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Measuring the effects of climate change on soybean yields

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Preliminary. Comments welcome.

Abstract

We develop an econometric model to study the effects of climate changes on crop yields in a multivariate framework, considering not only temperature variables but also those related to technological progresses, inputs and use of marginal lands. We focus on the case of soybeans since, unlike other commodities, its production is highly concentrated geographically. We model a panel of five countries (United States, Brazil, Argentina, China and India) that accounted for 90 percent of world's production from 1961 to 2013. Our results show an adaptation process in the long-run despite negative effects of climate change in the short-run.

Key Words: climate change; soybeans; yield; temperature; CO2
JEL: Q15, Q54

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1. Introduction

Due to its strong dependence on climate, the effects of climate changes on agriculture have been deeply studied. In particular, world food production has been a matter of global concern, particularly for less developed economies as outlined in the Stern Review. However, as Nordhaus (2013) suggests (based on the IPCC 4th Assessment Report) it is especially in the agricultural sector where the adaptation and mitigation processes have been taking place. These processes are driven by technological developments or managerial changes such as the displacement of crop areas, replacing those most affected by global warming with "modest warming" areas and, above all, the incorporation of technology (e.g. the use of seeds more resistant to climate variability or pesticides).

To meet future (and rapidly growing) global demand for food and energy, crop yields need to be increased. According to the latest FAO projections in Alexandratos et al. (2006), we will require a 70% increase in food production between 2005/07 and 2050 to feed an estimated world population of 9.1 billion people by 2050. However, there are threads or constraints in many regions to achieve this goal due to climate change.

Therefore, understanding and measuring the effect of climate change on different agricultural variables, such as crop yields, is a necessary and important first step to design public policies oriented to new investments that will tend to both reduce emissions and allow economies to adapt to climate change.

To achieve this goal, rigorous empirical studies of the climate changes effects in the agricultural sector should be developed. They should account for different aspects: the evaluation of adaptation processes, the distinction between short-term and long-term effects, and the possibility of non-linearities of this effect, among others. Econometric models, particularly those based on recent developments, can help to obtain a more general analysis of the effects of climate change on agriculture: controlling for collinearities of the different determinants of the variable of interest, including lagged effects, considering heterogeneous estimates and outliers as well as evaluating exogeneity.

In this paper we econometrically study the effect of climate changes on crop yield taking into account, apart from temperature variables, technological developments, inputs and use of marginal lands. We focus on soybean yields since unlike other commodities, soybean production has been highly concentrated geographically. Because of that, we estimate a model using a panel of five countries (United States, Brazil, Argentina, China and India) with the largest soybean production that accounted for 90 percent of world's production from 1961 to 2013. Using this panel give us more variability and more informative data about the consequences of a world-wide phenomenon as it is climate change.

The econometric approach followed in this study allows as to account for several key crucial issues of the empirical analysis that have not been considered (or only partially) in the literature. Because we pool time series and cross-sectional data we allow for commodity and time variability. We also disentangle long-run and short-run effects following an error correction representation. Furthermore, we assess the exogeneity of the explanatory variables in the model of soybean yields.

Our findings provide evidence for the soybean yield of the main five world producers that an adaptation process has been taking place in the long-run despite negative effects of climate change in the short-run. We detected these consequences in a model that controls for some technological variables and use of marginal lands.

The paper is organised as follows. Section 2 provides a review of the literature. Section 3 explains the econometric approach and the following section describe our data set. Section 5 presents our main results and robustness tests. Section 6 discusses the main findings. The last section concludes.

2. Literature Review

Since the pioneering works of Smith (1914) and Fisher (1925), an extensive empirical literature has been developed trying to statistically estimate the effects of climatic variables on the agricultural sector.

The awareness regarding global warming and its consequences has renewed the interest on studying this topic during the last decade. The assessment of the effects of climate changes on crop yields is a multidisciplinary topic. Economists, agronomists, meteorologists and other scientists have been studying the agricultural impact of climate changes.

In contrast to econometric studies, many of the agronomic analyses focus on estimating the effect of climate on crops yields from models based on controlled experiments that require previous knowledge of the plant physiology, climate conditions and soil properties. However, the usefulness of these models is limited because they only incorporate physical aspects of potential yield and do not consider technological and global factors that allow yields to change over time. Much of the agronomic literature has modelled the effects of climate change on a wide variety of crops and areas throughout the world, but at a micro (states or counties) level. Crop simulation models are also widely used in the meteorology field to predict crop production and yields in studies of the climate change impacts and thus, the calculations in the crop models are based on the existing knowledge of the physics, physiology and ecology of crop responses to the environment.

The empirical literature shows mixed evidence of the effect of climate changes on crop yields because there would be several factors that have reduced the harmful impacts of climate change: carbon fertilization, adaptation, trade and the declining share over time of agriculture in the economy (see Nordhaus, 2013). Lobell and Burke (2010) summarize the sources of divergence of different estimated models to get a more robust picture of likely climate change impacts. They conclude that statistical models, compared to process-based models, play an important role in anticipating future impacts of climate change and their usefulness is higher at broader spatial scales.

Using a county-level panel on crop yields, Chen et al. (2013) estimate the impact of climate change on corn and soybean yields in China. Their results suggest the existence of non-linearities and asymmetric relationships between yields and climate variables as it has been previously suggested in the literature (Schlenker and Roberts, 2009). Furthermore, they find that extreme high temperatures are always harmful for crop growth.

In this line, Lobell et al. (2011) study the impact of the change in climate trends on the yield of four large crops (corn, wheat, rice and soybeans, which account for 75% of the calories humans consume directly or indirectly) between 1980 and 2008 for all the countries of the world. The authors find that, at the global level, corn and wheat yields showed adverse effects for the largest producers and a net overall loss of 3.8% and 5.5%, respectively. The net impact on rice and soybean production was insignificant, with gains in some countries that balanced the losses of others. In turn, most of the impacts were due to changes in temperature trends and not precipitation. This result is consistent with many recent studies of the climate change effects on yields where changes in temperature are more important than changes in rainfall, at least at the national and regional levels (Reilly and Schimmelpfennig, 2010; Schlenker and Lobell, 2010). Crop yield losses on the hottest days drive much of the effect of temperature (Schlenker and Roberts, 2009). Furthermore, crops are more sensitive to extremely high temperatures during the phases of the growth cycle (Auffhammer, et al. 2012; Welch et al., 2010).

As Auffhammer and Schlenker (2014) state, one of the greatest challenges in empirical analyses is the identification of adaptation responses to changes in climatic conditions. In this sense, the adaptation process should be evaluated as a long-term effect, but short-run responses should also be taken into account. Burke and Emerick (2013) examine the effect of long-term changes in climatic variables on yields using county-level data in the United States. Their results indicate that the main crops in the U.S., corn and soybeans, are significantly and negative affected by long-term changes in extreme heat temperatures. Changes in short-term temperature extremes can be critical, especially if they coincide with flowering stage of many crops reducing their yield (Wheeler et al., 2000).

Several adaptation measures such as shifting planting dates or developing new crop varieties may mitigate the potential negative impacts of climate change on crop yield and production (Lobell et al., 2008; Cohn et al., 2016).

3. Econometric approach

Our data is an unbalanced panel of five countries (corresponding to the five largest soybean producers) with annual observations between 1961 and 2013. Although it is an unbalanced panel, we have at least 40 observations for each country and therefore, the number of time observations is large enough to obtain consistent estimates when including the lagged dependent variable.

As it is usual for this kind of data, we started by analysing univariate time and panel unit root tests (reported in Appendix). They indicate that all variables can be considered either stationary or trend-stationary. Although it is often believed that error correction models (ECM) are representations only of cointegrated processes, an error correction model is also isomorphic to dynamic (autoregressive-distributed lag) models for stationary data. Thus, we are able to take its advantages to capture both long and short-term dynamics through the estimation of a (single conditional) model which includes both differences and levels of the variables of the model. Therefore, the ECM is both a theoretically desirable and an empirically feasible approach to our data.

In our case, we estimated the following ECM to explain the changes in soybean yields (Δy_{it}). The estimated equation is:

$$\Delta y_{it} = \gamma_{it} + \delta_i t - \alpha \left[y_{it-1} - \beta' x_{it-1} \right] + \sum_{k=1}^{2} \rho_k \Delta y_{it-k} + \sum_{k=0}^{2} \lambda' \Delta x_{it-k} + \varepsilon_{it} \qquad (1)$$

where $i = 1, ..., N$; $t = 1, ..., T$; and k indicates lags. The vector x denotes the explanatory variables with either country and time (it) or only time (t) variation. This vector includes global and local climate variables as well as input variables (fertilizers or machinery) and the use of marginal lands. Section 4 describes in detail all the variables considered in the analysis and their sources.

Usually in the literature, climate variables that were used to econometrically evaluate their impact on agriculture were considered exogenous (e.g. temperature, precipitation, humidity, storms, among others). Due to the exogeneity and randomness of the climate in many economic applications, weather variables act as a "natural experiment" and, therefore, allow the researcher to statistically identify the causal effect of a variable on an economic result of interest. However, as Pretis (2017) warns, human activity affects the global climate and climate change impacts, in turn, on human activity. Empirically, this fact implies that if we want to estimate the effect of climate change on the economic activity, we would need to evaluate the exogeneity of variables within an economic-climate system. The analysis of exogeneity is crucial to obtain consistent estimates in a conditional model of economic or climatic variables.

In this line, we address the exogeneity of explanatory variables suspected not to be exogeneous. An instrumental variable (IV) estimation is used to validate the single-equation model approach, which at the same time will be useful to obtain consistent estimates in the case of error in variables associated with measurement errors of the climate variables used to reflect global warming as next explained.

In the case of our model we study the exogeneity of the global temperature variable that enters as long-run determinant of yields, as their interactions are likely to be long duration processes. Higher yields may imply expansion of land frontiers dedicated to this crop through deforestation. It has been a common practice, particularly in developing countries. In this way, this human activity may be an additional factor to global warming. That is why we considered the exogeneity issue taking an instrumental variable approach, using gas emissions (CO_2 and methane emissions) as instruments since they are originated in other economic activities other than cultivating crops.

Furthermore, climate is a very wide, general and complex concept that encompasses different measures (e.g. temperature, precipitation, humidity, among others). In fact, the climate influences what realizations of weather actually occur (Hsiang, 2016) and the difficulty of having well-defined measure of climate should be a matter of concern for the applied econometrician. We use several measures of climatic variables which are all proxies (thus, imperfect) of climate change. Therefore, IV estimates would give us a better identification of the effects of global warming on crop yields.

4. Data

Our primary dataset consists of annually series over a long-term period spanning from 1961 to 2013 ($T = 53$) for five countries ($N = 5$) with the largest soybean production (United States, Brazil, Argentina, China and India), a total of 265 observations. Unlike other commodities, soybeans production is highly concentrated geographically, these countries accounted for 90 percent of world soybean production during the analysis period. Table 1 reports the data description distinguishing which variables are available at the local or global level.

Demand for oilseeds, and particularly soybeans, has rapidly increased. It is one of the most valuable crops in the world, not only because of its use as oil seed but also as high-protein meal for animal and human feed as well as a source for biofuel production. Considering the five producers as a whole, soybeans production increased by 5% annually from 1961 to 2013. Average soybean yield (measured as hectogram per hectare) increased from 48,910 hectograms per hectare (hg/ha) in 1961-1965 to 111,878 hg/ha in 2011-2013. Out of the top five soybean production countries, Brazil reached 31,214 hg/ha in 2011 while India's highest yield was 13,530 hg/ha in 2012. The harvested area has almost quadrupled and the yield has doubled since 1961. During the sample period, climate changes and technological advances shifted the main production area to warmer latitudes. In the northern hemisphere the soybean production frontier moved towards the south while in the southern hemisphere the frontier shifted to the north.

Several global and local climate variables are considered in the analysis. It is usually indicated that the best predictor of soybean yield is a measure of extreme heat during growth periods considering a temperature threshold above 29°C (Schlenker and Roberts, 2009). Thus, using daily data of maximum temperature from the meteorological stations of each country's soybean production area, we construct a variable that measures the number of days in a year, during the growing phase of the crop,[1] in which the temperature exceeded 29°C. The data to construct this variable was obtained from the U.S. National Oceanic and Atmospheric Administration (NOAA). Other measures of global warming include the global temperature anomalies computed from land and ocean data as the temperature differences (in °C) relative to the 1951-1980 base period means reported by the GISTEMP team of the Carbon Dioxide Information Analysis Center (CDIAC). During our sample period, this variable showed a steady increase from a minimum of -0.21 °C in 1964 to a maximum of 0.71 °C by 2010.

Our vector of potential instruments includes CO_2 and methane emissions at the local and global level. Those variables have a clear and direct effect on global warming raising the world's temperature, and they are expected to affect yields only indirectly through the climate change.

In our estimations, we also considered the use of different fertilizers (that is, the use of inorganic manufactured products that supply plant nutrients) as a possible driver of the soybean yield increase during the last fifty years. Soybean usually has a high requirement for phosphorus (P_2O_5) and potassium (K_2O), but in certain countries (like Brazil) very little nitrogen (N) is applied to this crop.

[1]Soybeans growing season goes from December to April in Argentina, from December to February in Brazil, from June to September in China, from July to September in India and from June to September.

Table 1: Data description

Symbol	Description	Units	Global or local	Source
Y	Soybean yield	Hg/ha	Local	FAO
C	Arable Land + Land in Permanent Crops	1000 Ha	Local	USDA
I	Area equiped for irrigation	1000 Ha	Local	USDA
M	Number of 40 CV Tractor-Equivalents in use	Units	Local	USDA
F	Synthetic Fertilizer Consumption (N+P2O5+K2O)	Tonnes	Local	USDA
P_2O_5	Phosphate consumption	1000 tonnes	Local	IFA
K_2O	Potash consumption	1000 tonnes	Local	IFA
N	Nitrogen consumption	1000 tonnes	Local	IFA
L	Agricultural land	% of land area	Local	FAO
CO_2	CO2 emissions	Kt	Global and local	WDI
CH_4	CH4 emissions (CO2eq)	Gigagrams	Global and local	FAO
$temp$	Global annual temperature anomalies (relative to the 1951-1980 period means)	Degrees C	Global	CDIAC
$max29$	Days of growing season with maximum temperature above 29°C	Number of days	Local	NOAA

All variables are expressed in logs, with the exception of global temperature anomalies (temp) and the number of days with maximum temperatures above 29°C ($max29$).

5. Econometric results

Table 2 reports the coefficient estimates of levels and differences of the ECM that allows us to obtain long-run and short-run effects on soybean yields. Column (1) shows the fixed effects (FE-OLS) estimation. Column (2) corresponds to the IV estimation of the FE model (FE-IV) using global CO_2 emissions as an instrument of the global temperature anomalies. Finally, Column (3) reports the FE-IV estimation using two instruments: global CO_2 emissions and methane emissions.

Table 2: Fixed effects estimations

	FE-OLS		FE-IV		FE-IV	
	(1)	(2)	(3)	(4)	(5)	(6)
Adjustment coefficient	-0.30***	-0.37***	-0.46***	-0.53***	-0.46***	-0.53***
	(0.05)	(0.06)	(0.05)	(0.09)	(0.06)	(0.08)
Long-run effects						
Global temp. anomalies,	0.72**	0.45**	0.88***	0.63**	0.88***	0.63**
$temp_{t-1}$	(0.32)	(0.17)	(0.29)	(0.35)	(0.29)	(0.31)
Short-run effects						
Days w/max. temp. > 29°C,	-0.0005***	-0.0004***	-0.0003***	-0.0003***	-0.0004**	-0.0003***
$\Delta max29_t$	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0002)	(0.0004)
Irrigated to cropland ratio,		-0.84**		-0.78***		-0.77***
$\Delta ln(I/C)_{t-1}$		(0.19)		(0.18)		(0.18)
Cropland,		-1.32**		-1.30***		-1.30***
$\Delta ln(C_{t-1})$		(0.32)		(0.48)		(0.49)
Potassium consumption,		0.06*		0.09**		0.09**
$\Delta ln(K_2O_{t-1})$		(0.03)		(0.04)		(0.04)
$\Delta ln(Y_{t-1})$	-0.43***	-0.38***	-0.33***	-0.26***	-0.33***	-0.26***
	(0.06)	(0.06)	(0.08)	(0.07)	(0.08)	(0.06)
$\Delta ln(Y_{t-2})$	-0.12*	-0.09***	-0.05	0.09***	-0.05	0.09***
	(0.05)	(0.04)	(0.04)	(0.02)	(0.05)	(0.02)
Deterministic components						
Constant	2.91***	3.50***	4.38***	5.00***	4.39***	5.02***
	(0.50)	(0.57)	(0.51)	(0.82)	(0.52)	(0.78)
India × 1979		-0.46***		-0.42***		-0.41***
		(0.02)		(0.03)		(0.03)
Argentina × 2009		-0.39***		-0.38***		-0.38***
		(0.02)		(0.02)		(0.02)
trend × Argentina		0.004***		0.004***		0.004***
		(0.001)		(0.0004)		(0.0004)
trend × Brazil		0.003**		0.003***		0.003***
		(0.001)		(0.001)		(0.001)
trend × China		0.003**		0.002***		0.002***
		(0.001)		(0.0003)		(0.0004)
Country effects	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.38	0.50	0.36	0.48	0.36	0.48
Diagnostic tests						
Independence test:	14.69	14.69				
	[0.14]	[0.46]				
Anderson-Rubin Wald test:			17.73	15.07	9.27	7.90
			[0.00]	[0.00]	[0.00]	[0.00]
Sargan test, $\chi^2(1)$:					0.003	0.17
					[0.96]	[0.68]

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Clustered-standard errors reported in parentheses and p-values in brackets.

All estimations include time invariant country dummies that account for country's specific characteristics such as soil quality that can impact soybeans yields. At the same time, we controlled for shocks or extreme events that are specific to certain years and countries by selecting the significant impulse dummies through *Impulse Indicator Saturation* (IIS).[2]

[2]IIS is a technique that adds a 1-0 dummy variable for each observation as a regressor. These estimations are performed by *Autometrics* which solves the problem of having more potential regressors than observations by testing and selecting over blocks of variables. IIS was implemented considering

The null hypothesis of cross-sectional independent residuals of the estimations FE-OLS model is not rejected (Breusch-Pagan LM test). Therefore, since we did not find evidence of cross dependence in the estimated panel, we used clustered standard errors to control for both heteroscedasticity and serial correlation only.

FE-IV estimations in Columns (3) and (4) show a significant increase in the estimated coefficient of the global temperature anomalies with respect to the FE-OLS estimation. In both estimations. The reported Anderson-Rubin (1949) test is equivalent to estimating the reduced form of the equation (with the full set of instruments as regressors) and testing that the coefficients of the excluded instruments are jointly equal to zero. Furthermore, all the individual coefficients of excluded instruments in the reduced form were statistically significant.

As the case of FE-IV estimations, Columns (5) and (6) include two instrumental variables: global CO2 and methane emissions, we test for overidentifying restrictions. We report the Sargan test that validates the instrumental variables employed in this estimation as the null hypothesis that the error term is not correlated with the instruments is not rejected.

We can note that since the effect of temperature in the long-run changes in the IV estimation, we will focus on these (more consistent) estimates when analyzing results in the following section.

6. Discussing results

The estimated models of soybean yields (reported in Column (2) for FE-OLS and (4) for FE-IV estimation) suggest that soybean yields depend on: (a) global temperature anomalies, in the long-run and (b) extreme temperatures, irrigated areas, crop lands and potassium consumption, in the short run. For comparisons we also show in Columns (1) and (3) an autoregressive model with temperature variables only. We can appreciate that although the controls we use decrease the estimated effects of temperature, in particular that of global warming, we still found significant and different long-run and short-run effects of the temperature variables.

As regards global warming effects in the long-run, when the annual global temperature increases 0.1°C with respect to the 1951-1980 base period mean (the global anomaly variable), soybean yields rise about 6%, even after controlling for significant and country-specific linear trends. This result may indicate the existence of an adaptation process of soybeans in the long-run during the sample. Even after controlling from the use of marginal land and fertilizers, there are other factors that might explain this effect such as: the carbon fertilization effect (that is, the increase of CO_2 in the atmosphere that increase the rate of photosynthesis in plants), the use of resistant seeds or changes in management practices to new conditions.

However, in the short-run, ten additional days of maximum temperatures exceeding 29°C during the growing season of the crop will imply a decrease of 0.3% in its yield.

The results just described show the importance of distinguishing long-run and short-run effects for climate variables in as much as the process of adaptation is gradual and may take several years. In contrast, the negative effect of extreme events which may be associated with global warming has a contemporaneous impact according to our estimates.

a balanced panel since 1973.

We can remark that the adaptation process is maintained after controlling by fertilizer consumption and planting on marginal lands when they are measured as potassium consumption and the variation of crop land dedicated to soybean and the proportion of irrigated cropland (apart from a country specific trends for Argentina, China and Brazil), respectively. A 1% increase in the consumption of Potassium increases soybean yields in 0.09%. Extending the crop land frontier 1% decreases 1.3% yields while, keeping it fixed, a 1% rise in the proportion of irrigated to crop lands will give a 0.8% fall in yields. The last two results suggest that there exists decreasing marginal product of land for this oilseed when the cultivated frontiers are expanded.

Through the selected significant dummies, we were able to identify a decrease of 38% in soybean yield in Argentina in 2009 due to a historic drought and extremely high temperatures during the growing season of soybeans. The severe heat waves experienced in India in 1979 were also detected.

7. Final remarks

Measuring the effects of climate change is a complex task due to several issues such as the difficulty of finding an adequate measure of global warming, disentangling long-run and short-run effects and endogeneity issues that econometric models can help to solve. In the case of the consequences on agricultural variables there is an additional question to address: the need to evaluate the possible negative effects of global warming along with the ongoing processes of adaptation and mitigation.

This paper has contributed to understand these effects of climate change on crop yields focussing in the case of soybean, given the geographical concentration of this crop that allows us to estimate a panel of five countries. In this sense we contribute in at least three ways: i) we construct local temperature series measuring the extreme hot days during the crop's growing phase to include in the model apart from available global measures; ii) we include several controls to consistently estimate the marginal effect of global warming on soybean yield; iii) we perform an instrumental variable estimation to address the possible endogeneity of temperature variables in the model.

We found an adaptation process in the long-run despite negative effects of climate change in the short-run. The use of marginal lands and fertilizers also had a significant effect on soybean yields in the short-run. However, there are still several routes to improve this model. Future versions of this study will test for commodity and time poolability; evaluate possible nonlinearities in the relationships and consider other possible controls to model soybean yields.

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A. Appendix. Unit root tests

Table A1. Country and time-varying variables

Variable	Levin-Lin-Chu		Fisher			
			Dickey-Fuller		Phillips-Perron	
	$c+trend$	c	$c+trend$	c	$c+trend$	c
$ln(Y)$	-3.86**	-2.52**	32.72**	8.61	104.14**	12.52
$ln(C)$	-0.89	-1.98*	3.77	12.81	8.76	23.57**
$ln(I)$	0.00	-3.34**	7.88	11.63	1.46	25.05**
$ln(M)$	-2.10*	-5.58**	9.63	22.21*	3.68	47.81**
$ln(F)$	-3.07**	-6.05**	14.72	54.99**	11.46	47.93**
$ln(P2O5)$	-4.01**	-4.84**	20.91*	27.49**	15.95	27.58**
$ln(K2O)$	-2.72**	-4.21**	15.02	26.17**	13.96	22.26*
$ln(N)$	-2.78**	-6.68**	19.66*	57.95**	17.85	62.69**
$ln(L)$	-1.11	-3.41**	7.76	19.46*	22.05*	88.68**
$ln(CO2)$	-1.26	-0.42	14.41	13.54	8.61	15.61
$ln(CH4)$	-1.67*	-3.72**	21.59*	27.88**	7.88	17.16
$max29$	–	–	30.16**	36.95**	123.66**	115.58**
$\Delta ln(Y)$	-11.85**	-12.72**	150.41**	174.76**	354.60**	360.43**
$\Delta ln(C)$	-6.13**	-6.15**	61.88**	50.33	165.08**	163.26**
$\Delta ln(I)$	-1.99*	-1.65*	18.60*	20.45*	42.18**	43**
$\Delta ln(M)$	4.99**	-4.79**	38.42**	38.77**	102.42**	93.36**
$\Delta ln(F)$	-9.93**	-8.63**	86.71**	58.45**	214.87**	208.85**
$\Delta ln(P2O5)$	-9.99**	-9.98**	83.59**	85.60**	208.76**	225.22**
$\Delta ln(K2O)$	-10.95**	-10.68**	90.03**	92.89**	252.19**	269.64**
$\Delta ln(N)$	-8.92**	-7.72**	83.49**	57.35**	233.16**	220.27**
$\Delta ln(L)$	-2.77**	2.34**	34.19**	34.27**	144.36**	136.50**
$\Delta ln(CO2)$	-5.76**	-6.07**	40.53**	53.32**	135.52**	**155.45
$\Delta ln(CH4)$	-6.69**	-6.64**	41.87**	50.17**	114.08**	126.25**
$\Delta max29$	–	–	127.76**	154.43**	329.01**	336.01**

Note: Levin-Lin-Chu unit root test assumes a common autoregressive parameter for all panels and requires that the number of periods grow more quickly than the number of panels (N/T tends to zero); the adjusted t-statistic is reported. The Fisher-type test performs a unit root test based on augmented Dickey–Fuller tests and Phillips–Perron tests and requires the number of periods tend to infinity, both were performed with 2 lags length, the inverse chi-squared statistic is reported. * and ** indicate significance at the 5 and 1% level, respectively

Table A2. Time-varying variables

	Dickey-Fuller		Phillips-Perron	
Variable	$c + trend$	c	$c + trend$	c
$ln(temp)$	84.68**	1.11	140.99**	2.86
$ln(CO2)$	16.09	7.3	15.68	17.52
$ln(CH4)$	13.59	24.45*	9.84	32.88**
$\Delta ln(temp)$	184.1**	220.77**	360.43**	360.43**
$\Delta ln(CO2)$	15	26.84*	70.53**	81.52**
$\Delta ln(CH4)$	71.38**	65.11**	105.52**	109.46**

Note: The null hypothesis for the ADF and PP tests is that of unit root against the alternative of stationarity. * and ** indicate significance at the 5 and 1% level, respectively.