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Efficiency performance of Latin American vis-à-vis North American countries between 1980 and 2019

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Abstract

This article compares the behavior of total factor productivity between 16 Latin American countries and the United States and Canada for the period 1980-2019 using an order-m nonparametric estimator together with the Malmqüist index. The results showed a setback in terms of productivity in Latin America when comparing a period of 40 years from end to end. Consequently, the gap between the Latin American economies and the benchmark has widened. However, a good performance in terms of technical change can be observed between 2010 and 2019 in Latin American countries.

1. Introduction

We start with the premise that The Americas are divided into a North, made up of the United States and Canada, and a South which includes all of the Latin American countries and apart, the Caribbean. While North America experienced significant early productivity growth that brought these countries into the selected group of developed ones, by contrast, Latin America is still waiting to enter its productivity era.

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In 2010, inspired by a Krugman quote, Lora and Pagés argued that low productivity growth is the source of poor economic growth in Latin America, and attacking that cause should be the focus of the current economic debate. They even stated that while increasing the stocks of physical and human capital requires resources that are inaccessible in low-income countries, the boost in productivity may "simply" [quotes in the original] requires the willingness to transform policies and institutions in light of successful experiences elsewhere. That is why the volume published by the Inter-American Development Bank (IDB), The Age of Productivity, had as one of its purposes “to identify and propose political options to unleash an age of productivity in Latin America and the Caribbean” (Lora and Pagés, 2010).

Some might see that book as a collection of strategies ready to be reproduced in real life and others might disagree on its real possibilities. However, that is not discussed here. It is simply taken as motivation to observe the trajectory of total factor productivity in the long run from a comparative view. Due to the relative lag in Latin American economies, the problem was approached from an efficiency perspective. This research is related to the convergence theory, in particular the one that focuses on the catch-up process. However, it distances itself from this literature, first, because it starts from the concept of inefficiency instead of the concept of productivity, and, by definition, it does so in relative terms to a technological frontier. Second, it has the possibility of offering a characterization of multifactor productivity growth based on the evolution of its components, instead of doing it in terms of its potential sources of growth. Then, the decomposition identifies the source of the problem in the catch-up process, and this allows addressing the investigation of the sources of growth towards the most significant components.

Using data extracted from the Penn World Table database (Feenstra, Inklaar, and Timmer, 2015) for 18 American countries for the period 1980-2019, a nonparametric technique robust to outliers and extreme values was applied. The main results found are: First, the confirmation of the backwardness of the Latin American economies. Second, the main source of this delay is the difficulty in incorporating technical progress in a stage characterized by the speed of innovation and technology transmission. Finally, there are notable differences among the Latin American economies. In any case, the set of countries shows its worst performance in the 1980s while the last period analyzed shows an approach to the benchmark via global efficiency changes.

The following sections present a synthesis of the methodological approach (section 2), the previous research on Latin American gap productivity (section 3), and the data (section 4). Section 5 shows and discusses the results. Section 6 concludes.

2. Previous research

2.1 Productivity gap and catching-up

In economic theory, the concept of productivity can be explained as the technical relationship between an output and the inputs required to obtain it. Then, inefficiency is the gap between that observed technical relationship and its ideal or benchmark level. In this way, an economy is considered efficient if it is capable of achieving that benchmark. Otherwise, it would be technically inefficient.

At the same time, there is a wide consensus that increasing productivity in the long run is a way of raising living standards and its growth is, at least in principle, sustainable through technological advances. However, this growth is not simultaneous and equal in all countries, giving rise to a large literature on productivity measurement, economic growth, and technological catch-up (Abramovitz, 1986; Baumol, 1986; Barro and Sala-i-Martin, 2003; Mankiw, Romer and Weil, 1992; Caselli, 2005; Acemoglu, 2012, among others). In this way, differences between countries can be attributed to differences in productivity, and physical or human capital accumulation, among other factors. However, various studies suggest that differences in productivity explain most of the variation in per capita income observed across countries (Islam, 1995; Klenow and Rodriguez-Clare, 1997; Hall and Jones, 1999; Easterly and Levine, 2001; Caselli, 2016; Gallardo-Albarrán and Inklaar, 2021).

In general, changes in productivity occur when an index of outputs varies at a different rate than an index of inputs. In other words, raising productivity implies finding better ways to more efficiently use the existing production factors. Following Kumbhakar (2003), two questions arise then: how can productivity change be measured and what are the sources of these changes? One standard way to measure productivity changes is to compute variations in total factor productivity (TFP), that is, the efficiency with which the economy transforms its accumulated production factors into output and they are usually calculated as a residual, that is, as the portion of growth that cannot be accounted for by the accumulation of factors. However, according to Coelli, Rao, O´Donnell, and Battese (2005), TFP changes can also be calculated using nonparametric or parametric techniques to identify the production benchmark mentioned above and then construct what is known as the Malmqüist (1953) TFP productivity index. Finally, according to Balk (2001), one may identify various sources of productivity changes as technical change, efficiency change, and change in the scale of operations, and measure all these effects separately.

Economic research on efficiency measurement had a strong impulse since the middle of the last century after the articles of Koopmans (1951) and Debreu (1951) were published. In general, many efficiency analyses in economics are based on ratios, such as the ratio of an output divided by a specific input. However, ratios like this indicate the efficiency of one input but say nothing about the rest of the inputs involved in the production process.

In this sense, Farrell (1957) measures inefficiency taking into account several inputs at the same time, proposing that its magnitude would be given by the observed deviation from a hypothetical "best practices" frontier and, then, these measures of efficiency either expand outputs or contract inputs. Thus, the next question would be to specify the most appropriate methodology to identify such a frontier and the relevant variables that support the model.

There is extensive economic literature on efficiency analysis and productivity measurement based on frontier techniques. However, a large amount of this effort has been dedicated to studying the efficiency of organizations or certain productive sectors or regions within the same country. On the other hand, fewer articles address the problem of technological convergence or divergence between countries.

2.2 Nonparametric frontier analysis: an order-m estimator

Nonparametric methods are based on linear programming techniques and are, in general, deterministic. Though, statistical inference is available either by using asymptotic results (Kneip, Park, and Simar, 1998; Park, Simar, and Weiner, 2000) or by using the bootstrap (Simar and Wilson, 2000). The more common techniques within this methodology are Data Envelopment Analysis (DEA), introduced by Charnes, Cooper, and Rhodes (1978), and its Free Disposal Hull (FDH) variant which was first presented by Deprins, Simar, and Tulkens (1984). The difference between them is that the DEA reference units result from a convex linear combination of the different observed units, while FDH does not necessarily introduce convexity at the boundary. In addition to the well-known input- or output orientation, the nonparametric models can be measured along hyperbolic paths as proposed by Färe, Grosskopf, and Lovell (1985). Unlike the former, hyperbolic efficiency levels are not dependent on the slope of the production frontier in the neighborhood of the point at which either firm operates, thus avoiding certain controversies between constant and variable returns to scale models.

Despite their popularity, ordinary nonparametric model estimators have some disadvantages. Although they avoid the need for a priori specification of functional forms, it has long been recognized that these estimates of inefficiency are sensitive to outliers or extreme values in the data. However, some recent approaches to efficiency estimation have focused on solving these problems by estimating efficiency measured relative to some notion of a partial frontier, as order-m estimators suggested in Cazals, Florens, and Simar (2002), Daouia and Simar (2007), Wheelock and Wilson (2008), Wilson (2012), among others[3]. Following their proceedings, this article proposes a hyperbolic order-m efficiency model avoiding some of the ambiguity in choosing between an input- or output-orientation and, also,

[3] In addition, Tzeremes (2020) and Tzeremes and Tzeremes (2021) illustrate, respectively, how the order-m and order- estimators can be applied to construct a robust version of the Malmquist productivity indices in the Spanish hotel industry over the period 2004-2013.

obtaining robust estimates concerning outliers or extreme values. At the same time, and unlike ordinary DEA models, the order-m estimator has a root-n convergence rate when used to estimate the distance to a partial frontier, and therefore is useful for small-sample applications such as the one used in this study.

Consequently, a hyperbolic efficiency measure

$$\gamma(x,\ y) \equiv \left\{\left(\gamma x,\ \gamma^{-1} y\right) \in P\right\} \tag{1}$$

defined by Färe et al. (1985), gives the distance from the fixed point $(x,\ y)$ to P along the hyperbolic path $\left(\gamma x,\ \gamma^{-1} y\right), \gamma \in R^{1}_{++}$, which avoids some of the ambiguity cited above. It is also possible to extend the ideas of Cazals, Florens, and Simar (2002) to obtain an unconditional, hyperbolic measure of order-m efficiency. Consider a set of m iid random variables $\left\{\left(X_j,\ Y_j\right)\right\}_{j=1}^{m}$ drawn from the density $f(x,\ y)$ strictly positive and the random set

$$P_m \equiv \cup_{j=1}^{m} \left\{x \geq X_j,\ y \geq Y_j\right\} \tag{2}$$

For any $(x,\ y) \in R^{p+q}_{+}$, is defined as the random distance measure

$$\gamma_m(x,\ y) \equiv inf\left\{\left(\gamma x,\ \gamma^{-1} y\right) \in P_m\right\} \tag{3}$$

If $E\left(\gamma_m(x,\ y)\right)$ exists, then

$$\bar{\gamma}_m(x,\ y) \equiv E\left(\gamma_m(x,\ y)\right) = \int_0^{\infty} \left[1 - H\left(ux,\ u^{-1} y\right)\right]^m du \tag{4}$$

and an estimator of the expected hyperbolic order-m can be obtained. To implement this, it is necessary to fix the parameter m, the partial sample size that is determined as the value for which the number of super-efficient observations is constant. For more details, we suggest seeing the publications of Cazals, Florens, and Simar (2002) and Wilson (2012).

2.3 Malmqüist Total Factor Productivity Index

Having access to panel data, it is possible to analyze the changes and evolution of total factor productivity (TFP) between two time periods using the Malmqüist TFP Index. It was first introduced in the field of consumption theory by Malmqüist (1953) and later, Caves, Christensen, and Diewert (1982) applied the idea to productivity measurement in the context of production functions. One of the advantages of this analysis is that the Malmqüist TFP Index can use nonparametric methodologies and it allows decomposing the variations into efficiency changes and technical changes.

Suppose the following panel of $i = (1, ..., I)$ production processes observed in $t = (1, ..., T)$ periods in transforming a series of input vectors $x_i^t\left(x_{i1}^t, ..., x_{iN}^t\right) \in R_+^N$ into output vectors $y_i^t\left(y_{i1}^t, ..., y_{iM}^t\right) \in R_+^M$, then firm i´s change in productivity between periods t and $t + 1$ is measured by hyperbolic Malmquist index

$$MI_i = \left(\frac{C(\psi^{t+1})(x^{t+1}, y^{t+1})}{C(\psi^t)(x^t, y^t)}\right) \times \left[\left(\frac{C(\psi^t)(x^t, y^t)}{C(\psi^{t+1})(x^t, y^t)}\right) \times \left(\frac{C(\psi^t)(x^{t+1}, y^{t+1})}{C(\psi^{t+1})(x^{t+1}, y^{t+1})}\right)\right]^{\frac{1}{2}} \quad (5)$$

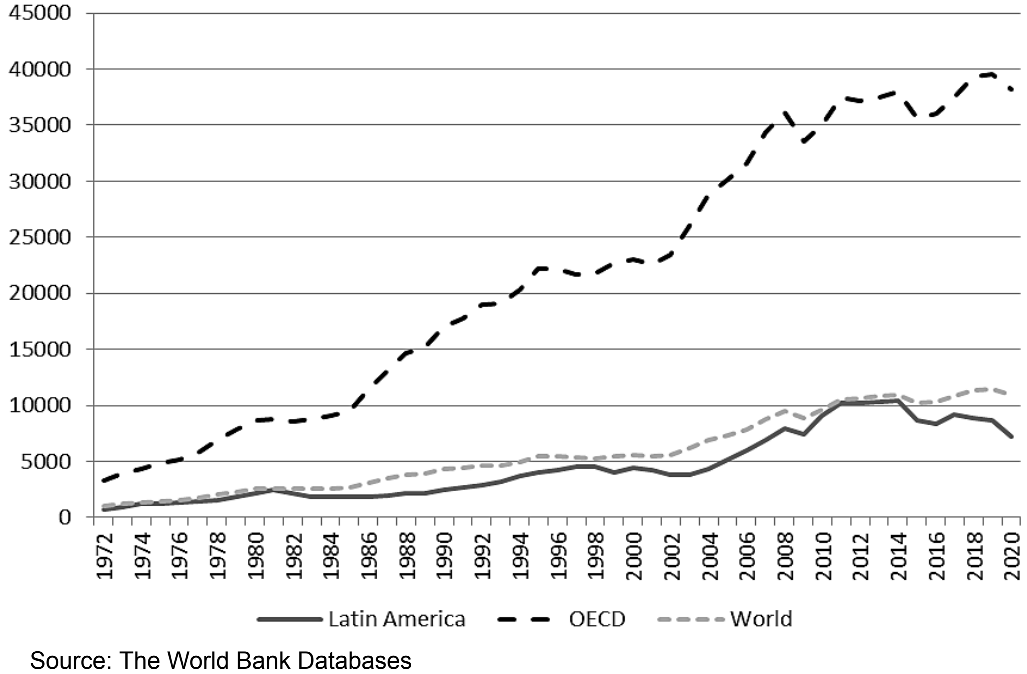
Kneip, Simar, and Wilson (2015) define the Malmquist index in terms of hyperbolic distances to avoid issues of existence and numerical difficulties. At the same time, they demonstrated that the index can be rearranged as the product between efficiency change and technical change. Then, if the Malmqüist index has a value greater than one, it indicates that the total factor productivity in period $t + 1$ is greater than in t or the opposite if it takes values less than one. A similar behavior takes place with the components of the index mentioned above, but it should be taken into account that, although the product of efficiency change and technical change by definition is equal to the Malmqüist index, its components could perform in opposite directions. Consequently, a Malmqüist index for the i-th firm can be expressed as:

3. Empirical background

3.1 Latin America

If there is something that characterizes most Latin American countries, it is slow economic growth (in terms of GDP per capita) for long periods that have made them poorer than the rest of the world (Figure 1). Now, the question is what factors have led to this result. Many researchers suggest that low investment and factor accumulation play a crucial role in growth performance in the region (De Gregorio, 1992; Astorga, Berges, and Fitzgerald, 2011) while others consider low productivity and low productivity growth to be the source of this failure in catching-up (Cole, Ohanian, Riascos, and Schmitz, 2005; Daude and Fernandez-Arias, 2010; Ferreira, Pessoa and Veloso, 2013).

Figure 1. GDP per capita (current US$). Latin America, OECD, and World



Source: The World Bank Databases

In fact, in a growth accounting framework, Ferreira, Pessoa, and Veloso (2013) showed that until the late 1970s Latin American countries had high productivity levels relative to the United States and the main determinants of poverty in the region were factors of production. On average, TFP in Latin America corresponded to 82% of the United States between 1960 and 1980 but after this period, they observed a fast decrease of relative TFP in the region, which fell to 54% of U.S. TFP in 2007, being the main explanation for Latin America stagnation. In this way, Maddison (1994) stated that between 1913 and 1950 Latin America performed very well compared with most of the rest of the world, and the region did not suffer significantly from the two world wars. Although their experience between 1950 and 1973 was better in per-capita terms than before 1950, it was not on the scale seen in Europe and Asia causing differences in productivity to widen. They also express that the problems in Latin American countries started in the 1980s when the supply of new foreign funds dried up and the service cost of existing debt soared because of rising interest rates. Nevertheless, they said that this is not the real cause of the dramatic slowdown. Rather, it was the result of misguided domestic policies.

McMillan, Rodrik, and Verduzco-Gallo (2014) highlight that labor flows from low-productivity activities to high-productivity ones are key drivers of development. In addition, they notice that since 1990 structural change has been growth-reducing in Latin America, where the bulk of the productivity performance is accounted for by differences in the pattern of structural change. That is, labor moving in the opposite direction that the mentioned above. They also identified three factors that help determine whether structural change contributes to overall productivity growth. In countries with a relatively large share of natural resources in exports, structural change has typically been growth-reducing, even though these sectors usually operate at very high productivity. By contrast, competitive or undervalued exchange rates and labor market flexibility have contributed to growth-enhancing structural change.

Fernandez-Arias and Rodriguez-Apolinar (2016) combine development accounting exercises with economic theory to assess the importance of total factor productivity and the accumulation of factors of production as engines of growth in Latin America. In agreement with Lora and Pagés (2010), they concluded that productivity in this region is not catching up with the frontier and it is about half its potential. The income gap with the United States is increasingly due to the productivity gap and they suggest that low total factor productivity, rather than a shortfall in available factors of production, is the key to understanding Latin America's low income relative to developed economies.

3.2 Country efficiency analysis

Most of the research on country efficiency analysis using frontier techniques was focused on industrialized countries and/or countries belonging to the OECD or the European Union. In general, the United States and Canada presented a very good performance in the TFP index and its components in the articles mentioned below, and the United States determined the technological frontier in all cases. Recall that frontier techniques capture performance relative to the best practice in the sample, where best practice represents a "frontier" to which each country is compared to.

Table 1 shows some of those papers that were selected according to the relevance of their contribution to the present analysis.

Table 1. Empirical background based on frontier techniques

Authors	Sample	Period	Observations

Färe, Grosskopf, Norris & Zhang (1994b)	17 OECD countries	1979-88	They use DEA and the Malmqüist TFP index to assess productivity growth in OECD countries. They find that the United States had slightly above-average growth due entirely to technological change and Japan had the highest productivity growth in the sample.
Ray & Desli (1997)	17 OECD countries	1979-90	Like Färe et al (1994), the authors analyze the evolution of productivity in OECD countries based on the Malmqüist TFP index. They find that for several years Norway, the United Kingdom, and the United States contributed positively to technical growth and, in the last period, Norway was solely responsible for the frontier shift.
Taskin & Zain (1997)	OECD countries	1965-90	Based on the Malmqüist TFP index, they investigate the catching-up hypothesis between groups of countries with high and low levels of per capita income. The results show that countries with low levels of initial per capita income recovered at a faster rate, while countries with relatively high incomes depended more on technological growth to increase their productivity.
Maudos, Pastor & Serrano (2000)	23 OECD countries	1965-90	They evaluate the convergence of labor productivity through the Malmqüist TFP index. The results obtained indicate that technical change has been performed against the convergence of labor productivity.
Delgado & Alvarez (2005)	15 EU countries	1980-97	They analyze the behavior of EU countries in a period when public policies have been implemented to facilitate efficiency improvements. The results show that advances in the European integration process have made efficiency improvements in the use of inputs.
Henry, Kneller & Milner (2009)	57 developing countries	1970-98	They simultaneously explore the determinants of the production frontier and efficiency through SFA. The results indicate significant differences in efficiency levels between countries and their evolution over time. Also, they show an important influence of trade and commercial policy in increasing production, both through technological progress incorporated into imported capital goods and efficiency improvements.
Pires & Garcia (2012)	75 countries	1950-2000	They use SFA to estimate a frontier and disaggregate TFP to analyze the changes in each of its components. They conclude that differences in productivity, especially in allocative efficiency, are responsible for most of the differences in the performance between industrialized and developing economies.
Haini (2020)	17 ASEAN countries	1980-2017	The author examines productivity and efficiency through SFA and the Malmqüist TFP index. The results show that technical progress is increasing over time and exhibits increasing returns to scale. However, technical change is slow.

There are few and, mostly, recent papers referring to frontier techniques applied at the aggregate level to Latin American economies. Marinho and Bittencourt (2007) estimate a stochastic frontier model for 19 countries between 1961 and 1990 and perform a disaggregation of the Malmqüist TFP Index. The authors highlight the poor TFP growth explained, in part, by the decrease in technical efficiency mainly occurring in the 1980s, and the low level of technological progress. The oil crisis in the 1970s with the debt crisis affecting all the region’s economies seems to have influenced this process that lasted until 1984. On the other hand, the authors note that some positive technical fluctuations appeared when the oil crisis occurred. A general result indicates a small positive change in TFP in the region over the entire period and this would explain the modest growth of real GDP per capita in Latin American countries during those years.

In the same way, Castillo, Salem, and Guasch (2011) analyze the Malmqüist TFP Index after estimating by SFA. Their paper aims to study the influence of R&D and human capital efforts on a country's knowledge absorption capacity. The functional form they use allows them to separate different effects: changes in efficiency, technological changes, and scale efficiency changes using data for 16 Latin American countries for the period 1996-2006. Like Marinho and Bittencourt (2007), they find that the greatest contribution to TFP was made by technological change while changes in efficiency were not very significant and the scale effect was negative in most of the cases, which could be explained by the production structure of these economies.

Araujo, Feitosa, and Bittencourt (2014) complement the analysis with the effects on allocative efficiency. They use a panel of 19 countries between 1960 and 2010 and find that TFP experienced a negative rate for the whole period driven by negative technical efficiency but tempered by technical progress. They consider that probably, several countries failed to follow the technological growth path that occurred in that period due to difficulties in the process of diffusion and adoption of modern technologies. Even so, they notice that most countries showed positive gains in the allocation of resources. Furthermore, these authors present TFP estimates divided into sub-periods and find that all countries presented negative TFP indices between 1962 and 1970 while the opposite was true (except Jamaica) in the 1990s and 2000s. Also, technical progress and economies of scale were positive while the allocative effects were mixed.

Kollias and Tzeremes (2021) analyze productivity growth levels and their convergence patterns in 17 Latin American countries in the period 1970-2014. They find that productivity levels between 1970 and 2014 decreased in all countries of the sample except for Colombia and Ecuador. On average, they show a gain in technical efficiency, and even when they assume economies of scale, the pure efficiency effects are greater than one. In contrast, technological changes were infrequent, so there was a delay in catching up and there were inefficiencies of scale in almost all countries. When they replicate the estimates by decades, they find similar results to Araujo, Feitosa, and Bittencourt (2014) concerning the 1980s. However, there would be productivity gains in all but the last one.

Tzeremes (2019) examines in a nonparametric frontier framework (conditional full and partial efficiency estimators) the effect of exports on technological change and technological catch-up levels of 16 Latin American countries. Overall, his findings suggest that up to a certain point, lower export shares enhance technological catch-up levels. Koengkan, Fuinhas, Kazemzadeh, Osmani, Alavijeh, Auza, and Teixeira (2022) evaluate the technical efficiency of 14 Latin American countries based on product, labor, and capital and electricity consumption data for the period 1990-2017. They compare the results obtained through DEA and SFA and establish an efficiency ranking for each one of these methodologies. They conclude that Panama and Chile have the highest efficiency scores.

However, none of the articles mentioned above use the methodology presented in this paper and therefore their estimates of inefficiency could be affected by outliers or extreme values in the data.

4. Data and variable description

We use panel data from 1980 to 2019 to estimate hyperbolic order-m efficiency measures for a sample of 16 Latin American countries: Argentina, Bolivia, Brazil, Chile, Colombia, Costa Rica, Ecuador, Guatemala, Honduras, Mexico, Nicaragua, Panama, Peru, Paraguay, Uruguay, and Venezuela plus the United States and Canada. The aim of including the latter is to make a more accurate estimate of the reference technological frontier and the distance between it and the Latin American economies. Here, the value of m was fixed to 14[4].

The data were extracted from the Penn World Table 10.0 database (Feenstra, Inklaar, and Timmer, 2015). The variables are real GDP (PPP in million US dollars of 2017) on the output side and the number of people employed (in millions), the capital stock (2017 PPP in millions of US dollars), and a human capital index based on years of schooling and return on education on the input side. Table 2 shows a summary of the sample data.

Table 2. Descriptive statistics

Variable	Observations		Mean	Std. Dev.	Min	Max
GDP (in mil. 2017 US$)	Overall	N=720	1109683.00	3195852.00	7160.11	20600000.00
	Between	n=18		3126022.00	22402.13	13400000.00
	Within	T=40		985652.60	-5020055.00	8266430.00
Capital Stock (in mil. 2017 US$)	Overall	N=720	4048007.00	11500000.00	20260.05	69100000.00
	Between	n=18		11400000.00	81112.68	48800000.00
	Within	T=40		3261708.00	-15800000.0	24300000.00

[4] All of the estimates were computed using the FEAR software package described by Wilson (2008)

					0	
Number of people employed (in millions)	Overall	N=720	18.43	32.78	0.54	158.30
	Between	n=18		33.13	1.08	132.34
	Within	T=40		6.03	-10.83	44.40
Human Capital Index	Overall	N=720	2.43	0.54	1.37	3.75
	Between	n=18		0.48	1.63	3.56
	Within	T=40		0.26	1.79	3.40

5. Results

The interpretation of the efficiency scores is as follows: An efficiency score of *x* means that the country uses *x* percent of the inputs and produces *x* percent of the output as a country that lies on the production frontier. This means that a value greater than 1 indicates inefficiency, while a lower efficiency score corresponds to a higher level of efficiency for a country. Taking the extremes of a period, a negative percentage change in the score means that the country experienced a gain in technological efficiency concerning a country on the production frontier.

Table 3. Hyperbolic order-m efficiency estimates and ranking of Latin American countries.

	1980		2019			%Δ	
Country	Estimate	Rank	Estimate	Rank	Geom. Mean full period	2019 vs 1980	Rank
Argentina	0.827	8	0.818	5	0.819	-1.033	5
Bolivia	0.982	18	0.918	15	0.924	-6.481	3
Brazil	0.825	7	0.841	8	0.833	1.971	12
Canada	0.746	2	0.752	2	0.733	0.902	8
Chile	0.840	11	0.754	3	0.796	-10.223	1
Colombia	0.869	14	0.824	6	0.853	-5.227	4
Costa Rica	0.860	13	0.858	14	0.877	-0.272	6
Ecuador	0.820	6	0.847	12	0.839	3.266	13
Guatemala	0.843	12	0.853	13	0.835	1.136	10
Honduras	0.871	15	0.932	16	0.871	7.008	16
Mexico	0.779	3	0.837	7	0.808	7.345	17
Nicaragua	0.886	16	0.799	4	0.867	-9.857	2
Panama	0.835	9	0.844	10	0.840	1.045	9
Paraguay	0.911	17	0.944	17	0.938	3.597	14

Peru	0.799	5	0.844	11	0.842	5.687	15
Uruguay	0.838	10	0.843	9	0.902	0.549	7
US	0.601	1	0.608	1	0.603	1.202	11
Venezuela	0.791	4	1.135	18	0.874	43.439	18

Table 3 shows the hyperbolic order-m efficiency estimates for the 18 economies of the sample. The United States and Canada headed the ranking at both the beginning and the end of the period. In contrast, the order of Latin American economies shows significant changes in both the top and bottom. The four most efficient economies in 1980, after the North American economies, were among the worst performers in terms of variation. This poor performance led Mexico, Peru, and Ecuador to lose several places, while Venezuela came last in the 2019 efficiency ranking. Guatemala, Costa Rica, Honduras, and Paraguay, ranked among the bottom eight in 1980, lagged, while Bolivia's boost failed to lift it out of this group. On the other hand, Chile, Nicaragua, and Colombia rounded out the podium in terms of efficiency gains, which was enough to improve significantly in the ranking.

Figure 2. Annual average technical (in) efficiency score evolution per region. 1980-2019

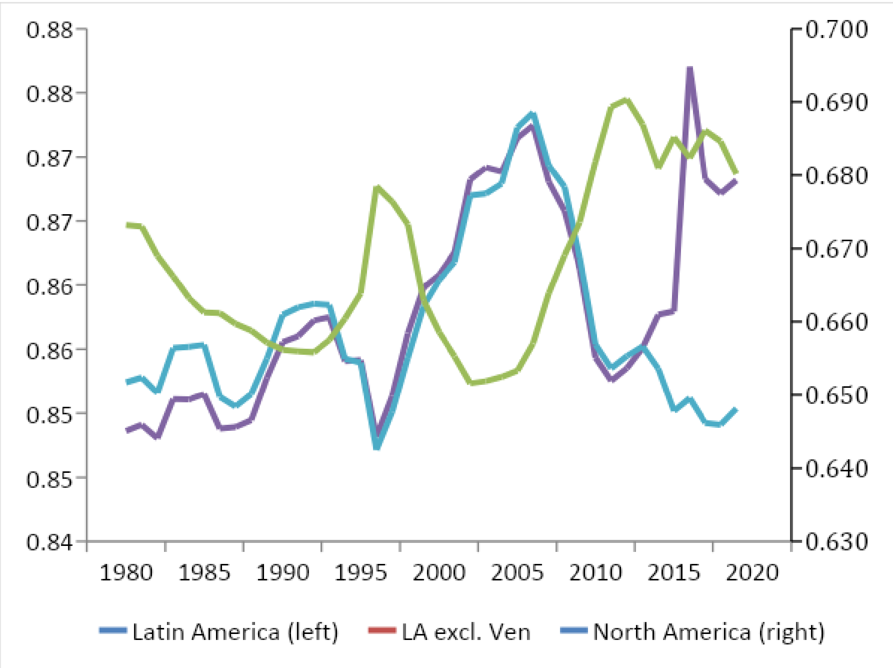


Figure 2 shows the evolution of the annual average scores of technical efficiency over the period considered. The first thing that stands out in the figure is the mirror dynamic of Latin versus North America (United States and Canada). Latin America shows higher levels of inefficiency during “The Lost Decade” of the 1980s and during the period of lower international capital liquidity from the late 1990s to 2006. This 10-year period led to surpassing the observed levels of inefficiency of The Lost Decade. In contrast, there was an increase in efficiency during the liberalization process in the early 1990s and the 2000s Commodity Boom. North American economies experienced improved efficiency levels contemporaneously with the period of international illiquidity and during the recovery after the 2008 global financial crisis with its epicenter in the United States.

The second noteworthy aspect of Figure 2 is the impact Venezuela has on Latin America's aggregate. At the beginning of the period, Venezuela is significantly more efficient than the subcontinent average. However, that converges with the average until 2011. From that year onwards, the economy experiences a significant increase in inefficiency while the rest of Latin America taken as a whole prolongs a period of recovery. That behavior explains the difference between the aggregates Latin America and Latin America excluding Venezuela.

Then, the hyperbolic order-m efficiency estimates were taken to perform the TFP Malmqüist index and its components. Table 4 displays the results for each country in the sample. Note that if TFP values are below one, it indicates that there has been a productivity loss in 2019 compared to 1980 and values greater than one indicate the opposite.

Table 4. Malmqüist TFP Index and its components: 2019 vs. 1980

Country	Global efficiency change (EFFCH)	Technical change (TECHCH)	Total factor productivity change (TFPCH)	TFPCH Rank
Argentina	1.010	0.954	0.964	6
Bolivia	1.069	0.468	0.500	16
Brazil	0.981	1.209	1.186	3
Canada	0.991	1.182	1.171	4
Chile	1.114	1.046	1.165	5
Colombia	1.055	0.794	0.838	7
Costa Rica	1.003	0.580	0.581	12
Ecuador	0.968	0.847	0.820	8
Guatemala	0.989	0.650	0.642	11
Honduras	0.935	0.368	0.344	18
Mexico	0.932	1.397	1.301	2
Nicaragua	1.109	0.490	0.544	15
Panama	0.990	0.557	0.551	14
Paraguay	0.965	0.460	0.444	17
Peru	0.946	0.844	0.799	9
Uruguay	0.995	0.802	0.797	10
US	0.988	1.374	1.358	1
Venezuela	0.697	0.812	0.566	13
Mean	0.985	0.824	0.810	
Latin America	0.985	0.767	0.753	
LA excl. Ven	1.004	0.764	0.765	
North America	0.990	1.278	1.265	

The Malmqüist TFP Index states that there was a significant productivity loss (TFPCH) for Latin American economies. Approximately 25% was lost mainly due to poor capacity to generate or take advantage of technological change (TECHCH) in a historical stage characterized by the acceleration of the innovation process and the transmission of technology. In contrast, North America increased its production capacity by more than 25%, mainly due to the same factor.

Only five economies experienced increases in multifactor productivity. In addition to the US and Canada, Mexico, Brazil, and Chile share this result. However, only the latter economy succeeded from simultaneous global efficiency gains (EFFCH) and technical change (TECHCH). Mexico and Brazil showed a better productive performance than Canada for the period considered.

Mexico, Peru, and Ecuador, which along with Venezuela had moved from the extreme to the extreme according to the order-m efficiency indicator, ranked in the first 13 places by the Malmquist index, with Mexico leading below the United States. Mainly technical change explained their productivity growth. On the other hand, Venezuela shows a loss of productive capacity explained by both components. However, the most salient fact is that has lost around 30% of its productivity due to the loss of overall efficiency.

Honduras and Paraguay lead the ranking of poor performance. Bolivia and Nicaragua were close behind. In all four cases, there was a loss of productive capacity due to negative technical change of close to 50%. This was slightly offset by overall efficiency gains in the cases of Bolivia and Nicaragua. If Venezuela is removed due to its poor performance in efficiency change, the average value for Latin America recovers 1 percentage point of growth.

The previous analysis corresponds to a long period, so it may be relevant to subdivide it. For this reason, the decomposition of the Malmqüist TFP Index was replicated dividing the data into decades. Table 5 displays the Malmqüist TFP Index mean and its components for each period.

The Lost Decade hurt Latin America’s productivity, but it also had an impact on developed economies. However, the following three decades coincide in showing a widening of the productivity gap being 1980-1990 the worst decade in terms of TFPCH. Between these years, Latin America experienced the greatest decline while North America experienced the greatest growth in multifactor productivity.

Table 5. Malmqüist TFP index mean summary in decades

	Global efficiency change (EFFCH)	Technical change (TECHCH)	Total factor productivity change (TFPCH)
	1980-1990		
Mean	0.996	0.908	0.904
Latin America	0.992	0.904	0.897
LA exc. Ven	0.995	0.906	0.900
North America	1.025	0.941	0.964
	1990-2000		
Mean	0.995	0.975	0.971
Latin America	0.995	0.962	0.957
LA exc. Ven	0.998	0.961	0.960
North America	0.996	1.085	1.081
	2000-2010		
Mean	1.004	0.988	0.990
Latin America	1.009	0.980	0.987
LA exc. Ven	1.007	0.983	0.988
North America	0.966	1.046	1.011
	2010-2019		
Mean	0.992	0.978	0.968
Latin America	0.990	0.972	0.960
LA exc. Ven	1.007	0.970	0.975
North America	1.003	1.021	1.025

Table 6 shows the performance of each economy in terms of technological change by decade. Difficulties in technological change became evident in the first decade. However, these difficulties persisted in the following two decades for Central

American economies -Honduras, Nicaragua, and Panama in particular- while the 2010s showed some South American economies –Chile, Peru, and Uruguay- with greater difficulties.

Table 6. Technical change geom. mean by decades

	1980s	1990s	2000s	2010s
Argentina	0.948	1.126	1.182	1.042
Bolivia	0.981	0.765	0.772	1.000
Brazil	0.833	1.090	1.031	1.044
Chile	0.916	0.915	1.056	0.868
Colombia	0.972	1.016	1.047	0.986
Costa Rica	1.003	1.042	1.049	0.948
Ecuador	0.835	1.030	0.975	1.042
Guatemala	0.958	0.979	1.005	1.050
Honduras	0.821	0.753	0.794	0.933
Mexico	0.836	1.002	0.946	0.980
Nicaragua	0.829	0.864	0.807	0.807
Panama	0.844	0.786	0.837	1.065
Paraguay	0.943	0.939	1.162	1.053
Peru	0.788	0.974	0.978	0.892
Uruguay	1.077	1.136	1.104	0.840
Venezuela	0.882	0.967	0.942	1.004
United States	1.028	1.092	1.043	1.047
Canada	0.855	1.078	1.049	0.995

These results coincide with some conclusions of the literature mentioned in section 3.2. Kolias and Tzeremes (2021) and Araujo et al (2014) found poor productivity performance over the whole period and in general lines. However, their estimates for Latin America showed productivity gains and positive technological change in the 1990s and 2000s. Marinho and Bitencourt (2007) also found positive technological change between 1975 and 1990. In contrast, our estimates show productivity declines and negative technological change for all periods. Differences in the behavior of overall efficiency are also found over several decades. Therefore, although the general idea that results from their reading is consistent with the one developed here, the combination of hyperbolic order-m efficiency estimates and Malmqüist TFP decomposition of multifactor productivity is robust to the Venezuelan, Honduran or Nicaraguan experiences so that the characterization of each period is more precise.

6. Concluding remarks

The present study makes available some evidence of a discussion that, with a certain regularity, takes place in the literature on economic development and Latin American economics. This set of countries is the subject of unceasing attention in the discipline. The idea that Latin America must move towards an “age of productivity” is what has motivated this study and the paper proposed to observe whether this mandate has been fulfilled.

Based on a robust methodological approach to calculate efficiency and the decomposition of total factor productivity using the Malmqüist index, the decline in multifactor productivity has been observed in Latin America when 40 years is contemplated. As a result, the gap between the Latin American economies and the more developed ones has widened.

The evidence shows that the greatest difficulty has been experienced in assimilating technology, mainly during the 1980s. This aspect did not improve significantly in the following decade. The benchmark countries have such a performance that it was unable to close the productivity gap. Regarding changes in technical and scale efficiencies, Latin America has shown pronounced difficulties with technological change and unstable efficiency performance. However, the results at the country level show differences both in relative and temporal terms, indicating the existence of relevant idiosyncratic behaviors.

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