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The effect of Amazon deforestation on global climate variables

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Abstract

We evaluate the effect of the Amazon deforestation on global climate variables: surface temperature, carbon dioxide and methane concentrations over the last fifty years. Our results show the Amazon deforestation effect on carbon dioxide concentration in the atmosphere since 1990. No similar effect is found for methane concentrations.

Keywords: climate change, deforestation, Amazon, gas emission.

1 Introduction

Despite the general consensus about the negative effect of the Amazon deforestation on global climate, there are no estimates quantifying its long-run effect using observational data. In an attempt to fill that gap, we extend Kaufmann, Kauppi and Stock (2006) –hereon, KKS– climate equations by incorporating the Amazon deforestation lands, recently recognized as the "International Statistic of the Decade" by the Royal Statistical Society.

Since available data on the Amazon deforestation start in the 70's, any study aimed to assess its effect on climate change should be necessarily based on short samples. At the same time, the available econometric methods to model persistent time series, in particular the cointegration analysis of the main climate variables (i.e. temperature, gas emissions and concentration) have been developed based on asymptotic properties, as well as on constant data generating process assumptions (Kaufmann et al. 2006, Pretis 2020, Bruns et al. 2020).

Given our interest in modelling long-run relationships, as well as evaluating the weak exogeneity of potential conditioning variables, we follow a system approach (Johansen 1995) bearing in mind that a great advantage of this approach is the invariance of the cointegration property to the extension of the information set (Juselius 2006). To deal with short samples and structural breaks, we simulate the asymptotic distribution of the trace test statistic.

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2 Incorporating deforestation into KKS climate equations

KKS estimate a climate system for three endogenous variables: global surface temperature and the atmospheric concentrations of CO_2 and CH_4.

2.1 Temperature equation

KKS temperature equation, reported in Equation (1), evaluates the long-run relationship between global surface temperature ($GLOBL$) and an aggregate for radiative forcing ($RFAGG$). KKS found a cointegration relationship assuming RF to be weakly exogenous.

$$GLOBL_t = \alpha + \beta_1 RFAGG_t + \mu_t \tag{1}$$

where β_1 captures the implied temperature sensitivity. Then, they estimate the corresponding error correction model (ECM) which also includes other short-run effects as SOI (Southern Oscillation Index) and NAO (Northern Atlantic Oscillation).

2.2 Concentration equations

The CO_2 and CH_4 concentrations equations in KKS are derived from the following identity, based on mass balance in the atmosphere:

$$x_t = \rho x_{t-1} + e_t + \eta_t \tag{2}$$

where x_t is the atmospheric concentration (CO_2 or CH_4) at time t and the previous period x_{t-1}, ρ is the retention rate, e_t denotes net emissions from human sources, and η_t denotes net flows from natural (non-human) sources. KKS approximate the net effect of temperature on natural flows of carbon to the atmosphere as follows,

$$x_t = \rho x_{t-1} + e_t + \theta GLOBL_t + \upsilon_t \tag{3}$$

where υ_t represents natural emissions unrelated to temperature.

If $\rho = 1$, then Δx_t, e_t and $GLOBL_t$ should cointegrate. Since KKS do not find cointegration, they estimate the previous equation in first differences.

Since the global surface temperature and the atmospheric concentration of CO_2 and CH_4 are determined jointly and to avoid the simultaneous equation bias, they use instrumental variables for temperature in the concentration equations (i.e., volcanic activity, SOI and temperature lagged values). Instead, we adopt a system approach to analyze cointegration.

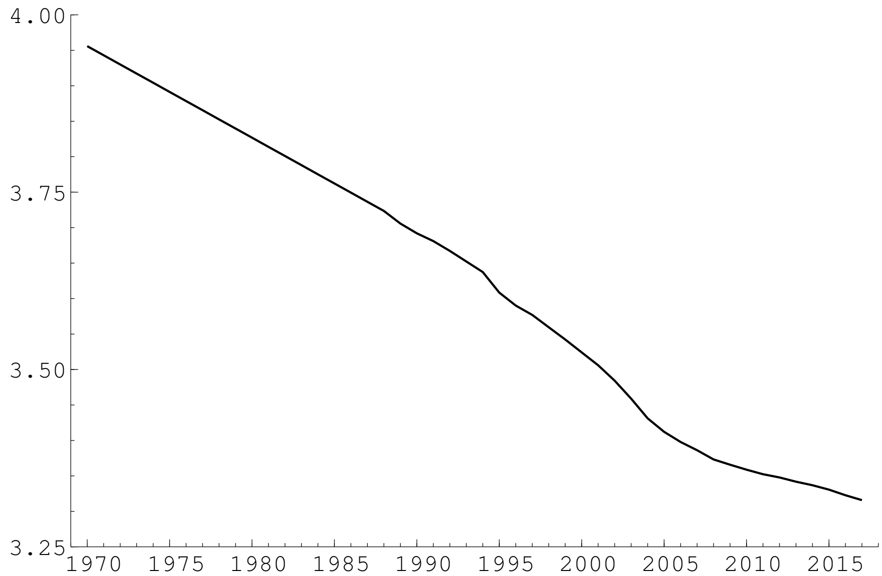
We extend Equation (3) by including the Amazon deforestation data:

$$\Delta x_t = e_t + \theta GLOBL_t + \lambda deforest_t + \upsilon_t \tag{4}$$

where $deforest_t$ accounts for the Amazon deforestation.

Such representation implies CO_2 and CH_4 concentration growth (Δx_t) to be I(1) and thus, x_t to be I(2).

Figure 1: Estimated Brazilian Amazon forest cover (million sq. km)



3 Data and methodology

Our dataset (Table 1) consists of annual series from 1972 to 2017 ($T = 46$), due to the Brazilian Amazon deforestation series coverage.

Table 1: Data description

Symbol	Description	Units	Source
$GLOBL$	Global Land-Ocean Temperature Index	$0.01°C$	NASA GISTEMP v4
RF	Global Radiative Forcing	W/m^2	Stern & Kaufmann (2014) and NOAA since 1979
CO_2	CO_2 atmosphere concentration	ppm	NOAA
ECO_2	CO_2 emissions from fossil-fuel combustion and industrial processes	GtC/yr	Boden et al. (2017)
CH_4	Methane atmospheric concentration	1,000 ppb	AGAGE
ECH_4	Methane emissions of CO_2 equivalent	1,000 kt	JRC/PBL
$deforest$	Estimated deforestation in Brazilian Amazon	million km^2	INPE-PRODES
SOI	Southern Oscillation Index	index	Australian BOM
NAO	North Atlantic Oscillation	index	NOAA

All variables are I(1), except for CO_2 and CH_4 which are I(2) and SOI and NAO which are I(0).

To analyze weak exogeneity, we follow Johansen's cointegration approach to distinguish between influences that move equilibria (pushing forces) and influences that correct deviations from equilibrium (pulling forces) which give rise to long-run relations.

To deal with short samples, breaks and step-dummies we simulate the asymptotic distribution of the trace test statistic for models including these components using the default wild bootstrap included in CATS (Doornik and Juselius 2017, Cavaliere et al. 2012).

4 Results

To evaluate cointegration and estimate Equation (1) and (4) we start by estimating three VAR models. The first model includes $GLOBL_t$ and $RFAGG_t$ as endogenous variables with one lag.

The second model includes the CO_2 concentration growth (ΔCO_2), the fuel-fossil CO_2 emissions (ECO_2) and $GLOBL_t$ as the endogenous variables with two lags; we included the Amazon deforestation as an exogenous variable. The largest losses of Brazilian forest were experienced during the nineties. From 1975 to 1989 the average annual deforestation was of 13,232 km^2; while from 1990 to 2004 this annual loss was 18,309 km^2, cumulating a 38% loss over the previous fifteen years. Hence, we included the Amazon deforestation in the system multiplied by a step dummy starting in 1990.[1] Also, an impulse dummy for 1990 is included unrestrictedly to achieve similarity in the cointegration test procedure as suggested in Nielsen and Rahbek (2000).

Finally, the third model includes the CH_4 concentration growth (ΔCH_4), the CH_4 emissions (ECH_4) and $GLOBL_t$ as the endogenous variables with two lags; while the Amazon deforestation since 1990 is introduced as an exogenous variable. Also, three impulse dummies are unrestrictedly included due to outliers: 1988, 1990 and 1997 to satisfy the multivariate normality assumption.

To test cointegration all systems initially included a linear trend in the cointegration space to allow for different deterministic trends in the variables (apart from their stochastic trends), as suggested by Juselius (2006). However, the linear trend was only significant in the $\mathrm{CH_4}$ system. At a 5% significance level, all VAR systems pass the usual diagnostic tests (Table 2).

Table 2: VAR diagnostic tests

	First VAR		Second VAR		Third VAR	
Test	Statistic	p-value	Statistic	p-value	Statistic	p-value
Autocorrelation - χ^2	4.34	0.36	4.85	0.85	15.97	0.07
Normality - χ^2	14.22	0.17	5.53	0.48	12.66	0.05
ARCH - χ^2	4.53	0.87	29.30	0.78	31.98	0.66

Using a 5% significance level, we found that in each system there is only one cointegration relationship. For the first system, none of the analyzed variables was weakly exogenous, indicating that certain radiative forcing components may also adjust to long-run deviations.[2] In the second and third systems, apart from the Amazon deforestation, the CO_2 and CH_4 emissions, but not their concentrations, were detected as weakly exogenous.

[1] We first included the entire sample deforestation variable along with the interaction term in the system, but only the latter was statistically significant. Furthermore, we tried different starting years for the step dummy and 1990 was the most significant.

[2] However, RF no longer adjusts when estimating the ECM which also controls for short-run effects such as SOI and NAO. The ECM estimations are not shown, but can be obtained from the authors upon request.

Table 3: Trace test

	Temperature equation		CO_2 equation		CH_4 equation	
r	Trace	p-value	Trace	p-value	Trace	p-value
0	52.49	0.00	73.41	0.04	93.63	0.01
1	8.24	0.35	28.35	0.37	43.14	0.08
2			2.76	0.85	15.68	0.15
Adjustment coefficients (α)						
	$\Delta GLOBL$	-0.72	$\Delta GLOBL$	-0.18	$\Delta GLOBL$	24.4
		{-4.9}		{-3.0}		{5.1}
	$\Delta RFAGG$	0.03				
		{2.5}				
			$\Delta\Delta CO_2$	-1.73		
				{-8.0}		
			ΔECO_2	-0.04		
				{-0.6}		
					$\Delta\Delta CH_4$	-0.52
						{-3.4}
					ΔECH_4	10.2
						{1.1}

Note: p-values based on the bootstrap and t-statistics reported in braces.

Given the long-run parameter estimates and following KKS framework, one possible normalization is (t-statistic reported in braces):

$$\widehat{GLOBL}_t = \underset{\{23.1\}}{0.596} RFAGG_t \tag{5}$$

$$\Delta\widehat{CO}_{2t} = \underset{\{2.6\}}{0.18} ECO_{2t} + \underset{\{2.7\}}{1.01} GLOBL_t + \underset{\{3.3\}}{0.20} (deforest \times S1990)_t \tag{6}$$

$$\Delta\widehat{CH}_{4t} = \underset{\{5.6\}}{0.01} ECH_{4t} + \underset{\{5.5\}}{0.02} GLOBL_t + \underset{\{0.3\}}{0.0002} (deforest \times S1990)_t \underset{\{-10.1\}}{-0.001}\, t \tag{7}$$

A main finding is that the Amazon deforestation has a long-run effect on CO_2 concentration growth, but not on CH_4 even if part of the rainforest has been replaced by cattle ranching. Results suggest that an increase of 100 thousand square kilometers in Brazilian Amazon deforestation will increase CO_2 concentration growth in about 0.2 parts per million (about 1% of the CO_2 atmospheric concentration growth between 1972 and 2017).

5 Conclusions

As often indicated, the Amazon rainforest is a key responsible for carbon sequestration, and thus CO_2 is released back into the atmosphere when deforestation takes place. Following a system approach and dealing with short samples and structural breaks, our results reveal that the Amazon deforestation has had a long-run effect on CO_2 concentrations since 1990, but we have no evidence of a similar effect on CH_4.

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