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Agricultural productivity growth in Latin America and the Caribbean: an analysis of climatic effects, catch-up and convergence*

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This paper investigates whether climatic adjusted total factor productivity (CATFP) in Latin America and the Caribbean (LAC) is converging, converging to different steady states or exhibit absolute convergence, that is the process does not require (government) interventions to reach its equilibrium path. We use data from the University of East Anglia's Climatic Research Unit and from the Food and Agriculture Organization for 28 LAC countries over a 54-year period (1961–2014) to estimate random parameters stochastic production frontier models to calculate CATFP and then use cross-sectional regressions and an error correction model to analyse CATFP convergence across countries in the region. The results show that technological progress is the main driver of CATFP growth in the region and there is no absolute convergence, that is CATFP gaps across countries will not decrease over time and least performing countries will not grow faster than better performing ones without targeted policies. However, CATFP across LAC exhibits conditional convergence towards different steady states. Technological progress plays a critical role in raising the steady state level of CATFP with an overall average of 2.22 per cent per annum.

Key words: agriculture, catch-up, climatic effects, convergence, total factor productivity.

1. Introduction

Agriculture is an important sector in the economies of Latin America and the Caribbean (LAC) countries for a number of reasons. On average, farming accounted for 38 per cent of the land area and for 4.7 per cent of the gross domestic product (GDP) in 2015–2017. Moreover, the region produces about 23 per cent of global agricultural exports while employing 16 per cent of the regional workforce (ECLAC, 2014; OECD-FAO, 2019). Agriculture in LAC is also important globally because it represents 15 per cent of the world's farmed area, thus constituting a great reserve of arable land and one of the

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most diverse and complex farming systems on the planet (OECD-FAO, 2019).

Farm output depends largely on environmental and agro-climatic conditions such as soil type, typography, temperature and precipitation patterns. Climate change is expected to have significant repercussions in production decisions, choice and use of inputs, and on agricultural productivity (IPCC, 2014; Stevanović *et al.* 2016; Mccarl *et al.* 2016). Output and productivity losses will likely increase food prices and adversely affect all dimensions of food insecurity, which in turn would impact social well-being not only for LAC countries but worldwide (e.g. Irz *et al.* 2001; Alston *et al.* 2009; Baldos and Hertel, 2014). Several studies have shown that agricultural production is particularly vulnerable to climatic conditions in least developed countries (LDCs) and this situation is compounded by low levels of investment in agricultural research (Heisey, 2001; Stads *et al.* 2016). For instance, a number of studies have found considerable variability in total factor productivity (TFP) growth across LAC countries and very low growth rates in many cases (Ludena *et al.* 2007; Bharati and Fulginiti 2007; Avila *et al.* 2010; Hofman *et al.* 2017; Lachaud *et al.* 2017).

In order to design policy instruments to enhance the resilience of agriculture, it is important to quantify the effects that climatic variables have on production and productivity growth. Accounting for the effect of climatic variables on output is essential so that reliable productivity measures can be derived (Njuki *et al.* 2019; Chambers and Pieralli, 2020). In addition, the exclusion of climatic variables in the production function, something that has been quite common, is a classic example of omitted variables (Griliches, 1957). This practice can lead to biased parameter estimates and in turn to misleading TFP measures (e.g. Lachaud *et al.* 2017; Njuki *et al.* 2019; Julien *et al.* 2019).

Another important issue is to evaluate whether countries are becoming more efficient over time. In the production frontier literature, this phenomenon is known as 'catch-up' and it can be defined as movements towards the agricultural frontier of the best performing country or as efficiency change improvements (Färe *et al.* 1994; Kumbhakar *et al.* 1997; Kumar and Russell 2002). In the analysis below, we use a true random parameter stochastic production frontier (TRP-SPF) model discussed in more detail in the methodology section. At this early point, it is useful to underscore that when the SPF is specified as a random parameters model the assumption of a common frontier can be relaxed given that heterogeneity in technology and parameter estimates are specific to a decision-making unit (Tsionas, 2002). In other words, in the standard SPF model inefficiency is measured with respect to a frontier that is common to all decision-making units in the sample. In contrast, the TRP-SPF makes it possible to segregate unit-specific inefficiency from technological differentials across units (Akhavein *et al.* 1997; Tsionas, 2002). Thus, in this study 'catching up' denotes improvements in efficiency change over time and is a measure of how different countries are moving towards their own frontier.

Another different but important research question is whether agricultural TFP in the region is increasing and can be sustained while reducing its dispersion across countries over time, a notion known as absolute σ-convergence (Lichtenberg 1994; Sala-i-Martin 1996; McCunn and Huffman 2000; Wang *et al.* 2019). An alternative convergence concept is whether countries with lower TFP levels grow relatively faster than those with higher ones, which is known as absolute β-convergence (Solow 1956; Baumol 1986; De Long 1988; Barro 1991, 1997; Mankiw *et al.* 1992). These two notions of absolute convergence (σ and β) imply that TFP levels across countries are moving towards a common steady state (e.g. Sala-i-Martin 1996; Miller and Upadhyay 2002). In addition, we investigate whether agricultural TFP levels in the region are conditionally β-convergent (e.g. Miller and Upadhyay 2002). This latter notion assumes that convergence is contingent upon policy choices made by each country or country-specific characteristics; therefore, conditional β-convergence would lead towards different steady states across countries (Sala-i-Martin, 1996; Miller and Upadhyay 2002; Liu *et al.* 2011).

Several studies have investigated convergence in US agriculture and other regions of the world (e.g. Ball *et al.* 2004; Liu *et al.* 2011; Ball *et al.* 2014); however, only a few have focused on LAC (e.g. Ludena *et al.* 2007; Astorga *et al.* 2011). Salient contributions to the empirical convergence literature include Barro (1991), Baumol (1986), De Long (1988), and Mankiw *et al.* (1992). It is important to note that TFP convergence analysis in agriculture has important policy ramifications for sustaining productivity (Di Liberto *et al.* 2008; Espoti 2011; Ball *et al.* 2014).

This study pursues two objectives. First, we estimate the impact of climatic effects on production and compute a climatic adjusted total factor productivity (CATFP) index to assess how changes in temperature and precipitation patterns affect output and productivity. Second, we investigate climate-adjusted total factor productivity convergence in the region and assess whether agricultural policy interventions are needed to ensure its occurrence. To this end, in this article, we estimate true random parameters stochastic production frontier models to calculate and analyse CATFP. Then, we use cross-sectional regressions to analyse absolute convergence, and panel data techniques to derive an error correction model (ECM) to examine long-run dynamics of CATFP and to test for conditional convergence. The few studies in the region that investigate convergence rely on time series analyses, which might lead to biased estimates in the presence of cross-sectional dependence (Westerlund 2007; Cavalcanti *et al.* 2015; Gengenbach *et al.* 2016; Ertur and Musolesi 2017). In this paper, we use panel data unit root and cointegration tests that account for cross-sectional dependence and provide robust estimates while allowing for different steady states across countries.

Our analysis confirms the importance of accounting for environmental factors and climatic effects across countries when estimating agricultural production frontiers and computing productivity indexes. The analysis reveals that climatic effects have had adverse impacts on production and productivity and that country-level time-invariant environmental factors have a heterogeneous effect across countries. There is no evidence of absolute convergence, that is on average, countries in the region would not arrive to their steady developmental path without government interventions. However, the findings do reveal that some countries in the region conditionally converge towards different steady states due to access or use of the best available technologies and technological progress. Technological progress plays a critical role in reaching and raising the steady state level of CATFP. Therefore, government interventions and country-specific policies would be needed to encourage CATFP convergence in LAC. The remainder of this paper is structured as follows: Section 2 presents the theoretical framework; Section 3 focuses on the data; Section 4 presents the results; and Section 5 contains a summary and concluding remarks.

2. Theoretical framework

We first use true random parameters stochastic production frontier (TRP-SPF) models to estimate agricultural production frontiers. The TRP-SPF captures unobserved heterogeneity, through observation specific intercept and slope parameters, reflecting the effects of technological, environmental and input quality not captured explicitly in the data and potentially affecting the production process. The model can also identify separately time variant technical efficiency (Greene, 2008). Our TRP-SPF model specification is similar to the standard Random Parameter (RP) framework (Wooldridge, 2005) and to models in Tsionas (2002), and Greene (2005a, 2005b, 2008), where the slope parameters are random only across decision-making units and not over time. Cross-country variation captured by random slope parameters in the production frontier is the central focus of the TRP-SPF specification analysis (Greene 2008, p. 222). Examples of early contributions of this framework include Kalijaran and Obwona (1994), Tsionas (2002), Greene (2005a, 2005b) and more recent applications can be found in Lachaud *et al.* (2017) and Njuki *et al.* (2019). The TRP-SPF estimates are then used to calculate and decompose CATFP.

Specifically, we estimate the following TRP-SPF model:

$$y_{it} = \mu_i + \sum_{k=1}^{K} \beta_{ik} x_{kit} + \lambda_i T_i + \sum_{j=1}^{J} \eta_j z_{jit} + v_{it} - u_{it} \tag{1}$$

where y_{it} denotes the natural logarithm (log) of agricultural production for the i-th country in the t-th time period;x_{kit} is a ($1 \times K$) vector of inputs (expressed in logs), which includes land, labour, machinery, fertiliser, animal stock and feed; T is a time trend that accounts for technological progress; z_{jit}

is a set of climatic variables expressed in levels (Jones and Olken, 2010); μ_i is a country-specific, normally distributed random intercept parameter that captures time-invariant unobserved heterogeneity; and β_{ik} is an $(i \times k)$ matrix of random slope parameters that are normally distributed and account for heterogeneity in inputs used. All Greek letters are parameters to be estimated. The term v_{it} is a random error assumed to follow a normal distribution with mean zero and constant variance $(v_{it} \sim iidN(0, \sigma_v^2))$, and u_{it} is a non-negative unobservable random term that captures the inefficiency of the *i*-th country in period *t*. The inefficiency term u_{it} is assumed to follow a half-normal distribution. The specification of the climatic variables in Equation 1 follows the growing body of the related literature, which is based on year-to-year variation in climatic variables and has a strong causative interpretation that allows for the identification of the net effect of climatic variables on agricultural production and productivity (Dell *et al.* 2014). Equation 1 is estimated using maximum simulated likelihood (MSL) methods.

We then use the TFP index methodology proposed by O'Donnell (2016, 2018) to calculate and decompose CATFP. Specifically, the index that compares CATFP of country *i* at time *t* with that of country *m* in period *s* can be expressed as follows:

$$CATFPI_{msit} = \frac{CATFP_{it}}{CATFP_{ms}} = \frac{Y_{it}(X_{it})}{Y_{ms}(X_{ms})} \tag{2}$$

where $Y_{it} \equiv Y(y_{it})$and $X_{it} \equiv X(x_{it})$are aggregate output and aggregate input functions that are assumed to be non-decreasing, non-negative, and linearly homogeneous. Then, using the TRP-SPF model given by Equation 1 by taking its antilogarithm, Equation 2 can be rewritten as follows:

$$\begin{aligned} CATFPI_{msit} = {} & \left[e^{(\alpha_i - \alpha_m)}\right] \times \left[\prod_{k=1}^{K} \left(\frac{x_{kit}}{x_{kms}}\right)^{\beta_{ki} - b_k}\right] \times \left[e^{(\tau_t - \tau_s)}\right] \times \left[\prod_{j=2}^{J} \left(\frac{z_{jit}}{z_{jms}}\right)^{\eta_j}\right] \\ & \times \left[\frac{\exp(-u_{it})}{\exp(-u_{ms})}\right] \times \left[\frac{\exp(v_{it})}{\exp(v_{ms})}\right] \end{aligned} \tag{3}$$

The components in Equation 3 are as follows: the first right-hand term in square brackets is an index that captures country time-invariant unobserved heterogeneity (UH); the second term measures relative change in scale efficiency (SE), where $b_k = \frac{\hat{\beta}_k}{\sum_{i=1}^{K} \hat{\beta}_k}$ and $\hat{\beta}_k$ is an estimator of β_k; the third term is the relative change in technological progress (TP); the fourth term is the change in climatic effects (CE) given by variations in climatic conditions; the fifth component measures relative change in technical efficiency (TE) calculated according to Jondrow *et al.* (1982); and the last term, (SN), captures functional form error, statistical noise, and other sources that cannot be determined (O'Donnell 2016). All parameters written in Greek letters are as defined above.

2.1 Catch-up

Recall that catch-up denotes the movement of countries towards their own frontier coming from improvements in TE; hence, catch-up means that the term u_{it} is shrinking over time. Therefore, we can use the inefficiency estimates from equation 1, which are country-specific and time-varying, to measure the distance of a given country at a specific time with respect to its own frontier to investigate catch-up. Changes in TE are the cumulative sum over time where 1961 is the base year.

2.2 Convergence

We now turn to the analysis of CATFP convergence. As noted above, in this study we are concerned with two types of convergence (Miller and Upadhyay, 2002). First, absolute σ-convergence takes place when the cross-country distribution of CATFP levels decreases and gets tighter as time goes by (Miller and Upadhyay 2002). In comparison, β-convergence indicates there is a negative correlation between CATFP growth and levels implying that countries with low CATFP grow relatively faster than those with higher ones (Barro 1997; Baumol 1986; Solow 1956; Mankiw *et al.* 1992; Bernard and Jones 1996; Liu *et al.* 2011). The β-convergence could be *absolute* implying that all countries are converging towards a common steady state without government intervention, or *conditional* suggesting instead that each country is converging towards its own steady state as a consequence of national economic policies (e.g. Sala-i-Martin 1996; Miller and Upadhyay 2002; Liu *et al.* 2011).

We first test for absolute σ-convergence, based on cross-sectional data, using the following model (Lichtenberg 1994; Wang *et al.* 2019):

$$Var[(\log(CATFP_t)] = \theta_1 + \theta_2 T + \varepsilon_t \tag{4}$$

where the dependent variable is the variance of CATFP in log across countries in period t, T is a time trend, ε is a zero-mean random error term, θ_1 and θ_2 are parameters to be estimated. According to this specification, absolute σ-convergence occurs when the estimated parameter $\theta_2 < 0$ and is statistically significant.

Then, we test for the absolute β-convergence hypothesis, which is also based on cross-sectional data, to examine whether countries with lower CATFP levels will grow faster than their most productive counterparts, implying that all countries are moving towards a common steady state (Solow 1956; Barro 1997; Fung 2005; Ball *et al.* 2014). We test absolute β-convergence using the standard convergence equation:

$$G_i^{t_0-T} = \pi_1 + \pi_2 CATFP_{t_0} + \xi_i \tag{5}$$

where $G_i^{t_0-T}$ denotes CATFP growth in the i^{th} country between the initial and final periods represented, respectively, by t_0 and$T$, π_1 and π_2 are parameters to be estimated, and ξ is a random error term. A significant negative estimate of parameter π_2 is evidence of absolute β-convergence.

Subsequently, we test the conditional β-convergence hypothesis of CATFP using a more robust approach based on panel data Unit Root and Cointegration tests (Westerlund 2007). A time series with a convergent long-run trend should be either stationary or cointegrated because it has a common stochastic drift. That is, the series depicts a similar long-run pattern and it does not scatter over time. We test for the conditional β-convergence hypothesis using the following dynamic growth model:

$$\log(CATFP_{it}) = \theta_i + \psi_i \log(CATFP)_{it-1} + \gamma_i T + \varepsilon_{it} \tag{6}$$

where all variables are as previously defined and the parameters written in Greek letters are coefficients to be estimated. Given data limitations for LAC for our whole sample, we are unable to include additional variables in Equation 6 to test for conditional β-convergence as it is common in the existing literature. However, as argued by Miller and Upadhyay (2002) and Miketa and Mulder (2005), with the panel data approach there is no need to include additional explanatory variables to test for conditional convergence since the intercept responds to country-specific effects. By subtracting $log(CATFP)_{it-1}$ from both sides of Equation 6, we obtain the following error correction model (ECM):

$$\Delta\log(CATFP_{it}) = \theta_i + \alpha_i \log(CATFP)_{it-1} + \gamma_i T + +\varepsilon_{it} \tag{7}$$

where Δ denotes first difference and $\alpha_i = (\psi_i - 1)$ represents the error correction (EC) coefficient that measures the speed of adjustment towards the long-run equilibrium or steady state. A value of $\alpha_i \in [-1,0]$ indicates that CATFP levels converge monotonically towards the steady state; if $\alpha_i \in [-2,-1]$ we have oscillatory convergence; and, if $\alpha_i \in [-2,\infty]$ CATFP levels diverge.

3. Data

The data used in this study come from different sources. We use an FAOSTAT (2019) input–output dataset which is a balanced panel covering the 54-year period going from 1961 to 2014 for 28 LAC countries for a total of 1,512 observations.[1] This dataset, or earlier versions of it, has been used in several empirical studies (e.g. Bharati and Fulginiti 2007; Fuglie *et al.* 2012;

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[1] LAC countries are divided into three sub-regions: 1) Caribbean which includes The Bahamas, Dominican Republic, Cuba, Haiti, Jamaica, Puerto Rico 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, French Guiana, Guyana, Peru, Suriname, Uruguay, Paraguay, and Venezuela.

Table 1 Descriptive statistics ($N = 28$ countries, T = 54 years, sample size = 1512)

Variable	Unit	Mean	SD	Min.	Max.
OUTP (Production)	US dollars	5.93	15.70	0.00	150
MAC (Machinery)	40-HP tractor equivalent	47.25	131.76	0.02	1000
FER (Fertiliser)	'000 MT	316.36	1156.84	0.03	14000
ANS (Animal stock)	Livestock units (LU)	14.71	35.26	0.00	258.8
FED (Feed)	'000 MT	3097.20	8281.11	0.02	73000
LAN (Land)	hectares	5957.10	13438.65	2.00	93640
LAB (Labour)	'000 people	1473.53	2888.32	4.00	16345
$\mathrm{TMP}_{\mathrm{A}}$ (Temperature anomaly)	° C	0.18	0.42	−1.61	1.43
$\mathrm{TMP}_{\mathrm{AV}}$ (Monthly average temperature)	° C	23.31	3.89	7.93	27.06
$\mathrm{PRE}_{\mathrm{A}}$ (Precipitation anomaly)	Millimetres	−18.70	294.1	−1137.20	1558.0
$\mathrm{PRE}_{\mathrm{AV}}$ (Monthly average precipitation)	Millimetres	151.77	57.88	36.34	307.23

Kahsay and Hansen 2016; Lachaud *et al.* 2017). Output ($OUTP$) is given by the gross value of agricultural production which is an aggregate measure of 189 crop and livestock products, assessed at constant global-average prices from 2004–2006 in international 2005 US Dollars (see Fuglie *et al.* 2012 for more details). There are six conventional inputs: Land (LAN), Labour (LAB) Machinery (MAC), Fertiliser (FER), Animal Stock (ANS), and Animal Feed (FED). LAN is total agricultural land in hectares of rain-fed cropland equivalents defined as the weighted sum of rain-fed and irrigated cropland plus permanent pasture expressed in thousands of hectares; LAB is the total economically active population in agriculture expressed in thousands of persons; MAC is agricultural machinery in thousands of 40-horse power tractor equivalents derived by aggregating the number of 2-wheel tractors, 4-wheel tractors, and combine-harvesters used in the production process; FER represents the quantity of nitrogen, phosphorous and potassium applied in thousand metric tons; FED is defined as the quantity of dry matter-equivalent of total animal feed from crops, crop processing residues, animal and fish products measured in thousands of metric tons; and ANS is thousands of cattle, sheep, goat, pigs, chicken, turkeys, ducks and geese expressed in Livestock Unit (LU) equivalents weighted by the respective size of each specie (See Kawagoe *et al.* 1985 for further details) (Table 1).

Our climatic data are from the Climatic Research Unit (CRU) of the University of East Anglia Climatic Research Unit (CRU) (2013) covering the 1961–2014 period. Our model includes temperature and precipitation measured in degree Celsius and millimetres, respectively.[2] Specifically, we include monthly average temperature (TMP_{AV}) defined here as the average

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[2] See Harris, Jones, Osborn and Lister (2014) for more details about the climatic variables.

temperature across 12 months to capture weather conditions and temperature anomaly (TMP_A) measured as the deviation of each annual observation from the long-term mean (1901–2014) to capture climatic variability. We also include monthly average precipitation (PRE_{AV}) and precipitation anomaly (PRE_A), defined in a manner analogous to temperature.

Agricultural seasons vary widely across LAC countries, but our panel data is annual; hence, it is not possible to use more disaggregated climatic variables. This approach is consistent with Yang and Shumway (2016) who argue that using aggregate climatic data does not capture the substantial variation of climatic conditions within a decision-making unit but makes the empirical estimation possible. Climatic variables are adjusted for weather seasonality using the seasonal trend decomposition (STL) approach based on the local regression (LOESS) procedure. Details on this approach can be found in Cleveland *et al.* (1990), and Craigmile and Guttorp (2011).

4. Results

We estimate true random parameters production frontiers without (TRP*nc*) and with (TRP*c*) climatic variables using a Cobb-Douglas (CD) functional form to approximate the underlying technology. The CD specification makes it possible to derive TFP indexes that are consistent with axiomatic properties related to index numbers (O'Donnell 2016). We use different model specifications and then apply likelihood ratio (LR) tests to compare them.[3] In particular, we estimate the TRP*c* model allowing the parameters associated with the climatic variables to be either random (restricted) or non-random (unrestricted). To test the null hypothesis that $\eta_{ji} = \eta_j \forall j = 1, \cdots, J$ in equation (1), we use a LR test to compare the log-likelihood values of the unrestricted model (LR = 1,062) with those of the restricted model (971) which yields a LR test statistic equal to 182 with a *P*-value of 0.0001. This result indicates that the TRP*c* with non-random parameters for the climatic variables is preferable given our data. The results of the TRP*c* model with random climatic variables are reported in Table S1. Another specification issue concerns the estimated parameter that captures non-linear effects of precipitation on production which is very close to zero but the LR test indicates that this variable should be retained in the model. The findings suggest a significant non-linear effect of average monthly temperature on production (Table 2). In particular, a LR test is conducted to compare the unrestricted specification TRP*c* (including climatic variables) with the restricted specification TRP*nc* (excluding climatic variables). The LR test is used to evaluate the null hypothesis that all associated climatic parameters are zero: $\eta_1 = \eta_2 = \eta_3 = \eta_4 = \eta_5 = \eta_6 = 0$. The unrestricted and restricted log-

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[3] We perform multicollinearity tests for all conventional inputs and climatic variables using the "rmcoll" syntax in Stata 14 (Cameron and Travedi 2005). The evidence does not support the presence of multicollinearity.

Table 2 Estimates for the TRP-SPF Models without (TRP*nc*) and with climatic variables (TRP*c*)

$N = 1512$	Model TRP*nc*		Model TRP*c*	
Variable	Coeff.	SE	Coeff.	SE
Constant	10.984***	0.049	12.669***	0.077
MAC	0.068***	0.003	0.095***	0.004
FER	0.116***	0.003	0.065***	0.005
ANS	0.085***	0.005	0.258***	0.005
FED	0.067***	0.003	0.056***	0.005
LAN	0.383***	0.004	0.232***	0.007
LAB	0.306***	0.004	0.280***	0.006
T	0.0121***	0.000	0.019***	0.000
TMP_{A}			−0.021*	0.011
TMP_{AV}			−0.014***	0.002
$\text{TMP}^{2}{}_{\text{AV}}$			−0.003***	0.000
PRE_{A}			0.001***	0.000
PRE_{AV}			−0.002***	0.000
$\text{PRE}^{2}{}_{\text{AV}}$			1.9E-04***	0.000
λ	2.322***	0.194	2.568***	0.224
σ	0.164***	0.004	0.164***	0.004
σ_u	0.150	n/a	0.153	n/a
σ_v	0.064	n/a	0.056	n/a
RTS	1.03		0.99	
TE				
Mean	0.886		0.889	
SD	0.064		0.066	
Min	0.572		0.575	
Max	0.987		0.985	
Log-likelihood	997.05		1061.9	

Note: ***, **, * are 1 per cent, 5 per cent, and 10 per cent level of significance, respectively.
Conventional input variables are measured in natural log.
SE, Standard error; n/a, Not available.

likelihood values are 1,062 and 997, respectively, and the likelihood ratio test statistic is 130, which is higher than the critical $\chi^2_{95,6}$ value of 12.6. This result supports the TRP*c* model with climatic variables and thus is the one we employ to calculate and analyse CATFP. It is worth noting that all the parameters, including those for the climatic variables, are highly significant except the one for temperature anomaly which is significant at the 10 per cent level. Average parameter estimates for individual countries are reported in Table S2. The results in Table 2 show that an increase in average temperature (monthly and yearly) would have a significant and negative impact on production, and that the negative impact of the monthly average temperature is increasing over time. In addition, the findings show that an increase in precipitation anomaly has a positive and significant impact on production. This result is not surprising since the sample mean of precipitation anomaly is negative ($-PRE_A = -18.7$, see Table 1) implying that on average annual precipitation has been below the long-term average (1901–2014). Given that the long-term average is fixed, an increase in precipitation anomaly is associated with an increase in annual average precipitation in the region where approximately 90 per cent of farmland is rain-fed (Wani *et al.* 2009); hence, the positive effect on production.

4.1 Total factor productivity gap analysis

In the context of this study, the term gap is used to denote a significant difference in CATFP measures across countries. In Table 3, columns (1)-(6) report CATFP for 1961 and average CATFP across LAC countries per decade, column (7) shows CATFP for 2014, the last year of the data and column (8) displays the average annual growth rate of CATFP. We compare the CATFP of each country with that of Chile, which exhibits the highest CATFP in 2014 at 3.17 (column 7). 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. In other words, we use the performance of Chile in 1961 (CATFP = 1.0) as a benchmark but we could have chosen any other country or year and obtain consistent results, and this is precisely the attractiveness of the transitivity property (O'Donnell 2016).

Table 3 reveals significant gaps in CATFP across countries. By the end of the 1961–1970 decade, Chile had experienced an 8 per cent average per cent change growth in CATFP compared to 1961 and a number of other countries had also enjoyed significant productivity growth. Exceptions are Belize, Cuba, Ecuador, Guyana, and Trinidad & Tobago, all of which exhibited a decline in CATFP. Countries like Argentina, Dominican Republic, El Salvador, Jamaica, Paraguay and Peru experienced very little change; and, Haiti, Panama and Puerto Rico showed a sign of stagnation. The decades of the 70s and 80s were economically challenging compared to the 1990s in terms of average growth rates across countries. During the 2000s, Chile, Costa Rica, and Brazil increased considerably their gaps compared to the other countries. During that period, most countries in the region enjoyed substantial positive CATFP growth except for French Guiana, and Trinidad & Tobago where productivity kept declining. Belize, Panama, and to some extent Suriname displayed very little growth.

Only Cuba (−0.14 per cent), French Guiana (−0.21 per cent) and Trinidad & Tobago (−0.64 per cent) had negative CATFP growth rates over the 1961–2014 period, while Chile displayed the highest average growth (2.2 per cent), followed by Costa Rica (2.18 per cent) and Brazil (2.01 per cent). The average CATFP for all countries in LAC, has risen at an annual growth rate of 0.98 per cent over the 1961–2014 period.

We now provide a brief analysis of the components of CATFP growth. Figure 1 shows that technological progress (TP) has been the key driver of agricultural productivity gains in the region and this finding is consistent with several other studies (e.g. Bharati and Fulginiti 2007; Lachaud *et al.* 2017).

Table 3 CATFP, average CATFP by decade, annual and growth rate in LAC, 1961–2014 (Chile: 1961 = 1)

Countries	(1) Year 1961	(2) Decade 1961–1970	(3) Decade 1971–1980	(4) Decade 1981–1990	(5) Decade 1991–2000	(6) Decade 2001–2010	(7) Year 2014	(8) Annual growth rate (1961–2014)
Argentina	0.83	0.84	0.89	0.99	1.08	1.30	1.34	0.92
Bahamas	1.44	1.55	1.91	1.99	2.09	2.74	2.88	1.32
Bolivia	0.88	0.94	1.09	1.17	1.36	1.67	1.71	1.25
Brazil	0.65	0.70	0.76	0.93	1.17	1.83	1.88	2.01
Belize	1.02	0.99	1.14	1.26	1.41	1.43	1.45	0.67
Chile	1.00	1.08	1.19	1.48	2.08	3.08	3.17	2.20
Colombia	0.59	0.65	0.77	0.90	1.15	1.62	1.69	1.99
Costa Rica	0.94	1.01	1.27	1.45	2.03	2.98	2.95	2.18
Cuba	1.65	1.44	1.46	1.58	1.37	1.51	1.53	−0.14
Dominican Republic	0.93	0.92	0.94	0.97	0.93	1.27	1.27	0.6
Ecuador	1.43	1.37	1.28	1.39	1.54	1.83	1.84	0.47
El Salvador	0.59	0.60	0.66	0.67	0.72	0.85	0.85	0.71
French Guiana	0.72	0.68	0.60	0.53	0.66	0.62	0.64	−0.21
Guatemala	0.95	1.06	1.27	1.37	1.65	2.27	2.36	1.74
Guyana	0.83	0.78	0.78	0.80	0.93	1.14	1.17	0.65
Haiti	0.48	0.48	0.52	0.52	0.48	0.60	0.59	0.40
Honduras	1.23	1.38	1.50	1.59	1.76	2.47	2.52	1.37
Jamaica	1.87	1.90	1.92	1.91	2.21	2.59	2.61	0.64
Mexico	0.78	0.86	1.02	1.19	1.35	1.93	2.02	1.83
Nicaragua	1.10	1.16	1.21	1.01	1.04	1.48	1.49	0.57
Panama	0.84	0.84	0.92	0.94	0.90	0.93	0.93	0.19
Paraguay	0.80	0.83	0.92	1.00	1.02	1.22	1.25	0.85
Peru	0.83	0.87	0.89	0.93	1.05	1.45	1.45	1.06
Puerto Rico	1.28	1.28	1.32	1.47	1.63	2.00	2.02	0.87
Suriname	0.51	0.57	0.63	0.65	0.61	0.69	0.72	0.64
Trinidad and Tobago	1.27	1.19	1.09	0.98	0.95	0.92	0.90	−0.64
Uruguay	1.05	1.13	1.28	1.51	1.77	2.36	2.48	1.63
Venezuela	0.73	0.82	0.97	1.15	1.40	1.88	1.88	1.81
LAC								0.98

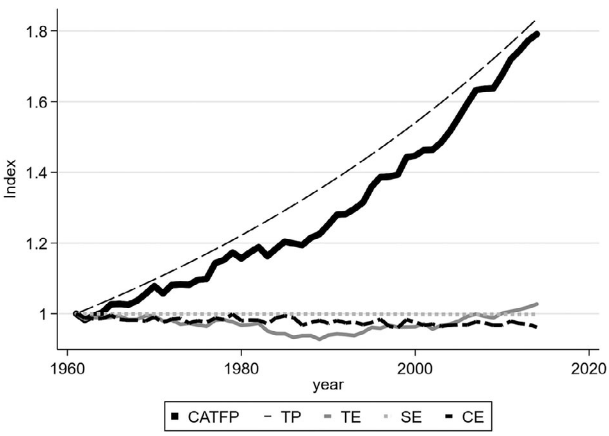

Figure 1 Cumulative CATFP, technical efficiency (TE), technological progress (TP), scale efficiency (SE) and climatic effects (CE) in LAC, 1961–2014 (1961 = 1).

The evolution of the scale efficiency measure indicates that it has remained quite flat over time without much of an effect on productivity. This result is consistent with the close to constant returns to scale of the technology (RTS = 0.99, see Table 2). On the other hand, technical efficiency was more or less constant during the first two decades followed by a decline and then a slight increase in the last decade. Finally, since the mid-1980s, CE has been decreasing suggesting a negative impact of climatic variability on productivity over time.

4.2 Catch-up

Recall that catch-up occurs when countries are getting closer to their own frontier and to examine this, we analyse the temporal behaviour of cumulated TE. Figure 2 reveals that South American countries had a downward trend over the first two decades and started catching up to their own production frontier in the middle of the 1980s followed immediately by Central American countries whereas for Caribbean countries catching up is not seen until the end of the 1990s.

The observed catch-up effect in South and Central America corresponds with successful macroeconomic structural reforms, undertaken by most countries in these sub-regions in the late 1980s and the beginning of the 1990s. These reforms included fiscal and monetary policies designed to control inflation, the adoption of a more flexible exchange rate regimes, and a shift away from import substitution policies that were detrimental to the region's most competitive farmers (Loayza and Fajnzylber 2005; Ludena 2010; Anderson and Valenzuela 2010; Corbo and Schmidt-Hebbel 2013; Nin-Pratt *et al.* 2015). On aggregate, the region saw a decline in catching up from 1960 to the 1980s, with a reversal from the 1990s onwards.

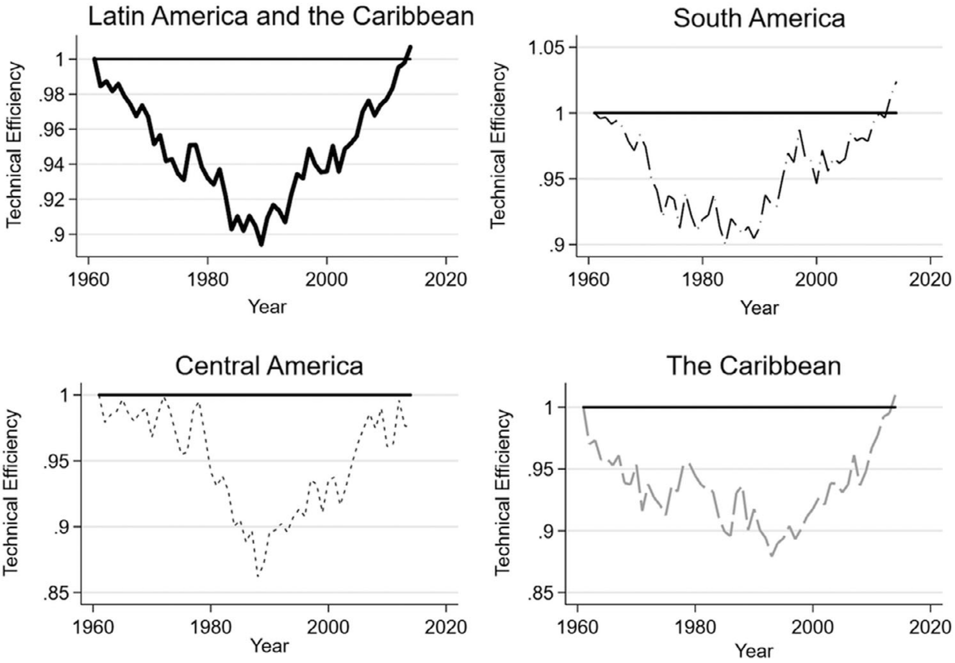

Figure 2 Technical efficiency ‘catch-up’ index for LAC, 1961–2014 (1961 = 1).

4.3 Convergence

Now we turn to the analysis of CATFP convergence, that is we examine whether dispersion of CATFP levels across countries are decreasing over time (absolute σ-convergence), or if there is a negative correlation between CATFP levels and its rate of growth (absolute or conditional β-convergence) (e.g. Lichtenberg 1994; Wang *et al.* 2019). We first test for absolute σ-convergence and the results, shown in Table 4, indicate a clear rejection of the σ-convergence hypothesis across all sub-regions since the estimated parameter for the time trend is positive. These findings are similar to those of McCunn and Huffman (2000), and of Liu *et al.* (2011) who do not find σ-convergence of agricultural productivity across US states. These authors argue that the rejection of this hypothesis is primarily due to short-term conditions, such as weather variability, demand shocks and farm pests among

Table 4 Absolute σ-convergence test results

Regions	Trend coefficient	SE	Adjusted R^2
LAC	0.002***	0.0001	0.87
South America	0.003***	0.0001	0.88
Central America	0.003***	0.0001	0.88
The Caribbean	0.002***	0.0001	0.83

Note: *** is 1 per cent level of significance.

other variables that likely affect agricultural outcomes. More generally, this result is consistent with the literature that finds no evidence of absolute convergence for developing countries which imply that convergence requires the implementation of specific government strategies and policies (Miller and Upadhyay 2002; Liu *et al.* 2011).

Second, we investigate absolute β-convergence, which occurs when there is a negative correlation between CATFP and its growth rate indicating that all LAC countries converge to the same steady state. We use five-year moving averages for CATFP growth to reduce random noise as in Ball *et al.* (2004). The results in Table 5 show that the estimated coefficients associated with initial CATFP levels (i.e. CATFP in 1961) have the wrong expected sign for absolute β-convergence across all sub-regions, except for South America or when considering LAC as a whole, and are not statistically significant. Thus, there is no evidence that the least performing countries are growing faster than the best performing ones in the region, indicating that CATFP levels are not converging to the same steady state.

As the analysis shows no evidence of absolute convergence, we now use a Panel Data approach to test whether CATFP levels in the region are conditionally β-convergent and thus moving towards different steady states. Applications of panel data to study conditional β-convergence include Suhariyanto and Thirtle (2001), Ball *et al.* (2004), Liu *et al.* (2011), Espoti (2011), Ball *et al.* (2014), and Wang *et al.* (2019). We test whether CATFP exhibits a unit root using Levin-Lin-Chu (LLC) (2002), Breitung (2000), and Hadri (2000) panel stationarity statistical tests. The data show the presence of a unit root in the CATFP series suggesting that it is non-stationary, i.e. there is no long-run dynamics across the series, or that the series are not stationary around a deterministic trend or level (Hamilton 1994). These three unit root tests are based on different assumptions. 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. Breitung (2000) argues that the LLC test loses power when individual-specific trends are taken into consideration. In contrast, the Hadri test is based on the null hypothesis that all panels are stationary versus the alternative that at least some of the panels contain unit roots. The findings of these tests are summarised in Table 6 and show consistently that the series are not stationary and the persistence of shocks in CATFP levels corroborate the

Table 5 Absolute β-convergence test results

CATFP Growth	$CATFP_{1961}$	SD
LAC	−0.004	0.004
South America	−0.002	0.009
Central America	0.003	0.014
The Caribbean	0.0003	0.005

Table 6 CATFP conditional β-convergence across sub-regions: panel unit root tests

Variable	Levels		First Differences	
	Statistic	*P*-Value	Statistic	*P*-Value
CATFP	LLC (bias-adjusted t^*)			
The Caribbean	2.09	0.982	−11.53	0.000
Central America	−0.13	0.444	−13.43	0.000
South America	2.05	0.980	−18.41	0.000
	Breitung (λ^*)			
The Caribbean	2.28	0.998	−8.51	0.000
Central America	3.26	0.999	−7.45	0.000
South America	4.39	1.000	−16.77	0.000
	Hadri (Z^*)			
The Caribbean	28.00	0.000	−1.89	0.970
Central America	43.18	0.000	−1.21	0.887
South America	44.31	0.000	−2.17	0.985

Note: *Is the name of test statistic. See LLC (2002), Breitung (2000) and Hadri (2000) for more details.

rejection of the absolute convergence hypotheses. However, as shown in Table 6, CATFP levels are stationary at first differences across all tests.

As the series are first difference stationary, the next step is to proceed to the analysis of cointegration for potential stationary linear combination among them, which would indicate that they are cointegrated. Before proceeding to the cointegration analysis, we test the hypothesis of cross-sectional dependence using the statistical test of Pesaran (2004) that is based on a fixed effects model as $T(54)>N(28)$ in our sample. The test strongly rejects the null hypothesis of cross-sectional independence for all sub-regions in LAC except for the Caribbean. Specifically, we find that the average absolute correlation of the residuals due to the presence of common shocks and unobserved heterogeneity that affect countries in Central America and South America is 0.164, and 0.14, respectively. This test is highly significant at the 1 per cent level across sub-regions. We next check the robustness of these results by performing the cross-sectional dependence tests developed by Friedman (1937) and Frees (1995), and both of these tests also reject the null hypothesis of cross-sectional independence at the 1 per cent level of significance. Hence, we conclude that there is enough evidence indicating the presence of cross-sectional dependence. In other words, there are common factors affecting CATFP estimates across Central American and South American countries; thus, conventional cointegration tests for time series data that assume cross-sectional independence are likely to yield misleading conclusions. The results of the cross-sectional independence tests are reported in Table S3.

Now, we go on with our cointegration examination starting with the Kao (1999) and Pedroni (2004) cointegration tests. Kao (1999) assumes a cointegrating vector that is the same across all panels and his tests consist of panel-specific estimates of means and do not allow for a time trend. In contrast, the Pedroni tests (1999, 2004) allow for panel-specific cointegrating vectors and the autoregressive coefficient to vary across panels. The results of these two tests, presented in Table 7, reveal that the null hypothesis of no cointegration is strongly rejected at the 1 per cent level of significance. This is true for all the five Kao tests statistics (Modified Dickey-Fuller, Dickey-Fuller, Augmented Dickey-Fuller, Unadjusted Modified Dickey–Fuller and Unadjusted Dickey-Fuller) and for the three Pedroni tests statistics (Modified Phillips–Perron, Phillips–Perron and Augmented Dickey-Fuller). Finally, we use the error correction cointegration tests for panel data developed by Westerlund (2007) and applied in recent empirical studies by Rassenfosse and Potterie (2012), Ball *et al.* (2014), and Pablo-Romero *et al.* (2017). The Westerlund, Kao and Pedroni tests assess the same null hypothesis of no cointegration, but the first one is less restrictive than the latter two because it offers the possibility to test the alternative hypothesis that just some of the panels are cointegrated.

The Westerlund (2007) tests evaluate the null hypothesis of no cointegration ($H_0 : \alpha_i = 0$) for all $i$using the group-mean tests labelled G_τ *and* G_α that do not constrain α_i (see equation 6) to be equal across countries, that is H_0 is tested against the alternative $H_a : \alpha_i < 0$ for at least one country. These tests are based on the null hypothesis of no cointegration for all cross-sectional units and the alternative is that at least some in the panel are cointegrated. In addition, Westerlund offers two other tests labelled P_τ *and* P_α that are based on the null hypothesis of no cointegration ($H_0 : \alpha_i = 0$) for all cross-sectional units and the alternative is $H_a : \alpha_i = \alpha < 0$ implying that all countries in the panel are cointegrated. We bootstrapped robust critical values for the test statistics (G_τ, G_α, P_τ, P_α) because our data exhibit cross-sectional dependence in the errors as explained above. Table 8 displays the outcomes of the Panel cointegration tests across the different sub-regions. The Akaike information criterion (AIC) is used to calculate the optimal length of lag

Table 7 Kao and pedroni panel cointegration tests

Kao	Statistic	*P*-value
Modified Dickey–Fuller *t*	−12.42	0.000
Dickey–Fuller *t*	−9.49	0.000
Augmented Dickey–Fuller *t*	−7.54	0.000
Unadjusted modified Dickey–Fuller *t*	−24.06	0.000
Unadjusted Dickey–Fuller *t*	−12.09	0.000
Pedroni		
Modified Phillips–Perron *t*	−11.83	0.000
Phillips–Perron *t*	−11.60	0.000
Augmented Dickey–Fuller *t*	−11.26	0.000

Table 8 Panel cointegration test across LAC sub-regions

Statistic tests	Value	Z-value	P-value*	P-value**	Value	Z-value	P-value*	P-value**	Value	Z-value	P-value*	P-value**
	The Caribbean				Central America				South America			
G_τ	−8.91	−21.30	0.00	0.02	−8.61	−21.73	0.00	0.00	−10.23	−34.91	0.00	0.00
G_α	−38.79	−10.42	0.00	0.00	−34.48	−9.35	0.00	0.00	−35.25	−12.32	0.00	0.00
P_τ	−22.25	−19.05	0.00	0.05	−23.15	−19.64	0.00	0.00	−33.78	−29.91	0.00	0.01
P_α	−35.85	−11.61	0.00	0.01	−33.19	−11.19	0.00	0.02	−30.68	−12.79	0.00	0.03

Note: The lags in the error correction equation are chosen according to the Akaike information criterion. P-values* are under the normal distribution and P-values** are robust values and based on the bootstrapped distribution (800 runs). Subscripts τ and α indicate different test statistics. See Westerlund (2007) for further methodological details.

for the series. Under the α and τ statistic tests the null hypothesis of cointegration cannot be rejected across all sub-regions (see Westerlund 2007 for details about the statistic tests).

The conclusion from the tests shown in Table 8 and discussed above is that the series are cointegrated, so we can now proceed to test the conditional β-convergence hypothesis of CATFP levels. We use the Pooled Mean-Group (PMG) and Mean-Group (MG) Models (Table 9) developed by Pesaran and Smith (1995), and Pesaran *et al.* (1997, 1999) to estimate the error correction

Table 9 Error correction model (ECM) for CATFP Conditional β-Convergence

Models	PMG Model		MG Model	
$N = 1484$	Coeff.	SE	Coeff.	SE
Long-run coefficients				
T	0.022***	0.001	0.013*	0.007
Short-run coefficients				
Error correction (α_i)	−0.036***	0.008	−0.115***	0.025
Log-likelihood	2588.4			

Note: ***, **, *, $^{\pm}$ are 1 per cent, 5 per cent, 10 per cent and 12 per cent level of significance, respectively. SE, Standard error.

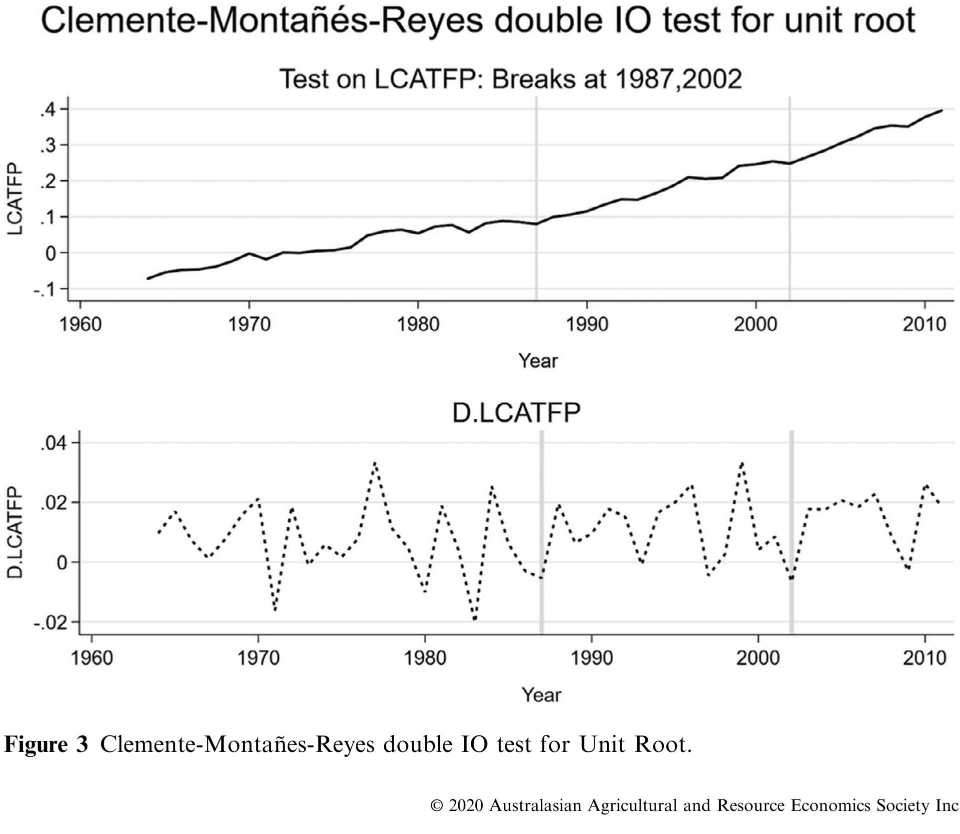

Figure 3 Clemente-Montañes-Reyes double IO test for Unit Root.

model. The MG consists of estimating N time series regressions and averaging the coefficients allowing intercepts, slopes, and error variances to vary across countries. On the other hand, the PMG Model is based on a

Table 10 PMG estimates error correction model (ECM) for CATFP conditional β-convergence with structural breaks

Models	1961–1987		1988–2002		2003–2014	
	Coeff.	SE	Coeff.	SE	Coeff.	SE
Long-run coefficients	0.015***	0.001	0.019***	0.001	0.021***	0.001
Short-run coefficients						
Error correction (α_i)	−0.091***	0.288	−0.064*	0.037	−0.041***	0.009
Log-likelihood	1283.9		696.6		1988.9	

Note: ***, **, *, $^{\pm}$ are 1 per cent, 5 per cent, 10 per cent and 12 per cent level of significance, respectively. SE, Standard error.

Table 11 ECM model for CATFP conditional β-convergence: country individual estimates

Country	α_i	
	Coeff.	SE
Argentina	−0.016**	0.008
The Bahamas	−0.018	0.037
Bolivia	−0.032**	0.015
Brazil	−0.034***	0.008
Belize	−0.017	0.167
Chile	−0.185***	0.048
Colombia	−0.031***	0.006
Costa Rica	−0.162***	0.038
Cuba	−0.021	0.022
Dominican Republic	−0.012*	0.006
Ecuador	−0.034**	0.019
El Salvador	−0.007*	0.004
French Guiana	−0.001	0.006
Guatemala	−0.069***	0.022
Guyana	−0.012	0.09
Haiti	−0.003	0.004
Honduras	−0.074**	0.037
Jamaica	−0.009	0.016
Mexico	−0.043***	0.010
Nicaragua	−0.018	0.014
Panama	−0.002	0.005
Paraguay	−0.016	0.012
Peru	−0.012**	0.009
Puerto Rico	−0.036**	0.015
Suriname	−0.006	0.006
Trinidad & Tobago	0.02	0.009
Uruguay	−0.02***	0.031
Venezuela	−0.041***	0.01

Note: ***, **, and *, are 1 per cent, 5 per cent, 10 per cent and 12 per cent level of significance, respectively. SE, Standard error.

combination of pooling and averaging coefficients and has the same properties as the MG estimator. However, PMG estimators are based on maximum likelihood and constrain long-run coefficients to be equal across countries. Several authors have applied the PMG and MG estimators in recent empirical work including Catao and Terrones (2005), Fedderke (2004), Kim *et al.* (2010), Ndambendia and Njoupouognigni (2010), and Calderón *et al.* (2015).

Country-specific observed or unobserved conditions can affect the speed of convergence of CATFP levels. Ball *et al.* (2004) use relative ratios of capital and intermediate goods as proxies for technical change to examine conditional convergence in agricultural TFP levels across states in the United States. Other studies use education, investment on research, health care supply in rural areas and a time trend as covariates to explain conditional convergence (e.g. Liu *et al.* 2011; Poudel *et al.* 2011; Wang *et al.* 2019). However, these data are not available for all LAC countries in our sample for the 1961–2014 period. Therefore, we assume that long-term CATFP levels are primarily driven by technological progress and short-term deviations from the steady state come from external shocks and country fixed effects (e.g. Miller and Upadhyay 2002; Miketa and Mulder 2005). To capture external shocks and short-term deviations, we implement the two-break Clemente, Montañes and Reyes (1998) statistical test that allows for the joint identification of the presence of a unit root in the series and for structural breaks. The results reveal two breaks in CATFP levels, one in 1987 and the other in 2002, as shown in Figure 3.

The results of the ECM for both PMG and MG estimators are presented in Table 9 for the whole 1961–2014 period. The estimated error correction (α_i) in Table 9, is significant and negative in both models suggesting that CATFP levels, on average, are converging across LAC countries. The error correction that represents the adjustment elasticity is estimated to be $\alpha_i = -0.036$ for the PMG model and $\alpha_i = -0.115$ for the MG model. These elasticities are quite different across the two models, but consistently indicate that, on average, the system is stable and when it is not at long-run equilibrium it would converge towards it. Recall that PMG estimators restrict long-run coefficients to be the same for all countries whereas MG estimators are unrestricted. Therefore, before continuing with the analysis, we compare PMG and MG estimators. Under the null hypothesis of the Hausman test, there are no differences between the two estimators and MG coefficients are consistent and efficient. The test leads to a Hausman statistic with a χ^2_1 distribution equal to 1.81 with a P-value = 0.178. Therefore, we conclude that PMG estimators outperform the MG model. The remaining analysis is thus based on the PMG specification.

The estimated coefficient of the error correction can be interpreted as the absolute proportion of disequilibrium that dissipates by the next period (as we have yearly data, i.e. the next year) and the negative sign means that CATFP is below its steady state value. In our context, the value of

$\alpha_i = -0.036$ from the PMG estimator (Table 9) indicates that CATFP levels in LAC are, on average below its equilibrium value, and that around 3.6 per cent of this estimated disequilibrium in the current year will dissipate by the following year and approximately 96.4 per cent will remain. These results imply very little adjustment towards the long-run equilibrium level which would take up to 37 years for full adjustment.[4] The results also show that technological progress raises the steady state CATFP growth rate by approximately 2.22 per cent per annum as shown in Table 9.

In Table 10, we report the results of the PMG model for the 1961–1987, 1988–2002 and 2003–2014 periods because of the structural breaks in 1987 and 2002. While the adjustment speed is higher during the 1961–1987 period, the estimated long-run parameter that captures technological progress is higher after 2002 implying that structural reforms implemented during this period were effective and that countries were able to move outward their frontier, implying raising steady states during this period compared to previous periods. We also found weaker convergence during the 1988–2002 period as the estimated coefficient of the error correction is only significant at the 10 per cent level of significance.

Although the average convergence speed for the whole 1961–2014 period given by the error correction is 3.6 per cent (Table 9 PMG), it exhibits high volatility across LAC countries ranging from 0.07 per cent (El Salvador) to 18.4 per cent (Chile) as shown in Table 11. CATFP levels for The Bahamas, Belize, Cuba, French Guiana, Guyana, Haiti, Jamaica, Nicaragua, Panama, Paraguay, Suriname, and Trinidad & Tobago are not converging because their estimated α_i is not statistically significant.

5. Summary and concluding remarks

In this article we investigate convergence of climatic adjusted total factor Productivity (CATFP) levels across Latin America and the Caribbean (LAC) countries. While addressing this issue is critical to elaborate effective policies to address changes in climatic conditions, minimise gaps in CATFP across countries and identify factors to raise their steady state levels, very few studies have focused on this topic in LAC countries. After estimating true random parameters stochastic production frontier models, we calculate and decompose CATFP into the following measures: technical efficiency change; scale efficiency change; technological progress (TP); climatic effects (CE); and statistical noise. The results show that climatic variability has negative impacts on agricultural production. In particular, an increase in average monthly and yearly temperature has severe adverse impacts on production and these impacts are significant and vary across sub-regions and countries. Policies that aim to encourage environmentally friendly production

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[4] This number is given by n in the solution of $0.964^n = 1$

technologies, and greater use of improved seeds and management techniques that enhance the resilience of farming systems to climatic variability are needed.

The evidence also shows that technical efficiency (TE) plays a minor role in CATFP growth in the region. These results imply a low learning by doing process in terms of technology absorption. The analysis per sub-region indicates that South and Central American countries have moved closer to their frontier whereas Caribbean countries take more time to catch-up. Therefore, technology absorption and managerial skills is of particular concern to Caribbean countries. We find that CATFP growth varies significantly across the LAC region and TP is the main driver of this growth.

We then use cross-sectional regressions to test CATFP absolute σ-convergence and β-convergence hypotheses in the agricultural sector in LAC. We find no evidence of σ-type nor β-type absolute convergence. These results suggest that countries with lower CATFP will not grow faster than better performing ones without the support from specific national economic policies. The findings also indicate that CATFP levels across countries are not converging towards a common steady state. Finally, we develop an error correction model (ECM) and use panel data techniques to test the conditional β-convergence hypothesis. The findings suggest that, on average, the system is stable and when CATFP is below its long-run equilibrium, it would converge towards such equilibrium at a speed of 3.6 per cent per annum. That is, countries in the region are moving very slowly towards their steady state. In addition, the analysis reveals that the convergence speed is quite heterogeneous across LAC countries. The analysis also shows that technological progress raises the steady state CATFP growth rate by 2.22 per cent per annum. This study highlights that CATFP gaps among countries in the region will not decrease over time without government intervention or implementation of targeted growth policies.

Data availability statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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Supporting Information

Additional Supporting Information may be found in the online version of this article:

Table S1 Estimates for the RP SPF (All parameters are random).

Table S2 Country-specific estimates: true random parameters stochastic production frontier with climatic effects (TRP*c*).

Table S3 Residual cross-sectional independence test results.