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Does the Expansion of Biofuels Encroach on the Forest?

Derya KELES[1], Johanna CHOUMERT[2], Pascale COMBES MOTEL[3], Eric N. KÉRÉ[4]

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Abstract

In this article, we explore the role of biofuel production on deforestation in developing and emerging countries. Since the 2000s biofuel production has been rapidly developing to address issues of economic development, energy poverty and reduction of greenhouse gas (GHG) emissions. However, the sustainability of biofuels is being challenged in recent research, particularly at the environmental level, due to their impact on deforestation and the GHG emissions they can generate as a result of land use changes. In order to isolate the impact of bioethanol and biodiesel production among classic determinants of deforestation, we use a fixed effects panel model on biofuel production in 112 developing and emerging countries between 2001 and 2012. We find a positive relationship between bioethanol production and deforestation in these countries, among which we highlight the specificity of Upper-Middle-Income Countries (UMICs). An acceleration of incentives for the production of biofuels, linked to a desire to strengthen energy security from 2006 onwards, enables us to highlight higher marginal impacts for the production of bioethanol in the case of developing countries and UMICs. However, these results are not significant before 2006 for developing countries, and biodiesel production appears to have an impact on deforestation before 2006 on both subsamples. These last two results seem

[1] PhD candidate in Economics, Laboratoire d'Economie Forestière (LEF), UMR INRA-AgroParisTech, 14 rue Girardet, CS 14216, F-54042 Nancy Cedex, France. Email: derya.keles@inra.fr, tel. 03.83.39.68.68

[2] Head of Research, Economic Development Initiatives (EDI) Limited, High Wycombe, United Kingdom. Email: j.choumert.nkolo@surveybe.com

[3] Professor in Economics, School of Economics and Centre d'Etude et de Recherche sur le Développement International (CERDI), UMR CNRS 6587, University of Clermont Auvergne, Clermont-Ferrand, France. Email: pascale.motel_combes@uca.fr

[4] Research Economist, African Development Bank, Abidjan, Ivory Coast. Email: e.kere@afdb.org

surprising and could be related to the role of biofuel production technologies and the crop yields used in their production.

Keywords

Biofuel production; land use change; forest cover loss; panel data

JEL codes

Q16 ; Q23; Q55

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1 Introduction

The Bioenergy with Carbon Capture and Storage (BECCS) has a favorable carbon footprint and can, under certain conditions, boost growth, reduce dependence on fossil fuel imports, increase investments in agriculture and boost agricultural productivity (Arndt et al., 2010). For these reasons, biofuels are at the heart of various initiatives aimed at developing renewable energies. The United Nations' Sustainable Development Goals (SDG) no 7 "Ensure access to affordable, reliable, sustainable and modern energy for all" by 2030 (UNDP, 2016) and the Sustainable Energy for All initiative (SEforALL), launched by former UN Secretary-General Ban Ki-Moon, aim to eradicate energy poverty and transform global energy systems to contribute to universal prosperity (Sustainable Energy for all, 2016). In addition, during the Paris Climate Conference, known as COP21, 40% of voluntary national contributions concerned measures to de-carbonize energies by introducing, for example, biofuels into the energy mix of the countries concerned (Gota et al., 2015). These initiatives have boosted biofuel production from 1,700 barrels per day in 2001 to 4,700 barrels per day in 2012. Despite this progress, investment in BECCS will need to increase fourfold to contribute significantly to the fight against climate change according to the Intergovernmental Panel on Climate Change (IPCC) (IPCC, 2015).

However, the production of biofuels is not without risk because of the "Agriculture, Forests and Other Land Uses" (AFOLU) sector, which is currently responsible for a quarter of global greenhouse gas emissions (GHG) (IPCC, 2015). Indeed, the crops destined for biofuel production induce land use change which can lead to deforestation. This land reallocation can be both indirectly detrimental to agricultural land as well as directly detrimental to forest land. In the former case, poverty reduction targets may be threatened by rising food prices. In the latter case, the sustainability of biofuel energies is called into question by the GHG emissions caused by deforestation linked to the production of biofuels. The main question is whether GHG emissions prevented by the use of biofuels as an energy source compensate for emissions caused by the loss of forest cover. One of the most important concerns is changes in indirect land use. Indeed, in developing and emerging countries, the main driver of biofuel expansion is indirect land use change. The decline of forest is related to the displacement of agricultural activities caused by the expansion of crops for the production of biofuels. This phenomenon is indirect and difficult to detect, especially since it only appears over a long period and can take place on an international scale (Andrade de Sá et al., 2013, Arima et al., 2011). In the United States, for instance, some land use dedicated to the production of food items has been moved to forest areas in developing countries (Searchinger et al., 2008).

The analysis of the biofuel-deforestation nexus is complex. The impact of biofuels on deforestation through land use change depends primarily on the type of crops used (Gao et al., 2012). The heterogeneity of the types of raw materials used in the production of bioethanol and biodiesel implies the existence of various transmission channels between biofuel production and deforestation. Not all crops are subject to the same type of land use changes and some are exploited on already agricultural or marginal land, especially in industrialized countries. Moreover, yield and price levels differ significantly by crop, which has an impact on production conditions and on the extent of land use change (Lapola et al., 2010). High crop yields allow an increase in the production of biofuels by an intensification of the exploitation of agricultural raw materials. In the case of indirect land use change, the productivity of the displaced agricultural activity comes into place. These changes depend partly on raw material market prices and on the demand elasticity (Lapola et al., 2010, Arima et al., 2011, Andrade de Sá et al., 2013). There are numerous studies at the global and national levels on the biofuel-deforestation nexus, but they are mainly based on simulations. Econometric studies are scant and mainly based on case studies at the subnational level. These studies allow easier access to accurate information about the types of raw materials used, their prices, yields and the share allocated to the production of biofuels (Gao et al., 2011).

To the best of our knowledge, however, no studies have yet been conducted within a cross-country panel framework. Firstly, this paper contributes to the literature by filling this gap and by providing empirical insights into the impact of biofuels on deforestation in developing and emerging countries. We use a new data-set based on time-series analysis of satellite images on

112 countries between 2001 and 2012, offering a unique level of precision concerning forest losses (Hansen et al., 2013). To address the endogeneity problem of the biofuel variable, we use panel econometric methods with instrumental variables. Secondly, this study is the first to analyse the effect of biofuels on deforestation according to the type of biofuel (bioethanol or biodiesel), the level of development, the density of forest cover and the acceleration of biofuel production. Our results show that bioethanol production contributes to increased deforestation in our sample of countries, and the effect is greater in low-density forest areas that may have already undergone anthropogenic changes. In other words, the development of bioethanol is more detrimental to degraded forests than to primary forests. Finally, the effect of bioethanol is significant over the period 2007-2012 and displays greater marginal effects than for the entire period. In contrast, we find no significant effect of biodiesel on deforestation in the total sample. By restricting the sample to Upper Middle Income Countries (UMICs) for the period 2001-2006, the effect of biodiesel on deforestation becomes positive and significant.

This article is organized as follows: Section 1 presents the literature review. We focus our attention on the contributions of empirical and geographical analyses on the relationship between biofuel production, land use change and deforestation. In Section 2, we present the empirical analysis by describing the construction of our database and our empirical model. Section 3 presents and discusses the results. Section 4 concludes.

2 Biofuel production, land use change and deforestation

2.1 Geographical analyses

Most articles that study biofuel production are based on geographical analyses and use remote sensing techniques (Rudorff et al., 2010, Adami et al., 2012, Ferreira et al., 2014). The mappings used take into account all of the physical characteristics of the crops concerned and make it possible to observe direct change in land use over a period of time. They provide qualitative and quantitative information on the development of biofuels and the loss of forest cover, but do not allow to investigate the classic determinants of deforestation (Gao et al., 2011). These biofuel production studies were mainly carried out on Brazil during the first decade of the 2000s and analysed the country's capacity to meet the demand for biofuels (Rudorff et al., 2010, Adami et al., 2012). Rudorff et al. (2010) show that in 2008/2009, 56.5% of the additional land required for sugarcane production expanded to pasture land, 40.2% to arable land and less than 3.5% to other land types, including forest areas. Adami et al. (2012) found that these figures are respectively 70%, 25% and 0.6% for the forest areas. The authors found that it would therefore not be necessary for Brazil to resort to further deforestation in the coming years to meet the demand for biofuels (Adami et al., 2012). However, Ferreira et al. (2014) show that the expansion of cultivated areas leads to a restructuration of land use and of the agrarian structure in the state of Sao Paulo and thus to a change in the state of the forest cover, especially when biofuel production activities are less productive. The authors map out 23 years, from 1986 to 2009 to analyse the evolution of land use over time and find that it is mainly Brazil's biofuel production policies that provide incentives to produce ethanol and, more generally, sugar, which has contributed to this agrarian restructuration.

Some studies use empirical techniques to confirm findings from mapping, measure and analyze changes in indirect land use and study the factors behind it (Barona et al., 2010, Arima et al., 2011, Castiblanco et al., 2013). Barona et al. (2010) use a geographical analysis to observe the displacement of land use over time (Ferreira et al., 2014), and regression analysis (Ordinary Least Square (OLS)) to capture the relationship between the expansion of cattle breeding and deforestation between 2000 and 2006 in Amazônia Legal. They find that the expansion of cattle breeding is responsible for deforestation rather than the exploitation of soybeans which is an underlying cause of deforestation. Arima et al. (2011) conducted a study on the same geographical area between 2003 and 2008 using mapping methods as well as statistical methods more adapted to the analysis of deforestation. The use of a spatial regression model allows them to capture the link between the expansion of mechanized agriculture and the conversion of pastures to forest frontiers. Extensive grazing activities are currently shifting to the cheapest land, that is, to forest areas, because of the expansion of mechanized farming. In order to control for the effect of variables specific to the geographical area and capture indirect long-term land reallocation linked to the expansion of soybean crops, the authors then run a panel model in which they introduce the lagged interest variable for a period. Thus, between 2003 and 2008, land allocated to soybean production is estimated to have spread over more than 39,000 km^2, mostly on agricultural land. When they do not control for indirect long-term land use change, a 10% decrease in this figure reduces deforestation by more than 4,000 hectares and by 25,000 hectares otherwise.

Finally, Castiblanco et al. (2013) use cartographic analysis to observe the change in land use in Colombia between 2002 and 2008, followed by a temporal model to determine the factors behind this phenomenon and the country's capacity to meet the demand for biodiesel by 2020. Palm plantations would tend to spread over pasture land, agricultural land and then to a lesser extent to forest land. A logit spatial model finally allows the authors to determine the probability of the expansion of palm oil crops on the territory by 2020. Because of the fragility of the ecosystems concerned, the authors conclude that the country should not pursue its objectives of accelerating the development of biodiesel by 2020.

2.2 Empirical analyses

Gasparri et al. (2013) and Gollnow and Lakes (2014) confirm the existence of direct and indirect land use changes using exclusively empirical methods, although their work is not focused on the biofuel issue. Gasparri et al. (2013) focus on the role of soybean expansion in Northern Argentina from 1972 to 2011 due to the global acceleration in the demand for meat. The authors find a link between the expansion of soybean crops and deforestation, which may involve the intensification of cattle breeding. However, the strength of this link depends on the incentive policies put in place by the State and the macroeconomic context observed during the periods under consideration. The authors begin by constructing a random effects panel model over 6-time periods and 17 departments to identify the role of soybean crops as a driver of deforestation and to analyze the effect of competing agricultural activities. The use of a temporal model for the Anta sector, one of the most deforested zones in Argentina, allows the authors to identify the major role of livestock production linked to the demand for meat and the role of soybean prices. The authors confirm the existence of an indirect change in land use and highlight the effects of soybean crop income supplements on the acceleration of deforestation. Gollnow and Lakes (2014) assume that there is a link between deforestation and soybean expansion through the displacement of livestock and test the strength of this link before and after the implementation of the plan to prevent and control deforestation through the PPCDAm (Plano de Ação para Prevenção e Controle do Desmatamento na Amazônia Legal - Action Plan for Prevention and Control of the Legal Amazon Deforestation) in 2004. They carry out their study on the municipalities of Brazil over a 9-year period from 2001 to 2012 and use the same method as Gasparri et al. (2013). They confirm the results stated by Gasparri et al. (2013) and find a close link between soybean expansion and deforestation by the displacement of land allocated to cattle. However, this correlation decreases after the implementation of the PPCDAm treaty from 2005 onwards, which is well in line with the important role of state policies in land allocation decisions (Gasparri et al., 2013).

Our paper more specifically builds on Andrade de Sá et al. (2013), who integrate the production of biofuels into an equation accounting for the classic determinants of deforestation. They rely on Pfaff (1999) and assume that the factors of deforestation are those that increase the rents associated with the expansion of agriculture: increase in the price of outputs, better agro-ecological conditions, lower input prices, better transport infrastructure, etc. They challenge the spatial econometric methods used in the literature that impose a structure of displacement in land use. In order to describe the process of indirect land use change, the authors proceed in several stages: (i) estimation of the indirect link between sugar cane exploitation in Sao Paulo and deforestation in the Amazon by the Generalized Method of Moments with the Arellano-Bond estimator; and (ii) estimation of the direct link between sugar cane exploitation and cattle expansion and then between cattle expansion and deforestation with a fixed effects panel estimator. With the Arellano-Bond estimator, the authors explain the number of hectares of land deforested by past deforestation, cattle herd and number of cultivated hectares of sugar cane, while controlling for potential endogeneity bias. The authors find a significant effect of cattle livestock on deforestation and the addition of interaction terms between cattle and sugarcane is indicative of an indirect land use change. In addition, the effect of bovine livestock on deforestation is sensitive to the number of hectares of sugarcane cultivated. The introduction of the lagged variables makes it possible to show that the effects of cattle expansion on deforestation are much greater over the long term than over the short term, which recalls the results of Arima et al. (2011). Thus, an additional livestock unit would induce 3 hectares of deforestation over the short and medium term and 4 hectares over the long term when the indirect effect of sugar cane is taken into account. Fixed-effect estimators confirm the existence of the indirect land use change. The authors find a negative correlation between the expansion of sugar cane and the presence of livestock in Sao Paulo and a positive correlation between the expansion of areas allocated to cattle breeding and loss of forest cover in the Amazon.

3 Data and econometric specification

3.1 Data

This section proposes a focus on the definition and measurement of deforestation and biofuel production. Descriptive statistics are provided in Table 5 in the Appendix.

3.1.1 Measuring forest cover loss

Defining “deforestation” is a crucial issue. In this paper, we consider the data issued by remote sensing methodology that burgeoned in the wake of the seminal presentation of Hansen et al. (2013). As a consequence, the term “forest loss” is preferred to “deforestation”. The definition of “forested areas” is different from that used in the Global Forest Resource Assessments (FRAs) conducted under the auspices of the Food and Agriculture Organization of the United Nations (FAO), which are rather based on a land use definition (Keenan et al., 2015). FRA data has attracted many criticisms such as the lack of homogeneity in the measurement methodology (see e.g. Grainger, 2008). The Hansen data are deemed to be based on a consistent definition of forests over time and space. Forests are defined according to a minimum threshold of percentage of tree cover (10%, 15%, 20%, 25%, 30%, 50%, 75%). “Forest loss” is reported when the percent of tree canopy cover falls below the threshold, using a resolution of 30 by 30 meters. Though the Hansen data have been criticized (e.g., Tropek et al., 2014), they are increasingly recognized as being more reliable than previous datasets. They, therefore, deserve greater attention in analyses of the drivers of forest dynamics (Hansen et al., 2014). The main implication of using such data is taking different thresholds of tree cover since the extent of forest is sensitive to it (Sexton et al., 2016). In addition, it is not possible to compute net forest losses as the difference between forest losses minus forest gains. It is worth noting that remote sensing measures of forest cover do not currently enable a distinction to be made between natural forests and tree plantations. Hansen's definition of forests encompasses "all vegetation taller than 5m in height" (Hansen et al., 2013 - Supplementary material).

3.1.2 Measuring biofuel production

We use aggregate biofuel production data from the United States Energy Information Administration (US EIA) (EIA, 2011) from 2000 to 2012. Descriptive statistics are provided in the Appendix (Table 5). These data are broken down into ethanol and biodiesel production and expressed in thousands of barrels per day. For the US EIA, biodiesel production comprises any fuel produced from biomass raw materials. Biodiesel production includes biofuels derived from soybean, canola or any other vegetable, animal or recycled oils and ethanol production includes biofuels produced from sugar and corn-based agricultural crops (EIA, 2011). Given the specificities of countries concerning biofuel production, our database is heterogeneous, which implies the existence of several outliers among our observations (Figure 4 in the Appendix).

3.2 Empirical evidence of the effect of biofuel expansion on forest loss

Our database is made up of 112 developing and emerging countries over the 2001-2012 period. Countries are classified according to their minimum level of forest cover for each degree of canopy cover. We follow the World Bank classification to distinguish the UMICs.

3.1.3 Basic econometric specification

The basic specification is a panel data model in which the dependent variable is $forestloss\%$, and represents the measure of forest loss taken from the Hansen dataset. % indicates the type of forest according to the density of canopy cover (10%, 30%, 50%, 75%):

$$\ln \mathrm{forestloss}\,\%_{\mathrm{it}} = \alpha_0 + \alpha_{\mathrm{i}} + \alpha_{\mathrm{t}} + \beta_1 \ln \mathrm{biofuels}_{\mathrm{it}} + \mathbf{X}'_{\mathrm{it}}\delta + \varepsilon_{\mathrm{it}} \quad (3)$$

Our interest variable is $biofuels$. This variable is broken down into bioethanol production $ethanol$ and biodiesel production $biodiesel$. We make a distinction between both variables to avoid misleading comparisons between them.[5]

A fixed-effect model seems more suitable than a random one when we expect a constant unobserved heterogeneity over time to have an impact on the dependent variable, as may be the case in our sample. α_0 ; α_i ; α_t stand for the constant, country and year fixed-effects, respectively. ε_{it} is the error term. Country fixed effects account for all characteristics such as distance to the Equator, landlockedness, and the quality of institutions that have an impact on forest cover loss but that do not vary much over the period under consideration. The use of a fixed-effect model is particularly suitable when the independent variables show a high intra-individual variance[6] (Table 5 in the Appendix) and when the sample is not random, as is the case with developing and emerging countries. Year dummies control for common unobservable variables such as the price of raw materials and fossil energies. **X** is the vector of control variables.

To analyse the relationship between biofuel production and forest cover loss in countries in the dataset with different types of forest coverage, we choose to gradually restrain our sample by introducing a filter for a minimum threshold of percentage of tree cover that a country presents

[5] Biodiesel and ethanol production display a moderate level of pairwise correlation (0.51). First, they are made of different types of feedstock (e.g., palm oil, soybean, jatropha for biodiesel production and sugarcane, cassava or maize for ethanol production) which result in various types of land-use and may be related to different local characteristics. For example, one possible feedstock for biodiesel is oil palm, for which the plantations are represented as forest area in the Hansen dataset (Tropek et al., 2014). Second, Choumert et al. (2017) highlight the difference on their impact on economic development, which may again result in differences in tree cover loss.

[6] As the use of a fixed-effect model relies on within-group transformation of the dependent variables, significant variation among individuals is needed. Even though some of our variables have higher between variation, the within variance stays relatively high considering the measurement units of the variables.

at each level of canopy cover $fosur\%$.[7] In the regressions where the sample is restrained, only the countries that have at least 10% forest cover at the studied level of canopy cover are included. We also include the regression without the restrained sample.

3.1.4 Dealing with potential endogeneity

Since biofuel production and land allocation decisions can be taken simultaneously, biofuel production can be suspected of endogeneity. Although any potential endogeneity is partly taken into account with country fixed-effects and temporal dummies, we tackle this issue further with instrumental variables.

Biofuel production is instrumented by wind speed and by the lagged biofuel production. Wind speed is a proxy for a given country's potential in wind energy production. Data on wind speed comes from the ERA Interim database from the European Center for Medium-Range Meteorological Forecasts (ECMWF). It is expressed in meters per second and has been calculated at a 10 meter high speed (Dee et al., 2011). It is supposed to have no impact on deforestation except through its effect on biofuel production.[8] This variable is considered as exogenous since it may represent a complementary or substitutable strategy to the development of biofuels as a renewable energy.[9] Moreover, lagged biofuel production would not have any effect on deforestation at time t in our specification as it only occurs after the change in land use. In addition, our model does not account for indirect land-use changes as it can only be observed over a longer period (Andrade de Sá et al., 2013).

[7] We have divided the initial forest cover of the country in 2000 (Hansen et al., 2013) by its total surface at each level of canopy cover (Food and Agriculture Organization, 2015)

[8] It could be argued that extreme meteorological events such as hurricanes could directly impact on forests while falling down trees and therefore initiate forest clearing. However, data on wind speed are average values and hardly account for such extreme events.

[9] On the one hand, the development of wind energy could be complementary to biofuel production because this renewable energy is generally not sufficient to reach countries' targets on GHG emissions (Panwar et al., 2011, IEA, 2015). Policies designed to integrate multiple objectives are thus increasing (IPCC, 2015) in emerging countries and to a lesser extent in developing countries (IEA, 2015, IEA, 2016, Mukasa et al., 2013) where there is a great need to improve both climate change mitigation and energy security. Here, the development of biofuel production could attract investments and make the development of the wind sector more profitable (IEA, 2015, Keeley and Ikeda, 2017). On the other hand, as both these energies can be used for the same purpose, they can be substitutes due to the existence of constraints on land availability and investment capacities (IEA, 2016).

3.1.5 Control variables

All socio-economic, agricultural and energy variables of the countries in our sample are defined and precisely described in Table 3 in the Appendix. Their descriptive statistics are also reported in Table 5. These control variables can be categorized into three distinct groups.

We first use socio-economic data on Gross Domestic Product (GDP) and population from the World Bank development indicators (World Bank, 2015). We use the following variables that represent socio-economic characteristics of countries to control for underlying causes of deforestation (Angelsen and Kaimowitz, 1999, Geist and Lambin, 2002); GDP per capita *gdppc,* squared GDP per capita *gdppc*2 and population *pop*. The GDP per capita variable in its level and its square are introduced to capture the existence of an Environmental Kuznets Curve (EKC) (Grossman et Krueger, 1995), although its existence has been debated in the literature (Choumert et al., 2013). The *pop* variable stands for the size of the country; it has not been shown to have a clear-cut effect on deforestation in the literature (Angelsen et Kaimowitz, 1999, Pfaff, 1999).[10]

Second, we use the following control variables to account for the profitability of agricultural activities: standardized rainfall *e_rain* and temperatures shocks *e_temp*, cereal yields *cer_yd* and Real Effective Exchange Rates (REERs) *reer* Other agricultural activities compete with biofuel production in terms of land use, especially when an increase in the associated rent has an impact on decisions of land use and deforestation (Pfaff, 1999, Andrade de Sá et al., 2013). We use climatic data on precipitations and temperatures from the Climatic Research Unit of the University of East Anglia (Santoni, 2016) to draw an index of standardized climatic shocks defined as the standardized difference of precipitations and temperatures to their long-term annual average. This allows us to capture potential “el Niño effects”. These phenomena can induce deregulation of climatic conditions in tropical countries, leading to significant impact on deforestation and

[10] Variables related to population density do not always exhibit high significance because of their ambiguous role on deforestation (Angelsen et Kaimowitz, 1999, Pfaff, 1999). In addition, this variable is often subject to endogeneity issues and to a high degree of collinearity with the other variables in the model (Angelsen and Kaimowitz, 1999, Pfaff, 1999). Indeed, it often loses its significance when many variables are added to the model as it responds to many other factors (infrastructures for example) (Pfaff, 1999).

agricultural activities such as droughts, fire… (Alencar et al., 2015). The cereal yields variable is taken from the World Bank development indicators (World Bank, 2015) and allows us to approximate the profitability of agricultural competing land uses (Lapola et al., 2010, Arima et al., 2011, Andrade de Sá et al., 2013, Searchinger et al., 2008). We introduce the REER variable to represent country competitiveness, excluding the oil sector. This variable was constructed from the 2016 CEPII database for the international trade analysis (Gaulier and Zignano, 2010). A depreciation of REERs induces an increase in the relative price of competing and of internationally tradable activities for the production of biofuels (wood, energy…) and may lead to a rise of the pressure on forest. This effect should be relevant for developing and emerging countries (Leblois et al., 2017) in which REERs variations are temporary due to their instability (Richards et al., 2012, Arcand et al., 2008). Indeed, in developed countries, a stable and sustainable increase in relative prices should increase investment opportunities in the forestry sector and have a positive effect on afforestation (Arcand et al., 2008).

Third, the energy supply potential of the countries in our sample is taken into account with crude oil reserves co_pr and natural gas reserves ng_pr variables that are taken from the US EIA and represent the estimated quantities of energetic resources that are highly likely to exist based on available geological data and existing technologies (EIA, 2011). Since biofuels can be considered as a substitute for fossil energies, the match between demand and supply for fossil fuels may thus modify the influence of biofuels on deforestation. Gas and crude oil reserve variables represent the potential of countries for fossil fuel production. Those that have larger fossil fuel reserves should be more likely to respond to energy security requirements, especially when they are subject to high energy needs.

4 Results and discussion

The results from the basic specification (equation 3) are provided in Table 1 below. We find that a 1% increase in bioethanol production should lead, *ceteris paribus*, to an average 0.143% forest cover loss, i.e., more than 5 million hectares over the entire period compared to the existing forest cover in 2000. This effect diminishes with the increase in the threshold on the canopy density percentage. It falls from 0.126% for countries that contain at least 10% of forest with a 10% level of canopy cover (i.e., approximately 4,500,000 hectares of forest cover loss) to 0.118% for countries that contain at least 10% of forest with a 30% level of canopy cover (less than 3,500,000 hectares). When we restrain the sample to take into account only countries with the highest threshold of canopy cover, the effect of bioethanol production becomes insignificant. Direct change in land use should thus only occur on less dense forest area where anthropogenic activities have likely already taken place. Moreover, countries that hold the highest threshold of canopy cover are not always similar to those that produce the greatest amount of bioethanol, and vice-versa. Consequently, when we restrain the sample, some countries that were among 20 of the world's largest biofuel producers (including Pakistan, Kazakhstan, Turkey, Argentina, India and China) no longer fulfil the condition of the minimum density of canopy cover that has to be reached in order to be included in the analysis (at least 10% of forest with a 30%, 50% and 75% threshold of canopy cover). This reinforces the idea that changes in land use may occur on agricultural land, at least at the initial stages of land use changes.

The rapid development of biofuel production during the last decade may also be one of the underlying causes of deforestation (Angelsen et Kaimowitz, 1999, Gasparri et al., 2014). Indeed, the effect of biofuel production on forest cover loss can occur as a result of a country's rise of income allowing for higher investment capacities and a more intensive use of forests (Gasparri et al., 2014). It might also occur through a positive effect on the growth and development of the country, such a hypothesis being reinforced by the positive and significant effect of the real GDP per capita on deforestation. In addition, the negative and significant effect of its squared shape indicated the presence of an increasingly pronounced EKC (Grossman et Krueger, 1995) as a stricter definition of deforestation is used. This phenomenon may confirm the existence of a forest transition, more pronounced in countries that host the densest forests. Thus, in these countries, the loss of forest cover slows down and reverses for lower levels of economic development than in countries that have less dense forests. This result seems consistent with a change in land-use, which is not likely to take place in forest with the highest level of canopy cover.

The negative effect of an increase in REERs on forest cover loss indicates that the effect of agricultural production on deforestation declines when the competitiveness of the economy is slowed down by the increase in relative prices of agricultural activities (Arcand et al., 2008). A REER appreciation makes the profitability of the export sector decreasing which penalize logging and agricultural activities. This result could be linked to agricultural activities being complementary to biofuel production and seems relevant only for countries that contain at least 10% of forest with a 10% to 30% threshold level of canopy cover. Again, the densest forests do not appear to be affected by direct land use change or thus by the profitability of agricultural activities.

We do not find any effect of biodiesel production[11] over forest cover loss in developing countries. One possible explanation may be related to the way the Hansen database is constructed (Tropek et al., 2014). In some countries (e.g., Malaysia and Indonesia) biodiesel production could result in forest cover gain due to the extension of palm oil plantations. In addition, our sample remains heterogeneous, which can attenuate the results obtained on biofuel production. Indeed, in Table 1, we take into account countries subject to varying issues in terms of economic development, natural resource exploitation and energy security. Still, following Gasparri et al. (2014), biodiesel production might not be likely to generate sufficient revenues to intensify the exploitation of forested area or to accelerate growth and development in the country.

[11] Results are available upon request.

Table 1 – Basic specification: ethanol production in developing countries

Variables	Forestloss10%	Restrained sample			
		Forestloss10%	forestloss30%	Forestloss50%	Forestloss75%
log(ethanol+1)	0.143	0.126	0.118	0.081	0.003
	(2.33)**	(2.00)**	(1.91)*	(1.29)	(0.04)
log(pop)	-0.458	-0.201	0.304	0.208	1.189
	(0.82)	(0.33)	(0.51)	(0.32)	(1.69)*
log(gdppc)	2.674	3.104	2.446	3.991	5.869
	(3.12)***	(3.59)***	(2.76)***	(3.78)***	(4.94)***
log(gdppc) squared	-0.180	-0.205	-0.160	-0.256	-0.308
	(2.95)***	(3.14)***	(2.41)**	(3.40)***	(3.85)***
e_rain	-0.003	0.018	0.011	0.007	-0.017
	(0.10)	(0.68)	(0.46)	(0.28)	(0.63)
e_temp	0.018	0.019	0.017	0.022	0.053
	(1.00)	(0.96)	(0.89)	(0.99)	(2.37)**
log(cer_yd)	-0.049	-0.206	-0.125	0.037	-0.073
	(0.48)	(1.47)	(0.83)	(0.20)	(0.33)
log(reer)	0.034	-0.197	-0.292	-0.165	-0.339
	(0.87)	(2.01)**	(2.07)**	(0.99)	(1.61)
log(co_pr + 1)	-0.173	-0.143	-0.202	-0.259	-0.078
	(1.73)*	(1.15)	(1.59)	(1.97)**	(0.89)
log(ng_pr + 1)	0.007	-0.038	0.002	0.056	0.118
	(0.08)	(0.45)	(0.03)	(0.59)	(1.85)*
r2	0.14	0.21	0.25	0.26	0.35
Adjusted r2	0.03	0.11	0.15	0.16	0.25
Number of obs.	1056	843	751	631	487
Number of countries	92	73	64	54	42
Time dummies[12]	Yes (F=5.26)	Yes (F=5.88)	Yes (F=4.79)	Yes (F=4.23)	Yes (F=3.52)
Test of fixed effect (FE) vs random effect (RE) [13]	FE (X^2=25.0)	FE (X^2=17.8)	FE (X^2=23.9)	FE (X^2=46.7)	FE (X^2=104.8)

** p<0.1; ** p<0.05; *** p<0.01*
Our variables are in a logarithm form to linearize the model, except for e_rain and e_temp. We add +1 to the logarithm variables with 0 in order to keep them. Standard deviations have been corrected to make them robust to the presence of heteroscedasticity.

4.1 The specific case of Upper Middle Income Countries

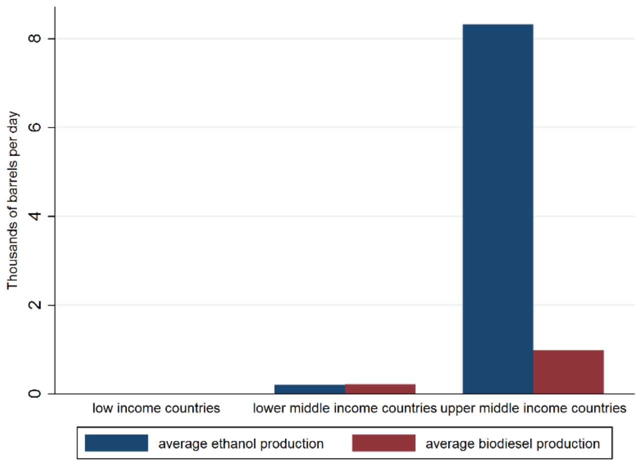
Many UMICs are endowed with large stocks of tropical primary forests. They have an intermediate position that makes dealing with low and high-income countries an issue for interpretation of the results. UMICs could more likely rely on their natural capital, which can, in

[12] We conduct a Fisher test for the significance of the temporal dummies.

[13] We run a xtoverid over-identification test which provides equivalent results to the Hausman FE vs RE effect test when taking into account the presence of heteroskedasticity in the model (Arellano, 1993). However, the inclusion of temporal dummies is not supported.

turn, result in greater biofuel production at the expense of forested areas. This risk is even greater as UMICs have shown accelerated adoption of biofuels in their energy policies (Castiblanco et al., 2013). Figure 1 below confirms this. UMICs, however, differ from lower middle income or low income countries, as their development level would allow their inhabitants to exhibit a positive willingness to pay for environmental protection (Vincent et al., 2014, Tait et al., 2016), which may lead to greater incentives for governments to preserve the environment, in particular with the introduction of targets on the use of renewable energies (Zhou and Thomson, 2009).

Figure 1 – Biofuel production according to country income level



Source: Authors' calculation from the US EIA (EIA, U., 2011)

Results presented in Table 2 below demonstrate the specific forest dynamics of UMICs. Indeed, we can observe that the effect of bioethanol production is strongly significant compared to results we obtain on all developing countries. An average 1% increase in bioethanol production per day would result in an average 0,214% loss of forest cover, i.e., more than 4,900,000 hectares, compared to the existing forest cover in 2000. Marginal coefficients remain stable when we use a stricter definition of deforestation but only up to a 50% level of canopy cover, where forest cover loss over our period would then be more than 3,400,000 hectares. In UMICs, biofuel production would imply a land use change on higher density forest than in the initial case, that is all developing countries. Nevertheless, the fact that biofuel production is not significant in countries that hold at least 10% forest with a 75% level of canopy cover allows us to confirm that land use change should not impact densest forests. As for developing countries, the REER has a negative impact on deforestation, which implies that its appreciation results in a decline in the profitability of agricultural and logging activities for exports and therefore in a reduction of the effect of biofuel production on deforestation.

Table 2 – Bioethanol production in UMICs

Variables	Forestloss10%	Restrained sample			
		Forestloss10%	Forestloss30%	Forestloss50%	Forestloss75%
log(ethanol+1)	0.214	0.193	0.197	0.210	0.064
	(3.66)***	(3.18)***	(3.24)***	(3.17)***	(0.93)
log(pop)	-0.862	-0.189	-0.180	-0.284	0.591
	(1.12)	(0.21)	(0.20)	(0.31)	(0.66)
log(gdppc)	-1.407	-0.281	-1.827	-2.247	0.479
	(0.58)	(0.11)	(0.68)	(0.78)	(0.15)
log(gdppc) squared	0.066	-0.005	0.091	0.120	-0.027
	(0.45)	(0.03)	(0.55)	(0.68)	(0.14)
e_rain	-0.077	-0.018	-0.034	-0.012	-0.005
	(2.20)**	(0.44)	(0.84)	(0.28)	(0.12)
e_temp	0.020	0.043	0.046	0.040	0.073
	(0.84)	(1.60)	(1.64)	(1.41)	(2.50)**
log(cer_yd)	-0.124	-0.282	-0.267	-0.307	-0.359
	(0.73)	(1.23)	(1.12)	(1.28)	(1.50)
log(reer)	0.045	-0.469	-0.629	-0.718	-0.767
	(1.19)	(3.13)***	(3.57)***	(3.04)***	(2.76)***
log(co_pr + 1)	-0.224	-0.156	-0.143	-0.111	0.037
	(2.35)**	(1.12)	(0.99)	(0.77)	(0.26)
log(ng_pr + 1)	-0.069	-0.053	0.033	0.014	0.054
	(0.62)	(0.46)	(0.26)	(0.10)	(0.56)
r2	0.23	0.31	0.35	0.32	0.34
Adjusted r2	0.11	0.19	0.23	0.20	0.22
Number of obs.	411	332	315	303	267
Number of countries	35	29	27	26	23
Time dummies	Yes (F=5,75)	Yes (F=6,29)	Yes (F=7,08)	Yes (F=6,43)	Yes (F=5,48)
Test of FE vs RE	FE (X^2=98,71)	FE (X^2=25,06)	FE (X^2=25,95)	FE (X^2=29,82)	FE (X^2=42,19)

** p<0.1; ** p<0.05; *** p<0.01*
Our variables are in logarithm to linearize the model, except for e_rain and e_temp. We add +1 to the logarithm variables with 0 in order to keep them. Standard deviations have been corrected to make them robust to the presence of heteroskedasticity.

We now analyze whether the temporal heterogeneity occurring over our period could partially explain the insignificant effect of biodiesel production on deforestation.[14] Indeed, Gasparri et al.

[14] One other possible reason is that the Hansen dataset, despite being more reliable, makes the distinction between forest cover and plantations difficult to account for. This could be problematic as the largest biodiesel producers are Indonesia, Malaysia and Thailand, whose biodiesel production is mainly based on palm oil feedstock.
Results are available upon request.

(2013) and Gollnow et Lakes (2014) observe that the effect of the policies implemented, as well as the macroeconomic context of the country, reveal coupling and decoupling periods between deforestation and expansion of mechanized agriculture. Similarly, Ferreira et al. (2014), show that agrarian restructuration that occurred in the State of Sao Paulo was partly linked to the incentive for ethanol production implemented by the Brazilian state beginning in the 1980s.

4.2 Acceleration of production since 2007

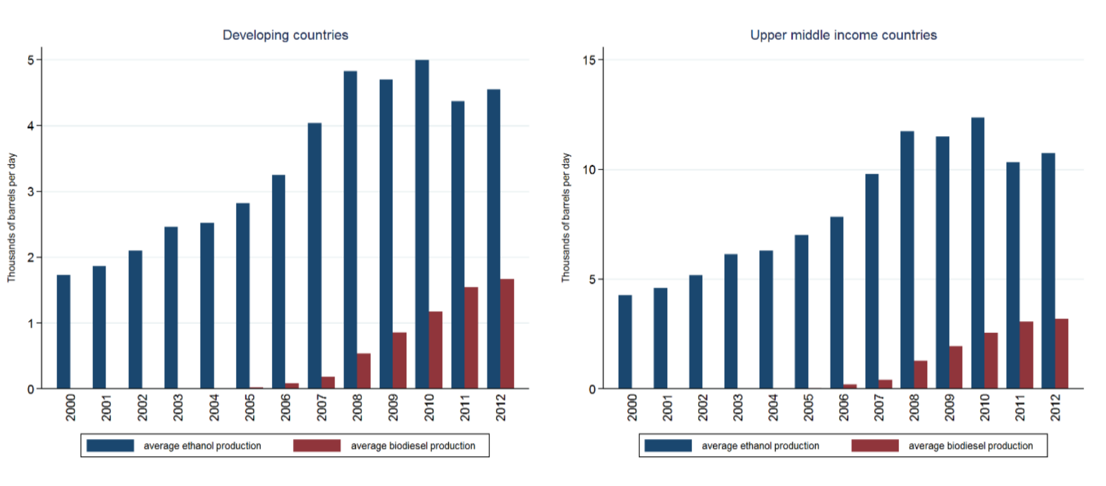
In order to account for the temporal heterogeneity over our period, we divide our sample into sub-periods, taking 2006 as the reference date. We run our baseline regression on all developing countries and on UMICs before 2006 and from 2007. Results are provided by threshold levels of canopy cover in the Appendix (table 6 to 12) in order to confirm the stability of results when a restricted definition of deforestation is used.

Several elements suggest that countries are not subject to the same challenges during these two sub-periods. We notice a difference in the rate of increase in biofuel production from 2006, especially for the production of biodiesel (Figure 2 below).[15] Fostering the use of renewable energies and accelerating biofuel development since 2006 could be linked to a strong motivation to maintain energy security (Zhou et Thomson, 2009, Wianwiwat and Asafu-Adjaye, 2013). Indeed, we observe a great increase in crude oil prices during the 2005-2008 period followed by oil price instability since the 2008 financial crisis (Figure 3 below). The acceleration in biofuel development since 2006 is confirmed by the numerous incentives that have been implemented for biofuel production in developing countries and mostly in UMICs over this period (Sorda et al., 2010, Zhou and Thomson, 2009). These measures mainly concern the acceleration of bioethanol production and to a lesser extent biodiesel production in countries where this kind of biofuel had already been developed previously.[16]

[15] A Chow test run on our specification estimated using OLS indicated the existence of a structural break in bioethanol and biodiesel production on developing countries and on UMICs.

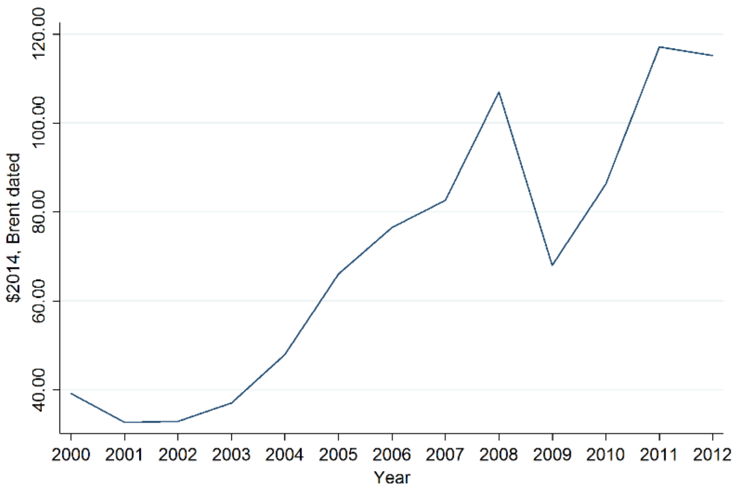
[16] In South America, Brazilian's bioethanol production has been reinforced with the introduction of "flex-fuel" vehicles in 2003 and rising oil prices, leading Brazil to implement their national biodiesel production plan in 2005 (Sorda et al., 2010, Zhou and Thomson, 2009). In Colombia and Argentina, where ethanol production has developed rapidly, 5%

Figure 2 - Evolution of biofuel production



Source: Authors' calculation from the US EIA data (EIA, U., 2011)

Figure 3 - Evolution of crude oil prices



Source: Authors' calculation from BP Global data (BP Global, 2015)

When looking at developing countries before 2006, our results in Table 6 in the Appendix indicate a significant impact of biodiesel production on forest cover loss, even for countries that hold at least 10% of forest with a 75% level of canopy cover (Table 7 in the Appendix). Marginal effects are much higher than in the case of bioethanol production, which can be an indication of a

mandatory blending targets for the use of biodiesel in fuels by 2008 and 2010 were introduced in 2005 and 2006. In South East Asia, Malaysia launched its national biofuels policy in 2006 (Sorda et al., 2010, Zhou and Thomson, 2009) and other countries such as Indonesia, Thailand and the Philippines developed the biodiesel and the bioethanol industry through the introduction of targets for the use of biofuels in transport in 2005 and 2007 (Zhou and Thomson, 2009).

larger direct land-use change for this type of biofuel. An average 1% increase of biodiesel production per day in developing countries would lead to an average 0.573% loss of forest cover or to an average 1.137% when taking a stricter definition of deforestation. These results are consistent with those found by Castiblanco et al. (2013), suggesting that biofuel crops mainly expand on agricultural and pastured land, and to a lesser extent on forested land.

If we restrain the sample to UMICs before 2006, biodiesel production remains significant (Tables 9 and 11 in the Appendix) with a higher marginal impact than for the entire sample. However, in all developing countries, the impact of biodiesel production in terms of land-use change seems to occur on forests with a higher level of canopy cover (Table 7 in the Appendix). This result is surprising and may be explained by lower yields for biofuel crops leading to larger changes in land-use in the least productive countries that hold forests with higher levels of canopy cover.

After 2006 in developing countries and in UMICs, the production of bioethanol remains significant and leads to a decline of forest cover from the lowest to the highest levels of canopy cover (Tables 8 and 12 in the Appendix). Marginal effects are higher than for the entire period, which would indicate an acceleration in bioethanol development. In UMICs, bioethanol production is also significant before 2006 (Table 10 in the Appendix), which confirms its major role in total biofuel production.

We also note that the acceleration in biodiesel development only occurs from the second period, making the results on biodiesel over the first period surprising. This result could be explained by less advanced biodiesel production technologies based on lower yield crops before 2006. Comparing our baseline specification over two different sub-periods in order to account for temporal heterogeneity allows us to demonstrate the existence of direct land-use changes in countries that contain forests with higher levels of canopy cover.

5 Conclusion

Biofuel development is at the heart of current debates on the use of renewable energy as a response to climate change, poverty and energy insecurity in developing and emerging countries (UNDP, 2016, Sustainable Energy for all, 2016, Gota et al., 2015, Choumert et al., 2017). Moreover, the effectiveness of this renewable energy on climate mitigation and on the enhancement of energy security is questioned both due to its direct and indirect effects on the displacement of agricultural activities toward forest areas.

The objective of this study was to explore the role of biofuels among classic determinants of deforestation in developing and emerging countries through the land-use change phenomenon. To the best of our knowledge, no studies have been conducted on this issue within a cross-country panel framework. In order to fill this gap in the literature, we conduct a fixed-effect panel analysis on 112 countries between 2001 and 2012 that allows us to account for country-specific determinants of deforestation. Our results allow us to extend the conclusions made by Rudorff et al. (2010) and Adami et al. (2012) who highlight the existence of a marginal direct land use change toward forest areas in Brazil between 2008 and 2009. Our results are also close to those of Gasparri et al. (2013) who find that biofuel production, and more specifically bioethanol production, has an effect on forest cover loss through its capacity to provide large amounts of revenue. However, our finding does not hold for higher density forest areas, which means that the development of bioethanol should not encroach on densest forests which are more likely to host primary forest, or only marginally. In order to account for the spatial heterogeneity in our sample, we restrict it to the specific case of UMICs and find a greater effect of biofuel production on higher-density forest areas. Then, to account for the temporal heterogeneity occurring over our period, we divide our sample into sub-periods and conduct the analysis from 2007 and before 2006. Results are surprising since biodiesel production appears to be significant before 2006 in all developing and emerging countries and starts to become more pronounced from 2007. This could be linked to less effective biodiesel production technologies before 2006, resulting in a larger displacement of land dedicated to biodiesel production.

Our results confirm the existence of direct land-use change on a global scale and call into question the relevance of biofuel production as a renewable energy, especially with indirect land use change occurring over long periods (Andrade de Sá et al., 2013). Moreover, the numerous measures that have been implemented to enhance biofuel production may have accelerated the agrarian restructuration that took place in Brazil over the past decade (See Ferreira et al., 2014). Therefore, high marginal coefficients obtained on bioethanol production after 2007 confirm the threat inflicted by such measures on forest areas in developing and emerging countries (Gasparri et al., 2013).

In order to broaden the scope of our study, it would be interesting to take into consideration the existence of indirect land-use changes. This would first necessitate obtaining precise information on the yields, prices and hectares of the share of raw material that enters the production of biofuels over a much longer period (Gao et al., 2011). The same information would be needed on displaced agricultural activities (Gao et al., 2011, Andrade de Sá et al., 2013, Arima et al., 2011). However, this data, when available, does not display the level of aggregation needed within a cross-country panel framework. Another way to reinforce the relevance of our study would be to include world prices of biofuel and fossil energies. Indeed, numerous studies highlight the strong effects of these prices in the relationship between biofuel production and forest cover loss (Hargrave et Kis-Katos, 2012, Angelsen and Kaimowitz, 1999, Gasparri et al., 2013). However, a fixed-effect panel framework does not support the introduction of such variables, which remain in the temporal dummies. A final extension of this work would be to add a variable describing the initial state of the forest at each period in a dynamic setting to account for this particular aspect of deforestation.

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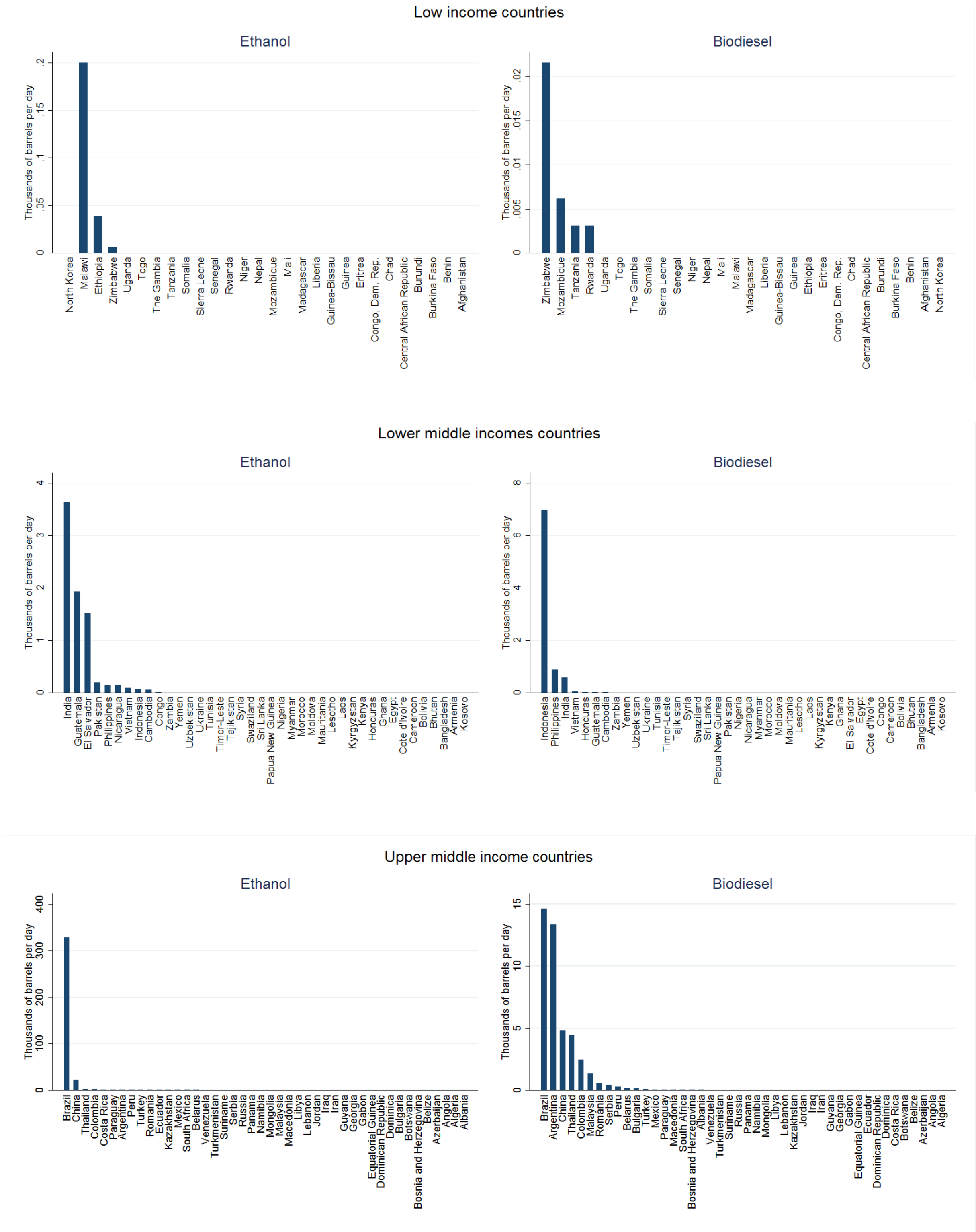
7 Appendix

Figure 4 - Average biofuel production per day over the period 2000-2012



Source: Authors' calculation from the US. EIA (EIA, U., 2011)

Table 3 - Description of variables

Name	Description	Units	Availability	Source	Notes
rain	Total annual rainfall	mm	1901-2014	Extracted by Olivier Santoni (Santoni, 2016) from the Climatic Research Unit ts 3.23 from the database of the East Anglia University (Harris et al., 2014)	
temp	Average annual temperatures	°C			
e_rain	Standardized difference of annual rainfalls to their long-term average	Mm	2000-2014	Authors' calculation from (Santoni, 2016)	Computing method: - Average of « preci » and « rain » calculated from 1901 to 2014 - Difference of « preci » and « rain » calculated from their long-term average in absolute value. - Division by the standard deviation
e_temp	Standardized difference of annual temperatures to their long-term average	°C			
sur_area	Total country's surface	1000 hectares	1960-2012	FAO (Food and Agriculture Organization, 2015) http://faostat3.fao.org/download/R/RL/E	The size of the country includes inland waters but excludes extraterritorial maritime areas. Possible variations in data may be related to updates and revisions.
wind	Wind speed at 10 meters height	m/s	1979-2014	Extracted from the European Center for Medium range Weather Forecasts (Dee et al., 2011) http://apps.ecmwf.int/datasets/data/interim-full-mnth/levtype=sfc/	
pop	Total population	-	1960-2012	World Development Indicator (World Bank, 2016) http://data.worldbank.org/indicator/SP.POP.TOTL	
gdppc	GDP per capita	constant 2005 USD		World Development Indicator (World Bank, 2016) http://data.worldbank.org/indicator/NY.GDP.PCAP.KD	World bank data have been discounted in constant 2010 USD after the completion of this article
cer_yd	Cereal yield	Kg per hectare of cultivated land		World Development Indicator (World Bank, 2016) http://data.worldbank.org/indicator/AG.YLD.CREL.KG	Included wheat, rice, but, barley, oats, rye, millet, sorghum, buckwheat and cereal mix

co_pr	Crude oil proved reserve	Billion barrels	1980-2015	International Energy Statistics from the US EIA (EIA, U., 2011) http://www.eia.gov/cfapps/ipdbproject/IEDIndex3.cfm?tid=5&pid=57&aid=6	Estimated quantities of energy resources with a high probability of existing, taking into account existing geological and technical data.
ng_pr	Natural gaz proved reserve	Billion cubic meter		International Energy Statistics from the US EIA (EIA, U., 2011) http://www.eia.gov/cfapps/ipdbproject/iedindex3.cfm?tid=3&pid=3&aid=6&cid=regions&syid=2000&eyid=2015&unit=TCF	
reer	Real Effective Exchange Rate	Non-oil exports and imports	1995-2015	Authors' calculation from the 2016 CEPII basis for the international trade analysis, weighting HS6 from the CEPII (Gaulier and Zignano, 2010) http://www.cepii.fr/CEPII/fr/bdd_modele/presentation.asp?id=1	Computing method: $REERs = \prod_{i=1}^{10} \left(\frac{ER_{part}}{ER_{country}} \times \frac{CPI_{country}}{CPI_{part}}\right)^{p_i}$ (1) with: $NEERs = \prod_{i=1}^{10} (\frac{ER_{part}}{ER_{country}})^{p_i}$ (2) Equation (1) represents the weighted average of the country's *country* Nominal Effective Exchange Rate (NEERs) relative to its 10 top partners *part* (2) and multiplied by the country's Consumer Price Index *CPI* on the one of its partner. p_i represents the weighting of each partner country according to his weight in the country's exports and imports from 2008 to 2012. 16 countries do not have exchange rate or CPI during the considered period and are not taken into account (Botswana, Belarus, Kosovo, Lesotho, Moldova, Namibia, North Korea, Russia, Somalia, Serbia, Swaziland, Tajikistan, Turkmenistan, Timor-Leste, Ukraine and Uzbekistan). An increase in REER indicates a loss in trade competitiveness linked to the appreciation of the countries' currency unit.

Table 4 – List of the countries in our sample

Developing countries	At least 10% of canopy cover	At least 30% of canopy cover	At least 50% of canopy cover	At least 75% of canopy cover
Afghanistan				
Albania*	Albania*	Albania*	Albania*	Albania*
Algeria*				
Angola*	Angola*	Angola*	Angola*	
Argentina*	Argentina*	Argentina*		
Armenia	Armenia	Armenia		
Azerbaijan*	Azerbaijan*	Azerbaijan*	Azerbaijan*	
Bangladesh	Bangladesh	Bangladesh	Bangladesh	
Belarus*	Belarus*	Belarus*	Belarus*	Belarus*
Belize*	Belize*	Belize*	Belize*	Belize*
Benin	Benin			
Bhutan	Bhutan	Bhutan	Bhutan	Bhutan
Bolivia	Bolivia	Bolivia	Bolivia	Bolivia
Bosnia and Herzegovina*	Bosnia and Herzegovina*	Bosnia and Herzegovina*	Bosnia and Herzegovina*	Bosnia and Herzegovina*
Botswana*				
Brazil*	Brazil*	Brazil*	Brazil*	Brazil*
Bulgaria*	Bulgaria*	Bulgaria*	Bulgaria*	Bulgaria*
Burkina Faso	Burkina Faso			
Burundi	Burundi	Burundi		
Cambodia	Cambodia	Cambodia	Cambodia	Cambodia
Cameroon	Cameroon	Cameroon	Cameroon	Cameroon
Central African Republic	Central African Republic	Central African Republic	Central African Republic	Central African Republic
Chad				
China*	China*	China*	China*	
Colombia*	Colombia*	Colombia*	Colombia*	Colombia*
Congo	Congo	Congo	Congo	Congo
Congo, Dem. Rep.	Congo, Dem. Rep.	Congo, Dem. Rep.	Congo, Dem. Rep.	Congo, Dem. Rep.
Costa Rica*	Costa Rica*	Costa Rica*	Costa Rica*	Costa Rica*
Cote d'Ivoire	Cote d'Ivoire	Cote d'Ivoire	Cote d'Ivoire	
Dominica*	Dominica*	Dominica*	Dominica*	Dominica
Dominican Republic*	Dominican Republic*	Dominican Republic*	Dominican Republic*	Dominican Republic*
Ecuador*	Ecuador*	Ecuador*	Ecuador*	Ecuador*
Egypt				
El Salvador	El Salvador	El Salvador	El Salvador	El Salvador
Equatorial Guinea*	Equatorial Guinea*	Equatorial Guinea*	Equatorial Guinea*	Equatorial Guinea*
Eritrea				
Ethiopia	Ethiopia	Ethiopia		
Gabon*	Gabon*	Gabon*	Gabon*	Gabon*
Georgia*	Georgia*	Georgia*	Georgia*	Georgia*
Ghana	Ghana	Ghana	Ghana	
Guatemala	Guatemala	Guatemala	Guatemala	Guatemala
Guinea	Guinea	Guinea		
Guinea-Bissau	Guinea-Bissau	Guinea-Bissau		
Guyana*	Guyana*	Guyana*	Guyana*	Guyana*
Honduras	Honduras	Honduras	Honduras	Honduras
India	India	India		
Indonesia	Indonesia	Indonesia	Indonesia	Indonesia
Iran*				

Developing countries	At least 10% of canopy cover	At least 30% of canopy cover	At least 50% of canopy cover	At least 75% of canopy cover
Iraq*				
Jordan*				
Kazakhstan*				
Kenya	Kenya			
Kosovo	Kosovo	Kosovo	Kosovo	Kosovo
Kyrgyzstan				
Laos	Laos	Laos	Laos	Laos
Lebanon*				
Lesotho				
Liberia	Liberia	Liberia	Liberia	Liberia
Libya*	Libya*			
Macedonia*	Macedonia*	Macedonia*	Macedonia*	Macedonia*
Madagascar	Madagascar	Madagascar	Madagascar	
Malawi	Malawi	Malawi		
Malaysia*	Malaysia*	Malaysia*	Malaysia*	Malaysia*
Mali				
Mauritania				
Mexico*	Mexico*	Mexico*	Mexico*	Mexico*
Moldova	Moldova	Moldova		
Mongolia*				
Morocco				
Mozambique	Mozambique	Mozambique	Mozambique	
Myanmar	Myanmar	Myanmar	Myanmar	Myanmar
Namibia*				
Nepal				
Nicaragua	Nepal	Nepal	Nepal	Nepal
Niger	Nicaragua	Nicaragua	Nicaragua	Nicaragua
Nigeria	Nigeria	Nigeria		
North Korea	North Korea	North Korea	North Korea	
Pakistan				
Panama*	Panama*	Panama*	Panama*	Panama*
Papua New Guinea	Papua New Guinea	Papua New Guinea	Papua New Guinea	Papua New Guinea
Paraguay*	Paraguay*	Paraguay*	Paraguay*	Paraguay*
Peru*	Peru*	Peru*	Peru*	Peru*
Philippines	Philippines	Philippines	Philippines	Philippines
Romania*	Romania*	Romania*	Romania	Romania*
Russia*	Russia*	Russia*	Russia*	Russia*
Rwanda	Rwanda	Rwanda		
Senegal	Senegal			
Serbia*	Serbia*	Serbia*	Serbia*	Serbia*
Sierra Leone	Sierra Leone	Sierra Leone	Sierra Leone	
Somalia				
South Africa*	South Africa*			
Sri Lanka	Sri Lanka	Sri Lanka	Sri Lanka	Sri Lanka
Suriname*	Suriname*	Suriname*	Suriname*	Suriname*
Swaziland	Swaziland	Swaziland	Swaziland	
Syria				
Tajikistan				
Tanzania	Tanzania	Tanzania	Tanzania	
Thailand*	Thailand*	Thailand*	Thailand*	Thailand*
The Gambia	The Gambia			
Timor-Leste	Timor-Leste	Timor-Leste	Timor-Leste	Timor-Leste
Togo	Togo			
Tunisia				

Developing countries	At least 10% of canopy cover	At least 30% of canopy cover	At least 50% of canopy cover	At least 75% of canopy cover
Turkey*	Turkey*	Turkey*	Turkey*	
Turkmenistan*				
Uganda	Uganda	Uganda	Uganda	
Ukraine	Ukraine	Ukraine	Ukraine	Ukraine
Uzbekistan				
Venezuela*	Venezuela*	Venezuela*	Venezuela*	Venezuela*
Vietnam	Vietnam	Vietnam	Vietnam	Vietnam
Yemen				
Zambia	Zambia	Zambia	Zambia	
Zimbabwe	Zimbabwe			

* Upper Middle Income Countries

Table 5 – Descriptive statistics

Variables		Mean	Std. Dev.	Min	Max	Observations
ethanol	overall	4.310592	44.7136	0	908.6192	N = 2603
	between		38.60318	0	441.0822	n = 202
	within		22.42655	-331.2316	471.8476	T-bar = 12.8861
biodiesel	overall	.8592422	4.843732	0	64	N = 2625
	between		3.650156	0	35.03346	n = 202
	within		3.223976	-29.87422	41.08304	T-bar = 12.995
pop	overall	3.09e+07	1.24e+08	9419	1.35e+09	N = 2769
	between		1.24e+08	9690.231	1.31e+09	n = 213
	within		5396437	-7.64e+07	1.34e+08	T = 13
gdppc	overall	11604.03	18430.79	134.8159	158602.5	N = 2514
	between		19360	146.0822	131555.2	n = 198
	within		1745.581	-1322.893	38651.33	T-bar = 12.697
e_rain	overall	.8626394	.6613087	.000233	5.815677	N = 2808
	between		.188711	.561871	2.488386	n = 216
	within		.6339319	-.7128776	4.18993	T = 13
e_temp	overall	2.072608	1.226348	.0005008	7.07183	N = 2834
	between		.8431126	.6680627	5.612913	n = 218
	within		.8922446	-.4736174	5.141408	T = 13
cer_yd	overall	3070.902	3668.727	110.1	74205.6	N = 2288
	between		2843.159	307.7462	28701.55	n = 177
	within		2319.333	-23630.64	48574.96	T-bar = 12.9266
reer	overall	398.7347	8067.366	1.425421	270094.3	N = 2160
	between		3788.362	81.23111	49060.42	n = 167
	within		7123.033	-48614.22	221432.6	T-bar = 12.9341
co_pr	overall	6.327095	27.85623	0	267.02	N = 2606
	between		26.92608	0	263.6262	n = 204
	within		6.491859	-126.7321	115.3553	T-bar = 12.7745
ng_pr	overall	30.08607	150.0153	0	1700	N = 2608
	between		148.2701	0	1683.077	n = 203
	within		19.24908	-426.3985	253.9715	T-bar = 12.8473

The between variance between represents the inter-individual variance of the observations, whereas the within variance represents the intra-individual variance of the observations.
N : total number of observations
n : number of countries
T : number of year
T-bar : Average number of years due to missing observations

Table 6 – Additional specifications: developing countries, before and after 2006

variables	Forestloss10% - restrained sample			
	before 2006		after 2006	
	Ethanol production	Biodiesel production	Ethanol production	Biodiesel production
log(ethanol+1)	0.128		0.386	
	(1.39)		(2.64)***	
log(biodiesel+1)		0.573		0.002
		(2.35)**		(0.03)
log(pop)	-1.012	-1.069	-1.313	-1.434
	(0.69)	(0.73)	(1.04)	(1.10)
log(gdppc)	3.955	4.388	3.414	3.032
	(1.80)*	(2.01)**	(1.67)*	(1.42)
log(gdppc) squared	-0.278	-0.316	-0.222	-0.169
	(1.75)*	(1.99)**	(1.54)	(1.12)
e_rain	0.089	0.089	-0.056	-0.061
	(2.01)**	(2.01)**	(1.61)	(1.72)*
e_temp	0.010	0.007	0.041	0.037
	(0.31)	(0.21)	(1.54)	(1.39)
log(cer_yd)	-0.164	-0.167	-0.282	-0.233
	(0.70)	(0.72)	(1.48)	(1.18)
log(reer)	-0.195	-0.199	0.018	-0.018
	(1.60)	(1.63)	(0.06)	(0.06)
log(co_pr+1)	-0.359	-0.350	-0.060	-0.019
	(1.66)*	(1.67)*	(0.36)	(0.11)
log(ng_pr+1)	0.046	0.028	0.306	0.216
	(0.38)	(0.23)	(1.99)**	(1.41)
r2	0.10	0.11	0.07	0.07
Adjusted r2	-0.12	-0.12	-0.17	-0.17
Number of obs.	431	431	411	417
Number of countries	72	72	70	70
Time dummies	Yes (F=3.37)	Yes (F=3.43)	Yes (F=3.14)	Yes (F=3.06)
Test of FE vs RE	RE (X^2=3.84)	RE (X^2=2.48)	FE (X^2=21.10)	FE (X^2=32.52)

** p<0.1; ** p<0.05; *** p<0.01*

Our variables are in logarithm to linearize the model, except for e_rain and e_temp. We add +1 to the logarithm variables with 0 in order to keep them. Standard deviations have been corrected to make them robust to the presence of heteroskedasticity.

Since the instrumentation strategy is not robust before 2006, the results for this period should be taken with caution. However, results for a non-instrumented panel are the same in terms of significance and magnitude.

The explanatory power of the model is weak, which leads us to obtain negative values for the adjusted r2. This result is reinforced by the sub-period division which, combined with the instrumentation, induces too few degrees of freedom.

Table 7 – Additional specification: biodiesel production before 2006 in developing countries

Variables	Forestloss10%	Restrained sample			
		Forestloss10%	Forestloss30%	Forestloss50%	Forestloss75%
log(biodiesel+1)	0.635	0.573	0.602	0.552	1.137
	(2.51)**	(2.35)**	(2.34)**	(2.24)**	(2.08)**
log(pop)	-1.846	-1.069	-0.279	-0.235	2.281
	(1.26)	(0.73)	(0.17)	(0.15)	(1.46)
log(gdppc)	5.277	4.388	3.830	6.892	9.094
	(2.47)**	(2.01)**	(1.67)*	(2.91)***	(3.57)***
log(gdppc) squared	-0.391	-0.316	-0.258	-0.464	-0.516
	(2.52)**	(1.99)**	(1.57)	(2.81)***	(2.88)***
e_rain	0.074	0.089	0.069	0.073	0.085
	(1.74)*	(2.01)**	(1.67)*	(1.71)*	(1.93)*
e_temp	0.016	0.007	-0.044	-0.065	-0.008
	(0.56)	(0.21)	(1.27)	(1.90)*	(0.21)
log(cer_yd)	0.009	-0.167	-0.085	0.049	0.007
	(0.05)	(0.72)	(0.33)	(0.17)	(0.02)
log(reer)	0.057	-0.199	-0.246	0.011	-0.458
	(1.23)	(1.63)	(1.26)	(0.05)	(1.15)
log(co_pr + 1)	-0.367	-0.350	-0.379	-0.376	-0.201
	(1.80)*	(1.67)*	(1.75)*	(1.65)	(1.02)
log(ng_pr + 1)	0.079	0.028	0.001	0.021	0.122
	(0.66)	(0.23)	(0.01)	(0.16)	(1.01)
r2	0.08	0.11	0.10	0.14	0.24
Adjusted r2	-0.14	-0.12	-0.14	-0.09	0.02
Nomber of obs.	531	431	378	318	246
Number of countries	89	72	63	53	41
Time dummies	Yes (F=3.76)	Yes (F=3.43)	Yes (F=2.28)	Yes (F=2.67)	Yes (F=3.72)
Test of FE vs RE	RE (X^2=15.13)	RE (X^2=2.48)	RE (X^2=11.08)	FE (X^2=23.80)	FE (X^2=59.93)

** p<0.1; ** p<0.05; *** p<0.01*

Our variables are in logarithm to linearize the model, except for e_rain and e_temp. We add +1 to the logarithm variables with 0 in order to keep them. Standard deviations have been corrected to make them robust to the presence of heteroskedasticity.

Since the instrumentation strategy is not robust before 2006, the results for this period should be taken with caution. However, results for a non-instrumented panel are the same in terms of significance and magnitude.

The explanatory power of the model is weak, which leads us to obtain negative values for the adjusted r2. This result is reinforced by the sub-period division which, combined with the instrumentation, induces too few degrees of freedom.

Table 8 - Additional specification: ethanol production after 2006 in developing countries

variables	Forestloss10%	Restrained sample			
		Forestloss10%	Forestloss30%	Forestloss50%	Forestloss70%
log(ethanol+1)	0.414	0.386	0.350	0.361	0.332
	(2.90)***	(2.64)***	(2.56)**	(2.15)**	(1.97)*
log(pop)	-1.551	-1.313	0.270	1.727	2.124
	(1.38)	(1.04)	(0.23)	(1.45)	(1.56)
log(gdppc)	1.824	3.414	2.778	3.956	6.785
	(0.97)	(1.67)*	(1.40)	(1.64)	(2.28)**
log(gdppc) squared	-0.149	-0.222	-0.195	-0.264	-0.453
	(1.32)	(1.54)	(1.38)	(1.60)	(2.28)**
e_rain	-0.043	-0.056	-0.028	-0.045	-0.103
	(1.38)	(1.61)	(0.89)	(1.32)	(2.84)***
e_temp	0.044	0.041	0.071	0.086	0.100
	(1.86)*	(1.54)	(2.99)***	(3.19)***	(3.28)***
log(cer_yd)	-0.148	-0.282	-0.166	-0.048	0.094
	(1.11)	(1.48)	(0.98)	(0.26)	(0.42)
log(reer)	-0.074	0.018	-0.219	-0.111	0.073
	(0.28)	(0.06)	(0.77)	(0.35)	(0.19)
log(co_pr + 1)	-0.085	-0.060	-0.107	-0.159	-0.189
	(0.49)	(0.36)	(0.63)	(0.94)	(1.21)
log(ng_pr + 1)	0.451	0.306	0.332	0.336	0.342
	(2.45)**	(1.99)**	(2.14)**	(2.28)**	(2.15)**
r2	0.07	0.07	0.08	0.12	0.19
Adjusted r2	-0.16	-0.17	-0.16	-0.13	-0.06
Nomber of obs.	522	411	373	313	241
Number of countries	89	70	63	53	41
Time dummies	Yes (F=3.90)	Yes (F=3.14)	Yes (F=2.48)	Yes (F=2.30)	No (F=1.46)
Test of FE vs RE	FE (X^2=60.29)	FE (X^2=21.10)	RE (X^2=13.88)	FE (X^2=19.84)	FE (X^2=43.16)

** p<0.1; ** p<0.05; *** p<0.01*

Our variables are in logarithm to linearize the model, except for e_rain and e_temp. We add +1 to the logarithm variables with 0 in order to keep them. Standard deviations have been corrected to make them robust to the presence of heteroskedasticity.

The explanatory power of the model is weak, which leads us to obtain negative values for the adjusted r2. This result is reinforced by the sub-period division which, combined with the instrumentation, induces too few degrees of freedom.

Table 9 – Additional specification: UMICs before and after 2006

Variables	Restrained sample – forestloss10%			
	Before 2006		After 2006	
	Ethanol production	Biodiesel production	Ethanol production	Biodiesel production
log(ethanol+1)	0.204		0.461	
	(1.66)*		(2.71)***	
log(biodiesel+1)		0.737		0.134
		(2.34)**		(1.56)
log(pop)	0.759	0.782	3.883	4.196
	(0.36)	(0.38)	(1.99)**	(2.03)**
log(gdppc)	-3.321	-2.710	17.482	20.200
	(0.60)	(0.53)	(2.33)**	(2.72)***
log(gdppc) squared	0.192	0.147	-1.133	-1.283
	(0.55)	(0.45)	(2.46)**	(2.77)***
e_rain	0.080	0.076	-0.093	-0.094
	(1.09)	(1.03)	(1.92)*	(1.84)*
e_temp	0.028	0.021	0.088	0.088
	(0.61)	(0.44)	(2.36)**	(2.31)**
log(cer_yd)	0.019	0.003	-0.188	-0.128
	(0.04)	(0.01)	(0.88)	(0.58)
log(reer)	-0.251	-0.253	0.165	-0.151
	(1.19)	(1.21)	(0.35)	(0.33)
log(co_pr+1)	-0.252	-0.295	-0.460	-0.456
	(0.95)	(1.25)	(2.27)**	(1.89)*
log(ng_pr+1)	0.065	0.066	0.307	0.102
	(0.48)	(0.48)	(0.67)	(0.21)
r2	0.20	0.19	0.34	0.31
Adjusted r2	-0.07	-0.08	0.10	0.07
Number of obs.	167	167	165	165
Number of countries	28	28	28	28
Time dummies	Yes (F=3.83)	Yes (F=3.89)	Yes (F=7.42)	Yes (F=6.48)
Test of FE vs RE	FE (X^2=22.34)	FE (X^2=23.82)	FE (X^2=59.96)	FE (X^2=34.18)

** p<0.1; ** p<0.05; *** p<0.01*

Our variables are in logarithm to linearize the model, except for e_rain and e_temp. We add +1 to the logarithm variables with 0 in order to keep them. Standard deviations have been corrected to make them robust to the presence of heteroskedasticity.

Since the instrumentation strategy is not robust before 2006, the results for this period should be taken with caution. However, results for a non-instrumented panel are the same in terms of significance and magnitude.

The explanatory power of the model is weak, which leads us to obtain negative values for the adjusted r2. This result is reinforced by the sub-period division which, combined with the instrumentation, induces too few degrees of freedom.

Table 10 – Additional specification: ethanol production before 2006 in UMICs

variables	Forestloss10%	Restrained sample			
		Forestloss10%	Forestloss30%	Forestloss50%	Forestloss75%
log(ethanol+1)	0.275	0.204	0.236	0.256	-0.287
	(2.29)**	(1.66)*	(1.83)*	(1.87)*	(1.23)
log(pop)	-1.019	0.759	0.863	0.190	2.342
	(0.49)	(0.36)	(0.41)	(0.09)	(1.09)
log(gdppc)	-5.508	-3.321	-8.106	-5.605	0.717
	(1.06)	(0.60)	(1.39)	(0.89)	(0.14)
log(gdppc) squared	0.286	0.192	0.518	0.338	-0.013
	(0.89)	(0.55)	(1.42)	(0.87)	(0.04)
e_rain	0.028	0.080	0.064	0.128	0.180
	(0.46)	(1.09)	(0.86)	(1.81)*	(2.40)**
e_temp	0.019	0.028	0.023	-0.002	0.053
	(0.49)	(0.61)	(0.47)	(0.04)	(1.05)
log(cer_yd)	0.061	0.019	-0.114	-0.167	-0.231
	(0.19)	(0.04)	(0.27)	(0.39)	(0.53)
log(reer)	0.104	-0.251	-0.518	-0.295	-0.117
	(2.43)**	(1.19)	(1.91)*	(0.98)	(0.27)
log(co_pr + 1)	-0.225	-0.252	-0.128	-0.088	-0.032
	(0.98)	(0.95)	(0.47)	(0.31)	(0.14)
log(ng_pr + 1)	0.118	0.065	0.038	0.020	0.177
	(0.87)	(0.48)	(0.27)	(0.14)	(1.33)
r2	0.18	0.20	0.25	0.24	0.29
Adjusted r2	-0.07	-0.07	-0.02	-0.03	0.02
Nomber of obs.	204	167	156	150	132
Number of countries	34	28	26	25	22
Time dummies	Yes (F=4.31)	Yes (F=3.83)	Yes (F=4.37)	Yes (F=3.85)	Yes (F=4.76)
Test of FE vs RE	FE (X^2=61.23)	FE (X^2=22.34)	RE (X^2=11.63)	RE (X^2=10.69)	FE (X^2=21.46)

** p<0.1; ** p<0.05; *** p<0.01*

Our variables are in logarithm to linearize the model, except for e_rain and e_temp. We add +1 to the logarithm variables with 0 in order to keep them. Standard deviations have been corrected to make them robust to the presence of heteroskedasticity.

Since the instrumentation strategy is not robust before 2006, the results for this period should be taken with caution. However, results for a non-instrumented panel are the same in terms of significance and magnitude.

The explanatory power of the model is weak, which leads us to obtain negative values for the adjusted r2. This result is reinforced by the sub-period division which, combined with the instrumentation, induces too few degrees of freedom.

Table 11 - Additional specification: biodiesel production before 2006 in UMICs

Variables	Forestloss10%	Restrained sample			
		Forestloss10%	Forestloss30%	Forestloss50%	Forestloss75%
log(biodiesel+1)	0.928	0.737	0.779	0.709	0.765
	(2.72)***	(2.34)**	(2.46)**	(2.37)**	(0.72)
log(pop)	-0.874	0.782	0.961	0.473	0.692
	(0.42)	(0.38)	(0.46)	(0.23)	(0.31)
log(gdppc)	-4.863	-2.710	-7.092	-4.712	0.260
	(0.98)	(0.53)	(1.35)	(0.82)	(0.05)
log(gdppc) squared	0.240	0.147	0.448	0.280	0.006
	(0.78)	(0.45)	(1.35)	(0.79)	(0.02)
e_rain	0.022	0.076	0.060	0.123	0.163
	(0.36)	(1.03)	(0.79)	(1.70)*	(2.07)**
e_temp	0.012	0.021	0.016	-0.006	0.054
	(0.29)	(0.44)	(0.31)	(0.13)	(1.06)
log(cer_yd)	0.032	0.003	-0.135	-0.184	-0.164
	(0.10)	(0.01)	(0.32)	(0.42)	(0.37)
log(reer)	0.106	-0.253	-0.515	-0.332	-0.591
	(2.42)**	(1.21)	(1.94)*	(1.01)	(0.92)
log(co_pr + 1)	-0.274	-0.295	-0.190	-0.175	0.010
	(1.28)	(1.25)	(0.80)	(0.70)	(0.05)
log(ng_pr + 1)	0.119	0.066	0.041	0.029	0.099
	(0.84)	(0.48)	(0.30)	(0.19)	(0.63)
r2	0.17	0.19	0.24	0.24	0.29
Adjusted r2	-0.10	-0.08	-0.03	-0.04	0.01
Nomber of obs.	204	167	156	150	132
Nomber of countries	34	28	26	25	22
Time dummies	Yes (F=4.36)	Yes (F=3.89)	Yes (F=4.47)	Yes (F=3.86)	Yes (F=4.56)
Test of FE vs RE	FE (X^2=60.20)	FE (X^2=23.82)	RE (X^2=8.49)	RE (X^2=9.80)	FE (X^2=21.12)

** p<0.1; ** p<0.05; *** p<0.01*

Our variables are in logarithm to linearize the model, except for e_rain and e_temp. We add +1 to the logarithm variables with 0 in order to keep them. Standard deviations have been corrected to make them robust to the presence of heteroskedasticity.

Since the instrumentation strategy is not robust before 2006, the results for this period should be taken with caution. However, results for a non-instrumented panel are the same in terms of significance and magnitude.

The explanatory power of the model is weak, which leads us to obtain negative values for the adjusted r2. This result is reinforced by the sub-period division which, combined with the instrumentation, induces too few degrees of freedom.

Tableau 12 – Additional specification: ethanol production after 2006 in UMICs

Variables	Forestloss10%	Restrained sample			
		Forestloss10%	Forestloss30%	Forestloss50%	Forestloss75%
log(ethanol+1)	0.431	0.461	0.468	0.528	0.535
	(2.59)**	(2.71)***	(2.74)***	(2.79)***	(2.66)***
log(pop)	1.304	3.883	3.686	3.779	4.641
	(0.76)	(1.99)**	(1.87)*	(1.91)*	(2.27)**
log(gdppc)	4.261	17.482	16.720	15.482	18.942
	(0.62)	(2.33)**	(2.19)**	(1.84)*	(2.03)**
log(gdppc) squared	-0.301	-1.133	-1.086	-1.017	-1.270
	(0.75)	(2.46)**	(2.32)**	(1.97)*	(2.24)**
e_rain	-0.054	-0.093	-0.094	-0.087	-0.119
	(1.29)	(1.92)*	(1.88)*	(1.71)*	(2.47)**
e_temp	0.090	0.088	0.090	0.090	0.074
	(2.84)***	(2.36)**	(2.25)**	(2.18)**	(1.96)*
log(cer_yd)	-0.229	-0.188	-0.217	-0.217	-0.157
	(1.42)	(0.88)	(0.99)	(0.99)	(0.69)
log(reer)	0.171	0.165	0.102	0.080	0.619
	(0.40)	(0.35)	(0.19)	(0.15)	(1.14)
log(co_pr + 1)	-0.346	-0.460	-0.474	-0.471	-0.590
	(2.02)**	(2.27)**	(2.28)**	(2.30)**	(3.08)***
log(ng_pr + 1)	0.324	0.307	0.523	0.507	0.094
	(0.83)	(0.67)	(1.00)	(0.96)	(0.17)
r2	0.27	0.34	0.33	0.34	0.37
Adjusted r2	0.04	0.10	0.10	0.09	0.13
Nomber of obs.	207	165	159	153	135
Number of countries	35	28	27	26	23
Time dummies	Yes (F=7.95)	Yes (F=7.42)	Yes (F=6.76)	Yes (F=6.28)	Yes (F=5.39)
Test of FE vs RE	FE (t=56.22)	FE (t=59.98)	FE (t=69.24)	FE (t=77.74)	FE (t=62.18)

** p<0.1; ** p<0.05; *** p<0.01*

Our variables are in logarithm to linearize the model, except for e_rain and e_temp. We add +1 to the logarithm variables with 0 in order to keep them. Standard deviations have been corrected to make them robust to the presence of heteroskedasticity.