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Productivity and the Performance of Agriculture in Latin America and the Caribbean

From the Lost Decade to the Commodity Boom

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Inter-American Development Bank
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TABLES

FIGURES

ACRONYMS

2FE	Two way Fixed Effects
AEZ	Agroecological Zones
AMG	Augmented Mean Group Estimator
CCE	Common Correlated Effects
CCEPc	CCE Cultivated Land Model
CCEPd	CCE Distance Model
CCEPn	CCE Pooled Neighbor Model
CCEPoc	CCE Output Composition Model
CD	Cross Sectional Dependence Test
CIPS	Cross Sectional Augmented
CMG	Heterogeneous CCE Model
CMGc	CMG Cultivated Land
CMGd	CMG Distance Model
CMGen	CMG Contiguous Neighbors Model
CMGn	CMG Pooled Neighbor Model
CMGoc	CMG Output Composition
CRS	Constant Returns to Scale
DEA	Data Envelopment Analysis
FAO	Food and Agriculture Organization of the United Nations
FD-OLS	First Difference Ordinary Least Squares
GDP	Gross Domestic Product
GMO	Genetically Modified Organisms
LAC	Latin America and the Caribbean
MG	Mean Group Model
OECD	Organization for Economic Co-operation and Development
OLS	Ordinary Least Squares
POLS	Pooled Ordinary Least Squares
PPS	Production Possibility Set
TFP	Total Factor Productivity
TGR	Technology Gap Ratio
TI	Traditional Index
SP	Specialization Index
R&D	Research and Development

Abstract

This study analyzes the performance of Latin America and the Caribbean's agriculture between 1980 and 2012 looking at the contribution of inputs, and total factor productivity (TFP) to growth in output per worker. A growth-accounting approach that goes along the lines of neoclassical growth accounting combined with Data Envelopment Analysis, allows us to measure TFP growth using output and input indices and also to decompose this growth into contributions of technical change and changes in technical efficiency. Our findings show that between 1980 and 2012, regional agricultural output per worker and TFP increased 82 and 45 percent, respectively, reducing the difference between TFP in LAC and in OECD countries. This improved performance of agriculture was the result of fast growth in the use of fertilizer, increases in land productivity, and growth in the use of capital that expanded cultivated area per worker. Higher productivity of the animal stock, fast growth in the use of feed and in the number of animals per worker, have increased the share of livestock in total output and also contributed significantly to the improved performance of agriculture. Observed growth patterns at the country level suggest that countries that increased input per worker have increased TFP at a higher rate than countries with limited access to capital and land. As a result of these growth patterns, the improved performance in the region has amplified differences in labor productivity between countries. Growing differences in labor productivity and the fact that the favorable shock in commodity prices that benefited LAC's agriculture in recent years has apparently ran its course, raise concerns for the future.

JEL Code: O13, O33, O54, Q16, Q18

Keywords: agriculture, technical change, total factor productivity, Latin America, Caribbean.

1. Introduction

This paper analyses three decades of agricultural growth in Latin America and the Caribbean (LAC) in the context of the structural changes that took place in the region with particular emphasis on the performance of agriculture in 2001-2012. From the late 1950s until approximately the mid-1980s, the import substitution industrialization model, followed by most countries in LAC, was blamed for the poor performance of the sector as it discriminated against agriculture through exchange rate overvaluation, export taxes, protection of the industrial sector and direct market interventions. After the “lost decade” of the 1980s, LAC started a major revamping of its macroeconomic policy frameworks, a drive that was consolidated in the 2000s and that resulted in improved performance of the agricultural sector.

But not only policy changes were behind the improved performance of agriculture in the region. Between 2002 and 2008, LAC benefited greatly of the more persistent and intense increase of prices of primary commodities since the 1980s. Even during the 2008 world-wide recession, some LAC countries still presented relatively high growth rates while commodity prices remained at record levels. Average growth in agricultural output per worker between 2001 and 2012 was 2.7 percent compared with 0.7 percent in the 1980s. Exports of agricultural products have grown at about 8 percent annually since the mid-1990s and at present they represent around a quarter of the region’s total exports. LAC has also become a bigger player in international markets, where it contributes with 13 percent of global agricultural trade up from 8 percent in the 1990s, and has also increased diversification of agricultural export markets and products.

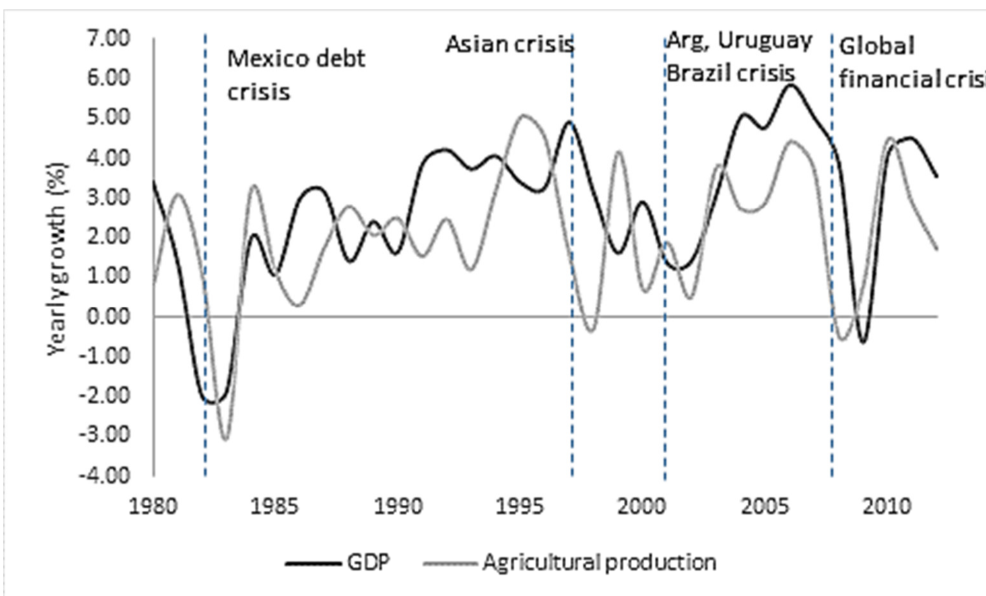
In a 2010 paper, Ludena analyzed total factor productivity growth in LAC’s agriculture between 1961 and 2007 and showed that LAC had the highest agricultural productivity growth among developing regions. The performance of agriculture in LAC was particularly strong in the last 20 years due to improvements in efficiency and the introduction of new technologies. In this study we extend Ludena’s work to analyze the performance of agriculture between 1980 and 2012 looking at the contribution of inputs, total factor productivity (TFP) and its components, efficiency and technical change, to growth in output per worker.

The paper is organized as follows. In the next section we present a short overview of policy changes in the region as a background to the empirical work. Section 3 presents the conceptual framework and approach, while section 4 describes the data and the empirical approach used to calculate TFP indices. Section 5 revisits the analysis of past performance of agriculture in LAC and looks at growth of output per worker and its decomposition into efficiency, technical change and input growth. The last section concludes.

2. Economic environment and agricultural growth in LAC: 1981-2012

Yearly growth rates of average Gross Domestic Product (GDP) and agricultural output for the region (Figure 2.1), allow us to identify three differentiated periods of LAC's economic performance that can be roughly identified with the 1980s, 1990s and 2000s. The period between 1980 and 1985 corresponds to the last years of the import substitution policies followed by most LAC countries, with the debt crisis in Mexico in 1982 marking the beginning of the wave of reforms implemented in the region during the 1990s. Figure 2.1 shows the recovery experienced by the region in the mid-1990s and also how successive financial crisis affected this recovery in 1997, 2002 and 2008.

Figure 2.1 Average GDP and agricultural production growth rate in Latin America and the Caribbean, 1980-2012



Source: Elaborated by authors using data from World Bank and FAO.

According to Anderson and Valenzuela (2010), from the late 1950s until approximately the mid-1980s, the development strategy followed by most LAC countries was aimed at encouraging import substitution industrialization. This policy, by means of import taxes supplemented in some countries through agricultural export taxes, reduced farmer earnings and harmed the region's most competitive farmers who benefit only slightly by farm credit and fertilizer subsidies. The extent of this reduction in earnings (when expressed as a nominal tax equivalent) peaked at more than 20% in the 1970s, and still averaged almost 10% in the later 1980s (Anderson and Valenzuela 2010).

By the 1980s, disillusionment with the results of the import substitution strategy were widely spread, and coinciding with the worst regional economic crisis since the Great Depression, the region underwent a shift in the prevailing development strategy. As Figure 2.1 clearly shows, following Mexico's mid-1982 declaration of financial insolvency, countries through the region began facing acute problems in servicing relatively high levels of accumulated debt with only limited access to fresh external finance. As the 1980s drew to a close, the average per capita product of LAC was 8 percent lower than at the beginning of the decade, average inflation had surged to the unprecedented level of nearly 1,000 percent and the net transfer of resources abroad was continuing at an annual rate of US $25 billion (Remmer, 1991).

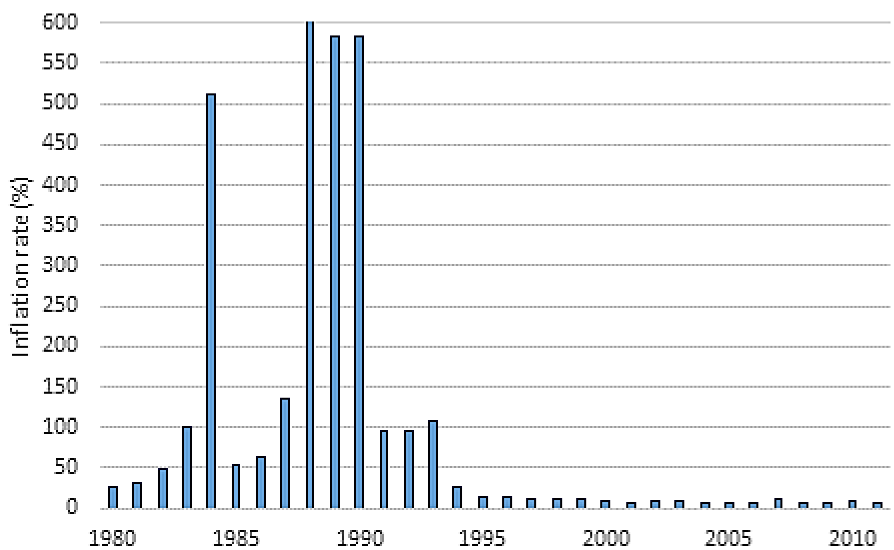
In the 1990s, LAC started a major revamping of its macroeconomic policy frameworks, a drive that was consolidated in the 2000s. The region went through three major regime changes in macroeconomic policy according to Corbo and Schmidt-Hebbel (2013). The first regime change was in fiscal policy. Since the 1970s and through the early 1990s, countries in the region followed unsustainable fiscal policies leading to fiscal crises and hyperinflation. According to Corbo and Schmidt-Hebbel (2013), fiscal orthodoxy replaced profligacy in the 1990s, a trend that was intensified in the 2000s. Fiscal trend deficits were dramatically curtailed or turned into surpluses, and public debt levels were generally reduced to low and sustainable levels.

For Corbo and Schmidt-Hebbel (2013), the second major change in macroeconomic policies was the shift from inflexible toward flexible exchange rate regimes, largely implemented after the Asian crisis of 1997-1998. Three major benefits for the region resulted from flexible exchange rates: avoidance of recurring currency crises (that often lead to financial repression and recessions), use of nominal exchange rate adjustment as a buffer against adverse foreign shocks avoiding costly unemployment and output losses, and allowing full conduct of an independent monetary policy.

The third component of the macroeconomic policy changes in the region was the monetary regime. Together with a flexible exchange rate, which is a necessary condition for exercising an independent monetary policy, central bank independence and inflation targeting have been part of the monetary regime of choice among many countries in the region (Corbo and Schmidt-Hebbel, 2013). The success of the change in monetary policy regimes is reflected in low inflation, which has declined in Latin America from the hyperinflation of the 1980s to an annual average of 34 percent in the early 1990s to 7 percent in the last five years (Figure 2.2).

Together with changes in macroeconomic policies, the region in general has deepened its trade and financial integration with the world economy, dismantling its massive historical barriers to trade in goods, services, and capital flows and putting in place a large number of multilateral and bilateral preferential trade agreements with major world trading partners. As a result of these changes, the average Nominal Rate of Assistance for all agriculture across the region in the 1990s and the first half of the 2000s became slightly positive, at around 5 percent, modifying the strong anti-trade and anti-agriculture bias of the past. At present, and according to Anderson and Valenzuela (2010), relatively few significant domestic producer subsidies or taxes are still in place in the region. The main exceptions are positive domestic support measures in Mexico and slightly negative measures in Argentina (excluding export taxes).

Figure 2.2 Average inflation rate in Latin America and the Caribbean, 1981-2012



Note: the bar for 1988 is truncated as the inflation average that year was 1,600%.
Source: Elaborated by authors using World Bank data.

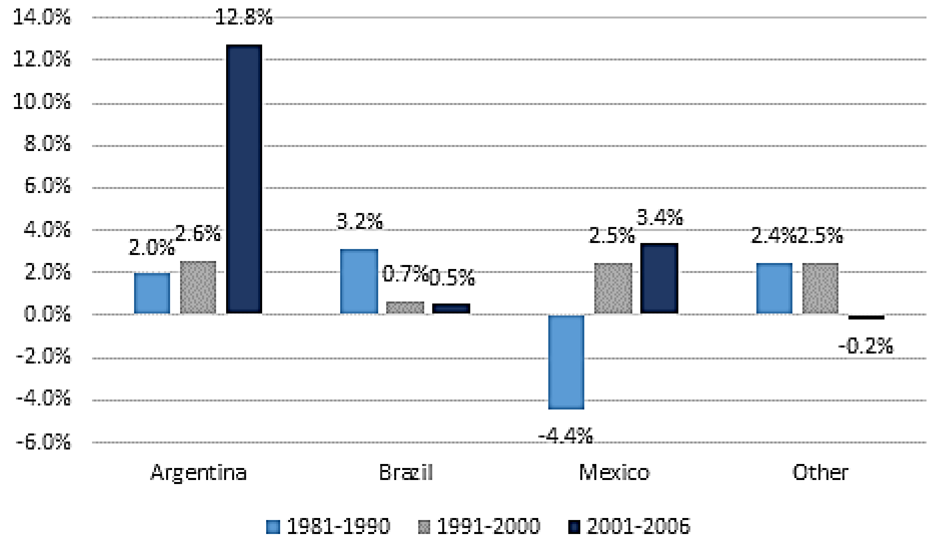
Agriculture in LAC benefited not only from changes in macroeconomic and agricultural policies but also from the reduction in assistance to non-farm tradable sectors since the 1990s (Anderson and Valenzuela, 2010). In particular, the significant reduction in border protection for the manufacturing sector and the indirect impact of this measure in the form of lower prices for non-tradables, together with the deregulation and privatization of services, have favored resource mobility across sectors.

Policy changes have also had consequences on the structure and evolution of the agricultural research system in LAC. The model of the national institutes of agricultural research (INIA's), the regions' predominant institutional form, has changed significantly. Changes in macroeconomic policies dismantled support infrastructure for services and the provision of inputs, credit and commercialization associated with the technological research institutes in various countries. There was also a change in the conception of rural development that displaced the focus on technology and prioritized improving living conditions of small-scale agriculture, affecting the structure and behavior of INIAs. Most recently, the new concept of "innovation systems" has been imposed as the paradigm of institutional development in the region. Under this approach, institutional leadership of the INIAs loses weight in favor of a multiplicity of actors (see Trigo et al. 2013).

In this context of institutional change, Trigo et al. (2013) concluded that there is under-investment in research activities and that the scarce available resources are highly concentrated in a few countries. On average, Brazil accounts for 50 percent of the resources allocated to agricultural research and development (R&D) in the region, which is in line with its share of 46 percent of total agricultural regional output in 2010. Brazil is followed by Mexico with 20 percent of regional expenditure in agricultural R&D and 12 percent of total output; and Argentina contributing 8 percent of R&D expenditure and 14 percent of total output. All other countries contribute the remaining 22 percent of R&D expenditure and produce 30 percent of agricultural output. Even though there has been an increase in the allocation of resources to R&D investment since the mid-1990s, growth in investment has been relatively low (0.9 percent yearly) and very uneven across countries as shown in Figure 2.3 (see Stads and Beintema, 2009).

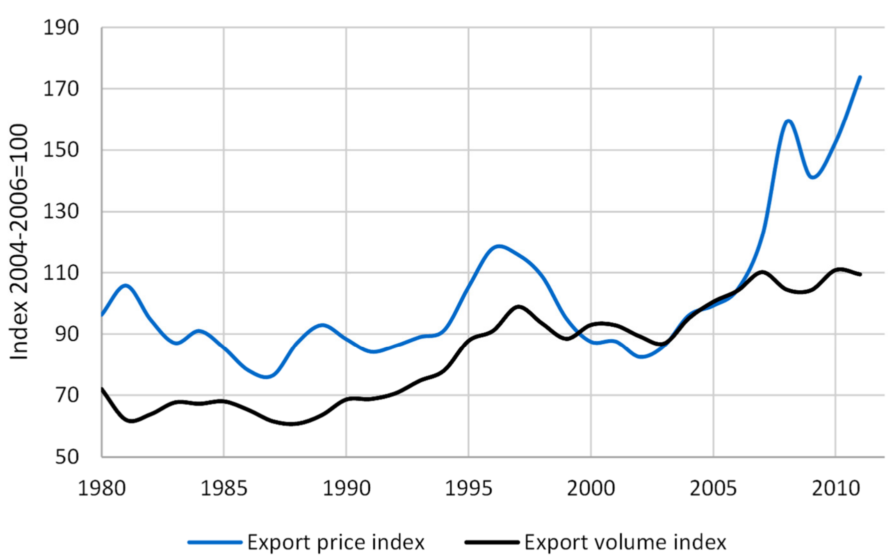
Not only policy changes were responsible of an improved environment for LAC's agriculture in recent year. As a result of the commodity price boom that started in the early 2000s, between 2002 and 2011 prices of agricultural exports from the region more than double (Figure 2.4). This favorable shock that benefited LAC's agriculture in recent years is assumed to have played a major role in the region's improved performance, adding to the policy changes discussed in this section. Many analysts now argue that the upward phase of the commodity cycle has run its course, which raises obvious concerns for the future.

Figure 2.3 Average growth of agricultural R&D investment for selected countries, 1981-2006



Source: Elaborated by authors based on ASTI data, 2014.

Figure 2.4 Trends in the volume of agricultural exports and export price of agricultural exports from LAC (Index=100 in 2004-2006)



Source: Elaborated by authors using data from FAO.

3. Conceptual Framework and Approach

3.1 The Use of Appropriate Technology

Representation of appropriate technology, transfer and adoption of technology across countries is an issue at the heart of the analysis of productivity growth in agriculture. An accepted view on the analysis of agricultural productivity adopts a Cobb-Douglas production function with constant returns to scale to estimate TFP. This approach assumes that countries have access to a common technology represented as $y=A\Pi x^{\alpha}$ where y and x are respectively output and input per worker and A represents TFP or the part of output not explained by inputs x. This view implies a uniform technology frontier for all countries, that is, all countries face the same "*A*" in the production function and differences in TFP reflect inefficiency or a gap from the frontier due to barriers to the adoption of technology, natural resources, lack of competitive markets or other efficient social arrangements (Jerzmanowski 2007).

An alternative view to the standard growth accounting analysis asserts that the technology frontier is not uniform, that is, not every country faces the same A in the production function above. Under this framework, countries choose the best technologies available to them, but their choice is limited by the fact that not all existing technologies are equally suited to every economy. One explanation for this is that appropriateness of the technology depends on the mix of inputs: depending on the relative stocks of labor, skills, and physical capital in a particular country, some technologies may be more or less productive than others. Under these assumptions, the A in the Cobb-Douglas production function becomes a function of inputs: $A = A(x)$ (Jerzmanowski 2007). As discussed in Basu and Weil (1998) and Acemoglu and Zilibotti (2001), the appropriate technology paradigm explains differences in income levels and the lack of convergence. For example, in the paper by Acemoglu and Zilibotti (2001), rich countries invent technologies that are compatible with their own factor mix, but these technologies do not work well with the very different factor mix of poor countries. As a consequence of this, the most productive technologies are inappropriate for developing countries and, even if adopted, do not raise their TFP levels.

In this section we present a model of appropriate technology adapted from Jerzmanowski (2007), which is part of a large literature that examines barriers to the transfer of technology across countries including Basu and Weil (1998); Parente and Prescott (1994); Segerstrom et al. (1990); Grossman and Helpman (1991) and Barro and Sala-i-Martin (1991) among others. We start by presenting the basic elements of the growth accounting method followed by the nonparametric approach to productivity analysis. We then combine elements of these two approaches to define a "*hybrid*" model where the Cobb-Douglas production function is defined as a frontier function and TFP is decomposed into an efficiency component, which is independent of the level of inputs, and a technology component expressed as a function of input per worker.

3.2 Growth accounting approach

Since the seminal agricultural studies by Griliches (1964) and Hayami and Ruttan (1985), much of the literature on agricultural productivity assumes a Cobb-Douglas production function with constant returns to scale to estimate TFP. Eberhardt and Teal (2013) reviewed this literature and refer to several studies applied to agriculture using the Cobb-Douglas function, including Craig et al. (1997); Cermeno et al. (2003); Bravo-Ortega and Lederman (2004), and Fulginiti et al. (2004). Under this approach, output per worker in country *i* is represented by a production function with the following characteristics:

$$y_i = F_i(x) = A_i \prod x_{ij}^{\beta_j} \tag{3.1}$$

where y_i is agricultural output per worker, x_{ij} is a set of observed inputs per worker and A_i is unobserved TFP with technology parameters β_j constant over time. The production function shifter A_i can be modeled borrowing from Fuglie (2011) as:

$$\ln(A_i) = T_i + \alpha_i + \sum \gamma_{ki} Z_{ki} + \varepsilon_i \tag{3.2}$$

that is, agricultural TFP in country *i* depends on the technology used (T); on observed differences in resource quality (Z) related, for example, to differences in agroecologies such as soil type, length of growing period due to temperature, rain regimes and water availability, and so forth. The term α_i captures country-specific effects on productivity not explained by technology and resource quality. The last element in (3.2) is a random variable (ε_i) capturing measurement error. Changes in A_i over time shift the production function and are interpreted as factor-neutral improvements in technology or production efficiency.

As discussed in Fuglie (2011), production elasticities β_j can be interpreted as the share of output that each input receives in payment for its contribution to the production process. Under certain assumptions these shares indicate the payments that the owners of these resources receive when inputs are paid their value-marginal product. In this way, econometric estimation of the parameters of the production function are used instead of input prices, which are normally not available, to define TFP and an index of TFP growth expressed in terms of growth rates:

$$\ln(TFP_i) = \ln(y_i) - \sum \beta_j \ln(x_{ij}) \tag{3.3}$$

$$\dot{TFP} = \dot{Y}_i - \sum \beta_j \dot{x}_{ij} \tag{3.4}$$

One of the disadvantages of this approach is that it involves strong technical and economic assumptions, like profit maximization and the imposition of a functional form. On the other hand, Fuglie (2011) argues that imposing more structure could be an advantage when dealing with data with a high degree of measurement error as it can help produce more plausible results.

3.3 Non-parametric approach

The nonparametric approach known as Data Envelopment Analysis (DEA) has become especially popular because it is easy to compute and does not require information about input or output prices or assumptions regarding economic behavior, such as cost minimization and revenue maximization. The method has been extensively applied to the international comparison of agricultural productivity. See, for example, Bureau et al. (1995), Fulginiti and Perrin (1997, 1999), Lusigi and Thirtle (1997), Rao and Coelli (1998), Arnade (1998), Chavas (2001), Suhariyanto et al. (2001), Suhariyanto and Thirtle (2001), Trueblood and Coggins (2003), Nin et al. (2003), Ludena et al. (2007), Alene (2010), and Nin-Pratt and Yu (2012).

In general, the nonparametric approach assumes that agricultural output per worker in country *i* is given by a production function of the form:

$$y_i = E_i \times F(x) \tag{3.5}$$

where *y* is output per worker, *x* is a vector of inputs used in production and *E* measures efficiency in the use of inputs and takes values between 0 and 1. The production function *F(x)* satisfies free disposal and constant returns to scale and represents the production possibility frontier or the maximum attainable output given inputs. Actual output *y* results from the product of potential output and efficiency. In this context the production set *S* is defined as:

$$S = \{(x, y): y \leq F(x)\} \tag{3.6}$$

The output distance function *D(x,y)* expresses the maximum proportional expansion of output given inputs, or the maximum increase in output (within *S*) given that inputs remain constant, which is captured by θ as follows:

$$D(x, y) = [sup\{\theta: (x, \theta y) \in S\}]^{-1} \tag{3.7}$$

where $D(x,y) \leq 1$ if and only if $(x,y) \epsilon S$, and $D(x,y) = 1$ implies that production takes place on the technological frontier. The distance function for a particular country i^* is estimated using linear programming.

Growth in output per worker between periods 0 and 1 can be represented, adapting notation from Kumar and Russel (2002) as:

$$\frac{y_1}{y_0} = \frac{E_1 \times F_1(x_1)}{E_0 \times F_0(x_0)} \tag{3.8}$$

where y_1 and y_0 represent output per worker in the final and initial period respectively, $F_1(x_1)$ is potential output that can be achieved using technology of the final period and the amount of inputs used in that same period and E_1 is efficiency of country i in the final period. Multiplying top and bottom by $F_0(x_1)$ or potential output that can be obtained using the technology of the initial period with inputs used in the final period we obtain the following expression:

$$\frac{y_1}{y_0} = \frac{E_1}{E_0} \times \frac{F_1(x_1)}{F_0(x_1)} \times \frac{F_0(x_1)}{F_0(x_0)} \tag{3.9}$$

Equation (3.9) is a decomposition of change in labor productivity between two periods for country i. The first term in the right hand side is the change in efficiency or the change in the distance to the frontier; the second term is the shift of the frontier between the two periods measured relative to the coordinates of country i in output space in the final period (potential output is measured with respect to x_1); and the last term is a measure of the change in potential output as a result of a change in the level of inputs, or movement along the frontier in the initial period.

The effect of changes in technology and inputs is path dependent, which means that we can build a similar index by multiplying top and bottom in (3.8) by $F_1(x_0)$ instead of using $F_0(x_1)$ as before. In that case the equivalent to equation (3.9) is the following:

$$\frac{y_1}{y_0} = \frac{E_1}{E_0} \times \frac{F_1(x_0)}{F_0(x_0)} \times \frac{F_1(x_1)}{F_1(x_0)} \tag{3.10}$$

In equation (3.10), the shift in the frontier is measured with respect to country i's coordinates in the production space in the initial period, and the last term represents movement along the frontier in the final period. Expressions (3.9) and (3.10) are equal only when technological change is Hicks neutral, in which case the shift in the frontier is independent of the value of the input-labor ratio. To avoid the problem of path dependence, Caves et al. (1982) adopted the "Fisher ideal" decomposition based on the geometric averages of the two measures of the effects of technological change and capital accumulation multiplying top and bottom of (3.9) by $[F_1(x_0)\ \ F_0(x_1)]^{1/2}$:

$$\frac{y_1}{y_0} = \frac{E_1}{E_0} \times \left[\frac{F_1(x_1)}{F_0(x_1)} \times \frac{F_1(x_0)}{F_0(x_0)}\right]^{1/2} \times \left[\frac{F_0(x_1)}{F_0(x_0)} \times \frac{F_1(x_1)}{F_1(x_0)}\right]^{1/2} \tag{3.11}$$

The advantage of this approach is that it imposes minimum restrictions on the production structure. On the other hand, because of its deterministic character it is not possible to evaluate the precision of the predicted efficiency levels if inputs and outputs are subject to stochastic variation. As the method constructs the production frontier based on efficient points, the efficiency and productivity measures obtained are naturally sensitive to outliers and measurement error.

Appendix B shows productivity growth values from a Malmquist index like (3.11) calculated using DEA methods. The Appendix also shows a comparison between the DEA Malmquist index and the results obtained using the growth accounting approach. Our findings show that the group of best performers is the same with both methods. The major differences between methods seems to be related to estimates for some "problematic" countries. Observed differences could result from poorly estimated shadow prices for some countries due to the dimensionality problem in DEA, or, from some countries differing significantly from the sample average, because of country specific factors, such as land scarcity, labor abundance, and so forth.

3.4 The "*hybrid*" approach: Appropriate technology

This approach goes along the lines of neoclassical growth accounting in defining TFP growth as the ratio of output and input growth, with the aggregate production function being defined as Cobb–Douglas with constant returns to scale (CRS). Within this neo-classical framework, it also disentangles technical change along the technological frontier from changes in technical efficiency. We follow Growiec (2012) who expresses *F(x) in* equation (3.5) as a generic function of the form:

$$F(x) = T(x)\ \prod x_{ij}^{\beta_j} \tag{3.12}$$

where the residual term, *T(x),* captures factor-dependent TFP and is a non-trivial function of inputs. If *T(x)* is found to be approximately constant (*T>0*), then *F(x*) represents the Cobb-Douglas production frontier and 'appropriateness of technology' would have no role to play. If *F(x*) is not Cobb–Douglas, then the 'appropriate technology' factor *T(x)* will necessarily co-vary with factor endowments, indicating that productivity gains can be obtained from changes in the input mix. As pointed out by Growiec (2012), studies quantifying TFP differences using the Cobb-Douglas or more flexible functional forms, might lead to results that are a direct consequence of the particular functional form. The current contribution avoids this problem thanks to the flexibility of the DEA approach, which does not require any parametric assumptions for the estimated production function. However, it is important to notice that the term *T(x)* may capture either the meaningful economic phenomenon of optimal technology choice given available inputs, or the systematic error associated with production function misspecification. It is not possible to distinguish empirically these two effects unless the dataset is extended beyond the information on input and output quantities (Growiec 2012).

Replacing *F(x)* in (3.5) by (3.12) we get:

$$y_i = E_i \times \left[T(x_i) \prod x_{ij}^{\beta_j}\right] \text{ where } A_i = E_i \times T(x_i) \qquad (3.13)$$

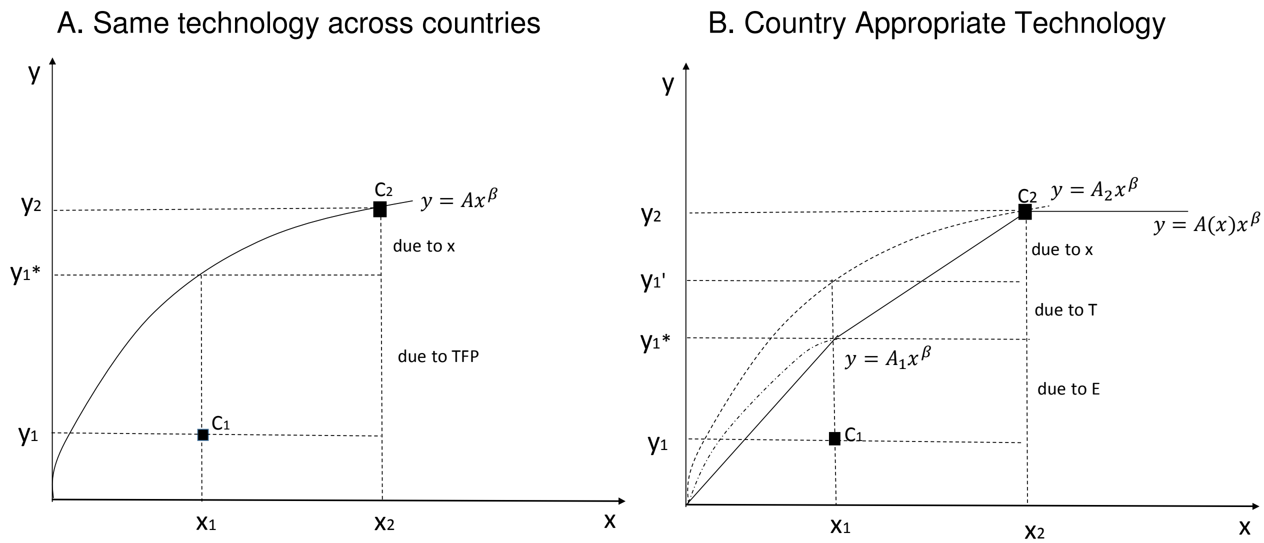
Notice that this hybrid model, unlike neoclassical growth-accounting, deals exclusively with the best practice technology, not the average practice technology. In other words, the expression in brackets is a frontier production function, TFP is decomposed into efficiency and available technology levels (E_i and $T(x_i)$) and actual output results from the product of potential output and efficiency (E_i). Using growth accounting approach (dropping the country index) we can express the output growth decomposition between period 0 and 1 as follows:

$$\frac{y_1}{y_0} = \frac{E_1}{E_0} \times \frac{T(x)_1}{T(x)_0} \times \prod \left(\frac{x_{j1}}{x_{j0}}\right)^{\beta_j} \qquad (3.14)$$

The expression in (3.14) is known in the growth-accounting literature as the “appropriate technology vs. efficiency” output growth decomposition (Basu and Weil, 1998; Jerzmanowski, 2007; Growiec, 2012). This specification allows for two determinants of TFP differences: country-specific levels of efficiency and country-specific levels of available technology, which is allowed to be factor specific: *T(x).*

Figure 3.1 illustrates the conceptual differences behind the standard growth-accounting and the appropriate technology conceptual frameworks. The left panel of Figure 3.1 represents a model of production where all countries have access to the same technology represented by the production function $y=Ax^{\beta}$. In this setting, differences in output per worker between an efficient country (C_2) and an inefficient country (C_1) are explained by TFP levels that result from inefficiency (measured as the distance of C_1 to the frontier given the level of input x_1 used); and by differences in the level of input x used (increasing inputs from x_1 to x_2 will reduce the difference in output per worker to differences in efficiency only).

Figure 3.1 Standard and appropriate technology levels accounting decomposition



Source: Adapted from Jerzmanowski (2007).
Note: The left panel assumes that technology $y = Ax^{\beta}$ is available to all countries and differences are due to input–labor level and TFP. Right panel: Technology is a function of input per worker and country 1 cannot access country 2's technology.

The right panel in Figure 3.1 represents production with appropriate technology. In this case, the true frontier is a function of input per worker. For each input-labor combination there is a particular production function (*A* is a function of *x*). The difference with the left panel is that in the right panel there is an intermediate level of output y_1' that C_1 cannot achieve with its present level of inputs. The difference y_1'-y_1* is due to appropriate technology. This means that to achieve productivity levels of C_2, C_1 can increase efficiency up to certain point but to catch-up with C_2, C_1 needs to increase input per worker to operate on C_2 production function and face TFP levels A_2 instead of A_1.

The empirics of the appropriate technology model do not differ from that used in the growth-accounting and DEA approaches. In this study we use the same approach used in the growth-accounting literature applied to agriculture to estimate the parameters of the Cobb-Douglas production function and to calculate the TFP indices for different countries. Thus, TFP values obtained are the same as those obtained using the growth-accounting approach. On the other hand, the construction of the global agricultural production frontier to determine technical efficiency of individual countries uses the DEA approach, thus efficiency estimates obtained here are equivalent to those used to estimate DEA Malmquist indices. By combining growth accounting and DEA methods, the appropriate technology approach does two things. First, and from a conceptual point of view, the appropriate technology approach appears to generate patterns of international productivity convergence and divergence that are more in line with reality than the results obtained from other endogenous models (Los and Timmer 2005). Second, it relaxes the assumption of the Cobb-Douglas functional form, allowing the contribution of inputs to output to be larger than total input derived from the Cobb-Douglas function because technology (T(x) and consequently TFP) depends on input endowments (Jerzmanousky 2007). The data used and a detailed account of the steps followed to obtain the different components of our model are presented in the next section.

4. Empirical Model and Implementation

4.1 Implementation

To explain output growth as the result of growth in the use of inputs, and TFP using the hybrid model presented in Section 3, we need data on agricultural output and inputs at the country level for countries in LAC as well as for other developing and high income regions. This global dataset is used to define the global agricultural production technology that serves as the reference to measure the performance of agriculture in LAC countries. The data used is described in section 4.2. We then proceed in several steps. The first is the econometric estimation of the parameters of the Cobb-Douglas global production function, the output elasticities of the different inputs (section 4.3). The second step is to use the estimated elasticities as weights to calculate the index of aggregated input (*X*) using input data described in 4.2. Third, using aggregate input from the previous step and total output (*Y*) as described in 4.2, we calculate *TFP* as the ratio of total output and total input for all countries: $TFP_i = A_i = Y_i/X_i$. Notice that so far, we followed the same steps and methodology that most studies in the literature using the growth-accounting approach to calculate TFP, obtaining information on output, total input and TFP: $Y = TFP \times (X)$. The next step is to decompose *TFP* into Efficiency and Technology: $TFP = E \times T$. To do this, and independently from the previous steps, we use the original output and input data to calculate technical efficiency for all countries in our sample using linear programming (DEA approach) as explained in section 4.6. Once we have calculated *E* we can calculate the technology component of TFP (*T*) using the TFP values from the previous step: $T = TFP/E$. Finally, with this last piece of information we have all the elements needed to decompose output growth into its components as defined by equation 3.13 of the hybrid model:

$$Y = A \times X = E \times T \times X \tag{4.1}$$

Results on output growth and its components in section 5 are all derived from (4.1), with each component calculated as explained in this section.

4.2 Data

Output and input data to estimate the parameters of the global production function used in this study are from the Food and Agriculture Organization of the United Nations (FAO 2014) covering a period of 51 years from 1961 to 2012. The final database includes 134 countries (Table 4.1), one output (total agricultural production), and six inputs (fertilizer, feed, livestock capital, crop capital, agricultural land and labor). Notice that even though our database covers the period between 1961 and 2012, results presented in section 5 focus on LAC's performance in the last 30 years of this period, starting in 1980. The complete database using 51 years of available information is used in the econometric analysis to estimate the Cobb-Douglas parameters.

Table 4.1 List of countries used to define the global agricultural production technology

Latin America and the Caribbean (26) Argentina, Bahamas, Barbados, Belize, Bolivia, Brazil, Chile, Colombia, Costa Rica, Dominican Republic, Ecuador, El Salvador, Guatemala, Guyana, Haiti, Honduras, Jamaica, Mexico, Nicaragua, Panama, Paraguay, Peru, Suriname, Trinidad and Tobago, Uruguay, Venezuela
Sub-Saharan Africa (40) Angola, Benin, Botswana, Burkina Faso, Burundi, Cameroon, Central African Republic, Chad, Republic of the Congo, Côte d'Ivoire, Democratic Republic of Congo, Ethiopia (former), Gabon, Gambia, Ghana, Guinea, Guinea-Bissau, Kenya, Liberia, Madagascar, Malawi, Mali, Mauritania, Mauritius, Mozambique, Namibia, Niger, Nigeria, Rwanda, Senegal, Sierra Leone, Somalia, South Africa, Sudan (former), Swaziland, Togo, Uganda, Tanzania, Zambia, Zimbabwe
South Asia South and the Pacific (18) Afghanistan, Bangladesh, Bhutan, Cambodia, China, Democratic People's Republic of Korea, India, Indonesia, Lao People's Democratic Republic, Malaysia, Mongolia, Myanmar, Nepal, Pakistan, Philippines, Republic of Korea, Sri Lanka, Thailand, Vietnam
Middle East and North Africa (19) Algeria, Bahrain, Egypt, Iran, Iraq, Israel, Jordan, Kuwait, Lebanon, Libya, Morocco, Oman, Qatar, Saudi Arabia, Syria, Tunisia, Turkey, United Arab Emirates, Yemen
High Income (Europe, North America and Australia/New Zealand) (23) Austria, Belgium-Luxembourg, Cyprus , Denmark, Finland, France, Germany, Greece, Ireland, Italy, Japan, Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, United Kingdom, United States of America (USA), Canada, Australia, New Zealand
Transition Economies (8) Albania, Bulgaria, Czechoslovakia (former), Hungary, Poland, Romania, USSR (former), Yugoslavia (former)

Source: Elaborated by authors based on FAO data (2014).

Output: Value of gross agricultural production expressed in constant 2004-2006 US dollars. It includes crop and livestock production.

Animal Feed: The amount of edible commodities (cereals, bran, oilseeds, oilcakes, fruits, vegetables, roots and tubers, pulses, molasses, animal fat, fish, meat meal, whey, milk, and other animal products from FAOSTAT food balance sheets) fed to livestock during the reference period. Quantities of the different types of feed are transformed into metric tons of maize equivalents using information of energy content for each commodity.

Fertilizer: Quantity of nitrogen, phosphorus, and potassium (N, P, K) in metric tons of plant nutrient consumed in agriculture by country and year.

Labor: Total economically active population in agriculture (in thousands), engaged in or seeking work in agriculture, hunting, fishing, or forestry, whether as employers, own account workers, salaried employees or unpaid workers assisting in the operation of a family farm or business. This measure of agricultural labor input, also used in other cross country studies is an uncorrected measure, which does not account for hours worked or labor quality (education, age, experience, and so forth). Figures for Nigeria were adjusted following Fuglie (2011).

Land: Includes land under temporary crops (doubled-cropped areas are counted only once), temporary meadows for mowing or pasture, land under market and kitchen gardens, land temporarily fallow (less than five years), land cultivated with permanent crops such as flowering shrubs (coffee), fruit trees, nut trees, and vines but excludes land under trees grown for wood or timber. Pasture land includes land used permanently (five years or more) for herbaceous forage crops, either cultivated or growing wild (wild prairie or grazing land). Quantities are expressed in thousands of hectares.

Capital stock: New series of capital stock from FAO (2014) covering the period 1975-2007 valued at 2005 constant prices as the base year and calculated by multiplying unit prices by the quantity of physical assets "in use" compiled from individual countries. The physical assets include assets used in the production process covering land development, irrigation works, structures, machinery and livestock. We use figures of gross fixed capital stock defined as the value, at a point of time, of assets held by the farmer with each asset valued at "as new" prices, at the prices for new assets of the same type, regardless of the age and actual condition of the assets. We divide capital stock into two components: A) *Crop capital includes land developments and equipment. Land Development* is the result of actions that lead to major improvements in the quantity, quality or productivity of land, or prevent its deterioration including on field land improvement undertaken by farmers (work done on field such as making boundaries, irrigation channels, and so forth); and other activities such as irrigation works, soil conservation works, and flood control structure, and so forth, undertaken by government and other local bodies. *Plantation crops* refers to trees yielding repeated products (including vines and shrubs) cultivated for fruits and nuts, for sap and resin and for bark and leaf products, and so forth). *Machinery and equipment,* includes tractors (with accessories), harvesters and thrashers, and hand tools. B) *Livestock capital includes animal inventory and livestock fixed assets.* Animal inventory is the *value of the stock* of cattle and buffalo, camels, horses, mules, asses, pigs, goats, sheep and poultry. Livestock fixed assets includes sheds constructed for housing cows, buffalo, horses, camels and poultry birds and *milking machines.*

4.3 Input Elasticities and the Cobb-Douglas Production function

The empirical framework to estimate input elasticities of the Cobb-Douglas production function follows Eberdhardt and Teal (2013) who developed an econometric approach that overcomes many of the problems found in the literature estimating the global agricultural production function. The salient characteristics of this approach are that it allows for parameter heterogeneity, cross-section dependence and variable nonstationarity. The interplay of these effects, if not accounted for in the model, leads to the breakdown of standard assumptions in the empirical estimators commonly applied in the literature. We briefly consider how these effects are introduced in the econometric model used in this study.

Technology heterogeneity reflects the differences in agro-climatic environment, agricultural output mix and level of commercialization observed across countries (see Eberhardt and Teal 2011 for a discussion on the arguments behind technology heterogeneity in the literature). From a theoretical standpoint, the assumption of differential technology across countries seems to be a desirable property for a global production model. However, Eberdhardt and Teal (2013) argue that in practice, "*perhaps due to the constraints imposed by estimation techniques or data availability, the empirical investigation of agricultural productivity was typically based on models which imposed technology homogeneity across countries, or only allowed for heterogeneity by splitting the sample into crude geographical groups*." In terms of the econometric model used here, technology heterogeneity means that instead of assuming that all countries share the same parameters β in the Cobb-Douglas production function, we assume that different countries have different parameters. The log-linear version of the heterogeneous technology Cobb-Douglas production function is then represented as follows:

$$y_{it} = \beta_i{}' x_{it} + \mu_{it} \tag{4.2}$$

Where y_{it} is agricultural output of country *i* in year *t*, x_{it} is a vector of inputs and β_i is a vector of parameters representing output elasticities of the different inputs for each country. The variable μ is a residual capturing the part of output not explained by inputs *x*. As we will show below, the model accommodates cross-section dependence and nonstationarity by explicitly modeling the residual μ in (4.2).

Why is technology heterogeneity important? As discussed in Eberhardt and Teal (2011), misspecification of technology parameter heterogeneity in itself may not be regarded as a serious problem for estimation if slope parameters vary randomly across countries and are orthogonal to included regressors and the error terms. If this is the case, the pooled regression coefficient represents an unbiased estimate of the mean of the parameter across countries (Durlauf et al., 2005, p.617, cited by Eberhardt and Teal 2011). Neglecting potential technology parameter heterogeneity in the empirical analysis has more serious implications if observable and/or unobservable variables are nonstationary as this could result in the breakdown of the cointegrating relationship between inputs and output creating nonstationary errors and producing potentially spurious results (Eberhardt and Teal 2013, p.29). Even if observed inputs and output cointegrate in each country equation (heterogeneous cointegration), the pooled equation does not, and pooled estimation will not yield the mean of the cointegrating parameters across countries.

The residual term in equation (4.2) is represented by Eberhardt and Teal (2013) as a function of country-specific effects (α_i) and a set of common factors f_t that can have different effects across countries, and a random measurement error ε_{it}.

$$\mu_{it} = \alpha_i + \lambda_i' f_t + \varepsilon_{it} \tag{4.3}$$

Notice that by defining $\mu_{it} = \alpha_i + \varepsilon_{it}$ we obtain the standard fixed effects panel model that assumes that output in the production function is determined by the use of inputs and by unobserved country-specific fixed effects. The fixed effects model and its extension that uses year dummy variables accounts for time-invariant and time-variant correlation across units. However, the violation of the homogeneity assumption of fix country and year effects leads to dependence in the error terms across countries. Eberhardt and Teal (2013) introduce the possibility of differential shocks between countries through the term $\lambda_i' f_t$ in (4.3) representing common unobserved effects to all countries that result in differential impacts in each country (the coefficients λ_i' are country-specific while factors f_t are common to all countries).

The model also allows for endogeneity of inputs as the input variables x_{it} are driven by a set of common factors g_{jt} and by the set (or subset) of factors f_t influencing output in equations (4.2) through μ_{it} in equation (4.3). This means that some unobserved factors driving agricultural production are likely to drive, at least in part, the evolution of the inputs:

$$x_{ijt} = \pi_{ij} + \delta'_{ij} g_{jt} + \phi_{ij} f_t + v_{ijt} \tag{4.4}$$

Note that equation (4.4) specifies that the level of input *j* used by country *i* in year *t* is a function of a country specific effect π_{ij}, of a set of unobserved factors g_{jt} affecting only inputs, and of the same f_t unobserved factors affecting output through μ_{it} in equation (4.3). If we assume that f_t and g_t, are stationary factors, the consistency of standard panel estimators such as a pooled fixed effect regressions with country-specific intercepts rests on the parameter values of the unobserved common factors: if the averages of λ'_i and ϕ_{ij} are jointly non-zero, then the fixed effects regression will be subject to the omitted variable problem and hence misspecified, since regression error terms will be correlated with the regressor, leading to biased estimates and incorrect inference as discussed in Eberhardt and Teal (2011). In the case of nonstationary factors, the consistency issues in the same setup are altogether more complex and will depend on the exact overall specification of the model (Kapetanios et al., 2011).

Finally, there is a general consensus in the literature that macro data series such as output and inputs should not be considered a priori as stationary processes for all countries analyzed, which also suggests that the evolution of TFP may be best represented as a nonstationary process. Nonstationarity is accommodated in Eberhardt and Teal (2013) model by specifying latent factors *f* and *g* as persistent over time:

$$f_t = \varrho' f_{t-1} + \epsilon_t \text{ and } g_t = \kappa' g_{t-1} + \epsilon_t \tag{4.5}$$

When $\varrho = 1$ and $\kappa = 1$, f_t and g_t are nonstationary variables. The importance of controlling for the time series properties of the production function model are stressed by Eberhardt and Teal (2011). For instance, they argue that "*the assumption of parameter homogeneity, commonly adopted in the mainstream literature on growth empirics, is shown to have much more serious implications in the nonstationary than in the stationary context: any deviation from the homogeneity assumption no longer simply affects the precision of our estimate of the parameter `mean', but will lead to the breakdown of cointegration and thus potentially spurious results*" (Eberhardt and Teal 2011, pg.28).

In sum, the final model assuming technology heterogeneity, cross-section dependence, endogeneity of inputs and nonstationarity is the following:

$$y_{it} = \beta_i{}' x_{it} + \mu_{it}$$

$$\mu_{it} = \alpha_i + \lambda_i' f_t + \varepsilon_{it}$$

$$x_{ijt} = \pi_{ij} + \delta'_{ij} g_{jt} + \phi_{ij} f_t + v_{ijt} \tag{4.6}$$

$$f_t = \varrho' f_{t-1} + \epsilon_t \text{ and } g_t = \kappa' g_{t-1} + \epsilon_t$$

4.4 Model Selection and Testing

We estimate the parameters of the Cobb-Douglas production function following the growth accounting approach. The parameter of interest in model (4.6) is the mean effect β, that is, the input coefficients in the Cobb-Douglas production function. As in Eberdhart and Teal (2013) we consider different models to estimate β that deal with unobserved heterogeneity, cross section dependence and dependence due to latent common factors. This implies different assumptions regarding β_i, λ_i' and α_i as well as ϱ' and κ' in (4.6). Following Eberdhart and Teal (2013) we divide these models into two groups. Pooled models assume parameter homogeneity, which means that all countries share the same slope parameters ($y_{it} = \beta' x$). The heterogeneous models on the other hand, assume country-specific input coefficients β_i. Within these two groups, different models are defined based on different assumptions on cross-section dependence and time series properties.

The group of pooled models includes the pooled ordinary least squares model (POLS) with year dummy variables; the two-way fixed effects (2FE) model, including country and year dummy variables to capture country and year specific effects; and first-difference ordinary least squares model (FD-OLS), used to address the problem of omitted variables and obtained by running a pooled OLS estimation of the regression of the difference y_t - y_{t-1} against x_t - x_{t-1} wiping out time invariant omitted variables.

Also in the group of pooled models is the common correlated effects (CCE) pooled estimator (Pesaran, 2006), that uses the cross-section averages of the observed output and input variables (averages of y and x) as proxies for the latent factors f_t, assuming that unobserved factors which influence productivity are common to all countries. This model is extended as in Eberhardt and Teal (2013) using different weight-matrices to calculate the cross-section averages used as proxies for the latent factors f. That is, instead of assuming the same cross-section simple average to capture the impact of unobserved effects, we assume that not all common effects affect countries in the same way so we use different weights to calculate the average. The different versions of the CCE model are the following: the CCEP-neighbor (CCEPn) model uses averages of contiguous neighbors for each country, assuming that common shocks between countries are transmitted only between neighboring countries; the CCEP-distance (CCEPd) model uses cross-section averages calculated using the inverse of the population weighted geographic distance between countries; the CCEP-cultivated land (CCEPc) model uses weights for every country pair that are constructed based on the share of cultivated land within each of twelve climatic zones as defined in Jaffe (1986) and used in Eberhardt and Teal (2013), a more detailed climatic classification than the four agroecological zones defined here to control for natural resource quality in the efficiency comparisons; and the CCEP-output composition (CCEPoc) model uses weights based on agricultural output composition (shares of different commodities in total output).

The second group of models allows for heterogeneous slopes (y_{it}=β_i'x). These models are able to accommodate the type of endogeneity presented in the original model (equation 4.6) to arrive at consistent estimates for common slope coefficients calculated as the mean of heterogeneous β_i. Simulations studies (for example, Coakley et al. 2006) show that results from these models are robust even when the cross-section dimension is small, when variables are non-stationary, and in the presence of weak unobserved common factors (spatial spillovers). The estimated β_i coefficients are averaged across panel members using different weights to obtain the average coefficients of the global production function.

Within this group we estimate the following models: the mean group (MG) model (Pesaran and Smith, 1995) in which the intercepts, slope coefficients, and error variances are all allowed to differ across groups. The model assumes away cross-section dependence (λ_i = 0) and estimates separately individual country regressions. The heterogeneous CCE model (CMG) estimates individual country regressions augmented by cross-section averages of dependent and independent variables using the data for the entire panel. As in the case of the CCE models, different versions of the CMG model are defined by using different weights to calculate the cross-section averages. The CMG-neighbor (CMGn) is the heterogeneous version of the CCEn (contiguous neighbors); the CMG-distance (CMGd) is the heterogeneous version of the CCEd (distance) using the inverse of the population weighted geographic distance between countries; the CMG-cultivated land (CMGc) model is the heterogeneous version of the CCE cultivated land (CCEc) model, where weights to define cross-section averages for each country are constructed based on the share of cultivated land within each climatic zones; the CMG-output composition (CMGoc) model is the heterogeneous version of the CCE output composition model and uses weights based on the proximity of countries measured as differences in shares of different commodities in total output. Finally, the augmented mean group estimator (AMG) (Eberhardt and Bond, 2009) is conceptually similar to the heterogeneous mean group version of Pesaran (2006) CCE estimator (CMG). The AMG model is implemented in three steps: a) a pooled regression model augmented with year dummies is estimated by first difference OLS and the coefficient on the year dummies are collected representing the common dynamic process between affecting all countries; b) the country specific regression model is then augmented with estimates from a); finally in c) country-specific parameters are averaged across the panel.

4.5 Results of the econometric analysis

First (Maddala & Wu, 1999) and second generation (Pesaran, 2007) panel unit root tests applied to output and input data used in this study (not reported) suggest that nonstationarity cannot be ruled out in this dataset. There is also strong evidence of the presence of cross-section dependence within the full sample dataset, based on the Pesaran (2004) cross-sectional dependence (CD) test. Eberdhart and Teal (2013) arrived to the same conclusions using a similar dataset than the one used in this study. It is then important to evaluate the different models according to how they deal with nonstationarity and cross-section dependence.

The econometric results for 15 different models (described in the previous section) are presented in Tables A1 and A2 in Appendix A. Diagnostic tests of nonstationarity and cross-section dependence of the residuals show that the pooled OLS and 2FE models cannot rule out nonstationarity but all other models show residuals that reject the null hypothesis of nonstationarity using the Pesaran (2007) CIPS test. The presence of non-stationary residuals reduces the precision of parameter estimates, invalidating t-statistics which makes the POLS and 2FE models unreliable. As in Eberdhart and Teal (2013), the CD test for cross-section dependence yields very mixed results. POLS and the 2FE models show relatively high mean absolute residual correlation (0.4) compared with correlation in other models ranging from 0.12 to 0.17. However, the CD test does not reject the null of cross-section independence in these models. Five of the 14 estimated models reject CRS: POLS, FD-OLS and CCEP among the pooled models and the heterogeneous CCG and climate version of the CCE (CCEd). The distance version of the pooled CCE model also rejects CRS but the labor coefficient is only significant at the 10 percent level.

We conclude from results in Appendix A that heterogeneous parameter models seem to perform better than the traditional pooled models with the neighbor and the crop share CMG showing best performance. These models reject nonstationarity, show no evidence of cross-section dependence and do not reject CRS. Table 4.2 presents results for these two models and the best performing pooled model (neighbor CCE) compared with estimates of the same models with CRS imposed. The CMG output composition model (CMGoc) performs better than all other models when CRS are imposed, with no significant changes in coefficient values. In contrast, the coefficient for labor in the CMGn model doubles and other coefficients also change significantly when CRS are imposed. Output elasticities from the CMGoc model are used to calculate the index of total input used in the calculation of TFP. These coefficients are: 0.15 for labor; 0.18 for crop capital; 0.23 for livestock capital; 0.02 for fertilizer; 0.24 for land, and 0.18 for feed.

Table 4.2. Best performing models, unrestricted and with CRS imposed

Variable	CCEPn Unrestricted	CRS-imposed	CMGn Unrestricted	CRS-imposed	CMGoc Unrestricted	CRS-imposed
Labor	0.0138		0.0674		0.0286	
	(0.156)		(0.129)		(0.127)	
Crop capital	0.237***	0.236***	0.183***	0.239***	0.164***	0.179***
	(0.0670)	(0.0631)	(0.0581)	(0.0537)	(0.0520)	(0.0463)
Livestock Capital	0.190***	0.188***	0.182***	0.196***	0.206***	0.227***
	(0.0679)	(0.0682)	(0.0298)	(0.0307)	(0.0276)	(0.0276)
Fertilizer	0.0202**	0.0204**	0.0216***	0.0243***	0.0196***	0.0201***
	(0.00913)	(0.00913)	(0.00513)	(0.00542)	(0.00521)	(0.00540)
Land	0.232	0.222**	0.243***	0.168**	0.267***	0.239***
	(0.144)	(0.0906)	(0.0768)	(0.0734)	(0.0943)	(0.0585)
Feed	0.154***	0.154***	0.206***	0.234***	0.189***	0.184***
	(0.0457)	(0.0455)	(0.0186)	(0.0191)	(0.0177)	(0.0181)
Constant	-2.426**	-2.341***	0.252	4.274***	-7.476**	3.198***
	(1.127)	(0.600)	(1.361)	(0.306)	(3.545)	(0.592)
Implied labor coeff.	0.181	0.180	0.232	0.139	0.183	0.150
Returns [a]	CRS	-	CRS	-	CRS	-
RMSE	0.088	0.088	0.052	0.057	0.051	0.054
Stationarity [b]	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)
Mean ρij [c]	0.131	0.129	0.124	0.125	0.127	0.131
CD(p) [d]	1.47	1.33	0.1	0.28	-1.04	-0.41
CD p value	0.141	0.184	0.921	0.776	0.297	0.682
Observations	6,834	6,834	6,834	6,834	6,834	6,834
Number of clist2	134	134	134	134	134	134

Standard errors in parentheses;

*** p<0.01, ** p<0.05, * p<0.1

Notes: 1) Dependent variable is log output per worker in all models. 2) a. CRS is constant returns to scale respectively. b. Pesaran (2007) CIPS test results: I(0) stationary, I(1) non-stationary. c. Mean Absolute Correlation coefficient. d. Pesaran CD test, H0: no cross-section dependence. CMGn= heterogeneous version of the common correlated effects or mean group common correlated effects using contiguous neighbors as weights to calculate cross-section effects and output composition; CMGoc= heterogeneous version of the common correlated effects or mean group common correlated effects using output composition (shares) as weights to calculate cross-section effects; RMSE = root-mean-squared error.

4.6 Agroecological Group Efficiency estimates

We use distance functions to measure output oriented technical efficiency for our sample of countries. We adjust these measures by including information on agroecological zones (AEZ) to account for differences in resource quality between countries. We do this in two steps. We first estimate distance functions pooling all countries in our sample to measure the distance of each country to the world frontier in each year. We then group countries by AEZ and estimate the distance of all countries to the frontier of their respective group. The distance function of a country in the kth group is defined as the maximum proportional expansion of output (θ) within the production possibility set (PPS) for that particular AEZ (S^k):

$$D^k(x,y) = [sup\{\theta: (x, \theta y) \in S^k\}]^{-1} \quad (4.7)$$

Technical efficiency with respect to the world metafrontier is defined in the same way but in this case the PPS is the union of all S^k (S^W):

$$D^W(x,y) = [sup\{\theta: (x, \theta y) \in S^W\}]^{-1} \quad (4.8)$$

The metafrontier envelopes the group frontiers of each AEZ which means that $D^k(x,y) \geq D^W(x,y)$ for all *k*. Following Rambaldi et al. (2002), we define the Technology Gap Ratio (TGR) in year *t* as the ratio of the two distances defined in (4.7) and (4.8):

$$TGR^k = \frac{D(x,y)^W}{D(x,y)^k} \leq 1 \quad (4.9)$$

Rearranging terms, we define the distance to the metafrontier as the product of the technology gap between group k's frontier and the metafrontier (TGR^k) and distance to the group's frontier:

$$D^W(x,y) = TGR^k \times D^k(x,y) \quad (4.10)$$

To estimate the distance function for a particular country *i** we solve the following linear programming problem:

$$D(x_{i*}, y_{i*}) = \max_{\theta,\lambda} \theta_{i*} \quad (4.11)$$

Subject to: $\theta_{i*} y_{i*} \leq \sum_{i=1}^{I} \lambda_i y_i$ and $x_{i*,j} \geq \sum_{i=1}^{I} \lambda_i x_{i,j}$ for inputs j={1,…J}, $\lambda_i \geq 0$ (4.12)

Table 4.3 presents a summary of efficiencies and TGR for LAC and other regions for the period 2001-2012 by AEZ (see Appendix C for details on country classification and a list of LAC countries by AEZ). Take the case of tropical sub-humid countries in LAC (El Salvador, Nicaragua and Venezuela). The distance to the frontier within this group is 0.84, which means that tropical sub-humid countries in LAC produce 16 percent below the potential production feasible given the available technology for the particular AEZ. At the same time, the maximum potential output at the frontier of tropical sub-humid countries in LAC is 0.87 (TGR=0.87), which means that with present technology, tropical sub-humid countries in LAC produce 0.84x0.87=0.73 of what can be produced at the world meta-frontier with the same amount and combination of inputs. Even if countries in LAC were to become efficient and produce at the frontier, they will still be producing 13 percent less output than countries at the meta-frontier, a gap probably related to differences in resource quality and potential between tropical sub-humid countries and other agroecologies. Tropical sub-humid countries have been able to reduce this gap and have reached TGR values greater than 0.9. Potential production (frontier) in LAC's temperate humid countries (Chile and Uruguay) is closer to production at the meta-frontier (0.94) as this countries can use technologies developed in high income temperate-humid countries that play an important role in defining the meta-frontier.

Table 4.3. Average Efficiency and Technology Gap Ratios for different regions by AEZ, 2001-2012

Region	Agroecological Zone (AEZ)		Agroecological Group Efficiency	Technology Gap Ratio (TGR)
Latin America and the Caribbean	Temperate	Sub-humid	0.96	0.88
		Humid	0.77	0.94
	Tropical	Sub-humid	0.84	0.87
		Humid	0.87	0.86
Sub-Saharan Africa	Temperate	Sub-humid	0.87	0.75
	Tropical	Sub-humid	0.81	0.94
		Humid	0.91	0.91
Asia (South and Pacific)	Temperate	Sub-humid	0.89	0.92
		Humid	0.94	0.94
	Tropical	Sub-humid	0.96	0.85
		Humid	0.97	0.98
Middle East and North Africa	Temperate	Sub-humid	0.87	0.82
	Tropical	Sub-humid	0.71	0.91
		Humid	0.76	0.60
High Income	Temperate	Sub-humid	0.93	0.94
		Humid	0.88	0.95
Transition Economies	Temperate	Sub-humid	0.87	0.80
		Humid	0.96	0.94

Source: Elaborated by authors.

5 Growth and Performance of LAC's Agriculture, 1981–2012

5.1 Agricultural growth decomposition

Results of the growth decomposition analysis for a sample of 26 LAC countries are presented in Table 5.1. The table shows growth rates for the region calculated as the simple average of growth rates of individual countries. The average yearly growth of total agricultural output between 1981 and 2012 was 2.1 percent while output per worker and per hectare increased at 1.9 percent and TFP grew at 1.2 percent per year. Three periods with contrasting performance can be distinguished in Table 5.1, roughly matching the different policy regimes discussed in Section 2. It is worth noting that average growth of output between 1991-2000 and 2001-2012 was similar (2.4). However, the main difference between the two periods is that during 2001-2012, two thirds of the growth in output comes from TFP growth, while the contribution of TFP to output growth in the 1990s is 50 percent. That is, the main source of output growth during the last decade has been TFP and not input growth.

Table 5.1. Average growth rates of agricultural output, input and output and input per worker and hectare for various periods

Variable	1981-1990	1991-2000	2001-2012	1981-2012
Output	1.5	2.4	2.4	2.1
Input	1.0	1.2	0.8	0.9
Total Factor Productivity	0.5	1.2	1.7	1.2
Output per worker	0.9	2.3	2.4	1.9
Input per worker	0.4	1.0	0.8	0.7
Output per hectare	0.7	2.0	2.7	1.9
Input per hectare	0.2	0.8	1.1	0.7

Source: Elaborated by authors.

The first period is one of poor performance and corresponds to the "lost decade" of the 1980s, starting in 1982 and ending at the beginning of the 1990s. During this period we observe the lowest output growth rate of the last 30 years (1.5 percent growth in total output and only 0.9 percent growth in output per worker), very slow growth in input per worker (0.4 percent) and modest improvements in TFP (0.5 percent). Growth in output and input per hectare are also the lowest observed in the last 30 years (0.7 and 0.2 percent, respectively).

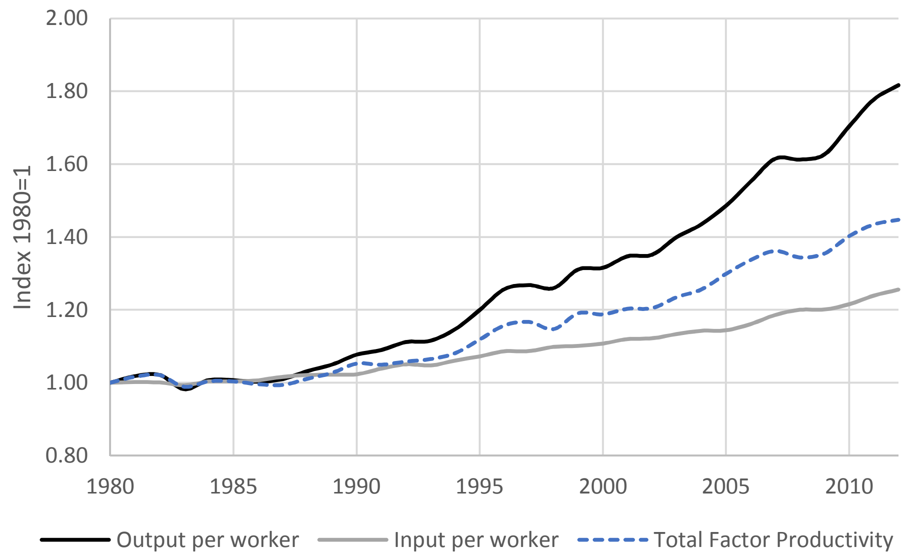
Figures in the second column of Table 5.1 show that the poor performance of the 1980s is followed by a period of recovery that coincides with the revamping of macroeconomic policies of the early 1990s in the region discussed in Section 2. This recovery is interrupted by the Asian crisis of 1997-1998. During this period, growth in total agricultural output accelerates to 2.4 percent per year while growth in output per worker and per hectare almost triples to 2.3 and 2.0 percent respectively. In the same period, growth in input per worker more than doubles to 1.0 percent and the growth rate of input per hectare is 4 times bigger (0.8 percent) than that of the 1980s.

Changes in macroeconomic policies that started in the 1990s were consolidated in the 2000s after the Asian crisis. A favorable macroeconomic environment and high commodity prices during this period resulted in the best performance of the agricultural sector of the last 30 years. Average growth in total output and in output per worker for the period was 2.4 percent, output per hectares increased at 2.7 percent per year and growth in TFP averaged 1.7 percent reaching 2.0 percent between 2001 and 2005 (see Figure 5.1). As it happened with the Asian financial crisis of the 1990s, the crisis of 2008 interrupts this period of high growth but because of better policies, when the global financial crisis struck, the size of macroeconomic imbalances in the region were manageable and domestic policy did not amplify the recession as it did in the past.

These different periods can be better visualized in Figures 5.1 and 5.2. Figure 5.1 shows indices of the evolution of output and input per worker and TFP (taking the value of 1 in 1980), and Figure 5.2 displays the evolution of growth rates of these variables for the period analyzed. We observe in Figure 5.1 that between 1980 and 2012, agricultural output per worker increased 82 percent while by the end of the period, the total amount of inputs used was 26 percent higher than in 1980. As a result, inputs used in agricultural production were 45 percent more productive (TFP) in 2012 than in 1980.

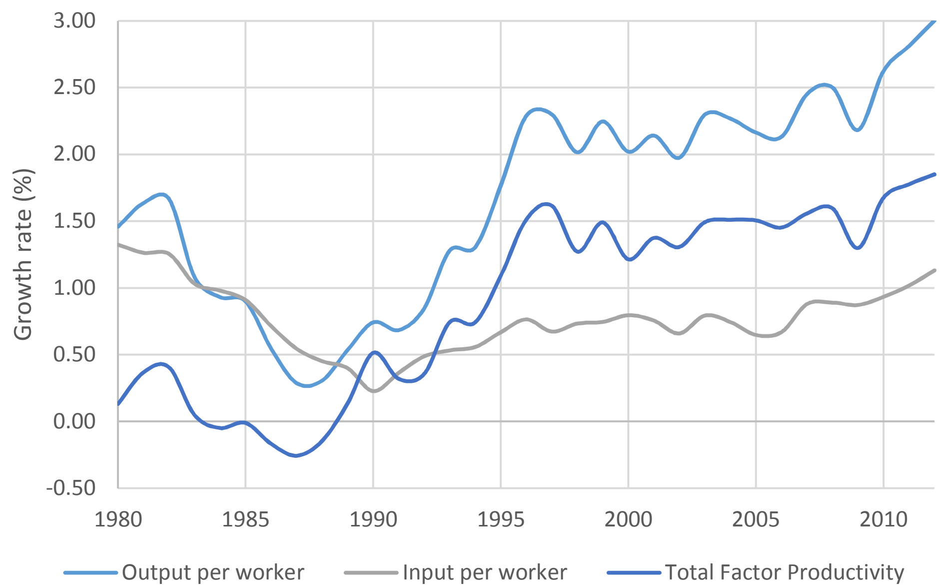
Figure 5.2 shows that the crisis of the 1980s resulted in decreasing rates of growth in output and input per worker, and TFP. Growth trends changed in the 1990s and output, input and TFP grew steadily until they stabilized in the second half of the decade. Between 1995 and 2012, the growth rate of output per worker and TFP fluctuated around 2.5 and 1.5 percent, respectively. In contrast, growth in input per worker remained stable and close to 0.7 percent until 2002, it accelerated after that year, and reached 1.1 percent in 2012, signaling a change with respect to growth patterns of previous years.

Figure 5.1 Evolution of LAC's agricultural output per worker and its components, total input per worker and TFP, 1980-2012



Source: Elaborated by authors.

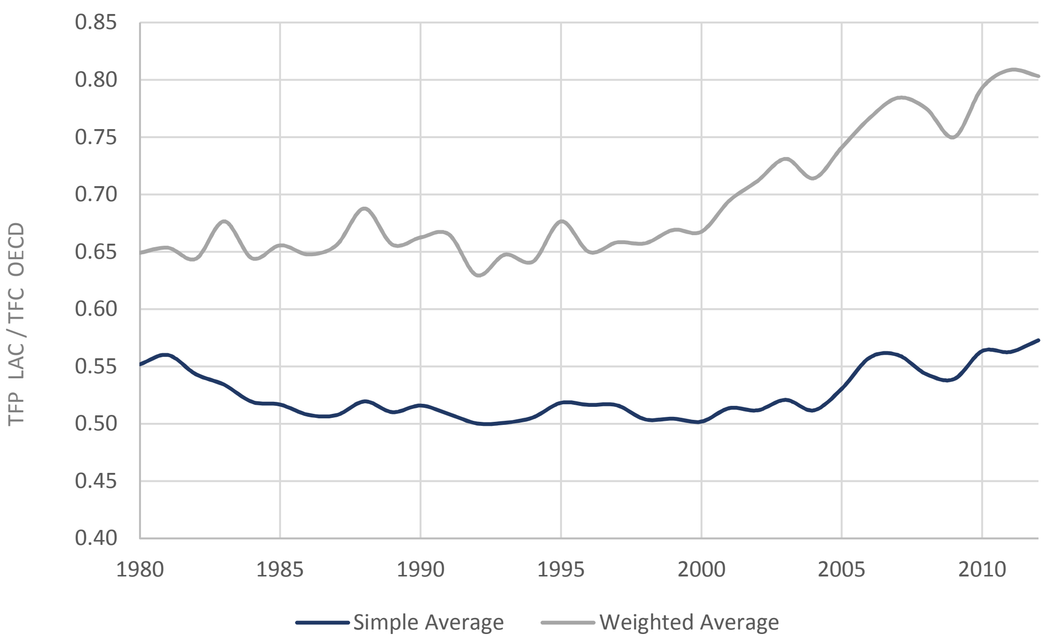
Figure 5.2 Evolution of growth rates of LAC's agricultural output per worker and its components, total input per worker and TFP, 1980-2012



Source: Elaborated by authors.

The performance of agriculture in the region in recent years has improved not only compared with its own performance in the past but also relative to that of other countries. Figure 5.3 shows simple and weighted averages of LAC's TFP levels between 1981 and 2012 relative to agricultural TFP levels in OECD countries. Considering that the average share of the large agricultural producers (Brazil, Mexico and Argentina) in total regional output was close to 75 percent on average between 1981 and 2012, we should interpret the weighted regional TFP level in Figure 5.3 as mostly reflecting the TFP level of these three countries. On the other hand, all countries contribute equally to the simple average TFP level in Figure 5.3, which makes this index a better indicator of the evolution of average TFP of all 26 LAC countries. The weighted average of LAC's TFP was 65 percent of that in OECD countries in 1981 and shows no significant changes until the year 2000. It is only after 2000 that TFP growth accelerates with TFP increasing from 67 to 80 percent of TFP levels in the OECD, significantly reducing the productivity gap between the region and the OECD countries.

Figure 5.3 Latin America's TFP levels relative to TFP levels in OECD countries (OECD TFP=1)



Source: Elaborated by authors.
Note: OECD countries are 24 high income OECD countries including Western Europe, USA, Canada, Japan, Korea, Australia and New Zealand.

The simple average TFP levels in Figure 5.3 tell a different story. According to the simple average index, TFP levels in LAC in 1980 were 55 percent of those in OECD countries and decreased to 50 percent in the early 1990s, only showing signs of recovery after 2005. However, this recovery has only brought relative TFP levels in LAC to their values in 1980: the productivity gap with the OECD in 2012 is the same that we observed in 1980. The comparison of the two indices in Figure 5.3 reveals that the three largest countries in the region have performed better than the average and have been driving agricultural growth in recent years.

The decomposition of TFP into efficiency and technical change is presented in Table 5.2. TFP growth during the period analyzed was driven by technical change, which grew at an average rate of 0.9 percent between 1981 and 2012. On the other hand, growth in efficiency was close to 0 in the 1980s, became negative in the 1990s (-0.3 percent), and increased to 0.9 percent per year in the 2000s. These results show that technical change, the shift in the production frontier, was more important to TFP growth between the 1980s and 1990s. However, during the last decade, it is efficiency, the catch-up to the technological frontier in different AEZ what explains most of the growth in TFP.

Table 5.2 Growth rate of agricultural TFP and its components in LAC, 1981-2012

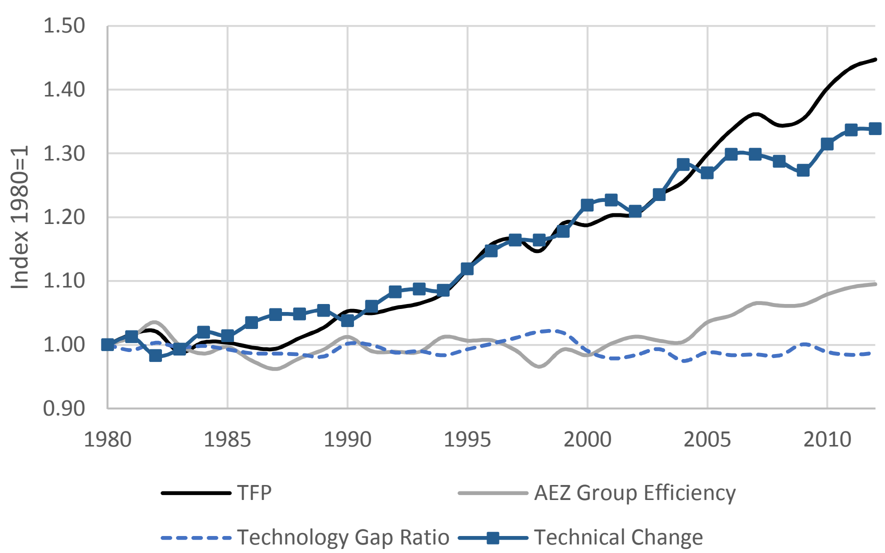
Component	1981-1990	1991-2000	2001-2012	1981-2012
Total Factor Productivity	0.5	1.2	1.7	1.2
AEZ Group Efficiency	0.1	-0.3	0.9	0.3
Technology Gap ratio (TGR)	0.0	-0.1	0.0	0.0
Technical change	0.4	1.6	0.8	0.9

Source: Elaborated by authors.

Note: Efficiency is a measure of a country's distance to the technological frontier in its agroecological zone (AEZ); TGR measures the distance between the AEZ frontier and the global meta-frontier and Technical Change measures shifts in the meta-frontier.

How do we interpret these growth patterns and what are their implications for agricultural production in the region? First, growth in technical change means that movements in the global technological frontier have benefited the region as LAC can potentially produce more output per unit of input than in the past as the result of global technical change. Figure 5.4 shows that the index of technical change with value 1 in 1980 increased to a value of 1.35 in 2012, which means that the region can potentially produce 35 percent more output in 2012 than in 1980 using the same amount of inputs as the result of new technologies that have shifted the global frontier. Second, note that we used the word "potentially" when referring to the benefits of movements in the global technological frontier. This is because potential output given available technology is not always reached as different constraints could prevent countries in the region taking advantage of available technology (for example, the effect of policy, public investment or the lack of it, and institutional constraints). The effect of these variables is captured by the efficiency component of TFP. Efficiency in this context is a measure of the distance between productivity in a country and potential productivity defined by the technological frontier in their own agroecological group. Efficiency growth means that a country that produced below its potential was able to overcome some of the constraints that prevented it to reach this AEZ potential and as a result increased productivity catching-up to the global technological frontier, reducing the gap between actual and potential TFP.

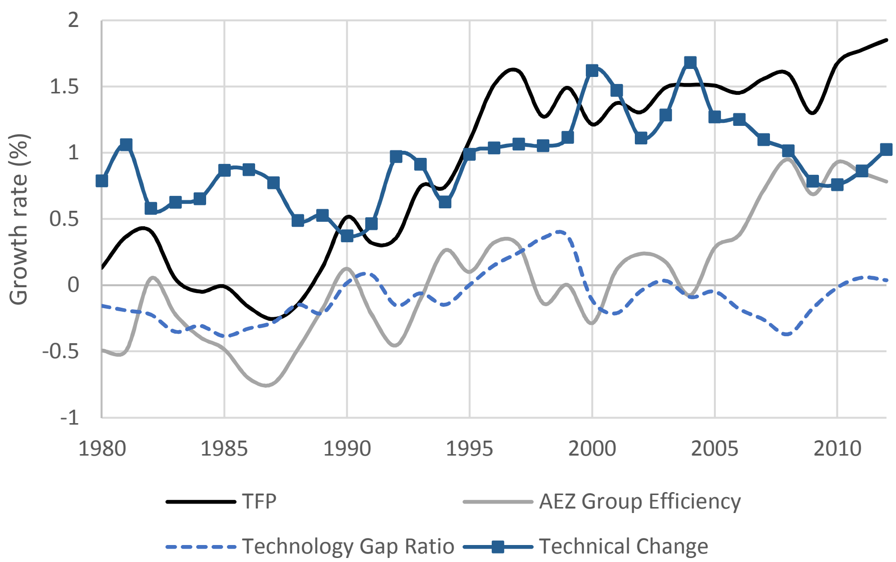
Figure 5.4 Evolution of LAC's agricultural output per worker, TFP and its components, 1980-2012



Source: Elaborated by authors.

Figure 5.5 shows that LAC benefitted from growth in the global technological frontier, in particular between 1995 and 2005, a period during which the frontier expanded at rates greater than 1 percent. During the crisis of the 1980s, agricultural growth performance in LAC was poor relative to that in other countries, with efficiency growth rates reaching -2.0 percent. Factors behind the region's poor macroeconomic performance affected also the agricultural sector, which was not able to keep pace with productivity growth at the technological frontier and as a result of this, the world technological frontier expanded faster than productivity in LAC. The improved performance of agriculture in the 1990s did not result in significant increases in efficiency because the recovery coincided with the fastest expansion of the global technological frontier: LAC's agriculture was not falling behind the world's frontier but was not growing fast enough to catch up to productivity in other regions. It is only in the 2000s, with steady growth in the region and a slowdown in the expansion of the technological frontier, that productivity in the region starts catching up with the global frontier. Efficiency growth became positive in 2005 while technical change slowed down after 2000 (Table 5.2 and Figure 5.5). As a result of these changes, efficiency and technical change contributed similarly to TFP growth in the last years of the period analyzed. Note that we do not find significant changes in TGR, which means that differences in productivity between AEZs and the meta-frontier are stable and only fluctuate around their mean values, probably reflecting differences in resource quality and potential.

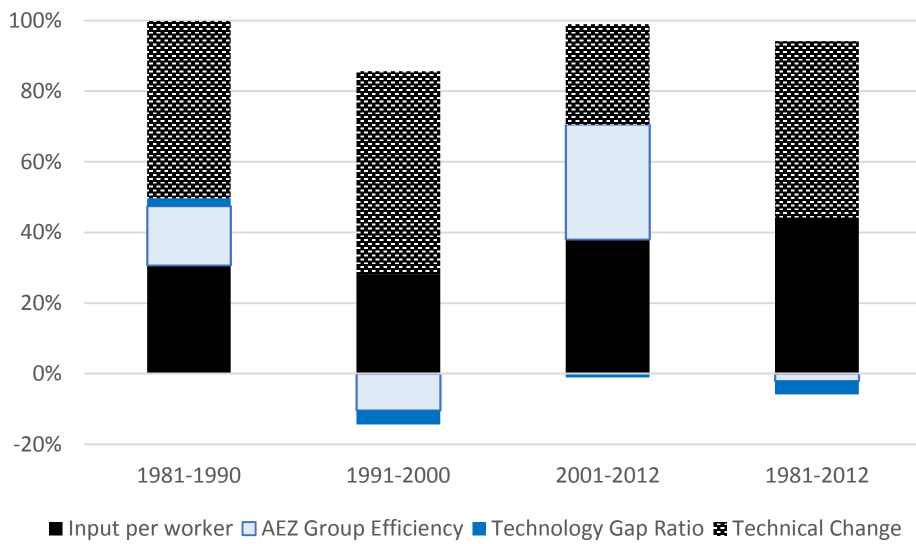
Figure 5.5 Evolution of LAC's growth rates of TFP growth rates and its components: Efficiency and Technical Change, 1980-2012



Source: Elaborated by authors.

We show the contribution of inputs, efficiency and technical change to growth in output per worker in Figure 5.6. Considering the whole period, we found that inputs and TFP have contributed similarly to growth in output per worker. The increased use of inputs explains 50 percent and TFP explains 56 percent of total growth, with a negative contribution of efficiency and TGR (-2.0 and -4.0 percent, respectively). Comparing different subperiods, we observe that the contribution of inputs to growth in output per worker increased from 30 in the 1980s to 40 percent in the 1990s and has remained stable until 2012. Between 2001 and 2012, approximately 60 percent of growth in output per worker is explained by TFP growth, while 40 percent of this growth is the result of growth in inputs. Changes during this period occur in TFP components, where improved efficiency in the 2000s explains about 30 percent of output growth.

Figure 5.6. Contribution of Efficiency, Technical Change and Input per worker to growth in LAC's agricultural output per worker in different periods.



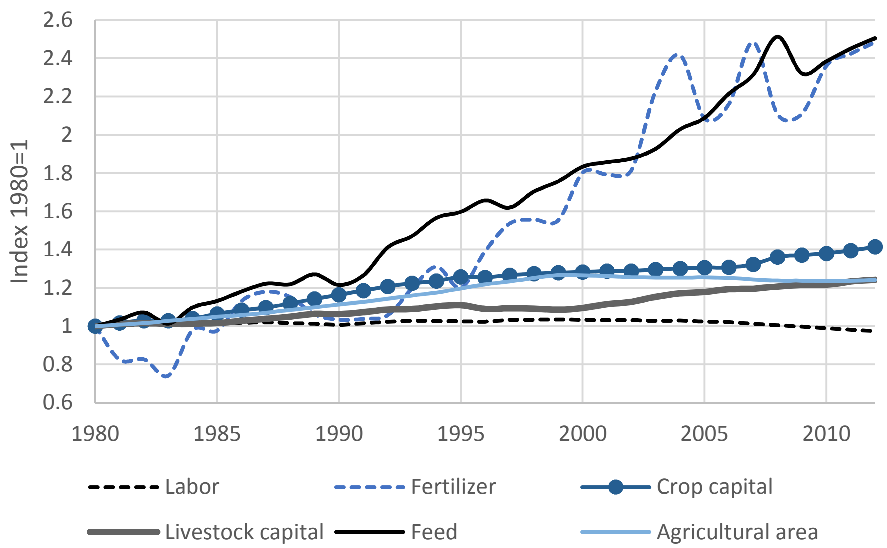
Source: Elaborated by authors.

In sum, after the poor performance of the 1980s, growth trends in LAC changed in the 1990s and output, input and TFP grew steadily until they stabilized in the second half of the last decade. Indices of the evolution of output and input per worker and TFP (showed in Figure 5.1) indicate that between 1980 and 2012, agricultural output per worker increased 82 percent and by the end of the period the total amount of inputs used was 26 percent higher than in 1980. As a result, inputs used in agricultural production were 45 percent more productive (higher TFP) in 2012 than in 1980. Agriculture in LAC improved its performance in 2001-2012 not only relative to the region's performance in the past, but also relative to other countries, reducing the gap between TFP in the region and TFP in OECD countries. Are these improvements in the performance of the agricultural sector reflected in changes in output and input structure? In the next section we analyze changes in the mix of inputs and outputs and relate these changes with the improved performance observed in the last decade.

5.2 Changes in the use of Inputs

The input mix used in agricultural have shown changes during the period analyzed, responding to policy changes and the adoption of new technologies. We observe fast growth in the use of fertilizer and feed, slower growth in the use of capital, no growth in agricultural area that reached its maximum value in 2000 and became negative in recent years, and no growth in the use of labor which increased only 3 percent between 1980 and 2002 and decreased after 2009. Figure 5.7 shows that quantities of fertilizer and feed used in 2012 are 2.5 times bigger than in 1980 while crop and livestock capital increased 40 and 24 percent respectively, with most of this growth occurring in the last decade.

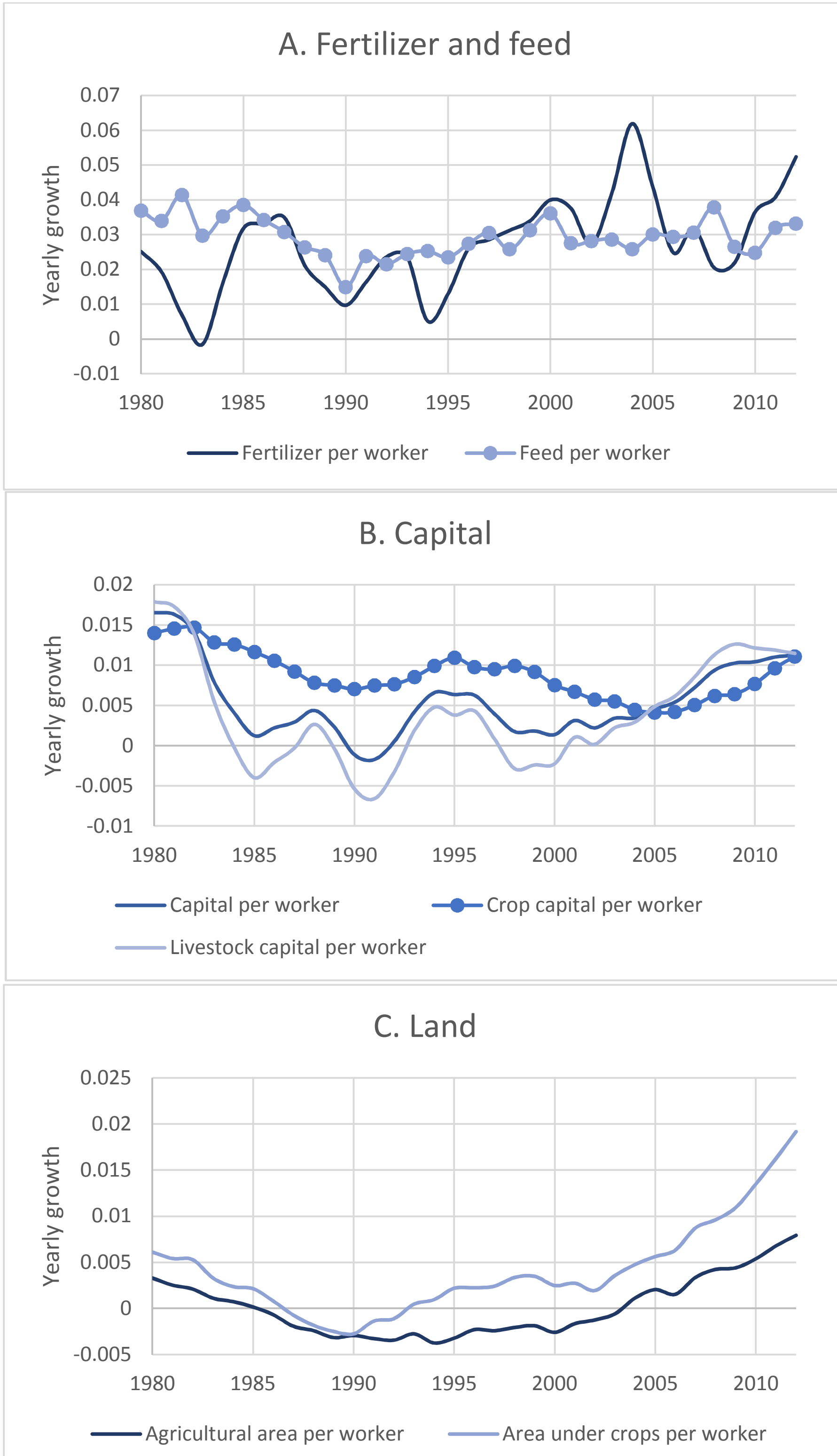
Figure 5.7 Evolution of inputs used in LAC's agricultural production, 1980-2012 (Index 1981=1)



Source: Elaborated by authors.

These changes are reflected in growth rates of fertilizer and feed per worker greater than 3 percent and growth rates of capital and land close to 1 percent (Figure 5.8). Growth in fertilizer use increased from an average rate of approximately 2.5 percent in the 1980s and 1990s to 3.7 percent in the 2000s and use of feed increased steadily at approximately 3 percent per year between 1981 and 2012. How did changes in the input mix reflect in productivity of crop and livestock production? We analyze these changes in the next section.

Figure 5.8. Growth rate of the use of inputs in LAC's agricultural production, 1980-2012 (percentage)



Source: Elaborated by authors.

5.2.1 Partial productivity and input mix in crop production

Total growth in crop output per worker can be decomposed into growth in output per crop area (land productivity) and growth in crop area per worker:

$$\frac{Yc}{W} = \frac{Yc}{A} \times \frac{A}{W} \tag{5.1}$$

where *Yc* is crop output, *W* is number of workers in agriculture and *A* is crop area (area under annual and permanent crops). Crop output per hectare can be further decomposed into fertilizer per hectare and output per unit of fertilizer used (fertilizer productivity).

$$\frac{Yc}{A} = \frac{Frt}{A} \times \frac{Yc}{Frt} \tag{5.2}$$

Finally, crop area per worker (*A/w*) depends on the amount of capital used in crop production per worker (*Kc/w*) and on the productivity of this capital measured as the area cultivated per unit of crop capital used (*A/Kc*):

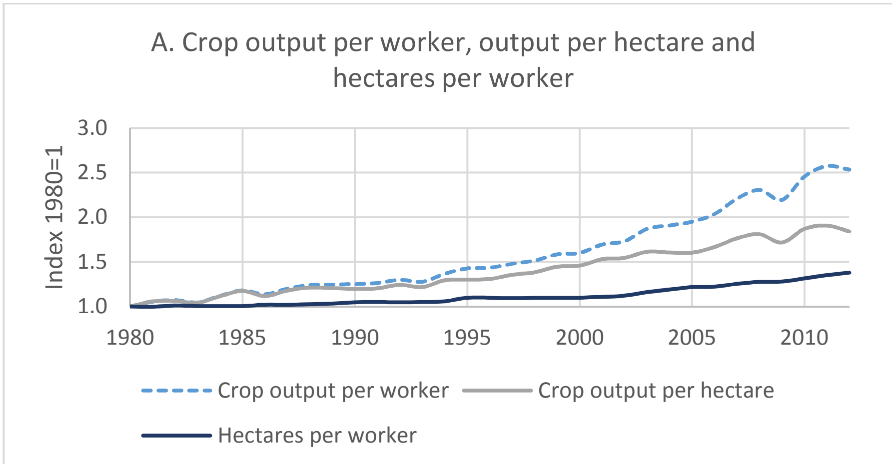
$$\frac{A}{W} = \frac{Kc}{W} \times \frac{A}{Kc} \tag{5.3}$$

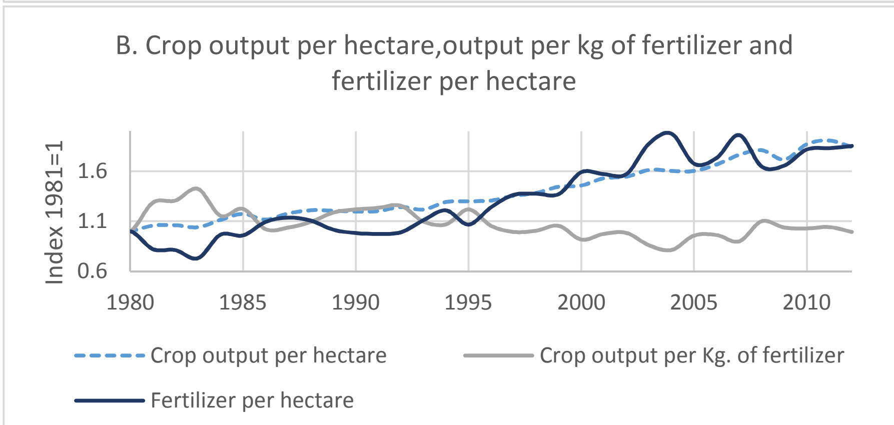
Figure 5.9 presents results of this decomposition. Note that with the information available we can separate inputs used in crop and livestock production, the only exception being labor for which we don't have allocation across sectors. Results for crops and livestock (in the next section) refer to total labor in agriculture.

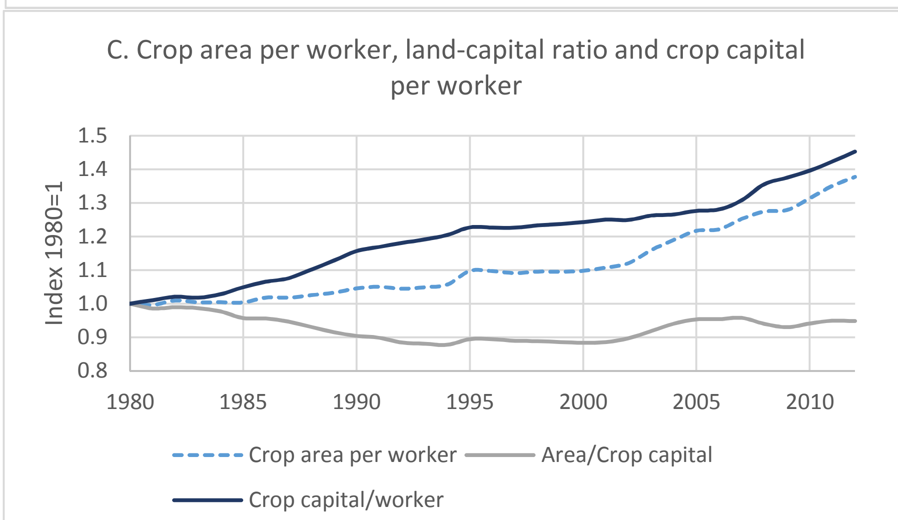
Figure 5.9 shows that growth in crop output per worker accelerates to 3.7 percent in the 2000s compared with an average of 2.2 percent for the period 1980-2000 (Figure 5.9.A). Higher growth in the last decade is the results of faster growth in the use of cropland per worker which increased at an average yearly rate of 1.3 percent compared to only 0.2 to 0.6 percent between 1980 and 1990. While growth in land productivity explained 80 percent of total crop output per worker in the 1980s and 1990s, its contribution decreases to 45 percent in the 2000s as the result of an increase in the use of arable land per worker, which explained 55 percent of total output growth in the last decade.

Land used in crop production was 90 percent more productive in 2012 than in 1980 and the increase in land productivity shown in Figure 5.9.B (*Yc/A*) appears to be related to fast growth in the use of fertilizer per hectare (4.3 percent in the 1980s, 2.9 percent in the 1990s and 3.8 percent in the 2000s). This growth is higher than losses in fertilizer productivity of about 0.5 percent that resulted from increased fertilizer use. As Figure 5.9 shows, the region is using almost twice as much fertilizer per hectare in 2012 than in 1980. On the other hand, the increase in arable land per worker observed in the 2000s (Figure 5.9.C), appears to be related to higher use of crop capital per worker, which is expected to have increased labor productivity. According to our figures, investment in crop capital increased at an average rate of 1.3 percent during the 1980s and 1990s but growth slows down in the first half of the 2000s. However, this slowdown in investment occurs simultaneously with an increase in capital productivity reflected in the increase number of hectares of cultivated crop land per dollar of crop capital stock. These changes in crop capital productivity could be related in part to the adoption of new technologies for land preparation, zero tillage and use of herbicides and genetically modified organisms (GMO) varieties as occurred in soybean production.

Figure 5.9 Crop output and decomposition into partial productivity measures in LAC, 1981-2012







Source: Elaborated by authors.

5.2.2 Partial productivity and input mix in livestock production

Livestock output per worker (Y_L/W) is the result of average productivity of the animal stock or output per animal (Y_L/S) and the number of animals per worker (S/W):

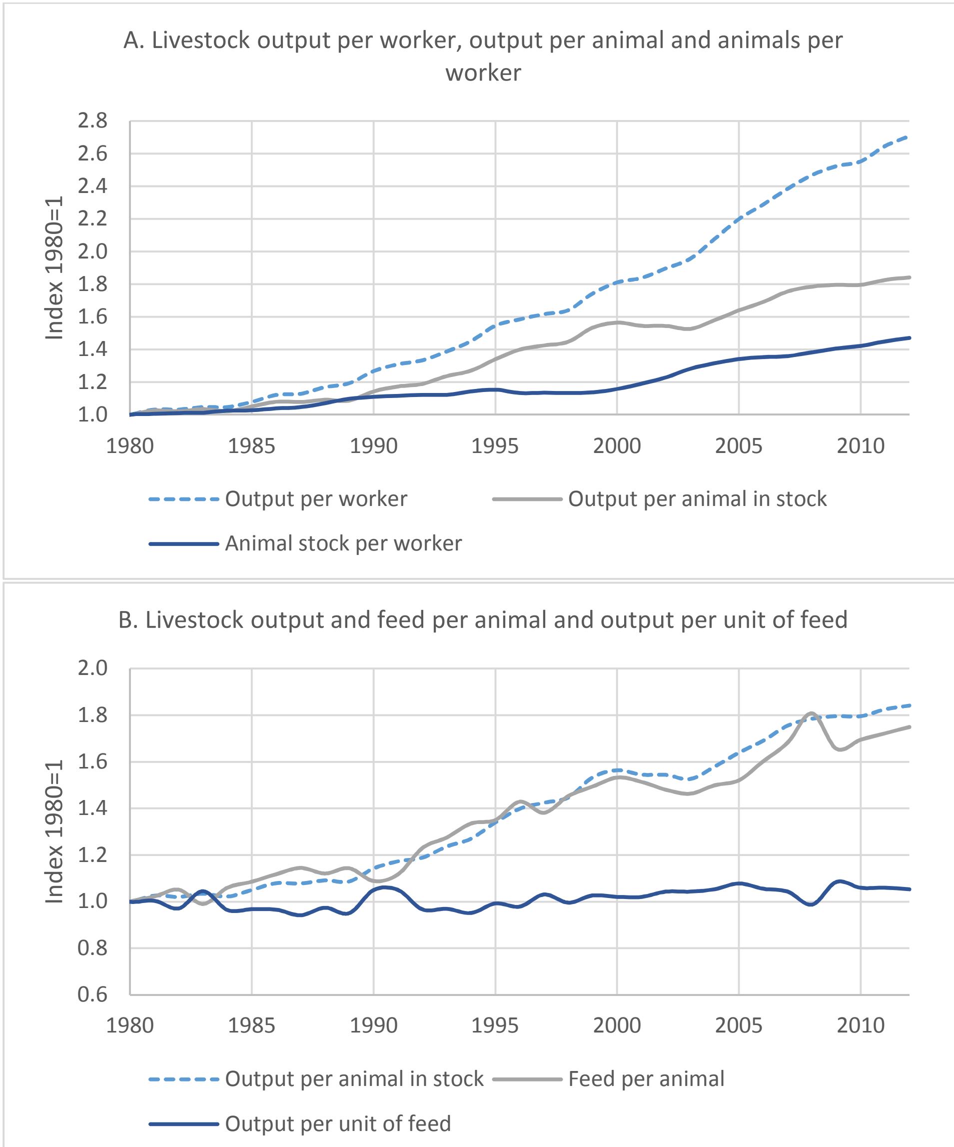
$$\frac{Y_L}{W} = \frac{Y_L}{S} \times \frac{S}{W} \tag{5.4}$$

We decompose animal productivity (Y_L/S) into feed supplied per animal and feed productivity:

$$\frac{Y_L}{S} = \frac{Feed}{S} \times \frac{Y_L}{Feed} \tag{5.5}$$

Figure 5.10 shows that during the 1980s, growth at a rate of 2.4 percent was slower than growth in any other period. This is explained by low growth in animal stock per worker (1 percent) and relatively low growth in animal productivity (1.3 percent). The 1990s show a very different growth pattern, and it is explained mostly by increases in animal productivity. As in the case of crop productivity, growth in livestock output per worker accelerated in the 2000s to a yearly average growth rate of 4 percent, a change that we decompose into growth in output per animal (1.8 percent) and growth in the number of animals per worker (2.1 percent). The contribution of growth in output per animal and of growth in the number of animals per worker to total growth during this period was 45 and 55 percent, respectively. In 2012 the animal stock in LAC was 80 percent bigger and animals are 90 percent more productive than in 1980s. Most of the growth in output comes from the feed supplied per animal unit rather than from feed productivity.

Figure 5.10 Livestock output and decomposition into partial productivity measures in LAC, 1981-2012

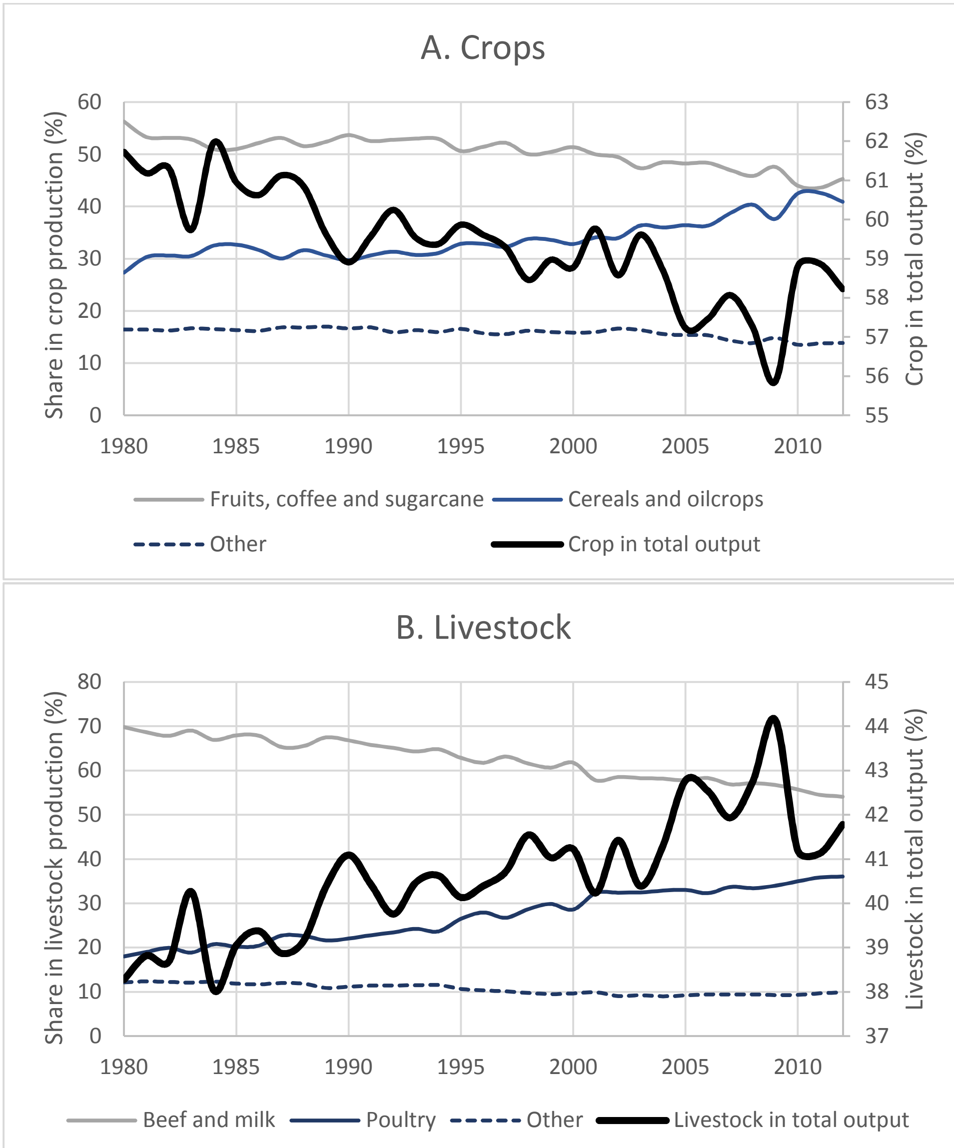


Source: Elaborated by authors.

5.3 Changes in output composition

The improved performance of agriculture in the 2000s occurred simultaneously with changes in the composition of outputs. Figure 5.11 shows that the share of livestock output in total output increased from 38 percent in 1980 to 42 percent in 2012, but most importantly, we observe significant changes in the composition of crop and livestock output. In the case of crops, oil crops and cereals have increased their share from 27 percent in 1980 to 33 percent in 2000 and 41 percent in 2012, reducing the share of fruits, coffee and sugarcane from 56 percent in 1980 to 45 percent in 2012. In the case of livestock production, poultry production doubled its share from 18 percent in 1980 to 36 percent in 2012 while the share of beef and milk production in total livestock output decreased from 70 percent in 1980 to 54 percent in 2012.

Figure 5.11 Evolution of the share of crop and livestock production in total output and changes in the composition of crop and livestock output



Source: Elaborated by authors using FAO (2014) data.

To better understand changes in LAC's agricultural output composition, we calculate measures of output composition and specialization using 164 crop and livestock primary products from FAO (2014). We use two indicators from Gutiérrez de Piñeres and Ferrantino (1997) frequently used to analyze changes in the composition of exports and imports. The first indicator is the cumulative production experience index (C_{it}), which measures the cumulative production between period 1 and period t divided by the total cumulative production in the period analyzed (from 1 to T), defined as follows:

$$c_{it} = \frac{\sum_{t=1}^{t} Y_{it}}{\sum_{t=1}^{T} Y_{it}} \tag{5.6}$$

where y_{it} is output of commodity *i* in year *t* expressed in constant prices of 2004-2006 US dollars. The variable c_{it} has properties similar to that of a cumulative distribution function taking on values at or near 0 at the beginning of the sample period ($t = 1$) and mounting to 1 in the final year ($t = T$). A traditional commodity is one with a higher proportion of total production at the beginning of the period. In contrast, a non-traditional commodity shows a higher proportion of output later in the period. We define a Traditionality Index (TI) for each commodity and country by taking the mean of the cumulative production experience index for the period 1980-2012. A detailed explanation of how these indices are calculated is presented in Appendix D.

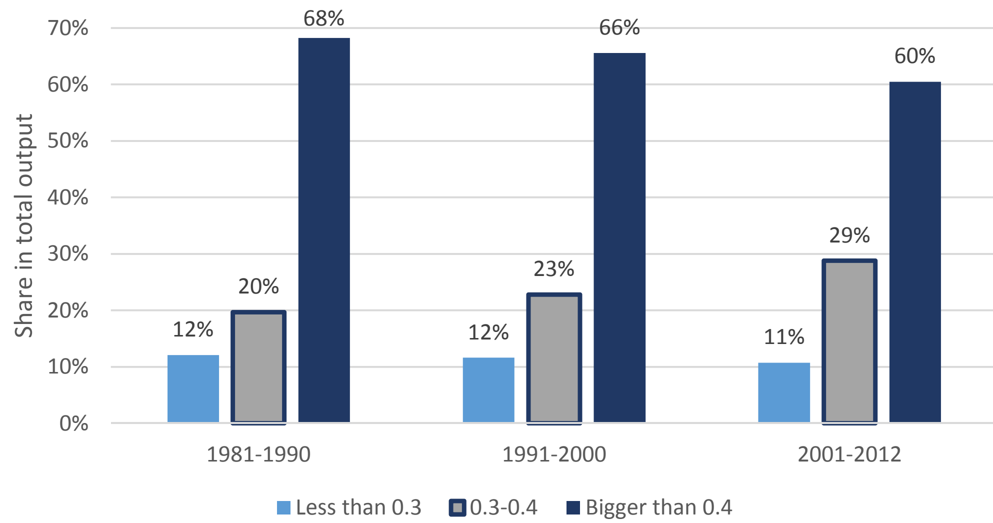
The second indicator is a measure of specialization:

$$SP_{it} = \sum_{k=1}^{164} (s_{ikt})^2 \tag{5.7}$$

where s_{ikt} is the share of commodity *k* in total output of country *i* in year *t,* where 164 is the total number of commodities. A value of 1 means that only one commodity is produced while a score approaching 0 implies a high degree of diversification.

Figure 5.12 shows shares in total output in different years of commodities grouped by the Traditionality Index. Traditional commodities (TI bigger than 0.4) represented 67-68 percent of total output in the 1980s and 1990s falling to 60 percent in 2008-2012 as the result of an increase in the share of the group of commodities with TI values between 0.3 and 0.4 (from 19 percent in 1981-1985 to 29 percent in 2008-2012).

Figure 5.12 Share in total output of commodities grouped by Traditionality Index



Source: Elaborated by authors using data from FAOSTAT.
Note: Traditionality Index takes values between 0 and 1: the closer to 1 is the value of the index, the more "traditional" is the commodity.

Table 5.3 presents the list of commodities with TI bigger than 0.3 with their corresponding TI value and their share in total output in different years.

Table 5.3.Traditionality index and share in total output per period by commodity in LAC, 1981-2012

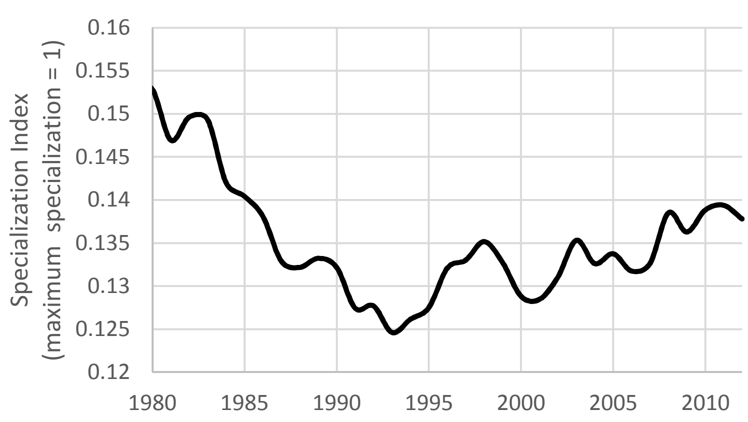
Commodity	Traditionality Index	Output share per period (percent)		
		1981-1990	1991-2000	2001-2012
Beef	0.47	19.2	18.9	17.0
Maize	0.47	5.3	5.5	5.5
Tomatoes	0.47	1.6	1.7	1.4
Sugarcane	0.46	8.9	8.5	9.2
Goat meat	0.46	0.2	0.2	0.1
Pig meat	0.45	3.4	3.4	3.5
Vegetables fresh, other	0.45	0.5	0.4	0.3
Sheep meat	0.45	0.6	0.4	0.3
Milk	0.45	8.5	9.0	8.3
Eggs	0.44	1.8	1.9	2.0
Paddy rice	0.44	3.4	3.0	2.6
Bananas	0.44	3.5	3.4	2.6
Cassava	0.44	2.3	1.7	1.3
Oranges	0.43	2.6	2.9	1.9
Tobacco	0.43	0.8	0.7	0.7
Cotton lint	0.43	1.6	0.9	0.9
Cotton seed	0.42	0.7	0.4	0.4
Honey	0.42	0.3	0.2	0.2
Groundnuts	0.41	0.3	0.2	0.2
Coffee	0.41	2.8	2.2	1.9
Cabbage	0.41	0.1	0.1	0.0
Sweet potatoes	0.40	0.1	0.1	0.0
Beans	0.40	1.9	1.7	1.3
Cocoa beans	0.38	0.5	0.3	0.2
Sorghum	0.38	1.4	0.8	0.7
Avocado	0.38	0.6	0.5	0.6
Coconuts	0.37	0.2	0.2	0.2
Onions	0.37	0.4	0.4	0.4
Chicken meat	0.37	4.1	6.8	9.4
Potatoes	0.36	1.4	1.3	1.0
Mangoes	0.35	1.0	1.0	0.9
Pineapples	0.35	0.5	0.6	0.7
Grapefruit	0.35	0.1	0.1	0.1
Lemons	0.34	0.6	0.7	0.8
Watermelons	0.34	0.1	0.1	0.2
Soybeans	0.33	5.1	6.5	10.7
Fresh fruit, other	0.33	0.2	0.2	0.2
Plantains	0.33	0.9	0.8	0.6
Chilies, green	0.32	0.3	0.4	0.4
Pumpkins	0.31	0.1	0.1	0.1
Sesame seed	0.31	0.1	0.0	0.0
Carrots	0.30	0.1	0.2	0.1
Total		87.9	88.4	89.3

Source: Elaborated by authors using data from FAOSTAT.

For the region as a whole, traditional commodities with the largest share in output are beef, sugarcane, milk, maize, pig meat, bananas, rice, oranges, coffee, eggs, cassava, tomatoes, and cotton. The most important of the non-traditional commodities are soybean and chicken meat. These commodities represented 9 percent of LAC's agricultural output in 1981-1990 and increased their share to 20 percent in 2001-2012. Other commodities in this group reduced their share in total output from 9 percent in 1981-1990 to 7 percent in 2001-2012, which indicates that the changes in output structure observed in the last 30 years are mostly related to growth in soybean and chicken meat production.

The Specialization Index (SP) in Figure 5.13 shows that the degree of output diversification in LAC's agriculture is high, with average values between 0.12 and 0.16 during 1980-2012. Nonetheless, changes in the value of the index appear to be related to the crisis of the 1980s and the policy changes that followed. The evolution of the SP Index in Figure 5.13 shows that during the 1980s the region diversified its production, which is reflected in the reduction of the SP from 0.15 to 0.12. With policy changes and a better environment for agriculture in the 1990s, the SP Index grew to reach a value of 0.14 in 2012. Comparing changes in SP and the TI Index we conclude that, agriculture in the region went through a period of diversification that resulted in increased contribution of non-traditional commodities in total output as the result of policy changes, external shocks and the availability of new technologies. However, only two of these commodities continue to grow significantly in the 2000s with the region moving to similar levels of specialization than in the past but now with an increased participation of soybeans and chicken meat production in total output.

Figure 5.13 Specialization index of agricultural production in LAC, 1980-2012



Source: Elaborated by authors using data from FAOSTAT.
Note: Specialization Index takes values between 0 and 1, with a value of 1 meaning that only one commodity is produced.

5.4. Country performance

Table 5.4 shows average growth rates of output and input per worker, and TFP and its components (efficiency and technical change) between 1981 and 2012. Sixteen of the 26 countries show growth in output per worker higher than 2.0 percent. Brazil, Nicaragua, Costa Rica, Uruguay, Dominican Republic and Ecuador, all growing at more than 2.5 percent yearly, were the best performing countries of the last 30 years. Table 5.4 also shows that Costa Rica, Brazil, Peru, Chile, Ecuador, Nicaragua, Bolivia and Paraguay were the countries with the highest increase in TFP between 1981 and 2012.

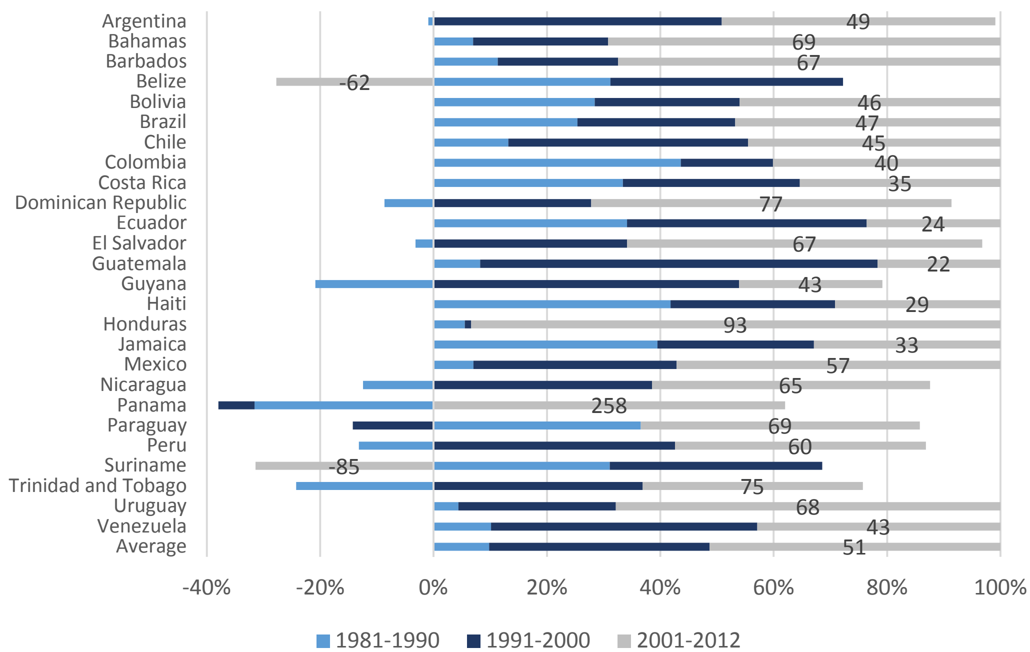
Table 5.4 Growth rate of agricultural output and input per worker, TFP and its components, 1981-2012

Country	Output	Input	Total Factor Productivity (TFP)	Efficiency (EFF)	Technical Change (TC)
Brazil	5.1	2.6	2.5	1.5	0.9
Nicaragua	3.2	1.4	1.7	1.5	0.2
Costa Rica	2.8	0.3	2.5	1.7	0.9
Uruguay	2.8	1.2	1.5	0.5	1.0
Dominican Republic	2.8	1.8	0.9	-0.4	1.4
Ecuador	2.7	0.8	1.9	0.2	1.7
Bahamas	2.5	0.9	1.5	0.4	1.2
Chile	2.5	0.2	2.3	0.0	2.3
Honduras	2.4	1.2	1.2	0.0	1.2
Venezuela	2.3	0.9	1.4	0.2	1.3
Paraguay	2.3	0.7	1.6	0.7	0.8
Mexico	2.3	0.8	1.5	0.5	1.0
Peru	2.2	-0.1	2.4	1.6	0.7
Guyana	2.2	0.9	1.3	-0.8	2.1
Barbados	2.2	2.8	-0.6	-0.2	-0.4
Jamaica	2.1	1.1	0.9	1.0	-0.1
Colombia	1.9	0.9	1.0	-0.1	1.0
Argentina	1.8	0.3	1.5	-0.2	1.8
Guatemala	1.5	0.5	1.0	0.5	0.5
El Salvador	1.2	0.6	0.5	0.1	0.4
Bolivia	1.0	-0.6	1.6	-0.1	1.7
Belize	0.5	-0.1	0.5	-0.1	0.7
Panama	0.3	0.8	-0.5	-0.8	0.3
Trinidad and Tobago	0.1	-1.1	1.2	0.9	0.3
Suriname	-0.5	-0.4	-0.1	-0.3	0.2
Haiti	-0.9	0.0	-0.9	-1.8	1.0
LAC	2.1	0.9	1.2	0.3	0.9

Source: Elaborated by authors

How did countries performed in different subperiods and how much of total growth in the period is explained by growth in the last decade? This is shown in Figure 5.14 that compares the contribution of growth in different sub-periods to total growth in 1981-2012. Half of total regional growth between 1981 and 2012 occurred in the last decade and only 10 percent between 1981 and 1990. For most countries, more than 40 percent of total growth occurred in the last decade with Costa Rica and Ecuador being the exception among best performing countries. These two countries show steady growth during the whole period analyzed. Only Suriname and Belize show negative growth in the last decade.

Figure 5.14 Contribution of growth in different subperiods to total growth for LAC countries, 1981-2012 (percentage)



Source: Elaborated by authors.

Table 5.5 ranks countries by average growth rate in agricultural output per worker between 2001 and 2012. Best performing countries are Brazil, Honduras, Dominican Republic, Nicaragua, Barbados, Uruguay, Paraguay and Bahamas. These countries increased output per worker at yearly rates of 3.0 percent or more, with an average growth rate of 4.9 percent, also showing the highest growth in input per worker and TFP (2.2 and 2.7 percent respectively). In contrast, Jamaica, Suriname, Panama, Ecuador, Bolivia, Guatemala, Trinidad and Tobago and Haiti showed growth in output per worker and TFP below 1 percent (average of 0.9 percent) and growth in input per worker close to 0. The group of countries growing at rates close to the regional average includes Argentina, Chile, Colombia, Costa Rica, Guyana, Mexico, Peru, El Salvador and Venezuela. Average growth rate in output per worker between 2001 and 2012 for this group was 2.6 percent, with growth of input per worker of 1.1 percent and TFP growth of 1.5 percent. Notice that between 2001 and 2012 more than two thirds of growth in output per worker in some countries was the result of growth in TFP, including Chile, Paraguay, Peru, Nicaragua, Bahamas and Argentina. In some cases like Suriname, Bolivia and Guatemala, TFP growth accounted for all growth in output per worker.

The decomposition of TFP growth in Table 5.6 shows that the group of countries with high TFP growth has performed better than the average group because of catching-up to the technological frontier (efficiency growth). On average, the contribution of spillovers from movements in the technological frontier have had a similar impact in both groups (1.1 percent) but efficiency gains were 0.8 percent among best performers and only 0.2 in the average group. However, different growth patterns can be observed within groups. For example, Nicaragua's high TFP growth is mostly explained by efficiency gains, which might be related to the recovery of Nicaragua's agriculture after civil war. In contrast to Nicaragua, another poor country like Bolivia shows negative growth in efficiency but a high rate of technical change. A possible explanation for this is that Bolivia has benefited from spillovers (for example, from Brazil and Argentina) that contributed to the agricultural boom of its Western region (Santa Cruz) and the development of soybean production for export. With production in other regions lagging behind, the overall effect for the country is almost zero growth in efficiency.

Table 5.5 Growth rate of agricultural output, input per worker and TFP in LAC countries, 1981-2012

Country	1981-1990			1991-2000			2001-2012		
	Output	Input	TFP	Output	Input	TFP	Output	Input	TFP
Brazil	4.5	2.4	2.0	4.4	2.1	2.2	6.3	3.2	3.0
Honduras	0.7	0.7	0.1	0.1	-0.2	0.2	5.7	2.8	2.9
Dominican Republic	-0.9	0.5	-1.4	3.0	2.2	0.8	5.7	2.6	3.0
Nicaragua	-0.6	0.2	-0.7	4.7	3.0	1.7	5.0	1.2	3.8
Barbados	-0.2	3.1	-3.3	1.7	1.6	0.1	4.7	3.5	1.1
Uruguay	1.8	0.2	1.6	2.0	0.8	1.2	4.2	2.5	1.7
Paraguay	4.1	1.8	2.2	-1.3	-0.3	-1.0	3.9	0.7	3.2
Bahamas	2.0	0.3	1.7	1.5	1.6	0.0	3.7	0.9	2.7
Peru	-0.4	-1.8	1.5	3.7	0.7	3.0	3.2	0.6	2.6
Mexico	1.1	0.6	0.5	2.4	0.5	1.9	3.2	1.3	1.9
Chile	1.6	-0.7	2.3	3.1	0.9	2.2	2.7	0.4	2.3
Venezuela	0.7	-0.9	1.6	3.6	1.2	2.3	2.7	2.1	0.6
El Salvador	-1.2	-0.1	-1.1	1.8	1.0	0.8	2.7	1.0	1.7
Costa Rica	3.1	-0.1	3.1	2.8	-0.3	3.1	2.6	1.1	1.5
Guyana	-1.9	0.6	-2.6	6.3	0.4	5.9	2.4	1.6	0.8
Argentina	0.5	-0.6	1.0	2.8	0.8	2.0	2.2	0.7	1.5
Colombia	2.8	1.3	1.5	0.9	0.3	0.6	1.9	1.1	0.8
Jamaica	2.4	1.4	0.9	1.9	1.4	0.5	1.9	0.6	1.3
Suriname	-1.3	0.7	-2.0	-2.6	-0.3	-2.2	1.8	-1.5	3.3
Panama	-0.9	-0.7	-0.3	-0.2	1.4	-1.6	1.8	1.6	0.2
Ecuador	2.8	0.8	2.0	3.8	0.3	3.5	1.7	1.2	0.5
Bolivia	0.9	-1.6	2.5	0.8	0.0	0.8	1.3	-0.2	1.4
Guatemala	0.3	-0.2	0.4	3.5	2.0	1.5	0.9	-0.2	1.1
Trinidad and Tobago	-1.6	-2.4	0.8	0.9	-1.3	2.2	0.8	0.1	0.6
Haiti	-1.2	-0.4	-0.8	-0.8	0.7	-1.4	-0.6	-0.1	-0.5
Belize	0.8	0.9	0.0	2.0	0.4	1.7	-1.1	-1.2	0.0
Average	0.8	0.2	0.5	2.0	0.8	1.2	2.7	1.1	1.7

Source: Elaborated by authors.

Note: Countries ranked based on average growth rate in agricultural output per worker between 2001 and 2012, from best to worse performer.

Table 5.6 Growth rate of TFP, Efficiency and Technical Change in agriculture for LAC countries, 1981-2012

Country	Total Factor Productivity (TFP)	Efficiency Change (EFF)	Technical Change (TC)
Costa Rica	2.5	1.7	0.9
Brazil	2.5	1.5	0.9
Peru	2.4	1.6	0.7
Chile	2.3	0.0	2.3
Ecuador	1.9	0.2	1.7
Nicaragua	1.7	1.5	0.2
Bolivia	1.6	-0.1	1.7
Paraguay	1.6	0.7	0.8
Bahamas	1.5	0.4	1.2
Best TFP growth Performers	2.0	0.8	1.1
Argentina	1.5	-0.2	1.8
Uruguay	1.5	0.5	1.0
Mexico	1.5	0.5	1.0
Venezuela	1.4	0.2	1.3
Guyana	1.3	-0.8	2.1
Honduras	1.2	0.0	1.2
Trinidad Tobago	1.2	0.9	0.3
Guatemala	1.0	0.5	0.5
Average Performers	1.3	0.2	1.1
Colombia	1.0	-0.1	1.0
Dominican Republic	0.9	-0.4	1.4
Jamaica	0.9	1.0	-0.1
El Salvador	0.5	0.1	0.4
Belize	0.5	-0.1	0.7
Suriname	-0.1	-0.3	0.2
Panama	-0.5	-0.8	0.3
Barbados	-0.6	-0.2	-0.4
Haiti	-0.9	-1.8	1.0
Poor TFP growth Performers	0.2	-0.3	0.5

Source: Elaborated by authors.

Note: Countries ranked based on average growth rate in agricultural output per worker between 2001 and 2012, from best to worse performer.

Are there differences in performance associated with differences in agroecology? Table 5.7 compares average growth of TFP and its components in the four AEZ used in this study. Countries in temperate zones show higher TFP growth rates than tropical countries (1.8 and 1.9 compared with 1.2 and 0.9 in temperate and tropical zones, respectively). This difference is mostly explained by higher growth rates of technical change in temperate countries (1.2 and 1.6 in Sub-humid and humid temperate countries compared to 0.6 and 0.8 percent in Sub-Humid and Humid tropical countries respectively). In other words, the world technological frontier moved faster for temperate countries than for tropical countries, resulting in an advantage for temperate countries in LAC.

Table 5.7 Average growth in TFP, Efficiency and Technical Change by agroecological zone, 1981-2012

Component / Agroecological Zone	1981-1990	1991-2000	2001-2012	1981-2012
Total Factor Productivity (TFP)				
Temperate Sub-humid	1.8	1.2	2.2	1.8
Temperate Humid	2.0	1.7	2.0	1.9
Tropical Sub-Humid	-0.1	1.6	2.0	1.2
Tropical Humid	0.1	1.1	1.4	0.9
Efficiency (EFF)				
Temperate Sub-humid	1.1	-0.3	0.8	0.5
Temperate Humid	-0.1	-0.4	1.1	0.2
Tropical Sub-Humid	-0.4	1.0	1.1	0.6
Tropical Humid	0.1	-0.7	0.8	0.1
Technical change (TC)				
Temperate Sub-humid	0.8	1.5	1.4	1.2
Temperate Humid	2.1	2.0	0.9	1.6
Tropical Sub-Humid	0.3	0.6	0.9	0.6
Tropical Humid	0.1	1.8	0.6	0.8

Source: Elaborated by authors.

Note: See appendix for definitions and country classification by AEZ.

This advantage for temperate LAC countries could be explained as an effect of the appropriate technology hypothesis considered in this study, where high income countries generate new technologies adapted to their own production conditions. Table 5.8 seems to support this hypothesis. It shows average growth of different variables for countries grouped by performance between 2001 and 2012. Differences in growth rates between groups suggest that best performing countries were able to accelerate growth in output per worker using labor-saving technologies, that increase investment per worker, particularly capital for crop production. Increased capital allowed best performing countries to incorporate more land to crop production while reducing the number of workers in agriculture. In contrast, countries in the group of poor performers show negligible increase in crop capital per worker, a growing labor force in agriculture (0.8 percent compared with -1.2 percent growth among best performers) and unlike other countries, a reduction in land per worker in recent years. Notice that countries in the average and best performing groups have similar growth patterns and show no significant differences in TFP growth. The difference in performance appears to be related to higher investment in crop and livestock capital and faster incorporation of land to production.

Table 5.8 Average growth rates of different variables for countries grouped by growth in output per worker, 2001-2012 (percent)

Variable	Poor		Average		Best
Agricultural exports/imports ratio	-0.9		1.1		4.0
Export price	6.2		6.5		7.6
GDP per capita (US 2005 ppp)	2.3		2.3		1.7
Output per worker	1.1	**	2.7	**	5.2
Input per worker	0.1	**	1.1	**	2.2
Efficiency (EFF)	0.8		0.7		1.9
Technical change (TC)	0.9		0.9		1.0
Total Factor Productivity (TFP)	1.1	*	1.6		2.9
Fertilizer per worker	4.0		3.6		11.8
Feed per worker	1.6		3.2		4.6
Crop capital per worker	0.0	**	0.8	**	2.3
Livestock capital per worker	1.1	*	1.0	**	2.6
Agricultural area per worker	-1.0	**	0.7		1.5
Arable land per worker	-0.5	**	0.8	*	2.2
Traditionality index	-0.4		-0.4		-0.6
Specialization index	0.6		0.6		0.5
R&D/AgGDP	-5.1		-0.6		0.0
R&D	-2.0		2.0		3.9
Labor	0.8	**	-0.5	*	-1.2

Source: Elaborated by authors.

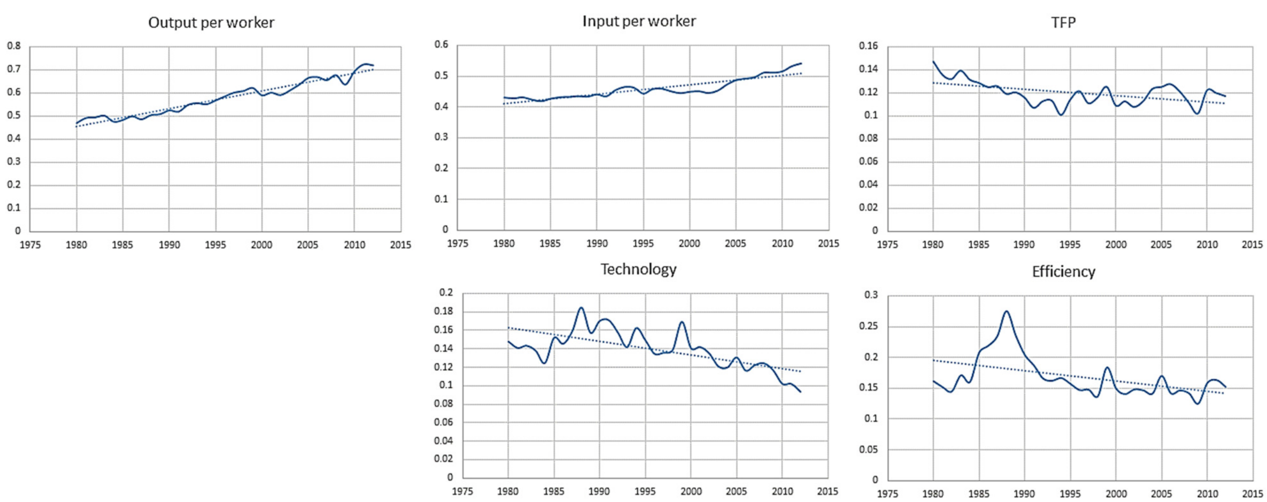
Note: * and ** mean that growth rates are significantly different at the 5 and 1 percent level, respectively.

The observed growth patterns suggest that countries that were able to increase labor productivity through capital investment and increased land-labor ratios were the ones performing better, while countries with limited access to capital and land are among the poor performers in the last decade. It is important to notice that faster growth in input per worker is not only associated with better performance in terms of growth in output per worker, which is to be expected, but also with a better performance in TFP growth. On average, countries with highest TFP growth also show the highest growth rates in input per worker and countries with low TFP growth are those with lowest growth in input per worker.

How did this growth pattern and the use of labor saving technologies affect poor countries, which are mostly those with low levels of labor productivity? We use a sigma-convergence model (Barro and Sala-i-Martin, 1992), derived from growth theory (Solow, 1956) to look at the implications of recent growth for different countries. Sigma-convergence occurs when the dispersion of real per capita income across a group of economies falls over time (a decline in the variance of individual observations).

Figure 5.15 plots the trend of the variance of agricultural output per worker and its components for the period 1980-2012. Improved performance in the region has increased the differences in labor productivity between countries as shown by the positive trend of the variance of this variable. However, this effect does not relate to growth improvements in TFP. Increased TFP, efficiency and technical change actually reduced differences in labor productivity. The growing variability in labor productivity is the result from different possibilities to increase input per worker across countries in the region.

Figure 5.15 Trends in the variance of agricultural output per worker and its components in LAC, 1980-2012



Source: Elaborated by authors.
Note: Values are of the variance of the natural log of the different variables. Coefficients of the trend lines are all highly significant.

A way to summarize the contribution of efficiency (E), factor endowments (F) and available technology or potential TFP (T) to output differences is the variance decomposition. Aggregating inputs, the Cobb-Douglas production function can be expressed as $Y = A \times F$, where A is TFP and is equal to $A = E \times T$, or the product of efficiency and available technology. The variance of log output per worker can be decomposed as:

$$Var(lnY) = Var(lnT) + Var(lnE) + Var(lnF) + 2Cov(T,E) + 2Cov(T,F) + 2Cov(E,F) \quad (5.8)$$

Table 5.9 presents the contribution of factors, efficiency and technology to the variation of output per worker in agriculture. Results show that differences in labor productivity across countries between 1981 and 2012 are explained mostly by differences in input levels. These conclusions are valid for all periods, which mean that the importance of inputs as determinants of labor productivity has changed very little in the last four decades. Differences in labor productivity are the result of low intensity in the use of inputs per worker and can be reduced only in part by improved efficiency. Countries using low levels of input per worker can still increase TFP but up to a certain point. Long-run growth in agriculture for poor countries in the region will require not only TFP improvements but also more intensive use of inputs and capital per worker to catch-up with labor productivity levels in most productive countries. This result is in agreement with the difference between best and poor performers in Tables 5.5 and 5.8. Best performing poor countries like Honduras and Nicaragua significantly increased input per worker together with TFP, which resulted in a significant increase in labor productivity and growth in efficiency. In contrast, countries in the group of poor performers like Bolivia, Guatemala, Haiti and Belize, show poor growth in output per worker together with slower growth in TFP and no improvements in efficiency. As shown in Table 5.6, efficiency growth for Honduras and Nicaragua in 2001-2012 was 4.0 and 2.7 percent respectively. This compares to efficiency growth of 0.0 and 0.6 percent in Bolivia and Guatemala, respectively.

Table 5.9 Contribution of efficiency, technology and inputs to the variation of output per worker in agriculture in LAC, 1981-2012

Period	Efficiency	Technology	Inputs
1981-1990	0.11	0.09	0.80
1991-2000	0.09	0.12	0.79
2000-2011	0.11	0.11	0.78
1981-2012	0.10	0.13	0.77

Source: Elaborated by authors.

6 Conclusions

During the 2000s, a favorable macroeconomic environment and high prices of primary commodities contributed to the best performance of LAC's agricultural sector of the last 30 years, with steady growth of TFP, output and input per worker and a reduction of the TFP gap between the region and OECD countries. Several changes that occurred in the last decade contributed to the improved performance of agriculture in the region. First, acceleration of crop production per worker as the result of fast growth in the use of fertilizer that increased land productivity; second, a more intensive use of capital in crop production that expanded the cultivated area per worker in best performing countries; third, changes in output composition, with a growing importance of production of soybean and chicken meat in the region; finally, observed growth patterns at the country level suggest that countries with significant increases in input per worker have experienced faster TFP growth than countries with limited access to capital and land and slow growth in input per worker

One question that remains open refers to the role played by policy and institutional changes and high commodity prices in the improved performance of agriculture in recent years. Many analysts now argue that the upward phase of the commodity cycle has run its course at the same time that we observe less favorable external markets and a deterioration of the policy environment in several countries. These new developments raise obvious concerns for the future of agriculture in the region. A second question relates to the factors that explain different performances between countries in the region. Why did some poor countries fall behind while others were able to achieve fast growth and catch-up to the frontier? Growing differences in labor productivity seem to be mostly the result of differences in the use of inputs per worker, differences in natural resource quality and in the availability and efficient use of new technologies in different agroecologies. More work is needed to better understand these differences. Finally, an important question that needs to be answered refers to the role that R&D investment played in the performance of the region in recent years particularly in best performing poor countries like Nicaragua, Honduras, Paraguay and Peru with less developed research systems than those in larger and richer countries like Argentina, Brazil, Chile, Mexico and Uruguay. A better understanding of these issues could contribute to identify policy and investment strategies to sustain agricultural growth in the future, adapted to the different possibilities and structural characteristics of the countries in the region.

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APPENDIX A: ECONOMETRIC RESULTS

Table A.1 Cobb-Douglas production function's parameter estimates using Pooled regressions

Variable	POLS (1)	Two-way FE (2)	FD-OLS (3)	CCEP (4)	CCEPn (5)	CCEPd (6)	CCEPc (7)	CCEPoc (8)
Labor	–0.0555***	0.174***	–0.0593	0.107	0.0138	0.134	–0.120	0.0723
	(0.00304)	(0.0176)	(0.0997)	(0.151)	(0.156)	(0.132)	(0.110)	(0.131)
Crop capital	0.265***	0.179***	0.283***	0.364***	0.237***	0.323***	0.194***	0.362***
	(0.00867)	(0.00968)	(0.0635)	(0.0614)	(0.0670)	(0.0542)	(0.0434)	(0.0673)
Livestock capital	0.219***	0.280***	0.235***	0.328***	0.190***	0.335***	0.347***	0.357***
	(0.00733)	(0.0101)	(0.0565)	(0.0680)	(0.0679)	(0.0630)	(0.0923)	(0.0757)
Fertilizer	0.111***	0.0513***	0.00454	0.0136***	0.0202**	0.0140***	0.0124***	0.0129**
	(0.00498)	(0.00259)	(0.00277)	(0.00426)	(0.00913)	(0.00416)	(0.00427)	(0.00543)
Land	2.52e–05	0.515***	0.344***	0.288**	0.232	0.334***	0.253**	0.253**
	(0.00571)	(0.0200)	(0.0829)	(0.130)	(0.144)	(0.117)	(0.108)	(0.117)
Feed	0.174***	0.118***	0.0922***	0.109***	0.154***	0.1000***	0.0951***	0.104***
	(0.00795)	(0.00478)	(0.0246)	(0.0263)	(0.0457)	(0.0277)	(0.0319)	(0.0272)
Constant	6.994***			–2.43***	–2.426**	1.937	4.489***	0.208
	(0.0456)			(4.24e–06)	(1.127)	(1.337)	(0.856)	(1.140)
Implied labor coefficient	0.175	0.031	–0.018	0.003	0.181	0.028	–0.022	–0.016
Returns	DRS	IRS	DRS	CRS	CRS	CRS	CRS	CRS
RMSE	0.412	0.154	0.079	0.071	0.088	0.071	0.072	0.072
Stationarity [a]	I(1)	I(1)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)
Mean ρij [b]	0.416	0.388	0.124	0.173	0.131	0.159	0.143	0.152
CD(p) [c]	0.28	0.19	–0.99	–2.92	1.47	–0.08	–2.43	–2.15
CD p value	0.783	0.852	0.323	0.003	0.141	0.935	0.015	0.031
Observations	6,834	6,834	6,700	6,834	6,834	6,834	6,834	6,834
R-squared	0.917	0.777	0.465	0.976	0.963	0.976	0.975	0.975
No. of countries	134	134	134	134	134	134	134	134

Notes: 1) Robust standard errors are in parentheses; 2) *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$; 3) Dependent variable is log output per worker in all models except for the transformation in (2) (see Coakley et al. 2006) and in (3), which is the model in first differences; 4) CCEP = Pesaran common correlated effects; CCEPn = CCE where cross-section averages are averages of contiguous neighbors for each country; CCEPd = CCE where cross-section averages are calculated using the inverse of the population-weighted distance between countries; CCEPc = CCE where weights for every country pair are constructed based on the share of cultivated land within each of 12 climatic zones; CCEPoc = CCE where weights for every country pair are constructed based on the share of different commodities in total output; MG = Pesaran's mean group; CMG= heterogenous version of the CCE or MG CCE and its extensions using different weights: contiguous neighbors (CMGn), distance (CMGd), climate (CMGc), and output composition (CMGoc); AMG= Eberhardt and Bond (2009) augmented MG estimator ; CD = Pesaran cross-section dependence test for panels ; CRS = constant returns to scale; DRS = decreasing returns to scale; FE = fixed effects; IRS = increasing returns to scale ; RMSE = root-mean-squared error; 5) a. Pesaran (2007) CIPS test results: I(0) stationary, I(1) nonstationary; b. Mean absolute correlation coefficient; c. Pesaran CD test, H0: no cross-section dependence.

Table A.2 Cobb-Douglas production function's parameter estimates using Heterogeneous technology models

Variable	MG (9)	CMG (10)	CMGn (11)	CMGd (12)	CMGc (13)	CMGoc (14)	AMG (15)
Labor	–0.0134	0.135	0.0674	0.0359	0.0722	0.0286	0.0953
	(0.128)	(0.133)	(0.129)	(0.128)	(0.132)	(0.127)	(0.123)
Crop capital	0.147**	0.159***	0.183***	0.147***	0.141***	0.164***	0.194***
	(0.0598)	(0.0498)	(0.0581)	(0.0520)	(0.0491)	(0.0520)	(0.0626)
Livestock capital	0.205***	0.207***	0.182***	0.201***	0.193***	0.206***	0.232***
	(0.0303)	(0.0283)	(0.0298)	(0.0297)	(0.0305)	(0.0276)	(0.0320)
Fertilizer	0.0207***	0.0180***	0.0216***	0.0187***	0.0153***	0.0196***	0.0261***
	(0.00546)	(0.00562)	(0.00513)	(0.00521)	(0.00471)	(0.00521)	(0.00566)
Land	0.263***	0.262***	0.243***	0.221***	0.290***	0.267***	0.231***
	(0.0857)	(0.0896)	(0.0768)	(0.0827)	(0.0895)	(0.0943)	(0.0864)
Feed	0.164***	0.182***	0.206***	0.188***	0.182***	0.189***	0.167***
	(0.0172)	(0.0178)	(0.0186)	(0.0172)	(0.0181)	(0.0177)	(0.0175)
Constant	6.922***	–1.237	0.252	1.768	2.852	–7.476**	6.118***
	(0.975)	(3.706)	(1.361)	(3.566)	(2.327)	(3.545)	(0.915)
Implied labor coefficient	0.19	0.31	0.232	0.26	0.25	0.183	0.25
Returns	CRS	CRS	CRS	CRS	CRS	CRS	CRS
RMSE	0.064	0.051	0.052	0.051	0.050	0.051	0.064
Stationarity [a]	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)
Mean pij [b]	0.132	0.132	0.124	0.129	0.124	0.127	0.133
CD(p) [c]	5.41	–1.08	0.1	1.94	–2.31	–1.04	0.77
CD p value	0.000	0.282	0.921	0.053	0.021	0.297	0.440
Observations	6,834	6,834	6,834	6,834	6,834	6,834	6,834
Number of countries	134	134	134	134	134	134	134

Source: Author's estimation.

Notes: 1) Standard errors in parentheses;

2) *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$;

3) Dependent variable is log output per worker in all models. MG= Pesaran's mean group; CMG = heterogeneous version of the common correlated effects or MG common correlated effects and its extensions using different weights: contiguous neighbors (CMGn), distance (CMGd), climate (CMGc), and output composition (CMGoc); AMG = Eberhardt and Bond (2009) augmented mean group estimator; CRS = constant returns to scale;

a. Pesaran (2007) CIPS test results: I(0) stationary, I(1) nonstationary.

b. Mean Absolute Correlation coefficient.

c. Pesaran CD test, H0: no cross-section dependence.

APPENDIX B: A COMPARISON OF GROWTH-ACCOUNTING AND DATA ENVELOPMENT ANALYSIS (DEA) METHODS

The use of a global Cobb-Douglas production function to estimate TFP in this study introduces a number of restrictive assumptions, particularly constant production elasticities which result in the use of constant input shares across all countries, and the need to aggregate crop and livestock outputs into a single output measure. Another important assumption made when using the Cobb-Douglas production is that of Hicks neutral technical change. We relaxed this assumption by using the "*hybrid*" approach that combines growth accounting and DEA methods as discussed in Section 3, but the other constraints resulting from the use of the global Cobb-Douglas production still apply here and affect our results.

A more flexible approach to measure TFP is the one that uses DEA to calculate the Malmquist TFP index number. The advantage of this method is that it does not make any of the restrictive assumptions made by the growth accounting-Cobb-Douglas approach and that it does not require any price data to aggregate inputs and outputs, information that is seldom available for international comparisons or if available could be distorted due to government intervention in most developing countries. On the other hand, this method is susceptible to the effects of data noise that can become particularly important in the presence of data error and poor dimensionality. The method can also suffer from the problem of "unusual" shadow prices, when degrees of freedom are limited (Coelli and Rao, 2005). This last point is important because even though the method does not explicitly use prices it uses implicit shadow prices derived from the shape of the estimated production possibility set. According to Coelli and Rao (2005), information on shadow prices and shadow shares "can provide valuable insights into why various authors have obtained widely differing TFP growth measures for some countries, when applying these Malmquist DEA methods."

The Malmquist index measures the TFP change between two different time periods by calculating the ratio of the distance of each data point relative to a common technological frontier. Following Färe et al. (1994), the Malmquist index between period *t* and *t + 1* is given by:

$$M_o = \left[M_o^t \times M_o^{t+1}\right]^{1/2} = \left[\frac{D_o^t(x^{t+1}, y^{t+1})}{D_o^t(x^t, y^t)} \times \frac{D_o^{t+1}(x^{t+1}, y^{t+1})}{D_o^{t+1}(x^t, y^t)}\right]^{1/2} \qquad \text{(B.1)}$$

This index is estimated as the geometric mean of two Malmquist indices, one using as a reference the technology frontier in t $\left(M_o^t\right)$, and a second index that uses the frontier in *t + 1* as the reference $\left(M_o^{t+1}\right)$. The distance function $D_o^t(x^t, y^t)$ measures the distance of a vector of inputs (*x*) and outputs (*y*) in period *t* to the technological frontier in the same period *t*. On the other hand, $D_o^{t+1}(x^t, y^t)$ measures the distance between the same vector of inputs and outputs in period *t*, but in this case to the frontier in period *t + 1*. The other two distances can be explained in the same fashion. Färe et al. (1994) showed that the Malmquist index could be decomposed into an efficiency change component and a technical change component, and that these results applied to the different period-based Malmquist indices. It follows that

$$M_o = \frac{D_o^{t+1}(x^{t+1}, y^{t+1})}{D_o^t(x^t, y^t)} \times \left[\frac{D_o^t(x^{t+1}, y^{t+1})}{D_o^{t+1}(x^{t+1}, y^{t+1})} \times \frac{D_o^t(x^t, y^t)}{D_o^{t+1}(x^t, y^t)} \right]^{1/2} \tag{B.2}$$

The ratio outside the square brackets measures the change in technical efficiency between period *t* and *t + 1*. The expression inside the brackets measures technical change as the geometric mean of the shift in the technological frontier between *t* and *t + 1* evaluated using the frontier at *t* and at *t + 1,* respectively, as the reference. The efficiency change component of the Malmquist index measures the change in how far observed production is from maximum potential production between period *t* and *t + 1* and the technical change component captures the shift of technology between the two periods. A value of the efficiency change component of the Malmquist index greater than one means that the production unit is closer to the frontier in period *t + 1* than it was in period *t*: the production unit is catching up to the frontier. A value less than one indicates efficiency regress. The same holds for the technical change component of total productivity growth, signifying technical progress when the value is greater than one and technical regress when the index is less than one. The method has been extensively applied to the international comparison of agricultural productivity.

To define the input-based Malmquist index, it is necessary to define and estimate the distance functions, which requires a characterization of the production technology and of production efficiency. We assume, as in Färe et al. (1998), that for each time period *t = 1, 2, …, T* the production technology describes the possibilities for the transformation of inputs x^t into outputs y^t, or the set of output vectors **y** that can be produced with input vector **x**. The technology in period *t* with $y^t \in R_+^m$ outputs and $x^t \in R_+^n$ inputs is characterized by the production possibility set (PPS) as follows:

$$L^t = \{(y^t, x^t): \text{such that } x^t \text{ can produce } y^t\} \tag{B.3}$$

Having defined the PPS, distance functions are estimated using linear programming that measures efficiency as the ratio of a weighted sum of all outputs over a weighted sum of all inputs. The weights are obtained solving the following problem (Coelli and Rao, 2001):

$$\max_{p,w} \sum_{k=1}^{m} p_k y_{ik} \Big/ \sum_{j=1}^{n} w_j x_{ij} \quad , \tag{B.4}$$

subject to

$$\sum_{k=1}^{m} p_k y_{ik} \Big/ \sum_{j=1}^{n} w_j x_{ij} \leq 1 \qquad \mathrm{i = 1,...,r}$$

$$p_k, w_j \geq 0 \qquad \mathrm{k = 1,...,m;\ j = 1,...,n} \quad ,$$

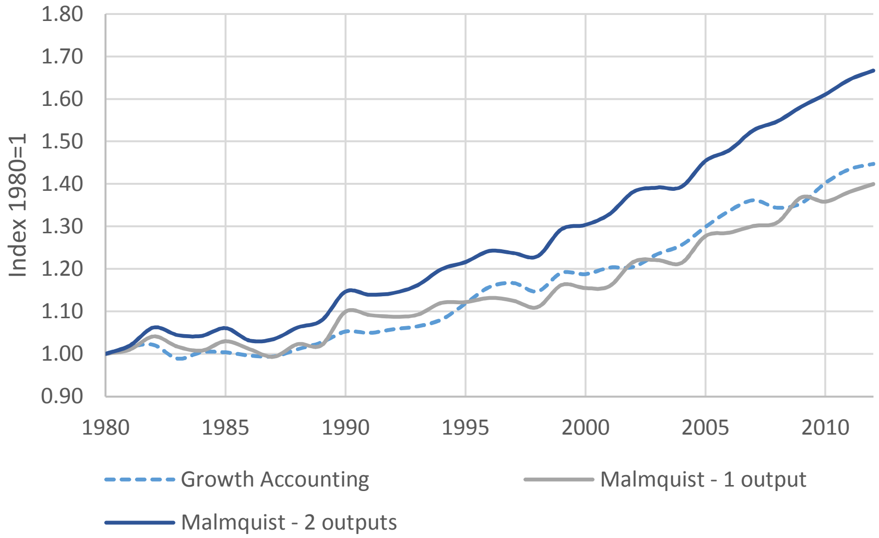
where the optimal weights p_k and w_j are respectively output *k* and input *j* shadow prices. Problem (AI.4) clearly shows the intuition behind this approach to measure efficiency but cannot be used as such because it has an infinite number of solutions. To solve that problem we normalize the ratio by imposing $\sum_{j=1}^{n} w_j x_{ij} = 1$ (Coelli and Rao, 2001). With this new constraint, the dual problem becomes the following (with *p* and *w* different from ρ and ω):

$$\begin{aligned}
&\max_{\rho,\omega} \sum_{k=1}^{\mathrm{m}} \rho_{\mathrm{k}} y_{ik} \\
&s.t. \\
&\sum_{j=1}^{n} \omega_j x_{ij} = 1 \\
&\sum_{k=1}^{m} \rho_k y_{ik}{}_{i} - \sum_{j=1}^{n} \omega_j x_{ij} \leq 0 \qquad \mathrm{i = 1,...,r} \\
&\rho_k, \omega_j \geq 0 \qquad \mathrm{k = 1,...,m;\ j = 1,...,n}
\end{aligned} \tag{B.5}$$

Problem (AI.5) allows for total flexibility in choosing shadow prices.

TFP results obtained with the growth accounting approach (GA) presented in Section 5 are compared with Malmquist TFP indices calculated using DEA methods (Figure B.1).

Figure B.1 Average TFP indices for LAC calculated using the accounting method and DEA methods with aggregated agricultural output and two outputs (crops and livestock), 1980-2012

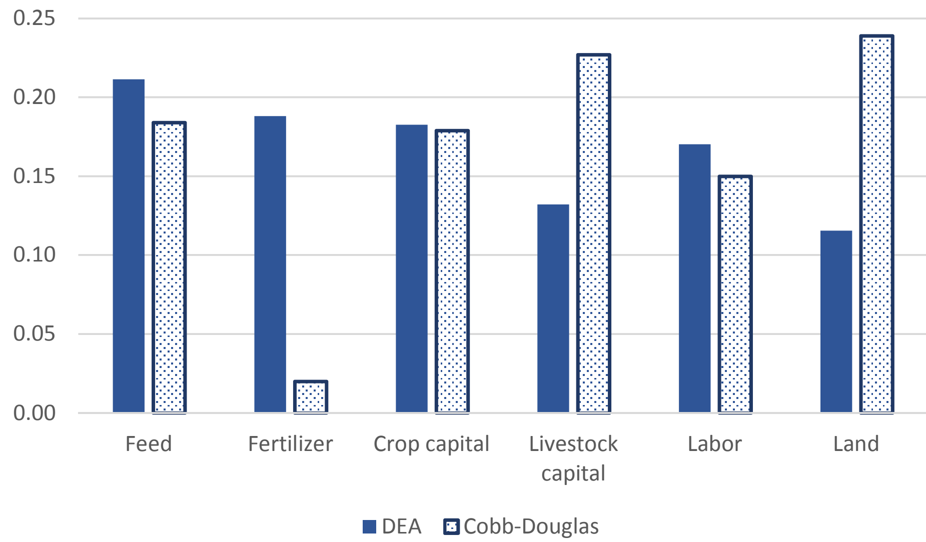


Source: Author's calculation.

Average TFP estimated for the region result in almost identical trends and overall TFP growth between the growth-accounting method and the Malmquist using aggregated output. The Malmquist index with two outputs gives higher TFP estimates (67 percent growth with respect to 1980 compared with 45 and 40 percent obtained with growth-accounting and 1 output-Malmquist respectively). Despite higher estimates obtained with the 2 output-Malmquist, the three indices show the same TFP growth path for LAC with correlation of 0.99.

Figure B.2 compares average input shadow shares obtained using DEA to estimate the Malmquist index with input shares from the estimated Cobb-Douglas function. Biggest differences are in fertilizer, land and livestock capital coefficients, but despite differences in input shares, average TFP estimates for the region lead to similar results using both methods, particularly if we estimate the Malmquist TFP index using aggregated output as in the growth-accounting approach.

Figure B.2 Average 1981-2012 Input shares from DEA and the estimated input shares from the Cobb-Douglas production function

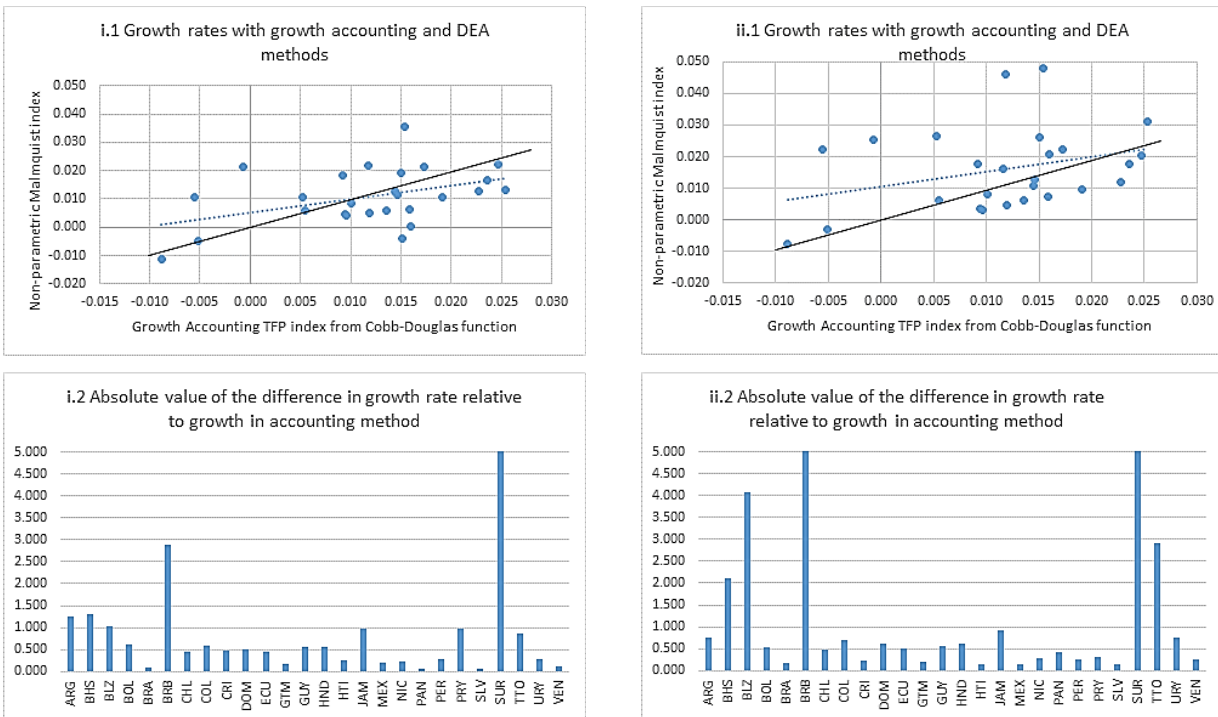


Source: Elaborated by authors.

Figure B.3 compares results obtained with the DEA-Malmquist approach to those obtained with the growth-accounting method at the country level (average growth rates 1981-2012). If both methods deliver exactly the same TFP growth rate, all points should be on the 45° line in figures B.3.A, so distance to the line reflect differences in TFP estimates by the different methods. The figures show countries along the 45° line which means that ranking country performance using the different methods will result in a similar order of countries, that is, the group of best performers would be the same with both methods. On the other hand, a regression between the Malmquist and the growth-accounting results (dotted line in Figure B.3i.1) shows that the Malmquist-DEA approach with one output tends to overestimate low growth rates and underestimate high growth rates compared to the growth-accounting method (distance between the 45o line and the dotted line). Differences are larger when the 2-output Malmquist is used and with two outputs the DEA method obtains on average higher growth rates than those using GA although differences are smaller at high growth rates (Figure B.3ii). The major differences between methods appear to be related to estimates for some "problematic" countries. In our sample the most problematic cases seem to be Surinam and Barbados. There are also arge differences between methods in the cases ofr Argentina, Bahamas, Belize, Jamaica, Paraguay and Trinidad and Tobago. Notice that the same countries show the biggest differences with the growth-accounting TFP estimates when Malmquist index is calculated with two outputs, but these differences become much larger when using DEA with two inputs. Also notice that in the case of Argentina, the results using 2-output Malmquist are closer to results obtained using growth-accounting.

Figure B.3. Comparison of TFP growth rate using the growth accounting and the Malmquist DEA method with one and two outputs (averages 2001-2012)

i. One output (agriculture) ii. Two Outputs (crops and livestock)



Source: Elaborated by authors.
Note: Values in i.2 and ii.2 are calculated as abs($TFP_{MALMQUIST}$ - TFP_{GA}) / abs (TFP_{GA}). The solid line is the 45o line indicating the points where growth rates are equal between methods. The dotted line represents the relationship between DEA and GA methods obtained by regressing growth rates from DEA methods against the GA growth rates.

Coelli and Rao (2005) comparing results of Malmquist-DEA methods with those obtained from a Tronqvist Index using similar FAO data than the one used here for 93 countries, concluded that the observed differences between estimates could result from poorly estimated shadow prices for some countries due to the dimensionality problem in DEA. If shadow shares are well estimated, problems could arise from some countries differing significantly from the sample average because of country specific factors such as land scarcity, labor abundance, and so forth. Notice that in our sample, most countries showing the biggest differences in TFP rates between methods are Caribbean countries and one is a small Central American country with similar resource endowments. Table B.1 presents as a summary, average TFP growth rates for all countries in different periods calculated using the three methods discussed here.

Table B.1. TFP growth rates calculated using growth accounting and Malmquist-DEA methods, 1981-2012 (percentage)

Country	Growth Accounting	Malmquist-1 output	Malmquist-2 outputs
Argentina	1.5	-0.4	2.7
Bahamas	1.5	3.6	4.8
Belize	0.5	1.1	2.7
Bolivia	1.6	0.6	0.7
Brazil	2.5	2.2	2.0
Barbados	-0.6	1.0	2.2
Chile	2.3	1.3	1.2
Colombia	1.0	0.4	0.3
Costa Rica	2.5	1.3	3.1
Dominican Republic	0.9	0.5	0.4
Ecuador	1.9	1.1	1.0
Guatemala	1.0	0.8	0.8
Guyana	1.4	0.6	0.6
Honduras	1.2	0.5	0.5
Haiti	-0.9	-1.1	-0.8
Jamaica	0.9	1.8	1.8
Mexico	1.5	1.2	1.3
Nicaragua	1.7	2.1	2.2
Panama	-0.5	-0.5	-0.3
Peru	2.4	1.7	1.8
Paraguay	1.6	0.0	2.1
El Salvador	0.5	0.6	0.6
Suriname	-0.1	2.2	2.5
Trinidad and Tobago	1.2	2.2	4.6
Uruguay	1.5	1.9	2.6
Venezuela	1.4	1.3	1.1
Average	1.2	1.1	1.6
Standard Deviation	0.9	1.0	1.3

Source: Elaborated by authors

APPENDIX C: AGROECOLOGICAL ZONES

Classification of countries in four main agroecologies was done using information from Lee et al. (2005) who used lengths of growing period (LGPs) and three climatic zones—tropical, temperate, and boreal—to define 18 zones. Table C.1 details definition of global agro-ecological zones (AEZs) used in Lee et al. (2005), with the first six AEZs corresponding to tropical climate, the second six to temperate and the last six to boreal.

Table C.1 Definition of global agro-ecological zones (AEZ)

LGP in days	Moisture regime	Climate zone
0-59	Arid	Tropical Temperate Boreal
60-119	Dry semi-arid	Tropical Temperate Boreal
120-179	Moist semi-arid	Tropical Temperate Boreal
180-239	Sub-humid	Tropical Temperate Boreal
240-299	Humid	Tropical Temperate Boreal
>300 days	Humid; year round growing season	Tropical Temperate Boreal

Source: Based on Lee et al. (2005).

To define the AEZs for this study we used information of area of pasture and cropland in the different AEZs to determine the predominant agroecology in each country. With this information we grouped the 134 countries in our sample in four major groups: Temperate Humid, Temperate Sub-humid, Tropical Humid and Tropical Sub-Humid. The Humid groups include the Humid and Humid year round growing season while the Sub-Humid groups include the Sub-humid, moist semi-arid and arid agroecologies. Only two countries were defined as belonging to the Boreal climate zone so they were assigned to the temperate groups.

Table C.2. Classification of LAC countries by agroecological zone

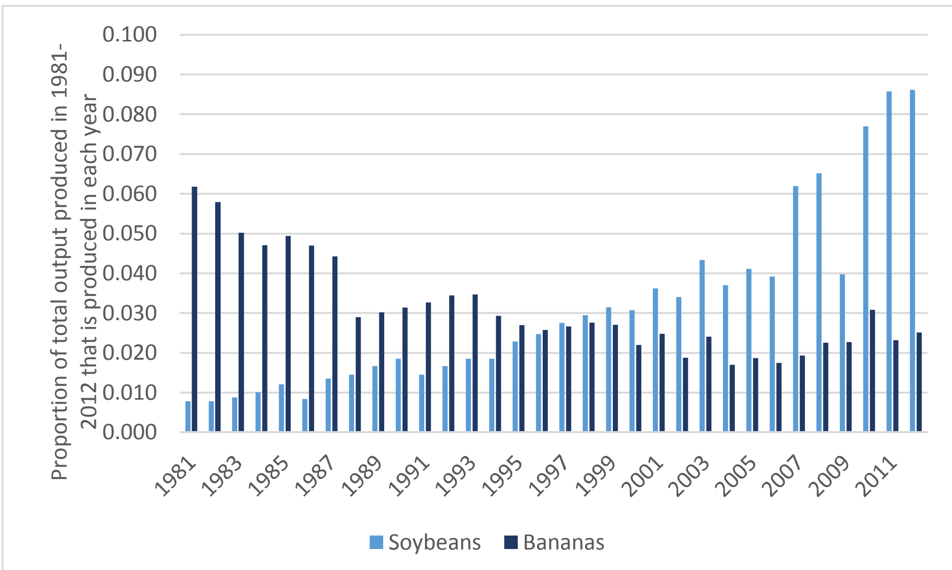
Country	Sub-region	Agroecological Zone (AEZ)	
El Salvador	Central America	Tropical	Sub-humid
Venezuela	Andean	Tropical	Sub-humid
Nicaragua	Central America	Tropical	Sub-humid
Honduras	Central America	Tropical	Humid
Bahamas	Caribbean	Tropical	Humid
Barbados	Caribbean	Tropical	Humid
Jamaica	Caribbean	Tropical	Humid
Dominican	Caribbean	Tropical	Humid
Costa Rica	Central America	Tropical	Humid
Haiti	Caribbean	Tropical	Humid
Trinidad and Tobago	Caribbean	Tropical	Humid
Panama	Central America	Tropical	Humid
Brazil	NE South America	Tropical	Humid
Ecuador	SA, Andean	Tropical	Humid
Guyana	NE South America	Tropical	Humid
Belize	Central America	Tropical	Humid
Surinam	NE South America	Tropical	Humid
Mexico	Central America	Tropical	Humid
Colombia	Andean	Tropical	Humid
Guatemala	Central America	Tropical	Humid
Bolivia	Andean	Temperate	Sub-humid
Paraguay	Southern Cone	Temperate	Sub-humid
Peru	Andean	Temperate	Sub-humid
Argentina	Southern Cone	Temperate	Sub-humid
Chile	Southern Cone	Temperate	Humid
Uruguay	Southern Cone	Temperate	Humid

Source: Elaborated by authors

APPENDIX D: TRADITIONALITY INDEX

We use the example of Paraguay and two commodities *i* (soybeans and bananas) to show how the cumulative production experience index (C_{it}) and the traditionality index (T_i) are calculated. The first step is to calculate the total amount of each crop produced between 1981 and 2012. We then divide production of each crop in each year by the respective total for the period to find the proportion of total output of each crop that is produced in each year. Results of these calculations are shown in Figure D.1.

Figure D.1 Annual distribution of total the total production of soybeans and bananas produced by Paraguay between 1981 and 2012 (total output for 1981-2012= 1)

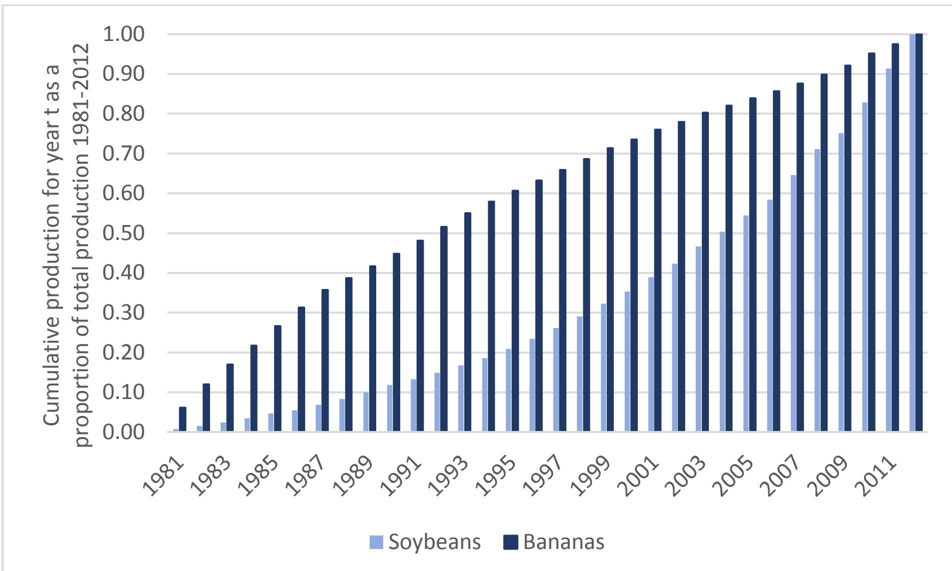


Source: Elaborated by authors

The figure shows that a high proportion of banana production between 1981 and 2012 was produced in the 1980s with this proportion decreasing over time. On the other hand, a much larger proportion of total soybean production was obtained by the end of the period (almost 9% of total output in 2011 and 2012 compared with only 2.5 percent for bananas in the same years). These numbers reveal that banana is the more "traditional" crop of the two, as production of soybeans was insignificant at the beginning of the period increasing its importance in the 2000s as a "new" crop.

We use values in Figure D.1 to calculate the cumulative production experience index (C_{it}) for each year t and each crop by adding up the values for each crop between 1981 and a particular year t. So for example: $C_{soybean,1981}$ = 0.08; and $C_{bananas,1981}$ = 0.06, that is, the value of the first bar corresponding to 1981. For the year 1982 the value of the cumulative index is the sum of the values represented by the 1981 and 1982 bars in Figure D.1. $C_{soybean,1982}$ = 0.016; and $C_{bananas,1982}$ = 0.12, and so on, ending with a value of 1 for both crops in 2012. In this way we obtained the cumulative production experience index C for each crop in Figure D.2.

Figure D.2 Cumulative production experience index (Cit) for soybeans and bananas in Paraguay (total production 1981-2012 = 1)

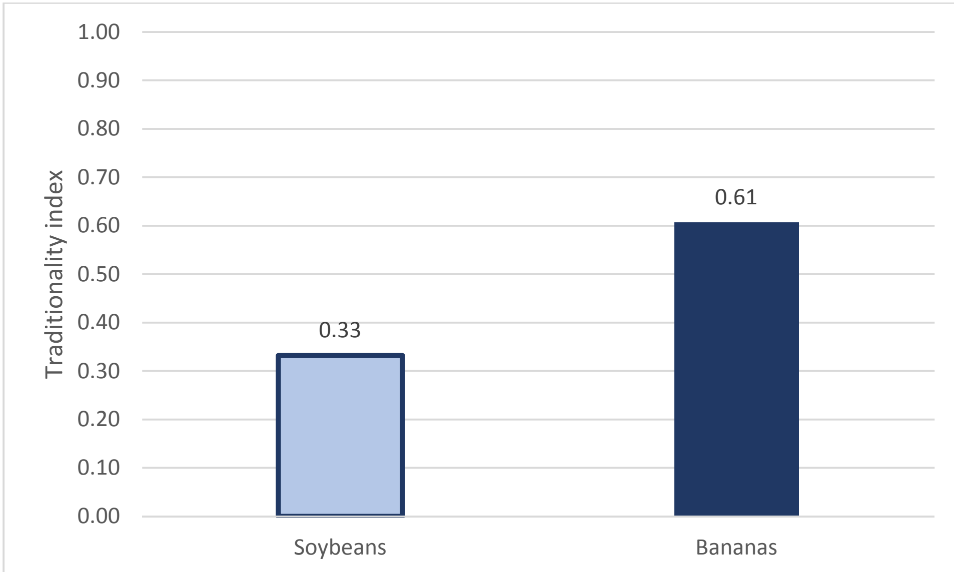


Source: Elaborated by authors

The C_{it} index in Figure D.2 shows that banana production is more traditional than soybean in Paraguay, or that Paraguay has more production experience in banana than in soybean given that it has been producing significant amounts of banana since the beginning of the period (the bars in the figure for banana are higher than those for soybean during the whole period.

The average of the annual values in Figure D.2 for each crop is what we call the traditionality index (Ti). The values of the index are presented in Figure D.3. This index can be understood as an indicator of the differences between bananas and soybeans observed in Figure D.2. A value of 0.6 for bananas and 0.3 for soybeans are the average difference between the C_{it} values represented by the bars in Figure D.2. The higher the T_i index the more traditional the commodity.

Figure D.3 Traditionality index (T_i) for soybeans and bananas in Paraguay



Source: Elaborated by authors