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Panel evidence on the impact of tourism growth on poverty, poverty gap and income inequality

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Panel Evidence on the Impact of Tourism Growth on Poverty, Poverty Gap and Income Inequality

Abstract

Using a panel of 13 tourism-intensive economies for the period 1995-2012, this paper shows that rising growth in tourism which is proxied by tourism receipts to GDP ratio has an impact on poverty conditional on the poverty measure used. Using a panel Vector Autoregression method, there is little evidence to suggest that growth in tourism reduces headcount poverty. However, the poverty gap measure shows that the amount of money needed to help the poor out of poverty is significantly reduced. Based on different types of Gini coefficient, the results fail to find an improvement in income inequality resulting from tourism growth. Alternative measures such as relative poverty and poverty gap may be considered to better assess the impact of tourism on the poor.

Key words: Tourism growth, headcount poverty, poverty gap, Gini coefficient.

Introduction

Tourism has long been considered important for economic development particularly in developing countries, and for its potential to reduce poverty (see Bryden 1973, Clancy 1999, Scheyvens 2007). This comes from the trickle-down theory where expansion in the tourism sector leads to economic growth that eventually reaches the poorer segments of the population. Copeland (1991) explains that the main mechanism by which an inbound tourist boom changes national welfare is through an increase in the relative price of nontraded goods and services that foreign tourists consume in the destination country (Sahli and Nowak 2007). This increase in the relative price of the host country's exports to imports is said to lead to a national welfare gain in terms of an increase in real income. While several earlier studies such as Hawkins and Mann (1997) and Sinclair (1998) argued that this has not been the case, empirical evidence on the poverty reducing potential of tourism growth to date remains mixed (see Croes 2014, Croes and Vanegas 2008, Job and Paesler 2013, Klytchnikova and Dorosh 2013, Saayman et al. 2012,

Vanegas et al. 2015). An excellent review of this literature is provided by Croes and Rivera (2016) and key studies providing empirical evidence are summarized in Table 1.

More recently, attention has however focused on whether tourism growth is pro-poor, that is, whether tourism benefits poor people more than non-poor people (Ashley and Roe 2002, Schilcher 2007). Using a theoretical model, Copeland (1991) was the first to show that the benefits in real income might have different distributional impacts on different segments of the society, thereby affecting the income distribution. Bartik (1991) argues that as tourism development occurs, income distribution will worsen as economic growth arising from tourism expansion will raise property values to a greater extent than it increases real wages or employment prospects. Although there has been considerable empirical examination on the pro-poor issue of tourism growth, there is no consensus on this issue (see Goh et al. 2015, Incera and Fernandez 2015, Lee 2009, Lee and O’Leary 2008, Li et al. 2016, Wen and Sinha 2009). An extensive review of this literature is provided by Alam and Paramati (2016) who used a panel data on 49 developing countries from 1991 to 2012 and found the existence of the Kuznets curve in the relationship between tourism growth and income inequality.

[Table 1]

The above mentioned studies have however focused on the impact of tourism on either poverty or income inequality but not both. Given that the effects on poverty and income growth are mixed, it is imperative to examine if there is a trade-off between these outcomes, i.e. what if an improvement in one measure takes place at the expense of the other? This has implications on whether tourism development should be reduced or increased depending on the aims of the tourism expansion policy. Some studies which have used the social accounting matrix or the computable general equilibrium model have tried to make a comparison of the impact on both poverty and income distribution. For instance, Blake et al. (2008) concludes that for Brazil, effects on all income groups from a 10% increase in demand by foreign tourists are positive but the lowest income households benefit by less than some higher income groups. For Thailand, Wattanakuljarus and Coxhead (2008) find that the growth of inbound tourism demand raises aggregate household income but worsens the income distribution between the poorest 80% and

richest 20% of agricultural and non-agricultural workers. Gatti (2013) shows that inbound tourism in Croatia raises aggregate resident welfare but reduces income inequality measured by the Atkinson index. While Njoya and Seetaram (2017) show that the tourism industry in Kenya is pro-poor using the Foster-Greer-Throbecke poverty measure, Croes and Rivera (2017) simulated a 1% increase in tourism receipts in Ecuador and found that the lowest and low income households benefitted the most.

With the exception of Mahadevan et al. (2016), by and large, most of the general equilibrium studies such as the use of computable general equilibrium (CGE) models examined poverty using aggregate household income and considered income effects based on income quintiles. However, the poverty measure in the general equilibrium framework is representative of a household and does not capture economy-wide poverty headcount, which more accurately depicts a country's situation. The income quintiles used in the general equilibrium framework on the other hand are broad and *ad hoc* and do not capture income inequality accurately (Haughton and Khandker 2009). There are other criticisms levied at the general equilibrium analyses (see Asafu-adjaye and Mahadevan 2012) such as they provide only a snap shot analysis of the country's situation and they do not consider any changes in structural conditions in the economy that might have occurred over time. In addition, the models are heavily dependent on the base year from which the data used was calibrated. Last but not least, all general equilibrium studies are based on a specific country with non-comparable poverty and income inequality measures across the studies, and hence these results cannot be generalized.

In this paper, to overcome the limitations based on available and comparable cross country data, a panel of 13 tourism-intensive economies spanning the period 1995- 2012 is used to examine the impact of tourism on not just poverty (measured by headcount index) and income inequality (measured by Gini coefficient) but also on poverty gap. To our knowledge, our study is the first to undertake such analyses (using two different poverty measures and three income inequality measures for robustness) within a single framework. The poverty gap measures the depth/intensity of poverty by considering how much of the shortfall from the poverty line can be reduced (World Bank 2005). It goes further than the poverty headcount, which only takes into account the number of poor people. Our poverty measures capture how poor they are, which is

important. The choice of these 13 economies over a larger random sample is explained in the section on data and variables.

As an empirical tool, we use a recently improved version of the standard panel VAR method used by Grossman et al. (2014) and Love and Ariss (2014) to provide reliable estimates. The panel data vector autoregression (VAR) estimation was used to allow a more enriching analysis using more information with a larger set of cross sectional observations over a long time period, thereby providing more reliable estimates (Baltagi 2008). However, unlike Alam and Paramati (2016), we do not use panel co-integration analysis as our data fail to show any evidence of a long-run relationship between the variables of interest. Thus we use the panel VAR model which captures the short run relationships and adjustments amongst variables. In addition, the panel VAR estimates enable the effect of tourism increase on the variables to be traced over time through the impulse response functions (IRFs). This is particularly useful from a policymaker's perspective to consider the effect and assessment of tourism expansion policy over time. Furthermore, our model is able to test and determine the direction of causation between all the variables. In the case of the panel cointegration long-run relationship estimated by Alam and Paramati (2016), it presupposes a contemporaneous uni-directional relationship from tourism to income inequality. Moreover, the incorporation of variables such as foreign direct investment and trade in their long-run model ignores possible multicollinearity issues.

To avoid these issues, we estimate a panel VAR which treats all variables in the system as endogenous. Our results show that although tourism does not lead to a reduction in poverty headcount or income inequality, it reduces the poverty gap. This important result points to the need for a major rethink of the use of the common poverty headcount measure to consider a more appropriate measure given by the depth of the poverty. The paper however does not attempt to provide explanations underlying the evidence on the empirical relationships as that will require a well-defined structural model which lies outside the scope of this study.

Data and Variables Used

The study of Alam and Paramati (2016) used a panel of developing countries to examine the existence of the Kuznets curve which underlies the concept of economic development

particularly in developing countries. Here, a different set of countries is chosen based on how important the tourism sector is to the economy. First, for tourism to potentially affect the poor via GDP, it is vital that tourism is a significant sector in the economy (Bird 1992). That is, the tourism-GDP share cannot be too low. Thus we use Bryden's (1973) criterion to only consider countries whose share is no less than 4% were chosen in order to make the case that tourism could potentially trickle down to the poor via GDP. While some may argue that this is low, it is not far from Bryden's (1973) criterion that a tourist country is one in which tourism accounts for about 5% of GDP. The second criterion for the chosen set of countries is that for valid estimation and interpretation of panel results, there needs to be enough time-series observations of the countries in the panel (Baltagi 2008). While annual headcount poverty measures may be available for countries, comparable income inequality measures are however very sparse in time series unless they are extrapolated, which would not be accurate. Computing comparable reliable data on poverty and income inequality for a set of countries using the same benchmark is a formidable task (Haughton and Khandker 2009).

The need to obtain comparable data on tourism, poverty, and income inequality measures dictated the available sample of 13 countries (see Table 1) from 1995 to 2012 and this provided a sample of 234 observations. While availability of data is a limitation of this study, we however take the view that research should not be hampered solely by data. Thus it is acknowledged that the use of panel data here is an exploratory analysis but it allows the examination of the impact of tourism on poverty, poverty gap, and income inequality within the same framework for the first time.

Similar to Croes and Rivera (2017) and Li et al. (2016), tourism in this paper is measured using tourism receipts. When using a set of countries within a single analytical framework, it is important to account for the different sizes of the economies. Hence tourism receipts to GDP ratio is used. With poverty, we use the most common measure given by the headcount poverty ratio (P^0) which is the proportion of poor people in the country defined by

$$P^0 = \frac{H}{N} \quad (1)$$

where H is the number of people below the most recently available international poverty line of \$1.25 day in 2005 purchasing power parity prices and N is the country's total population. The problem with P^0 is that, although the number of poor people may not increase, any increase in population size would imply that the country is better off and has reduced its poverty incidence. In addition, all poor people are considered equally poor. Thus if the poor become poorer, the headcount poverty ratio does not change.

Poverty gap (P^1) on the other hand measures the shortfall of a poor person i 's daily income (Y_i) from the poverty line (Y_p) expressed as a ratio of Y_p and defined by

$$P^1 = \frac{1}{N} \sum_{i=1}^H \left(\frac{Y_p - Y_i}{Y_p} \right) \quad (2)$$

The numerator in equation (2) refers to the amount of money needed to bring a poor person out of poverty and the ratio in the brackets is a proportion of that income shortfall with respect to the poverty line. This ratio is then summed to include all the poor people with regards to the total population. But not all poor people are treated equally as they are distinguished by how poor they are by measuring how far away from the poverty line they are. If the incomes of the poor improve but are still below the poverty line, then poverty gap will decrease. Thus the impact on measured poverty of a gain in income by a poor person increases in proportion to the distance of the person from the poverty line (Todaro and Smith 2015). In this way, the poverty gap places greater emphasis on the distribution of the poor because of its sensitivity to the depth of poverty measured by how poor the poor are (ibid).

Data for tourism receipts, GDP shares, poverty headcount, and poverty gap were obtained from the World Development Indicators while income inequality (which refers to the disproportionate distribution of a country's national income among households) was measured by two different types of Gini coefficient for robustness. One set of Gini coefficients was obtained from the World Development Indicators and the other set was from the Standardized World Income Inequality Data (SWIID) version 5.1 of Solt (2014). The SWID database is said to contain a large set of conversion factors for the Gini coefficients based on different income and

consumption concepts to obtain comparable estimates based on gross income (pre-tax) reported as Gini market and net income (post-tax) reported as Gini net.

Empirical Model and Results

Table 2 shows the mean of all the variables used. Prior to undertaking the analysis using STATA, a battery of panel unit root tests commonly used in the literature was performed. These include the test of Levin et al. (2002), Breitung (2000), Im et al. (2003) test, and Hadri's (2000) LM test. Apart from the Hadri test, the other tests share the common null hypothesis of a unit root and the alternative of stationarity. However, for reasons that unit root tests suffer from low power against alternative hypotheses of persistent but stationary processes, Hadri reverses and tests the null hypothesis of stationarity against the alternative of a unit root. Results of the panel unit root tests on all variables concerned indicate that they are I(0) processes and for brevity, these results are not reported but are available upon request. Given that these are I(0) variables, there is no evidence of a long-run cointegration relationship amongst them. Accordingly, we use the levels of the measure of tourism, poverty and income inequality in the model.

[Table 2]

As mentioned earlier, we use the panel data VAR method developed by Abrigo and Love (2015) that combines the traditional VAR approach with panel data. A panel VAR of lag order three is estimated based on the Akaike Information Criteria¹, leading to the following specification:

$$\begin{aligned}
 Tourism_{it} = & a_{10} + a_{11}Tourism_{it-1} + a_{12}Tourism_{it-2} + a_{13}Tourism_{it-3} + \\
 & b_{11}Poverty_{it-1} + b_{12}Poverty_{it-2} + b_{13}Poverty_{it-3} + \\
 & c_{11}Gini_{it-1} + c_{12}Gini_{it-2} + c_{13}Gini_{it-3} + f_i + d_{it} + e_{1,it} \quad (3)
 \end{aligned}$$

$$\begin{aligned}
 Poverty_{it} = & a_{20} + a_{21}Tourism_{it-1} + a_{22}Tourism_{it-2} + a_{23}Tourism_{it-3} + \\
 & b_{21}Poverty_{it-1} + b_{22}Poverty_{it-2} + b_{23}Poverty_{it-3} +
 \end{aligned}$$

¹ Braun and Mitnik (1993) show that estimators of a VAR whose lag length differs from the true lag length are inconsistent as are the impulse response functions and variance decompositions derived from the estimated VAR.

$$c_{21}Gini_{it-1} + c_{22}Gini_{it-2} + c_{23}Gini_{it-3} + f_i + d_{it} + e_{2,it} \quad (4)$$

$$Gini_{it} = a_{30} + a_{31}Tourism_{it-1} + a_{32}Tourism_{it-2} + a_{33}Tourism_{it-3} + \\ b_{31}Poverty_{it-1} + b_{32}Poverty_{it-2} + b_{33}Poverty_{it-3} + \\ c_{31}Gini_{it-1} + c_{32}Gini_{it-2} + c_{33}Gini_{it-3} + f_i + d_{it} + e_{3,it} \quad (5)$$

where *Tourism* denotes tourism receipts as a proportion of GDP;

Poverty denotes headcount poverty and poverty gap (but estimated separately);

Gini denotes income inequality and ‘*i*’ and ‘*t*’ refer to country and time, respectively.

In applying the VAR procedure to panel data, the imposed restriction is that the underlying structure is the same for each cross-sectional unit. Since this constraint is likely to be violated in practice, one way to overcome the restriction on the parameters is to allow for individual country heterogeneity in the variables by introducing fixed effects, denoted by f_i in the model. Since these fixed effects are correlated with the regressors due to lags of the dependent variables, the mean-differencing procedure commonly used to eliminate fixed effects would create biased coefficients. To avoid this problem, the forward mean-differencing is employed (see the Helmert procedure in Arellano and Bover 1995) to preserve orthogonality between the transformed variables and lagged regressors so that lagged regressors can be used as instruments. As the model also uses time dummies d_{it} to capture any time trend in the dependent variable which is expected to vary from country to country, there is a country subscript ‘*i*’ associated with the time dummies. Such a country-specific time dummy is uncommon in the standard VAR model but is an important feature in the panel data VAR model (see Abrigo and Love 2015 for technical details).

The model is estimated using the Generalised Method of Moments and panel Granger causality tests are undertaken using the Wald test. The results of the panel regression are not reported to conserve space given that the individual lagged parameters do not provide any meaningful interpretation other than its effect on the dependent variable concerned. Table 3 reports the results obtained. Based on the *p*-values, it can be seen that tourism share does not affect the headcount poverty or the income inequality. However, it affects the poverty gap at the 1% level

of significance while there is no reverse Granger causality from the poverty or income inequality measures to tourism share.

[Table 3]

To forecast the impact of tourism's share on the poverty gap over time, we generate the IRFs which describe the time profile of the reaction of one variable to the shock in another variable. The results remain largely unchanged and are robust to different ordering of the variables. Both the IRFs and their confidence intervals were then estimated using the standard errors generated with Monte Carlo simulations to address any small size bias. Orthogonalising the VAR's shocks is required so that the shocks tracked by the IRFs are uncorrelated (Kilian 2001). The 95% confidence intervals are reported in the shaded area and the IRFs lie within these intervals implying that the estimates are statistically significant.

[Figures 1a and 1b]

It can be seen in Figure 1(a) that the impact of a one standard deviation increase in tourism share reduces the level of poverty gap in the following year by -0.8 but there are upward adjustments in the response of poverty gap to this shock in subsequent years. The effect of a tourism shock on poverty gap is however seen to dissipate (i.e. the effect goes to zero) after five years, showing that the panel VAR estimates are stable and do not explode over time. To evaluate the overall effect of tourism shock on poverty gap over time, Figure 1(b) shows the cumulative effect, which suggests that an increase in tourism share by a standard deviation has its largest effect on reducing poverty gap after two years, while over a period of five years, the effect is to lower the poverty gap by no less than 0.5.

Conclusion

The panel data analysis provides evidence that income distribution is not affected by tourism growth and thus the pro-poor tourism growth hypothesis is not supported based on the sample of tourism-intensive countries. The more interesting observations, however, pertain to the measure of poverty. Our results show that tourism growth fails to reduce the number of poor people given

by the headcount poverty. While this common poverty measure used by almost all previous studies has the virtue that it is simple to construct and easy to understand, this ratio however fails to indicate how poor the poor are, and hence the ratio does not change if people below the poverty line become poorer (Haughton and Kandker 2009).

Nevertheless, there is evidence that tourism growth reduces the poverty gap in that, the poor do earn more to the extent that they earn enough to bring them over the poverty line. A further implication of this result is that there is a lowering of the the minimum cost of eliminating poverty because the poverty gap shows how much money would have to be transferred to the poor to bring their incomes up to the poverty line. This is a positive outcome for a tourism focused policy. Thus whether or not a tourism promotion campaign is effective depends on the type/form of poverty reduction the government targets. Future research should unveil the underlying causes for the different result on the poverty measures.

It has however been argued that as an economy develops, a more relevant poverty measure is that of relative poverty measured by the comparison of the poor's mean income (be it at the lowest 20% or 40% of the income distribution) to the median or average per capita income of the economy (Jantti and Danzinger 2000). The relative notion of poverty is one that allows the benchmark identifying poor households to change with relevant economic circumstances, and thus absolute and relative poverty being different concepts, can move independently of one another (Mahadevan 2007). With relative poverty, the benchmark of real income will rise when average real income rises (Jantti and Danzinger 2000) and this makes it an appropriate measure to consider changes that may occur as the countries develop. Future research could focus on this measure to validate the proposition here but it is beyond the scope of this paper due to the unavailability of data for the panel of countries at this stage to test this.

Table 1 Some Empirical Studies on the Impact of Tourism on Poverty and Income Inequality

| Studies | Data | Empirical Method | Findings |
|------------------------------------|---|---|--|
| Alam and Paramati (2016) | 49 developing countries, 1991-2012 | Panel Co-integration | Income inequality increases. Evidence of Kuznets curve. |
| Blake et al. (2008) | Brazil | CGE model | Tourism is not pro-poor. |
| Blake (2003) | East Africa | Social Accounting Matrix | Tourism is not pro-poor. |
| Wattanakuljarus and Coxhead (2008) | Thailand | CGE model | Tourism is not pro-poor. |
| Croes (2014) | Costa Rica and Nicaragua, 1980-2010 | Error Correction Model | Tourism matters for poverty reduction in Nicaragua but not for Costa Rica. |
| Croes and Rivera (2017) | Ecuador | Social Accounting Matrix | Tourism is pro-poor. |
| Croes and Vanegas (2008) | Nicaragua, 1980-2004 | VAR model and Co-integration | Poverty is reduced. |
| Gatti (2013) | Croatia | CGE model | Income inequality decreases. |
| Goh et al. (2015) | 31 provinces in China, 1970-2010 | Granger Causality Test and Gini decomposition | Income inequality decreases. |
| Haddad et al. (2013) | Regions in Brazil | Input-Output model | Regional income inequality decreases. |
| Incera and Fernandez (2015) | Galicia in Spain | Social Accounting Matrix | Slight increase in income inequality. |
| Klychnikova and Dorosh (2013) | Panama | Social Accounting Matrix | Tourism significantly benefits the poor. |
| Lee (2009) | US Counties, 1990 and 2000 | Across time comparison | Income Inequality increases in tourism-dependent counties |
| Lee and O'Leary (2008) | US cities, 1990-2000 | Panel regression model | Income Inequality increases |
| Li et al. (2016) | 30 provinces in China, 1997-2010 | Panel regression model | Income inequality decreases. |
| Mahadevan et al. (2016) | Indonesia | CGE model | Tourism is not pro-poor. |
| Muchapondwa and Stage (2013) | Botswana, Namibia, and South Africa | Social Accounting Matrix | Tourism is not pro-poor. |
| Njoya and Seetaram (2017) | Kenya | CGE model | Tourism is pro-poor. |
| Saayman et al. (2012) | South Africa | Social Accounting Matrix | Tourism reduces poverty but is not pro-poor. |
| Vanegas et al. (2015) | Costa Rica, 1970-2012 Nicaragua, 1980-2012 | Autoregressive distributed lag bounds test for co-integration | Poverty is reduced. |
| Wen and Sinha (2009) | Regions of China, 1986-2004 | Gini coefficient spatial distribution analysis | Regional income inequality decreases. |

Table 2 Average Tourism Share, Poverty and Gini Coefficient over 1995-2012

| Country | Tourism Share (%) | Poverty Measures | | | Gini Coefficient (%) | | |
|--------------------|-------------------|-----------------------|--------------------------------|-------------|----------------------|--------------------|-----------------------|
| | | Headcount Poverty (%) | Std. Dev. of headcount poverty | Poverty gap | Gini from WDI | Gini net from SWID | Gini market From SWID |
| Armenia | 4.15 | 7.59 | 7.68 | 1.66 | 33.73 | 36.25 | 41.81 |
| Bulgaria | 8.42 | 1.05 | 1.84 | 0.33 | 31.70 | 28.79 | 32.23 |
| Costa Rica | 7.53 | 4.07 | 1.78 | 2.16 | 48.42 | 43.92 | 45.20 |
| Dominican Republic | 10.29 | 4.32 | 1.93 | 1.31 | 49.44 | 45.14 | 46.92 |
| Estonia | 9.32 | 0.55 | 0.37 | 0.44 | 33.64 | 34.05 | 41.33 |
| Georgia | 4.42 | 14.86 | 3.17 | 4.95 | 40.46 | 44.49 | 46.82 |
| Honduras | 55.45 | 21.18 | 6.28 | 9.34 | 56.11 | 50.08 | 52.13 |
| Hungary | 5.86 | 0.03 | 0.09 | 0.02 | 28.22 | 28.33 | 42.93 |
| Kyrgyz Republic | 4.09 | 17.24 | 14.75 | 4.30 | 33.97 | 35.94 | 39.51 |
| Panama | 6.99 | 9.32 | 5.03 | 4.73 | 54.87 | 49.35 | 50.74 |
| Thailand | 7.64 | 1.86 | 3.90 | 0.30 | 41.81 | 53.89 | 47.97 |
| Slovenia | 5.30 | n.a. | n.a. | n.a. | 26.91 | 23.12 | 34.01 |
| Czech Republic | 4.50 | n.a. | n.a. | n.a. | 26.43 | 25.66 | 38.52 |

Notes: n.a. means not available and Std. Dev. stands for standard deviation.

Tourism share is the ratio of tourism revenue over GDP.

Gini net is based on gross income measures while Gini market is based on post-tax income

Source: Data was compiled from World Development Indicators (WDI) and the Standardized World Income Inequality Data (SWID).

Table 3 Causality Results from Panel-VAR using Generalised Method of Moments

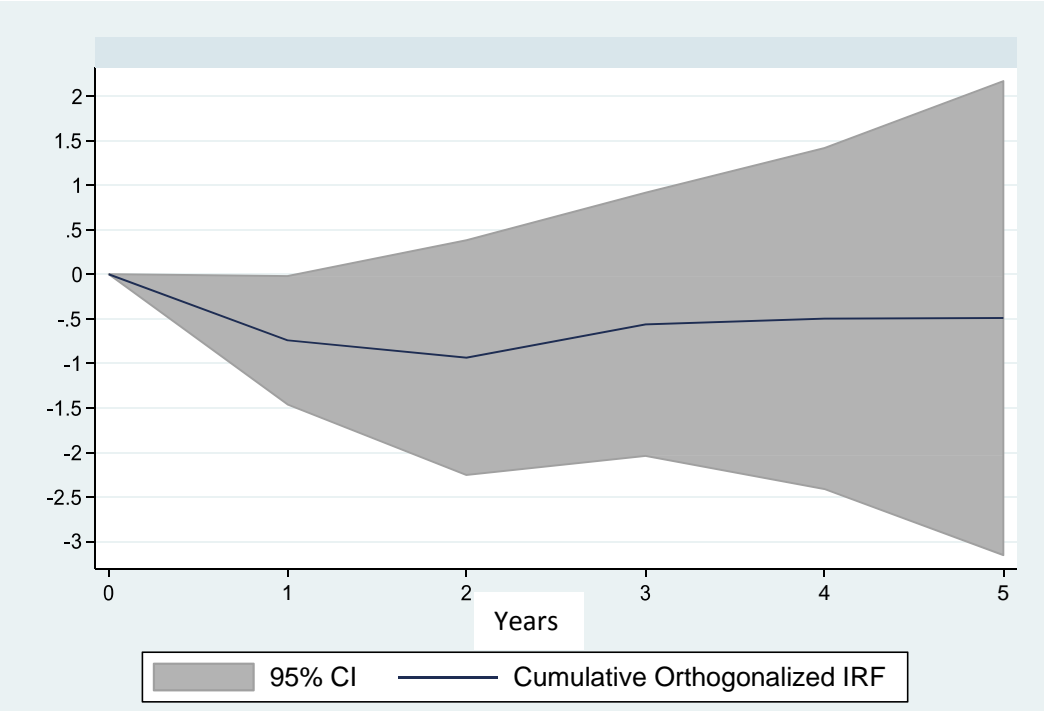
| Null hypothesis | Wald test statistic | p-value | Decision on hypothesis |
|---|---------------------|---------|------------------------|
| Tourism does not Grange cause Headcount poverty | 5.317 | 0.150 | Fail to reject |
| Headcount poverty does not Grange cause Tourism | 1.806 | 0.614 | Fail to reject |
| Tourism does not Grange cause Poverty gap | 12.838 | 0.005 | Reject |
| Poverty gap does not Grange cause Tourism | 4.886 | 0.180 | Fail to reject |
| Tourism does not Grange cause WDI Gini | 5.997 | 0.314 | Fail to reject |
| WDI Gini does not Grange cause Tourism | 3.552 | 0.112 | Fail to reject |
| Tourism does not Grange cause SWID Gini net | 1.911 | 0.591 | Fail to reject |
| SWID Gini net does not Grange cause Tourism | 1.594 | 0.661 | Fail to reject |
| Tourism does not Grange cause SWID Gini market | 1.173 | 0.760 | Fail to reject |
| SWID Gini market does not Grange cause Tourism | 4.317 | 0.229 | Fail to reject |

Note: The degrees of freedom for the test statistic is 3 as a panel VAR of lag order 3 is fitted.

Figure 1(a) Impulse Response Function of Poverty Gap to a Standard Deviation shock in Tourism Share



Figure 1(b) Cumulative Impulse Response Function of Poverty Gap to a Standard Deviation shock in Tourism Share



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