Agricultural Productivity Growth in Latin America and the Caribbean (LAC):
An Analysis of Climatic Effects, Convergence, and Catch-up

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Abstract

This study estimates a Climate Adjusted Total Factor Productivity (CATFP) for agriculture in Latin America and Caribbean (LAC) countries. Climatic variability is introduced in 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 CATFP convergence is found across all South American countries, Costa Rica, Mexico, Barbados and The Bahamas. Using IPCC 2014 scenarios, the study shows climatic variability induces significant reductions in productivity over the 2013-2040 period. Estimated productivity losses due to climatic variability range from USD 12.7 to 89.1 billion in the LAC region depending on the scenario and the discount rate.

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Key Words: Agriculture, Total Factor Productivity, Climate Effects, Convergence, Forecasting, Latin America, Caribbean.

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1. **Introduction**

Economists and policy makers have understood the importance of agriculture in the development process for some time (e.g., Johnston & Mellor, 1961), while the 2007-2008 financial and economic crises brought heightened attention to food security and food prices among other factors. The social upheaval experienced in several countries where people took to the streets to protest against escalating food prices (Diao et al., 2008), has highlighted the importance of achieving food independence. 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).

Furthermore, agriculture plays an important role in overall economic growth in Latin American and the Caribbean (LAC) countries (World Bank, 2003), and it has significant spillover effects on other sectors of the economy (Hazell & Roell, 1983; Krueger et al., 1991; Federico, 2005). According to the Economic Commission for Latin America and the Caribbean (ECLAC, 2014), in 2012, the sector accounts for nearly 5% of Gross Domestic Product (GDP), employs 16% of the workforce and produces about 23% of the total exports of the region.

Perry et al. (2005) have estimated that when accounting for the multiplier effect on other sectors, agriculture's share of Gross Domestic Product (GDP) in Latin America is about 50% higher than what official statistical estimates indicate. Another reason to focus on agricultural productivity among LAC countries, as pointed out by Chomitz and Buys (2007) and Stonich (1989), among others, is the rising challenge imposed by climate change, natural resource depletion and environmental degradation. According to the International Food Policy Research Institute (IFPRI, 1995), approximately 200 million hectares of land in Latin America were degraded during 1970-1995, and all the countries in the region, with the exception of Argentina, had lost more than 5% of its forests. Moreover, since 1960, roughly 60% of forests in Central America have been destroyed. More recent data from FAO (2010) reveals that South America had the largest net loss of forests between 2000 and 2010 worldwide, which is estimated at 4.0 million hectares per year. Moreover, the forest cover continues to decrease in all countries in Central America with the exception of Costa Rica. These data reveal that the expansion of the

agricultural frontier is still ongoing in several LAC countries, which can be a contributor to climatic variability and thus can affect agricultural productivity (Geist & Lambin, 2000).

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. One the other hand, recent evidence from the fifth assessment report (AR5) of the Intergovernmental Panel on Climate Change (IPCC) suggests that adverse impacts of climatic variability are more pronounced in LAC than other regions of the world and are likely to be even worst 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 and livestock economic activities are responsive and vulnerable to climatic variability and latest research findings highlight important prospective adverse impacts on LAC agricultural sector by 2020 especially due to an increase in temperature levels and changes in precipitation patterns (e.g., Vergara et al., 2013). Finally, while several studies (e.g., Mendelson & Dinar, 2003; Müller et al., 2010; Lobell et al., 2011; Ramirez et al., 2010) have shown that agricultural productivity in Least Developing Countries (LDCs) is vulnerable to climatic variability, few studies have focused on this topic in LAC. Therefore, a comprehensive analysis of the relationship between agricultural productivity and climatic variability is critical for LAC.

Several studies have examined agricultural productivity growth in LAC, some focusing on specific countries (e.g., Bravo-Ureta & Cocchi, 2004; Gasques et al., 2012), others on several LAC countries (e.g., Bharati & Fulginiti, 2007; Ludena et al., 2005), while yet others have considered LAC along with countries from other parts of the globe (e.g., Bravo-Ortega & Lederman, 2004; Coelli and Rao, 2005; Ludena, 2010). However, all these studies have neglected the impact of climatic variability on agricultural productivity despite its potential significance and implications regarding effective policy responses to sustain output growth.

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.[4] A better way to look at it 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 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).

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 including forecasts to 2040 of possible productivity paths for LAC. In order to achieve that objective, our conceptual framework and research methodology follows these steps: 1) Develop a database that includes different types of climate variables, agricultural output, and conventional inputs (tractors, fertilizer, animal stock, land and labor); 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 and at the sub-regional level; 4) Forecast possible TFP paths for LAC countries to 2030-2040.

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

The remainder of this paper is structured as follows: section two presents the analytical framework; section three focuses on the data; section four presents the results; and section five is devoted to the conclusion and a discussion of policy implications.

2. **Analytical 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 the 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 there is correlation between unobserved heterogeneity and conventional inputs (e.g., land, labor, and machinery) included in the production model and 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 country random effects in the TRE model.

The GTRE model proposed by Colombi et al., (2011, 2014) has an error term 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 considered to be not under the country decision maker control (e.g., geological makeup of a country and other physical features or characteristics). Unlike the three-step Tsionas and Kumbhakar (2014) estimator, 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.

2.1 *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 have not been exploited yet in most empirical work. In this section, we present the 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:

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

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; β is a (*K×1*) vector of unknown parameters to be estimated; and Z_{jit} represents the j-th climate 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 ($v_{it} \sim iid\ (0, \sigma_v^2)$) ; 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 other Greek letters 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) for obtaining transitive TFP indexes which is in contrast with the more flexible and popular Translog (O'Donnell, 2012; O'Donnell and Nguyen, 2012).[5]

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 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 a SML method, which consists of maximizing the log-likelihood based on a simulated estimate of the density

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[5] 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.

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 random draws from Halton sequences as the simulation method and exploit 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 (GTREM):

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

Technical efficiency is computed through simulation using the LIMPEP package software developed by Greene (2012) and are 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:

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

where $\sigma = \sqrt{\sigma_v^2 + \sigma_u^2}$, $\lambda = \frac{\sigma_u}{\sigma_v}$ 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 $SRTE = E[\exp(-u_{it})\,/\,\varepsilon_{it}]$. Analogously, the persistent inefficiency counterpart is derived as $E = E[\exp(-A_i)/\varepsilon_{it}]$. Finally, following Kumbhakar et al., (2014), we compute a total TE measure as:

$$TE_{it} = SRTE_{it} * LRTE_i \tag{5}$$

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.

2.2 *Climate Effects Index (CEI)*

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

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

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 $\exp(\hat{C}_{it})$, 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.

2.3 *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 $XI_{ksit} \equiv X_{it}/X_{ks}$.

Given the assumption of the 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 right-hand term 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).

2.4 *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 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 possibility frontiers of the least performing countries are moving with respect to the frontier of the best performing ones (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 Europe (average TFP) by using Europe as the reference frontier. [6]

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 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, least productive 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. 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 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 those papers, and others, have used conventional time series unit root and co-integration techniques to study convergence. 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). 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.

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

We first start by testing the presence of a unit root among CATFP estimates. The presence of a unit root in the CATFP series suggests 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:

$$CATFP_{it} = \alpha_0 + \rho CATFP_{it-1} + \omega_{it} \tag{10}$$

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 the CATFP estimates for some countries to contain 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 tests. 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. Breitung has argued 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 based on the residuals because they do not entail the ad hoc assumption of cross-sectional dependence, which requires that time series are 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 recently 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 total factor productivity 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 combines 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 below:

$$\Delta CATFP_{it} = \omega_0 + \vartheta_i CATFP_{it-1} + \sum_{\substack{j=1 \\ i \neq j}}^{m} \tau_j \Delta CATFP_{jt} + \sum_{\substack{j=1 \\ i \neq j}}^{m} \varsigma A_j CATFP_{jt-1} + \mu_{jt} \tag{13}$$

where $\varsigma_j = \vartheta \tau_j$ and the error correction term is the residual from equation 11, which is used as an adjustment process to capture long-run dynamics. The term ϑ_i is the adjustment coefficient that measures the speed at which CATFP converge 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. 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 by. We also apply both MG and PMG estimators and use the Hausman test to discriminate between the two.

2.5 *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 SE does not show any suspicious pattern in terms of structural break or unit root (see Figure 5). However, climatic variability (our focus) and TE (see Figure 6) present some interesting features such as potential structural breaks and the presence of a unit root that require special attention.

The forecasts are based on the assumption that TE, SE, TP and CE jointly determine the temporal behavior of CATFP, and they are computed using a forecasting panel data approach, which consists of 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:

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

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

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

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

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

where *d* 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; and, all the other variables are as defined earlier.

2.5.1 *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, 2010).

Two new categories of climate scenarios have been developed by IPCC (2014a): the Representative Concentration Pathways (RCPs) and the Shared Scenarios Pathways (SSPs). The former refers to a set of assumptions regarding future GHG emissions and the latter to potential world development paths depending on chosen policies. There are four types of RCPs (RCP2.6; RCP4.5; RCP6; RCP8.5) and they represent possible changes in GHG emissions and are defined in terms of *radiative forcing* comparing emissions of the year 2100 relative to pre-industrial values. Correspondingly, the SPP outlines the intensity of policy needed for climate adaptation and mitigation (IPCC, 2014a). There are five SPPs: Sustainable Pathway (SSP1), Moderate Pathway (SSP2), Rocky Road (SSP3), and Taking the Fast Road (SSP5). SSP3, which is equivalent to the old "A2" scenario from previous IPCC Special Report on Emissions Scenarios (SRES), 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 moderately level of

economic development and a focus on local socio-economic solutions.[7] According to ECLAC (2010), the "A2" and "B2" scenarios are the most suitable ones to investigate and project economic impacts of climatic variability across developing countries given their characteristics in terms of economic growth and technology adoption. Therefore, we simulate the impacts of climatic variability on TFP and agricultural production under three different scenarios until the year 2040. Specifically, climatic variability projections are based on the SSP3 (A2) and SPP2 (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. Therefore, we use the sub-regional average for this group. Likewise, as projected rainy days across the region are not available, they are modeled 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.

3. DATA

3.1 *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 LAC countries for a total of 1352 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.

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

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 level of production in LAC, our group of particular interest 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.

3.2 *Climate 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 precipitations (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.

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.

[Table 1]

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) and 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 ($0.5° \times 0.5°$ latitude/longitude). Annual data are then calculated as the 12-month average (Harris et al., 2014).[8] 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 and such variable allows capturing more variability in the climate variables.

Climate variables vary considerably across countries. In particular, the number of rainy days ranges widely, with an average of 163 days with a standard deviation of 60 days (Table 1). Similarly, significant differences are also observed in precipitation patterns across countries.

4. RESULTS

As can be seen in Table 2, all parameters for the variables that capture traditional inputs across models and groups of countries are statistically significant at the 1% level, and regularity

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

conditions from production economic theory, which require that partial output elasticities be nonnegative, are satisfied uniformly.

Following Rabe-Hesketh and Skrondal (2005), for the GTREM models we only include the mean variables from the auxiliary regression (see equation 2) that are statistically significant. These results also suggest that the parameters for the climate variables are statistically significant across models (Table 2). Moreover, the λ parameter, the signal-to-noise ratio, is highly significant across models revealing the importance of inefficiency in total output variability. Likewise, the coefficient of σ_α 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 do not account for transient and persistent inefficiencies would lead to biased TFP measures because any time invariant inefficiency is lumped with country unobserved heterogeneity.

As explained above, we estimate two sets of models GTRE and GTREM. As shown in Table 2, the means of fertilizers, animal stock, labor, maximum temperature and rainy days appear to be correlated with country unobserved heterogeneity and a Wald test suggests that the associated parameters are significantly different from zero at the 1% level. The Wald test supports the validity of the GTREM. 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.

4.1 *Parameters*

Estimates of the parameters of the GTREM Model for LAC countries are reported in the fourth column of Table 2. Results suggest that agricultural production in LAC is most responsive to labor, animal stock, and land. 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, 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 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 rising temperature. 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 farmers and governments own change in practices 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.

4.2 *Climate Effects Indexes*

We first start by assessing the impact of each climate 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]

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 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, the *CEI* shows a downward slope with values lower than one within a narrow range, which suggests a slow but negative climate impact on production over time. According to these results, we can expect more somber repercussions of climatic variability on agricultural production.

[Figure 2]

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 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]

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4.3 *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 3 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. However, it is worth noting that the CATFP indexes presented in Table 3 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 and this is precisely the attractiveness of the transitivity property (O'Donnell and Nguyen, 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 4.5), and a significant part of this growth is attributable to TE change.

[Table 3]

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 3, 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.

4.4 *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]

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 4, Nicaragua (SRTE=0.903) and El Salvador (SRTE=0.908) followed by Trinidad and Tobago (SRTE=0.917) seem to have more difficulties in using the best available technologies.

[Table 4]

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 4, 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 5).

[Table 5]

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 average of 0.014% per year (Table 5). Finally, TP and CATFP follow similar trends with slight variations in the 1980-2000 period.

[Figure 5]

4.5 *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 5). 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 in the last two decades.

[Figure 6]

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.

4.6 *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.[9] 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 countries by exploring the possible existence of long-run linkages among CATFP series. Table 6 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

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[9] 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.

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 6).

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 6]

We run four co-integration tests developed by Westerlund (2007). The first two denoted as G_t and G_a, are called 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 start testing the hypothesis of cross-sectional dependence using the Breusch-Pagan LM test. In all cases, South America, Central America and the Caribbean, the tests suggest consistently and significantly that there is cross sectional dependence and the statistics for each sub-region respectively are $\chi^2_{36}=1649.4$, $\chi^2_{28}=1328.3$ and $\chi^2_{28}=1344.5$. 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 7 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 there are common factors that affect the cross-sectional units (LAC countries), as in Westerlund (2007), we bootstrapped robust critical values for the test statistics.

[Table 7]

The results show, under the four Westerlund statistical tests, that 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 of equation 13. Table 8 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 CATFP estimates. The parameter that captures the co-integrating vector (τ) 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 South American countries, Costa Rica, Mexico, Barbados and The Bahamas are converging to that of Brazil, but with different short-run responses (PMG estimators).

[Table 8]

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4.7 *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, 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 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 7). 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 7]

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 is 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 8.

[Figure 8]

Under all IPCC scenarios as defined earlier (p14), SSP3 (A2), SSP2 (B2), and our baseline, 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 SSP3 scenario, in comparison to the relatively low-emissions SSP2 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 baseline.

[Table 9]

As shown in Table 9, productivity drops by 2.4% and 10.7% under the SSP2 (B2) and SSP3 (A2) scenarios, respectively, compared to the baseline, the average climate variables 1960-1990. Likewise, we use the two scenarios and the counterfactual to compute the impact of climatic variability on production. For this computation, we combine the climate data from the different scenarios with those of the GTREM estimated frontier (equation 3) keeping all the other variables (conventional inputs) constant at their mean values throughout the 2013-2040 period. That is, we incorporate only the variation in the climatic variables. The results show that under the SSP2 (B2) and SSP3 (A2) scenarios, on average, output drops by 9% and 20% respectively in the region by 2040 compared to the baseline (average 1960-1990). This 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, 2010). The results show that, under the SSP3 (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 SSP2 (B2) scenario (Table 9).

5. 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 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 26 LAC countries between 1961-2012 to estimate different 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. We use 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 of 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.

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 2.3%-10.7%, on average, between 2013 and 2040.

6. 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 sub-regions and countries. 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 productivity in LAC can be expected to decrease by 2.3%, 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 infrastructures. Nonetheless, these results clearly suggest that, given the importance of agriculture in the LAC countries, if appropriate adequate 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 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 the region. Consequently, it is critical to promote efficient irrigation water use, and invest wisely in sustainable irrigation infrastructures/technologies across countries. Several studies show that irrigation leads to more productive and yield higher output growth (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 inefficiencies. 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), so it will be fundamental to increase the flow of both public and private investments in R&D in the region. 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 aspects. 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. 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. Therefore, 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) does not contribute 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 of these 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.

Table 1: Descriptive Statistics (N=26 countries, T=52 years, Sample size= 1352)

Variable	Mean	Std. Dev.	Min	Max
PRODUCTION (PROD)	6031825	1.55E+07	9480	1.50E+08
TRACTORS (TR)	48.63373	136.9652	0.029	1000
FERTILIZER (FER)	330735.7	1146489	85	1.10E+07
ANIMAL STOCK (AS)	13603350	32856550	16305	244833000
LAND (LA)	5533.329	12572.67	9	79929.8
LABOR (LB)	1352	2986.0	3.83	16342.0
TEM	28.3	3.7	12.80	31.8
PRECIP	1904.4	2003.5	436.10	41918.0
Anomaly	0.2	0.1	0.05	0.6
WD	162.8	60.6	43.40	262.1

Table 2: GRTE and GTREM estimates for Agricultural Production Frontier Models for LAC countries

Models	GTRE		GTREM	
NT=1352	Coeff.	S.E.	Coeff.	S.E.
Intercept	6.971***	0.093	6.971***	0.093
Tractor (TR)	0.123***	0.004	0.086***	0.001
Fertilizer (FER)	0.125***	0.004	0.072***	0.001
Animal Stock (AS)	0.288***	0.007	0.215***	0.005
Land (LA)	0.172***	0.008	0.173***	0.002
Labor (LB)	0.229***	0.006	0.404***	0.006
T	0.007***	0.000	0.010***	0.000
Temperature (TEMP)	-0.075***	0.028	-0.213***	0.061
Precipitation (PRECIP)	0.070***	0.020	0.021***	0.007
PRECIP STDEV	-0.215***	0.048	-0.240***	0.016
RD	-0.155***	0.017	-0.088***	0.013
Mean (FER)			0.096***	0.002
Mean (AS)			0.091***	0.005
Mean (LB)			-0.204***	0.006
Mean (TEM)			0.207***	0.061
Mean (RD)			-0.069***	0.014
λ	1.941***	0.203	59.32***	17.131
σ	0.165***	0.005	0.165***	0.005
σ_u	0.147	n/a	0.191	
σ_v	0.076		0.003	
A_i	0.019		0.026	
α_i	2.330		1.957	
RTS	0.9350		0.9350	
Log-likelihood	-14.07		21.56	

Notes:*,**,*** are 10%, 5%, and 1% level of significance respectively

S.E.: Standard error.Variables are measured in natural log.

n/a: non available

RTS: Returns to Scale

Table 3: Cumulative CATFP by decade in LAC, 1961-2012 (Brazil: 1961=1)

Countries	1961	1971	1981	1991	2001	2012	Cumulative Growth (diff 1961-2012)	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

Table 4 : Mean Transient (SRTE) and Persistent (LRTE) Technical Efficiency (TE), across LAC countries, 1961-2012

Country	Transient Short-run TE	Persistent Long-run TE	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

Source: Authors calculations.

Table 5: Growth Rates of CATFP Components in LAC, 1961-2012

Country	TE	SE	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
LAC	0.014	-0.003	1.097

Table 6: Panel Unit Root Tests across sub-regions

South America	Test	p-value	root
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	Test	p-value	root
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	Test	p-value	Root
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)

Table 7: Panel Cointegration test across LAC Sub-regions

Statistic tests	Value	Z-value	P-value	R. P value	Value	Z-value	P-value	R. P-value	Value	Z-value	P-value	R. P-value
	South America				Central America				Caribbean			
Gt	-3.1	-3.2	0.00	0.00	-2.5	-2.4	0.01	0.15	-2.7	-2.2	0.00	0.01
Ga	-25.5	-6.8	0.00	0.01	-12.3	-2.7	0.01	0.18	-11.0	-1.5	0.00	0.06
Pt	-9.2	-2.5	0.00	0.00	-6.7	-2.5	0.01	0.12	-5.3	-2.0	0.00	0.02
Pa	-28.3	-10.8	0.00	0.01	-11.6	-4.5	0.00	0.15	-11.3	-3.4	0.00	0.00

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

R. : Robust

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				

Notes: a, b, c are 1%, 5%, and 10% level of significance respectively

S.E.: Standard error. Variables are measured in natural log.

Table 9: Economic Cost and productivity loss in LAC due to Climatic Variability by 2040

	CATFP Growth (%)		Present Value Loss (billion US $)					
			Discount Rate 0.5%		Discount Rate 2%		Discount Rate 4%	
	(A2)	(B2)	(A2)	(B2)	(A2)	(B2)	(A2)	(B2)
LAC w.r.t. Baseline	-10.73	-2.35	89.1	33.2	58.9	21.9	34.2	12.7

Source: Authors calculations.

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

A. Maximum Temperature

B. Precipitation

C. Rainy days
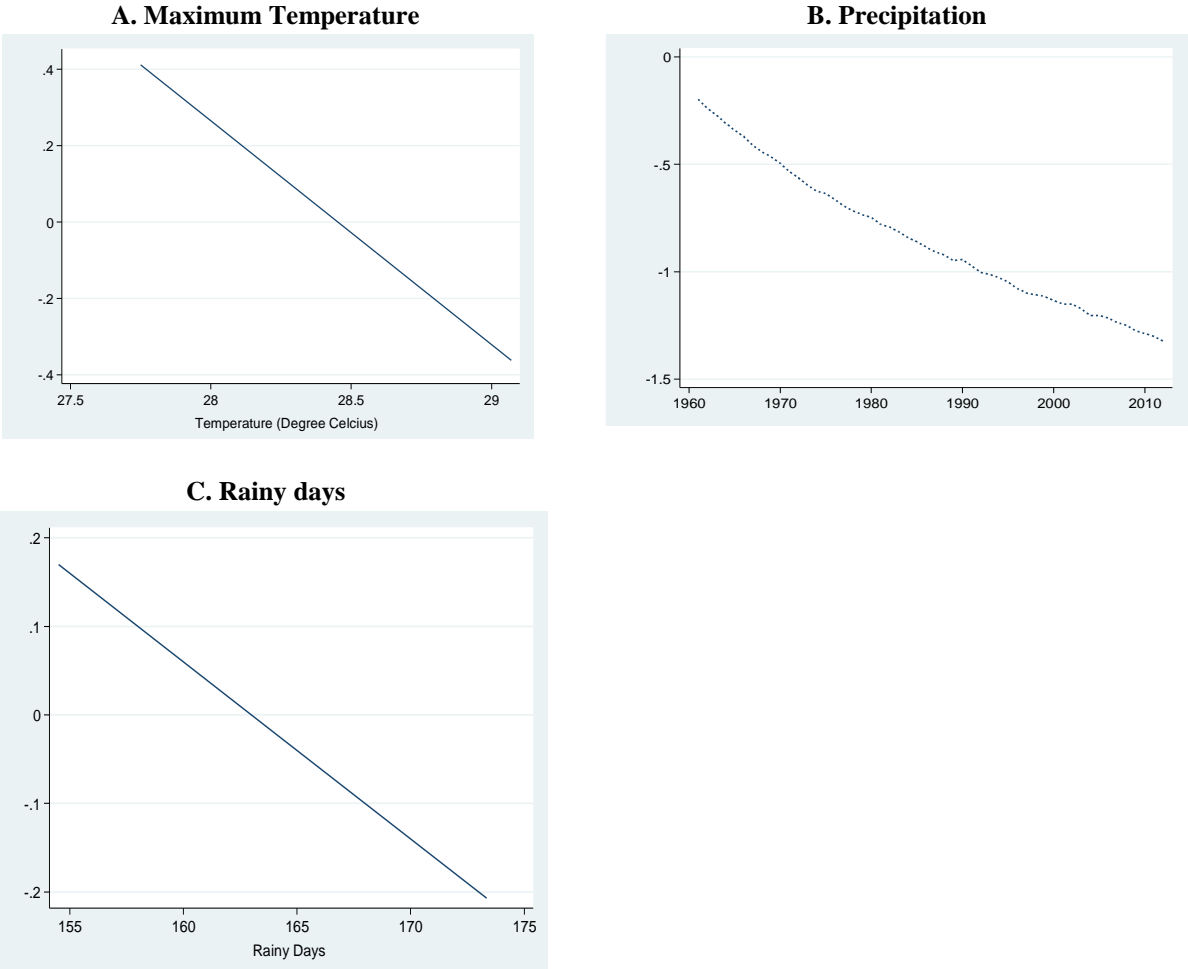
Source: Authors calculations based on FAO and CRU data.

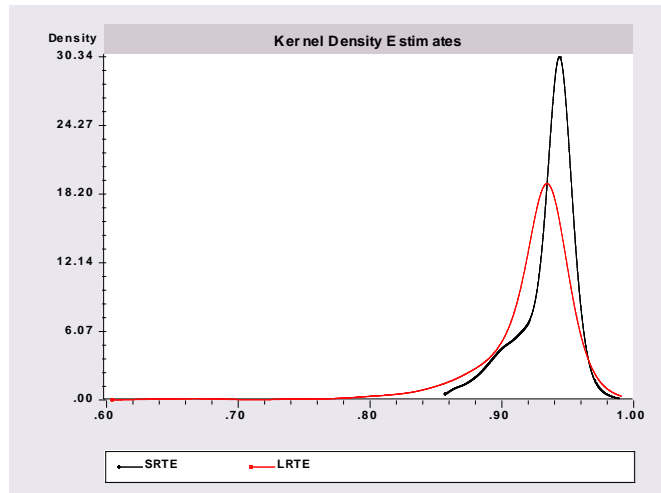**Figure 2: Mean Climate Effects Index (CEI) across LAC countries, 1961-2012**
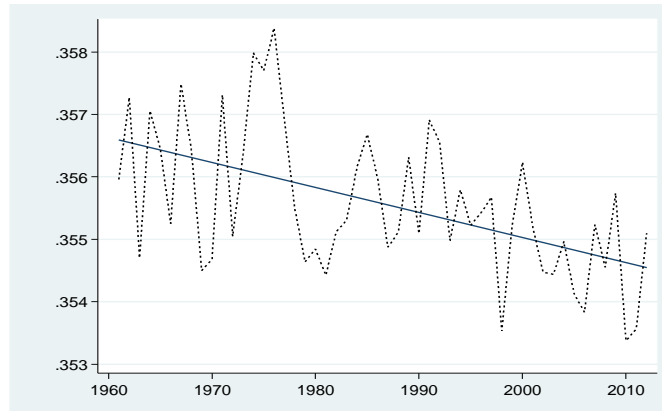
Source: Authors calculations.

Figure 3: Relative change in output in LAC countries due to climatic variability
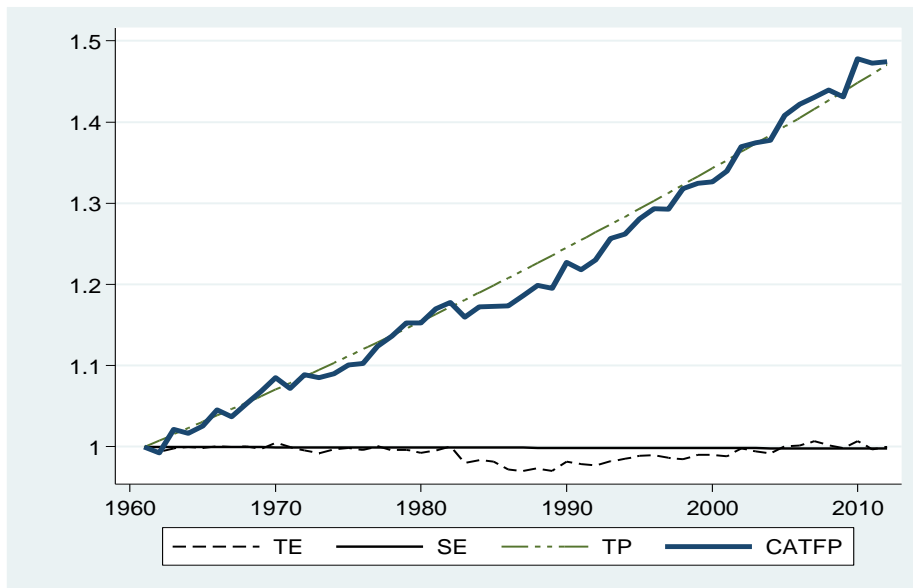
(1961-2000 vs 2001-2012) (%)
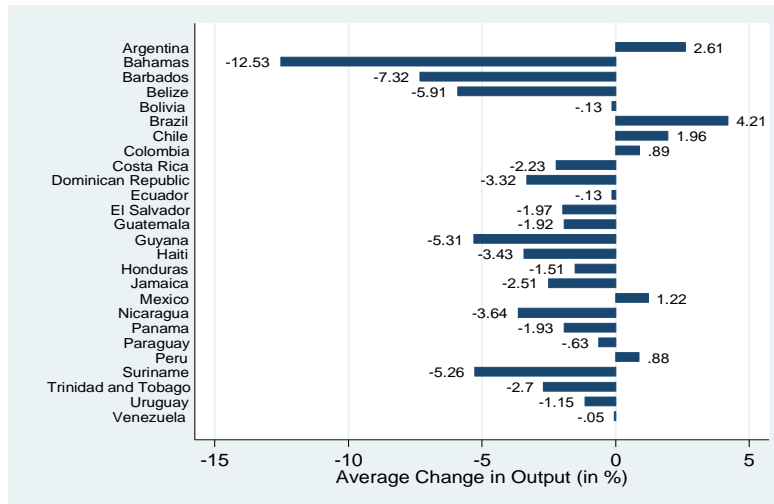
Source: Authors calculations.

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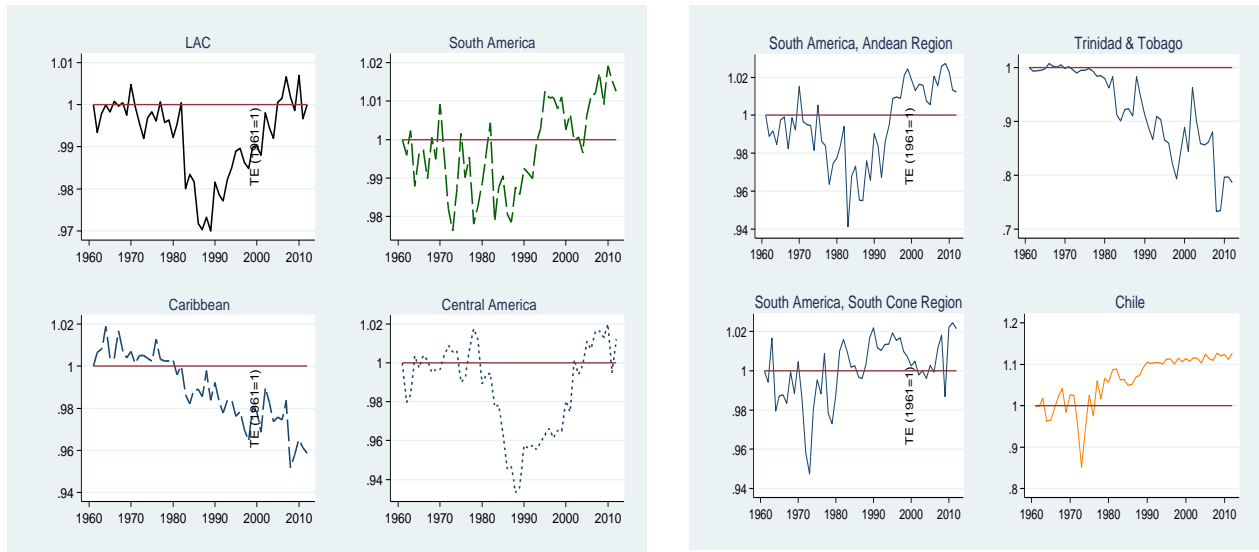

Source: Authors calculations.

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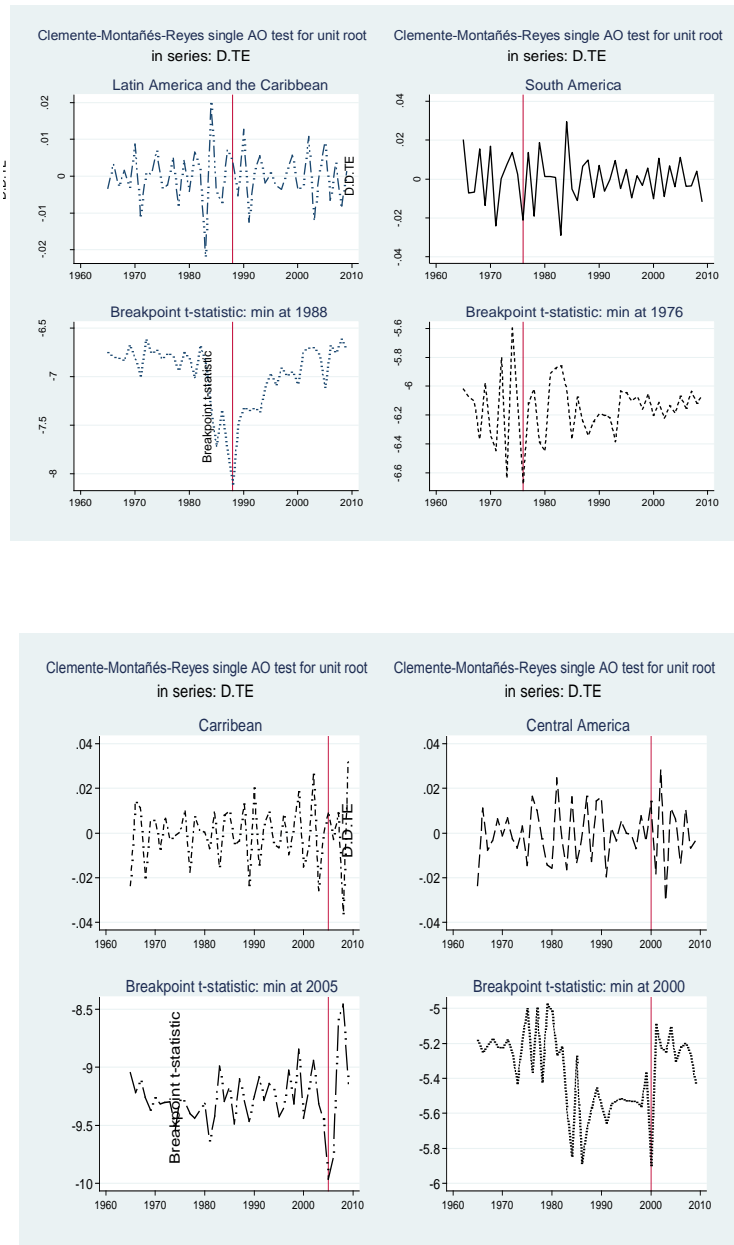

Source: Authors calculations.

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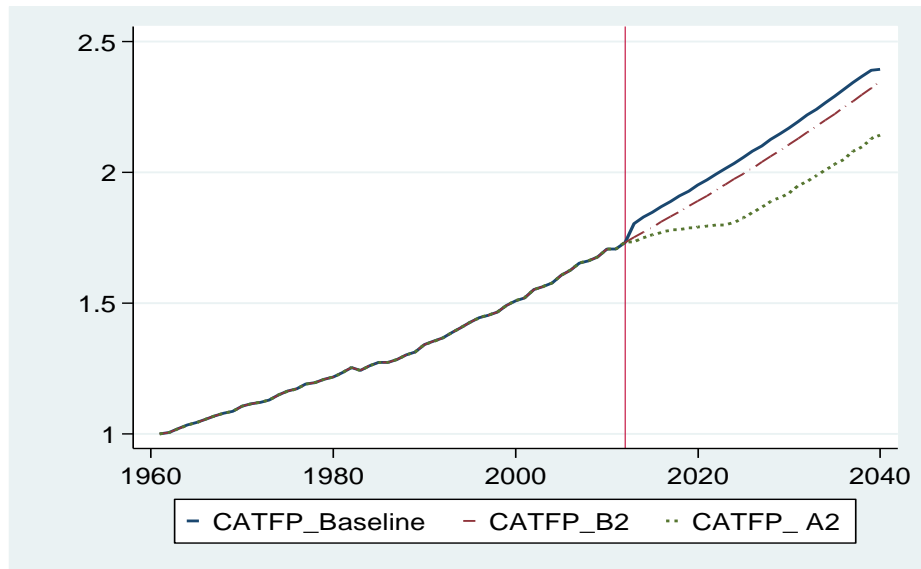

Source: Authors calculations.

Figure 7: Structural break and Unit Root test for LAC and Sub-Regions, 1961-2012

Source: Authors calculations.

Figure 8: Historical and Projected Cumulative CATFP across LAC countries, 1961-2040 (1961=1)

Source: Authors calculations.

APPENDIXES

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

	Maximum Temperature		Precipitation	
	Scenario A2	Scenario B2	Scenario A2	Scenario B2
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
DR	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	1.8	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	1.73	1.33	-13.87	-4.33
Average	1.73	1.33	-13.87	-4.33
South America	4	2.5	-40	-20

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