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An analysis of climatic effects, convergence and catch-up

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ACRONYMS

ADF	Augmented Dickey-Fuller Regressions
AS	Animal Stock
ASTI	Agricultural Science and Technology Indicators Dataset
CAM	Climate Anomaly Method
CATFP	Climate Adjusted Total Factor Productivity
CD	Cobb-Douglas Functional Form
CE	Climate Effect
CEI	Climate Effect Index
CRU	Climate Research Unit
CSIRO	Commonwealth Scientific and Industrial Research Organization
DMT	Daily Mean Temperature
DTR	Diurnal Temperature Range
ECLAC	Economic Commission for Latin America and the Caribbean
ECM	Error Correction Model
FAO	Food and Agriculture Organization
FER	Fertilizers
FIML	Full Information Maximum Likelihood
GDP	Gross Domestic Product
GHG	Greenhouse Gas
GTRE	Generalized True Random Effects
GTREM	Generalized True Random Effects Mundlak Model
HIC	High Income Countries
IFPRI	International Food Policy Research Institute
IPCC	Intergovernmental Panel on Climate Change
IPS	Im-Persaran-Shin Test
JLMS	Jundrow, Lovell, Materov and Schmidt Estimator
LA	Land
LAC	Latin America and The Caribbean
LB	Labor
LDC	Less Developed Countries
LLC	Levi-Lin-Chu Test
LRTE	Long Term Technical Efficiency

MENA	Middle East North Africa
MG	Mean Group Estimator
MLE	Maximum Likelihood Estimators
NCAR	National Center for Atmospheric Research
PMG	Pooled Mean Group Estimator
PRECIP	Precipitation
RCM	Regional Climate Modeling System
RCPs	Representative Concentration Pathways
RD	Rainy Days
SE	Scale Efficiency
SML	Simulated Maximum likelihood
SPF	Stochastic Production Frontier model
SRES	Special Report on emissions scenarios
SRTE	Short Term Technical Efficiency
SSA	Sub-Sahara Africa
SSPs	Shared Scenario Pathways
TE	Technical Efficiency
TEM	Annual Maximum Temperature
TFP	Total Factor Productivity convergence
TP	Technological Progress
TR	Tractors
TRE	True Random Effects
WMO	World Meteorological Organization

ABSTRACT

This study estimates Climate Adjusted Total Factor Productivity (CATFP) for agriculture in Latin America and Caribbean (LAC) countries, while also providing comparisons with several regions of the world. Climatic variability is introduced in Stochastic Production Frontier (SPF) models by including average annual maximum temperature, precipitation and its monthly intra-year standard deviations, and the number of rainy days. Climatic conditions have a negative impact on production becoming stronger at the end of the 2000s compared to earlier periods. An Error Correction Model is applied to investigate catch-up and convergence across LAC countries. Argentina defines the frontier in LAC and TFP convergence is found across all South American countries, Costa Rica, Mexico, Barbados and The Bahamas. Using IPCC 2014 scenarios, the study shows that climatic variability induces significant reductions in productivity (2.3% to 10.7%), over the 2013-2040 period. Estimated output losses due to climatic variability range from 9% to 20% in the LAC region depending on the scenario considered. .

JEL Code: D24, Q54, O47, E27.
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I. INTRODUCTION

The agricultural sector plays a critical role in the economy of Latin American and Caribbean (LAC) countries. According to the Economic Commission for Latin America and the Caribbean (ECLAC, 2014), in 2012, the sector accounted for nearly 5% of Gross Domestic Product (GDP), employed 16% of the workforce and produced about 23% of the total exports of the region. The relatively low and heterogeneous increase in Total Factor Productivity (TFP) growth across LAC countries is one of the main challenges facing agriculture according to the Inter-American Development Bank's Agriculture and Natural Resources Sector Framework.

Recent studies have shown that increasing agricultural productivity is fundamental for long-term poverty alleviation and for overall economic growth (e.g., World Bank, 2008). Agriculture plays an important role in overall economic growth in LAC countries (World Bank, 2003), and it has significant spillover effects on other sectors of the economy (Hazell and Roell, 1983; Krueger et al., 1991; Federico, 2005). Most studies in agricultural productivity in the region are outdated and ignore unobserved heterogeneity and climatic effects. The most recent published study is Ludena (2010), which is based on data available up to 2007. Policy decisions made on outdated data can be misleading; thus, agricultural productivity studies in the region need to be updated.

On the other hand, agricultural productivity in LAC countries, as pointed out by Chomitz et al., (2007), among others, is facing the rising challenge imposed by climate change, natural resource depletion and environmental degradation. For instance, recent data from FAO (2010) reveals that South America had the largest worldwide net loss of forests between 2000 and 2010, estimated at 4.0 million hectares per year. Furthermore, forest cover continues to decrease in all countries in Central America with the exception of Costa Rica. These data reveal an ongoing expansion of the agricultural frontier in several LAC countries, which can be a contributor to climatic variability and can affect agricultural productivity (Geist and Lambin, 2000). According to the World Bank (2012), rising global temperatures would have devastating impacts on LAC, a region that is expected to suffer severe consequences. By the same token, recent evidence from the Intergovernmental Panel on Climate Change (IPCC) suggests that climatic variability is expected to have more pronounced adverse effects in LAC than in other regions of the world and these effects are likely to become more serious in the future (e.g., IPCC, 2014a; IPCC, 2014b; Stern, 2013).

Specifically, climate projections indicate that temperatures will rise by between 1.6 ^{o}C and 4 ^{o}C in the region by the end of the twenty-first century while changes in precipitation levels are expected to range between -22% and 7% for Central American countries; and, these changes would be more heterogeneous across South American countries. Farming activities are responsive and vulnerable to climatic variability and recent research findings highlight important prospective adverse impacts on the LAC agricultural sector by 2020, especially due to an increase in temperature levels and changes in precipitation patterns (e.g., Vergara et al., 2013). The adverse impacts of climatic variability on agricultural production are gaining more attention in the research arena, with an increasing number of studies focusing on the interrelation among climatic variability, agriculture, the food system, and the associated adaptation costs (e.g., Dell et al., 2014; Mendelsohn and Dinar, 2003; Mukherjee et al., 2013; Nelson et al., 2009).

Several studies have shown that agricultural productivity in least developed countries (LDCs) is vulnerable to climatic variability (e.g., Mendelson and Dinar, 2003; Müller et al., 2010; Lobell et al., 2011); however, few such studies have focused on LAC. Therefore, a comprehensive analysis of the relationship between agricultural productivity and climatic variability is critical for LAC as well as for the rest of the world.

The objective of this study is to support the analysis of agricultural productivity growth across LAC countries, with a special focus on the introduction of climate variables to produce Climate Adjusted Total Factor Productivity Indexes (CATFP). This study will also provide a comparative analysis of the convergence of TFP in agriculture within LAC countries and between LAC and other regions in the world, and including forecasts to 2040 of possible productivity paths for LAC.

In order to achieve our objective, the conceptual framework and research methodology include the following steps: 1) Develop a database that incorporates different types of climate variables, agricultural output, and conventional inputs (tractors, fertilizer, animal stock, land and labor) as well as public spending on agricultural research, to the extent that this data is available, across countries. The database developed covers the period going from 1961 to 2012; 2) Use Stochastic Production Frontier (SPF) methods along with panel data techniques to estimate alternative frontier models; compute and decompose TFP into a Technical Efficiency (TE) index, Technological Progress (TP), a Scale Efficiency (SE) index and Climate Effects (CE) which makes it possible to identify the main drivers of productivity growth across countries; 3) Use panel data unit root co-integration tests and the Error Correction Model (ECM) to analyze catch-up and convergence within LAC countries, at the sub-regional level, and to investigate whether LAC countries are converging to developed country TFP levels whenever it is possible; and 4) Forecast possible TFP paths for LAC countries to 2030-2040.

The remainder of this paper is structured as follows. Section 2 contains an overview of the recent empirical literature on climate-production-economics. Section 3 provides the conceptual framework used to estimate the different models, compute the climate effects index and TFP, and to undertake the forecasts. Section 4 presents a descriptive analysis of the data and some issues encountered. Section 5 contains the results and analysis, and the paper ends with concluding remarks and policy implications for climate adaptation and mitigation programs for LAC.

II. LITERATURE OVERVIEW

There has been recently a growing body of literature that investigates the impact of weather events such as temperature, precipitation, drought and so forth on economic outcomes. First of all, it is worth noting that unlike weather that varies on a day-to-day basis and climate change, which is a long-term gradual change in average weather conditions, climatic variability can be seen as a yearly fluctuation in weather around a long-term average value.[1] A good way to look at this, as explained by Dell et al. (2014), is that climate change can be interpreted as a distribution in which climatic variability is a draw or a specific realization. This emerging literature, based on panel data estimators, is motivated by the failure of cross sectional analysis to establish a clear causative relationship between climate variables and economic output (Dell et al., 2014). Therefore, this approach uses year-to-year variation to capture contemporaneous effects of climate variables on economic outcomes. Specifically, it employs a reduced form panel data approach, and has a strong causative interpretation that allows identifying, in our context, the net effect of climatic variability on agricultural production and productivity (see Dell et al., 2014 for an extensive review of the literature).

Another feature of importance is how climate variables are modeled. The functional form or the way climate variables enter in the production or objective function varies across studies

[1] See http://www.climate.noaa.gov/education/pdfs/ClimateLiteracy-8.5x11March09FinalHR.pdf

depending on their objectives. For instance, Burke and Leigh (2010) use a first difference approach; Hughes et al. (2011), and Hsiang and Jina (2014) incorporate the variables at their levels; Bruckner and Ciccone (2011), Dell et al. (2012), and Maccini and Yang (2009) take the logs of the climate variables.

Furthermore, the type of data used to identify the impact of climatic variability also matters. There are several types of data in the literature that are utilized to identify climatic shocks such as ground station data, satellite data, reanalysis data, and gridded data (see Dell et al., 2014 for details). The latter group, which is what we use in this study, offers a more complete coverage compared to the other types because it interpolates station data over a grid, providing a balanced panel data set which is desirable for aggregate studies (Dell et al., 2014).

III. CONCEPTUAL FRAMEWORK

We investigate the impact of climatic variability on agricultural production and productivity by using Stochastic Production Frontiers (SPF) and panel data techniques. The SPF method basically estimates a benchmarking production frontier which serves to evaluate the performance of each country in the sample. We estimate and test two sets of model specifications that vary according to the treatment of the climatic variables and unobserved heterogeneity.

First, to account for country unobserved heterogeneity, such as unmeasured land quality and environmental conditions that are not captured explicitly in the data and which potentially affect production, we estimate the Generalized True Random Effects (GTRE) model as suggested by Colombi et al. (2011, 2014). A similar approach has also been presented recently by Tsionas and Kumbhakar (2014), and Filippini and Greene (2014).

Second, the random effects specification assumes the absence of correlation between unit specific effects and independent variables (Greene, 2008). However, if correlation between unobserved heterogeneity and conventional inputs (e.g., land, labor, and machinery) included in the production model is ignored then the resulting estimates would be biased and inconsistent. Therefore, we use the proposition of Farsi et al., (2005) and apply the Mundlak (1978) adjustment to mitigate this problem and estimate what we call the Generalized True Random Effects Mundlak (GTREM) model.

Both the GTRE and GTREM models are estimated by Simulated Maximum Likelihood (SML). GRTE is an extension of the True Random Effects (TRE) proposed by Greene (2005a, 2005b). TRE models separate time variant inefficiency from time invariant country specific unobserved heterogeneity. Consequently, TE estimates from TRE models offer information on the time-varying component of inefficiency. Nevertheless, TRE models do not differentiate unobserved country heterogeneity from time invariant inefficiency. Therefore, country time invariant inefficiency and unobserved heterogeneity is captured as a combined country random effects in the TRE model.

The GTRE model proposed by Colombi et al., (2011, 2014) has an error structure that is decomposed into four elements and thus makes it possible to account separately for the usual noise in the data, country unobserved time-invariant heterogeneity, time-varying or transient inefficiency and time invariant or persistent inefficiency. Herein, the transient inefficiency is interpreted as short-term TE (SRTE) associated with changes in managerial skills or disruptions resulting from the adoption of new technologies. By contrast, persistent inefficiency can be seen as long-run TE (LRTE) due to structural or institutional factors which evolve slowly overtime. While LRTE and country unobserved heterogeneity are both time invariant effects, a major difference between them is that the latter is always beyond the control of decision makers (e.g., geological makeup of a country and other physical features or characteristics). Unlike the three-step estimator proposed by Tsionas and Kumbhakar (2014), and the Full Information Maximum Likelihood (FIML) estimation proposed by Colombi (2011), we use a recent one step estimator approach, based on simulation methods and on the Butler and Moffitt (1982) formulation, suggested by Filippini and Greene (2014) who argue that it is more efficient and unbiased.

We then use the estimated parameters from the GTRE SPF model to derive measures of climatic impacts based on the methodology developed in Hughes et al., (2011). Subsequently, we measure CATFP and decompose it into TE, TP, SE and CE using the approach suggested by O'Donnell (2010, 2012), which satisfies basic axiomatic and economic properties. Finally, we undertake a full analysis of CATFP.

3.1 Panel Data Stochastic Production Frontiers

There have been recent developments in panel data SPF analysis that make it possible to separate country time invariant heterogeneity from time varying and time invariant inefficiencies (e.g., Colombi et al., 2014). However, these new panel data SPF techniques are largely unexploited in most empirical work. In this section, we present our basic model specifications that incorporate these new techniques.

We start with the panel data GTRE frontier model suggested by Colombi et al. (2014), and Tsionas and Kumbhakar (2014), which, using a balanced panel data set, is given by:

$$y_{it} = \alpha_0 + \alpha_i + \sum_{k=1}^{K} \beta_k x_{kit} + \xi T + \sum_{j=1}^{J} \eta_j z_{jit} + A_i + v_{it} - u_{it} \qquad (1)$$

where y_{it} denotes the natural logarithm (log) of output for the *i*-th country in the *t*-th time period; x_{kit} is a (*1×K*) vector of inputs expressed in logs; *T* a time trend; and Z_{jit} represents the *j*th climatic variable for the *i*-th country in the *t*-th time period. The term v_{it} is a random error that is assumed to follow a normal distribution with mean zero and constant variance (v_{it} ~ *iid* $(0, \sigma_v^2)$); and u_{it} is a non-negative unobservable random error, which captures the inefficiency of the *i*-th country in period *t*. The inefficiency error term u_{it} is assumed to follow a half-normal distribution. The term A_i represents a country time invariant inefficiency component and it has a half normal distribution with underlying variance σ_A^2; and $\alpha_i \sim N(0, \sigma_\alpha^2)$ is a country specific random constant that captures the unobserved heterogeneity which is assumed to be uncorrelated with the covariates (e.g., Wooldridge, 2002, p.252); and α_0 is a common country constant. The Greek letters β_k, ξ and η_j are parameters to be estimated. There are *NT* observations (*N* countries for *T* years).

We use the Cobb-Douglas (CD) functional form to approximate the underlying technology of the SPF model in equation (1). Thus, the estimated parameters can be interpreted directly as partial elasticities of production. The CD functional form is chosen because it is globally consistent with economic and index number theories (i.e., non-negativity, monotonicity and homogeneity) required to obtain transitive TFP indexes which is in contrast with the more flexible and popular Translog (O'Donnell, 2012; O'Donnell and Nguyen, 2012).[2]

Greene (2005a, 2005b) has shown that we cannot use the Maximum Likelihood Estimator (MLE) for TRE models because there is no closed form of the integral of the associated log-likelihood function. By relaxing the assumption of normal distribution of the time-invariant effect and assuming instead a skew normal distribution, Filippini and Greene (2014) show that, as is the case with the TRE models, the GTRE specification can be estimated by an SML method, which consists of maximizing the log-likelihood based on a simulated estimate of the density function (Greene, 2001; Train, 2002). Specifically, we denote $\varphi = \alpha_i - A_i$ as the time invariant effect that has a skew normal distribution with parameters $\gamma = {}^{\sigma_A}/_{\sigma_\alpha}\ and\ \theta = \sqrt{\sigma_A^2 + \sigma_\alpha^2}$. Following Bhat (2001) and Greene (2005b), we use a procedure that relies on random draws from Halton sequences as the simulation method and that exploits the Butler and Moffitt (1982) formulation to estimate the models.

Recall that the GTRE model is based on the assumption that the regressors are not correlated with country specific effects. To account for this correlation, we use the Mundlak adjustment specification, which is also estimated by SML. The Mundlak correction model first defines an auxiliary regression to capture the correlation between the country specific effect and the independent variables as follows:

$$\alpha_i = \sum_{k=1}^{K} \theta_k \bar{x}_k + \delta_i \tag{2}$$

where $\bar{x}_k = \frac{\sum_{t=1}^{T} x_{kt}}{T}$ and $\delta_i \sim N(0, \sigma_\delta^2)$ represents the random variable that drives the random parameter. Equation 2 can then be inserted in equation 1 to obtain the Mundlak corrected GTREM model:

$$y_{it} = \alpha_0 + \delta_i + \sum_{k=1}^{K} \beta_k x_{kit} + \xi T + \sum_{j=1}^{J} \eta_j z_{jit} + \sum_{k=1}^{K} \theta_k \bar{x}_k + A_i + v_{it} - u_{it} \tag{3}$$

[2] We first estimate the models using a Translog functional form, but these models, as expected, fail to satisfy the non-negativity of partial elasticities of production with respect to the inputs at all points in the dataset.

Technical efficiency is computed through simulation using the LIMPEP package software developed by Greene (2012) and is based on the Jondrow, Lovell, Materov, and Schmidt (JLMS) estimator (Jondrow et al., 1982). More precisely, the transient efficiency value is derived from the following expression:

$$E\,[\mathrm{u_{it}}/\varepsilon_{\mathrm{it}}] = \frac{\sigma\lambda}{1+\lambda^2}\left[\frac{\varphi(\beta_{\mathrm{it}})}{1\mathrm{t}\phi(\beta_{\mathrm{it}})} - \beta_{\mathrm{it}}\right] \quad (4)$$

where $\sigma = \sqrt{\sigma_\upsilon^2 + \sigma_u^2}$, $\lambda = \frac{\sigma_u}{\sigma_v}$ represents the signal-to-noise ratio that captures the weight of inefficiency in the total error term, σ_u and σ_v are the standard deviations of the inefficiency term and the statistical noise of the composite error respectively, and $\varepsilon_{it} = v_{it} - u_{it}$. The terms $\varphi(\beta_{it})$ and $\phi(\beta_{it})$ are the standard normal and conditional density functions respectively. Subsequently, we compute $SRTE = E[\exp(xu_{it}) \,/\, \varepsilon_{it}]$. Analogously, the persistent inefficiency counterpart is derived as $= E[\exp(-A_i)/\varepsilon_{it}]$. Finally, following Kumbhakar et al., (2014), we compute total TE as:

$$TE_{it} = SRTE_{it} * LRTE_i \quad (5)$$

In the empirical application, the dependent variable (y_{it}) is the natural logarithm of agricultural production, x_{kit} is a set of inputs which includes tractors (TR), fertilizers (FER), animal stock (AS), land (LA) and labor (LB); the smooth time trend, *T,* captures technological progress; Z_{jit} comprise annual average maximum temperature, annual average precipitation, annual average rainy days, and monthly intra-year standard deviations of maximum temperature, precipitation and rainy days; and the Greek letters represent parameters to be estimated.

3.2 Climate Effects Index (CEI)

We initially compute the change in output attributed to the climatic variables($\hat{C}_{it}$), using the estimated parameters from equation 3, which is the preferred model as explained below. Thus:

$$\hat{C}_{it} = \sum_{i=1}^{J} \hat{\eta}_j z_{jit} \quad (6)$$

The next step is to derive and compute the climate effects index (*CEI*), which captures the joint effects of climatic variables on production (Hughes et al. 2011). The CEI_{it}, which is equal to $\exp\mathrm{j}(\hat{C}_{it})$, is then used to investigate the impact of changes in maximum temperature, and rainy day patterns on production across countries and over time. The *CEI* is non-negative by construction and values less than 1 indicate a negative impact on production, values greater than 1 imply positive effects, and values equal to 1 reveal no impact.

3.3 O'Donnell TFP decomposition

Following O'Donnell (2012), for each country in each group, we define TFP as the ratio of aggregate output to aggregate input. More formally, TFP for country *i* in year *t* is

$$TFP_{it} = \frac{Q_{it}}{X_{it}} \tag{7}$$

where $Q_{it} \equiv Q\ (y_{it})$ is an aggregate output, and $X_{it} \equiv X\ (x_{it})$ *is* an aggregate input. The index that compares TFP of country *i* in year *t* with TFP of country *k* in year *s* is

$$TFP_{ksit} = \frac{TFP_{it}}{TFP_{ks}} = \frac{QI_{ksit}}{XI_{ksit}} \tag{8}$$

where $QI_{ksit} \equiv Q_{it}/Q_{ks}$ and $XI_{ksit} \equiv X_{it}/X_{ks}$.

Assuming a Cobb-Douglas technology, equation 1 can be re-written as:

$$TFP_{ksit} = \prod_{m=1}^{M} (\frac{x_{mit}}{x_{mks}})^{\beta_m\left(\frac{r-1}{r}\right)} \times \prod_{j=2}^{J} \left(\frac{z_{jit}}{z_{jks}}\right)^{\eta_j} \times \left(\frac{T_{it}}{T_{ks}}\right)^{\xi} T \times \frac{\exp(-u_{it})}{\exp(-u_{ks})} \tag{9}$$

The TFP index in equation 9 satisfies all the economically relevant axioms from index number theory. The first term on the right-hand is a measure of scale efficiency change where *r* captures returns to scale and the Greek parameters are coefficients to be estimated. The second component on the right-hand side captures climatic effects and the third technological progress. The last component measures the output-oriented technical efficiency change and it is derived from equation 5 (Kumbhakar et al., 2014).

3.4 Catch-up and Convergence

Catch-up is typically used to denote movements towards a country's own frontier (Kumbhakar et al., 2005; Kumar and Russell, 2002). Recall that the inefficiency (or efficiency) estimate from equation 5 measures the distance of a given country at a specific time with respect to its frontier. Therefore, when catch-up takes place the term u_{it} is shrinking overtime. In other words, a country that is catching-up experiences a relative increase in TE (or decrease in technical inefficiency) over time. It should be noted that the overall TE expression in equation 5 is used in the calculation of TE. We analyze the catch-up process by studying the temporal behavior of TE across LAC countries relative to their own frontiers. This exercise can be repeated for the other countries in the full sample.

Convergence, another issue of significance in the analysis of productivity across countries, is a measure of how the production frontiers of the least performing countries are moving with respect to the one of the best performers (Barro, 1997; Baumol, 1986; Solow, 1956). Therefore, we investigate how CATFP of low performing countries in LAC evolves overtime relative to that of high performing ones in the region. In other words, we are investigating convergence in terms of CATFP across LAC countries. In addition, we examine whether CATFP across LAC countries is converging to that of more developed countries using Europe as the reference frontier. [3]

Barro (1991), Baumol (1986), De Long (1988), and Mankiw et al., (1992) have provided some of the most significant contributions to the empirical convergence literature. These authors have interpreted a negative relationship between the initial level of income and subsequent growth rates as a sign of convergence. That is, given *"n"* countries in a group with different initial CATFP levels, if countries with lower initial CATFP grow faster than those with a higher one, slower growth countries are approaching the frontier of the better performers over a given time horizon. This notion of convergence is known as β-convergence.

A more robust approach to test the convergence hypothesis across countries is based on panel data Unit Root and Co-integration tests (Westerlund, 2007). A time series with a convergent long-run trend should be either stationary or co-integrated because it has a common stochastic drift (Hamilton, 1994). That is, the series depicts a similar long-run pattern and it does not scatter over time. Some previous studies examine convergence either in terms of technical

[3] Section 4.3 discusses why the United States was not included in the present analysis.

efficiency (e.g., Cornwell and Wächter, 1999; Ludena et al., 2007), income per capita, labor productivity or TFP (e.g., Bernard and Jones, 1996; Rao and Coelli, 2004). Most of these and other related papers have used conventional time series unit root and co-integration techniques to study convergence. However, applying classical time series methods might lead to the wrong conclusion of the non-stationary of a series because the analysis is not based on structural equations and does not account for the cross-sectional dependence of the data (Westerlund, 2007). Instead, we apply panel data unit root tests, which have been used in just a few productivity studies (e.g., Ball et al., 2004; Suhariyanto and Thirtle, 2001; Ludena, 2010; Liu et al., 2011). In addition, we consider panel data co-integration tests to explore the existence of a long-run uniform trend among CATFP estimates across LAC countries. The application of this latter methodology has been even more limited in the productivity literature.

First, we test the presence of a unit root among CATFP estimates. The presence of a unit root in the CATFP series would suggest that it is non-stationary. Stationarity is important for long-run dynamics because it implies that the mean and all auto-covariances of CATFP are finite and do not change over time (Hamilton, 1994). Specifically, we consider the following auto-regressive (AR) process:

$$CATFP_{it} = \alpha_0 + \rho CATFP_{it-1} + \omega_{it} \qquad (10)$$

where α_0 and ρ are parameters to be estimated and ω_{it} is assumed to be white noise. Under the null hypothesis that CATFP estimates contain a unit root, we perform the Im-Pesaran-Shin (IPS) (2003) and Levil-Lin-Chu (LLC) (2002) tests. The LLC test assumes a common autoregressive parameter in the panel, which means that it is not permissible for some countries to contain CATFP with unit roots while others do not. LLC (2002) have argued that individual unit root tests in time series analysis has limited power and instead have suggested a group unit root test. In addition, we perform the IPS test because it relaxes the assumption of the common autoregressive coefficient of the LLC test. This IPS test allows for heterogeneity of the autoregressive roots between cross sections. Both the LLC and IPS tests are based on a *t-test* and Augmented Dickey-Fuller (ADF) regressions. Moreover, we conduct the Breitung (2000) panel data unit root test who argues that the LLC and IPS tests loose power when individual specific trends are taken into consideration. This last test is performed to check the robustness of the LLC and IPS results. One of the advantages of the Panel unit root tests used here is that they account for both the time-series and cross-sectional dimensions of the data (Westerlund, 2007). Another advantage of using panel data unit root tests is that the estimators are normally distributed (Ball et al., 2004).

We next proceed to the analysis of co-integration tests for non-stationary series. A stationary linear combination of two or more non-stationary CATFP series implies that they are co-integrated (Hamilton, 1994). As in the case of panel-data unit root tests, we use panel-data co-integration tests that are arguably more powerful than those of the conventional time series method, where the latter is based on the residuals. The former does not entail the ad hoc assumption of cross-sectional dependence. In addition, the panel-data co-integration tests do not require time series data to be independent across units, and do not impose the common-factor restriction for long-run and short-run parameters (e.g., Banerjee et al., 1998; Kremers et al., 1992).

We use the error-correction co-integration tests for panel data developed by Westerlund (2007) and applied in recent empirical studies (e.g., Rassenfosse and Potterie, 2012). These tests are based on structural parameters as opposed to the time series co-integration tests that are based on residuals as stated above. We first specify the long-run relationship among CATFP estimates across sub-regions and LAC countries as:

$$CATFP_{it} = \alpha_0 + \sum_{\substack{j=1 \\ i \neq j}}^{m} \tau_j CATFP_{jt} + \mu_{jt} \tag{11}$$

where *m* represents the number of countries in the sub-region, $CATFP_{it}$ denotes the TFP of the reference country and $CATFP_{jt}$ is the productivity level of the other countries relative to the reference one at the beginning of the period. Then, we specify the following Error Correction Model (ECM), which incorporates both the long-run relationship and the short-run effect:

$$\Delta CATFP_{it} = \sum_{\substack{j=1 \\ i \neq j}}^{m} \tau_j \Delta CATFP_{jt} - \alpha_i (CATFP_{it-1} - \alpha_0 - \sum_{\substack{j=1 \\ i \neq j}}^{m} \tau_j CATFP_{jt-1}) + \mu_{jt} \tag{12}$$

Equation 12 is then re-parameterized to obtain the expression:

$$\Delta CATFP_{it} = \omega_0 + \vartheta_i CATFP_{it-1} + \sum_{\substack{j=1 \\ i \neq j}}^{m} \tau_j \Delta CATFP_{jt} + \sum_{\substack{j=1 \\ i \neq j}}^{m} \varsigma_j CATFP_{jt-1} + \mu_{jt} \qquad (13)$$

where $\varsigma_j = -\alpha_i \tau_j$ and the error correction term is the residual from equation 11, which is used as an adjustment factor to capture long-run dynamics. The term ϑ_i is the adjustment coefficient that measures the speed at which CATFP converges to the equilibrium value. This approach basically consists of testing the null hypothesis of absence of co-integration using a conditional panel ECM by inferring that the error-correction term is zero (Westerlund, 2007). In other words, if $\vartheta_i < 0 \Rightarrow$ there is error correction, and therefore $CATFP_i$ and $CATFP_j$ are co-integrated. On the other hand, if $\vartheta_i \geq 0$ CATFP estimates are not co-integrated and therefore there is no evidence of long-run dynamics. The other parameter of interest τ_j captures long-run relationships among CATFP estimates.

We use the Mean-Group (MG) and Pooled Mean-Group (PMG) estimators developed by Pesaran and Smith (1995), and Pesaran, Shin and Smith (1997, 1999) to estimate equation 13. These estimation methods differ from conventional Fixed Effects and Random Effects estimators because these methods relax the assumptions of homogeneity of intercepts and of slopes, which have been shown to be unsuitable (IPS, 2003; Phillips and Moon, 2000). Basically, MG estimators consist of estimating *N* Time-series regressions and averaging the coefficients and they allow intercepts, slope coefficients and error variances to vary across countries. On the other hand, PMG estimators are based on a conjunction of pooling and averaging coefficients and they share the same properties with MG estimators. However, PMG estimators are based on Maximum Likelihood and they constrain long-run coefficients to be equal across countries. Catao and Terrones (2005), Fedderke (2004), Kim et al. (2010), and Njoupouognigni (2010), among others, have applied both PMG and MG estimators in recent empirical work. We also apply both MG and PMG estimators and use the Hausman test to discriminate between the two (Pesaran et al., 1999).

3.5 Forecasting

In this sub-section, we present the forecast framework of CATFP across LAC countries for the 2013-2040 period. The forecast is based on panel data techniques because this approach makes it possible to control econometrically the unobserved differences across countries that are eventually correlated with climatic variability. It is straightforward to forecast Technological Progress given a Cobb-Douglas specification with a time trend, and Scale Efficiency does not show any suspicious patterns in terms of structural break or unit root (see Figure 5). However, climatic variability (our focus) and TE (see Figure 6) exhibit potential structural breaks and the presence of a unit root that require special attention. Specifically, the presence of structural breaks leads to an unexpected shift in the time series data, which can produce significant forecasting errors (Hamilton, 2014). As discussed in the results section below, TE estimates do contain a structural break and are stationary at first-difference.

The forecasts are based on the assumption that the temporal behavior of CATFP is jointly determined with TP, TE, SE, and CE, which are computed with a forecasting panel data approach based on a system of equations (e.g., Baltagi, 2008). While we consider that TE, SE, TP and CE can be modeled using stochastic relationships that depend on their past values and an external shock, it is assumed that there is a non-stochastic relationship between these aforementioned components and CATFP. That is, the latter relationship can be interpreted as an identity. Specifically, we have:

$$TP_{it} = \alpha_i + \alpha_1 T + \varepsilon_{1it} \tag{14}$$

$$\Delta TE_{it} = \beta_i + \beta_1 T + \beta_2 d + \beta_3 dT + \beta_4 \Delta TE_{it-1} + \varepsilon_{2it} \tag{15}$$

$$SEI_{it} = \gamma_i + \alpha\gamma_1 T + SE_{it-1} + \varepsilon_{3it} \tag{16}$$

$$CE_{it} = \delta_i + \delta_1 T + CE_{it-1} + \varepsilon_{4it} \tag{17}$$

$$CATFP_{it} = TP_{it} \times TE_{it} \times SE_{it} \times CE_{it} \tag{18}$$

where *d* in equation 15 is a dummy variable equal to 0 before the structural break and 1 after. We expect the interaction of the dummy with the time trend to be statistically significant. All the other variables are as defined earlier.

3.5.1 Forecasts of Climatic Variables

We use the estimated parameters for equation 3 for the simulation exercise and the underlying assumption is the absence of climate adaptation to lessen the adverse impact of climatic variability. The latter is compatible with the climate change literature where a 30 year window is considered as a short-term forecast period (ECLAC, 2010a).

Two new categories of climate scenarios have been developed by the 5th IPCC report (IPCC, 2014a) since the 4th report: the Representative Concentration Pathways (RCPs) and the Shared Scenarios Pathways (SSPs). The RCP scenarios are greenhouse gas (GHG) emission concentration trajectories developed for the 5th IPCC report that incorporate simulations of oceans and atmosphere, and capture land use change, as well as short-lived GHG emissions. The SSPs scenarios are equivalent to the 4th IPCC report and refer to potential world development paths depending on chosen policies.

There are four types of RCPs (RCP2.6, RCP4.5, RCP6 and RCP8.5) and they represent possible changes in GHG emissions defined in terms of *radiative forcing* comparing emissions of the year 2100 relative to pre-industrial values. Correspondingly, the SSPs RCPs outline the intensity of policies needed for climate adaptation and mitigation (IPCC, 2014a). There are five SSPs: Sustainable Pathway (SSP1), Moderate Pathway (SSP2), Rocky Road (SSP3), Regional Pathways (SSP4) and Taking the Fast Road (SSP5). SSP3 is equivalent to the former "A2" scenario in the previous IPCC Special Report on Emissions Scenarios (SRES), and assumes a heterogeneous world, high GHG emissions, increasing population, regional oriented economic development and slow technological progress. In contrast, the SSP2 is very close to the "B2" SRES that incorporates relatively low emissions with a moderate level of economic development and a focus on local socio-economic solutions.[4] Henceforth, we use the terminologies A2 and B2 for the remaining discussion.

In general terms, the four RCP models represent an emission concentration range higher that the SRES scenarios. RCP 4.5 considers concentrations equivalent to scenario B1, RCP 6 is lightly higher than the levels of scenario A1B (especially after 2100) and the RCP 8.5 is somewhat higher than A2 until 2100 and closer to scenario A1F1. RCP 2.6 is the lowest emission concentration of all scenarios considered. It is worth mentioning that under most of these scenarios, major climate change effects are expected only after 2050, a point that should be considered when analyzing the results below that only look until 2040.

According to ECLAC (2010a), the A2 and B2 scenarios are the most suitable ones to investigate and project economic impacts of climatic variability across developing countries given their

[4] http://climate4impact.eu/impactportal/help/faq.jsp?q=scenarios_different

characteristics in terms of economic growth and technology adoption. Therefore, we simulate the impacts of climatic variability on TFP and agricultural production until the year 2040 under the A2 and B2 scenarios, as well as a counterfactual case. Specifically, climatic variability projections are based on the A2 and B2, and subsequently, in order to evaluate the economic impacts of climatic variability on production and productivity, we use a third scenario, the counterfactual, in which we keep the climatic variables constant at their mean for the last 30 years of the data (1982-2012).

Temperature and precipitation projections are from the Regional Climate Modeling system (RCM) and are driven by two models: the fourth-generation atmospheric general circulation model (ECHAM-4); and the Hadley Centre Coupled Model version 3 (HADCM-3). The baseline references for temperature and precipitation are 1960-1990 averages. Given that LAC is quite heterogeneous and climatic variability is expected to be distributed unevenly across countries, we use country projected mean annual maximum temperature and precipitation until 2050 to reconstruct the time series of annual observations for temperature, precipitation intensity and anomaly (see Table A in the appendix). Nonetheless, we do not have such information at the country level for South America; thus we use the sub-regional average for all countries in this group. Likewise, as projected rainy days across the region are not available, we generated this data using panel data forecasts based on past information and external shocks as described above. Using all this information, we compute the climate effects until the year 2040.

IV. DATA

4.1 Data on Output and Inputs

The data used to estimate the models are from different sources. First, we use an FAO data set, which is a balanced panel covering a 52-year period from 1961 to 2012, for 112 countries for a total of 5,824 observations. This dataset contains The Value Agricultural Gross Output (Y), which combines aggregate crop and livestock products, measured in thousands of constant 2004-2006 international dollars.

There are five different conventional inputs: Tractors, Fertilizer, Animal Stock, Land, and Labor. As defined by FAOSTAT (2014), *TR* are thousands of agricultural tractors used in the production process; *FER* is measured as the quantity of nitrogen, phosphorous and potassium in thousand metric tons; *AS* is thousands of cattle, sheep, goat, pigs, chicken, turkeys, ducks and geese expressed in livestock unit (LU) equivalents; *LA* is measured as arable land and permanent crops expressed in thousands of hectares; and, *LB* is the total economically active population in agriculture expressed in thousands of persons.

The full sample can be divided into the following five groups based on geographical location: LAC, Asia, Sub-Sahara Africa (SSA), the Middle East and North Africa (MENA), and Europe. In the full sample, LAC includes 26 countries, Asia contains 18 countries; SSA comprises 28 countries; MENA has 19; and Europe 21 countries (See Table 1). Table 2 shows the list of countries per region.

The level of production in LAC, our main focus in this study, is quite dispersed and the country with the highest level of production (Brazil) has roughly more than nine times the average production in the region. A similar observation characterizes the level of output across the different groups as shown in Table 2. In fact, the standard deviation of production is higher than the mean in all five groups, suggesting considerable disparity across countries and groups.

We also note the large dispersion in the sample regarding inputs used. Agricultural production appears to be the most labor-intensive in Asia. Use of fertilizer and animal stock vary considerably across groups and countries. On the other hand, land varies moderately across LAC and Asia and the same remark is valid regarding the average utilization of tractors between TE and Asia.

4.2 Climatic Variables

In addition, we use the climatic dataset of Harris et al., (2014) which covers the years 1961 to 2012. This dataset contains annual mean total precipitation (PRECIP) measured in millimeters (mm), rainy days (RD) measured as the number of rainy days, and annual maximum temperature (TEM) measured in degree Celsius (^{o}C).

According to climate model simulations, climate change causes variations in frequency and intensity of precipitation (Chou et al., 2012). Therefore, a good alternative to capture the impacts of precipitation on agricultural production is by considering its frequency (how often it rains) and its intensity (quantity). Number of rainy days and precipitation quantity are often used as such measures, respectively (Kumar et al., 2011). Therefore, the number of RD can be considered as a measure of precipitation frequency. Kumar et al., (2011) argue that rainfall, rainy-day frequency and maximum temperature are important factors to consider when analyzing the sensitivity of agricultural production due to climatic variability, particularly in rain-fed regions. According to Wani et al., (2009), almost 90% of the farmland in LAC is rain-fed. By the same token, the World Bank reports that rain-fed agriculture plays a critical role in Sub-Saharan Africa and it accounts for nearly 96% of the cropland in that region.[5]

TEM is based on two indicators: the Daily Mean Temperature (DMT) and the Diurnal Temperature Range (DTR). DMT is calculated as the median between the observed daily maximum and minimum temperatures whereas DTR is the difference between the daily maximum and minimum temperatures. Finally, TEM is calculated by adding half of the DTR to the DMT (Harris et al., 2014) and it is used as a measure of extreme temperature because it captures temperature at the time of day when evaporation is higher.

[5] http://water.worldbank.org/topics/agricultural-water-management/rainfed-agriculture.

Table 1: Descriptive Statistics for the Region Groups

(N=112 countries, T=52 years, Sample size=5824)

Variables	Production	Tractors	Fertilizers	Animal Stock	Land	Labor	Temperature	Precipitation	Rainy Days
Units	Millions Int'l $	000'	000' tons	Millions cattle	000' ha	000' of pers.	Celcius degrees	mm	No.
A) Regions in Least Developed Countries (LDCs)									
Region 1: LAC									
N=26 countries, T=52 years, Sample size =1352									
Mean	6032	48.6	330736	13603	5533.3	1547	28.3	1904.4	162.8
Std. Dev.	15500	137	1146489	32857	12572.7	2986	3.7	2003.5	60.6
Min	10	0	85	16305	9	4	12.8	436.1	43.4
Max	150000	1000	11000000	244833	79929.8	16342	31.8	41918	262.1
Region 2: SSA									
N=28 countries, T=52 years, Sample size=1456									
Mean	2142	6.4	48077	6459	4462.9	3339	30.8	1062.8	96.3
Std. Dev.	3702	22.3	141268	9680	5944.9	4517	3.1	1078.3	55.3
Min	66	0.002	10	43	81	46	23.5	0.9	7.4
Max	38000	195	1400000	68331	40500	34870	37.2	41976	305.7
Region 3: Asia									
N=18 countries, T=52 years, Sample size=936									
Mean	26500	388.9	2356067	36519	21173.5	34326	23.5	1576.1	129.1
Std. Dev.	67800	991.8	7218940	81225	42114.8	77350	8.1	807.4	60.6
Min	48	0.001	50	210	100	78	5	174.2	21.9
Max	570000	7200	54000000	377935	171917	390980	32.8	3635.8	287.5
Region 4: MENA									
N=19 countries, T=52 years, Sample size=988									
Mean	3778	58.6	247457	4083	4518	1608	28	208.6	29.9
Std. Dev.	6695	160.1	471417	6188	6721	2439	4.4	186.2	27.6
Min	4	0.001	10	7	1	2	15.2	6.1	3.2
Max	41000	1200	2500000	29486	28792	10517	35.2	1001.9	124.3
B) Regions in More Developed Countries (MDCs)									
Region 5: Europe									
N=21 countries, T=52 years, Sample size =1092									
Mean	15000	444.2	1503830	13227	14463	2183.8	13.4	799.9	156.5
Std. Dev.	23900	598.3	3110169	26755	43194	5028.5	5.1	279.4	43.8
Min	213	3.1	5558	128	110	26.9	0	0.6	39.3
Max	150000	3200	31000000	180222	240300	29502	25.4	1915.6	256

The Harris dataset was originally generated by the Climatic Research Unit (CRU) at the University of East Anglia (2013), which works in concert with the World Meteorological Organization (WMO), NOAA, and other international climate institutions and programs. The CRU time series dataset is constructed using the Climate Anomaly Method or CAM (Peterson et al., 1998), which consists essentially of comparing data from several climatic stations to that of a base period (1961-1990) to screen anomalies. To be included in the gridding operations, each station series must include enough data for a base period average (1961-1990). Outliers are defined as values that are more than 3.0 standard deviations away from the normal, (4.0 for precipitation). Thus, to enable the screening of outliers, monthly standard deviations are calculated for each station. Temperature and precipitation data are based on monthly climatic observations and station anomalies are interpolated into high-resolution grids (0.5◦×0.5◦ latitude/longitude). Annual data are then calculated as the 12-month average (Harris et al., 2014).[6] As in Barnwal and Kotani (2013), in addition to the mean of the climate variables, we use the intra-annual standard deviation, which is a measure of monthly deviation within a year to capture variability.

Climate variables vary considerably across and within groups of countries. In particular, the number of rainy days ranges widely, from an average of 96 in Africa to about 163 with a standard deviation of 60 in LAC (Table 2). Similarly, significant differences are also observed in precipitation patterns across groups. For instance, average precipitation in North America (Table 2) is around 635 mm per year whereas in LAC it is nearly three times that figure.

4.3 Data Issues

First of all, the variable Feed is not included in the estimations because its incorporation in several models led to negative parameters and thus to violations of a key regularity condition of production economic theory (e.g., Asia, SSA). In addition, we were unable to estimate the models for the High Income Countries (HIC) group as in Ludena (2010), which would comprise some European countries, North America, South Africa, and Oceania. We estimated several models with and without climate variables and we also performed individual country time series estimations. However, in all these trials, not only the estimated parameters are non-positive but they are not statistically significant. One of the consequences of these results is that we were not able to conduct the convergence analysis between LAC countries and the United States. We do however compare CATFP and its growth across LAC countries and the other four aforementioned regions.

Furthermore, we explored the Agricultural Science and Technology Indicators (ASTI) dataset, from the International Food Policy Research Institute (IFPRI), to obtain public spending on research and development (R&D). Unfortunately, these data start in 1981 posing a severe constraint for a significant number of countries over a good number of years. In addition, these

[6] See Harris et al., 2014 for more details regarding the methodological approach to measure these variables.

data are not available for a number of countries in the sample. Therefore, it was not considered as a variable in the production frontier models and any analyses of sub datasets for which ASTI data is available is left for future research.

Table 2: List of Countries used in the Analysis

1. Latin America and the Caribbean
Argentina, The Bahamas, Barbados, Bolivia, Brazil, Belize, Chile, Colombia, Costa Rica, Dominican Republic, Ecuador, El Salvador, Guatemala, Guyana, Haiti, Honduras, Jamaica, Mexico, Nicaragua, Panama, Paraguay, Peru, Suriname, Trinidad & Tobago, Uruguay, Venezuela

2. Asia
Afghanistan, Bangladesh, Cambodia, Democratic People's Republic of Korea, India, Indonesia, Japan, Malaysia, Mongolia, Myanmar, Nepal, Pakistan, Philippines, Republic of Korea, Sri Lanka, Thailand, Vietnam

3. Sub-Saharan Africa
Angola, Benin, Burkina Faso, Burundi, Cameroon, Central African Republic, Chad, Congo, Ivory Coast, Democratic Republic of Congo, Gabon, Gambia, Ghana, Guinea, Kenya, Malawi, Mauritius, Mozambique, Nambia, Niger, Nigeria, Senegal, Sudan, Togo, Uganda, Tanzania, Zambia, Zimbabwe

4. Middle East and North Africa
Algeria, Bahrain, Egypt. Iran, Iraq, Israel, Jordan, Kuwait, Lebanon, Libya, Morocco, Oman, Qatar, Saudi Arabia, Syria, Tunisia, Turkey, United Arab Emirates, Yemen

5. Europe
Albania, Austria, Bulgaria, Cyprus, Denmark, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Netherlands, Norway, Poland, Portugal, Romania, Spain, Sweden, Switzerland, United Kingdom

V. RESULTS

5.1 Econometric Models

As can be seen in Tables 3 and 4, all parameters for the variables that capture traditional inputs across models and groups are statistically significant at the 1% level, and regularity conditions from production economic theory, which require that the partial output elasticities be nonnegative and less than one, are satisfied with the exception of labor in the GTRE for the fourth region (Europe) and land still in the GTRE model for the fifth group (MENA). The GTREM model, which accounts for country unobserved heterogeneity and corrects for possible correlations between the heterogeneity term and conventional inputs, resolves the latter irregularity for both Europe and MENA (see Table 4).

Table 3: GTRE estimates for Agricultural Production Frontier Models

Models	LAC (n=1352)		SSA (n=1456)		ASIA (n=936)		EUROPE (n=1092)		MENA (n=988)	
	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.
Intercept	6.971***	0.093	3.281***	0.175	3.175***	0.08	3.385***	0.141	7.897***	0.769
TR	0.123***	0.004	0.035***	0.002	0.088***	0.002	0.214***	0.004	0.152***	0.015
FER	0.125***	0.004	0.015***	0.002	0.118***	0.003	0.132***	0.006	0.154***	0.011
AS	0.288***	0.007	0.229***	0.005	0.301***	0.006	0.639***	0.008	0.204***	0.023
LA	0.172***	0.008	0.501***	0.008	0.337***	0.007	0.058***	0.006	-0.019	0.018
LB	0.229***	0.006	0.156***	0.008	0.141***	0.005	-0.01**	0.005	0.333***	0.022
T	0.007***	0	0.009***	0	0.008***	0	0.003***	0	0.012***	0.001
TEMP	-0.07***	0.028	-0.088*	0.053	0.054***	0.013	0.521***	0.015	-0.231	0.202
TEMP STDV			0.149***	0.011	0.116***	0.007	0.571***	0.017	0.139***	0.051
PRECIP	0.070***	0.02	0.048***	0.016	0.009	0.023	0.021***	0.007	0.525***	0.079
PRECIP STDEV	-0.21***	0.048	n/a	n/a	0.068***	0.017	-0.03***	0.009	-0.42***	0.067
RD	**-0.155****	0.017	0.904***	0.017	0.604***	0.02	-0.10***	0.018	-0.58***	0.086
RD STDEV			-0.79***	0.012	-0.380***	0.0123	0.056***	0.011	0.694***	0.07
λ	1.941***	0.203	1.534***	0.197	4.690***	0.557	1.760***	0.233	0.605**	0.262
σ	0.165***	0.005	0.158***	0.006	0.156***	0.004	0.107***	0.004	0.391***	0.023
σ_u	0.147	n/a	0.133		0.152		0,092		0.202	
σ_v	0.076		0.086		0.032		0.053		0.334	
A_i	0.019		0.054		0.003					
α_i	2.33		3.173		1.7					
RTS	0.935		0.936		0.985		1.02		0.824	
Log-likelihood	-14.07		-371.72		263.52		132.23		-387.43	

Notes:*, **, *** are 10%, 5%, and 1% level of significance respectively
S.E.: Standard error. Variables are measured in natural log.
n/a: non-available

Following Rabe-Hesketh and Skrondal (2005), for the GTREM models we only include the mean variables from the auxiliary regression that are statistically significant (see equation 2). These results also suggest that the parameters for the climate variables are statistically significant across models and regions except for precipitation in the GTRE model for the Asian countries (Table 3) and precipitation in the GTREM model for the SSA countries. Moreover, the λ parameter, the signal-to-noise ratio, is highly significant across models revealing the importance of inefficiency in output variability. Likewise, the coefficient of α_i is highly significant across models implying the importance of segregating transient, and persistent inefficiencies from country time invariant heterogeneity. The results suggest that confounding time invariant heterogeneity with either time variant or time invariant inefficiency significantly affects efficiency estimates. Consequently, the models that account for transient and persistent inefficiencies would lead to more robust TFP measures because time invariant inefficiency is identified separately from unobserved heterogeneity.

As explained above, we estimate two sets of models, GTRE and GTREM. As shown in Table 4, the means of various conventional inputs and climate variables appear to be correlated with country unobserved heterogeneity across all regions and a Wald test suggests that the associated parameters are significantly different from zero at the 1% level. The Wald tests support the validity of the GTREM across all regions. In addition, a LR test comparing the GTREM and GTRE models confirms that, at the 1% level of significance, the former outperforms the latter. Therefore, the subsequent analysis focuses on the GTREM model unless otherwise indicated.

Table 4: GTREM estimates for Agricultural Production Frontier Models

Models	LAC (n=1352)		SSA (n=1456)		ASIA (n=936)		EUROPE (n=1092)		MENA (n=988)	
	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.
Intercept	6.971***	0.093	4.556***	0.351	2.771***	0.05	4.196***	0.137	8.817***	0.727
TR	0.086***	0.001	0.044***	0.003	0.111***	0.002	0.179***	0.003	0.206***	0.017
FER	0.072***	0.001	0.015***	0.002	0.023***	0.002	0.065***	0.005	0.129***	0.01
AS	0.215***	0.005	0.379***	0.019	0.391***	0.004	0.478***	0.007	0.173***	0.02
LA	0.173***	0.002	0.272***	0.028	0.294***	0.005	0.020***	0.006	0.132***	0.023
LB	0.404***	0.006	0.495***	0.026	0.251***	0.005	0.092***	0.01	0.366***	0.021
T	0.010***	0	0.002**	0.001	0.011***	0	0.007***	0	0.009***	0.001
TEMP	-0.21***	0.061	-0.91***	0.308	-0.266***	0.045	0.182***	0.027	-0.359*	0.19
TEMP STDEV			0.154***	0.014	0.110***	0.004	0.440***	0.014	0.145***	0.049
PRECIP	0.021***	0.007	0.01	0.019	-0.051***	0.016	0.038***	0.005	0.513***	0.075
PRECIP STDEV	-0.24***	0.016			0.094***	0.009	0.039***	0.008	-0.42***	0.063
RD	-0.08***	0.013	0.938***	0.02	0.142***	0.023	0.142***	0.023	-0.59***	0.084
RD STDEV			-0.78***	0.014	-0.207***	0.007	-0.020**	0.009	0.697***	0.066
Mean (TR)					-0.080***	0.00211				
Mean (FER)	0.096***	0.002			0.210***	0.003	0.311***	0.007		
Mean (AS)	0.091***	0.005	-0.16***	0.02						
Mean (LA)			0.263***	0.029					-0.20***	0.03
Mean (LB)	-0.20***	0.006	-0.36***	0.027	-0.213***	0.006	-0.09***	0.011		
Mean (TEM)	0.207***	0.061	0.919***	0.316	0.394***	0.045	0.078***	0.03		
Mean (PRECIP)					-0.098***	0.017				
Mean (RD)	-0.06***	0.014			0.570***	0.025	-0.57***	0.027	-0.51***	0.025
λ	59.32***	17.131	1.048***	0.22	7.255***	0.977	2.612***	0.285	1.317***	0.213
σ	0.165***	0.005	0.17***	0.009	0.105***	0.002	0.095***	0.003	0.452***	0.019
σ_u	0.191		0.124		0.104		0.088		0.36	
σ_v	0.003		0.025		0.014		0,034		0.273	
A_i	0.026		0.025		0.04		0,018		0.04	
α_i	1.957		2.804		2.204		3.244		0.071	
RTS	0.935		0.93		1.07		0.832		1	
Log-likelihood	21.56		-347		447.07		303.22		-364.52	

Notes:*, **, *** are 10%, 5%, and 1% level of significance respectively
S.E.: Standard error. Variables are measured in natural log.
n/a: non-available

A quick look at Table 4 shows that extreme temperature has a highly negative impact on SSA countries and a more moderate negative one on Asian, and the MENA countries. One possible explanation for these results is the observed difference in area under irrigation among these three regions. Irrigation plays a critical role in reducing the impact of extreme temperature on agricultural production (Lobell et al. 2008). According to FAO (2011), irrigated land accounts for 39% of cultivated land in Asia, 22.7% in Northern Africa and only 3.2 in SSA. In addition, the estimated parameter for the standard deviation of extreme temperature is positive across these three regions suggesting that a decrease in the mean of extreme temperature would be favorable for these regions. Unfortunately, according to IPCC (2014a) and James and Washington (2013), temperatures in Africa and also in most parts in Asia are projected to rise faster than the global average increase during the 21st century. In addition, as can be seen in Table 4, the number of rainy days has a positive impact on production at the current mean level for SSA and Asian countries. However, a considerable deviation from the current mean would have an adverse effect on production.

By contrast, MENA countries have a limited number of rainy and, at the current mean of this variable, the impact is negative on production while an increase from this level would benefit agricultural production. The same observation is made for precipitation regarding the region (precipitation intensity). In addition, the findings show that an increase in both temperature and precipitation would be favorable for production in Europe. Rainy days have a positive impact on production in Europe at the current level. However, the standard deviation is negative indicating that any deviance from the mean would negatively affect production. One interesting issue to note is that there is quite a difference between the quantity of precipitation and rainy days and often the countries that have the highest level of precipitation do not have the highest number of rainy days. In the subsequent subsection, we analyze in more detail the results for LAC countries, which are the main focus of this report.

5.2 Latin America and the Caribbean (LAC): A Closer Look

5.2.1 Parameters:

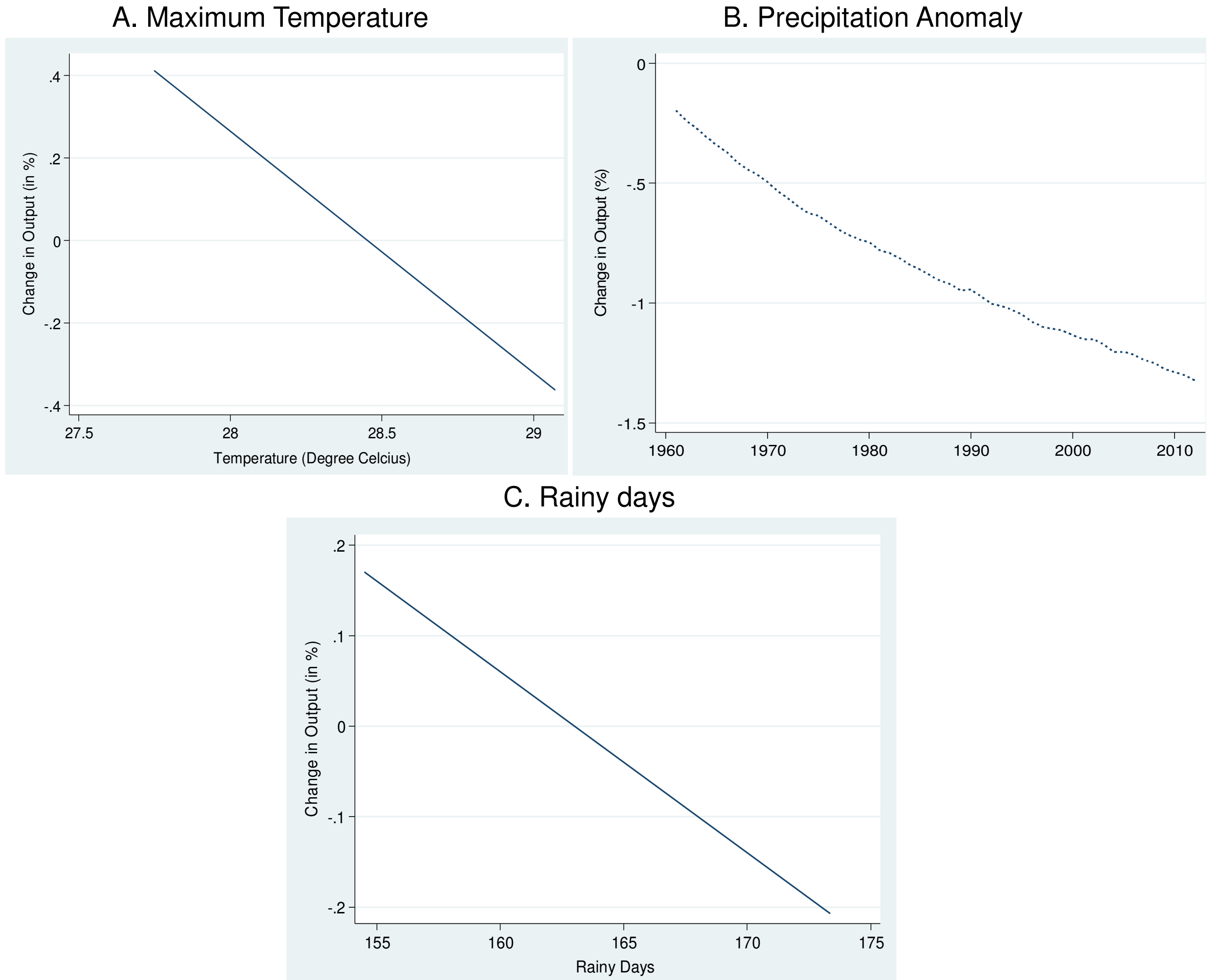
Estimates of the parameters of the GTREM Model for LAC countries are reported in the second column of Table 4. Results suggest that agricultural production in LAC is most responsive to labor, animal stock, and land. As shown in Table 4, extreme temperature has a negative and significant impact on agricultural production whereas average precipitation has a small but positive effect on output. The negative impact of maximum temperature on production largely outweighs that of the precipitation. In addition, any deviation from the average precipitation is considered as an anomaly and it has a severe negative impact on production. In fact, a 10% average increase in this anomaly would yield a 2.4% decrease in production. Further, precipitation frequency, measured as the number of annual rainy days, also has a negative impact on production at the current mean level (163 rainy days) and an increase of 10% in the number of rainy days is expected to decrease output, on average, by nearly 0.75%, *ceteris paribus*. These results do corroborate some previous findings that point out that changes in precipitation patterns and more significantly deviation from the current mean have significant effects on runoff, erosion and flooding, with adverse impacts upon agriculture in LAC countries (e.g., Andressen et al., 2000; Cotrina, 2000).

On the other hand, the results indicate that maximum temperature has an adverse effect on production as explained above. According to the IPCC (2014a), temperature estimates might increase between 1.4 ^{o}C and 5.8 ^{o}C by the year 2100. By the same token, the World Bank (2012) asserts that an increase of 4 ^{o}C in the global temperature over the next 100 years would have a devastating impact on LAC, one of the regions that would be most affected by a warmer climate. Combining these predictions with our results, *ceteris paribus*, we could expect that an increase in the average maximum temperature (28.3 ^{o}C), by 4 ^{o}C or 5.8 ^{o}C would lead to a reduction in production of approximately 3% and 4.5%, respectively. Of course, the *ceteris paribus* assumption might be too strong and we expect that technological progress and changes in practices by farmers and governments will increase the capacity to adapt and thus moderate the adverse effects of climatic variability. However, these results highlight the urgency of undertaking adequate and effective measures to mitigate the impacts of climatic variability on agricultural production and to promote adaptation strategies.

5.2.2 Climate Effects Indexes

We first start by assessing the impact of each climatic variable on production over time, *ceteris paribus*. Figure 1A illustrates the marginal effect of increases in temperature during the 1961-2012 period. Overall, maximum temperature has a decreasing effect on agricultural production in the region.

Figure 1: Effects of Maximum Temperature, Precipitation Anomaly and Rainy days on the Change in Output in LAC, 1961-2012



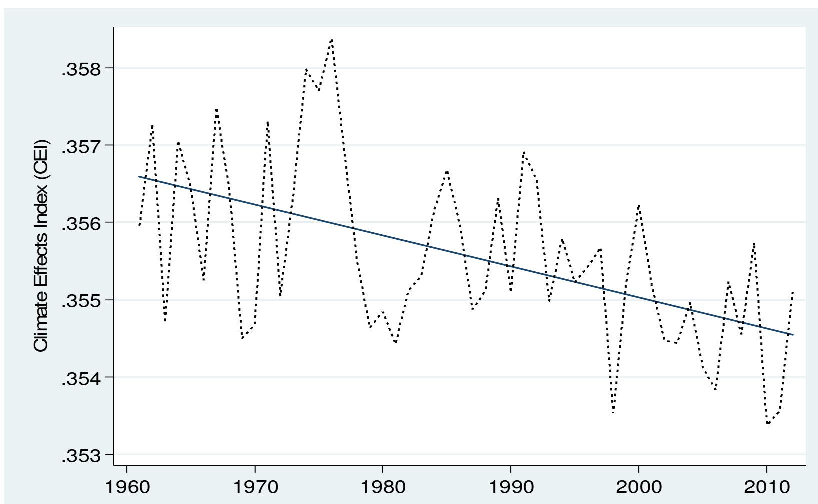
Source: Authors calculations based on FAO and CRU data.

We do know from the GTREM SPF model results that the partial elasticity of the variable precipitation with respect to output has a small but positive effect on production. Figure 1B shows the impact of the standard deviation of precipitation on production across LAC countries for the 1961-2012 period. The findings suggest that since the 1970s deviations in precipitation have had a more substantial negative impact on production with an average output decline of up to 1.3% in the last decade.

Finally, we explore the agricultural production response to precipitation frequency. The average number of rainy days in the sample is 163 and most Central American, South America Andean and the Caribbean countries have a precipitation frequency greater than the sample average. As displayed in Figure 1C, on average, a number of rainy days greater than the sample average can be expected to have an adverse negative impact on production.

Figure 2 illustrates the mean climate effects index (CEI), across LAC countries from 1961 to 2012, constructed from the estimated coefficients of the GRTEM SPF model and equation 6. Recall that CEI captures the joint effect of annual average maximum temperature, precipitation frequency, intensity and anomaly on agricultural production, *ceteris paribus*. Thus, on average for LAC, the *CEI* shows a downward slope with values lower than one within a narrow range, which suggests a slow but negative overall climate impact on production over time. According to these results, we can expect more somber repercussions of climatic variability on agricultural production.

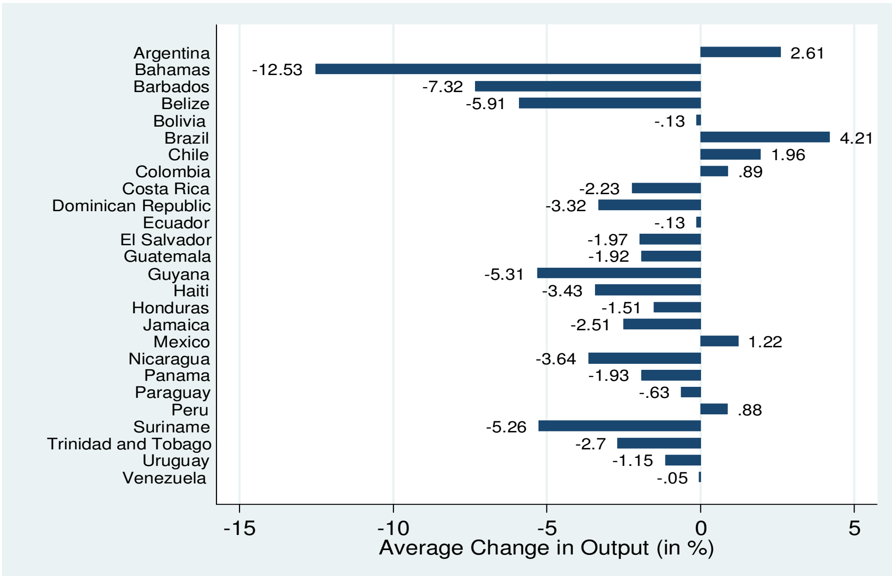
Figure 2: Mean Climate Effects Index (CEI) for LAC countries, 1961-2012



Source: Authors calculations

In addition, using the mean CEI, we compute the percent change in production in 2001-2012 relative to 1961-2000 as a result of changes in climate variables. Figure 3 reveals that climatic variability, *ceteris paribus*, has reduced output by between 0.05% (Venezuela) and 12.55% (The Bahamas), on average, in the last decade compared to earlier ones. Furthermore, our results suggest that the effects of climatic variability fluctuate significantly across LAC sub-regions and across countries. In particular, climatic variability has been more detrimental to Caribbean and Central American countries and all these countries have been affected negatively by changes in climatic patterns with the exception of Mexico. In contrast, the combined effects of temperature and precipitation (frequency, standard deviation and intensity) seem to have had a positive impact on production in Argentina, Brazil, Chile, Colombia, Mexico and Peru, ranging from 0.88% to 4.2%.

Figure 3: Relative Change in Output (1961-2000 vs 2001-2012) due to Climatic Variability in LAC Countries



Source: Authors calculations.

5.2.3 Total Factor Productivity Gap Analysis:

We now turn to the analysis of gaps in total factor productivity growth. In the context of this study, the term gap is used to denote a sustained difference in CATFP measures across countries. Table 5 shows cumulative CATFP across LAC countries per decade and the last column reports the annual average growth rate. More specifically, we compare the CATFP of each country with that of Brazil, which exhibits the highest CATFP in 1961. It is worth noting that the CATFP indexes presented in Table 5 are transitive, which means that they can be used to compare consistently the productivity of all countries to that of any country chosen as a reference at any specific point in time (O'Donnell and Nguyen, 2012). In other words, we use the performance of Brazil in 1961 as a benchmark but we could have chosen any other country and year and obtained consistent results (rankings) and this is precisely the attractiveness of the transitivity property (O'Donnell and Nguyen, 2012).

Table 5: Cumulative CATFP by decade in LAC, 1961-2012 (Brazil: 1961=1)

Countries	1961	1971	1981	1991	2001	2012	Cumulative Growth	Growth Rate
Argentina	0.86	0.96	1.05	1.18	1.32	1.47	0.61	1.05
The Bahamas	0.73	0.79	0.97	1.06	1.19	1.37	0.65	1.26
Barbados	0.77	0.86	0.94	1.05	1.16	1.32	0.55	1.06
Bolivia	0.81	0.90	0.96	1.09	1.23	1.33	0.51	0.96
Brazil	1.00	1.11	1.15	1.36	1.54	1.80	0.80	1.15
Belize	0.81	0.90	1.00	1.12	1.24	1.38	0.57	1.06
Chile	0.81	0.93	1.09	1.24	1.38	1.60	0.79	1.33
Colombia	0.84	0.95	1.06	1.18	1.30	1.49	0.64	1.12
Costa Rica	0.82	0.96	1.06	1.23	1.24	1.54	0.72	1.25
Dominican Republic	0.77	0.85	0.93	1.03	1.16	1.35	0.58	1.10
Ecuador	0.77	0.85	0.95	1.07	1.17	1.30	0.54	1.04
El Salvador	0.73	0.79	0.86	0.90	0.97	1.25	0.53	1.07
Guatemala	0.58	0.67	0.75	0.85	0.95	1.07	0.49	1.20
Guyana	0.61	0.67	0.75	0.75	0.94	1.04	0.44	1.07
Haiti	0.68	0.80	0.88	0.98	1.06	1.09	0.42	0.95
Honduras	0.75	0.85	0.95	0.97	1.08	1.31	0.56	1.09
Jamaica	0.67	0.77	0.82	0.92	1.04	1.17	0.50	1.09
Mexico	0.52	0.61	0.71	0.75	0.88	1.00	0.48	1.30
Nicaragua	0.75	0.86	0.78	0.69	0.94	1.29	0.54	1.07
Panama	0.85	0.96	1.05	1.14	1.18	1.31	0.46	0.86
Paraguay	0.81	0.90	1.00	1.12	1.23	1.39	0.57	1.06
Peru	0.84	0.94	1.00	1.05	1.30	1.49	0.65	1.12
Suriname	0.78	0.89	0.99	1.10	1.16	1.28	0.51	0.99
Trinidad and Tobago	0.82	0.93	1.00	1.03	1.08	1.10	0.28	0.59
Uruguay	0.75	0.79	0.93	0.98	1.08	1.33	0.58	1.14
Venezuela	0.68	0.84	1.00	1.07	1.32	1.47	0.79	1.52
LAC								1.10

Note: The penultimate column presents the cumulative growth for the entire period, 1961-2012

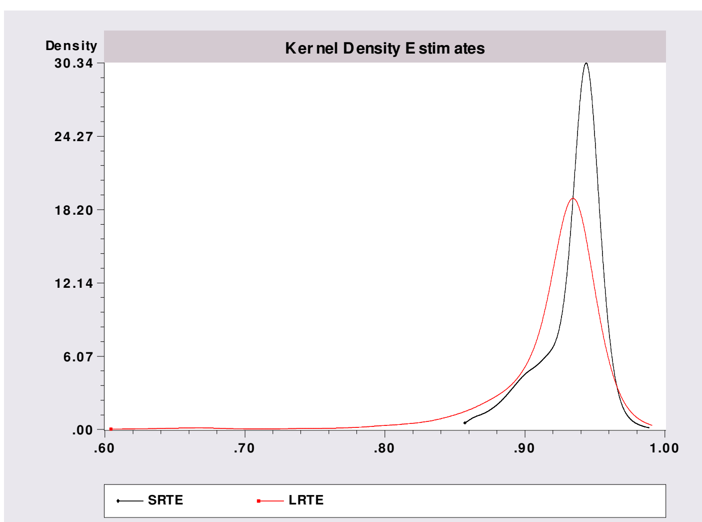
By 1971, Brazil had experienced a cumulative 11% growth in CATFP compared to 1961 and most other countries had also enjoyed significant productivity growth except for Uruguay that showed very little change. The decade of the 1980s was economically challenging compared to the previous one. In the 1980s, most countries experienced positive growth Nicaragua being a notable exception, but the average growth was lower than the previous decade. During the 1990s, countries such as Guyana and, to a lesser extent, Honduras, Trinidad and Tobago, El Salvador and Mexico showed little productivity growth while productivity kept declining in Nicaragua. On the other hand, it is worth noting that from 1990 to 2012 there was a big jump in Chile's CATFP (see Figure 6 in the Catch-up Analysis Section 5.4), and a significant part of this growth is attributable to TE change.

For the entire period of analysis, when we compare the initial level in 1961 with the level reached in 2012, Brazil, Chile and Venezuela had an accumulated CATFP of 80%, 79% and 79% respectively, followed by Costa Rica (72%), and The Bahamas and Peru with 65% each. Trinidad and Tobago (28%), Haiti (42%), Guyana (44%) and Panama (46%) have the lowest cumulative growth. Though Brazil has initially the highest CATFP in 1961, over the 1961-2012 period Venezuela has the highest average annual rate of CATFP growth (1.52%), followed by Chile (1.33%) and Mexico (1.30%). As shown in Table 5, on average for all countries in LAC, CATFP has been increasing over time at an annual growth rate of 1.1%. By contrast, Trinidad and Tobago (0.59 %), Panama (0.86 %), Haiti (0.95%) and Bolivia (0.96%) grew at the lowest rates.

5.3 Total Factor Productivity Components

We now discuss the different types of technical efficiency, namely SRTE, LRTE and overall TE. Figure 4 presents the kernel density distribution of SRTE (transient) and LRTE (persistent). LRTE has a long left tail which includes TE values below 60% whereas the SRTE distribution is less skewed and contains some TE values that are slightly below 90%. In addition, the distribution of LRTE is more dispersed.

Figure 4: Kernel Distribution of Persistent (LRTE) and Transient (SRTE) Technical Efficiency in LAC countries



These findings imply that in terms of managerial skills, adoption and use of current technologies captured by STRE, LAC countries are doing fairly well. As displayed in Table 6, Nicaragua

(SRTE=0.903) and El Salvador (SRTE=0.908) followed by Trinidad and Tobago (SRTE=0.917) seem to have the most difficulty in using the best available technologies.

Table 6: Panel Unit Root Tests across sub-regions

Region	Unit Root Test	test	p-value	root
South America	Levin-Lin-Chu (LLC)	2.99	0.99	I(1)
	Im-Pesaran-Shin (IPS)	-1.21	0.11	I(1)
	Breitung	7.73	1	I(1)
Central America	Levin-Lin-Chu (LLC)	1.37	0.91	I(1)
	Im-Pesaran-Shin (IPS)	-1.46	0.07	I(1)
	Breitung	6.32	1	I(1)
Caribbean	Levin-Lin-Chu (LLC)	3.84	0.99	I(1)
	Im-Pesaran-Shin (IPS)	2.67	0.99	I(1)
	Breitung	7.17	1	I(1)

Source: Authors calculations.

On the other hand, structural factors and institutional reforms, which take a long period to change, seem to be another important obstacle for LAC countries in reaching their agricultural frontier. Therefore, more effort is needed by policy makers to promote reductions in persistent inefficiency in the agricultural sector in the region. In particular, as shown in Table 6, countries that are the most affected by those factors are Nicaragua (LRTE=0.85), Trinidad and Tobago (LRTE=0.88), Bolivia (0.89), Venezuela and El Salvador (0.90). Furthermore, Argentina, with the highest overall average TE at 0.90 for the 1961-2012 period, is the reference frontier. By contrast, Nicaragua (average overall TE=0.77%), Trinidad and Tobago (0.82%), Bolivia (0.82%) and El Salvador (0.83%) are the countries furthest away from Argentina.

The Returns to Scale (RTS) measure for LAC is estimated to be 0.95 implying that the technology exhibits decreasing returns to scale. The estimated parameter of the time trend, $\xi = 0.011$, reveals that LAC countries experienced an annual average technological progress (TP) equal to 1.01% over the sample period. In addition, Figure 5 shows that TP has been the key driver of agricultural productivity in LAC. On the other hand, the evolution of SE indicates that it has remained quite flat, decreasing at a 0.003% annually, without much of an effect on productivity and this result is consistent with the nature of decreasing returns to scale of the technology (see Table 7).

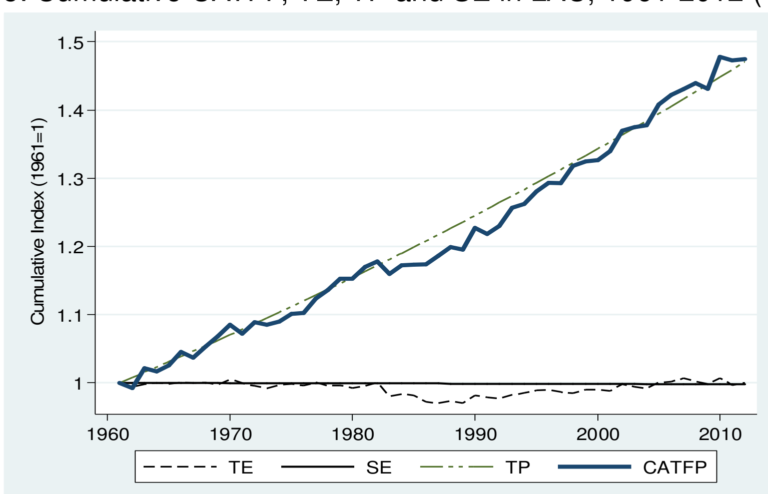
Table 7: Panel Cointegration test across LAC Sub-regions

Statistic tests	Value	Z-value	P-value	Robust P value	Value	Z-value	P-value	Robust P value	Value	Z-value	P-value	Robust P value
	South America				Central America				Caribbean			
Gt	-3.1	-3.2	0	0	-2.5	-2.4	0.01	0.15	-2.7	-2.2	0	0.01
Ga	-25.5	-6.8	0	0.01	-12.3	-2.7	0.01	0.18	-11	-1.5	0	0.06
Pt	-9.2	-2.5	0	0	-6.7	-2.5	0.01	0.12	-5.3	-2	0	0.02
Pa	-28.3	-10.8	0	0.01	-11.6	-4.5	0	0.15	-11.3	-3.4	0	0

Notes: These statistic tests are derived in Westerlund (2007).

As shown in Figure 5 below, TE was relatively constant during the first two decades followed by a decline in the 1980s and 1990s, and then a slight increase in the last decade. Over the entire period, TE increased at an average of 0.014% per year (Table 7). Finally, TP and CATFP follow similar trends with slight variations in the 1980-2000 period.

Figure 5: Cumulative CATFP, TE, TP and SE in LAC, 1961-2012 (1961=1)



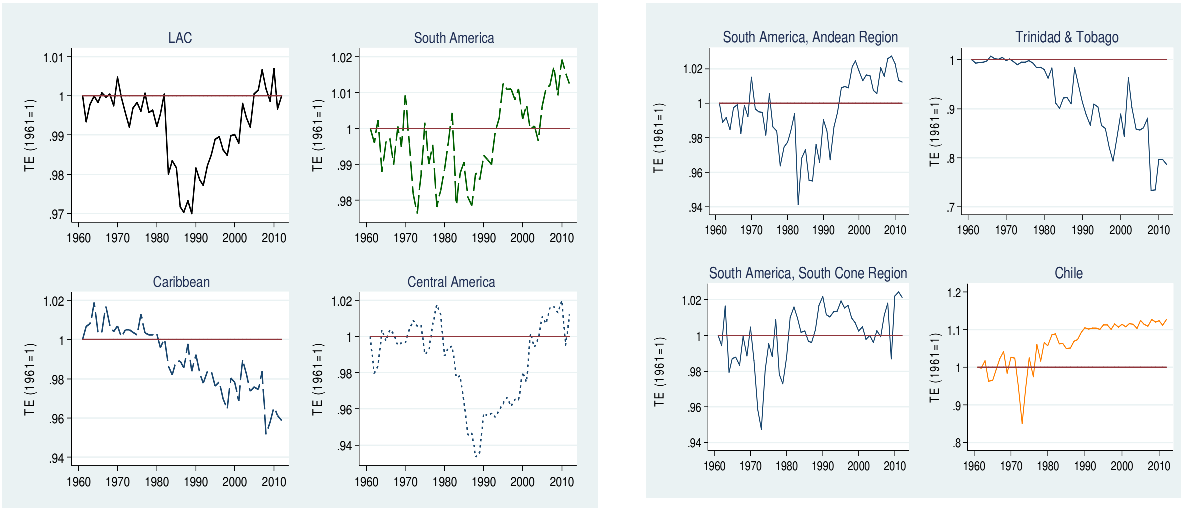
Note: CATFP = Climate Adjusted Total Factor Productivity;
TE = technical efficiency; SE = Scale efficiency; TP = Technical progress
Source: Authors calculations.

5.4 Catch-up

Recall that catch-up occurs when countries are getting closer to their own frontier due to increases in Technical Efficiency (TE) (Kumbhakar et al., 2005; Kumar and Russell, 2002). In order to examine the catch-up process, we analyze TE across LAC and over time. Results suggest that Venezuela (0.44%), Chile (0.25%), Mexico (0.22%), The Bahamas (0.18%) and Costa Rica (0.17%) had the highest average annual TE reflecting the best performance in handling existing agricultural technologies (Table 7). Note that these same countries were among the most productive ones. These findings suggest that TE is a key factor in explaining productivity differences in the region. By contrast, Trinidad and Tobago (-0.49%), Panama (-0.23%), and Haiti (-0.15%) depicted the lowest average rates indicating that these last countries face low learning-by-doing in the use of existing technologies and confront structural and institutional obstacles that prevent them from catching-up to their own frontier. To have a better picture of the catch-up process, instead of using a simple average that does not have a time dimension, we now proceed to analyze the temporal behavior of TE.

Figure 6 reveals that South American countries started catching-up to their own production frontier in the middle of the 1980s whereas Central American countries joined the catch-up path in the late 1980s. On the other hand, the Caribbean countries do not exhibit signs of catch-up. The observed catch-up effect in South and Central America might correspond to successful structural reforms undertaken by most countries in these sub-regions in the late of the 1980s and the beginning of the 1990s (Loayza and Fajnzylber, 2005). On aggregate, the region saw a decline from 1960 to the 1980s, with a reversal of the catch-up trend from the 1990s onwards. These results are consistent with Ludena (2010), who also observed this catching up effect over the last two decades.

Figure 6: Technical Efficiency "Catch-up" Index for LAC and Sub-regions, 1961-2012 (1961 = 1)



Source: Authors calculations.

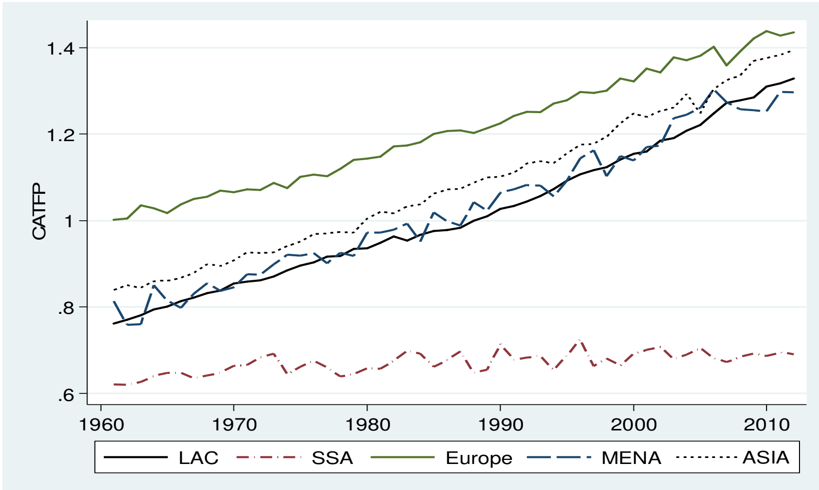
In South America, the Southern Cone countries and in particular Chile started caching-up to their frontier even early in the mid 1970s. The Andean region undertook the catch-up path almost two decades later (beginning of the 1990s) compared to the Southern Cone region. On the other hand, in the Caribbean, Trinidad and Tobago did not show a catching-up trend.

5.5 Regional Comparisons of CATFP Growth in Agriculture

Figure 7 illustrates the evolution of CATFP across Asian, SSA, MENA, European and LAC countries for the period 1961-2012. Average CATFP is highest for Europe, followed by Asia while MENA and LAC exhibit lower and similar trends. Before the 2000s, productivity was slightly higher in MENA than LAC; however, after that period and especially in the mid 2000s LAC performed better. On the other hand, CATFP in SSA has been stagnant since the mid 1970s while in all other regions it has been converging to that of Europe that has on average the highest CATFP. We analyze convergence across regions more formally below.

Our TFP results for SSA countries, which account for climatic effects and unobserved heterogeneity, differ from those (conventional TFP) in Fulginiti et al. (2004) and Nin-Pratt and Yu (2010) who found increasing productivity performance in this region since the mid 1980s. The papers just cited likely overestimate TFP because they ignore climatic effects and unobserved heterogeneity and in addition do not separate transient from persistent TE. Our productivity analysis is consistent with Lachaud et al., (2015) who examine the difference between TFP and CATFP for LAC and find that the former index is always higher than the latter indicating that, *ceteris paribus*, the climatic effect has an adverse impact on agricultural productivity.

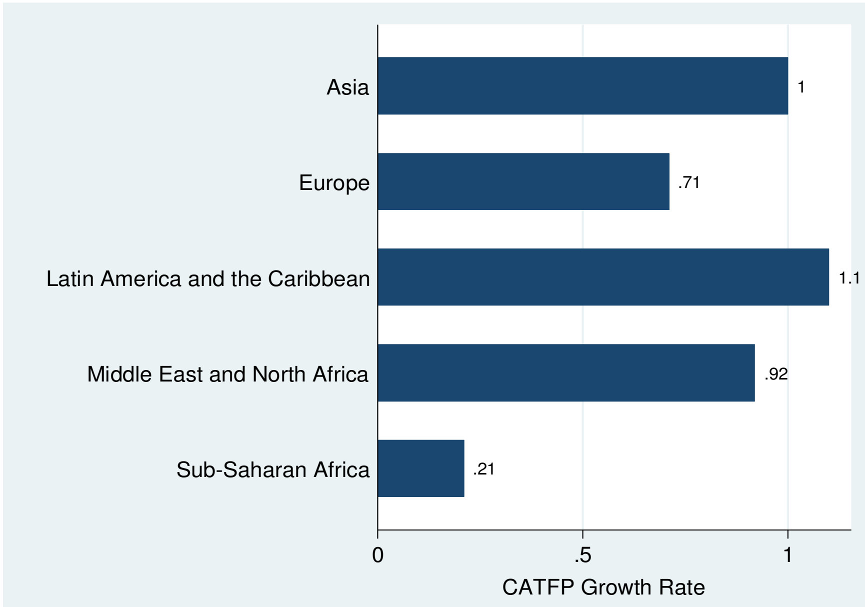
Figure 7: Cumulative CATFP across world regions, 1961-2012 (Europe, 1961=1)



Source: Authors calculations.

Furthermore, as shown in Figure 8, CATFP has grown across all regions in the last three decades, except for SSA, but at different rates. LAC countries grew faster at an annual rate of 1.1%. By contrast, SSA grew only at 0.21% and is the region that displays the lowest rate of technological progress (0.2% as shown in Table 4). Our results are similar to those of Ludena (2010) who found that LAC exhibited higher TFP growth rate (1.1%) compared to Asian countries (1%) and SSA (0.21%) and in most cases TP is the main.

Figure 8: Average Annual CATFP Growth across Regions, 1961-2012



Source: Authors calculations.

5.6 Convergence

Convergence takes place when the TFP of least performing countries grows relatively faster than that of high performing ones (Barro, 1997; Baumol, 1986; Solow, 1956). In this section, we investigate convergence and its speed across and within sub-regions using panel data regression techniques as explained earlier.[7] Brazil is considered as the reference country for the convergence analysis within LAC because it has the highest initial CATFP in 1961. First, we test whether CATFP estimates are stationary across LAC sub-regions and within individual countries by exploring the possible existence of long-run linkages. Table 8 presents the results of LLC, IPS and Breitung Panel Unit Root tests (Breitung, 2000; IPS, 2003; LLC, 2002). Specifically, we test the null hypothesis that CATFP estimates embody a unit root against the alternative that they are stationary. In the case of LLC, we specify a test with panel-specific means without time because $T > N$ in the dataset (see LLC, 2002). The LLC bias-adjusted *t* statistics are 2.99, 1.37 and 3.84 for South American, Central American and the Caribbean countries, respectively. These *t* statistics indicate that we cannot reject the null hypothesis that the panels contain a unit root in all three cases (Table 8).

[7] LAC countries are divided into three sub-regions: 1) Caribbean which includes Barbados, The Bahamas, Guyana, Suriname, Dominican Republic, Haiti, Jamaica and Trinidad and Tobago; 2) Mexico and Central America which includes Mexico, Belize, Costa Rica, El Salvador, Guatemala, Honduras, Nicaragua and Panama; and 3) South America comprises Argentina, Bolivia, Brazil, Chile, Colombia, Ecuador, Peru, Uruguay, Paraguay, and Venezuela.

To lessen the impacts of cross-sectional correlation, we subsequently eliminate the cross sectional means from the CATFP estimates and results do not change except for South America. That is, when accounting for cross sectional similarities across South American countries, CATFP estimates in this region are stationary. In addition, findings from the IPS root test, which allows the autoregressive parameter (see equation 10) to vary across countries, corroborate the results of the LLC tests. That is, CATFP estimates present a unit root and we fail to reject the null hypothesis at the 1% level of significance. Given the characteristics of the sample, i.e., N is small relatively to T, evidence from LLC and IPS tests suggests potential existence of divergence in TFP estimates across LAC countries over time. Further, we carry out the Breitung test to check the robustness of the results by including individual-specific trends and evidence indicates persistency in CATFP estimates across sub-regions. We therefore conclude that CATFP estimates are non-stationary and we subsequently proceed to the co-integration analysis.

Table 8: Estimates for Error Correction Model (ECM)

Models	Model PMG		Model MG	
N=874	Coeff.	S.E.	Coeff.	S.E.
τ	0.57[a]	0.057	0.8[a]	0.121
ϑ	-0.91[a]	0.023	-0.97[a]	0.035
$\Delta CATFP_j$	-0.24[a]	0.068	-0.40[a]	0.066
Log-likelihood	1373.9			

Note: a, b, c are 1%, 5%, and 10% level of significance respectively.
S.E.: Standard error. Variables are measured in natural logs

We run four co-integration tests developed by Westerlund (2007). The first two denoted as G_t and G_a, are group-mean tests, and they do not constrain α_i to be equal (see equation 13). These tests are conducted to assess the alternative hypothesis that $\alpha_i < 0$ for at least one country, which would indicate that, on average, CATFP estimates in the panel are co-integrated (Westerlund, 2007). On the other hand, the other two tests, labeled P_t and P_a, evaluate the alternative that all countries in the panel are co-integrated.

Before proceeding to the co-integration analysis, we test the hypothesis of cross-sectional dependence using the Breusch-Pagan LM test (Westerlund, 2007). The tests suggest consistently and significantly that there is cross sectional dependence in all three LAC sub-regions (South America, Central America and the Caribbean). The statistics for each sub-region are χ^2_{36}=1649, χ^2_{28}=1328 and χ^2_{28}=1344 (respectively). These results clearly suggest that there are common factors affecting CATFP estimates across all the sub-regions; thus, conventional co-integration tests for time series data that assume cross-sectional independence are likely to yield misleading conclusions.

Table 9 displays the outcomes of the Panel co-integration tests across the different sub-regions. The Akaike Information Criterion (AIC) is used to calculate the optimal length of lag and lead for the ECM equation. Because the results of the Breusch-Pagan LM tests reveal that there are common factors that affect the cross-sectional units (LAC countries), as in Westerlund (2007), we obtained robust critical values for the test statistics by bootstrapping.

Table 9: Mean Transient (SRTE) and Persistent (LRTE) Technical Efficiency

Country	Transient Short-run TE	Persistent Long-run TE	Technical Efficiency (TE)
Argentina	0.953	0.946	0.902
The Bahamas	0.937	0.931	0.872
Barbados	0.947	0.938	0.887
Bolivia	0.920	0.892	0.821
Brazil	0.942	0.936	0.882
Belize	0.942	0.929	0.876
Chile	0.927	0.912	0.846
Colombia	0.943	0.934	0.881
Costa Rica	0.946	0.938	0.888
Dominican Republic	0.947	0.941	0.891
Ecuador	0.952	0.945	0.900
El Salvador	0.908	0.908	0.825
Guatemala	0.940	0.930	0.874
Guyana	0.938	0.926	0.869
Haiti	0.946	0.936	0.885
Honduras	0.923	0.911	0.841
Jamaica	0.944	0.934	0.881
Mexico	0.932	0.923	0.860
Nicaragua	0.903	0.849	0.770
Panama	0.932	0.923	0.861
Paraguay	0.939	0.923	0.867
Peru	0.931	0.924	0.861
Suriname	0.938	0.929	0.872
Trinidad and Tobago	0.917	0.888	0.816
Uruguay	0.928	0.923	0.856
Venezuela	0.913	0.905	0.827
Min	0.903	0.849	0.770
Max	0.953	0.946	0.902
Mean	0.913	0.905	0.827

Source: Authors calculations.

The results show that, under the four Westerlund statistical tests, the null hypothesis of co-integration cannot be rejected across all sub-regions when ignoring the cross-sectional dependence. However, when accounting for common factors that affect countries in the region, it appears that only CATFP levels for the South America sub-region as a whole are co-integrated. On the other hand, the panel tests for the other sub-regions reveal there is no co-integration and only CATFP levels for some countries share a long-run dynamic relationship with that of Brazil. In particular, the results suggest that CATFP estimates are co-integrated for Costa-Rica, Mexico and Guatemala in Central America and for The Bahamas, Barbados and Jamaica in the Caribbean region.

We therefore use PMG and MG estimators to fit the ECM (equation 13). Table 10 presents the results of the ECM for only the countries that have their CATFP co-integrated. We report the estimated parameters of the short-run effects and long-run dynamic relationships among the CATFP estimates. The parameter (τ) that captures the co-integrating vector is highly significant and equal to 1.41 for the PMG and 1.48 for the MG models. In addition, there is a significant difference between short-run coefficients (α_i) across the two models. Hence, we compare them by testing the null hypothesis that the estimated parameters for the MG model are consistent against the alternative that those for the PMG model are not. The test leads to a Hausman statistic with a χ_1^2 distribution equal to 0.72 with a P-value = 0.396. Therefore, we conclude that the PMG outperforms the MG model indicating the homogeneity of the long-run estimated coefficient of CATFP across LAC countries. The results imply that, on average, the CATFP level of the South American countries, and Costa Rica, Mexico, Barbados and The Bahamas are converging to that of Brazil, but with different short-run responses (PMG estimators).

Table 10: Growth Rates of TE, SE and CATFP in LAC, 1961-2012

Country	Technical Efficiency (TE)	Scale Efficiency (SE)	Climate Adjusted TFP (CATFP)
Argentina	-0.032	-0.002	1.052
Bahamas	0.175	-0.005	1.256
Barbados	-0.028	0.001	1.057
Bolivia	-0.111	-0.005	0.963
Brazil	0.071	-0.004	1.154
Belize	-0.021	-0.007	1.060
Chile	0.245	-0.004	1.335
Colombia	0.032	-0.003	1.123
Costa Rica	0.172	-0.006	1.255
Dominican Republic	0.011	-0.003	1.099
Ecuador	-0.041	-0.004	1.044
El Salvador	-0.012	-0.002	1.071
Guatemala	0.120	-0.005	1.202
Guyana	-0.015	-0.002	1.067
Haiti	-0.145	-0.001	0.946
Honduras	0.008	-0.004	1.089
Jamaica	0.005	-0.001	1.092
Mexico	0.222	-0.004	1.304
Nicaragua	-0.016	-0.004	1.065
Panama	-0.228	-0.003	0.857
Paraguay	-0.031	-0.005	1.056
Peru	0.038	-0.004	1.124
Suriname	-0.087	-0.004	0.992
Trinidad and Tobago	-0.488	0.000	0.586
Uruguay	0.053	-0.003	1.136
Venezuela	0.438	-0.004	1.522
Min	-0.488	-0.007	0.586
Max	0.438	0.001	1.522
Mean	0.014	-0.003	1.097

Source: Authors calculations.

We now analyze CATFP convergence across LAC, SSA, MENA, Asia and Europe. As before, we first run the LLC, IPS and Breitung Panel Unit Root tests and the findings indicate that CATFP estimates embody a unit root in all regions (see Table B in the Appendix). We then proceed to the four Westerlund co-integration tests, which show that all CATFP estimates are co-integrated (see Table C in the Appendix). Finally, we use the ECM model (equation 13) to analyze if the CATFP estimates for LAC, SSA, MENA and Asia are converging to those of

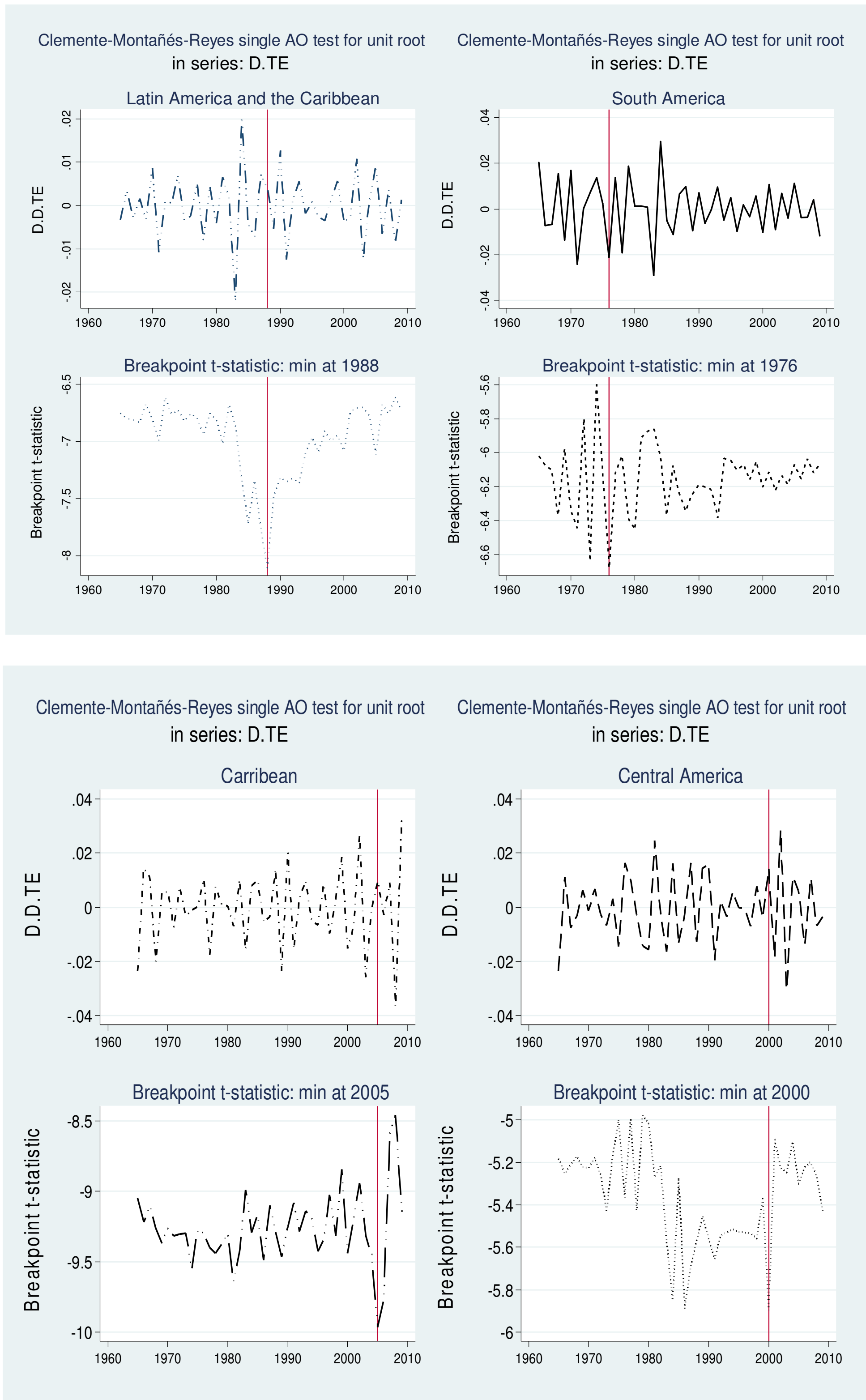
Europe, the region with the highest CATFP. The results of the PMG model show that only CATFP for SSA is not converging whereas LAC, MENA and ASIA are converging with similar short-run dynamics (see Table D in the Appendix). These findings confirm the results shown earlier in Figure 7.

5.7 Forecasting Agricultural Productivity and Output Growth

As stated above, the TE forecasts are based on panel data estimation methods. Before proceeding to the estimation, we start by testing whether the TE series are stationary and contain any structural break over time. This action is motivated by the behavior of TE patterns in the catch-up analysis (see Figure 6). A structural break can be seen as a change in TE series due to economic policies, institutional reforms or some other external shock. Having a structural break can affect the results of a unit root test.

There are different models that allow testing for structural breaks and unit root tests separately, but there are advantages of testing both jointly. This joint test avoids bias towards non-stationary and unit root, and makes it easy to determine the timing of the break (Glynn et al., 2007). In our context, we use the so-called endogenous Additive Outlier (AO) structural break test that is based on the assumption that changes occur rapidly and only affect the slope of the estimates (Clemente et al., 1998). Here we fail to reject the null hypothesis of a unit root test for the TE series. The results show that the first difference of TE is stationary and the structural break appears at different periods across South American (1976), Central American (2000) and the Caribbean (2005) countries (see Figure 9). When considering LAC as a whole, we note that the break detected by the test is in 1988, which is around the time of structural reforms in the region (Corbo and Schmidt-Hebbell, 2013).

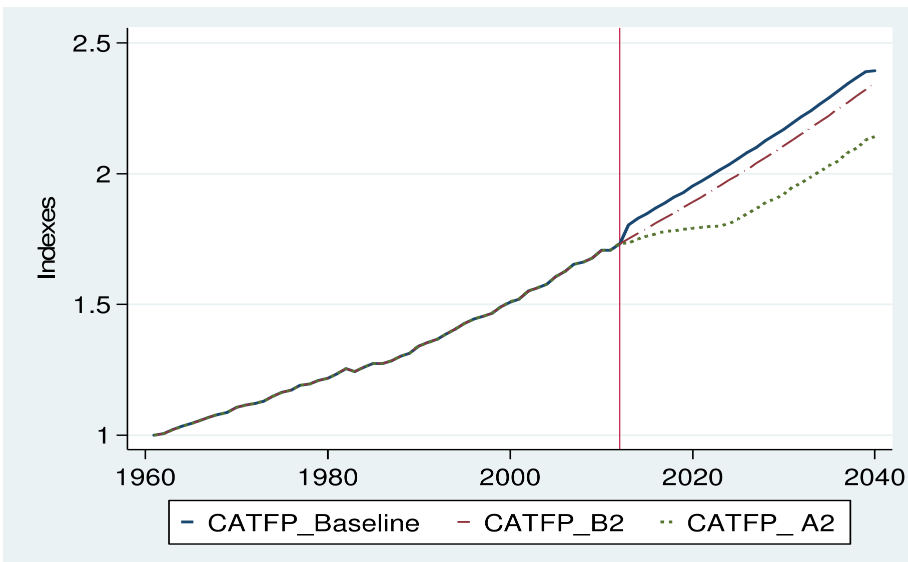
Figure 9: Structural break and Unit Root tests for LAC and Sub-Regions, 1961-2012



Source: Authors calculations.

The findings regarding the structural break and unit root are considered when proceeding to the forecast as explained below. Before making out-of-sample forecasts, we first conduct a static forecast (one-step-ahead forecast), which consists of using actual values of all lagged variables in the model. The results show that the static forecasts fit the data quite well. We then perform dynamic forecasts (more than a one-step-ahead forecast) for the last 10 years of the data in the sample, which are compared to the actual data. Again, the findings show that our model specification produces relatively good forecast estimates compared to the observed data. Finally, we proceed to the forecasts of CATFP for the 2013-2040 period, which is displayed in Figure 10.

Figure 10: Historical and Projected Cumulative CATFP in LAC, 1961-2040 (1961=1)



Source: Authors calculations.

Under all IPCC scenarios discussed earlier A2, B2, and our counterfactual, CATFP will keep increasing during the forecast period but at different rates. As expected, CATFP levels grow at a slower rate under the high emissions A2 scenario, in comparison to the relatively low-emissions B2 scenario. We then use our baseline case to evaluate the impact of climactic variability on both productivity and production. In order to do so, we use the forecasted CATFP to calculate its annual growth rate and we then compute the relative percent difference between the two scenarios with respect to our counterfactual (1982-2012).

Table 11: Productivity change and Economic Cost due to climatic variability by 2040 in LAC

	Scenario A2 (high emissions)	Scenario B2 (low emissions)
CATFP growth in LAC w.r.t. baseline by 2040 (%)	-10.7	-2.4
Discount rate	Present Value Loss (billions of US $)	
4.0%	34.2	12.7
2.0%	58.9	21.9
0.5%	89.1	33.2

Source: Authors calculations.

As shown in Table 11, productivity drops by 2.4% and 10.7% under the B2 and A2 scenarios, respectively, compared to the counterfactual where the climatic variables are held at their 1982-2012 average. Likewise, we use the two scenarios and the counterfactual to compute the impact of climatic variability on output. To compute the loss in output, we combine the climatic data from the different scenarios with the estimates of the GTREM frontier (equation 3) keeping all other variables (conventional inputs) constant throughout the 2013-2040 period at their mean values. That is, we consider the estimated production frontier from equation 3 and incorporate only the variation in the climatic variables under all three scenarios. Loss in output is then calculated as the relative percent difference in estimated output for the period 2013-2040 for scenarios A2 and B2 with respect to the counterfactual scenario. The results show that under the B2 and A2 scenarios, on average, output drops by 9% and 20% respectively in the region by 2040 compared to the baseline (average 1982-2012). The respective loss in output during the 2013-2040 forecast period amounts to US $21.9 and US $58.9 billion in present value terms at a 2% discount rate. Furthermore, we perform a sensitivity analysis by using 0.5% and 4% as discount rates, which facilitates comparisons with other studies that use similar rates (e.g., ECLAC, 2010a). The results show that, under the A2 scenario, the region can expect output losses ranging from US $34.2 to nearly US $89.1 billion with the 4% and 0.5% discount rates, respectively. Similarly, output losses would vary between US $12.7 and US $33.2 billion under the B2 scenario (Table 11).

There are several studies that analyze the impact of changes in productivity in agricultural GDP. However, most are focused on specific countries in South and Central America, such as the studies developed by the IDB and ECLAC (IDB-ECLAC 2014a, 2014b; IDB-ECLAC-DNP, 2014; CEPAL, 2009, 2010b, 2010c, 2010d, 2013, 2014). For example, ECLAC (2010d) estimates impacts between 2.8% and 5.4% of 2007 GDP by 2050 using 4% and 0.5% discount rates, respectively. On the other hand, Fernandes at al. (2012) estimate losses ranging from US $26 to US $44 billion in net revenues from the export of wheat, soybean, maize and rice in South and Central America by 2050 stemming from the adverse impact of climate change on agricultural production.

VI. SUMMARY AND CONCLUSIONS

This study examined the impact of climatic variability and country unobserved heterogeneity on TFP growth and investigated productivity gaps, catch-up and convergence processes in several world regions with emphasis on Latin America and the Caribbean (LAC). In addition, we forecasted possible effects of climate change on Climate Adjusted Total Factor Productivity (CATFP) and on output to 2040 for LAC countries. We combine data from the University of East Anglia's Climatic Research Unit with FAO data for 112 countries worldwide between 1961-2012 to estimate alternative Stochastic Production Frontier (SPF) model specifications. Specifically, climatic variability is introduced in the SPF models by including average annual maximum temperature, precipitation, wet days and their monthly intra-year standard deviations. The model of choice is a Generalized True Random Effects Mundlak estimator, which makes it possible to identify country unobserved heterogeneity from transient and persistent inefficiencies. Therefore, we investigate the impacts of alternative assumptions regarding unobserved heterogeneity and the omission of climatic variables on technical efficiency (TE) and Total Factor Productivity (TFP). TFP is derived using a multiplicatively-complete index, recently suggested by O'Donnell (2010, 2012), which satisfies all axioms coming from index number theory. The associated estimated coefficients from the SPF models are then used to construct a climatic effects index across countries and over time that captures the impact of climatic variability on agricultural production. An Error Correction Model is then applied to investigate catch-up and CATFP convergence across LAC countries.

The results for LAC countries indicate that the combined effect of temperature, precipitation anomaly, and precipitation frequency have an adverse impact on output and agricultural productivity in the region. By contrast, the quantity of precipitation has a positive effect. Moreover, the results show that the combined effect of all climatic variables considered (i.e., the climate effect index) has, on average, an increasingly negative impact on production over time.

In addition, there is considerable variability in TFP change across LAC countries and, overtime, within countries. Climatic variability affects production and productivity unevenly across time and space and has a particularly negative effect in most Caribbean and Central American countries. Comparisons across regions for the period 1961-2012 reveal that CATFP is highest in Europe followed by Asia, and then by MENA and LAC, which exhibit similar trends. In contrast, CATFP in SSA has been stagnant since the mid 1970s while in all other regions it has been converging to that of Europe. LAC countries grew faster at an annual rate of 1.1%. By contrast, SSA grew at the lowest rate (0.21%). These results imply that previous TFP studies that have omitted climatic variables have likely generated biased results.

Moreover, the analysis suggests that technological progress (TP) has been the key driver of agricultural productivity growth in LAC whereas technical efficiency (TE) has fluctuated up and down over time in the region. These results highlight the importance of local government investments in research and development generally, and in promoting adaptation strategies in particular to reduce the impact of climatic variability.

The impact of climatic variability on agricultural productivity is a global issue with potential worldwide consequences on food security, particularly for people who are most vulnerable and least able to cope with this adversity. The international community has an important role to play in promoting regional climate adaptation programs, and in providing technical and financial assistance to local governments in LAC because projections show that climatic effects will decrease productivity growth in the region by 2.4%-10.7%, on average, between 2013 and 2040.

One of the drawbacks of this study is the use of aggregate data to study the impact of climatic variability. While the model specification presented here to capture the climatic effects fits well with recent developments in the climate-economic literature for aggregate data (see Dell, Jones and Oken, 2014), results might change when focusing on specific countries and regions within countries. Therefore, future research in this area could expand the application of this methodology to individual countries or sub-regions to better capture the climatic effects in countries as big as Brazil and as small as Ecuador or Honduras, where there are different production systems associated with regional agro-ecological zones.

VII. POLICY IMPLICATIONS

The main finding of this study is that climatic variability has negative impacts on production and productivity. These adverse impacts are significant and vary across countries, sub-regions and regions. On the basis of information from the fifth assessment report from the IPCC (2014), climatic variability will reduce productivity across LAC countries in the scenarios considered. Specifically, our forecast revealed that between 2013 and 2040 climatic effects can be expected to decrease productivity in LAC by 2.4%, under the B2 scenario (relatively low emissions), and 10.7%, under the A2 scenario (high emission case), with respect to a baseline scenario. The latter assumes no change in climatic variables relative to the average for the 30 year period 1982-2012. The forecasted economic cost ranges between US $12.7 and US $89.1 billion dollars in the region depending on the scenario and the discount rate used. Consistent with Stern (2013), these numbers are very conservative because they do not take into consideration extreme weather impacts (e.g., hurricanes) and the resulting damage to agricultural infrastructure. Nonetheless, these results clearly suggest that, given the importance of agriculture in the LAC countries, if appropriate and immediate actions are not undertaken then climatic variability can be expected to change the economic development path of the region.

The impact of climatic variability is not merely a regional problem given the critical role LAC agriculture plays and will continue to play in terms of global food security, poverty alleviation and inequality reduction especially for vulnerable people living in rural areas. Increasing land use for agricultural purposes in LAC will not be an option for land-constrained countries and neither a viable and sustainable alternative for non-constrained ones. There is no doubt that increasing productivity will have to be the path to thwart the challenges from climatic variability, among other obstacles, in order to insure global food security.

The results show that precipitation has a positive impact on production; however, under IPCC prediction scenarios, precipitation is expected to decrease considerably across the region, where more than 90% of farming is rain-fed. This situation will create more pressure on water resources in LAC. Consequently, it is critical to promote efficient irrigation water use, and invest wisely in sustainable irrigation infrastructure/technologies across countries. Several studies show that irrigation leads to higher productivity (e.g., Boshrabadi et al., 2008; Cheesman and Bennett, 2008; Rahman, 2011).

In addition, the results show that country unobserved heterogeneity is significant, and it is different from transient and persistent inefficiency. Therefore, policy measures should be implemented on a country by country basis taking into consideration the predominant agro-ecological characteristics of each location.

Technological progress (TP) is identified as the main driver of CATFP growth. TP is essentially driven by research and development (R&D) and the subsequent adoption of new technologies and practices. Therefore, it is fundamental to increase the funding of both public and private investments in R&D as well as the support to extension services (e.g., Alston, Pardey and Roseboom, 1998; Alson, Beddow and Pardey, 2009). Countries that are closer to the regional frontier, which is the best management practice in the region, need to increase their R&D investments in order to push the frontier outwards. Investment in R&D should be oriented to programs focusing on adaptation and mitigation strategies to cope with climate change, and to increase the absorptive capacity of existing technologies, among other topics. For instance, more investments and coordination among stakeholders are needed to encourage environmentally friendly production technologies and to generate improved seeds and management techniques that enhance the resiliency of farming systems to climatic variability (Cooper et al. 2008). There is a lack of recent quantitative information regarding the rates of return to agricultural research in the region. Recent estimates, for a small sample of countries in the region, suggest that the average rate of return for agricultural research for the 1981-2006 period is estimated at 16%, with a range between 7.1% and 35% (Lachaud, 2014). In addition, Lachaud (2014) shows that doubling agricultural research in the region, ceteris paribus, would generate a 22% increase in production. In sum, there is need for governments to promote research in agriculture by supporting universities and extension activities, encouraging private initiatives, and looking for international support to fund this work.

The evidence also shows that on average technical efficiency (TE) has not contributed much to CATFP growth in the region. These results imply a low-learning by doing process in terms of technology absorption. In addition, a detailed analysis revealed that persistent inefficiency, which refers to institutional reform and governance, plays a critical role in increasing overall TE in the region. The catch-up analysis per sub-region indicates that South American and Central

American countries are getting closer to their frontier whereas the Caribbean countries are still struggling to catch-up. Therefore, this problem of technology absorption and governance is of particular relevance to the Caribbean countries. Investment in training, education and structural reform in the sector can play an important role for the Caribbean. Moreover, special attention should be devoted to Central American and Caribbean countries for which CATFP estimates are not converging to that of Brazil, the reference frontier.

Finally, according to the fifth assessment report of the IPCC (2014a), developing countries, including LAC, are lagging in the implementation of adaptation programs in various dimensions including knowledge generation (related to access and adoption of existing technology), governance (related to persistent inefficiency) and finance. These issues, except for the finance component, are reflected in our results. While the effects of climatic variability on production and productivity are clear, it would be important to analyze the level of investments needed to offset these impacts. There are many issues and sub-sectors to be considered when evaluating the economic cost of climatic variability and, each requires different investment levels and types. For example, according to the National Center for Atmospheric Research (NCAR) and the Commonwealth Scientific and Industrial Research Organization (CSIRO), reported in Nelson et al., (2009), the investment needed in agricultural research to counteract the effects of climatic variability on nutrition in the region ranges from US $392 to US $426 million. The corresponding figures for irrigation expansion and related efficiency enhancements are US $30.5 to US $128.5 million. These needed investments have direct bearing on regional and national financial institutions such as the Inter-American Development Bank in terms of possible effective interventions in the sector. On the other hand, countries in the region need to develop strategies to secure the required funding and technical expertise to implement adequate adaptation programs to face the current and forthcoming repercussions of climatic variability.

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APPENDIXES

Table A: Projected Mean of Climate Variables (2040) w.r.t. to the IPCC baseline (1960-1990)

Countries	Maximum Temperature		Precipitation	
	Scenario A2	Scenario B2	Scenario A2	Scenario B2
The Bahamas	1.53	1.75	-9.8	-12.41
Barbados	1.86	1.93	-4.15	-24.07
Belize	2.38	2.39	-13.56	-5.5
Dominican Republic	1.81	2.13	10.18	5.74
Guyana	2.73	3.16	11.59	-7.3
Haiti	2.01	2.05	23.34	24.38
Jamaica	1.66	1.75	-16.99	-20.85
Trinidad	2.27	2.53	12.24	-16.49
Suriname [1]	1.8	1.89	-4.03	-11.51
Average	*1.8*	*1.89*	*-4.03*	*-11.51*
Costa Rica	1.6	1.23	-12.47	-3.08
El Salvador	2.03	1.4	-15.23	-2.44
Guatemala	2	1.43	-12.73	-0.1
Honduras	1.83	1.4	-15.7	-7.18
Panama	1.4	1.23	-7.97	-2.36
Nicaragua	1.9	1.37	-17.93	-7.31
Mexico [1]	1.73	1.33	-13.87	-4.33
Average	*1.73*	*1.33*	*-13.87*	*-4.33*
South America [2]	4.0	2.5	-40	-20

Source: Authors calculations.
Notes: [1] Values for Mexico and Suriname use their respective sub-regional average as the data are not available for these countries; [2] Values for South America use the sub-regional average for all countries, as such information was not available at the country level in this sub-region.

Table B: Panel Unit Root Tests across Regions

Region	Unit Root Test	test	p-value	root
LAC	Levin-Lin-Chu (LLC)	6	1.0	I(1)
	Im-Pesaran-Shin (IPS)	5.07	1.0	I(1)
	Breitung	6.15	1.0	I(1)
SSA	Levin-Lin-Chu (LLC)	0.5	0.69	I(1)
	Im-Pesaran-Shin (IPS)	-1.29	0.09	I(1)
	Breitung	0.3	0.62	I(1)
MENA	Levin-Lin-Chu (LLC)	4.31	1.0	I(1)
	Im-Pesaran-Shin (IPS)	-2.16	0.92	I(1)
	Breitung	1.98	0.97	I(1)
ASIA	Levin-Lin-Chu (LLC)	6.95	1.0	I(1)
	Im-Pesaran-Shin (IPS)	4.06	1.0	I(1)
	Breitung	4.34	1.0	I(1)
EUROPE	Levin-Lin-Chu (LLC)	12.1	1.0	I(1)
	Im-Pesaran-Shin (IPS)	5.47	1.0	I(1)
	Breitung	7.17	1.0	I(1)

Source: Authors calculations.

Table C: Panel Co-integration test across Regions

Statistic tests	Value	Z-value	P-value	Robust P-Value
Gt	-3.58	-3.00	0.001	0.028
Ga	-18.47	-1.90	0.029	0.075
Pt	-7.09	-3.28	0.001	0.02
Pa	-18.24	-3.04	0.001	0.065

Notes: These statistic tests are derived in Westerlund (2007).
Source: Authors calculations.

Table D: Estimates for Error Correction Model (ECM) per region

Models		Model PMG	
N=204		Coeff.	S.E.
Regions	τ	2.49***	0.236
LAC	ϑ_i	-0.475	0.067
	$CATFP_i$	0.677	0.160
SSA	ϑ_i	1.267***	0.077
	$CATFP_i$	-1.63***	0.367
MENA	ϑ_i	-0.487***	0.070
	$CATFP_i$	0.77***	0.125
ASIA	ϑ_i	-0.471***	0.066
	$CATFP_i$	0.66***	0.172
Log-likelihood		451.45	

Notes: Europe is the reference region.
*, **, *** are 10%, 5%, and 1% level of significance respectively
S.E.: Standard error