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The economic impact of global uncertainty and security threats on international tourism

Casiano Manrique-de-Lara-Peñate [a], María Santana Gallego [b], Elisabeth Valle Valle [b,*]

[a] University of Las Palmas de Gran Canaria, Spain
[b] University of the Balearic Islands, Spain

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ABSTRACT

Uncertainty and safety issues limit the expansion of the tourism sector. Previous literature has explored the impact of security problems on tourist flows, especially terrorism. However, the difficulty of measuring tourism in monetary terms has limited the ability to evaluate the economic costs of security and uncertainty. This paper brings together a worldwide gravity model for international tourist arrivals from 1995 to 2016 and an inter-country input-output model for estimating the economic impact of terrorism, corruption and economic policy uncertainty in monetary terms. The research provides estimates of variations in tourist arrivals and value added under different scenarios, ranging from total security to maximum insecurity and uncertainty values at country and regional levels. Results show that the value added generated by tourism would increase by 14.3% if uncertainty and insecurity in each of the countries fell to their minimum level, and would decrease by 17.5% if they increased to their maximum level.

1. Introduction

Across the globe, the importance of tourism has grown over recent decades, but these international flows are highly sensitive to external shocks that cause uncertainty and pose risks to tourists. Therefore, security has become a key factor for tourism demand. Moreover, the impact of the COVID-19 pandemic on the tourism sector has been devastating for the economies of many countries, and it seems clear that guaranteeing tourist safety will be crucial for the recovery to come. In the present research we analyze the impact that uncertainty and security threats have on international tourism demand, focusing on three different variables, namely, terrorism and corruption to measure insecurity, and the World Uncertainty Index (WUI) to measure general uncertainty at the country level. These data exist for both origin and destination countries, and thus we can estimate not only how tourist arrivals vary due to changes in these variables at the country and regional levels, but also changes in the value added in seven country-aggregated regions (Africa, Asia, Europe, Latin America, the Near East, Oceania, and the USA & Canada).

There is an extensive body of literature that explores the impact of security threats on tourism flows. Previous papers have focused on estimating how safety issues, mainly terrorism and political stability, affect tourist arrivals (Ghalia et al., 2019; Groizard et al., 2022; Llorca-Vivero, 2008; and Neumayer and Plümper, 2016, among others). However, changes to GDP or value added caused by the variation of tourism demand have not yet been quantified. Fourie et al. (2020) investigate the effects of insecurity—namely, terrorism, crime, and corruption—on international tourist flows and their paper is used as a baseline for the first step of our analysis. Then, we improve their estimates by expanding the database to generate different scenarios and by providing a quantification, in monetary terms, of variations in tourism demand under each scenario.

The present article contributes to the existing literature by combining a gravity model with an input-output (IO) model to analyze the impact of security threats and global uncertainty on tourism demand and value added worldwide. Quantifying the economic impact of changes in tourism demand give us a more complete idea of the real effects of uncertainty and security issues. This is a relevant analysis, as measuring tourism losses in monetary terms implies a better understanding of the real cost of uncertainty and security threats, and it enables policies to be designed that both increase security and promote the tourism sector. Moreover, quantifying changes in monetary terms would allow to better evaluate the effectiveness of such policies. Indeed, our research aims to provide a methodological framework for quantifying, in terms of value added, changes to tourism caused by variations in its determinants.

* Corresponding author.
E-mail address: Elisabeth.valle@uib.es (E.V. Valle).

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Firstly, we define a gravity model for worldwide tourism movements for the period 1995–2016 to estimate the effects of terrorism, corruption, and global uncertainty on bilateral tourist arrivals. Then, changes to tourism demand are calculated using predicted tourism flows under different scenarios, ranging from the extreme case of total security—with zero terrorist attacks, zero corruption, and no uncertainty—to the minimum and maximum average levels of insecurity at country and regional levels. Secondly, we convert these changes into monetary terms (value added) using inter-country IO tables.

For the impact analysis we use the *Inter-Country Input-Output (ICIO) Tables* published by the OECD (2021). This database provides information on 64 countries (36 OECD countries and 28 non-OECD economies), the rest of the world, and offers split tables for China and Mexico. It covers 36 industries, and the period for which information is provided stretches from 1995 to 2015. The last period available in the ICIO Tables, year 2015, is used as a reference to calculate changes in value added. Moreover, this is one of the years in the database with the most data available to predict tourism flows using the gravity model. Although other recently developed global multiregional input-output databases exist, such as the Eora by Lenzen et al. (2013) used in Nguyen et al., (2021), EXIOPOL by Tukker et al. (2013) used for example in Bouwmeester and Oosterhaven (2013), the Global Trade Analysis Project (GTAP) by Aguiar et al. (2019) widely used as an example in the article by Andrew and Peters (2013), and the World Input-Output Database (WIOD) from the European Commission (Timmer et al., 2015), used by Bolea et al. (2021) and Fan and Liu (2021), none of them include non-resident expenditure. In this sense, the ICIO database calculates, for the first time, the consumption of non-residents, which allows us to analyze the added value generated by tourism expenditures, disaggregated by country of origin for all the countries included in the database.

The paper is organized as follows: section 2 provides a review of relevant literature, section 3 explains the data and methodology applied, section 4 presents the results obtained under the different scenarios considered, and finally, section 5 offers conclusions and implications.

2. Literature review

Tourism demand and the determining factors behind such demand have been extensively explored over the past decades. A large and expanding body of literature explores the factors that influence tourists' destination choice, such as income, prices, travel costs, and tourist attractions. Among the determinants of tourism movements are safety and security, key concerns when tourists decide where to travel. Early papers, such as those by Enders and Sandler (1991), Enders et al. (1992), Pizam and Mansfeld (1996), Sönmez (1998), Sönmez and Graefe (1998), and Araña and Leon (2008), found that terrorism has a negative impact on tourism flows. This topic is still extensively studied in tourism economic literature (Raza and Jawaid, 2013, Bassil et al., 2019; Samitasa et al., 2018; Walters et al., 2018; Mitra et al., 2018; among others), albeit with more sophisticated econometric techniques and up-to-date databases. In general, all these papers find that the expected effect of terrorism on international tourism movements is negative.

Regarding corruption, the impact of this variable has been less investigated than terrorism. However, the effect of perceived corruption on tourism has been analyzed in articles by Das and Dirienzo (2010), Propawe (2015), Saha and Yap (2015), Lv and Xu (2017), Demir and Gozgor (2018), and Linda and Nzama (2020). Although the negative impact of corruption on tourism is not as clear as the impact of terrorism, in general, empirical papers estimate fewer tourist arrivals to more corrupt countries. Therefore, it seems that corruption affects tourist arrivals as it causes uncertainty about tourist safety and the total cost of the trip.

Finally, uncertainty is expected to affect the perception that tourists have about the security of a destination, since concerns for safety have deterred travel to several countries. Previous research on the effect of uncertainty on tourism demand has focused on the use of the Economic Policy Uncertainty Index (EPU) developed by Baker et al. (2016), but it only measures geopolitical risk and is only available for a small group of countries. In any case, previous research has shown that uncertainty reduces tourism movements (Chen et al., 2020; Demir and Gozgor, 2018; and Lu et al., 2020). The study by Gozgor et al. (2021) explores the role of global uncertainty on tourism demand by using a more specific measure of global uncertainty, the World Uncertainty Index (WUI), which accounts for global economic and political uncertainties and is available for a larger sample of countries (Ahir et al., 2018). These authors find that uncertainty negatively affects tourist arrivals and hold that tourists are not only affected by local uncertainty and risk but by global events, because the perceived risk associated with international travel increases.

So, although the influence of insecurity, mainly measured by terrorism and political instability, on tourism has been widely analyzed in the tourism literature, previous research has frequently considered isolated cases to study specific violent events or specific countries. Moreover, previous papers focus mainly on quantifying the effect of security threats and political instability on tourism demand in terms of their impact on tourist arrivals. The main reason for the widespread use of tourist arrivals as a proxy for tourism demand is the availability of such data. To estimate a gravity model, bilateral tourism flows are required, and the main source of this data is the United Nations World Tourism Organization (UNWTO, 2021), which has provided information on tourist arrivals for all countries in the world, broken down by country of origin, since 1995. However, there is no paper that quantifies, in monetary terms, the variations in tourism movements caused by changes in security and uncertainty.

Fourie et al. (2020) carried out a comprehensive study of the impact of security threats on international tourism movements. Using a dataset containing a large number of countries around the world, the authors considered three measures of insecurity—terrorism, crime, and corruption—to isolate their individual effects. Their results show that tourists prefer traveling to countries with similar levels of safety and security as their origin country, i.e., that tourists from stable countries prefer traveling to countries with the same conditions, while tourists from unstable countries are more tolerant to insecurity at the destination country. Although we follow the paper by Fourie et al. (2020) to define a gravity model for bilateral tourism movements, we contribute to the existing literature in several ways: (i) we incorporate the world uncertainty index (WUI) into the analysis,[1] (ii) we apply a more up-to-date methodology for estimating the gravity model, (iii) we generate different scenarios of insecurity, (iv) and we quantify, in monetary terms, variations in tourism under each scenario.

Tourism analyses, IO tables, and IO models have been friends for a long time (Polo and Valle, 2012), and despite the many drawbacks of using IO tables for policy modelling (See WTO, 2014), they are invaluable tools for description analyses, as they represent goods and production accounts in any economy. Leontief introduced IO analysis in Leontief, 1936, and Archer (1978) conducted one of the first applications of impact analysis for the tourism activity using IO multipliers. He discussed the concept of tourism multipliers, considering the pros and cons of this type of model.

Dwyer et al. (2004) emphasized that these models have been surpassed by computable general equilibrium (CGE) models, which can incorporate all kinds of price effects into their analyses and which are able to consider all types of income flows and their redistribution in the economy. Zhou, Yanagida, Chakravorty, and Leung (1997) acknowledged price rigidity as the main shortcoming of IO models. This rigidity

[1] Due to data availability, if global uncertainty and crime rates are simultaneously introduced, notably, the sample size is reduced by a third. Moreover, as a robustness check, crime rates at origin and destination countries were also included in the gravity model, but they were not significant. For this reason, crime rates are not considered in the present research.

implies no resource reallocation and therefore a low degree of modelling flexibility. Blake and Sinclair (2003) have also discussed the advantages and disadvantages of IO versus CGE models. They highlight the fact that the aforementioned rigidities reduce the ability of IO models to be useful in policy analyses. CGE models can easily incorporate instruments like taxes and subsidies which can be used to compensate for tourism crises, like the ones studied by these authors. Not necessitating price and wage inflexibility, CGE models can also be used to consider the impact of different levels of demand and supply responses as well as different hypothesis about the ways public and foreign sector deficits are treated. But Dwyer also recognizes several types of criticism against the use of CGE models by tourism researchers, notable of which is that there is no standard CGE model (WTO, 2014).

The fact is that IO models have been and are still widely used in economic impact analyses of tourism. They are still permanently used as a preliminary estimation of the impact of the tourism sector on the economy. Recent examples of such analyses include Klijs et al. (2016), Pintassilgo et al. (2016), De Santana Ribeiro et al. (2017) and Tohmo (2018). Covering issues specifically related to terrorism is the article by Toh et al. (2004), who analyze the impact of two powerful bombs that destroyed two restaurants in Bali in 2002 using an IO model. The use of a standard model such as the IO model makes it possible to have clear starting hypotheses and comparability with other studies.

3. Data and methodology

Our empirical analysis involves two stages. Firstly, a gravity model for bilateral tourist arrivals is defined to estimate the parameters of interest. Tourism flows are predicted to generate the baseline scenario using actual data on terrorism, corruption, and global uncertainty. Then, we predict simulated tourism under five different scenarios with varying values of insecurity and global uncertainty. By doing this, changes in tourist arrivals to destination countries can be calculated based on variations in security and uncertainty at origin and destination countries.

Secondly, these predicted changes in tourism under the different scenarios equate to a proportional drop in tourist spending in the destination country, and these variations in tourist spending allow us to analyze, using the ICIO tables from the OECD, the impact on global value added across seven aggregated regions: Africa, Asia, Europe, Latin America, the Near East, Oceania, and the USA & Canada.

3.1. Gravity model for bilateral tourism

Gravity models of tourism demand have been extensively used in tourism research to estimate the determinants of bilateral tourism movements (see for instance, Khadaroo and Seetanah, 2008; Neumayer, 2004, 2010; and De Vita, 2014, among others). Indeed, Morley et al. (2014) showed that gravity models for tourism can be derived from consumer choice theory, while Santana-Gallego and Paniagua (2020) adapted the model used by Anderson (2011) to explain bilateral tourism.

Predictions for our baseline model and the five different scenarios are obtained by defining a similar specification and database as in Fourie et al. (2020) but applying some improvements to the estimate of the gravity model. Thus, the model used in the present research for tourism demand is defined as follows:

$$\begin{aligned} Tou_{ijt} = {} & \beta_o + \beta_1 LnGDPpc_{it} + \beta_2 LnGDPpc_{jt} + \beta_3 RTA_{ijt} \\ & + \beta_4 LnPrice_{ijt} + \beta_5 GE_{it} + \beta_6 GE_{jt} + \gamma_1 Terror_{it} + \gamma_2 Terror_{jt} \\ & + \gamma_3 Corrup_{it} + \gamma_4 Corrup_{jt} + \gamma_5 WUI_{it} + \gamma_6 WUI_{jt} + \\ & + \lambda_{ij} + \lambda_t + \varepsilon_{ijt} \end{aligned} \quad (1)$$

where Ln denotes a natural logarithm and sub-indices i, j, and t refer to the destination, origin, and year, respectively. The dependent variable is the number of tourist arrivals to destination country i from origin country j during year t. The sample covers tourism flows for 143 origin/destination countries for the period 1995–2016. Data on bilateral tourism was collected from the UNWTO (2021).[2]

Fourie et al. (2020) estimated their gravity model for tourism demand by applying an ordinary least squares (OLS) estimator with panel fixed effects. However, we improve on their methodology by estimating equation (1) and applying the Poisson pseudo-maximum likelihood estimator (PPML) proposed by Santos-Silva and Tenreyro (2006, 2010). We apply the PPML procedure because it overcomes known biases when estimating gravity equations by OLS: specifically, the existence of heteroskedastic residuals and zeros in the dependent variable. The specification includes country-pair (λ_{ij}) and year (λ_t) fixed effects that absorb any time-invariant country-specific determinant (such as annual average temperature, number of beaches, kilometers of coastline, etc.) or fixed pair determinant (such as having a common language, common religion, common colonial background, distance, etc.). Therefore, time-invariant tourism determinants do not need to be included in the specification. Indeed, Egger and Nigai (2015) and Agnosteva et al. (2014) show that the pair fixed effects are a better measure of bilateral trade costs than the standard set of gravity variables. Here, however, it is important to mention that since the variables of interest are time-varying and country-specific, time-varying fixed effects, which control for multilateral resistance to tourism, cannot be included in this regression (see Harb and Bassil, 2018).[3]

Equation (1) includes a set of time-varying country-specific controls, such as the log of GDP per capita ($LnGDPpc_{it}, LnGDPpc_{jt}$) and the quality of institutions, measured by government effectiveness (GE_{it}, GE_{jt}), in destination and origin countries. Moreover, there is a dummy variable that takes the value one if both countries belong to the same regional trade agreement (RTA_{ijt}) and a proxy for relative price competitiveness ($LnPrice_{ijt}$). This price variable—measured by prices in the destination country relative to those in the origin country—is generated as the price level ratio of the PPP conversion factor to the market exchange between the destination and origin countries. Data for regional trade agreements are taken from the Regional Trade Agreements Information System (World Trade Organization, 2018), while data on GDP per capita and relative price competitiveness are obtained from the World Development Indicators (World Bank, 2018). Finally, the government effectiveness measures are taken from the World Governance Indicators by Kaufmann et al. (2011).

The variables of interest for the simulation analysis are a set of proxies associated with insecurity and a measure of global uncertainty in countries around the world. As in Fourie et al. (2020), the variables used to measure safety and security are terrorism and corruption. Regarding terrorism ($Terror_{it}, Terror_{jt}$), the number of terrorist attacks with fatalities (per 100,000 inhabitants) is considered. Using the number of terrorist attacks with fatalities—instead of just the number of terrorist attacks, as in Neumayer (2004), Llorca-Vivero (2008), and Feridun (2011)—allows us to control for the intensity of the shock. The number of successful terrorist attacks is obtained from the Global Terrorism Database (National Consortium for the Study of Terrorism and Responses to Terrorism, 2015), while data on population is taken from the World Development Indicators. The Global Terrorism Database defines terrorism as "the threatened or actual use of illegal force and violence by a non-state actor

[2] One limitation of tourism data that are disaggregated by origin is that there are many missing values. The UNWTO does not discriminate between zeros and data that are not reported, so sources of tourists are not homogeneous for all destination countries.

[3] The methodology proposed by Heid et al. (2021) and Yotov (2022) suggest including domestic tourism (along with international tourism) in the dependent variable of the gravity model to estimate destination-specific variables. However, this methodology requires obtaining data on domestic tourism, and the interpretation of the parameter is in terms of differences between international and domestic tourism flows. Since, data availability of homogeneous tourism flows would considerably reduce our database, and we are interested in the effect of threats on inbound tourism (i.e., not in relation to domestic flows), this method does not fit the purpose of our analysis.

to attain a political, economic, religious, or social goal through fear, coercion, or intimidation."

Regarding corruption $(Corrup_{it}, Corrup_{jt})$, we use the Global Corruption Perception Index from Transparency International (2018). This index measures perceived (not actual) levels of public sector corruption, ranging from 10 (most corrupt) to 0 (least corrupt).[4] It is a composite index based on surveys and professional assessments, and it reflects the views of observers from around the world, including experts living and working in the countries surveyed. This is an appropriate variable for the present analysis since the choice of destination by a tourist is usually based on perceived rather than actual corruption.

Finally, we use the World Uncertainty Index (WUI_{it}, WUI_{jt}) to measure global uncertainty. This variable tracks uncertainty across countries by identifying the word "uncertainty" (and variations) in country reports from the Economist Intelligence Unit. The index has a quarterly frequency (we took the maximum value for each year), and it is available for 143 countries. An advantage of this variable over the Economic Policy Uncertainty Index is that it is available for a larger sample of countries and can be used to compare uncertainty across countries. The WUI is generated using frequency counts of the word "uncertainty" (and variations) in quarterly Economist Intelligence Unit (EIU) country reports. Then, to make it comparable between countries, the index is scaled by the total number of words in each report. The reports discuss major political and economic developments in each country and include analyses and forecasts of political, policy, and economic conditions. So, the WUI measures political and economic uncertainties such as Brexit, the 9/11 attacks, the SARS outbreak, the Euro debt crisis, and US presidential elections.

Our baseline scenario is specified using predicted tourist arrivals based on actual values of controls and the measures of security and global uncertainty during the sample period (1995–2016). For the simulation analysis, five different scenarios are defined. In the first scenario (S1) we consider the three variables of interest at both the destination and the origin to be equal to zero (representing a totally safe scenario). Then, the minimum and maximum values of the level of security for each origin and destination country are considered in the second (S2) and fourth (S4) scenarios, respectively. Finally, the minimum and maximum average values of the level of security for the region where the destination country is located are used to define the third (S3) and fifth (S5) scenarios, respectively. Regions are grouped using the United Nation classification (See Annex 3). As an example, for Austria, the baseline prediction is generated using Austria's WUI and actual terrorism and corruption data from 2015. Then, the five scenarios for the country are generated: one with (S1) total security, i.e., all variables of interest are equal to zero; two with Austria's minimum (S2) and maximum security values (S4) over the sample period; and two more using the minimum (S3) and maximum values (S5) seen in Western Europe during the sample period. By doing this, different scenarios based on a likely range of uncertainty and security indicators can be defined, considering not only the minimum and maximum values for a specific country during the sample period but also for the region to which it pertains.

Once equation (1) is estimated, the resulting parameters are used to generate predicted tourist arrivals for each tourist destination (using the actual values of each explanatory variable). Bilateral tourism flows are then aggregated per destination country to generate total (predicted) tourist arrivals, calculated as the sum of arrivals from each origin country to a particular destination, and creating the baseline scenario. Then, these predicted tourist arrivals for the baseline model and year 2015 (which is used as the reference year since it is the last year available in the ICIO database) are compared to predictions generated for the aforementioned five different scenarios. Here, it is important to note that in order to generate predictions (for both the baseline and simulated scenarios), the values for the control variables are taken from year 2015. So, predicted tourist arrivals in the baseline and in the five scenarios differ only due to changes in the uncertainty and security proxies. An interesting aspect of our analysis is that we define simulated scenarios considering security changes not only at the destination, but also the origin country and region.

3.2. The OECD's inter country input-output tables

Input-output tables (IOTs) describe the production structure of different sectors, as well as the sale and purchase relationships between producers and consumers within an economy. IOTs can be divided into intermediate consumption matrices, final demand matrices, and primary input matrices. Fig. 1 shows the format of the OECD's harmonized national IOTs.

From these tables we can apply the standard IO demand model that allows for the production vector satisfying a predetermined final demand vector to be calculated. Since IOTs distinguish flows by origin, the equilibrium condition between production and use by sector is set as follows:

$$y = A^I y + d^I \tag{2}$$

where A^I is the matrix of domestic intermediate input coefficients and d^I is the vector of final demand for domestic goods and services. An estimate of production associated with tourism y_T can be obtained by solving equation (3) for the predetermined final demand vector d_T^I, which stands for tourists' demand for goods and services:

$$y_T = A^I y_T + d_T^I. \tag{3}$$

Then, intermediate consumption, value added, employment, and imports due to tourism can be calculated for each branch, multiplying the corresponding coefficients by the activity levels. In this way, we can calculate the share that tourism contributes to value added and employment across the whole economy.

An inter-regional IOT is a table that follows the same basic layout as a single IOT—as described above—but which displays each industry as many times as countries are considered, differentiating between those industries located in the country that is the focus of the study and those located outside that country, as if they were different industries.

This produces an inter-regional IOT with several geographic areas (as many as countries considered) and the peculiarity that each country has the exact same set of industries.

The OECD did this for 69 countries and 36 industries from 1995 to 2015, and the format of the resulting IOTs can be seen in Fig. 2.

Following the structure described by Isard (1951) and elaborated upon by Isard et al. (1960), and using the notation established by Miller and Blair (1985) in their seminal treatment of inter-regional IOTs, and in Hara (2008) and Miller and Blair (2009), we use r to denote the country that serves as the object of study and s to denote the rest of the countries. In this context, the entire ICIO table can be divided into lower order sub-matrices, as shown below in the following expression:

$$Z = \begin{pmatrix} Z^{rr} & Z^{rs} \\ Z^{sr} & Z^{ss} \end{pmatrix} \quad F = \begin{pmatrix} F^r \\ F^s \end{pmatrix} \quad V = \begin{pmatrix} V^r & V^s \end{pmatrix} \tag{4}$$

The first sub-matrix, Z^{rr}, describes in-country transactions, i.e., outputs originating from industries in the country that are used as inputs by industries in the same country. This corresponds to the domestic inter-

[4] Originally, the Corruption Perception Index ranged from 10 (least corrupt) to 0 (most corrupt), but for a more straightforward interpretation of the parameters the variable was redefined and now ranges from 0 (least corrupt) to 10 (most corrupt) in order to obtain a negative coefficient when corruption deters tourism. Moreover, in 2012, the scale of the corruption index changed from 0 to 10 to 0–100. Thus, data for years 2012 and 2013 have been rescaled in order to make them comparable to previous years.

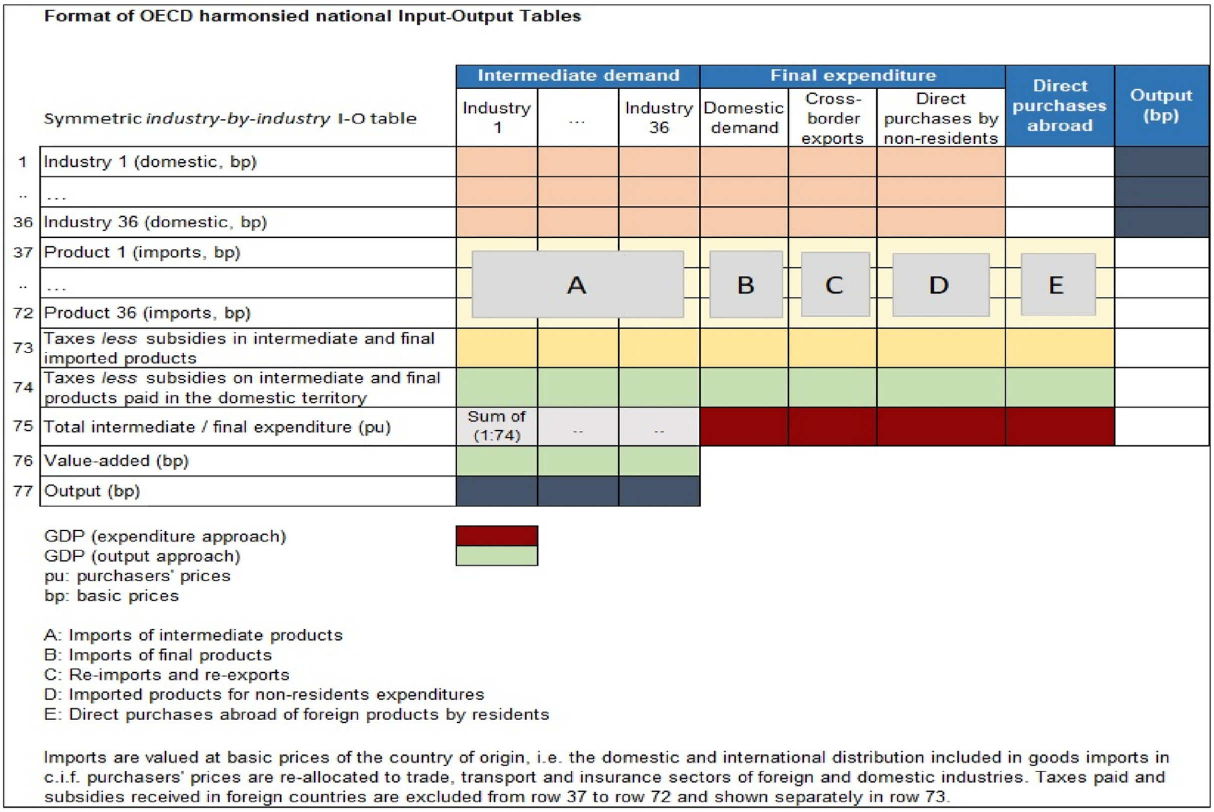

Fig. 1. Format of the harmonized OECD national input-output tables.
Source: OECD

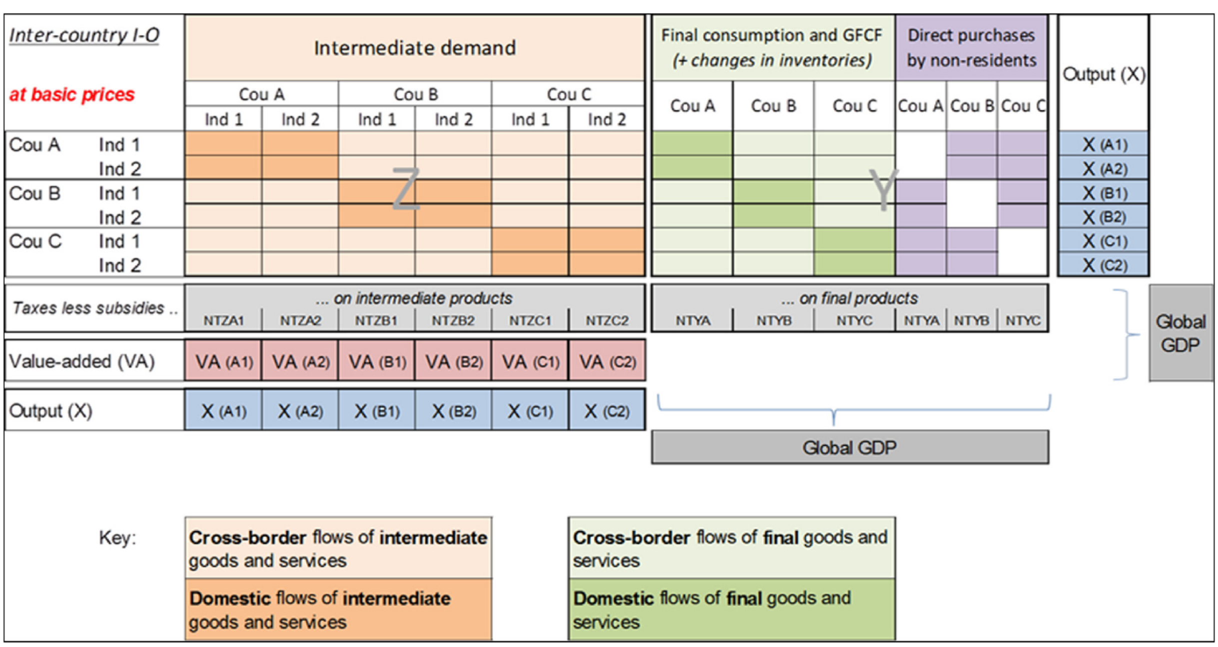

Fig. 2. Format of OECD input-output tables.
Source: OECD

industry matrix of a single national IOT.

The other sub-matrix in the diagonal, Z^{ss}, describes extra-country transactions between industries outside of the country. That is, outputs produced outside the country that end up being used as inputs by industries also located outside the country.

Inter-country flows are captured in sub-matrices Z^{rs} and Z^{sr}, which represent flows from country r to the rest of the countries s, and from the rest of countries s to country r, respectively.

Final demand is also disaggregated into two matrices: F^{r}, which includes final demand from within country r, and F^{s} , which includes final demand from the other countries considered. The same goes for value-added vectors V^r and V^s .

The rows of this combined IO matrix describe all the uses given to that industry's output, and the columns describe the inputs required for its production. The main peculiarity is that the level of disaggregation includes country distinctions, and this is precisely what allows us to examine the links between one country and the rest.

The equilibrium condition between production and use by sector and country r and the rest of the countries s is set as follows:

$$\left\{\begin{bmatrix} I & 0 \\ 0 & I \end{bmatrix} - \begin{bmatrix} A^{rr} & A^{rs} \\ A^{sr} & A^{ss} \end{bmatrix}\right\}\begin{bmatrix} x^r \\ x^s \end{bmatrix} = \begin{bmatrix} f^r \\ f^s \end{bmatrix} \tag{5}$$

where $\begin{bmatrix} A^{rr} & A^{rs} \\ A^{sr} & A^{ss} \end{bmatrix}$ is the complete matrix of a two-country IO model.

The complete (I-A) matrix will be larger than that of a single model. If both countries are divided into n sectors, the single matrix would be of size n × n and the full two-country model would be 2n × 2n.

The OECD's ICIO tables consider 69 countries (see Annex 1) and 36 industries (see Annex 2), so we end up working with 2484 sectors.

4. Empirical analysis and results

By linking the input-output model with the tourism flows predicted by our gravity model, we can analyze how global uncertainty and insecurity—measured using the variables of terrorism, corruption, and the WUI—would affect world tourism demand, and therefore, the value added that would have been generated were there total certainty and security around the world, versus a world with minimum values for the three variables and a world with maximum values for the three uncertainty and insecurity proxies.

4.1. Descriptive data

Before analyzing the effects of global uncertainty and security, we must set the starting point in the baseline scenario. It should be noted that there is no complete coincidence between pairs of countries considered in the gravity model and the ICIO data. In fact, the flows that can be analyzed with the gravity model account for 66% of the total tourism demand provided for by the ICIO. In the comments that follow we take into account only the part of the flows whose sources coincide.

In Table 1 we can see 2015 tourism demand in millions of USD for regions around the world. The rows show the origins and the columns the destinations of tourism demand. Thus, we can see in the first row of Table 1, outbound tourism from Africa, the total value of which was 2187 million USD and was concentrated primarily in the USA & Canada (697), followed by Europe (505). Globally, outbound tourism from Europe stands out, as it was responsible for a total of 250,300 million USD, with the most important destination being the region itself (164,507). Outbound tourism from Asia is in the second position worldwide (170,469), with the Asian region itself being the main destination (82,590) followed by the USA & Canada (50,311). The totals of the columns in Table 1 represent inbound tourism to each of the regions, with Europe boasting the highest inbound tourism figure (223,779), followed by the USA & Canada (141,007).

If we take only into account the outbound tourism from each region to the other regions, we can see that in Africa, Latin America, and the Near East, more than 95% of their outbound tourism was directed at the rest of the regions, while Europe (34%), Asia (52%), Oceania (87%), and the USA & Canada (74%) saw a much higher intensity in outbound tourism toward countries in the same region. If we only consider total outbound tourism not including movements within regions, three of these regions represent 85% of total tourism flows abroad. This is the case for Asia (30%), the USA & Canada (26%), and Europe (29%).

Below, in Table 2, we see the distribution of worldwide value added that was generated by the tourism demand analyzed in Table 1. The row totals indicate the value added generated around the world by outbound tourism from the region indicated in the row. The column totals indicate the value added that was generated by total outbound tourism in the region indicated in the column (including from the region itself).

Reading the first row of Table 2, we can see that total outbound tourism from Africa generated a total of 2187 million USD of value added in economic sectors worldwide, most of which was in the USA & Canada (603), Asia (537), and Europe (521).

Fig. 3 shows, in millions of USD, the value of inbound and outbound tourism, and the value added that was generated by total tourism in each region. The comparison between the value of inbound and outbound tourism shows whether a region spends more on tourism activities in the rest of the world than what the rest of the world spends on this region. Africa, the Near East, Oceania, and the USA & Canada have a positive balance (i.e., inbound tourism > outbound tourism), while the rest of the regions are net tourism issuers, Europe being the only one to have a nearly balanced position and Asia being the greatest net contributor to world tourism value added.

Inbound tourism does not translate into an equal amount of value added generated by total tourism activities. Therefore, more than the value of inbound tourism, the relevant figure for a region lies in the value added generated in this region by tourism activities throughout the world. Regions like Africa, Asia, and Latin America generate more value added from total tourism activities than their corresponding values of inbound tourism, while the opposite is true for the rest of the regions.

4.2. Simulation analysis

With the situation in 2015 fully described, we proceed to estimate the impact that the five security scenarios would have on tourism demand and value added. In the first scenario (S1), we simulate a totally safe world without uncertainty. The minimum values for the three variables are considered for each country in the second scenario (S2) and the minimum values for each of the 17 regions defined by the United Nations in the third scenario (S3). In the fourth scenario (S4), the maximum values for the three variables of interest for each country are considered, and finally the maximum values for each of the 17 regions are considered in the fifth scenario (S5).

By defining these scenarios, we explore what would happen in an extreme (and unrealistic) scenario of complete security and certainty, but

Table 1
Tourism demand 2015 (millions USD).

	Africa	Asia	Europe	Latin America	Near East	Oceania	USA & Canada	Total outbound tourism
Africa	14	429	505	20	410	112	697	**2187**
Asia	1694	82,590	14,065	1563	3777	16,470	50,311	**170,469**
Europe	2346	19,675	164,507	1905	21,337	3832	36,699	**250,300**
Latin America	108	1162	2554	682	326	438	17,073	**22,344**
Near East	92	1302	2508	41	459	217	4105	**8725**
Oceania	190	5360	3169	96	204	2192	5338	**16,548**
USA & Canada	1865	23,086	36,473	5060	5236	3957	26,784	**102,461**
Total inbound tourism	**6310**	**133,605**	**223,779**	**9368**	**31,749**	**27,218**	**141,007**	**573,035**

Source: own creation

Table 2
2015 value added (millions of USD).

	Africa	Asia	Europe	Latin America	Near East	Oceania	ROW	USA & Canada	Total outbound tourism
Africa	48	537	521	46	330	100	2	603	**2187**
Asia	3687	70,620	29,652	3507	4786	14,274	122	43,822	**170,469**
Europe	6355	50,552	134,976	5893	16,274	3974	228	32,048	**250,300**
Latin America	356	2922	2770	709	335	389	11	14,851	**22,344**
Near East	193	1892	2352	141	364	206	7	3571	**8725**
Oceania	424	5654	3413	349	319	1739	17	4632	**16,548**
ROW	0	0	0	0	0	0	0	0	**0**
USA & Canada	2662	29,390	34,419	5229	4719	3649	73	22,320	**102,461**
Total inbound tourism	**13,724**	**161,567**	**208,104**	**15,874**	**27,126**	**24,331**	**460**	**121,848**	**573,035**

Source: own creation

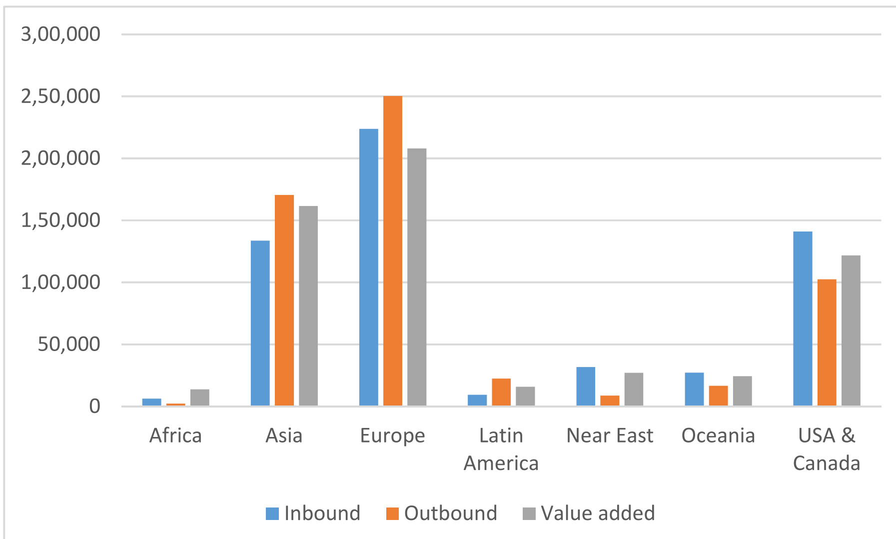

Fig. 3. Tourism flows and value added generated in 2015 (millions USD).
Source: own creation

we also adjust the variables, providing a realistic range of possible levels of insecurity and uncertainty, as we consider the minimum and maximum values taken by each proxy during the sample period (1995–2016) in each country. We also consider the minimum and maximum values observed in each region, since certain contagion effects can be expected. That is, tourism flows are sensitive not only to the risk associated with each country but also to the risk in the surrounding countries in the region.

4.2.1. Baseline scenario and predicted tourism flows

As discussed in the previous section, to generate the tourism flows in the different simulations, we estimate equation (1) by PPML, including country-pair and origin-year fixed effects as well as a set of controls at the destination level for a sample of 143 countries for the period 1995–2016. Estimates are presented in Table 3 and results show that income level at the origin yields the expected positive effect while income at destination is not significant. Belonging to a common regional trade agreement has a positive impact on international tourism movements and the proxy for relative price competitiveness is significantly negative, suggesting that tourist arrivals are larger for relatively cheaper destinations.

Regarding the variables of interest, the estimated parameters are as expected. Note that higher values of the variables of interest imply higher risk and uncertainty. The estimated effects of the variables at the destination level are significantly negative, indicating that more risk and uncertainty in the destination country reduce tourist arrivals. For origin countries, the estimated parameters for corruption and WUI are significantly negative, suggesting that when global uncertainty and corruption increase in the source country, people travel abroad less (or prefer traveling domestically). Surprisingly, the estimated parameter for terrorism in the origin country yields a significantly positive effect. This result was also found by Fourie et al. (2020), and although the interpretation is not straightforward, it might indicate that citizens are replacing domestic tourism with traveling internationally when terrorist attacks happen in the origin country. That is, they would prefer to travel

Table 3
Estimates of the gravity model for bilateral tourism.

Variable	Coefficient
$LnGDPpc_{it}$	−0.145
$LnGDPpc_{jt}$	1.079***
RTA_{ijt}	0.0824*
$LnPrice_{ijt}$	−0.150**
GE_{it}	0.0881*
GE_{jt}	−0.233***
$Terror_{it}$	−0.131***
$Terror_{jt}$	0.0122***
$Corrup_{it}$	−0.125***
$Corrup_{jt}$	−0.0521*
WUI_{it}	−0.0357*
WUI_{jt}	−0.0576**
Observations	99,043
Number of pairs	8037
Pseudo R-squared	0.9847

Robust standard errors clustered by pair.
***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.
i, j, and t refer to the destination, origin, and year.
Pair and year fixed effect included but not reported.

abroad instead of domestically when insecurity increases in their home country, maybe because they perceive it as safer.

The baseline scenario consists of the predicted tourism flows obtained with the estimated parameters from the model and uses the values of the explanatory variables from year 2015. Predicted tourism flows are then generated for each country pair, changing the safety and security parameters of the model, and then aggregating by country of origin. In doing this, new total tourist arrivals for each destination country are calculated. These new flows are compared with the baseline scenario to compute variations in tourism flows under each of the five simulated scenarios.

First scenario (S1): total certainty and security (zero terrorism, corruption, and global uncertainty).

Tables 4 and 5 present the results of the first scenario in which we analyze the impact of absolute certainty and security on tourism demand and value added through the variables of terrorism, corruption, and global uncertainty. In this first scenario tourism demand worldwide, as well as the value added that is generated by this demand, increases by 106.4%. The regions that would benefit the most under this hypothetical scenario (with increases of more than 100%) are the Near East, Africa, Latin America, and Asia, as they are regions containing areas with higher levels of insecurity.

The totals of the rows in Tables 4 and 5 are the same because the total demand must be equal to the total value added. These totals by row indicate that outbound tourism from Africa would increase by 139.0% in this scenario, the largest increase in any region, with Africa itself (212.2%) and the Near East (197.6%) benefitting the most.

The totals of the columns in Table 4 show us how inbound tourism would vary in each of the areas considered if there were total certainty and security in all countries in the world. In this scenario we can see important positive impacts, the largest being in the Near East, with a 175.6% increase in inbound tourism, and Africa, with a 161.3% increase.

The totals of the columns in Table 5 indicate the variation in value added that would occur due to inbound tourism from all the world (including the region itself). Comparing the data from Tables 4 and 5, we see that if there were total certainty and security worldwide, Africa would experience a 161.3% increase in inbound tourism (the largest increase coming from Africa itself, by 212.2%), and the value added that would be generated in Africa due to total tourism demand would increase by 138.0%.

Fig. 4 summarizes, in percentage terms, the variation in the value of inbound and outbound tourism, and the value added generated by total tourism in each region in the totally safe and certain scenario.

4.2.2. *Second scenario (S2): lowest level of insecurity and uncertainty by country*

Fig. 5 shows the results of the variation in inbound and outbound tourism and value added if we make the prediction with the minimum values observed for the insecurity and uncertainty proxies in each country during the 1998–2016 sample period compared to the baseline scenario. The consequences on tourism demand and value added would be positive. There would be a global increase of 14.26% in tourism demand and value added.

The most affected region in this scenario would be Europe, with a 15.95% increase in its outbound tourism, and then Oceania, with a 15.64% increase in its outbound tourism. If we analyze inbound tourism, we can see that the Near East would experience the greatest impact, a 24.87% increase in total inbound tourism, followed by Africa, with a 18.31% increase in its total inbound tourism.

We can analyze the difference between variations in the value added that would be generated in this scenario. The value added that would be generated in the Near East by world tourism demand would increase by 21.93%.

4.2.3. *Third scenario (S3): lowest levels of insecurity and uncertainty by region*

Fig. 6 provides results from another estimation in which we consider the minimum values for the uncertainty and insecurity proxies for each of the 17 regions defined by the United Nations classification (See Annex 3), instead of the minimum values for each country, which were used in Fig. 5. In this way we provide information on how countries are affected not only by their own levels of insecurity and uncertainty, but also the degree of insecurity and uncertainty of surrounding countries. In this scenario, the consequences on tourism demand and value added are positive and greater with respect to the predictions made with the minimum country-level values for the insecurity and uncertainty proxies (Fig. 5). In this scenario, we see a total increase of 57.65% in tourism demand and value added.

The region that would benefit the most is Asia, with a 72.7% rise in its outbound tourism, followed by Latin America, with a rise of 60.7% in its outbound tourism. If we analyze total inbound tourism, we can see that the region experiencing the greatest positive impact would be Asia, with an 87.5% rise in inbound tourism, followed by the Near East (86.1%).

We can also analyze the variations in value added generated, and we see that the value added generated in the Near East by total tourism demand would increase by 79.7% in this scenario.

4.2.4. *Fourth scenario (S4): highest levels of insecurity and uncertainty by country*

Fig. 7 shows the results of the variation in tourism demand and value added when we make the prediction with the maximum observed values of the insecurity and uncertainty proxies for each of the countries during the 1998–2016 sample period compared to the baseline scenario. In this fourth scenario, there would be a general fall in tourism demand and value added of 17.5%.

The most affected regions would be the Near East, with a 22.1% decrease in outbound tourism, and Latin America, with a 21.4% drop in its outbound tourism. The least affected region in this scenario would be Oceania, with a fall in its outbound tourism of 13.9%. In terms of inbound tourism, we can see that the Near East would be the most impacted region, with a 29.1% drop in total inbound tourism. The least affected region would be Oceania, where inbound tourism would decrease by 6.2%.

We can also explore the variations in the value added generated. We

Table 4
Impact on tourism demand in the first scenario.

	TOTAL SAFETY	Destination							
		Africa	Asia	Europe	Latin America	Near East	Oceania	USA & Canada	Total outbound tourism
Origin	Africa	212.2	187.4	122.2	190.3	197.6	78.4	93.7	139.0
	Asia	185.4	136.6	124.6	177.2	185.2	82.7	91.1	118.9
	Europe	154.8	159.1	93.6	143.4	182.4	51.1	67.0	102.7
	Latin America	195.7	176.8	126.9	160.0	186.9	78.9	98.5	109.1
	Near East	177.0	165.3	126.0	169.4	187.7	70.4	82.0	113.8
	Oceania	137.2	128.9	75.7	115.7	138.1	42.0	61.0	85.4
	USA & Canada	147.0	132.1	90.9	146.1	138.7	53.7	57.1	96.1
	Total inbound tourism	161.3	139.6	95.6	151.7	175.6	70.6	77.9	106.4

Source: own creation

Table 5
Impact on value added in the first scenario.

	TOTAL SAFETY	Destination								
		Africa	Asia	Europe	Latin America	Near East	Oceania	ROW	USA & Canada	Total outbound tourism
Origin	Africa	173.2	167.3	132.1	165.6	192.9	86.8	162.4	94.0	139.0
	Asia	155.2	135.1	122.3	148.9	159.9	85.5	147.1	91.5	118.9
	Europe	133.3	124.4	94.2	112.2	168.5	64.8	122.9	67.5	102.7
	Latin America	128.6	131.4	124.7	150.7	168.9	86.4	115.7	98.5	109.1
	Near East	144.4	141.7	128.0	142.5	176.8	82.4	144.1	82.2	113.8
	Oceania	115.8	115.1	81.6	100.5	114.4	44.6	88.2	61.4	85.4
	USA & Canada	129.0	118.1	93.3	132.5	127.8	62.8	113.6	57.8	96.1
	Total inbound tourism	138.0	128.1	98.7	128.9	159.7	75.8	126.9	78.5	106.4

Source: own creation

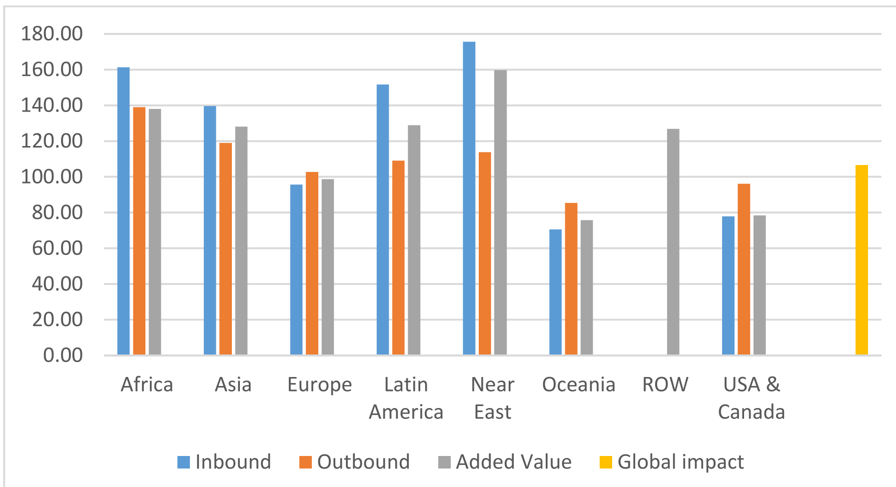

Fig. 4. Percentage change in tourism flows and value added generated in the first scenario.
Source: own creation

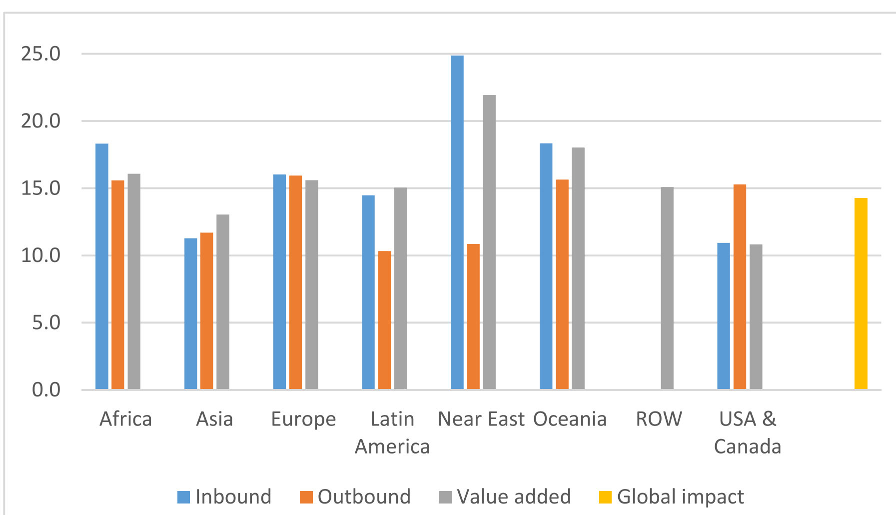

Fig. 5. Percentage change in tourism flows and value added generated if each country reaches its minimum level of insecurity and uncertainty.
Source: own creation

can see that the value added generated in the Near East by world tourism demand would fall by 24.7% in this scenario.

4.2.5. Fifth scenario (S5): highest levels of insecurity and uncertainty by region

In Fig. 8, we present the second approximation that considers maximum values for the uncertainty and insecurity proxies, but this time for each of the 17 different regional classifications made by the United Nations (see Annex 3) instead of the maximum values of the proxies for each country, which can be seen in Fig. 7. Thus, we cover how the countries are affected not only by their domestic levels of insecurity and uncertainty, but also by the degree of insecurity and uncertainty in

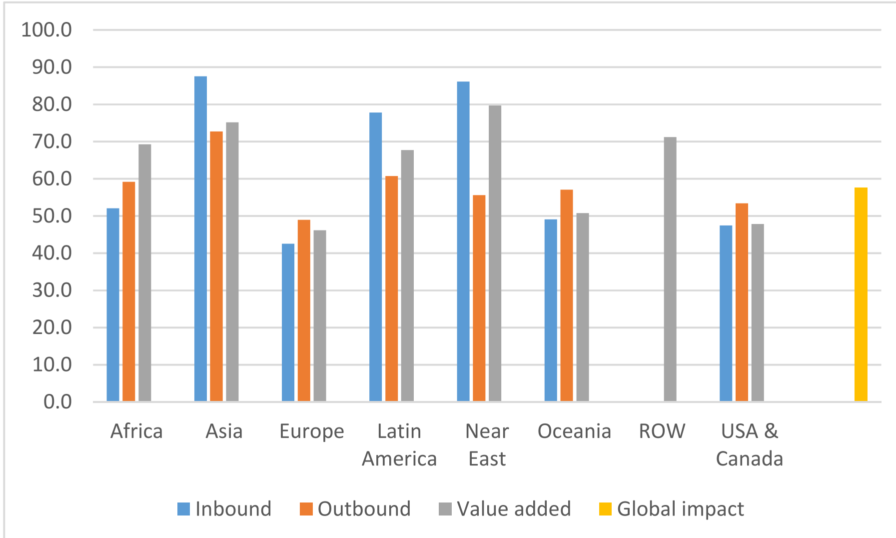

Fig. 6. Percentage change in tourism flows and value added generated if each country were to have the minimum average value of insecurity and uncertainty from the region to which it belongs.
Source: own creation

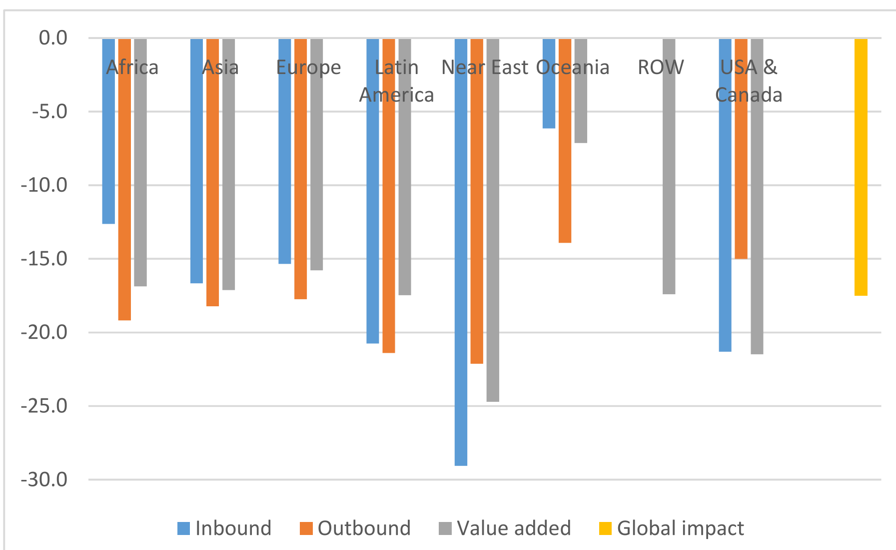

Fig. 7. Percentage change in tourism flows and value added generated if each country reaches its maximum level of insecurity and uncertainty.
Source: own creation

surrounding countries. Here, we can see a total decrease of 47.1% in tourism demand and value added.

The most affected region in this scenario would be Europe, with a 54.2% drop in its outbound tourism, followed by Africa, with a 45.3% decline in outbound tourism. Considering inbound tourism, we can see that the Near East would experience the greatest negative impact: a fall of 99.5% in its inbound tourism. The region with the least negative impact would be Oceania, with a fall in inbound tourism of 13.5%.

Finally, we can study the differences in the variations in the value added that would be generated in this scenario. The value added generated in the Near East and Oceania by total tourism demand would fall by 87% and 16.6%, respectively.

5. Conclusions

The ICIO database represents the first time that the consumption of non-residents has been calculated in a multiregional IO framework. Thanks to this, the value added that stems from tourism expenditure by country of origin can be analyzed for all of the countries included in the database, and this is precisely our starting point. The contribution of this article is its bringing together of the gravity model and the input-output model to analyze how uncertainty and insecurity around the world—measured with variables for terrorism, corruption, and global uncertainty (WUI)—would affect world tourism demand, and thus, the value added generated under varying levels of insecurity and uncertainty.

To summarize our main results, we have found that worldwide tourism demand would increase by 106.4%, along with value added generated, if there were total certainty and security in all countries. If the values of uncertainty and insecurity in each of the countries across the world fell to their minimum levels, there would be a total increase of 14.3% in tourism demand and value added. If the values of the variables in each of the countries fell to the minimum level observed in the region to which they belong, there would be a total increase of 57.7% in tourism

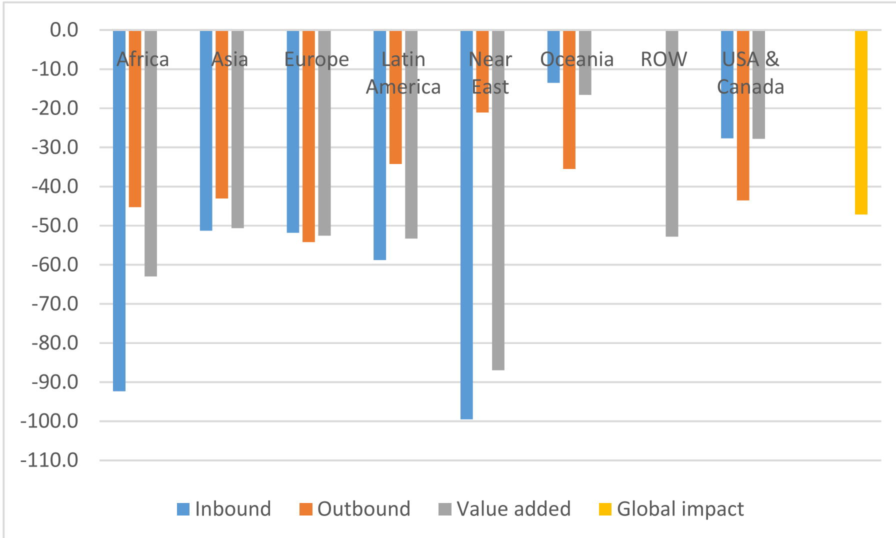

Fig. 8. Percentage change in tourism flows and value added generated if we apply to each country the maximum average value of insecurity and uncertainty from the region to which it belongs.
Source: own creation

demand and value added. Moreover, if the values of uncertainty and insecurity in each of the countries in the world increased to their maximum levels, there would be a total fall of 17.5% in tourism demand and value added. If the values of the variables of interest in each of the countries increased to the maximum level observed in the region to which they belong, there would be a total drop of 47.1% in tourism demand and value added.

With regard to management implications of the present research, it seems clear that making investments to improve security and reduce uncertainty—not only in one's own country, but in nearby countries, too—contributes to improving the economic impact of tourism. Moreover, quantifying in monetary terms the effect of changes on tourism demand under different scenarios, would allow to better designs policies to promote the sector and to better evaluate their effectiveness. Today, more than ever, in the face of the pandemic that we are experiencing, this issue should be taken into account. Finally, this research aims to provide a methodological framework for quantifying the impact, in terms of value added, of changes in tourism demand caused by variations in its determinants. For instance, this methodology can be used in future research to explore the economic impact caused by shocks such as financial crises, natural disasters, and political instability, among others.

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Declarations of competing interest

None.

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Annex 1. Countries

OECD code	OECD countries	Non-OECD code	Non-OECD economies
AUS	Australia	ARG	Argentina
AUT	Austria	BRA	Brazil
BEL	Belgium	BRN	Brunei Darussalam
CAN	Canada	BGR	Bulgaria
CHL	Chile	KHM	Cambodia
CZE	Czech Republic	CHN	China (People's Republic of)
DNK	Denmark	COL	Colombia
EST	Estonia	CRI	Costa Rica
FIN	Finland	HRV	Croatia
FRA	France	CYP	Cyprus[2]
DEU	Germany	IND	India
GRC	Greece	IDN	Indonesia
HUN	Hungary	HKG	Hong Kong, China
ISL	Iceland	KAZ	Kazakhstan

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OECD code	OECD countries	Non-OECD code	Non-OECD economies
IRL	Ireland	MYS	Malaysia
ISR	Israel[1]	MLT	Malta
ITA	Italy	MAR	Morocco
JPN	Japan	PER	Peru
KOR	Korea	PHL	Philippines
LVA	Latvia	ROU	Romania
LTU	Lithuania	RUS	Russian Federation
LUX	Luxembourg	SAU	Saudi Arabia
MEX	Mexico	SGP	Singapore
NLD	Netherlands	ZAF	South Africa
NZL	New Zealand	TWN	Chinese Taipei
NOR	Norway	THA	Thailand
POL	Poland	TUN	Tunisia
PRT	Portugal	VNM	Viet Nam
SVK	Slovak Republic	ROW	Rest of the World
SVN	Slovenia	CN1	China - Activities excluding export processing
ESP	Spain	CN2	China - Export processing activities
SWE	Sweden		
CHE	Switzerland		
TUR	Turkey		
GBR	United Kingdom		
USA	United States		
MX1	Mexico - Activities excluding Global Manufacturing		
MX2	Mexico - Global Manufacturing activities		

Note: Data are presented for 64 countries (i.e. 36 OECD countries and 28 non-OECD economies), the Rest of the World and split tables for China and Mexico. In the data files, country x industry = NA means the information is not available for the observed combinaison. For "intermediates", "value added" and "output", data for Mexico and China are split into MX1,MX2 and CN1,CN2, respectively.
Notes.
1. The statistical data for Israel are supplied by and under the responsibility of the relevant Israeli authorities or third party. The use of such data by the OECD is without prejudice to the status of the Golan Heights, East Jerusalem and Israeli settlements in the West Bank under the terms of international law.
2. ***Footnote by Turkey:*** The information in this document with reference to "Cyprus" relates to the southern part of the Island. There is no single authority representing both Turkish and Greek Cypriot people on the Island. Turkey recognizes the Turkish Republic of Northern Cyprus (TRNC). Until a lasting and equitable solution is found within the context of the United Nations, Turkey shall preserve its position concerning the "Cyprus issue". ***Footnote by all the European Union Member States of the OECD and the European Union:*** The Republic of Cyprus is recognised by all members of the United Nations with the exception of Turkey. The information in this document relates to the area under the effective control of the Government of the Republic of Cyprus.

Annex 2. Industries

Industry_Code	Industry
D01T03	Agriculture, forestry and fishing
D05T06	Mining and extraction of energy producing products
D07T08	Mining and quarrying of non-energy producing products
D09	Mining support service activities
D10T12	Food products, beverages and tobacco
D13T15	Textiles, wearing apparel, leather and related products
D16	Wood and products of wood and cork
D17T18	Paper products and printing
D19	Coke and refined petroleum products
D20T21	Chemicals and pharmaceutical products
D22	Rubber and plastic products
D23	Other non-metallic mineral products
D24	Basic metals
D25	Fabricated metal products
D26	Computer, electronic and optical products
D27	Electrical equipment
D28	Machinery and equipment, nec
D29	Motor vehicles, trailers and semi-trailers
D30	Other transport equipment
D31T33	Other manufacturing; repair and installation of machinery and equipment
D35T39	Electricity, gas, water supply, sewerage, waste and remediation services
D41T43	Construction
D45T47	Wholesale and retail trade; repair of motor vehicles
D49T53	Transportation and storage
D55T56	Accommodation and food services
D58T60	Publishing, audiovisual and broadcasting activities
D61	Telecommunications
D62T63	IT and other information services
D64T66	Financial and insurance activities

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Industry_Code	Industry
D68	Real estate activities
D69T82	Other business sector services
D84	Public admin. and defence; compulsory social security
D85	Education
D86T88	Human health and social work
D90T96	Arts, entertainment, recreation and other service activities
D97T98	Private households with employed persons

Annex 3. Regions following the classification of United Nations

OECD code	United Nations
1	Australia and New Zealand
2	Central Asia
3	Eastern Asia
4	Eastern Europe
5	Latin America and the Caribbean
6	Melanesia
7	Micronesia
8	Northern Africa
9	Northern America
10	Northern Europe
11	Polynesia
12	South-eastern Asia
13	Southern Asia
14	Southern Europe
15	Sub-Saharan Africa
16	Western Asia
17	Western Europe

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