our sample restricting the statistical power of potential identification strategies, we only focus on international trade in this paper.

[11] Low and middle income countries, according to the 2015 World Bank definition.

[12] And on a much smaller scale other emerging economies such as China.

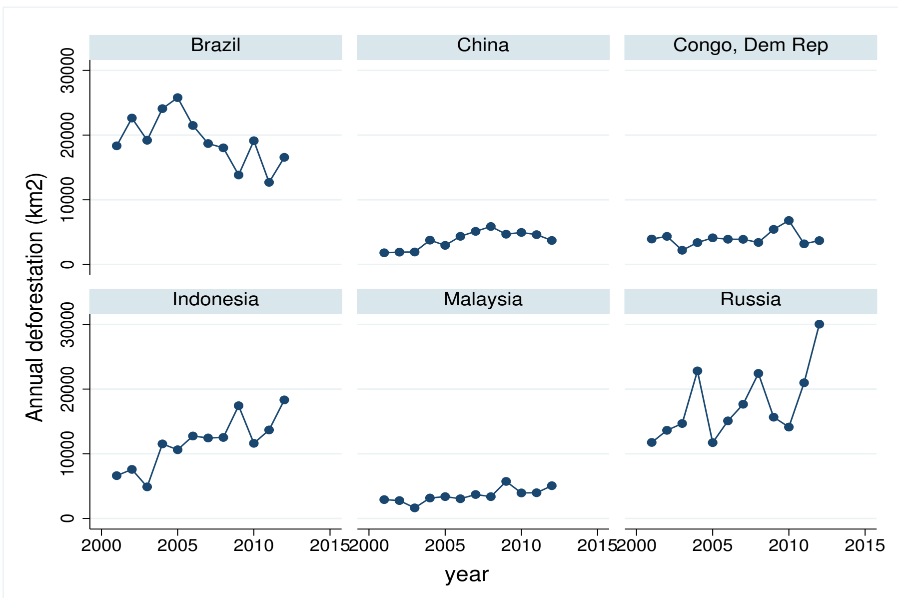

Figure 4: Deforestation in the biggest developing countries, deforestation in 2001-2012 superior to 40,000 km^2

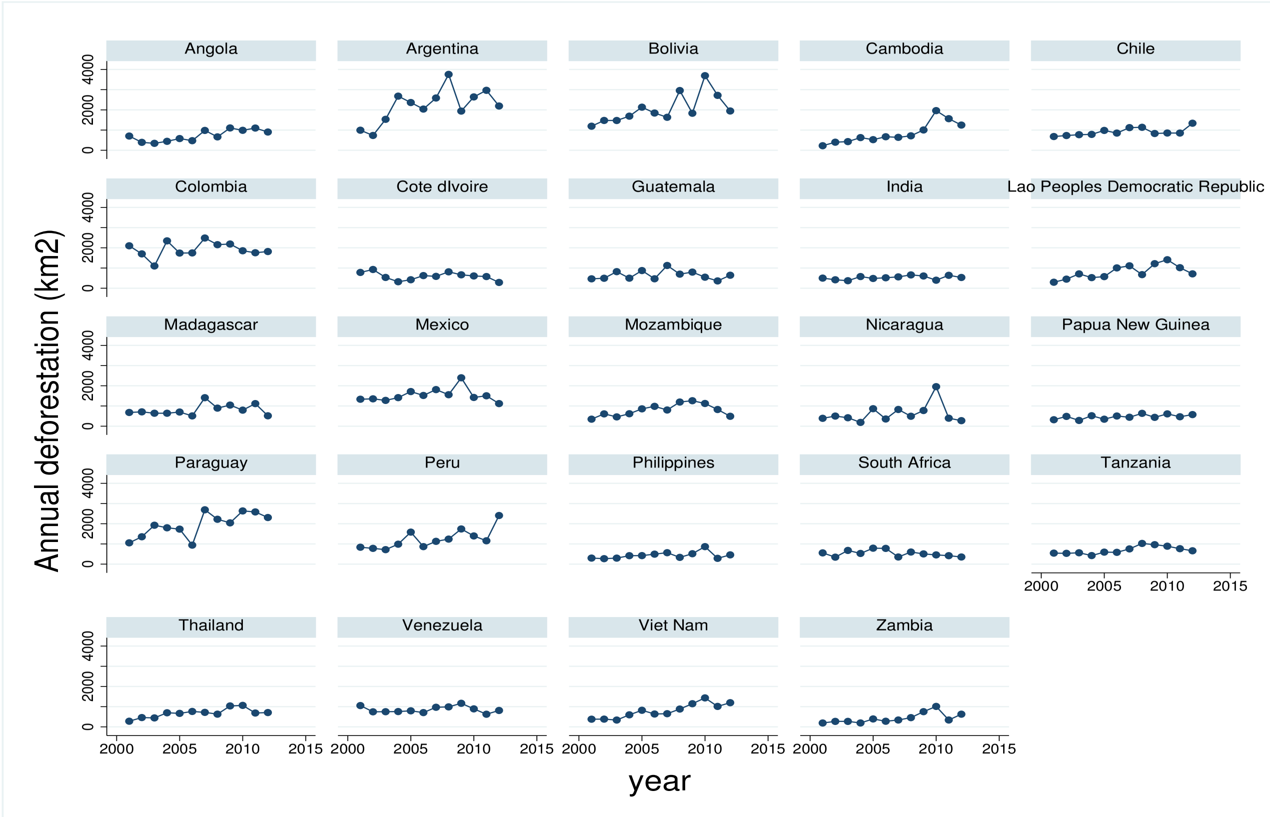

Figure 5: Deforestation in other developing countries, deforestation in 2001-2012 superior to 6,000 km^2

4 The underlying causes of deforestation: an update

In this section, we first review the regressors used and the sources of variables, we then describe the model and finally derive the results at the global level and per continent in order to look at potential geographical heterogeneity in determinants of deforestation.

4.1 Variables

Our paper aims to understand what drove deforestation over the past ten years in low and middle income countries. In order to put our findings in perspective with existing studies on previous time-periods, we use the explanatory variables commonly present in the literature (described in section 2.2). This section make the inventory of such determinants, mentioning (in brackets and in italics) the name of the variables tested in our empirical analysis. Summary statistics are available in Table 7, Appendix A.2.

To account for the effect of development, we introduce the *GDP per capita* (constant 2005 US$) and its annual growth rate (*GDP pc growth, 2005 constant*).

We use different variables to control for the influence of institutions. To account for the influence of the democratic scale (*polityII*: from most democratic to most autocratic) and political stability (*durable*) from the IVpolitics project, Polity IV (2009). The literature also widely uses two other variables provided by the Freedom House (2014) to test institutions : *political rights* and *civil liberties*. Values vary between 1 and 7, a high score indicating poor institutional quality.

We additionally test governance on resource use, taking an index of control of corruption, of rule of law, and an index of political stability and absence of violence, all provided by the Worldwide Governance Indicators (WGI) database[13]. The measures of governance are in units of a standard normal distribution, with zero mean and standard deviation of one. They range from approximately -2.5 to 2.5, with higher values corresponding to better governance.

Population pressure is measured by the mean country population density (*population density*: thousands of people per square km).

Agricultural expansion is known to be the primary cause of forest conversion. We thus consider an index of annual agricultural production (*Crop*

[13] World Bank, see http://info.worldbank.org/governance/wgi/index.aspx, (Kaufmann et al., 2009).

production index (2004-2006 = 100)). We also tested the role of cultivated land (*agricultural land*: percentage of country surface area) and the *agricultural value added* (as a percentage of GDP), the latter has been removed since it explained fewer variations of deforestation, the dependant variable. An additional variable for agricultural trade was extracted from the FAO statistical database: the lagged total value (quantity not available) of exports of forestry and agricultural commodities. All those variables are extracted from the FAO website as at December 2014.

Finally, the influence of international trade is controlled for using the openness rate (*Openness at 2005 constant prices*: the sum of import and export values as a percentage of total GDP) and the relative comparative advantage (*Terms of trade*: relative prices of exports in terms of imports), as defined by and extracted from the World Bank data website.

4.2 Model

We next turn to the regression model. To this end, we use a country fixed effect regression model[14], with clustered standard errors to address within-group correlations. Failure to control for within-cluster errors correlation can lead to misleadingly narrow confidence intervals, large t-statistics and low p-values. In order to correct such bias we used bootstrapped standard errors in the calculations of statistics. The model is the following:

$$dfrst_{i,t} = \alpha + \beta X_{i,t} + C_i + \epsilon_{i,t}, \tag{1}$$

where X is the vector of explanatory variables presented above, C_i are the country-specific fixed effects and ϵ the error term. Country fixed effects are dummy variables[15] controlling for every unobserved country specificity that does not vary through time (such as educational, cultural or other institutional factors that do not vary in the short term *e.g.* willingness to implement conservation policies).

We lagged the potentially endogenous variable stacked in X (*Crop production index*, *GDP per capita* and its squared value, *Openness*, *Agricultural and forest export value per surface exploited*) in order to avoid reverse causality issues in our regressions. Indeed, the effects of explanatory variables can be biased by effects in the opposite direction *i.e.* by the effects of the deforestation rate on the drivers of deforestation.

[14] Following results of the Hausman test, very robust to specification choice and compatible with results in other databases (Aisbett et al., 2013; Barbier, 2004).

[15] i.e. variables that take the value one if the observation corresponds to country i, and zero elsewhere.

Note that all variables are assumed to be stationary, avoiding spurious regression problems in panel fixed effects estimations. A dynamic stochastic process is considered stationary when there is no unit root. Unit root is the violation of the stationarity hypothesis in the sense that the dynamic process is a linear function of the same process in the past. For instance, the deforestation rate has a unit root if the deforestation rate at time t is a linear function of the deforestation rate at the previous period t-1. In other words, the stochastic dynamics of the variable are not a function of time and are relatively stable over time (parameters of mean and variance are constant over time).

We performed the most used first generation panel unit root tests (Levin et al., 2002; Im et al., 2003) and do not find any unit root in the dynamics of our variables, as explained below. All in all, the spurious regression problem needs to be put in perspective given the small time dimension of our panel data set.

Table 2: Drivers of 2001-2010 deforestation, OLS, FE in Low-Income Countries: specification robustness

	(1) (OLS, FE) dfrst (standardized)	(2) (OLS, RE) dfrst (stand.)	(3) (GMM) Annual deforestation (log km2)	(4) (OLS, FE) dfrst (stand.)
L.Annual deforestation (log km2)			-0.0509	
			(0.0842)	
GDP per capita, (log, 2005 constt, -1) (standardized)	0.826^{***}	0.294^{***}		-0.982
	(0.207)	(0.0895)		(1.390)
squared GDP per capita, WPT (log, 2005 constt, -1) (standardized)				1.733
				(1.334)
GDP pc growth (2005 constt) (standardized)	0.0306^{*}	0.0191		0.0354^{**}
	(0.0181)	(0.0190)		(0.0165)
Population density (log) (standardized)	1.315^{***}	0.224^{***}		1.417^{***}
	(0.472)	(0.0763)		(0.502)
Agricultural land (% country area, -1) (standardized)	0.0355	-0.180^{**}		0.0974
	(0.218)	(0.0750)		(0.209)
Openness at 2005 constant prices (%, -1) (standardized)	0.120^{*}	0.214^{***}		0.124^{*}
	(0.0682)	(0.0734)		(0.0648)
Terms of trade (standardized)	-0.107^{***}	-0.0569^{**}		-0.112^{***}
	(0.0318)	(0.0258)		(0.0317)
Crop production index (2004-2006 = 100, -1) (standardized)	0.0490	0.110^{***}		0.0566^{*}
	(0.0360)	(0.0404)		(0.0332)
polityII (standardized)	-0.00291	0.0516		-0.00428
	(0.0380)	(0.0388)		(0.0368)
durable (standardized)	0.0152	0.0307		0.0133
	(0.0647)	(0.0591)		(0.0650)
GDP pc growth (2005 constt)			0.00511	
			(0.00506)	
GDP per capita, (log, 2005 constt, -1)			1.246^{***}	
			(0.352)	
Population density (log)			0.668	
			(0.889)	
Openness at 2005 constant prices (%, -1)			-0.000357	
			(0.00168)	
Agricultural land (% country area, -1)			0.0170	
			(0.0167)	
Terms of trade			-0.00231	
			(0.00183)	
Crop production index (2004-2006 = 100, -1)			0.000328	
			(0.00223)	
PolityII			0.00139	
			(0.0136)	
Durable			0.0182^{*}	
			(0.0107)	
Constant	0.226^{***}	0.136	-4.758	0.226^{***}
	(0.0462)	(0.0997)	(4.250)	(0.0454)
Observations	1150	1150	896	1150
R^2	0.109			0.111
Adjusted R^2	0.102			0.104
between	0.0.433	0.1541		0.0361
within	0.1086	0.0879		0.1114
overall	0.0433	0.1494		0.0373
AB p-value of AR(2)			0.6799	
P-value of Sargan test			0.0000	
P-value of Wald test			0.0000	

Standard errors in parentheses, robust to country clustering
* $p < .1$, ** $p < .05$, *** $p < .01$

Table 2 shows the result for different specifications, panel with fixed effects (column 1), random effects (column 2), generalized method of moments (GMM, Arellano & Bond (1991), column 3) and testing the EKC in a panel fixed effects framework (column 4).

The first model (panel ordinary least squares, with fixed effect (FE), first column of Table 2) is our benchmark model and is based on the hypothesis that that the unobserved individual factors (for instance the culture of a country) are captured by individual intercepts (C_i are fixed effects). In the random effects (RE) model (second column of Table 2), the unobserved factors are captured by random variables with the same variance. The C_i coefficients are independent.

If we relax the hypothesis of correlation between individual effects and covariates, the individual constant terms have a random distribution between deforesting countries. In this case, individual effects are no longer fixed but become random. The main advantage of this kind of model is that it reduces the number of parameters to estimate. But at the same time, if the number of observations is not enough to approximate the population, the RE estimator might be inconsistent.

The fixed effect model (column 1) is preferred in our case: it is more suitable when the entities are not random, like in a sample of developing countries. Using country fixed effects, i.e. capturing country specificities that are fixed through time, is very useful to control for unobservable characteristics, e.g. cultural, institutional and policy drivers. The idea is that whatever the effects of the omitted variables are at one time, we consider they have the same effect at a later time. In other words, Model 3 is the best only if we believe that there are no omitted variables or if the omitted or unobserved factors are uncorrelated with the explanatory variables.

We also introduce the lag of the deforestation rate into the set of explanatory variables and find that, in a differenced GMM framework (Arellano & Bond, 1991), the unit root level is low and not statistically significant, leading to limited serial correlation of the residuals (column 3, Table 2). Besides checking for non-stationarity (*i.e.* dependence of a given observation to previous states of the variable) of our explained variable, such specification is much more robust in a time series analysis. It controls better for changes over time for each series and allows standard statistical tests to be run for time series analysis, that fit our analysis since we have 10 years of observations for each country.

The model estimated in column 4 is just an extension of the model estimated in column 1 but it takes into account the EKC hypothesis by adding a GDP squared term. Finally, the model estimated by GMM is a dynamic panel model and focuses on the potential presence of endogeneity issues when the deforestation rate has some effects on the drivers of deforestation. A lagged endogenous term $Y_{i,t-1}$ is thus added to the equation (1) in the right-hand term.

Showing the results of these 4 models ensures the robustness of our estimates to different model specifications.

4.3 Results

Overall OLS-FE results from Table 2 are consistent with the existing literature reviewed in Table 1. Both *GDP growth* and lagged *GDP per capita* are positively and significantly related to deforestation and provide outline evidence of an empirical relationship between economic activity and environmental degradation in line with the first part of the Kuznets Curve. However, the concavity of the Kuznets curve was not found to be robust to different specifications: the square of GDP per capita is often found to be not significant (as shown in Table 2, column 4). Although this may be due to the short temporal depth of our panel and the fact that we only consider developing countries, it is consistent with previous results from a literature survey (Choumert et al., 2013).

Moreover, we find that *population density* is a significant driver of deforestation. This result is in accordance with the theoretical literature and several empirical studies using older data (Table 1).

In contrast to previous studies, political institutions (*polity II, durable*)[16] were not found to have a robust significant effect on the tropical deforestation process at a global level. For instance, Nguyen-Van & Azomahou (2007) and Damette & Delacote (2011, 2012) used the *political right* index while Culas (2007) looked at secure property rights and better environmental policies, all of those studies found evidence of a negative impact of institutional quality on deforestation level. Although institutions were also found not significant in other studies based on older FAO data (Aisbett et al., 2013), the different period considered is a potential explanation for the discrepancies between our findings (2001-2010) on institutional impacts and those from previous literature (1961-1994). Finally, the short time dimension of our panel and the cross-country framework may also explain that we fail to apprehend the potential impact of the evolution of lower scale institutions, such as forest-governance regimes, land tenure and rights.

Agricultural production, proxied by the lag of *Crop production index*,

[16] Other institutional variable were tested: control of corruption, rule of law and political stability and absence of violence, (Kaufmann et al., 2009), as well as civil liberties and political rights from the Freedom House (2014); they were all found to be non-significant, cf. tables 9 and 10 in Appendix A.4.

is also positively related to deforestation rates (and significant in 2 out of 4 specifications, column 2 and 4 of Table 2) confirming it to be a main driver of deforestation. Furthermore, the proportion of *agricultural land* is only significantly related to deforestation in the RE model. In this case the coefficient is negative: in other words, the higher the amount of agricultural land, the lower the deforestation. This result may be explained by the fact that when the quantity of agricultural land is high, the residual forest cover is thus low. Consequently, the marginal value of the forest is high and countries are likely to reduce their deforestation activity.

Finally, we derive a more novel result concerning trade variables. It may be considered that the openness of economies[17] plays a role in the land use changes following the hypothesis that the more open a country is, the more it is probable that a shock in potential agricultural export values or, to put it differently, variations in agricultural commodity prices, will have an impact on land use. To our knowledge, this result is new. Previous studies did not focus on trade and those testing its potential role as a driver of deforestation at a global level, such as Nguyen-Van & Azomahou (2007) using the openness rate, did not find a significant effect. In this paper, we find evidence that trade seems to have been a major driver of deforestation in the period 2000-2010, regarding both coefficients and statistical significance of the *Openness* and *Terms of trade* variables. As a consequence, it may be considered that the openness of countries may play a role in land use changes. Given the numerous significant variables and the significant effects of international trade and agricultural production, the impact of agricultural commodity export value is analyzed more deeply in section 5.

4.4 Analysis per continent

We follow on from the existing literature that, notably, estimated the determinants of deforestation per continent because of differences in forest composition, in institutional history etc. Among the papers that have taken this approach, we can cite the seminal work of Cropper & Griffiths (1994) on population pressure, the synthesis of Barbier & Burgess (2001) or more recently the work of Kuusela & Amacher (2015) on institutional changes. We thus test the underlying causes of deforestation per continent, and our results are given in Table 3.

[17] Defined as the percentage of the value of exports and imports in GDP.

Table 3: Drivers of 2001-2010 deforestation, OLS, FE in Low-Income Countries, by continent

	(1) (Africa) dfrst (stand.)	(2) (Latin Am. & W. Indies) dfrst (stand.)	(3) (Asia & Pac.) dfrst (stand.)	(4) (Eur., Central Asia, North Af. & M. East) dfrst (stand.)
GDP per capita, WPT (log, 2005 constt, -1) (standardized)	0.332*	0.120	0.158	0.500***
	(0.197)	(0.749)	(0.724)	(0.164)
GDP pc growth (2005 constt) (standardized)	0.0276	−0.00279	−0.203	0.0439***
	(0.0290)	(0.0503)	(0.194)	(0.0128)
Population density (log) (standardized)	0.774***	8.141**	5.827	−0.987**
	(0.243)	(3.023)	(4.178)	(0.435)
Agricultural land (% country area, -1) (standardized)	−0.182	−1.434	2.764**	0.0162
	(0.114)	(0.969)	(1.306)	(0.434)
Openness at 2005 constant prices (%, -1) (standardized)	0.0525	0.698	0.274	0.0590
	(0.0596)	(0.475)	(0.205)	(0.0368)
Terms of trade (standardized)	−0.0256	−0.155***	0.0112	−0.0431**
	(0.0207)	(0.0458)	(0.160)	(0.0174)
Crop production index (2004-2006 = 100, -1) (standardized)	−0.000814	−0.139*	0.179	0.0513**
	(0.0163)	(0.0813)	(0.179)	(0.0230)
PolityII (standardized)	0.0282	−0.126	−0.0307	−0.0378
	(0.0335)	(0.251)	(0.0686)	(0.0769)
Durable (standardized)	0.0570**	0.179	0.0974	−0.0103
	(0.0282)	(0.200)	(0.107)	(0.0298)
Constant	0.294	1.419**	−0.873	−0.574***
	(0.225)	(0.662)	(1.950)	(0.169)
Observations	440	241	179	290
R^2	0.096	0.146	0.357	0.137
Adjusted R^2	0.077	0.113	0.323	0.109

Standard errors in parentheses, robust to country clustering
* $p < .1$, ** $p < .05$, *** $p < .01$

Given the limited size of the samples, the results are not very conclusive and few effects identified at the global level are found to be significant at a more detailed geographical scale. However, the significance of some region-specific drivers emphasizes the need of specific analysis by continent, by providing evidence of some discrepancies between geographical regions.

First, our results suggest that in Asia the only driver found to be significant is agricultural land expansion. It also seems to be driving the impact of this variable globally because it is found to be non-significant in every other continent. This can be explained by the fact that agriculture is more intensive in Asia, weakening the link between agricultural production level and forest clearance. The same kind of rationale may be put forward for explaining the fact that population density is not significant in Asia, where population density is high but also very heterogeneous, which could blur the relationship with deforestation. Moreover, the model explains a larger proportion of deforestation variations for Asian countries than for other continents, where R-squared does not exceed 15%.

Economic development (*GDP per capita*) has been positively and significantly related to forest losses in Sub-Saharan Africa (GDP per capita, significant at the 10% level) since 2001, but not in Latin America or Asia. The importance of GDP per capita in Africa might be explained by the fact that GDP is low in this poorest continent. Economic activity is more strongly focused on primary production explaining why deforestation is directly related to GDP per capita. In European developing countries both economic development and shocks of value added (*GDP growth rate*) are significant at the 1% level. In richer European countries, economic development is more strongly related to marginal economic development, new markets, new exports of agricultural products, explaining the visible link between deforestation and the growth rate of GDP. However, and in contrast with Sub-Saharan Africa, the sample of European, Middle Eastern and North African countries is highly heterogeneous, probably explaining why richer countries, that are also countries with higher forest cover[18], are deforesting more.

Our analysis by continent also suggests that trade impacts deforestation in different ways. In Latin America and Europe, a degradation in the terms of trade (*i.e.* an increase in the value of the variable) decreases the amount of resource conversion. This result is in line with Barbier et al. (2005) and can be explained by the fact that in those continents commercial agriculture has a larger impact on deforestation (Hosonuma et al., 2012). In addition, a higher index of crop production decreases the rate of deforestation. Also, in Europe, the higher the openness rate of the economy, the more forests are

[18] In that sample low income countries have also very limited forest cover.

harvested (openness significant at the 5% level).

Finally we found that *political stability* significantly increases deforestation in Sub-Saharan Africa, in contrast to previous studies that showed an opposite relationship between institutional quality and deforestation, as already mentioned in the previous subsection. This global result hides discrepancies accross continents, Bhattarai & Hammig (2001) found that better political institutions helped reducing deforestation in Africa and Latin America. They used the variables provided by the *Freedom House* (*civil liberties* and *political rights*) and conclude that development of democracies could ultimately lead to a decrease in the pressure over natural resources. The authors however also found the opposite result for the Asian continent, where restrictive policies of human rights were often coexisting with active forest policies (e.g. China). Nguyen-Van & Azomahou (2007) and Damette & Delacote (2011, 2012) used the same index but without clustering countries by continents, and they also found that it helped reducing deforestation. However, as Bohn & Deacon (2000) highlighted, ownership risk can lower natural resources depletion by slowing down investments. Similarly, an improvement in political stability in a region such as Sub-Saharan Africa may have reduced ownership risk and increased investment in resource use. This is also consistent with the positive impact of durability of regimes on deforestation found in Table 2 column 3.

5 A focus on international trade

In order to properly assess the role of trade, a major determinant both in amplitude and significance in the global analysis of the previous section, we first (section 5.1) analyze trade considering the exports value as an opportunity cost. Second (section 5.2), trade will be looked at through the lens of the forest transition hypothesis, differentiating distinct transition phases.

Finally, in section 5.3, we will try to estimate to what extent REDD+ policies could compensate the deforestation due to trade activity.

5.1 Agricultural exports as opportunity cost

Looking at the impact of trade, two major points arise. First, higher competitiveness (meaning lower *terms of trade*) and higher *agricultural exports* (in value) both boost deforestation over the study period. This gives a sense of the link between global demand, emerging from international commodity markets, and forest clearance: the more competitive a country is, the more it may export primary sector commodities, leading to higher pressure on land use.

Second, to go further, we examine the interaction of the *value of agricultural exports* with the amount of land under agriculture (column 2 of Table 4). This last index is a good proxy for forest scarcity, since it is well known that agricultural expansion is the first cause of deforestation. As shown in Table 4, the variable is significant and with a negative sign. This means that the greater the amount of past deforestation, the less trade in the primary sector drives deforestation. In other words, when croplands are already abundant, international trade does not induce further conversion, but even decreases it.

As a robustness check we replaced the proportion of agricultural land by the remaining forest cover (in square km) in the preceding year (t-1). Results are shown in column 2 of Table 4 and are similar[19]. The same reasoning can be applied, the higher the amount of forest remaining (the less the resource is scarce) the higher the positive influence of international trade on deforestation.

This result can be explained in terms of the opportunity cost of using an additional unit of the resource, or to put it differently, in terms of comparative advantage in land use. In countries with large forest stocks, there is a strong incentive to specialize in deforestation and agricultural activities in order to develop, since the resource is abundant (and thus cheap to extract). In countries with a low stock of forest remaining, the opportunity cost of specializing in the production of goods that are intensive in this type of activity is much higher. Cutting down an additional unit of forest is expensive and the few remaining forests may provide important environmental services and meet local wood supply needs. The same reasoning can be applied to the study by Robalino & Herrera (2010) which finds that opening up to trade may not always imply deforestation in a developing economy. Countries with low remaining forest stocks will prefer to import goods that are intensive in land use, while countries with large forest stocks will prefer to export goods that are intensive in land use.

Finally, we test the impact of the political regime on agricultural trade dynamics but we do not find evidence of a significant relationship. Indeed, the coefficient of the variable resulting from the interaction of the democratic level of political regimes and agricultural exports' lagged value (column 5 of Table 4) was found to be non-significant under such a model specification (while it is sometimes found to be significant, cf. column 3 Table 10 of the Appendix A.4) and thus does not seem to be robust.

[19] The opposite sign is explained by the fact that forest resource endowment is negatively linked with agricultural land and rather proxies its scarcity.

Table 4: Drivers of 2001-2010 deforestation, OLS, FE in Low-Income Countries

	(1) dfrst (stand.)	(2) dfrst (stand.)	(3) dfrst (stand.)	(4) dfrst (stand.)	(5) dfrst (stand.)
GDP per capita, WPT (log, 2005 constt, -1) (standardized)	1.082***	1.072***	0.974***	1.533***	0.947***
	(0.230)	(0.213)	(0.247)	(0.303)	(0.270)
GDP pc growth (2005 constt) (standardized)	0.0308*	0.0307*	0.0307*	0.0282	0.0364**
	(0.0160)	(0.0165)	(0.0161)	(0.0239)	(0.0181)
Population density (log) (standardized)	1.690***	1.705***	1.758***	1.666**	1.330***
	(0.494)	(0.511)	(0.474)	(0.633)	(0.427)
Openness at 2005 constant prices (%, -1) (standardized)	0.0889	0.0893	0.0884	0.113	0.110*
	(0.0590)	(0.0573)	(0.0575)	(0.0961)	(0.0646)
Terms of trade (standardized)	−0.108***	−0.113***	−0.118***	−0.123***	−0.0919***
	(0.0292)	(0.0303)	(0.0310)	(0.0386)	(0.0285)
Crop production index (2004-2006 = 100, -1) (standardized)	0.0721*	0.0775**	0.0630*	0.0666	0.0628*
	(0.0369)	(0.0366)	(0.0372)	(0.0572)	(0.0368)
Agricultural land (% country area, -1) (standardized)	0.0895	−0.229		−0.0949	0.153
	(0.225)	(0.218)		(0.374)	(0.197)
Agricultural exports (value) per km2 (log, -1) (standardized)	0.231**	0.709***	0.253**	0.306**	0.240**
	(0.110)	(0.244)	(0.114)	(0.118)	(0.113)
Forestry exports value per km2 (log, -1) (standardized)	−0.0991	−0.0928	−0.105	−0.124	
	(0.0694)	(0.0671)	(0.0703)	(0.0820)	
Agricultural land (-1) × Agricultural exports (log, -1) (stand.)		−0.618***			
		(0.225)			
Forest land cover (log, -1) (standardized)			−0.796		
			(1.226)		
Forest land cover (log, -1) × Agricultural exports (log, -1) (stand.)			0.199**		
			(0.0819)		
Agric. exports value (log, -1) × phase 2 of forest transition (stand.)				0.546*	
				(0.320)	
Agric. exports value (log, -1) × phase 3 of forest transition (stand.)				−0.479***	
				(0.161)	
Agric. exports value (log, -1) × phase 4 of forest transition (stand.)				0.00663	
				(0.141)	
PolityII (standardized)					0.0278
					(0.0631)
Agricultural exports × PolityII					0.114
					(0.0757)
Constant	0.653***	0.684***	0.639***	1.140***	0.544***
	(0.107)	(0.104)	(0.130)	(0.160)	(0.130)
Observations	1136	1136	1136	790	1130
R^2	0.120	0.132	0.131	0.168	0.121
Adjusted R^2	0.113	0.124	0.123	0.155	0.113

Standard errors in parentheses, robust to country clustering
* $p < .1$, ** $p < .05$, *** $p < .01$

5.2 Trade and forest transition

In this section, we evaluate the effect of agricultural trade in the light of the forest transition concept (Mather, 1992; Culas, 2012; Wolfersberger et al., 2015).

We clustered the countries of our sample depending on their position on the forest transition curve, that is also called the transition phases. In doing this, we follow Hosonuma et al. (2012)[20] who distinguishes four stages:

- Phase 1: undisturbed forests
- Phase 2: intensive deforestation
- Phase 3: transition is occurring
- Phase 4: net forest cover is increasing

Results are given in Table 4. The forest transition dummies are not shown since they implicitely lie within country fixed effects.

The agricultural exports value shows opposite signs depending on the countries' phase of forest transition. In phases 1 and 2, agricultural exports increase deforestation. On the contrary, the opposite effect is found once a transition is reached, that is for countries in phase 3. The effect is not significant in countries of phase 4, probably due to the limited amplitude of the effect.

Looking at the size of the coefficient, we can interpret it as follows:

- an increase of 1 standard deviation of the agricultural exports value would imply a drop of one third of a standard deviation in forest cover relative to country size in countries that are in phase 1.
- this effect is even more significant (more than doubled) in countries in phase 2 of forest transition.
- the countries that are in the third phase of forest transition would see this effect eliminated, and even experience on average a drop of about 20% of one standard deviation of relative deforestation ($.306 - 0.479 = -.17$).

Our results can be interpreted through the lens of the forest transition theory: because the natural resource is abundant and the cost of extraction

[20] We dropped some countries from our sample in order to keep Hosonuma et al. (2012)'s original classification that is only available for 100 countries, corresponding to 88 developing countries of our restricted sample.

is low in countries in phases 1 and 2, the value of internationally traded agricultural commodities provides a source of income and opportunities for development. This may explain why deforestation is boosted by agricultural exports value in phase 1 and (to an even greater degree) phase 2. The higher the value of agricultural commodities exported for each square km harvested in the past year the higher the relative deforestation. This can be interpreted by the fact that those countries are less developed and have a relatively high level of forest cover remaining. Their opportunity cost of cutting another hectare of forest is thus rather low while for some of them there is potential for development led by agricultural exports. In countries in phase 3, the opposite relationship is found: trade in the primary sector lowers deforestation. In these countries in the late transition phase, cutting down an additional hectare of forest is costly, with regard to the low remaining stock of the resource (high opportunity cost). This effect may also be interpreted spatially at an infra-national scale: the remaining forests are far from the market, (and thus have a higher extraction cost). They also have a high environmental value, for instance as an important reservoir of terrestrial biodiversity. Moreover, trade in the agricultural sector may help to provoke a transition by importing agricultural products into those countries that are almost ending their forest transition.

These results show the usefulness of considering a country's forest transition phase in REDD+ policies, especially for those countries in the earlier phases.

5.3 REDD+ policies to compensate for trade effects?

REDD (Reducing Emissions from Deforestation and forest Degradation) was officially created during the Bali (2007) and Copenhagen (2009) Conferences Of Parties (COP), with the objective of protecting the world's remaining primary forests. In 2008, at the Poznan meeting, REDD became REDD+, as it was decided to broaden the mechanism and integrate activities enhancing carbon stocks and promoting sustainable forest management.

Essentally, REDD+ is based on three phases. During the first phase, countries have to define a national strategy, with the help of grants. Most countries are currently in this phase. During the second phase, participants will have to implement their REDD+ strategies, and to develop policies and measurement tools. Finally, countries will then receive payments based on their performance for deforestation avoided and low-carbon development efforts during the last phase.

Initial enthusiasm of developing countries for REDD+ projects seem to have halted, and the use of such mechanisms has thus been reduced over recent years (Simonet et al., 2014). The main factors causing such reduction are probably the low current price of carbon on international markets and the lower capacity of new countries entering the mechanism to deal with its complexity and the red tape it generates. However, it may also be explained by the objectives of REDD+: environmental protection and rural development, which can be perceived as being negative at the local level (Pokorny et al., 2013).

This reasoning can also be applied at the national level, where, in current development paths, agricultural development generally means more land cultivated and thus more deforestation. Although it could be based on rational and efficient land intensification and sustainable land-use, Phelps et al. (2013) emphasize the possibility for intensified agriculture to actually increase future deforestation. Indeed, a more productive agriculture might lead to increases in rents and thus favour the expansion of croplands, at the expense of forests. The authors underline the importance of this possible outcome as agricultural intensification has become a centrepiece of public policies to reduce deforestation.

Finally, REDD+ mechanisms need to be cost-effective and give the right incentive, i.e. efficiently compensating for opportunity costs of hindered agricultural development.

In order to offer a rough cost-benefit analysis of REDD+, we try in this section to estimate structurally the average elasticity[21] of deforestation to the potential value of agricultural exports per land unit (square km). Using a log-log estimation in accordance with (Kennedy, 1981), we provide a coefficient revealing the average elasticity of the dependent variables to variations in independent variables. The result is an average elasticity for the whole sample of countries, which may not be suitable for discussing country-specific examples since we have a very heterogeneous sample of countries.

Table 5 (column 1) shows that, on average, a decrease of 10%in potential value of agricultural exports would decrease deforestation by 1%. This would mean compensating Indonesia for a loss of 300 million dollars (10%) of exports in order to reduce its deforestation level by 1% (about 116 square km annually). Even if they are not very robust, especially due to the high degree of heterogeneity of our sample, such calculations give an order of magnitude of what would be needed to make REDD+ efficient.

[21] Elasticity is the effect of the variation of an independent variable on the dependent variable, i.e. in our case the impact of a 1% variation in one determinant on deforestation rate, all other things being equal.

Table 5: Estimation of elasticity of deforestation relative to agricultural and forest exports value changes, OLS, FE in Low-Income Countries

	(1) Annual deforestation (log km2)	(2) Annual deforestation (log km2)
GDP per capita, WPT chain (log, 2005 constt, -1)	0.691***	0.774***
	(0.188)	(0.219)
GDP pc growth (2005 constt)	0.000491	0.00181
	(0.00474)	(0.00593)
Population density (log)	0.433	1.006
	(0.636)	(0.704)
Openness at 2005 constant prices (%, -1)	−0.0420	−0.0887
	(0.154)	(0.186)
Terms of trade	−0.00319***	−0.00350**
	(0.00104)	(0.00138)
Agricultural exports (value) per km2 (log, -1)	0.102*	0.242***
	(0.0557)	(0.0795)
Forest exports (value) in per km2 (log, -1)	0.0256	0.0517
	(0.0437)	(0.0514)
log Agricultural land (% country area, -1)	0.510	−0.0620
	(0.528)	(0.734)
Agricultural exports value (log, -1) × phase 2 of forest transition		−0.0564
		(0.101)
Agricultural exports value (log, -1) × phase 3 of forest transition		−0.630***
		(0.236)
Agricultural exports value (log, -1) × phase 4 of forest transition		0.0173
		(0.116)
Constant	−1.379	2.725
	(2.950)	(3.698)
Observations	1121	783
R^2	0.062	0.116
Adjusted R^2	0.055	0.104

Standard errors in parentheses
* $p < .1$, ** $p < .05$, *** $p < .01$

The other result from Table 5 (column 2) is meaningful and should orientate future forest-related public policies and their coordination at the global level. One can see that an average increase of 5% in the value of exported products from the primary sector causes an additional deforestation of one percentage point in countries in phase 1. As commonly noted in economic theory, countries tend to specialize their production in goods for which they have a relative advantage. These countries are characterized by a high level of forest cover, and a low level of economic development. They need to clear forests and make space for agriculture. This allows them to generate income and employment and to meet food and energy demands. Those countries become suppliers of primary goods, at the expense of their forests.

Trade does not seem to significantly influence the rate of deforestation in countries in phases 2 and 4 in that specification. However, in countries in phase 3 of forest transition, the average elasticity is estimated at -0.4% (0.24-0.63), meaning that an increase in agricultural export value in the primary sector would tend to decrease deforestation. It is much easier to reduce deforestation in such countries, since they have natural incentives to do so (higher opportunity cost of forest clearance and lower gains from the export of primary products). Such a negative relationship may be explained by the fact that countries at the end of their forest transition need forest land cover to maintain a constant quality of agriculture (forest cover provides multiple local ecosystem services including certain to agricultural production) and even increase it by intensifying their agricultural production that has moved up from smallholder production to an industrial level.

One may now wonder what should be the appropriate REDD+ response to such economic mechanisms. How can a country with forests be compensated, financially, for loss of international exports? Trade is, above all, a source of income that can be reinvested in the economy, increasing local demand and so on. In addition, although less quantifiable, participation in the global market allows links to be created with other countries. If REDD+ funding does not take these aspects into account, then developing countries will receive suboptimal compensation, thus undermining their economic development path. Moreover, lowering the pressure on forest resources by increasing the intensification of agricultural production also has a cost that will have to be included in international agricultural prices in the long-run. The trade-off between clearance of forest land cover and either reducing agricultural exports or intensifying agriculture will only be modified by REDD+ programs through an increased opportunity cost of forest clearance.

6 Conclusion

In this paper we offer an update of the determinants of deforestation in developing countries at a national level since the 2000s. To do this, we have used new satellite data, as opposed to the previously widely-used data provided by the FAO.

In order to be able to discuss our results in the light of existing studies, we adopted a similar approach to that developed in several papers since the 1990s. That is, we regressed the yearly deforestation rate per country over the 2001-2010 period on a set of economic, demographic and institutional variables. By doing this, we aimed to identify the underlying causes of deforestation.

First, we found that economic development, agricultural activity and population pressure remain important drivers of deforestation at a national level. Second, in our sample, institutional quality did not contribute to reducing forest depletion. This result holds when controlling for a wide range of indicators, such as the control of corruption, the level of political stability or the degree of civil liberties within countries. Third, and most important, we identified trade as playing a crucial role in driving deforestation. An increase in agricultural exports at the national level decreases the proportion of forest area in a country, but this effect depends on the country's characteristics. Indeed, we showed that it was driven by countries with a large amount of remaining forest cover, and a low level of development. Considering the country's current specific transition phase would thus perhaps improve policies designed to fight against deforestation, by making incentives better adapted to each type of country.

Overall, the variation in the rate of deforestation explained in our cross-country framework is limited and the remaining variations need to be elucidated in future work. This underlines the need to control for other types of determinants, such as infrastructure development, but also conservation policies (e.g. in Brazil where the latter played a large role in the decade under consideration), that should be studied at a more detailed geographical scale. Moreover, access to forests: proximity to cities and road access and presence of payments for ecosystem services may also play a huge role at a subnational level. Finally, better controlling for agricultural commodity price shocks and the types of crops that could be cultivated on current forest lands, may increase the variation of the dependent variable that we explain in our analysis.

An extension of our work may be to consider forest quality, e.g. primary vs. secondary forest, for instance by using the intact forest landscape data. Quality does play a role in conservation incentives, in a sense, but should also be taken into account in the REDD+ mechanism since it is associated with very different levels of net carbon storage.

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A Appendix

A.1 Sample

Table 6: List of (128) countries in the sample, by continent.

(1) (Africa)	(2) (Latin Am. & W. Indies)	(3) (Asia & Pac.)	(4) (Eur., Central Asia, North Af. & M. East)
Angola	Argentina	Bangladesh	Afghanistan
Benin	Belize	Bhutan	Albania
Botswana	Bolivia	Cambodia	Algeria
Burkina Faso	Brazil	China	Belarus
Burundi	Chile	Fiji	Bosnia and Herzegovin
Cameroon	Colombia	India	Bulgaria
Central African Repub	Costa Rica	Indonesia	Croatia
Chad	Cuba	Lao Peoples Democrati	Egypt
Comoros	Ecuador	Malaysia	Estonia
Congo, Dem Rep	El Salvador	Mongolia	Georgia
Congo, Rep	Guatemala	Nepal	Hungary
Cote dIvoire	Guyana	Pakistan	Iran (Islamic Republi
Djibouti	Haiti	Papua New Guinea	Iraq
Equatorial Guinea	Honduras	Philippines	Jordan
Eritrea	Jamaica	Samoa	Kazakhstan
Ethiopia	Mexico	Solomon Islands	Latvia
Gabon	Nicaragua	Sri Lanka	Lebanon
Gambia	Panama	Thailand	Libya
Ghana	Paraguay	Timor-Leste	Lithuania
Guinea	Peru	Tonga	Macedonia
Guinea-Bissau	Suriname	Viet Nam	Moldova
Kenya	Trinidad and Tobago		Montenegro
Lesotho	Uruguay		Morocco
Liberia	Venezuela		Poland
Madagascar			Romania
Malawi			Russia
Mali			Serbia
Mauritania			Slovakia
Mauritius			Syrian Arab Republic
Mozambique			Tajikistan
Namibia			Tunisia
Niger			Turkey
Nigeria			Turkmenistan
Rwanda			Ukraine
Senegal			Uzbekistan
Sierra Leone			Yemen
South Africa			
Sudan			
Swaziland			
Tanzania			
Togo			
Uganda			
Zambia			
Zimbabwe			

A.2 Descriptive statistics

Table 7: Summary statistics

Variable	Mean	Std. Dev.	Min.	Max.	N
Proportion of forest cover in 2000	0.372	0.313	0	0.979	1792
Forest land cover (km^2)	233491.512	808158.322	0	7550353.5	1792
Annual average deforestation (km^2)	704.641	2632.609	0	30039.799	1536
Annual deforestation rate (share of total forest land cover)	0.019	0.202	0	4.993	1512
DEF_relative (rate of variation)	0.007	0.042	0	1	1512
Total deforestation (2001-2012, km^2)	8455.688	30443.904	0	230469.734	1792
DEPENDANT VARIABLE					
Annual deforest. rate (prop. of country area, $dfrst$)	0.001	0.002	0	0.017	1536
INDEPENDENT VARIABLES					
PPP converted GDP per capita (2005 constt)	2757.345	2911.084	133.16	15065.311	1762
GDP pc growth (2005 constt)	3.041	5.699	-62.466	102.777	1768
Population (headcount, 000)	41748.41	150941.768	70.818	1330141.25	1408
Population density (inh/km^2)	0.095	0.135	0.002	1.199	1408
Country total land area	740120.373	1851262.792	720	16381390	1792
Agricultural land (% country area)	43.108	21.355	0.449	91.16	1652
Crop production index (2004-2006 = 100)	103.047	19.986	42.36	290.86	1656
Terms of trade	111.839	35.438	21.218	262.089	1748
Openness at 2005 constant prices (%)	81.853	36.629	18.776	223.563	1408
Export value of agricultural products	36064.347	98303.588	18.781	1284360.375	1530
Export value of forest products	6789.199	21239.148	0	223129.016	1772
PolityII (Polity IV (2009))	3.092	5.87	-10	10	1680
Durable (Polity IV (2009))	16.063	16.574	0	97	1680
Control of corruption (Kaufman index)	-0.507	0.591	-1.91	1.56	1661
Civil liberties index	3.826	1.589	1	7	1766
Control of corruption (Kaufmann index)	-0.507	0.591	-1.91	1.56	1661
Political stability and absence of violence (Kaufmann index)	-0.447	0.861	-3.18	1.31	1657
Rule of law (Kaufmann index)	-0.544	0.658	-2.11	1.37	1662
Political rights	3.959	1.973	1	7	1766
Civil liberties index (Freedom House)	3.826	1.589	1	7	1766
Forest transitioned countries (Hosonuma et al. (2012))	1.266	1.735	0	4	1792

A.3 Variables definition and sources

Table 8: Variable descriptions

Concept	Proxy / variable name	Definition	Source (originally from)	Acquisition date
DEP. VARIABLE				
Relative deforestation	Annual deforest. rate ($dfrst$)	annual deforestation proportion of country land surface	authors calculations based on Hansen et al. (2013)	Dec. 2014
INDEP. VARIABLES				
Income	PPP converted **GDP per capita** (2005 constant US$)	Sum of gross value added divided by midyear pop.	World Bank (World Penn tables)	Retrieved online in Dec. 2014
Annual income growth	**GDP per capita growth** (%, in 2005 constant US$)	Annual % growth rate of GDP at market prices, constant local currency	World Bank	Retrieved online in Dec. 2014
Population density	**Population density**	Inhabitants per km^2	World Bank	Retrieved online in Dec. 2014
Relative cultivated land (share of country area)	**Agricultural land** (%)	proportion of land area that is arable, under permanent crops, & under permanent pasture	FAO	Retrieved from the World Bank website in Dec. 2014
Agricultural production	**Crop production** index	Production volume of edible crops (2004-2006 = 100)	FAO	Retrieved from the World Bank website in Dec. 2014
Terms of trade	**Terms of trade**	Relative price of exports in terms of imports	World Bank	Retrieved online in Dec. 2014
Openness to trade	**Openness**	Value of exports and imports as proportion (%) of GDP, at 2005 constant prices	World Bank	Retrieved online in Dec. 2014
Agricultural export value	**Export value of agricultural products**	Sum of the value of all exported (crops and livestock[1]) products	FAO	Retrieved from the FAOstat website in June 2015
Forestry export value	**Export value of forest products**	Sum of the value of all exported forestry products	FAO	Retrieved from the FAOstat website in June 2015
Institutional quality	**Political regime score** 'polityII'	Scale ranges from -10 (strongly autocratic) to 10 (strongly democratic)	Polity IV (2009)	Retrieved online in June 2015
Institutional quality	**Regime durability** 'durable'	Number of years since the most recent regime change	Polity IV (2009)	Retrieved online in June 2015
Institutional quality	**Control of corruption** (Kaufmann index)	Measures corruption & institutional framework to prevent corruption	Kaufmann et al. (2009)	Retrieved online in June 2015
Institutional quality	**Political stability** and absence of violence (Kaufmann index)	Perceptions of the likelihood that the govnmt will be destabilized by unconstitutional or violent means	Kaufmann et al. (2009)	Retrieved online in June 2015
Institutional quality	**Rule of law** (Kaufmann index)	perceptions agents have confidence in & abide by the rules of society[2]	Kaufmann et al. (2009)	Retrieved online in June 2015
Institutional quality	**Political rights** index (Freedom House)	Score 0 to 4 points for each of 10 political rights indicators	the Freedom House (the Freedom House, 2014)	Retrieved online in June 2015
Institutional quality	**Civil liberties** index (Freedom House)	Score 0 to 4 points for each of 15 civil liberties indicators	the Freedom House (the Freedom House, 2014)	Retrieved online in June 2015
Forest transition	Forest transition phases	from 1 to 4 (cf. section 5.2)	Hosonuma et al. (2012) classification	

Note: since datasets from many different sources are distributed on the World Bank website, we retrieved them from that interface.
[1] Excluding fisheries and forestry.
[2] e.g. the quality of contract enforcement, property rights, the police, and the courts, as well as the likelihood of crime and violence.

A.4 Institutions

Table 9: Drivers of 2001-2010 deforestation, OLS, FE in Low-Income Countries: testing institutional variables

	(1) dfrst (standardized)	(2) dfrst (standardized)	(3) dfrst (standardized)	(4) dfrst (standardized)
GDP per capita, WPT (log, 2005 constt, -1) (standardized)	1.158***	1.157***	1.156***	1.121***
	(0.265)	(0.266)	(0.266)	(0.197)
GDP pc growth (2005 constt) (standardized)	0.0229	0.0230	0.0227	0.0284*
	(0.0186)	(0.0189)	(0.0188)	(0.0162)
Population density (log) (standardized)	1.952***	1.951***	1.967***	1.738***
	(0.452)	(0.461)	(0.457)	(0.440)
Openness at 2005 constant prices (%, -1) (standardized)	0.125**	0.126**	0.126**	0.130**
	(0.0612)	(0.0586)	(0.0576)	(0.0638)
Terms of trade (standardized)	−0.0912***	−0.0912***	−0.0931***	−0.0977***
	(0.0271)	(0.0263)	(0.0248)	(0.0278)
Agricultural land (% country area, -1) (standardized)	0.168	0.169	0.165	0.135
	(0.229)	(0.225)	(0.226)	(0.207)
Agricultural exports (value) per km2 (log, -1) (standardized)	0.223**	0.224**	0.223**	0.267***
	(0.100)	(0.0992)	(0.0984)	(0.0982)
Control of corruption (Kaufmann index) (standardized)	0.00493			
	(0.0722)			
Rule of law (Kaufmann index) (standardized)		0.00110		
		(0.0588)		
Political stability and absence of violence (Kaufmann index) (standardized)			0.0213	
			(0.0550)	
Civil liberties index (standardized)				0.172
				(0.113)
Political rights (standardized)				−0.0400
				(0.0503)
Constant	0.641***	0.640***	0.644***	0.593***
	(0.118)	(0.119)	(0.119)	(0.0895)
Observations	1107	1107	1106	1230
R^2	0.103	0.103	0.103	0.108
Adjusted R^2	0.096	0.096	0.097	0.102

Standard errors in parentheses, robust to country clustering
* $p < .1$, ** $p < .05$, *** $p < .01$

Table 10: Drivers of 2001-2010 deforestation, OLS, FE in Low-Income Countries: testing institutional variables

	(1) dfrst (standardized)	(2) dfrst (standardized)	(3) dfrst (standardized)
GDP per capita, WPT (log, 2005 constt, -1) (standardized)	1.047^{***}	0.999^{***}	0.915^{***}
	(0.196)	(0.224)	(0.235)
GDP pc growth (2005 constt) (standardized)	0.0315^{*}	0.0208	0.0322^{*}
	(0.0180)	(0.0137)	(0.0183)
Population density (log) (standardized)	1.697^{***}	1.704^{***}	1.716^{***}
	(0.448)	(0.454)	(0.448)
Openness at 2005 constant prices (%, -1) (standardized)	0.122^{*}	0.107^{*}	0.116^{*}
	(0.0643)	(0.0631)	(0.0641)
Terms of trade (standardized)	-0.0965^{***}	-0.0920^{***}	-0.0841^{***}
	(0.0270)	(0.0276)	(0.0261)
Agricultural land (% country area, -1) (standardized)	0.216	0.141	0.225
	(0.210)	(0.222)	(0.224)
Agricultural exports (value) per km2 (log, -1) (standardized)	0.268^{***}	0.257^{***}	0.299^{**}
	(0.0997)	(0.0964)	(0.115)
polityII (standardized)	−0.00670		0.0270
	(0.0397)		(0.0628)
durable (standardized)		0.00238	
		(0.0598)	
autocratic (standardized)		0.0215	
		(0.0267)	
Agricultural exports × polityII			0.125^{*}
			(0.0749)
Constant	0.632^{***}	0.607^{***}	0.527^{***}
	(0.0968)	(0.109)	(0.114)
Observations	1160	1170	1130
R^2	0.108	0.106	0.115
Adjusted R^2	0.102	0.100	0.108

Standard errors in parentheses, robust to country clustering
* $p < .1$, ** $p < .05$, *** $p < .01$