Chapter

Tourism Specialization, Income Distribution, and Human Capital in South America

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Abstract

In the present chapter, we analyze the relation between tourism specialization, income distribution, and human capital in South America between 1995 and 2015. Causality is studied by applying different approaches. On one hand, the panel data Granger causality test and the test proposed by Dumitrescu and Hurlin are conducted. On the other hand, the individual causality test for each country is considered by applying the classical Granger causality and a novel symbolic causality test. The results suggest that tourism specialization measured as arrival/population (TSA) and receipts/exports (TSR) and human capital cause income distribution. The estimated regressions suggest the existence of a Kuznets curve between tourism specialization and income distribution in South America, presenting threshold for TSA equal to 53.20% and TSR equal to 19.98%. Under these thresholds, tourism specialization increases income inequality, but overpassing them the income distribution improves. In addition, human capital has also a positive effect on income distribution.

Keywords: tourism, income distribution, human capital, causality, panel data, Kuznets

1. Introduction

Inequality is one of the main problems in South America; it is both cause and consequence of the region's polarized structures. The tourism sector has been considered by many governments as strategic. They have been investing in developing the sector to improve not only employment, currency balance, and tax revenue but also poverty and income distribution. Actually, it is believed that tourism may indirectly reduce poverty by the generation of employment, the diffusion of technical knowledge, the stimulation of research, and the development and accumulation of human capital. International organisms such as the Inter-American Development Bank (IADB) and World Bank (WB) have designed programs to develop the tourism sector in Latin American countries, helping to reduce poverty and to improve income distribution.

Considering the WB indicators, world tourism receipts were USD 1.4 trillion with 1.2 billion of international tourism arrivals around the world in 2015. In 1995, South America received 12.9 million of tourist representing 2.47% of the world arrivals. This participation reached 3.16% in 2015 because South American tourism arrivals increased at an average annual rate of 5.55%. This represents a better performance respect to the total world with an average rate of 4.25% and developed regions such as North America or the European Union with average rates of 2.31 and 2.94%, respectively.

It is asserted in [1] that despite the recent economic downturn, tourism remains a large and growing sector of the global economy, and for many countries, the tourism industry represents a key contributor to gross domestic product (GDP), with tourism specialization (defined as tourism arrivals as a percentage of population and expenditure as percentage of GDP) increasingly being seen as a catalyst for economic recovery and development. In 1995, South American ratio receipts/exports were 7.57%, below the world level of 8.47% of exports. However, in 2016 the South American ratio arrives to 7.62% overpassing the world ratio of 6.71%. Therefore, we note an increase in the tourism specialization of South American countries in these 20 years increasing respect to the world.

There are also some facts concerning the income distribution. According to the SWIID dataset, in 1995 the average world income distribution measured by the Gini index was 38.76 and reduced to 36.46 in 2015. South America is one of the most unequal regions of the world; in 1995 the average Gini index was 47.96 and it reduced to 42.50. It means that South American income distribution improves 11% in the last 20 years. Even more, income distribution improves in all South American countries in the considered period. South America is one of the most unequal regions in the world related to wealth or income distribution (see [2]). The measure of inequality, as the wealth distribution measured by land property distribution, shows that South America is the most unequal region in the planet with a Gini of 0.85 compared with Europa (0.57), Africa (0.56), and Asia (0.55).

When considering the human capital per person, the average South America levels are above the average world levels. In 1995 the human capital per person was 2.22 in the world and 2.27 in South America; in the 2015 the indicator increases to 2.59 in the world and 2.74 in South America, showing rates of 16.8% and 20.6% in the whole period, respectively.

The present chapter aims to study the impact of tourism specialization and human capital on income distribution in South America for the period 1995–2015. Different causality tests are applied considering panel data and individual country approaches. First, a panel data Granger causality test and the test proposed by Dumitrescu and Hurlin [3] are applied. As a second approach, a novel symbolic causality test is applied to each South American country comparing the results with the classical Granger test. The novel symbolic approach will also allow testing multidimensional causality. In particular, the simultaneous causality between tourism specialization and human capital (TS, HC) to income inequality (GINI) will be tested.

In the second step, we want to estimate the relationship between income inequality, tourism specialization, and human capital considering two measures of tourism specialization (number of arrivals over population and tourism receipts over exports). As far as we know, this is the first work focusing on the causality between tourism specialization, human capital, and income distribution and the first study to apply a symbolic causality test in tourism economics.

The chapter is organized as follows. Section 2 reviews the literature about income inequality and tourism, summarizing the main results. Section 3 describes the econometric methodology to be applied and the data source. Section 4 presents the main empirical results. Finally, Section 5 draws some conclusions and indicates some future lines of research.

2. Literature review

Positive and negative impacts of tourism have been highlighted by the vast literature analyzing tourism. On the past decades there have been discussions about the possibility of tourism as a tool for development and poverty reduction. It is introduced in [4] the pro-poor tourism (PPT) as a key approach. This refers to tourism that generates net benefits for the poor (benefits greater than costs). The authors give some insight on the mechanism behind the tourism sector as a factor reducing poverty and improving income distribution: (1) It has higher potential for linkage with other local enterprises (particularly agricultural, artisan production, and other services); (2) it is labor intensive; (3) it has potential in poor countries and areas with few other competitive exports; (4) tourism products can be built based on natural resources and culture which are assets that some of the poor have; and (5) it facilitates partnerships between small business and the wider tourism industry.

However, studies on this approach seem to find mixed evidence. It is argued in [5, 6] that tourism might not be effective as a tool for poverty reduction but might instead increase the dependency of the "south" on "northern" transnational corporations (TNCs). It is asserted in [7] that tourism presents a potential distribution problem because local income may go preferentially to profits rather than to wages. It is suggested in [8] that the structure of tourism sector in the country is important; it is not the same impact in distribution a country with national firms or international firms, and leakage can also happen if the tourism inputs are imported than produced in the country. It is highlighted in [9] that tourism can contribute to employment and income generation. It is indicated in [10] that tourism promotes international understanding. It is remarked in [11] that tourism contributes to entrepreneurship and small, medium, and microenterprise (SMME) development. Finally, it is remarked in [12] that tourism can generate funding and political support for conservation.

Even if most of the studies focused on the pro-poor tourism approach, it is important to remark that poverty is distinct from inequality. The former can be defined by considering the financial income level below which people are described as poor (applying the so-called "poverty line"). The latter focuses primarily on the distribution of economic factors across the whole population and requires a comparative analysis within that society. In addition, note that it is possible to find countries with high poverty and a better income distribution than countries with low poverty and a worse income distribution. For instance, Georgia in 2011 had a low-income distribution (41.8) respect to South Africa (58.2). However, international poverty (poverty gap at USD 1.9 a day) in South Africa (4.9%) was less than in Georgia (6.2%). Consider an extreme case, when there is nothing to distribute, we may have an egalitarian distribution but poverty would be very high. However, when the average per capita income is very high, the dispersion is likely to increase, generating a worse income distribution. Actually, the negative impacts of economic growth volatility on income distribution have been remarked in the literature; see for instance [13–16]. For the negative effects of income volatility on the income distribution in Latin America, see [17].

Although the literature relating tourism and poverty is larger than the studies about the impact of tourism in income distribution, we can find some recent works. It is investigated in [18] the ways in which tourism can be a means to reduce social inequality or alleviate its impact. It is found in [19] that the tourism has a positive effect on income inequality in top 43 tourism arrival countries. Even more, they found a Kuznets curve between tourism and income inequality. In [20] 13 tourism-intensive economies are analyzed, and no improvement in income inequality resulting from tourism growth is found. It is studied in [21] the tourism and income distribution for 49 developing countries finding evidence of the Kuznets curve in the relation between tourism growth and income inequality. It is found in [22, 23] evidence of income distribution improvement in Brazil and Croatia, respectively. It is analyzed in [24–26] the income distribution among regions in China, finding that income inequality decreases. However, it is found in a previous study that the concentration of tourism in the coast affected the regional income distribution in China (see [27]). In the same way, it is studied in [28] the US cities in the period 1990–2000, finding evidence of income inequality increasing.

3. Methodology

The causality between inequality and tourism specialization is analyzed applying two basic approaches, panel data and individual time series. In the first case, we applied two different tests. The first test implies to treat the panel data as one large stacked set of data, and then perform the Granger causality test in the standard way, with the exception of not letting data from one cross-section enter the lagged values of data from the next cross-section. This method assumes that all coefficients are the same across all cross-sections. A second test is suggested by Dumitrescu and Hurlin (see [3]) and follows the opposite assumption that all coefficients are different across cross-sections. Dumitrescu and Hurlin's test of homogeneous non-causality assumes under the null hypothesis that there is no causal relationship for any of the units of the panel and considers a heterogeneous panel data model with fixed coefficients (in time). It also specifies the alternative hypothesis as heterogeneous causality, which assumes that there is a causal relationship from x to y for at least one subgroup of individuals.

The second approach will be to test causality considering each individual country. Symbolic causality test (see [29, 30]) is applied and compared with the well-known Granger causality test. The concept of symbolization is related with dynamical systems theory and the study of nonlinear systems, which can exhibit bifurcation and chaos. Symbolization involves transformation of raw time-series measurements into a series of discretized symbols that are processed to extract information about the generating process. In this way, we can search for nonrandom patterns and dependence by transforming a given time series $\{x_{(1)}, x_{(2)}, \ldots, x_{(T)}\}$ into a symbolic string $\{s_{(1)}, s_{(2)}, \ldots, s_{(T)}\}$, where $s_{(i)}$ takes a value for a finite alphabet, generally composed by two or four symbols.

Symbolic non-causality implies to consider time series X and Y sized $T + 1$, and the symbolized time series can be expressed as $Sx = \{sx_{(1)},sx_{(2)},\ldots,sx_{(T+1)}\}$ and $Sy = \{sy_{(1)},sy_{(2)},\ldots,sy_{(T+1)}\}$. To test causality, we have to define two new series, grouping Sx and Sy in the following way:

$$Sxy = \{(sx_{(1)},sy_{(2)}),(sx_{(2)},sy_{(3)}),\ldots,(sx_{(t-1)},sy_{(t)}),\ldots,(sx_{(T)},sy_{(T+1)})\} \quad (1)$$

$$Syx = \{(sy_{(1)},sx_{(2)}),(sy_{(2)},sx_{(3)}),\ldots,(sy_{(t-1)},sx_{(t)}),\ldots,(sy_{(T)},sx_{(T+1)})\} \quad (2)$$

Note that in the first case $(sx_{(t-1)},sy_{(t)})$, x is preceding y, and in the second case $(sy_{(t-1)},sx_{(t)})$, y is preceding x. Intuitively, it implies that in case of non-causality, all the possible pairs $(sx_{(t-1)},sy_{(t)})$ and $(sy_{(t-1)},sx_{(t)})$ are equally probable. Then detecting a more probable frequency in a determined pattern will imply rejection of non-causality. It is found in [29, 30] that we can define a statistics distributed as a Chi-2 with $n-1$ degree of freedom, where $n = a^2$, "a" is the number of symbols in the alphabet and "2" represents the considered pair.

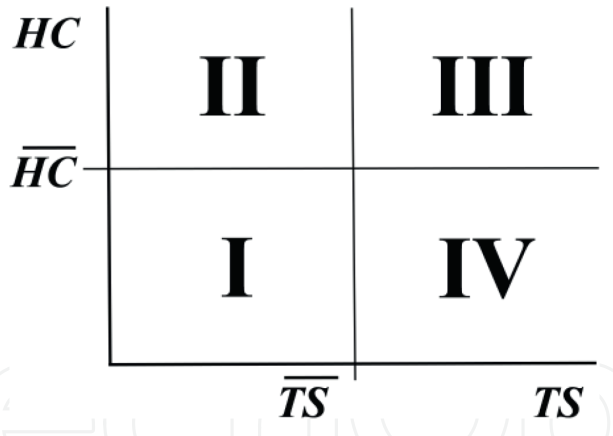

Figure 1.
Two-dimensional variable (tourism specialization and human capital) is transformed into a four-symbol variable. Source: own elaboration.

Note that the symbolic causality test will allow studying multidimensional causality. In particular, causality considering the bidimensional variable tourism specialization and human capital (TS, HC) on one hand, and income inequality (GINI) on the other hand. At first, the bidimensional variable (TS, HC) is transformed in a symbolic time series applying the regions defined in **Figure 1**, with four symbols: (I) low TS and low HC; (II) low TS and high HC; (III) high TS and high HC; and (IV) high TS and low HC.

As a second step, the relationship among the variables is estimated by considering panel data regression. At first, a panel unit root test is applied to check for non-stationarity, which would suggest the application of panel data cointegration. Four unit root tests are applied (Levin, Lin, and Chu t; Im, Pesaran, and Shin W-stat; ADF -Fisher Chi-square; PP-Fisher Chi-square).

We conduct a dynamic panel data analysis for 10 South American countries for the period between 1995 and 2015. Eq. (3) introduces income inequality as a function of tourism specialization, human capital, and the government expenditure increment as a control variable:

$$\text{GINI} = \alpha_0 + \alpha_1(\text{TS}) + \alpha_2(\text{TS})^2 + \alpha_3(\text{HC}) + \alpha_4(\Delta\text{GOV}) \tag{3}$$

Note that in the case of tourism specialization, a squared term will be tested. Concavity implies that $\alpha_2 < 0$ and the strictly positive domain of the TS require that $\alpha_1 > 0$. The maximum coefficient is given by $\text{TS}^* = -\alpha_1/(2\alpha_2)$ with a maximum level of GINI^* at $\alpha_0 - (\alpha_1^2/4\alpha_2)$.

We apply the difference generalized method of moments (GMM) framework (see [31, 32]). This estimator overcomes a potential weakness in the Arellano and Bond DPD estimator (see [33]). Instead of only lagged levels, which are often poor instruments for first differenced variables, especially if they follow a random walk, the estimator includes lagged differences in addition to lagged levels. Although the present estimation includes variables such as GDP which generally presents unit root processes, we will also estimate the Arellano-Bond DPD without considering GDP and HC in order to compare results to the Arellano-Bover/Blundell-Bond method. In addition, we estimate fixed effects (FE) and random effects (RE) in order to compare the resulting coefficients, using the corresponding FE and RE functional general form, given by:

$$(\text{GINI})_{i,t} = \alpha_i + \beta_1(\text{TS}_{i,t}) + \beta_2(\text{TS}_{i,t})^2 + \beta_3(\text{HC}_{i,t}) + \beta_4(\Delta\text{GOV}_{i,t}) + \mu_i + \varepsilon_{i,t} \tag{4}$$

where $GINI_{i,t}$, $TS_{i,t}$, $HC_{i,t}$, and $\Delta GOV_{i,t}$, respectively, determine the level of Gini index, the tourism specialization, the human capital, and the difference of the government expenditure as %GDP in country *i* during year *t*. The fixed effects decomposition of the error term is given by $\nu_{i,t} = \mu_i + \varepsilon_{i,t}$ with μ_i being the country-specific effect and $\varepsilon_{i,t}$ the error component of the model.

If a model for panel data includes lagged-dependent explanatory variables, the simple estimation procedures are asymptotically valid only when there are a large number of observations in the time dimension (T). The currently available response to this problem is to first difference the equation to remove individual effects and then estimate using instrumental variables (IV), given by the values of the dependent variable (see [33–35]). This treatment leads to consistent but not efficient estimates, because it does not make use of all the available moment conditions. Hence, we use the difference generalized method of moments (GMM) framework as mentioned before, estimating the following equation:

$$\begin{aligned}\Delta(GINI)_{i,t} \;=\; & \beta_1\Delta(GINI)_{i,t-1} + \beta_2\Delta TS_{i,t} + \beta_3\Delta(TS_{i,t})^2 \\ & + \beta_4\Delta HC_{i,t} + \beta_5\Delta^2 GOV_{i,t} + \Delta\varepsilon_{i,t} \end{aligned} \tag{5}$$

with country $i = 1,2, \ldots, n$ at year $t = 1, \ldots, T$ and all the variables being first differences, i.e., $\Delta X_{i,t} = X_{i,t} - X_{i,t-1}$ for all variables $X = (GINI, TS, HC, \Delta GOV)$. Parameter β_1 indicates to what degree current GINI is determined by the value of previous GINI. By using a dynamic model, we measure both short-run and long-run coefficients; the latter are obtained by dividing each of the coefficients by $(1 - \beta_1)$. In addition, we would avoid the problem of non-stationarity by differencing the data.

The dataset includes two main variables (income inequality and tourism specialization), as well as human capital (HC) and ratio government expenditure/GDP (GOV) for 10 South American countries for the period 1995–2015:

1. Income inequality (GINI) is measured by the Gini index. Data is derived from the Standardized World Income Inequality Database (SWIID) Version 6.1. The variable is called *gini-disp*. It is an estimate of Gini index of inequality in equivalized (square root scale) household disposable (post-tax, post-transfer) income, using the Luxembourg Income Study data as the standard.

2. Tourism specialization (TS) is measured by two variables: (1) international tourism as receipts over exports (TSR) and (2) international tourism as number of arrivals over the country population (TSA). The source of the three variables is the World Development Indicators (WDI) published by the World Bank.

3. Human capital (HC) is obtained from the variable (*hc*) in the Penn World Table, version 9.0. The variable represents the index of human capital per person, based on years of schooling, as in [36], and returns to education, as in [37].

4. Government expenditure over GDP (GOV) is measured by the general government final consumption expenditure (% of GDP) obtained by the World Development Indicators (WDI) published by the World Bank.

Since per capita GDP is related with human capital and there is also a close relation between tourism and economic growth, for instance, in the tourism-led growth hypothesis, this variable was not considered.

Variable	Mean	Std. dev.	Min.	Max.	N
Year	-	-	1995	2015	210
GINI	46.65	4.63	36.00	54.60	210
Receipts/exports (TSR)	6.50	4.41	0.84	23.13	210
Arrivals/population (TSA)	12.13	17.99	1.23	84.39	210
Human capital (HC)	2.51	0.26	1.86	3.05	200
Government expenditure (%GDP)	13.41	3.10	5.01	22.73	209

Table 1.
Summary statistics.

Table 1 contains the descriptive statistics for the variables (mean, standard deviation, minimum, and maximum), which are used in the econometric analysis.

Note that for the 10 South American countries in the period 1995–2015, we should have 210 observations, but due to human capital and government expenditure have missing values, we have to work with an unbalanced panel data. In this period, the mean value of the GINI was 46.65 with a minimum of 36 corresponding to Venezuela in 2015 and a maximum of 54.6 in Bolivia in 2000. Tourism specialization as receipts over exports presents a minimum of 0.84% for Venezuela in 2011 and a maximum for Uruguay in 1996 with 23.13%. When specialization is measured as arrivals over population, the minimum of 1.23% corresponds to Brazil in 1995 and the maximum of 84.39% to Uruguay in 2011. We appreciate that Uruguay is the most specialized country in South America considering that it rank the fourth position in arrivals but has the lowest population. On the other hand, Uruguayan tourism receipts have the largest importance in exports than the 10 countries.

The minimum human capital corresponds to Brazil in 1995 with 1.86 and the maximum corresponds to Chile in 2014 with 3.05. Government expenditure presents a minimum of 5.01% in Venezuela in 1996 and a maximum of 22.73 for Colombia in 1999.

4. Empirical results

There are a number of different approaches to test causality in a panel context. As previously mentioned, two different tests will be applied: Granger and Dumitrescu and Hurlin causality tests.

Table 2 shows the results for the first Granger causality test under the assumption of homogeneous coefficients for the world, indicating causality from tourism specialization measured by receipts over export (TSR) to GINI. In addition, Granger test indicates that human capital also causes income distribution.

It is noted in [3] that the assumption of homogeneous coefficients βi leads to fallacious inference because a homogeneous specification of the relation between the studied variables does not allow for interpreting causality if it differs across countries (i.e., the direction of causation shifts between countries). Therefore, we test the homogeneous non-causality (HNC) hypothesis by taking into account the heterogeneity of both the regression model and the causal relation. **Table 3** shows the results according to the test, following [3].

Assuming heterogeneity of the coefficients between countries, both measures of tourism specialization (TSR, TSA) cause income distribution. In this case, bidirectional causality between human capital and income distribution is detected, and income distribution seems to cause government expenditure.

Null hypothesis	F-statistic	Prob.
TSR does not Granger cause GINI	9.295	0.003*
GINI does not Granger cause TSR	0.000	0.995
TSA does not Granger cause GINI	1.106	0.294
GINI does not Granger cause TSA	0.035	0.852
HC does not Granger cause GINI	19.189	0.000*
GINI does not Granger cause HC	0.007	0.935
GOV does not Granger cause GINI	1.223	0.270
GINI does not Granger cause GOV	0.569	0.452

Source: Own calculations. One lag was considered.
**Rejection of the null hypothesis.*

Table 2.
Causality test assuming the homogeneity of coefficients (common coefficients).

Null hypothesis	W-Stat.	Zbar-Stat.	Prob.
TSR does not Granger cause GINI	8.721	13.493	0.000*
GINI does not Granger cause TSR	0.917	−0.385	0.700
TSA does not Granger cause GINI	5.433	7.647	0.000*
GINI does not Granger cause TSA	1.925	1.408	0.159
HC does not Granger cause GINI	16.098	26.214	0.000*
GINI does not Granger cause HC	13.016	20.813	0.000*
GOV does not Granger cause GINI	1.429	0.525	0.600
GINI does not Granger cause GOV	4.598	6.163	0.000*

Source: Own calculations. One lag was considered.
**Rejection of the null hypothesis.*

Table 3.
Causality test assuming the heterogeneity of coefficients (individual coefficients).

Table 4 presents the Granger non-causality test for each country. Note that tourism specialization is causing income inequality for 9 of the 10 countries considering at least one of the two measures of tourism specialization. Chile is the exception where tourism specialization measured as arrivals/population seems to be caused by GINI. In the case of human capital, most of the countries present bidirectional causality with respect to GINI. Brazil is the exception where non-causality is detected in any direction. In the case of the government expenditure, only four countries (Argentina, Ecuador, Paraguay, and Uruguay) suggest causality running from GINI to government expenditure.

Table 5 presents the symbolic causality test results. Most of the results are similar to Granger non-causality; note that the test detects causality running from tourism specialization to income distribution for five countries; in the case of TSA, we detect bidirectional causality for four countries, and non-causality is detected in three countries. When testing causality between human capital and income distribution, bidirectional causality is detected in four cases, in four cases causality that is running from HC to GINI and two cases detect non-causality. Finally, government expenditure seems to be causing GINI just in the case of Colombia.

Figures 2 and **3** show interesting results originated in the symbolic causality test. The average frequencies relating the past level of tourism specialization and

Country	TSR to GINI	GINI to TSR	TSA to GINI	GINI to TSA	HC to GINI	GINI to HC	GOV to GINI	GINI to GOV
Argentina	49.367***	0.877	22.325***	0.367	58.180***	1.181	1.5034	9.944***
Bolivia	1.042	0.793	6.455**	1.5557	20.110***	8.499**	2.479	0.202
Brazil	5.531**	0.161	0.565	0.729	2.616	0.789	0.514	1.435
Chile	0.551	1.296	0.128	8.439***	4.463*	8.737***	1.343	0.935
Colombia	1.242	0.233	9.033***	2.510	8.262**	21.554***	1.473	0.170
Ecuador	5.137**	4.658**	4.622**	1.256	15.127***	37.146***	0.687	21.552***
Paraguay	12.355***	0.509	3.749*	2.345	26.011***	25.745***	2.792	6.597**
Peru	4.448*	0.028	3.602*	0.504	6.553**	0.494	0.568	1.774
Uruguay	2.106	0.169	3.562*	1.116	7.613**	22.885***	1.261	3.133*
Venezuela	5.426**	0.444	0.2914	0.427	12.303***	7.097**	2.087	0.073

Source: Own calculations. One lag was considered.
**Rejection of the null hypothesis 10%.*
***Rejection of the null hypothesis 5%.*
****Rejection of the null hypothesis 1%.*

Table 4.
Granger non-causality test for the 10 South American countries in 1995–2015.

Country	TSR to GINI	GINI to TSR	TSA to GINI	GINI to TSA	HC to GINI	GINI to HC	GOV to GINI	GINI to GOV
Argentina	2.00	2.00	16.40**	7.20	12.80**	3.20	2.00	3.20
Bolivia	16.40**	3.20	10.00**	7.20	12.80**	3.20	5.20	3.20
Brazil	0.40	0.80	0.40	0.00	16.40**	12.80**	7.60	3.20
Chile	20.40**	10.00**	13.20**	20.00**	16.40**	12.80**	0.40	0.80
Colombia	14.80**	3.60	5.20	5.20	6.80	6.80	9.20**	2.00
Ecuador	16.40**	5.20	16.40**	12.80**	20.00**	7.20	5.20	7.20
Paraguay	7.60	2.00	1.20	5.20	16.40**	12.80**	1.20	3.20
Peru	13.20**	7.20	13.20**	20.00**	10.00**	3.20	0.40	0.80
Uruguay	3.20	2.00	16.40**	10.00**	0.80	0.00	5.20	3.20
Venezuela	7.60	5.20	0.40	0.40	16.40**	12.80**	2.00	0.80

Source: Own calculations. One lag was considered.
***Rejection of the null hypothesis of non-causality at 5%.*

Table 5.
Symbolic non-causality test for the 10 South American countries in 1995–2015.

the present income distribution are different depending if the measure is receipts/exports or arrivals/population. Note that when the specialization is measured by TSR, past low levels of specialization (high specialization) are related with low levels of Gini (high levels of Gini). On the contrary, when the measure is TSA, past low levels of specialization (high specialization) are related with high levels of Gini (low levels of Gini). When considering specialization in monetary terms (receipts/exports), the causality goes in the direction of increased inequality. This effect seems to be particularly important in countries such as Bolivia, Chile, Colombia, Ecuador, and Peru. However, with a physical measure (arrivals/population), the result is the desired one. Specialization in tourism derived of an increase of arrivals related to the country population seems to improve income distribution.

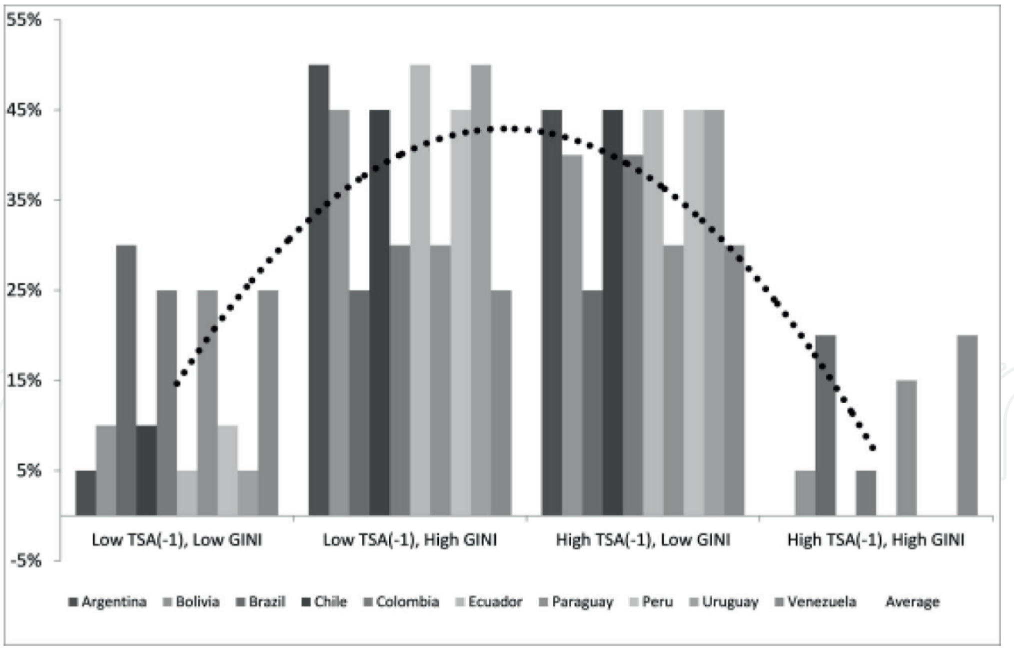

Figure 2.
Frequencies of previous TSA (specialization in arrivals) and present Gini in South America. Source: Own elaboration based on the symbolic causality test.

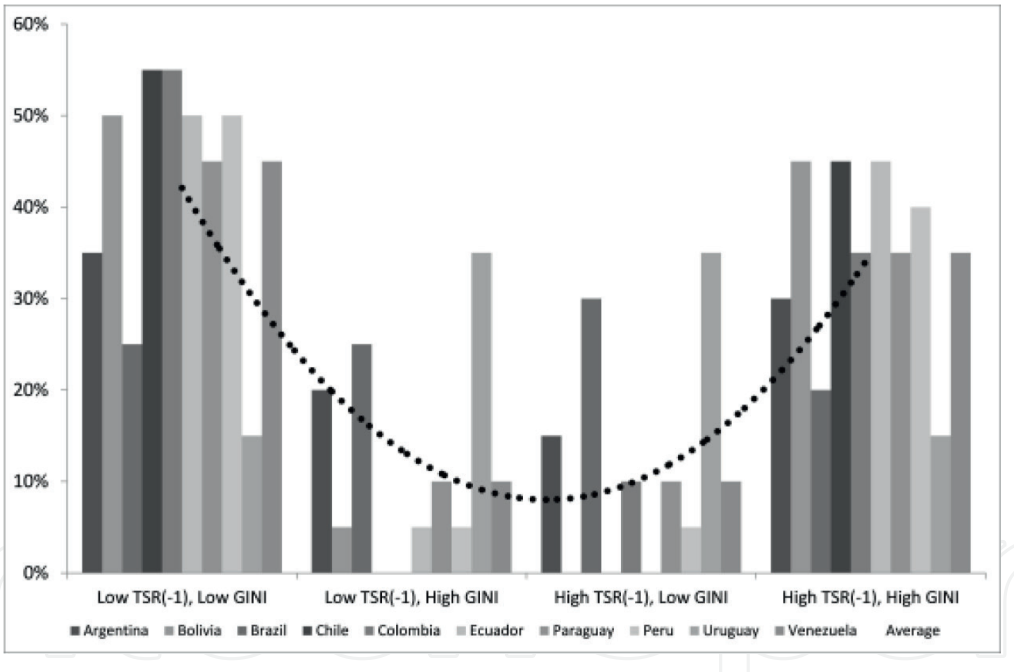

Figure 3.
Frequencies of previous TSR (specialization in receipts) and present Gini in South America. Source: Own elaboration based on the symbolic causality test.

Table 6 presents the result for multidimensional causality from a bidimensional variable (X1, X2) to GINI. Note that when a bidimensional variable composed by tourism specialization (TSR or TSA) and human capital is tested with GINI, most of the results suggest a bidirectional causality or causality running from the bidimensional space (TS, HC) to GINI. The results would suggest that economic regimes of high human capital and tourism specialization are causing income inequality improvements and regimes of low tourism specialization and low human capital are causing more inequality. In some cases, especially when TS is measured as arrivals/population, there is a bidirectional causality; improvements in income distribution cause a larger human capital and larger tourism

Country	(TSR, TSA) to GINI	GINI to (TSR, TSA)	(TSR, HC) to GINI	GINI to (TSR, HC)	(TSA, HC) to GINI	GINI to (TSA, HC)	(HC, GINI) to TSA	TSA to (HC, GINI)
Argentina	28.0**	28.0**	26.4**	23.3	47.2**	28.0**	45.6**	37.6**
Bolivia	37.6**	23.2	40.8**	24.8	42.4**	31.2**	31.2**	29.6**
Brazil	18.4	15.2	34.4**	18.4	26.4**	28.0**	34.4**	44.0**
Chile	48.8**	47.2**	53.6**	45.6**	47.2**	50.4**	61.6**	44.0**
Colombia	31.2**	20.0	37.6**	23.3	31.2**	32.8**	40.8**	21.6
Ecuador	47.2**	31.2**	53.6**	32.8**	53.6**	37.6**	42.4**	42.4**
Paraguay	24.8	16.8	29.6**	28.0**	32.8**	29.6**	37.6**	24.8
Peru	37.6**	45.6**	37.6**	28.0**	32.8**	34.4**	39.2**	28.0**
Uruguay	34.4**	36.0**	31.2**	24.8	47.2**	15.2	32.8**	23.2
Venezuela	21.6	15.2	40.8**	32.8**	28.0**	23.3	26.4**	20.0

Source: Own calculations. One lag was considered.
***Rejection of the null hypothesis of non-causality at 5%.*

Table 6.
Bidimensional symbolic non-causality test between (TS, HC) to GINI and TSA to (HC, GINI).

specialization in terms of arrivals over population. This result is interesting to test the causality between tourism specialization and the bidimensional variable composed by human capital and income inequality. Is it possible that countries with larger levels of human capital and better income distribution attract more international tourists? The results present a bidirectional causality for most of the countries. However, in the case of Colombia, Uruguay, and Venezuela, causality is running from human capital and income distribution considered simultaneously, to tourism specialization as arrival/population. It means that in general (but in particular in these three countries), more human capital per person and a better income distribution seem to attract more international tourists over population.

As a second step, the panel unit root test checks for non-stationarity. **Table 7** shows the panel unit root test results after applying four tests (Levin, Lin and Chu t; Im, Pesaran and Shin W-stat; ADF -Fisher Chi-square; PP-Fisher Chi-square) to GINI, TSR, TSA, HC, and GOV. The tests seem to reject the null hypothesis for GINI, TSR, TSA, and HC. However, the tests do not reject the null hypothesis for the GOV; in this case the first difference is stationary. Then we will apply the FE, RE, and the dynamic panel data methodology, aiming to estimate the coefficient of the relation among GINI, tourism specialization, and human capital in the case of South America.

Eq. (3), where GINI depends on tourism specialization, human capital, and government expenditure, was estimated using FE and RE. **Table 8** presents the post-estimation test on the model. The Hausman test rejects the RE model in the two versions of the tourism specialization. The Wooldridge test was applied, detecting autocorrelation in the FE model, and the Wald test was conducted, detecting heteroskedasticity. These findings suggest that the application of the Arellano-Bover/Blundell-Bond linear dynamic panel-data estimation is more efficient than the FE model.

Table 9 shows the results of the estimation of Eq. (3) applying FE and dynamic panel data methodologies for the two tourism specialization.

The models are all significant for the two tourism specialization measures and considering the FE and dynamic panel data methodologies. In general, the signs of the variables are as expected; note that the results suggest the existence of a Kuznets

Variable	H0: unit root	Levin-Lin-Chu	IM, Pesaran, and Shin W-stat	ADF-Fisher Chi-square	PP-Fisher Chi-square
GINI	None	−4.185***		38.647***	73.053***
	Intercept	−1.634**	1.143	21.411	0.645
	Trend	−3.695***	−1.913**	30.052*	14.145
TSR	None	−1.822**		20.628	22.140
	Intercept	−2.358***	−1.783**	26.792	28.319
	Trend	5.423	3.393	6.046	11.853
TSA	None	7.768		3.355	3.574
	Intercept	2.871	4.074	14.168	10.379
	Trend	−2.048**	−1.150	36.618**	13.766
HC	None	6.560		5.140	0.053
	Intercept	1.046	3.946	13.603	17.365
	Trend	−1.683**	−1.511*	41.228***	13.602
GOV	None	1.707		3.720	2.276
	Intercept	0.985	−0.102	21.806	27.745
	Trend	0.567	0.325	15.669	19.338
ΔGOV	None	−13.211***		169.623***	180.063***
	Intercept	−10.838***	−9.116***	110.527***	141.800***
	Trend	−10.048***	−8.906***	91.043***	113.642***

Source: Own calculations.
**Rejection of the null hypothesis at 10%.*
***Rejection of null hypothesis at 5%.*
****Rejection of null hypothesis at 1%.*

Table 7.
Panel unit root test for the variables GINI, TSR, TSA, HC, and GOV.

	TSR	TSA
Hausman	H0: random effects	
Chi2 (Prob>Chi2)	15.90 (0.00)*	9.94 (0.04)*
Wooldridge	H0: no autocorrelation	
F	570.09 (0.00)*	400.86 (0.00)*
Wald	H0: heteroskedasticity	
Chi2 (Prob>Chi2)	1797.21 (0.00)*	1024.62 (0.00)*

Source: Own calculations.
**Rejection of the null hypothesis.*

Table 8.
Hausman, autocorrelation, and heteroskedasticity post-estimation tests for Eq. (1).

curve between tourism specialization and GINI with the exception of the FE model when considering arrivals/population as measure of specialization. However, as mentioned, FE models suffer autocorrelation and heteroskedasticity. The found inverted U-shape would suggest that for low levels of tourism specialization, the income inequality increases until it arrives to a maximum GINI; after that, increasing tourism specialization improves income distribution. Note that the thresholds

(GINI)i,t				
	Fixed effect	**Arellano-Bover/ Blundell-Bond**	**Fixed Effect**	**Arellano-Bover/ Blundell-Bond**
(GINI)i,t-1		0.941		0.984
		(21.16)***		(54.24)***
(TSR)i,t	0.890	0.291		
	(2.49)**	(3.57)***		
(TSR^2)i,t	−0.027	−0.007		
	(−2.45)**	(−2.84)***		
(TSA)i,t			−0.524	0.067
			(−3.24)***	(2.32)**
(TSA^2)i,t			0.003	−0.001
			(2.61)**	(−3.57)***
(HC)i,t	−9.634	−1.812	−9.004	−2.587
	(−10.32)***	(−3.13)***	(−9.02)***	(−3.29)***
Δ(GOV)i,t	−0.187	0.003	−0.070	0.037
	(−1.98)*	(0.13)	(−1.43)	(1.58)
c	66.934	5.656	74.159	6.465
	(19.20)***	(1.90)*	(31.56)***	(2.98)***
Specification	53.86 [0.00]	20393.85 [0.00]	491.95 [0.00]	7822.32 [0.00]
Autocorrelation		−1.71 [0.09]		−1.19 [0.23]
		−1.62 [0.10]		−1.67 [0.09]
Sargan test		2.72 [1.00]		7.64 [1.00]
Number of obs.	200	190	200	190

Source: Own calculations. t statistics in parentheses () and p-value in square brackets [].
*$p < 0.10$.
**$p < 0.05$.
***$p < 0.01$.

Table 9.
FE and dynamic panel-data estimation for South America.

where the maximum GINI is obtained can be computed by deriving the estimated long-run relationships. Therefore, the income distribution improves overpassing the threshold of ratio receipts/exports equal to 19.98% or arrivals/population equals to 53.20%.

Note that as expected, the human capital sign is negative. It means that independent of arriving to the tourism specialization threshold, an increase in human capital also improves income inequality. On the other hand, government expenditure is not significant.

5. Conclusion

Tourism has been considered as an important economic sector with positive economic impacts. In this sense, governments have invested in tourism infrastructure and international organism such as IADB and WB and have promoted and designed tourism development programs helping to improve employment, poverty, and income distribution in South America.

In recent decades, a large and growing literature has found a growing relation between tourism and the economic growth. However, very few works have analyzed the relation with income distribution. The present work is the first study analyzing the impact of tourism specialization on income distribution in South America considering also the impact of human capital and general government expenditure. It is also the first work to apply symbolic causality test allowing detecting possible nonlinear causality between the variables and permitting to test multidimensional causality. In this sense, the tests suggest causality running from tourism specialization to income distribution when applying data panel tests (Granger or Dumitrescu) and when applying causality tests (Granger and symbolic) for each country individually considered. In addition, human capital is also causing income distribution. The symbolic causality allowed testing causality between the bidimensional variable composed by human capital and tourism specialization (both simultaneously considered) and income inequality. The results suggest a bidirectional causality between these variables. It means that tourism specialization and human capital improve income inequality and a better income distribution increases tourism specialization and human capital. More interesting results show that in the case of considering human capital and income inequality as a bidimensional variable and testing causality with specialization measure by arrivals/population, it is detected bidirectional causality for six countries. However, in countries such as Colombia, Paraguay, Uruguay, and Venezuela, the causality runs from human capital and inequality to tourism arrivals/population. It would mean that in these cases, a better performance in human capital and income distribution would attract tourist over the population rate growth.

Another important result is that symbolic causality suggests that causality is different when the specialization measure is monetary (TSR) than when it is physical (TSA). The test shows that past levels of tourism specialization in terms of exports worsen the income distribution. However, when the specialization increases in terms of arrivals over country population, the income distribution improves. This phenomenon deserves a deeper analysis in the future. One possible explanation about tourism specialization related with a worse income distribution may be that the income from tourism is not arriving homogenously to the different sectors of the population. For instance, large amounts of receipts could be entering the large tourist firms (international hotels, malls, and restaurants). However, specialization in arrivals makes much possible a more homogeneous distribution of the benefit of tourism on the country population due to a large dispersion of tourists (more arrivals working as fragmentation of total receipts).

The estimated regression suggests the existence of a Kuznets curve as in [19, 21]. It is an inverted U-shape relation between tourism specialization and income distribution with a maximum for tourism receipts/exports equal to 19.98% and tourism arrivals/population equal to 53.20%. Tourism specialization under these thresholds increases income inequality, but after arriving to these thresholds, the income distribution improves. It seems that at low levels of tourism specialization, the income inequality grows but as long as the specialization arrives to a threshold, the income distribution starts to improve. This effect is independent of the fact that human capital also impacts positively on income distribution. It means that policies trying to increase human capital per person and overpassing the threshold of tourism specialization have high probabilities of improving income distribution in South American countries.

Further lines of research include studying these relationships and causalities in other regions of the world. The present work was focused on analyzing the impact of tourism specialization on income distribution, but another line of research could be to study the impact of human capital and income distribution attracting international tourism. As a third line of research would be to different implications of the specialization measures, TSR and TSA.

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