Does tourism reduce income inequality? *

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January 30, 2024

Abstract

We employ a panel Autoregressive Distributed Lag (ARDL) modeling to address the key question of whether short- and long-run income distribution equality can be fostered by tourism, conditioning on a standard set of socio-economic control variables. The Pooled Mean Group (PMG) estimation on a panel of 120 countries from 1995 to 2020 indicates a positive impact of tourism on income inequality, leading to increased inequality in both the long and short run. Interestingly, when we examine the impact on developed and developing countries separately, divergent patterns emerge. In the long run, tourism is linked to reduced inequality in developed countries but increased inequality in developing countries. In the short run, this effect is positive regardless of the country type. These results hold true across various standard measures of income inequality, such as the Gini index, Theil index, Palma ratio, and Atkinson index.

Keywords: Income distribution, Inequality, Tourism receipts, Panel ARDL.
JEL Classification: C32, E25, E27, Z32.

*M. Camacho is grateful for the support of grant PID2022-136547NB-I00. Errors are our responsibility. Data and codes that replicate our results are available from the authors' websites.

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1 Introduction

The United Nations World Tourism Organization (UNWTO) is responsible for the promotion of tourism geared towards the achievement of 17 universal Sustainable Development Goals (SDGs), adopted by all United Nations Member States in 2015 as a blueprint to achieve a better and more sustainable future. In particular, the organization offers leadership and support to the tourism sector in tourism policies worldwide, promoting tourism as a driving force towards, among other goals, economic growth (SDG#8), poverty eradication (SDG#1), and inequality reduction (SDG#10).

Concerning the first goal, the comprehensive literature review conducted by Brida et al. (2016) asserted that, with few exceptions, international tourism plays a pivotal role in fostering economic growth. Regarding the second objective, Harrison and Pratt (2019) found that there is a prevailing consensus in the literature regarding the substantial contribution of international tourism to poverty alleviation. These insights imply that promoting the tourism industry can be a strategic lever for economic activity, solidifying tourism as a key factor in the fight against poverty.

While the impact of tourism on growth and poverty has been extensively explored, there is less consensus in empirical studies regarding the direction and magnitude of tourism's influence on income inequality. A recent meta-analysis by Zhang (2021) examined a broad set of empirical econometric studies and found that evidence regarding the effects of tourism development on income inequality remains inconclusive and varied.

Theoretical considerations suggest that international tourism may have a positive impact on income equality. Proponents of the pro-poor tourism approach argue that tourism creates job opportunities, enhances resource allocation efficiency, and reduces regional disparities. The tourism trickle-down effect posits that economic benefits spread across various sectors, promoting income equality. Empirical studies by Haddad et al. (2013), Li et al. (2016), Beheshti et al. (2017), Lv (2019), Shahbaz et al. (2020), Nguyen et al. (2021), and Subramaniam et al. (2022) support the idea that tourism contributes to fair income distribution.

Conversely, theoretical arguments also suggest that tourism could contribute to income inequality. Harrison and Pratt (2019) posit that non-poor residents may benefit more from increased tourism, potentially exacerbating national income disparities. Empirical findings by Alam and Paramati (2016), Raza and Shah (2017), Uzar and Eyuboglu (2019), Oviedo-Garcia et al. (2019), and Porto and Espinola (2019) align with this perspective, indicating that tourism development can contribute to income inequality.

The mixed evidence recently presented by Chi (2021), Ghosh and Mitra (2021), and Fang et al. (2021) in their analyses of country panels suggests caution in generalizing the long-run influence of tourism on inequality to all world countries. Utilizing long-run panel data approaches, these three studies found that the effects of tourism on inequality are closely tied to the country's development level. For highly developed nations, the long-run impact of tourism on inequality was considered statistically insignificant. However, in developing economies, the effects of tourism on inequality varied. Chi (2021) reported positive effects in level and cubic terms and negative effects in squared terms, Ghosh and Mitra (2021) identified negative effects in level and positive effects in squared terms, whereas Fang et al. (2021) observed a significant negative impact.

In this paper, we aim to contribute to the ongoing debate on the role of tourism in income inequality through an empirical analysis that incorporates several key elements allowing for a comprehensive and reliable representation of global economic conditions. The first element is the sample coverage. Some studies have examined a limited and unbalanced number of countries, and their results often pertain to case studies focused on individual countries for specific periods. Moreover, there may be a sample selection bias, as the countries investigated for the relationship between tourism and inequality tend to be destinations characterized by a high propensity for tourism. By contrast, we employ a broad set of 120 countries with observations spanning from 1995 to 2020, offering a comprehensive and globally representative perspective. This expanded sample coverage enhances the generalizability and applicability of our findings, providing a robust foundation for drawing meaningful conclusions about the relationship between tourism and income inequality.

The second aspect defining our approach pertains to the modeling strategy. Given the substantial persistence of income inequality with minimal changes over short periods, it becomes imperative to include lagged values of the time series as explanatory variables in our modeling approach. To address this, we employ the Panel Autoregressive Distributed Lags (ARDL) model, which adeptly captures the historical patterns and dependencies inherent in income inequality dynamics. This strategic modeling choice addresses the issue of endogeneity bias, ensuring consistent estimates despite the potential presence of endogeneity.

Transitioning to the third key element of our study, we address a significant gap in the existing literature, which predominantly focuses on the long-term effects of tourism on income inequality while omitting the short-run impact and transitional dynamics in the model strategy. This omission raises concerns about potential inaccuracies in estimating the true relationships between these variables when only the long-run dynamics are considered. By incorporating both short-run effects and transitional dynamics into our investigation, we aim to provide a more comprehensive understanding of the nuanced interplay between tourism and income inequality. Our panel ARDL approach allows us to capture not only the long-term consequences but also the short-term and transitional influences, thereby offering a more accurate and reliable depiction of the relationship between tourism and income inequality across diverse economic settings.

The last essential element of our empirical analysis relates to robustness. Recognizing the diverse metrics used to gauge income inequality existing in the literature, we employ the panel ARDL model across multiple standard measures, including the Gini index, Theil index, Palma ratio, and Atkinson index. This approach ensures that our findings are robust and not contingent on a single inequality metric. Additionally, we explore the robustness of our results by conducting a thorough investigation across different subsets of our sample. Specifically, we stratify the analysis based on the development status of countries, distinguishing between developed and developing nations. This allows us to uncover variations in the impact of tourism on income inequality across diverse economic contexts, contributing to the generalizability and reliability of our results.

Defined by these four elements, our model jointly explores the long- and short-run relationship between tourism development and income inequality, incorporating standard control variables such as GDP per capita, foreign direct investment, age dependency, and trade openness.[1]

[1] Among others, these covariates are also considered in studies by Chi (2021), Fang et al. (2021), Ghosh and Mitra

The Pooled Mean Group (PMG) results reveal a significantly negative error correction term, substantiating the presence of a long-run relationship among the variables under consideration. We observe that it takes between 5 and 8 years for income inequality to revert to equilibrium following a deviation, with the specific duration dependent on the measure of inequality employed in the analysis.

Our primary findings reveal overwhelming evidence that tourism fosters income inequality worldwide. Notably, our results suggest that a 1% increase in international tourism receipts is associated with a statistically significant long-run increase in inequality by 0.008% in the Gini index, 0.124% in the Theil index, 0.012% in the Palma ratio, and 0.052% in the Atkinson index, underscoring the robustness and statistical significance of this relationship across various measures of inequality employed in the analysis. Upon closer examination of the long-run impact on developed and developing countries individually, we discover that tourism is associated with a statistically significant decrease in income in developed countries, while concurrently contributing to a statistically significant increase in inequality in developing countries. Importantly, these results hold regardless of the measure of inequality used in our analysis.

Transitioning from the analysis of long-run to short-run dynamics, our investigation unveils compelling evidence that tourism exerts a fostering effect on income inequality in the short run. This impact persists consistently across various scenarios: when examining the entire sample of countries, when stratifying the sample into developed and developing nations, and when employing different measures of income inequality in the analysis. The consistently positive impact of tourism on inequality underscores the nature of the short-term positive relationship between these two variables.

The observed impact of tourism on inequality of this study suggest that policy recommendations for developed and developing countries differ. For policymakers in developed countries, where tourism decreases inequality in the long run but not in the short run, our results suggest using sustainable tourism development as a strategy for long-term reduction of income inequality, although formulating effective policy recommendations requires a nuanced understanding of the timing and dynamics of tourism's impact on income distribution. Thus, policy strategies should be cognizant of the initial positive effect on inequality in the short run and implement complementary policies to address any short-term adverse impacts while capitalizing on the long-term benefits of tourism development in reducing income inequality.

In contrast, developing countries address the challenge of tourism fostering income inequality in both the short and long run. Policymakers can address this issue by adopting a comprehensive and tailored approach informed by insights from the existing literature. This approach involves implementing pro-poor tourism initiatives to prioritize the inclusion of local communities, investing in skills development and education for increased employment opportunities, and introducing social welfare programs targeting vulnerable populations affected by income disparities. Strengthening regulatory measures to ensure fair labor practices and equal opportunities, fostering community engagement and empowerment, and promoting economic diversification are additional strategic considerations.

(2021), Mahadevan and Suardi (2019), Li et al. (2016), Croes and Rivera (2017) and Kim et al. (2016).

The article is organized as follows. Section 2 provides detailed specifications of the model used in the analysis, outlining the specification tests and estimation process. In Section 3, the data is described, and the main findings are highlighted. Finally, Section 4 concludes the article and suggests potential avenues for future research.

2 Panel ARDL

In the context of our study, the model entails specifying the dynamics of a measure of income inequality, denoted as I_{it}, as a function of its own lags and contemporaneous and lagged values of k control variables included in the vector X_{it}, which helps addressing endogeneity issues. Here, the subscripts i, with $i = 1, \ldots, N$, and t, with $t = 1, \ldots, T$, represent the country and time, respectively.[2]

To capture the short- and long-run relationship between income inequality and tourism, including the transition dynamics to a potential long-run equilibrium, we employ the panel ARDL(p,q) model, expressed as:

$$I_{it} = \mu_i + \sum_{j=1}^{p} \alpha_{ij} I_{it-j} + \sum_{j=0}^{q} \gamma'_{ij} X_{it-j} + \epsilon_{it}. \tag{1}$$

Here, μ_i denotes the country-specific fixed effect; α_{ij} represents the scalar coefficients of the lagged measure of inequality; X_{it-j} is the k-dimensional contemporaneous and lagged vector of regressors, encompassing tourism and other control variables; γ_{ij} is the vector of coefficients of the control variables; and ϵ_{it} is the error term, independently and normally distributed across countries with mean zero and constant variance σ_i^2.

In principle, the panel can be unbalanced, and the number of lags may vary across countries. However, for this application, we adopt common values for T, p, and q across countries. The optimal combination of p and q is determined based on the smallest values of Bayesian Information Criterion (BIC).[3] Additionally, our analysis intentionally omits the consideration of time trends or the inclusion of other fixed regressors. This intentional omission simplifies the modeling framework, allowing for a more straightforward interpretation of the relationship between tourism and income inequality.[4]

Reparametrizing (1), the panel ARDL(p,q) model leads to the following error specification:

$$\Delta I_{it} = \mu_i + \Phi_i (I_{it-1} - \theta'_i X_{it}) + \sum_{j=1}^{p-1} \varphi_{ij} \Delta I_{it-j} + \sum_{j=0}^{q-1} \beta'_{ij} \Delta X_{it-j} + \epsilon_{it}, \tag{2}$$

where Δ is the first difference operator. Terms in first difference, the scalars φ_{ij} and the vectors β_{ij} reflect short-run dynamics that relate income inequality to its past values and the regressors. The error correction term, $I_{it-1} - X'_{it-1}\theta_i$, represents the long-run component of the model and defines the long-run or equilibrium relationship between income inequality and the set of regressors. The

[2] This modeling approach is particularly suitable when dealing with large values of T and N. Remarkably, our empirical application aligns with this ideal condition, further enhancing the suitability of the approach for our study.

[3] The Akaike Information Criterion (AIC) yielded qualitatively the same results.

[4] The model offers researchers the flexibility to tailor the specification to their preferences, whether that involves incorporating time trends or introducing other fixed regressors.

error correction coefficients, Φ_i, indicate how quickly variables converge/diverge to equilibrium following a change in the regressors. A significant and negative coefficient of the error correction term is treated as an evidence of cointegration, confirming the existence of a stable long-run relationship.[5]

The estimation process of the panel ARDL model typically involves a two-stage procedure. In the first stage, stationarity tests are applied to verify whether the variables of interest are stationary or not.[6] Specifically, we employed the Pesaran (2007) simple test in heterogeneous panels with cross-section dependence to assess unit roots. Subsequently, tests for the null hypothesis of no cointegration against the alternative of cointegration among the variables are routinely conducted. In our empirical application, following Samargandi, Fidrmuc, and Ghosh (2015), we rejected the null hypothesis if the error correction coefficients, Φ_i, were significantly negative.[7]

To obtain the averaged effects on income inequality the heterogeneous panel can be estimated by several approaches differing with reference to the degree of potential country-specific heterogeneity allowed for the parameters. The Mean Group (MG) estimator, proposed by Pesaran and Smith (1995) derives the parameter estimates by fitting separate ARDL models for each country without any restriction and calculating the coefficients as unweighted means of the estimated coefficients. The Pooled Mean Group (PMG) estimator, proposed by Pesaran et al. (1999), constraints the long-run slope coefficients to be the same but allows intercepts, short-run coefficients, the speed of adjustment to the long-run equilibrium values and error variances to differ across countries. Finally, the Dynamic Fixed Effect (DFE) estimator constrains all the slope coefficients and error variances to be identical across countries.

Pesaran et al. (1999) demonstrated that under the assumption of log-run slope homogeneity, the Mean Group (MG) method provides consistent but inefficient estimates, while the Pooled Mean Group (PMG) method ensures both consistency and efficiency. Additionally, when log-run slope homogeneity holds, the Dynamic Fixed Effects (DFE) approach may yield inconsistency concerning PMG estimates if homogeneity is mistakenly imposed on the short-run coefficients.

In accordance with these statistical properties, it is common practice to use tests within the framework proposed by Hausman (1978) to discern among MG, PMG, and DFE procedures. Initially, a first test evaluates the null hypothesis of no systematic differences between PMG and MG, tested using a standard chi-square statistic. If this null is not rejected, PMG estimation is deemed the most appropriate, suggesting homogeneity of long-term coefficients. Subsequently, a second test is applied, comparing PMG and DFE. If the null hypothesis of no systematic differences between these two alternatives is retained using a chi-square statistic, it suggests that PMG estimation remains the preferred choice. This result indicates homogeneity in the long-term coefficients but heterogeneity in the short-run coefficients.

[5] If $\Phi_i = 0$, there would be no evidence of a long-run relationship. The term must not be lower than -2.

[6] Unit root pre-testing is not essential in this approach, as it is valid for both stationary and non-stationary regressors, requiring only that the variables cannot be integrated of order 2.

[7] This approach was chosen due to the mixed order of integration, I(0) and I(1), exhibited by the variables of interest.

3 Empirical application

3.1 Data description

This study employs a panel-data approach, utilizing annual data from 120 countries spanning the period 1995-2020, to investigate the dynamic relationship between income inequality and tourism through the panel ARDL model described above. Following the approaches of Chi (2021), Fang et al. (2021), and Ghosh and Mitra (2021), the study focuses on income inequality as the dependent variable, measured by the Gini index. The Gini index assesses inequality by comparing cumulative proportions of the population against cumulative proportions of income received. A Gini index of zero signifies perfect equality, where everyone receives the same income, while a Gini index of 100 indicates maximal inequality among a country's citizens.

The panel of Gini coefficients used in this study has been extracted from the UNU-WIDER's World Income Inequality Database (WIID), a comprehensive and reliable dataset providing world-wide distributional data, including developed and developing countries. The database uniquely integrates national data to systematically trace the evolution of income levels across all segments, computed from micro-data. This systematic approach enables meaningful comparisons between countries and facilitates analysis over extended time periods.

Moving to the data on the explanatory variables of income inequality, we obtained information from the World Development Indicators (WDIs) provided by the World Bank. Our primary variable of interest is tourism development. As in Chi (2021), Ghosh and Mitra (2021), Mahadevan and Suardi (2019), Li et al. (2016), Croes and Rivera (2017) or Kim et al. (2016), tourism development is proxied by international tourism receipts. This variable encompasses the expenditures by international inbound visitors, including payments to national carriers for international transport.

In addition to tourism development, we follow Raza and Shah (2017) and Ghosh and Mitra (2021) and also include Foreign Direct Investment (FDI) and trade openness, both as a share of GDP. FDI encompasses the sum of equity capital, reinvestment of earnings, and other capital associated with a resident in one economy having control over the management of an enterprise resident in another economy. Trade openness is defined as the sum of exports and imports of goods and services measured as a share of GDP.

Consistent with Fang et al. (2021), we introduce the age dependency ratio (ADR) as an additional control variable that seeks to connect demography with economic inequality. This variable could play a significant role in determining income distribution, particularly in relation to social expenditures. Specifically, ADR represents the proportion of dependents (individuals younger than 15 or older than 64) to the working-age population (those ages 15-64). This control captures variations in the proportions of children, elderly individuals, and working-age people in the population, reflecting the dependency burden borne by the working-age population concerning children and the elderly.

Taking into account the influence of macroeconomic factors on income inequality, Berisha et al. (2020) proposed controlling for real GDP per capita to capture the impact of these factors. Their rationale is rooted in the idea that as income levels increase within a country, the financial sector tends to expand, fostering economic growth and potentially affecting the income disparity between rich and poor. This observation aligns with the results of Chi (2021), who discovered a significant impact of GDP per capita on income distribution.

While the Gini index serves as the most widely utilized proxy for income inequality, ensuring the robustness of our findings across diverse measures of income distribution, we extend our analysis to include three alternative inequality metrics. Specifically, we incorporate the Theil index, Palma ratio, and Atkinson index, all sourced from the World Income Inequality Database (WIID). This comprehensive approach allows us to examine the dynamics of income inequality from multiple perspectives, providing a more robust understanding of the relationship between tourism and income distribution.

The Theil index belongs to the family of general entropy measures and equals to zero in the case of perfect equality, increasing as the distribution becomes more unequal. The Palma index is the ratio of national income shares of the top 10 percent of households to the bottom 40 percent. This ratio accounts for the bottom and top income, based on the empirical observation that difference in the income distribution of different countries is largely the result of changes in the tails of the distribution. The Atkinson index presents the percentage of total income that a given society would have to forego in order to have more equal shares of income between its citizens.

3.2 Empirical results

3.2.1 Baseline Specification

Prior to model estimation, panel tests of unit roots were conducted to assess the stationarity of variables and ensure that no variable is integrated of order 2. The extensive literature on panel unit root testing distinguishes between two generations of tests. The first assumes cross-sectional independence among units, while the second relaxes this assumption to allow for cross-sectional dependence.

To determine the appropriate strategy, we present the large panel cross-sectional dependence test developed by Pesaran (2004), called CD test, in Table 1 before choosing the type of panel unit root test. The table includes the (absolute) correlations, represented as the (absolute) values of the off-diagonal elements in the cross-sectional correlation matrix of residuals. Additionally, it displays the test statistics, which follow standard normal distributions under the null hypothesis of cross-sectional independence, along with their associated p-values. According to the table, the variables under consideration are likely to inhibit strong cross-section dependence at any reasonable confidence level.

In line with this finding, we employ in Table 2 the Pesaran (2007) simple test in heterogeneous panels with cross-section dependence to test for unit roots. To address cross-dependence, standard unit root regressions are augmented with the cross-section averages of lagged levels and first-differences of individual series. The null hypothesis assumes that all series are non-stationary, but the method is consistent under the alternative that only a fraction of the series is stationary. Test statistics below the 5% critical value of -2.08 (displayed in bold) indicate the presence of a unit root, which occurs for tourism, GDP per capita, age dependency ratio, and trade. Notably, the tests point that all the variables are stationary at first difference.

Since the variables are a combination of I(0) and I(1), the pooled estimation provided by the panel ARDL model is particularly appropriated to examine the long and short-run relationships between inequality and tourism. The estimation results are presented in Table 3, with all the variables, except FDI, in logarithms. The last two rows of the table show that, according to the test statistics and their associated p-values, imposing long-run homogeneity is overwhelmingly validated by the data. The Hausman test of the null hypothesis of no difference between the MG and PMG estimators yields a statistic of 6.85 with a p-value of 0.24, supporting long-run homogeneity at conventional significance levels. Additionally, the Hausman test fails to reject the null of heterogeneity in the short-run coefficients when comparing PMG and DFE, achieving a statistic of 0.09 and a p-value of 0.99. Based on these results, the analysis focuses solely on the PMG estimates, imposing heterogeneity in the short run and homogeneity in the long run coefficients.

Among others, Samargandi, Fidrmuc, and Ghosh (2015) argued that the ARDL model is more suitable than traditional panel cointegration tests due to the mixed order of integration in the set of variables of interest. The PMG estimates presented in Table 3 reveal a significant and negative error correction term, with an estimated impact of -0.14, supporting the evidence of a long-run cointegrated relationship among the discussed variables. The magnitude of this term indicates how quickly the variables converge to equilibrium in the presence of a deviation from the long-run. Specifically, our findings suggest that approximately 14 percent of the disequilibrium, measured by the error correction term, is restored in the upcoming years. Therefore, it takes about 7 years for income inequality to return to equilibrium.

The central point of this study is the relationship between income inequality and tourism. Table 3 documents that in the long term, there is indeed a statistically significant positive relationship. Specifically, the table reveals that a 1% change in international tourism receipts is associated with a positive impact on the Gini index by 0.008%, with other variables held constant. This result partially aligns with Chi (2021), who also identified a significant long-run impact of tourism on income inequality, observing an initial exacerbation followed by a reduction and subsequent amplification of income inequality as tourism grows, in line with an N-shaped Kuznets curve. The result also partially agrees with Raza and Shah(2017) and Ghosh and Mitra (2021), who obtained that a rise in tourism leads to initially rising inequality, which eventually diminishes as tourism grows, following a standard Kuznets curve. However, it contrasts with Fang et al. (2021), who found that tourism had a negative and statistically significant long-run impact on income inequality.

We now shift our focus to the outcomes related to the long-term influence on inequality resulting from changes in other covariates. As indicated by Table 3, FDI appears to diminish inequality significantly over the long term. This finding is in harmony with the observations of Raza and Shah (2017), Ravinthirakumaran and Ravinthirakumaran (2018), Ghosh and Mitra (2021), and Yuldashev et al. (2023), who have similarly identified that an upsurge in FDI inflows causes a decline in income inequality.

In parallel with the perspectives of Chi (2021) and Fang et al. (2021), our study acknowledges a positive impact of output per capita on the Gini index. However, unlike their results, this impact does not achieve statistical significance in our analysis. In this context, Siddique (2021) has highlighted the prevalent notion in the literature that inequality is a byproduct of economic development, suggesting that when a country's GDP per capita is high, inequality tends to be elevated.

Contrary to the assertions of Chi (2021), our investigation, in alignment with Raza and Shah (2017) and Ghosh and Mitra (2021), fails to unveil a statistically significant long-term association between trade openness and the Gini index at a 5% confidence level. Siddique (2021) sheds light on the complexity of the relationship between trade and inequality, emphasizing that the existing literature paints an ambiguous picture. His findings indicate that international trade might elevate market-Gini but has no impact or a negative impact on net-Gini.

Finally, Lee and Mason (2007) argued that the effects of an increase in the population dependency ratio on income distribution are not easily anticipated, emphasizing the crucial role played by public transfer programs. These programs involve the redistribution of resources from individuals in their productive ages to those who are not actively contributing to the workforce. In our investigation, age dependency emerges with a noteworthy negative effect on the Gini index. This finding diverges from the conclusions drawn by Fang et al. (2021), who identified a positive relationship between age dependency and the Gini index.

3.2.2 Sensitivity Analysis

A variety of sensitivity analyses were conducted to enhance the robustness of our findings. While our main focus will be on exploring the causal effects of tourism on inequality, examining these diverse analyses is crucial for ensuring the reliability and validity of our empirical results. The outcomes, displayed in Tables 3 and 4, help assess the stability of our findings under different conditions and provide a more comprehensive understanding of the relationship between tourism and income inequality.

It is worth emphasizing that, irrespective of the various robustness scenarios examined, the Hausman tests consistently and unequivocally favor PMG estimates. Furthermore, the presence of a significant and negative error correction term is a robust finding across all sensitivity analyses, providing consistent support for the existence of a long-run relationship among the variables under consideration. The speed of worldwide adjustment from the short to long run reveals an annual adjustment capacity ranging from 12% to 18%.

Several studies, including Chi (2021), provide evidence suggesting that the long-run relationship between tourism and income inequality may vary across developed and developing economies. As a first sensitivity analysis, we categorize the countries into these two groups based on the criteria established by the United Nations.[8] Notably, our findings reveal that tourism leads to an increase in income inequality within the lower group of economically developed countries. Conversely, it appears to play a role in alleviating income inequality in the higher economic development category. Importantly, both of these impacts are statistically significant.

Based on the result that tourism exhibits different effects on income inequality depending on the economic development category, policymakers can tailor their strategies accordingly aiming to narrow the income gap between the rich and the poor. As observed in the overall panel, there exists a

[8] The determination considers a broad range of socio-economic factors, including economic growth, life expectancy, health, education, and quality of life.

significant trade-off between tourism and income redistribution in developing countries, highlighting the challenge of implementing pro-poor tourism strategies. Nevertheless, the significantly negative relationship between tourism and inequality observed in developed countries suggests that tourism can be regarded as a means to achieve income equality in the long run.

Importantly, it is crucial to acknowledge that in the short run, our findings indicate a consistent pattern: tourism development tends to foster inequality, irrespective of whether the countries are developing or developed. This implies that, in the immediate term, income inequality may unavoidably experience adverse effects with the promotion of tourism. Therefore, formulating effective policy recommendations in developed countries requires a deep understanding of the timing and dynamics of tourism's impact of tourism on income distribution.

These results underscore the significance of accounting for short-run effects in dynamic panel regression when examining the relationship between tourism development and income inequality across countries. Omitting the short-run dynamics, Chi (2021), Fang et al. (2021), and Ghosh and Mitra (2021), yielded diverse conclusions. For the more developed nations, the long-run impact of tourism on inequality was deemed statistically insignificant. Conversely, in developing economies, the effects of tourism in inequality varied. Chi (2021) noted positive effects in level and cubic terms and negative effects in squared terms, Ghosh and Mitra (2021) identified negative effects in level and positive effects in squared terms, while Fang et al. (2021) reported a significant negative effect.

We now shift our focus to investigating the sensitivity of the results as we transition from using the Gini index as the primary measure of inequality to considering alternative metrics such as the Theil index, Palma ratio, and Atkinson index. In an effort to reinforce the credibility and robustness of our findings across diverse measures of income inequality, Table 4 replicates the entire analysis using these alternative inequality measures. The figures presented in the table highlight the consistency and reliability of our results: tourism consistently fosters inequality in the long run, both in the overall sample and within developing economies, while showing a negative impact on income inequality in developed economies. Additionally, our findings emphasize that tourism development consistently leads to an increase in income inequality in the short run regardless of the measure of inequality used in the analysis.

4 Conclusions

Although there is overwhelming empirical evidence suggesting a strong positive role of tourism in growth and poverty alleviation, the sign and size of the relationship between tourism and income inequality is less conclusive. Using a large sample of 120 countries, covering the period from 1995 to 2020, we employ a panel ARDL methodology to explore whether (or not) there is a relationship, be it short run or long run, between tourism and income inequality. This mitigates some limitations of previous empirical literature that explains either the short- or long-run effect.

Our findings tend to establish that tourism serves as a catalyst for increasing income inequality, both in the short and long run. This trend holds true not only on a worldwide scale but also replicates in developing countries, painting a stark contrast with the negative impact of tourism on inequality observed in developed economies. The robustness of our results is affirmed through extensive sensitivity analyses employing alternative measures of income inequality.

This duality emphasizes the need for nuanced policy considerations, suggesting that while tourism may offer promise for income redistribution in more advanced nations, it could exacerbate inequality challenges in developing regions. It underscores the necessity to redesign policy strategies by implementing pro-poor tourism measures to mitigate the adverse effects of tourism on income distribution in these countries. It suggests adopting strategies for promoting tourism managed in accordance with national strategic plans for tourism in line with UNWTO's sustainable tourism guidelines leading to growth and poverty reduction in conjunction with better distribution of income.

We look forward to future work addressing the following issues. We see a natural extension of our approach including variables related to labor market institutions, institutional and political mechanisms, and tax systems. Unfortunately, we were unable to include these variables in the model because of the lack of continuous data required for time-series analysis. Another interesting direction for future study would be to investigate the potential nonlinear relationships among the variables of interest. Nonparametric proposals, such as the one suggested by Camacho and Romeu (2023), also present interesting avenues for exploration.

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Table 1: Cross section dependence

Variables	Correl.	Abs. Correl.	CD-test	p-value
Tourism	0.39	0.48	75.35	0.00
GDP pc	0.27	0.51	51.06	0.00
FDI	0.11	0.24	21.22	0.00
Age dep	0.42	0.70	79.47	0.00
Trade	0.17	0.43	33.02	0.00
Gini	0.15	0.50	28.97	0.00
Theil	0.12	0.51	22.31	0.00
Palma	0.16	0.49	29.33	0.00
Atkinson	0.14	0.49	26.26	0.00

Notes: All variables, except for FDI, are expressed in logarithms. Following Pesaran (2004), the entries in the columns present both correlations and absolute correlations, along with cross-sectional dependence statistics and their associated p-values.

Table 2: Panel unit root test

Variables	Level	Differences
Tourism	**-1.69**	-2.39
GDP pc	**-1.38**	-2.59
FDI	-2.19	-3.13
Age dep	**-0.91**	-2.93
Trade	**-1.55**	-2.38
Gini	-2.58	-2.84
Theil	-2.56	-2.87
Palma	-2.57	-2.82
Atkinson	-2.53	-2.86

Notes: All variables, except for FDI, are expressed in logarithms. Following Pesaran (2007), entries in the columns display test statistics for both the levels and first-differences of the variables, with bold indicating the presence of a unit root.

Table 3: Panel ARDL results: Gini index

	All	Developed	Developing
	Long-run equation		
Tourism	**0.0085**	**-0.0527**	**0.0243**
	(0.0026)	(0.0133)	(0.0095)
GDP pc	0.0067	**-0.0273**	**-0.0571**
	(0.0054)	(0.0110)	(0.0051)
FDI	**-0.0005**	0.0003	-0.0006
	(0.0003)	(0.0003)	(0.0010)
Age dep	**-0.4192**	0.0308	**-0.7954**
	(0.0288)	(0.0236)	(0.0473)
Trade	-0.0039	-0.0314	**0.0995**
	(0.0040)	(0.0222)	(0.0206)
Error correction	**-0.1390**	**-0.2592**	**-0.1567**
	(0.0203)	(0.0338)	(0.0454)
	Short-run equation		
ΔTourism	0.0024	**0.0242**	0.0102
	(0.0039)	(0.0076)	(0.0074)
ΔGDP pc	-0.0080	**-0.0254**	0.0083
	(0.0092)	(0.0126)	(0.0253)
ΔFDI	-0.0004	0.0006	-0.0006
	(0.0004)	(0.0007)	(0.0006)
ΔAge dep	-0.0446	-0.0396	-0.1160
	(0.2053)	(0.1933)	(0.3071)
ΔTrade	-0.0041	**-0.0279**	0.0154
	(0.0093)	(0.0162)	(0.0137)
Constant	**0.6566**	**1.0070**	**0.8969**
	(0.0973)	(0.1337)	(0.2599)
	Hausman tests		
PMG vs MG	6.85	1.75	2.15
	[0.24]	[0.88]	[0.94]
PMG vs DFE	0.09	0.01	0.00
	[0.99]	[1.00]	[1.00]

Notes: Table entries present the result of the pool mean group estimation of ARDL(p,q), with the optimal lag lengths selected by BIC. The first column refers to the entire panel, while the subsequent two columns separate the panel into developed and developing countries. Standard errors are in parentheses, with bold indicating statistical significance at the 5% level. The last two rows show the Hausman test statistics, with p-values in squared brackets. All the variables, except for FDI, are in logarithms.

Table 4: Panel ARDL results: Theil, Palma and Atkinson

	Theil			Palma			Atkinson		
	All	Developed	Developing	All	Developed	Developing	All	Developed	Developing
	Long-run equation								
Tourism	**0.1245**	**-0.0763**	**0.0218**	**0.0118**	**-0.1324**	**0.1495**	**0.0516**	**-0.1099**	**0.0417**
	(0.0077)	(0.0251)	(0.0125)	(0.0067)	(0.0238)	(0.0726)	(0.0098)	(0.0208)	(0.0098)
GDP pc	**-0.1033**	0.0145	**-0.1501**	**-0.1117**	-0.0038	**1.4010**	**0.0627**	0.0007	**0.807**
	(0.0119)	(0.0171)	(0.0160)	(0.0068)	(0.0140)	(0.2561)	(0.0136)	(0.0151)	(0.0154)
FDI	**-0.0005**	**0.0013**	-0.0017	-0.0007	-0.0005	**-0.0792**	**0.0083**	0.0001	-0.0015
	(0.0002)	(0.0007)	(0.0022)	(0.0005)	(0.0005)	(0.0150)	(0.0011)	(0.0007)	(0.0010)
Age dep	**0.0828**	0.0710	**0.9618**	**0.2579**	0.0152	**-0.5881**	**-0.6853**	**0.1554**	**-0.9342**
	(0.0221)	(0.0498)	(0.1151)	(0.0342)	(0.0408)	(1.0154)	(0.0337)	(0.0469)	(0.0728)
Trade	**-0.0681**	**-0.1106**	**-0.1953**	**-0.1980**	-0.0165	0.1924	**0.1156**	**-0.1046**	**0.1077**
	(0.0122)	(0.0496)	(0.0374)	(0.0215)	(0.0419)	(0.1245)	(0.0229)	(0.0009)	(0.0272)
Error correction	**-0.1610**	**-0.2540**	**-0.1484**	**-0.1881**	**-0.2588**	-0.0164	**-0.1197**	**-0.2636**	**-0.1343**
	(0.0252)	(0.0337)	(0.0319)	(0.0248)	(0.0314)	(0.0162)	(0.0199)	(0.0322)	(0.0408)
	Short-run equation								
ΔTourism	0.0035	**0.0368**	0.0218	**0.0157**	**0.0505**	0.0149	0.0034	**0.0474**	0.0202
	(0.0076)	(0.0126)	(0.0187)	(0.0069)	(0.0131)	(0.0249)	(0.0076)	(0.0135)	(0.0408)
ΔGDP pc	-0.0261	**-0.0919**	-0.0280	-0.0142	**-0.0587**	-0.0618	-0.0232	**-0.0678**	-0.0101
	(0.0206)	(0.0438)	(0.0559)	(0.0219)	(0.0341)	(0.0841)	(0.0207)	(0.0287)	(0.0502)
ΔFDI	0.0002	0.0018	0.0004	0.0002	0.0012	-0.0008	-0.0009	0.0014	-0.0009
	(0.0010)	(0.0016)	(0.0014)	(0.0009)	(0.0012)	(0.0018)	(0.0008)	(0.0007)	(0.0010)
ΔAge dep	**-1.1664**	-0.2112	**-2.0926**	**-1.4063**	-0.1083	**-2.0047**	-0.2347	-0.3385	**-1.4987**
	(0.6163)	(0.3503)	(1.0043)	(0.6600)	(0.3551)	(1.1078)	(0.3781)	(0.3662)	(0.8463)
ΔTrade	0.0014	-0.0372	0.0536	0.0065	**-0.0539**	0.0439	-0.0134	-0.0423	0.0367
	(0.0252)	(0.0383)	(0.0454)	(0.0205)	(0.0295)	(0.0366)	(0.0192)	(0.0327)	(0.0304)
Constant	**0.6699**	**0.8157**	**0.5345**	**0.3569**	**0.1343**	0.0534	**0.3880**	**0.6224**	**0.5370**
	(0.1086)	(0.1104)	(0.1153)	(0.0494)	(0.0265)	(0.0715)	(0.0681)	(0.0803)	(0.1671)
	Hausman tests								
PMG vs MG	1.13	1.79	2.16	3.08	3.32	3.32	2.10	2.77	1.74
	[0.95]	[0.88]	[0.83]	[0.68]	[0.65]	[0.65]	[0.84]	[0.73]	[0.88]
PMG vs DFE	1.46	0.04	0.11	0.29	0.01	2.15	0.20	0.03	0.20
	[0.92]	[1.00]	[0.99]	[0.99]	[1.00]	[0.99]	[0.99]	[1.00]	[0.99]

Notes: See notes of Table 3.