

Universitat de les Illes Balears

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NEW CONTRIBUTIONS ON THE DETERMINANTS OF INTERNATIONAL TOURISM DEMAND: WEATHER, TRAVEL DISEASES AND INCOME

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I DECLARE:

That the thesis titles *New Contributions on the Determinants of International Tourism Demand: Weather, Travel Diseases and Income,* presented by Aon Waqas Awan to obtain a doctoral degree, has been completed under my supervision [and meets the requirements to opt for an International Doctorate (include only if appropriate)].

For all intents and purposes, I hereby sign this document.

Signature

Palma de Mallorca, April 09, 2019.



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D E C L A R AT I O N

This thesis has been supervised by Dr. Jaume Rossello Nadal and Dr. Maria Santana Gallego at the University of the Balearic Islands to achieve the PhD. in the Official Postgraduate Studies in Economic and Legal Sciences (Applied Economics).

Palma de Mallorca, April 09, 2019.

Jaume Rosselló Nadal

Maria Santana Gallego

Aon Waqas Awan



For my mother and teachers, sources of inspiration throughout the life.



Tourism carries a tremendous potential that must be acknowledged as essential for the future of world heritage. But without proper management, we can easily get out of control.

- BONNIE BURNHAMI



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ABSTRACT

In the last two decades, there have been significant researches that focus on association between climate change and tourism. However, researchers also have shown how income is more important variable than temperature, for international tourism demand. This thesis deeply analyzes three of these topics that include both short-term and long-term prospective. This thesis, not only, evaluated climate change effect on tourist flow, but also consider travel related diseases impact on international tourism demand. Moreover, most significant variable, income has been explored separately, with some new insights. The analysis includes both time series and panel data, with multiple statistical techniques including ARIMAX and Gravity model. The studies result will contribute significantly by overcoming current limitations and enhanced information for policy making.



RESUM

En les últimes dues dècades, s'han dut a terme múltiples investigacions que han centrat la seva atenció en les interrelacions entre el canvi climàtic i el turisme. Amb tot, els investigadors han mostrat com la renda acaba sent el més important que la temperatura a l'hora de determinar la demanda turística internacional. Aquesta tesi analitza amb profunditat tres temes que inclouen tant prospectiva a curt termini com a llarg termini. Aquesta tesi persegueix així, en primer lloc, avaluar l'efecte del canvi climàtic sobre el flux turístic de manera directe a través de l'anàlisi de les condicions meteorològiques sobre l'interès turístic d'un destí, en segon lloc, considerar l'impacte de les malalties relacionades amb els viatges sobre la demanda turística internacional i, en tercer lloc, aprofundir en la variable més significativa en el models de demanda, la renda, per millorar les prediccions a llarg termini. L'anàlisi es du a terme amb l'estudi de les sèries temporals i amb dades del panell, amb diverses tècniques estadístiques, incloent ARIMAX i els models gravitacionals. Els resultats dels estudis s'esperi que contribueixen significativament al coneixement de l'àrea i permetin una formulació de polítiques més acurada.



R E S U M EN

En las últimas dos décadas, se han realizado importantes investigaciones centradas en las interrelaciones entre el cambio climático y el turismo. En este sentido, sin embargo, los investigadores han demostrado que la renta acaba siendo una variable más relevante que la temperatura la hora de determinar la demanda turística internacional. Esta tesis analiza en profundidad tres temas que inciden en la prospectiva de la demanda turística a corto y a largo plazo. Esta tesis, persigue así, no sólo evaluar el los efectos de las condiciones meteorológicas sobre los flujos turísticos, sino que también considerar el impacto de las enfermedades infecciosas sobre la demanda turística internacional y finalmente analizar el papel de la renta con el fin de presentar algunas ideas nuevas sobre su impacto a largo plazo. El análisis incluye tanto series temporales como datos de panel, con múltiples técnicas estadísticas, como ARIMAX y el modelo de gravedad. El resultado de estudios se espera que puedan estos contribuir significativamente a superar las limitaciones actuales y permitan una mejora en la formulación de políticas más ajustada.



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ACRONYMS

UNWTO	United Nation World Tourism Organization
WHO	World Health Organization
IET	Instituto de Estudios Turísticos
TRI	Travel Related Illness
EVDE	Ebola Virus Disease Epidemic
CDC	Center for Disease Control
GDP	Gross Domestic Product
GTD	Global Terrorism Database
ARIMA	Autoregressive Integrated Moving Average
PPML	Poison Pseudo Maximum Likelihood





1

INTRODUCTION

As one of the fastest growing economic sectors in the world, tourism is increasingly recognized as a key contributor to job and wealth creation, economic growth, and poverty alleviation. Tourism has showed uninterrupted growth over time, despite occasional shocks, demonstrating the sector's strength and resilience. International tourist arrivals have increased from 25 million globally in 1950 to 278 million in 1980, 674 million in 2000, and 1,326 million in 2017. Moreover, with currently 1.2 billion tourists crossing borders each year, tourism has a profound and wide-ranging impact on societies and on countries' environment and economy (UNWTO, 2017). This sector represents a 10.4% of world GDP, 1 in 10 jobs (307 million jobs) and 7% of global exports (WTTC, 2018). What is more, tourism has grown faster than trade for the past five years. So, tourism sector ranks third after chemicals and fuels and



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ahead of automotive products and food. Indeed, in many developing countries, tourism is the top export category.

Noting the relevance of tourism sector, the United Nation's World Tourism Organization (UNWTO, 2016; 2017) has suggested that tourism can lead to improvements in multiple social, economic, cultural, and environmental dimensions of community development. The regional economy, tourism industry, and ecological environment form mutually interactive and interdependent relationships (Lai et al., 2018). Therefore, the understanding of the coupling relationship between tourism and the environment is important due to the complex interaction in environmental effects induced by tourism (Tang, 2015). Moreover, the friendly environment is not only an important for tourism sustainable development, but also can be a unique attraction for tourists. Therefore, it is necessary to maintain or improve the quality of tourism environment for a destination (Butler, 1991).

Climate also has an important influence on environmental conditions that can deter tourists. Because climate represents both a vital resource to be exploited and an important risk to be managed, it is expected that the integrated effects of climate, with shifts in both climatic means and extremes, will have profound impacts on tourism businesses and destinations. In general, climate influences the tourism industry by creating the foundation of destination attractiveness, such as snow cover, water level and vegetation (Martin, 2005; Scott et al., 2005). In addition, the length and quality of the season are greatly dependent on climatic factors.

The issue of climate is assumed to affect tourism in two ways. According to König (1998), it has direct impacts on tourism activities, such as many winter activities (skiing, snowmobiling, cross-country skiing, ice-fishing), summer/beach activities (surfing, sunbathing, swimming) and the possibilities to participate in these activities (see Bürki, 2000; Maddison, 2001; Hamilton et al., 2005). These effects may be both positive and negative. Climate also has indirect impacts, by affecting the natural and built environment and changing the attractiveness of the landscape (i.e., the physical environment the tourism industry is based on). The impacts and their intensity may vary in different regions depending on the type of tourism, the financial dependence



on tourism revenues and the manner of climate in the region (Abegg et al., 1998).

But, climate science shows that, during the 21st century, changes in the Earth's climate will take place at an unprecedented rate (Solomon et al., 2007). According to UNWTO (2017), the growing international awareness about the fast pace of climate change taking place on our planet, together with the impacts that such changes are having on the natural environment, on humans and their economic activities have sa.become evident. For tourism, climate change is not a remote event, but a phenomenon that already affects the sector and certain destinations in particular, such as mountain regions and coastal destinations.

Several studies have made progress in the profiling of literature on climate change and tourism. If we center our attention on weather patterns at tourist destinations and tourist generating countries can significantly affect the tourists' comfort and their travel decisions. Changing demand patterns and tourist flows will have impacts on tourism businesses and on host communities, as well as knock off effects on related sectors, such as agriculture, handicrafts or construction (UNWTO, 2017). The direct effect of the climate is a determinant of tourist choices and indirect effect is changing the environment that leads toward environmental diseases. And all these issues are crucial to depict future tourism scenarios in the long run.

The effects of the climate change on tourism demand has been recently widely investigated for different perspectives (Saarinen and Tervo, 2006; Amelung et al., 2007; Gössling et al., 2012; Becken 2013; Becken and Wilson, 2013; Pang et al., 2013; Rosselló-Nadal, 2014). In general terms, literature has identified temperatures, sunshine, and rainfall as important determinants of tourism demand, especially in the summer season. It should be noted how some recent literature underscore the limitations of a statistical modelling approach for understanding the tourism-climate behaviour (Gomez-Martin, 2005; Dubois and Ceron, 2006; Gössling and Hall, 2006; de Freitas et al., 2008; Moreno 2010; Gössling et al., 2010; Denstadli et al., 2011; Rutty and Scott, 2013). These limitations include, among others, the validity and/or structure of statistical databases, the importance of other climatic variables beyond temperature, the unknown role of weather extremes and other information in tourist



decision-making and the uncertainty about future tourism determinants like costs of transport, income and availability of leisure time (Gössling and Hall, 2006).

In this thesis, we focus on some of these limitations for evaluating effects of climate change on tourism. Then, first, we center our attention to the short-run relationship between weather and tourist behavior. In this context, although weather conditions are widely seen as an important factor for tourism behavior (Moreno et al., 2008; Bigano et al., 2005; Bigano et al., 2006; Atzori et al., 2018), relatively little is known about the extent if weather effects are present in the step of destination decision choice. It should be noted that the use of new distribution channels, the liberalization of the airline industry and the elimination of border controls between Europe's main countries have reduced the booking lead times (time between booking and the date of travel) being usual nowadays to book a trip just a few days in advance (Money and Crotts, 2003; Malighetti et al., 2009). With this shorter booking lead times, new determinants of tourist trips could have emerged. Then, it can be reasonably assumed that tourism interest to specific destinations could be dependent of weather conditions at the destination, as a pull factor.

Second, we center our attention in the fact that favourable climate conditions for tourism often also imply favourable conditions for infectious diseases, with the ensuing development constraints on countries' tourist sectors. Although, in general, tourists are reluctant to travel to countries with different infectious diseases (Page, 2009), trips to less developed countries with a prevalence of these diseases are still growing (Leder et al., 2013). Health problems are self-reported by 22% to 64% of travellers to the developing world and infectious diseases are frequently the most commonly perceived health risk for potential tourists when choosing a destination (Steffen et al., 2003). The major public health organizations of the world have said that climate change is an important public health issue (Manogaran et al., 2017). The climate change will possibly enhance the transmission of malaria and other climate-sensitive vector-borne diseases (Samuel et al., 2018). Hernández-Triana et al., (2018) come up with a spatial representation of potential distribution of the tropical disease



vector in the face of climate change, including future exposure data for Brazil. Previous papers have explored the impact of some specific disease outbreaks on tourism. However, they focused on a specific country or region. Moreover, quantification of indirect effects needs to be addressed properly.

Third, according to Tourism and the Sustainable Development Goals – Journey to 2030 (UNWTO, 2017), the rate of growth is slowing down gradually, from 3.8% in 2011 to 2.5% in 2030. This is the result of a combination of four factors, one of those is "a lower elasticity of travel to GDP" (UNWTO, 2017). Moreover, between 2010 and 2030, arrivals in emerging destinations (+4.4% a year) are expected to increase at twice the rate of those in advanced economies (+2.2% a year). Tourism stands out for its substantial adaptive capacity, which must be combined with other uncertainties concerning the implementation of future mitigation policies and their impacts on transportation systems, together with the wide range of climate change impacts on destinations and broader impacts on society and economic development (Rosselló, 2014). However, previous studies (Hamilton et al., 2005; Bigano et al., 2006; Hamilton and Tol, 2007; Rosselló and Santana, 2014) has evidenced how, despite the knowledge of the climate scenarios, the most important determinant is personal income. Consequently, a deeper knowledge of future tourism trends under scenarios of climate change requires a deeper knowledge about how personal income determines tourism demand.

In this context, this thesis aims to advance in the knowledge of three different specific topics:

1. How meteorological conditions are affecting tourist's destination interest considering both meteorological conditions in the origin and the destination regions.

2. How the map of global tourism can be affected by changes in the incidence of some of the most popular Travel Related Illness (TRI), most of them related to climate conditions.

3. How can we increase the understanding and forecasting of international tourism movements worldwide by a more accurate analysis of income, which is the main



determinant of tourism demand.

In Chapter 2, a deep analysis on *Meteorological conditions and Tourists Behavior* is presented. According to UNWTO (2016), in small island states and developing countries, where tourism is a major economic activity, any significant reduction in tourist arrivals will have serious impacts on income and employment, and consequently it generates further poverty.

The disregard of tourism in the literature of climate change highlighted the exclusion of climate determinants inside tourism demand models since the beginning of the century (Goh, 2012). In the revision of Crouch (1994), only a few papers included climate or weather condition as determining variables, and, frequently, with limited success. A feasible justification for this exclusion would be related to the interest of researchers and planners in economic variables such as income and/or price elasticity with the intention of forecasting tourism demand in an accurate way - the main concern for services industry through comparatively high fix cost - or, otherwise, with the purpose of evaluating the consequences of tax or exchange-rate policy. However, because climate is a relatively stable determinant, environmental variables do not have the required variability to be modeled and it is not correlated with the determining variable, so no bias in the estimated elasticity is expected. This would partially justify why they have been traditionally omitted in tourism demand models. Nonetheless, during the last years the use of meteorological variables in modeling tourism demand has increased (Follador et al., 2018; Li et al., 2017; Rosselló and Waqas, 2015; Rosselló and Santana, 2014; Gössling et al., 2012; Moore, 2010; Scott, 2003).

One of the limitations about the use of meteorological determinants and tourism behavior is in the lead time: the time between a booking and the trip. Thus, in the context of a lead time of some weeks or even months, it seems clear that although no meteorological predictions are available for trying to relate tourism behavior and meteorological conditions, the lead time is reducing. Last minute booking have become more popular. Consequently, one should expect that tourist reacts to changes in weather conditions that lead toward online searchers. The advancements of the



information technology have brought massive amount of big data generated by users, including search queries, social media mentions, mobile device positions, and others (Mayer-Schonberger and Cukier, 2013). In particular, search query data provide valuable information about tourists' intention, interests, and opinions. Tourists use search engines to obtain weather and traffic information and to plan their routes by searching for hotels, attractions, travel guides, and other tourists' opinions (Pan et al., 2011). Search query data, including content and volume data, are especially valuable to researchers. They can capture tourists' attention to travel destinations and can be extremely useful in accurately forecasting tourist volumes in a destination. The abundant search trends data are favorable sources for tourism forecasting in the Big Data era. However, they also bring challenges in the modeling process of tourism forecasts.

In Chapter 2, the relationship between the interest in visiting Majorca, evaluated through Google searches, and the meteorological conditions both in the country of origin (UK and Germany) and at the destination is investigated. Majorca is a popular "sun, sea, and sand" destination in the Mediterranean, known for its warm climate conditions. Thus, this research contributes to further knowledge of the interaction between weather and tourism by exploring the role of weather in determining interest in a popular "sun, sea and sand" destination, showing how weather conditions can contribute to the level of searches of this destination.

Chapter 3 presents an analysis on indirect effect of climate change though the analysis of *Disease incidence and Tourism Demand*. Climate change is a reality that affects our ecosystem as well as human health. The increasing release of greenhouse gases from the combustion of fossil fuels has already resulted in an increase in average global temperature. The impact of global warming is seen in the increased incidence of storms, hurricanes, floods, drought, natural disasters, polar changes and a substantial rise in sea levels (Asad and Carpenter, 2018).

The literature on the effect of health-related disasters or epidemics on tourism demand is scarce. Few papers have explored this issue, although there are some exemptions such as the effect on tourism of the Severe Acute Respiratory Syndrome



(SARS) in South-East Asia (Dombey, 2003; McKercher and Chon, 2004), the Foot and Mouth Disease in the UK (Frisby, 2002; Irvine and Anderson, 2005), influenza in Mexico (Monterrubio et al., 2010) and bed bug issues (Liu et al., 2015).

However, during the last fifteen years, there have been a number of health-related crises that caused risks to local communities and significant damage to the tourism sector (Glaesser, 2006; Kuo et al., 2008; Smith, 2006). As travel and tourism can facilitate the spread of epidemics, global institutions such as the World Health Organization (WHO) and the UN World Tourism Organization (UNWTO) are increasingly interested in understanding the cause, evolution and risk of an infection (Joffe and Haarhoff, 2002; Mason et al., 2005; Page et al., 2006); and advocating swift precautionary actions to reduce a health risk, often at the expense of complete scientific understanding (Sunstein, 2005).

Many of these recent crisis and disasters affecting tourism have been studied, but few papers explicitly explore health related crisis in developing countries. Novelli et al., (2018) analyzed the effect of the Ebola Virus Disease Epidemic (EVDE) on The Gambia, where, despite no reported cases, EVDE had devastating consequences. They highlighted the importance of consumer perception and preparedness and management failures' consequences, contributing to the broader debate on the indirect threat of epidemics on tourism in developing countries.

This chapter covers disease threats to international tourism demand. Increasing globalization, rapid urbanization and a warming climate now add to the complexity of disease control and prevention (Tong et al., 2016) .The Study used 4 travel related diseases (Malaria, Yellow Fever, Dengue, and Ebola), mostly environmental diseases, and applied eradication model. The impact of the diseases' eradication on the tourist demand was used to estimate the ensuing tourism expenditures and thus to provide a direct quantification of the benefits of different health policies in economic terms that could be compared with treatment costs in line to a strategy for implementing a global budget (Bishop and Wallack 1996; Bowser et al. 2013). Then, the novelty of this chapter lies in providing an economic estimation of the impact of the eradication of the main travel-related disease risk of infection at a global scale.



Finally, in order to get a more precise picture about the long run tourist map, Chapter 4 explores the special relationship between income and tourism (Long-term forecasting). Clearly, the climate change will affect international tourism, but that this effect is small compared to other expected changes in the industry, such as those due to population growth and change in per capita income (Hamilton et al., 2005). Consequently, we need to know more about income elasticity if we want to get a more accurate picture of future scenarios of tourism, considering climate change.

The last five decades have seen a rapid increase in worldwide tourism demand. As a result, international tourism has become increasingly important for worldwide economic development. Both the public and private sectors have channeled substantial resources into the industry. Furthermore, as both governments and businesses need high-quality tourism demand analysis to develop efficient public policy and make good business decisions, considerable efforts have been made to analyze tourism demand and develop explanatory models which help to inform these critical decisions (Peng et al., 2015).

The identification, analysis, and measurement of the impacts of the determinants of tourism demand are central to any effort to understand and explain changes in demand in the past and to anticipate the possible pathways of future tourism demand development. A number of variables have generally been examined and accepted in previous research as the main determinants of international tourism demand. However, significant distinctions can be drawn between the influences of different determinants for different visit purposes (Peng et al., 2015).

How does income influence individual's travel pattern? The majority of the research in the tourism area has found a positive association between income and tourism (Crouch, 1995). Chang and Chen (2013) pointed out leisure motivation have contributed to the positive effects of income on tourism. Crouch (1992) suggested the international tourism is mainly decided by discretionary income due to luxury good nature of international tourism. Kim et al., (2012) had proven that exception of future income influences outbound income via the personal income effects. Broadly speaking, literature on tourism approach believed that tourism demand is a function



of real disposable income (Park et al., 2011).

Martin et al., (2017) partitioned data by income level and by Continent to check whether the relative importance of each macroeconomic variable is indifferent to these two world features. Quite interesting, their results suggest that world income is important to high income countries and relative prices to low and middle income countries and that relative prices have a much lower impact in Europe, when compared to other continents.

Consequently, the objective of this chapter is to investigate the relationship between personal income and tourism demand income elasticity and evaluate the veracity of the hypothesis proposed in Morley (1998). The novelty lies in this chapter, is about personal income impact on international tourism demand, study used data of almost all destinations and origins from 1995-2016.

Finally, Chapter 5 summarizes the main results and conclusions obtained in the thesis. Moreover, an overview of climate change and long-term issues related to tourism demand is provided.



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2

THE INFLUENCE OF WEATHER ON INTEREST IN A "SUN, SEA AND SAND" TOURIST DESTINATION: THE CASE OF MAJORCA

Abstract: Last-minute decisions to take vacations overseas have become popular in recent years. Because of the reduction of the time between the booking and the trip (lead time), and because climate conditions are acknowledged to be key factors in tourism decisions, this chapter aims to investigate whether weather anomalies are becoming a new key determinant in tourism destination interest. Using data from Google Trends, different time series models are estimated analyzing if potential tourists' interest in Majorca, a popular Mediterranean "sun, sea and sand" destination, is determined by previous and contemporaneous weather conditions both at the destination and in two main tourists' countries of origin, Germany and UK. Results show how favorable weather conditions at destination but also adverse weather conditions at origin are significantly related to a higher interest in Majorca.

Keywords: Tourism, Destination interest, booking lead time, weather, extreme weather, Google Trends.



2.1. Introduction

Many aspects of the tourist industry are climate dependent, especially for many warm destinations in the northern hemisphere that attract regular flows of tourists from northern to southern latitudes, above all during the summer months. Interest in climate change issues and, more particularly, in the economic consequences of climate change, has fuelled a growing number of studies that evaluate the effects of climate change on tourism demand (Maddison, 2001; Lise and Tol, 2002; Amelung et al., 2007; Hamilton and Tol, 2007; Hopkins and Maclean, 2014; Rutty and Scott, 2014; Priego et al., 2015), showing that traditional warm destinations face an expected drop in attractiveness and international tourist market share.

In contrast with long-term climate issues, the short-run relationship between weather and tourism has its own interest appeal. In the specific case of the airline industry, extreme wind speeds can prevent aircraft from landing at their designated airports and, in general, adverse meteorological conditions cause delays, cancellations and accidents entailing big cost implications (Changnon, 1996; Eads et al., 2000; Kulesa, 2002; Koetse and Rietveld, 2009; Coffel and Horton, 2015). In fact, air transport sector is usually highlighted as being one of the highest users of climate information services (Chagnon and Chagnon, 2010) being possible to estimate the economic benefits of meteorological services in millions of USD for some specific airports (Von Gruenigen et al., 2014).

Within the tourist industry, not only airlines companies are affected by weather anomalies and weather extremes. Rind (1996), using the case study of a casino hotel in Atlantic City, shows how that greater degrees of sunshine are associated with greater amounts of compliance and tipping. Chen and Lin (2014) study the effects of weather on room demand in the Taiwanese hotel industry evidencing how typhoon and rain are negatively associated with group visitors while temperature and sunshine hours lead to an increase of group visitors. Falk (2015) analyzes of the impact of weather conditions on overnight tourists stays for nine provinces across German and



Austria. Results show that sunshine hours and temperatures in a given month have a significant and positive impact on domestic overnight stays in the same month for most of the provinces except for the capital of Vienna. Furthermore, sunshine hours can affect overnight stays mainly with a 1 year lag. The largest weather effects could explain up to 47 % of the variation in overnight stays for certain regions.

In this context, although weather conditions are widely seen as an important factor for tourism behavior, relatively little is known about the extent if weather effects are present in the step of destination decision choice. It should be noted that the use of new distribution channels, the liberalization of the airline industry and the elimination of border controls between Europe's main countries have reduced the booking lead times (time between booking and the date of travel) being usual nowadays to book a trip just a few days in advance (Money and Crotts, 2003; Malighetti et al., 2009). With this shorter booking lead times, new determinants of tourist trips could have emerged. Then, it can be reasonably assumed that tourism interest to specific destinations could be dependent of weather conditions in the country of origin, as a push factor, and/or weather conditions at the destination, as a pull factor.

In this chapter, the relationship between the interest in Majorca, evaluated through Google searches, and the meteorological conditions both in the country of origin (UK and Germany) and at the destination is investigated. Majorca is a popular "sun, sea and sand" destination in the Mediterranean, known for its warm climate conditions. Thus, this research contributes to further knowledge of the interaction between weather and tourism by exploring the role of weather in determining interest in a popular European "sun, sea and sand" destination, showing how weather conditions can contribute to the level of searches of this destination.



2.2. Weather and tourist demand behavior

The effects of the weather on demand has been widely investigated for different locations and tourism related sectors like transport, hotel industry, sky resorts,... (for recent surveys see Gössling et al., 2012; Becken 2013; Becken and Wilson, 2013; Pang et al., 2013; Rosselló-Nadal, 2014). In general terms, literature has identified temperatures, sunshine, and rainfall as important tourism behavior factors, especially in the summer season. Good weather conditions in a destination lead frequently to increases in tourism demand while outbound tourism demand can also be related to weather conditions, especially if some lags are considered. In the context of time series analysis, the pioneering study of Subak et al., (2000) analyze the impacts on different service sector activities of the anomalously hot summer of 1995 and warm period from November 1994 through to October 1995 in the UK. They show clear differences in the response to anomalous warm weather in winter and summer, with greater tourism demand sensitivity to winter anomalies.

However, because tourism is not exclusively explained by climate variability, the use of statistical models and the consideration of other tourism determinants have dominated the study of the relationship between tourism and climate and weather factors (Rosselló-Nadal, 2014). It should be noted how some recent literature underscore the limitations of a statistical modelling approach for understanding tourism-climate behaviour (Gomez-Martin, 2005; Dubois and Ceron, 2006; Gössling and Hall, 2006; de Freitas et al., 2008; Moreno 2010; Denstadli et al., 2011; Scott et al., 2012; Rutty and Scott, 2013). These limitations include, among others, the validity and/or structure of statistical databases, the importance of other climate variables beyond temperature, the unknown role of weather extremes and other information in tourist decision-making and the uncertainty about future tourism determinants like costs of transport, income and availability of leisure time (Gössling and Hall, 2006). These limitations remain unaddressed in the context of the evaluation of the effects of climate change on tourism demand and, consequently



results have to be taken as average approximations. However, in the context of the direct quantification of the short run relationship between weather and tourist behavior these limitations can be overcame.

In the context of time series analysis, Agnew and Palutikof (2006) analyze a set of climate indices, exploring current climate variability and its relationship with domestic and international tourism demand. They show that outbound tourist flows are more responsive to the preceding year's climate variability, whereas domestic tourism is more responsive to variability within the year of the trip. Rosselló et al. (2011) focus on outbound flows from the UK. They estimate the sensitivity of this tourist time series to weather anomalies, showing that mean temperature, heat waves, air frost and sunshine days are the weather variables that can be significantly related to the dynamics of time series for outbound British flows.

Other case studies that explore the relations between weather and tourism demand have also been reported, based on the hypothesis that meteorological and climate conditions can act as both pull and push factors in determining tourist decisions. Rosselló (2011) studies the effects of the North Atlantic Oscillation on European air traffic, finding that the breakdown of the North Atlantic Oscillation index into positive and negative fluctuations can be related to changes in revenue passenger kilometers. Otero-Giráldez et al., (2012) also show there to be a significant positive connection between the North Atlantic Oscillation as a meteorological indicator and tourism demand in Galicia (Spain), using time series modeling. Kulendran and Dwyer (2012) identify the relationship between climate variables such as maximum temperatures, relative humidity, sunshine hours and seasonal variations, defined as the repetitive and predictable movement around the trend line in holiday tourism demand to Australia.

Álvarez and Rosselló (2010) explore the possibility of improving a tourism demand model's predictive capacity by using meteorological explanatory variables, based on a case study of monthly tourist arrivals to the Balearic Islands. To do this, classic time series models and causal artificial neural networks are fitted and the results are



compared with those obtained using non-causal methods. The study indicates that the inclusion of meteorological variables can boost the predictive power. However, these results are not conclusive due to the lack of statistical significance of the tests used to measure the increase in predictive power.

Finally, Falk (2014) investigates the impact of weather on overnight stays in Austria during the peak summer season employing static and dynamic tourism-demand models showing how first-difference regression models show that average sunshine duration and temperatures have a positive impact on domestic overnight stays, whereas precipitation had a negative effect. For foreign overnight stays, he finds that the positive impact of temperatures and sunshine duration occurs only after a 1-year lag, with larger effects for visitors from neighboring countries.

Using Google Trends data on the interest on Majorca, this chapter aims to contribute to the literature on the interaction between weather and tourism in two main ways. First, it centers the attention on the purchasing time (approximated by the Google searches) and not in the trip time. Although searches on a tourism destination are not a direct indicator about purchasing behavior, previous research has found a strong correlation between both (Peng et al., 2013; Valex and Axelsson, 2014). Specifically, Bangwayo-Skeete and Skeete (2015) shows how Google searches on destination hotels and flights from source countries improves forecast results for tourism demand time series models indicating that it is possible to use Google query search data to accurately project future monthly tourist arrivals in the Caribbean. This point is especially relevant for revenue managers to understand consumer behavior and to establish the efficient price. Second, because Google trends statistics shows data at weekly periodicity, similar to Bangwayo-Skeete and Skeete (2015), it is possible to work with higher frequency data than previous meteorological and tourism literature (which has used monthly, quarterly and yearly data), a periodicity probably better suited to evaluate meteorological variability and its impacts.



2.3. Methodology

According to the previous literature the relationship between Google searches and weather data is explored through regression analysis. However, given that the interest appeal of this study resides in the short-run relationship between weather and tourism searches, the direct consideration of multiple regression model linking the original tourism variable and its determinants would not be suitable. This is because it is expected that main part of total variation of a tourist variable during a year would be probably characterized by a high level of seasonality that is determined, among other factors, by school and working holidays, special events and climate factors (but not weather ones). Consequently, a regression analysis between the original variables, in the case that the spurious relationship could be controlled, would lead to establish, mainly, the relationship between tourism seasonality and climate.

If the attention has to be focused on the impact of weather factors, a de-trending strategy has to be considered. With the use of high frequency data the use of an autoregressive integrated moving average (ARIMA) model have been presented as suitable tool (Díaz et al., 2005; Hor et al., 2005; Rosselló et al., 2011). First described by Box and Jenkins (1970), ARIMA models have been widely used in tourism demand modeling and forecasting for many years (Song and Li, 2008). The traditional formulation of an ARIMA model applied to Google searches can be specified as:

$$\phi_p(L)G_t = \theta_q(L)a_t$$
[2.1]

Where G_t are the Google searches for a given week t, a_t is the innovation or moving average term, and $\phi_p(L)$ and $\theta_q(L)$ are the lag operator polynomials for both and respectively. For estimation purposes, Expression 2.1 can be reformulated as:



$$G_{t} = \sum_{i=1}^{p} \rho_{i} G_{t-i} + \sum_{j=1}^{q} \theta_{j} a_{t-j} + \varepsilon_{t}$$
[2.2]

Where ρ and θ are parameters to be estimated and ε_r is the error term distributed normally and independently. As is habitual in time series modeling, conventional steps must be followed to identify the most suitable orders for the ARIMA model (Brockwell and Davis, 2009). Due to the tourism time series' strong seasonal behavior, different artificial variables can be considered in order to account for monthly effects. Thus M01, M02, M03, M04, M05, M06, M07, M08, M09, M10, M11 and M12 are artificial variables that account the number of days in each one on the different months. For instance, if a certain observation corresponds to a week where all the days belong to January, then M01=7 and the rest of dummy variables will be 0; if another one corresponds to a week with 3 days in July and 4 days in August, then M07=3, M08=4, and the rest of dummy variables will be 0. Once the long-run seasonal behaviors of the Google search time series have been captured, the information for the behavior of the weather variables can be included in the specification using the transfer function method (Box et al., 2013). From Equation 2.1 we get:

$$\phi_p(L)G_t = \theta_q(L)a_t + \beta_s m_s + \varphi_b^k(L)d(k)_t$$
[2.3]

where m_s refers to the monthly dummy variables mentioned above and β_s are the estimated parameters of each dummy variable, while d(k) is a vector of k weather variables that can potentially determine Google searches, and $\varphi_b^k(L)$ are the lag operator polynomials (or transfer function) for each of the determining d(k) variables. The parameterized version of the equation for estimation purposes can be written as:

$$G_{t} = \sum_{i=1}^{p} \rho_{i} G_{t-i} + \sum_{j=1}^{q} \theta_{j} a_{t-j} + \sum_{s=1}^{12} \beta_{s} m_{s} + \sum_{wl=1}^{r1} \pi_{wl} dl_{t-wl} + \sum_{w2=1}^{r2} \pi_{w2} d2_{t-w2} + \dots + \sum_{wk=1}^{rk} \pi_{wk} dk_{t-wk} + \varepsilon_{t}$$

$$(2.4)$$



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where π are the weather parameters of the transfer function to be estimated. In this chapter, initially, a maximum lag of 5 weeks is considered. In other words, it is hypothesized that the meteorological conditions, both in the origin and the destination, can determine Google searches from the same week to five weeks after. Afterwards, because a high correlation between weather variables is expected, the general-to-specific strategy (Hoover and Perez, 1999) is used to reduce the non-significant parameters and to get a reduced form of equation 2.4.

2.4. Data

Google trends site (http://www.google.com/trends/) provides the search intensity of any keyword for any specific geographical source market from January 2004 onwards. A weekly reporting interval is shown and the results are updated every Sunday. Because of the special aim of this chapter in analyzing the popularity of a "sun, sea and sand" tourist destination, the interest in Mallorca evaluated though Google searches website is taken as reference.

Mallorca is a popular "sun, sea and sand" destination in the Mediterranean, known for its warm climate conditions. According to official statistics (El Turisme a les Illes Balears, 2015), it had an annual volume of 9.6 million foreign tourists in 2014 (a figure that contrasts with the local population of 0.87 million inhabitants), with Germany (3.7 million tourists) and Britain (2.1 million) being the most popular markets of origin. Main differences between the two source markets include a more seasonal behavior for British tourists, who are more motivated by climate issues than German, who present a significant rate of second homes. Anyway, it is not surprising that, when the statistics from Google trends for Mallorca (or Majorca, in the case of UK) are reported, the most related searches are referred to weather and accommodation services.

Specifically, in this chapter, records for each search for "Mallorca" and "Mallorca



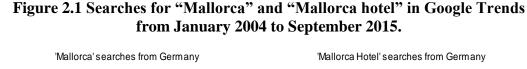
hotel" made in Germany and "Majorca" and "Majorca hotel" in the UK were gathered.

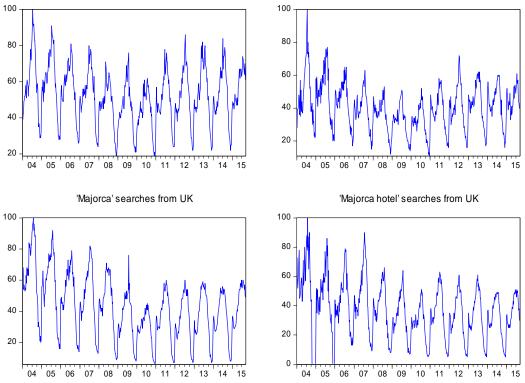
Thus, searches made at national level were taken as a reference. In this point it is important to note how it is possible to get data from Google trends on searches for some specific regions for both countries, a point that would make it possible to take more accurate weather data on origin. However, it is assumed that the weather conditions remain more similar at national level while differences in weather conditions between origin and destination can be more important. Consequently, this led to four time series, with an entry for each week that can be seen in Figure 2.1. As expected, a strong seasonal behavior pattern can be observed, highlighting the role of climate in the intensity of searches relating to Majorca.

It is important to note that Google reports both the raw search volume as well as search volumes that are normalized and scaled. Then, first interest is calculated as (number of queries for keyword) / (total Google search queries). Second, all of the interest data for the keywords is divided by the highest point of interest for that date range. This implies that if the overall search intensity for all the keywords is low in a given week due to a holiday period, the raw data is scaled appropriately to ensure meaningful inter-temporal comparisons.

Additionally it should be noted how, in some cases, it is possible to show a declining interest in trends for a specific topic even if absolute query volume is increasing (that can happen of global searches has a higher grow rate that this specific topic). Anyway, it is assumed that this scaling system does not interfere with this research study, since a given level of search intensity should make more of an impact in a period of low overall search intensity than a high one. Appendix 2.1 shows descriptive statistics of selected variables.







Source: Retrieved from https://www.google.com/trends/ on the 18th September 2015

The meteorological variables considered in this study take first daily average temperature, rainfall and maximum wind speed during a day. This original data was obtained from the respective National Weather Services in Spain (http://www.aemet.es/), the United Kingdom (http://www.metoffice.gov.uk/) and Germany (http://www.dwd.de/). The stations used as reference were based in the airport station of Palma de Mallorca (PMI), London Heathrow Airport (LON) and main Frankfurt weather (FRAN). Weekly records for average temperatures (AT), Rainfall (RAIN) and wind speed (W) were computed as averages within each week and can be observed in Figure 2.2.



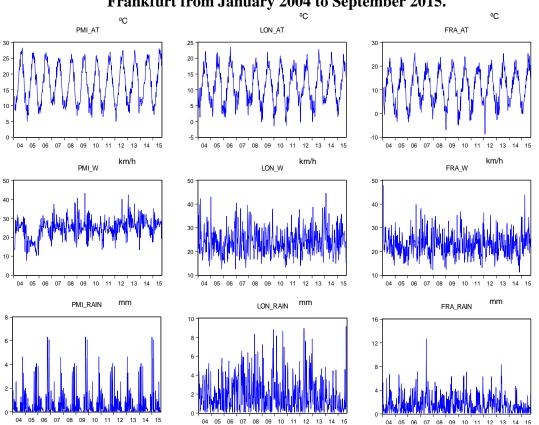
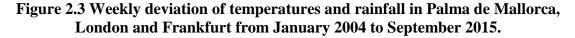


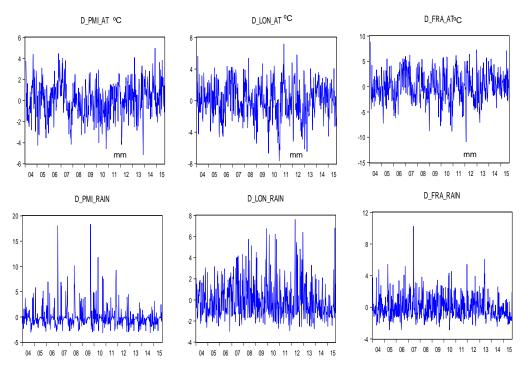
Figure 2.2 Weekly meteorological conditions in Palma de Mallorca, London and Frankfurt from January 2004 to September 2015.

Notes: PMI, LON and FRAN refer to Palma de Mallorca, London and Frankfurt, respectively. AT, W, and RAIN, refers to Average Temperature in Celsius Degrees, Wind maximum speed in km/h and rainfall in mm, respectively. Weekly records are obtained as daily averages.

Because of the strong seasonal component shown by the average temperature and rainfall variables and the specific aim of the study the expected mean temperature and mean precipitation for each week of the year were estimated using the values for the whole sample. Secondly, each observation's deviation from the expected meteorological conditions for each week was computed (Figure 2.3). Thus, temperature and rainfall are not considered directly but as the difference between the real temperature and the expected one. As it is shown in Figure 2.3, as expected, the highest variability for the temperature is observed in Frankfurt, while the highest variability of rainfall is observed by Palma de Mallorca Station. Anyway, it is clear that using these transformations the strong seasonal component is avoided.







Notes: D, refers to de difference between the real data and the weekly average during the period of analysis. PMI, LON and FRAN refer to Palma de Mallorca, London and Frankfurt, respectively. AT, W, and RAIN, refers to Average Temperature in Celsius Degrees, Wind maximum speed in km/h and rainfall in mm, respectively.

2.5. Empirical results and discussion

Based on the above considerations, Tables 2.1 and 2.2 present regression models that explain German and UK interest in web searches relating to "Mallorca" and "Mallorca Hotel" ("Majorca" and "Majorca Hotel" in the case of UK). The estimation results can be rated as satisfactory in terms of the significance of the parameters, the R-squared values, and the LM tests (used to validate the nonexistence of residuals autocorrelation). As expected dummy variables for the different months explain main part of the variation of the dependent variable in the four time series analyzed. Thus, the highest coefficients are obtained for the summer months and the lowest for the winter months. ARIMA terms show how no moving



average terms remain significant after the model reduction process while different autoregressive terms (AR) are kept.

In reference to the causal effects of the meteorological conditions, the general-tospecific strategy was applied using the backward stepwise technique, trying to obtain the best Akaike Info criterion. With this procedure, although all lags in all the explanatory variables were initially included only those significant at 10% level were kept. Then, less significant lags were discarded from the model in each round and new transfer functions were estimated without the discarded variables. The process was repeated until a model was found where all the variables were statistically significant at a 10 percent level at least.

In the four analyzed cases of Tables 2.1 and 2.2, the statistical significance of different of the weather variables evidences the relevance of weather conditions both in the country of origin and at the destination in determining Google searches on "Mallorca" and "Mallorca hotel". Sings of parameters show how, on the one hand, adverse meteorological conditions in the country of origin were found to be a determinant of a stronger interest in Mallorca. On the other hand, good meteorological conditions at the destination boost Google searches for data relating to Mallorca, especially in the case of UK. Thus, statistically, weather conditions in the country of origin were found to act as a push factor, while weather conditions at the destination are a pull factor.

In the case of Germany (Table 2.1), it seems clear that contemporary weather conditions in the origin, captured by wind conditions (FRA_W) and abnormal levels of temperatures (D_FRA_AT) and rainfalls (D_FRA_RAIN), but also with the weather conditions in the destinations captured by the abnormal level of temperature in the previous week (D_PMI_AT[-1]), determines the interest in "Mallorca". In other words it seems that colder, windy and wetter conditions in Germany, but also, hotter conditions in Mallorca are related to a stronger interest in Majorca for Germans.



		"Mallorca" sear	ches	"Mallorca hotel" searches			
	M01	7.118 *	***	5.620	***		
	M02	6.948 *	***	4.826	***		
	M03	7.358 *	***	4.958	***		
	M04	7.467 *	***	4.840	***		
m _s	M05	8.173 *	***	5.729	***		
	M06	8.095 *	***	6.281	***		
	M07	8.469 *	***	7.029	***		
	M08	7.831 *	***	6.512	***		
	M09	7.145 *	***	4.832	***		
	M10	6.810 *	***	3.705	***		
	M11	5.795 *	***	3.060	***		
	M12	5.390 *	***	2.546	***		
	AR(1)	0.890 *	***	0.478	***		
a_t	AR(2)	-		0.203	***		
	AR(4)	-		0.218	***		
	D_FRA_AT	-0.150 *	**	-			
d(k)	D_FRA_RAIN	0.273 *	***	-			
	FRA_W	0.085 *	**	0.213	**		
	FRA_W [-1]	-		0.214	**		
$\varphi_b^k(L)$	FRA_W [-2]	-		0.069	**		
	D_PMI_AT[-1]	0.320 *	***	-			
Equation Stati	stics						
Observations		606		602			
R-squared		0.931		0.895			
Adjusted R-squared		0.929		0.892			
Log likelihood		-1723		-1754			
Durbin-Watson stat Mean dependent var		2.038		2.020			
S.D. dependent var		52.472 15.803		40.475 13.805			
Akaike info cr		5.745		5.888			
LM(7)		0.480		0.83			

Table 2.1 Estimation results from Germany weekly models. Estimation periodJanuary 2004- September 2015

Specifically, 1 degree Celsius above the mean temperature in Frankfurt is related to decrease of 0.15 points in the Google Search Index; 1 additional liter of precipitation by squared meter above the expected rainfall is linked to an increase of 0.273 points; 1 additional km/sec. in the maximum wind speed in Frankfurt is related to 0.085 increase in the index; and 1 degree Celsius above the mean temperature in Palma is related to an increase of 0.15 points.



		"Majorca" sea	rches	"Majorca hotel" searche			
	M01	6.102	***		5.745	***	
	M02	5.487	***		5.377	***	
	M03	6.192	***		5.490	***	
	M04	7.134	***		6.496	***	
	M05	8.382	***		7.461	***	
	M06	8.653	***		8.287	***	
m_s	M07	9.381	***		9.344	***	
s	M08	8.907	***		8.407	***	
	M09	7.223	***		6.044	***	
	M10	4.691	***		3.796	***	
	M11	2.952	***		2.429	***	
	M12	2.842	***		2.196	***	
	AR(1)	0.479	***		0.587	***	
a_t	AR(4)	0.232	***		0.290	***	
ľ	AR(5)	0.149	***		_		
	D_LON_RAIN	0.178	*		-		
d(k)	D_PMI_AT	-			0.270	*	
u(n)	PMI_W	-0.106	***		0.270 -0.141	***	
	D_LON_RAIN(-1)	0.182	**		-		
	LON_W(-1)				0.095	**	
k (T)	LON_W(-2)	0.081	***		0.067	*	
$\varphi_b^k(L)$	LON_W(-4)	0.063	**		-		
	PMI_W(-1)	-0.111	***		-0.130	**	
	PMI_W(-2)	-0.133	***		-0.134	**	
Equation St	atistics						
N. Observa				601	6	502	
R-squared				0.931	0.895		
Adjusted R	-squared			0.929	0.892		
Log likeliho	boc			-1723	-1754		
Durbin-Wa				2.038	2.020		
Mean deper				52.472	40.47		
S.D. depend				15.803	13.805		
Akaike info	criterion			5.745		888	
LM(7)	1 * 4 1 0 4 4 4 1	• • • • • • • • • • • • • • • • • • • •	(50(0.480	().83	

Table 2.2 Estimation results from British weekly models. Estimation periodJanuary 2004- September 2015

***, ** and * stand for statistical significance at 1%, 5% and 10 % respectively. AR(t)

refers to the autoregressive terms with t lags

The results for "Mallorca hotel" searches go in line but with some differences. Thus, it has been found a higher dependence on the meteorological conditions during the last two weeks though the wind variable (FRA_W[-1] and FRA_W[-2]) although the rest of meteorological conditions in the origin are not significant. Additionally, local



conditions seem not to play a significant role in "Mallorca hotel" searches.

The results for British equation (Table 2.2) confirm also the main hypothesis. In the case of searches made in the UK (Table 2.2), rain and wind within the same week and during previous weeks shows statistical significance with "Majorca" and "Majorca hotels" searches. In this case, additionally, it seems clearer that these weather conditions at the destination play a significant role in determining Google Trend searches, since the higher the wind, the less searches that were recorded.

Finally, because it has been assumed that the meteorological conditions have emerged as new determinants of tourist interest jointly with the trend in the reduction of booking lead times, two subsamples for "Mallorca" searches for both Germans and British are considered.

The first subsample takes data from the first week of 2004 to the week 52 of 2009 (w1/2004 – w52/2009), while the second subsample considers data from the first week of 2010 to the week 37th of 2015, the last available in our sample (w1/2010 – w37/2015). Results are presented in Table 2.3.

Again, the estimation results are satisfactory in terms of the significance of the parameters and the regression statistics. Focusing on the meteorological variables, sings of parameters show again, how good meteorological conditions at the destination boost Google searches for Mallorca, although only one variable, the deviation of the average temperature, was found significant at 10% for the first subsample in the German case. On the other hand, adverse meteorological conditions in the country of origin were also found to be a determinant of a stronger interest in Mallorca. Again, in view of the significance of parameters it seems that better results are obtained for the second subsample, the newest one, for both case studies. In line with this idea, R-squared and Akaike info criterion shows better values for the second period of analysis providing evidence that the models with meteorological data works better for more recent data than other one.



		Germany			UK			
		Sample:	Sample		Sample:		Sample:	
		w1/2004 -	w1/2010		w1/2004 -		w1/2010	
		w52/2009	w37/201		w52/2009		w37/2015	
	M01	7.414 ***	6.899	***	7.772	***	5.753	*
	M02	7.197 ***	6.667	***	6.906	***	5.243	*
	M03	7.860 ***	6.860	***	7.965	***	5.012	*
	M04	7.741 ***	7.222	***	8.919	***	5.129	*
	M05	8.408 ***	8.100	***	10.481	***	5.226	*
m_s	M06	8.645 ***	7.712	***	10.546	***	5.209	*
	M07	9.048 ***	8.113	***	11.895	***	5.567	*
	M08	8.242 ***	7.624	***	11.477	***	5.538	*
	M09	7.325 ***	7.139	***	9.015	***	5.363	*
	M10	7.221 ***	6.483	***	5.870	***	4.778	*
	M11	6.211 ***	5.505	***	3.879	***	4.135	*
	M12	5.781 ***	5.059	***	3.783	***	3.661	*
	AR(1)	0.891 ***	0,91	***	0.785	***	0.602	*
a_t	AR(2)	-	-		-0.203	***	0.451	*
L	AR(4)	-	-		0.205	***	-0.208	*
	MA(1)	-	_		-0.493	***	0.505	*
	D_FRA_AT	_	-0,154	**	-0.+33		0.000	
	D_FRA_AI	- 0.232 *	-0,154 0.417	***	-		-	
d(k)	D_FRA_RAIN FRA_W	0.232	0.417	***	-		-	
d(k)	D_LON_RAIN	-	0.122		- 0.363	*	-	
		-	-		-0.143	**	- 0.474	*
		-	-		-0.143		-0.171	
	D_FRA_AT [-1]	-0.162 *			-		-	*
	D_LON_RAIN[-1]	-	-		-		0.306	*
	D_LON_RAIN[-2]	-	-		-	**	0.159	
$\varphi_b^k(L)$	D_LON_RAIN[-3]	-	-		0.385		-	*
$\varphi_b(L)$	LON_W [-2]	-	-		-		0.053	*
	LON_W [-4]	-	-	- او ماه ماه	-		0.070	~
	D_PMI_AT [-1]	0.368 *	0.480	***	-		-	
	PMI_W [-1]	-	-		-0.175	***	-	
	PMI_W [-2]	-	-		-0.132	**	-	
•	Statistics							
Observations		308	298		304		298	
R-squared		0.929	0.934		0.957		0.968	
Adjusted R-squared Log likelihood		0.925	0.931		0.954		0.965	
	Vatson stat	-882.259	-833.770		-887.121		-721.652	
	pendent var	2.072 53.705	1.951 51.198		2.003 5.981		2.021 35.668	
S.D. dependent var		53.705 16.575	51.198 14.884		5.981 6.250		35.668 15.215	
	nfo criterion	5.833	5.710		6.089		4.984	
LM(7)		1.37	1.04		1.33		1.45	

Table 2.3 Estimation results for Mallorca searches from Germany and UK.

***, ** and * stand for statistical significance at 1%, 5% and 10 % respectively. AR(t) refers to the autoregressive terms with t lags



2.6. Conclusion

The uses of the Internet, the liberalization of the airspace and fewer border restrictions have caused an increase in last-minute bookings and the reduction of the lead booking time. In the case of the "sun, sea and sand" tourist market, for many years industry was dominated by tour operators that created holiday/travel packages conceived to be sold to end customers some months prior to the trip. Nowadays, the market has changed and a great majority of international tourists uses internet to plan their trip and book some kind of tourism services (IET, 2013).

In this context, this chapter has explored meteorological conditions as new short-run factors determining tourist travel choices, investigating the role of weather variables in explaining short-term variability in Google searches relating to Majorca by its two main tourist markets: Germany and UK. The estimated statistical models provide evidence that the weather conditions in both the country of origin and at the destination are related to data recorded by Google Trends. Bearing in mind the limitations of this kind of models, which can only capture average tourist behaviors, results show clearly how as weather conditions improve at the destination or as they worsen in the country of origin, more searches relating to Majorca are reported by Google Trends. Additionally results show how the effect seems more evident for last data.

This research extended previous research by showing that beliefs about weather, in addition to actual weather, can affect travel behavior. Models that incorporate meteorological information, such as those developed in this chapter, could be essential for national and regional tourism organizations in assessing the effect of new weather conditions on tourism in a context of global warming. This knowledge is needed by public and private tourism organizations so that they can provide better strategic information to clients on how to manage weather impacts more effectively. However, the meteorological effects in origins have been considered at national level. The importance of differing regional climates (or even microclimates) for



tourism decision-making and behaviour could have its relevance as it has been evidenced in Hartz et al., (2006), Wilson and Becken (2011) or Rutty and Scott (2014). Consequently, future research would try to consider the regionalization of the tourism data.

Although the statistical results found in this chapter are enough to confirm the hypothesis on the relationship between weather and the interest in Mallorca, it should be noted how the use of autoregressive terms have two main effects on the empirical application carried out.

On the one hand, ensures that no spurious regression and that the captured effect is related to weather and not to climate. However, on the other hand, reduces the statistical significance of weather effects longer than a week. Thus, if a heat or a cold wave persists during some weeks, and, precisely this persistence motivates the interest on a tourist destination, the relationship between weather variables and tourism will be covered by the autoregressive terms. Future research would try to solve this dilemma.



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APPENDIX-2

APPENDIX-2.1

		Descriptive Statistics					
		Mean	Std. Dev.	Min	Max		
<i>d</i> (<i>k</i>)	Germany_Rain	-0.00882	1.690236	-2.55671	11.85757		
	Germany_Temp	0.012913	2.984256	-10.9894	8.153458		
	Germany_Wind	23.00056	4.939663	10.28571	40.28571		
	UK_Rain	-0.00587	1.872235	-2.63	7.9		
	UK_Temp	-0.00559	2.350428	-6.92601	6.238571		
	UK_Wind	24.0401	5.411508	11.71429	43.42857		
	PMI_Temp	0.067712	1.841402	-6.41667	6.009048		
	PMI_Wind	24.45391	5.37392	8	46.42857		
G_t	Germany_HotelSearch	40.09162	14.49937	11	100		
	Germany_MallorcaSearch	53.93762	16.57994	19	100		
	UK_HotelSearch	34.14035	18.3078	4	100		
	UK_MajorcaSearch	42.09552	20.02022	7	100		



3

INFECTIOUS DISEASE RISK AND INTERNATIONAL TOURISM DEMAND

Abstract: For some countries, favourable climatic conditions for tourism are often associated with favourable conditions for infectious diseases, with the ensuing development constraints on the tourist sectors of impoverished countries where tourism's economic contribution has a high potential. This chapter evaluates the economic implications of eradication of Malaria, Dengue, Yellow Fever and Ebola on the affected destination countries focusing on the tourist expenditures. A gravity model for international tourism flows is used to provide an estimation of the impact of each travel-related disease on international tourist arrivals. Next the potential eradication of these diseases in the affected countries show that, in the case of Malaria, Dengue, Yellow Fever and Ebola, the eradication of these diseases in the affected countries would result in an increase of around 10 million of tourist worldwide and a rise in the tourism expenditure of 12 billion dollars. By analysing the economic benefits of the eradication of Dengue, Ebola, Malaria, and Yellow Fever for the tourist sector - a strategic economic sector for many of the countries where these TRD are



present -, this chapter explores a new aspect of the quantification of health policies which should be taken into consideration in future international health assessment programmes. It is important to note that the analysis is only made of the direct impact of the diseases' eradication and consequently the potential multiplicative effects of a growth in the GDP, in terms of tourism attractiveness, are not evaluated. Consequently, the economic results can be considered to be skeleton ones.

Keywords: Travel-related illness; tourism; global health; economic impact.

3.1. Introduction

UNWTO (2019) estimates that worldwide international tourist arrivals (overnight visitors) increased 6% to 1.4 billion in 2018, clearly above the 3.7% growth registered in the global economy. In economic terms, the travel and tourist industry accounts for 10.2% of the World Gross Domestic Product (WTTC, 2014), a percentage that is often higher in less developed countries with favourable climate conditions. For many of these countries, tourism constitutes an important source of foreign exchange and income, which are expected to have positive repercussions on the general development of the country (Sharpley and Telfer, 2002). Nevertheless, favourable climate conditions for tourism often also imply favourable conditions for infectious diseases, with the ensuing development constraints on countries' tourist sectors.

Although, in general, tourists are reluctant to travel to countries with different infectious diseases (Page, 2009), trips to less developed countries with a prevalence of these diseases are still growing (Leder et al., 2013). Health problems are self-reported by 22% to 64% of travellers to the developing world and infectious diseases are frequently the most commonly perceived health risk for potential tourists when choosing a destination (Steffen et al., 2003).

Given the growing popularity of tourism trips to less developed countries and many



impoverished nations' economic dependence on tourism, this chapter aims to explore the relationship between the tourist industry and the presence of the most significant travel-related diseases (TRD). Using an aggregate perspective, the presence of Malaria, Yellow Fever, Dengue and Ebola is evaluated in destination countries, and the potential economic impact of the eradication of these TRD is estimated by focusing the analysis on international tourist arrivals. Despite the tourist sector's economic importance for many countries with warm climate conditions, plus potential tourists' sensitivity to the presence of some infectious diseases when choosing a destination and the relevance of health policies in less developed countries, to our knowledge this is the first time that a study of these characteristics has been undertaken.

Previous papers have explored the impact of some specific disease outbreaks on tourism. For instance, Kuo et al., (2008) investigate the impacts of infectious diseases including Avian Flu and severe acute respiratory syndrome (SARS) on international tourist arrivals in Asian countries. Their results indicate that the numbers of affected cases have a significant impact on SARS-affected countries but not on Avian Flu-affected countries. Similarly, McAleer et al., (2010) also study the impact of these two diseases on international tourist arrivals to Asia and, again, they obtain that SARS is more important to international tourist arrivals than is Avian Flu. Cooper (2006) analyses the reactions of the Japanese tourist industry towards SARS while Zeng et al., (2005) explore its impact for China. Regarding other types of diseases Blake et al., (2003) obtain that the foot and mouth disease (FMD) outbreak significantly reduced tourism expenditures in the UK.In general, this previous studies obtain a link between infectious disease and tourism although they are focused on a specific country or region.

The objective of this study is threefold: First, the association between the existence of TRD risk and international tourism movements is evaluated. To that end, a generalization of the gravity model for international tourism demand is defined, providing an estimation of the impact of each considered TRD on international tourism arrivals. Second, simulations of the potential eradication of these diseases at



a national level, and so the disappearance of the risk of infection, were considered and evaluated. Finally, the impact of the diseases' eradication on the tourist demand was used to estimate the ensuing tourism expenditures and thus to provide a direct quantification of the benefits of different health policies in economic terms that could be compared with treatment costs in line to a strategy for implementing a global budget (Bishop and Wallack, 1996; Bowser et al., 2014). Then, the novelty of this chapter lies in providing an economic estimation of the impact of the eradication of the main travel-related disease risk of infection at a global scale.

The chapter is organized as follows; Section 3.2 briefly revised some papers that explore the effect of TRD on tourism; Section 3.3 presents the data and methodology used; Section 3.4 discusses the results of the empirical analysis where the impacts of TRD risk on inbound tourism are estimated; Section 3.5 presents a simulation analysis where the effect of eradication of the infectious diseases are obtained and the impact on tourism expenditure is evaluated; Section 3.6 concludes.

3.2. Travel-related diseases and tourism

The growth in the number of international tourist flows reflects the rapid movement of large population groups, which may pose an increased risk of travel-related illnesses, particularly communicable diseases. Poor socioeconomic conditions, inadequate sanitation, and cultural differences between the travellers' countries of origin and their travel destinations all contribute to this increase (Abdullah et al., 2000). The most common reasons why tourists seek medical care tend to be for gastrointestinal illnesses, fevers and skin disorders (Gautret et al., 2009) and it has been found that 30% of tourists had to seek medical attention for colds, nausea, stomach upsets, and diarrhea while visiting tropical islands (Pearce, 1981) and that 62% of tourist visits to tropical island nursing clinics were due to respiratory, digestive, skin/eye, and genitourinary disorders (Wilks et al., 1995). In the case of Australians travelling abroad it has been shown that infectious disease the cause a



2.4% of death (Schmierer and Jackson, 2006). Although tourist ignorance and carelessness are often the cause of these real risk situations, the perceived risk of disease clearly affects tourist behaviour, especially in their choice of tourist destination.

Turning to the effects of disease on destinations, the avian flu and severe acute respiratory syndrome (SARS) epidemics are good examples of outbreaks that have had a big media impact with important health policy controversies in recent years (Pongcharoensuk et al., 2012). A drop of 12 million arrivals to Asian and Pacific countries following the outbreak of the avian flu epidemic has been estimated (Wilder-Smith, 2006). The World Travel and Tourism Council estimated that approximately 3 million people in the tourist industry lost their jobs following the SARS outbreak in the most severely affected countries of China, Hong Kong, Vietnam and Singapore, resulting in losses of over \$20 billion (WTTC, 2003). Another example of a temporary disease with significant effects on tourism was the impact of foot and mouth disease on tourist expenditures in the UK (Blake et al., 2003). Among the study's key findings, tourism revenue in 2001 fell by almost $\pounds 7.5$ billion and some 21% of this amount was attributable to a fall in domestic tourism, with Scotland and London being the UK's hardest hit areas. Scotland experienced a fall of £2 billion, equivalent to 27% of the total UK drop in tourist expenditure, while London saw a drop of $\pounds 1.25$ billion; that is, 16.8% of the total UK decrease in tourist expenditure.

However, aside from temporary episodes of epidemic diseases that have made the news in recent years, different endemic TRD are also acknowledged to influence the destination chosen by millions of tourists each year. Malaria and Dengue are the most prevalent pathogens among ill returned travellers; diseases that could probably be combated through specific health policies to eradicate them (Freedman et al., 2006), Malaria has been identified as the most common specific diagnosis in ill returned patients with a systemic febrile illness (Gautret et al., 2009), and Sub-Saharan African and Indian Ocean islands have been highlighted as a major source of Malaria among European ill returned patients. According to the World Health



Organization (WHO), globally, an estimated 3.3 billion people are at risk of being infected with Malaria or of developing a disease, with 1.2 billion being at high risk (WHO, 2014). For all these reasons, Malaria is the first TRD analysed in this chapter.

Dengue is now also considered to be one of the major causes of fever in ill returned travellers who may even serve as important sentinels of new outbreaks of Dengue in Dengue-endemic areas. The Dengue virus is the second most commonly identified pathogen responsible for fever, particularly in patients returning from Southeast Asia. The incidence of Dengue has been considered to be higher than that of other so-called typical travel-related diseases, such as vaccine-preventable hepatitis A and typhoid fever (Gautret et al., 2009). Consequently Dengue is also analysed in our study.

Another of the most important diseases considered in this chapter, in terms of the risk to travellers, is Yellow Fever. A traveller's risk of catching Yellow Fever is determined by various factors, including their immunization status, travel location, the season, the length of exposure, occupational and recreational activities while travelling, and the local rate of virus transmission at the time of travel. Although reported cases of human disease are the main indicator of the disease risk, case reports may be missing due to low transmission levels, a high level of immunity in the population (because of vaccinations, for example), or the failure of local surveillance systems to detect cases (WHO, 2016).

Finally, in addition to Malaria, Dengue, and Yellow Fever, Ebola is also chosen for the economic analysis in this chapter because of its media impact during 2014 and 2015. It should be noted that, in 2014, airlines suspended flights to Ebola-hit African countries, a key component of the tourist sector, and various promising candidate vaccines have been assessed. The effect of the Ebola crisis on travel and tourism is being felt across the whole of Africa, more than in almost any other sector, due to the heightened perceived risk of travel (Nyarko et al., 2015). The major impact will be through the demand side; that is, discretionary spending in the form of travel and tourism, with international tourism being hit the most and also domestic tourism. In the event of the spread of Ebola, the World Bank has noted that the output forgone



due to Ebola in 2015 alone in the three countries is estimated to account for more than \$1.6 billion, over 12 percent of their combined GDPs (World Bank Group, 2015).

3.3. Methodology and data

3.3.1. Methodology

Different techniques have emerged during recent decades, aimed at evaluating the economic impacts of infectious diseases. Methods proposed in the literature that measures the economic impact of vector-borne diseases at country level can be classified into micro-based and macroeconomic approaches (Basili and Belloc, 2015). On the one hand, micro-based methods are founded on individual or household specific measures of the economic effects of a disease, which are then aggregated at a national level. It is argued that micro-based measures tend to underestimate the true economic impact of infectious diseases, because they do not capture a number of macroeconomic factors and externality effects (Sachs and Malaney, 2002; Bloom and Fink, 2014).

On the other hand, macroeconomic approaches follow a traditional cross-country perspective, in which variations in economic outcome variables at country level are explained as a function of variations in population health repressors. However, due to the two-way causality between economic outcomes and infectious disease incidence, this perspective suffers from endogeneity problems (Acemoglu and Johnson, 2007). In other words, health status influences people's absolute and relative income levels, while, in turn, economic status is a determinant of health. For both categories, there are additional evaluation problems, such as how to handle future benefits and costs, particularly long-term effects, and whether and how to discount future effects.

Within an aggregate framework, time series models are presented as a suitable methodology when the effects of transitory epidemic diseases have to be evaluated



(Min, 2005; Kuo et al., 2008; Wang, 2009; Rossello, 2011). Then, an autoregressive moving average model, sometimes together with an exogenous variables, can be used to estimate the effects of these diseases in each SARS and avian flu-infected country. The incidence of the illness is introduced in the model using dummy variables during the periods of the illness incidence. However, time series models are probably not the most suitable tool when the effect of a relatively stable variable has to be evaluated, and this could be the case here, where the presence (or incidence) of a certain disease in a country is expected to present a low level of variability over the years.

Because the aim of this chapter is to evaluate the effect of TRD on tourism and because these determinants are expected to have a high structural component, a gravity equation is used to explain tourism flows, while also considering the potential time variability of the determinants. The gravity equation method suggests that different international flows (i.e. trade, tourism, migrations, foreign direct investment etc.) are expected to increase with the economic size of a country and to decrease as the distance between country pairs grows. Additionally, a set of other determining variables, such as the presence of diseases at the destination, can also be included. From a methodological point of view, in comparison with other studies that evaluate the economic impact of health policies, by focusing the analysis on the tourist sector, the endogeneity problem often pointed out in similar economic studies is avoided. Thus, although it is easy to believe that health status influences tourist arrivals to a certain country, it is more difficult to believe that tourist arrivals are a determinant of health in this country.

This framework has been extensively used for empirical exercises due to its goodness of fit, above all to explain international trade (Deardorff, 1998; Anderson and Wincoop, 2003). Since tourism is considered to be a special type of trade in services, gravity equations have also been used to estimate the magnitude of tourism flows in different contexts (Eilat and Einav, 2004; Kimura and Lee, 2006; Santana-Gallego et al., 2010; Fourie and Santana-Gallego, 2011; Falk, 2016). Although the application of the gravity equation method has been supported by the international trade theory for many years, only recently the use of a gravity equation has recently justified in



the context of tourism by the use of the consumer theory (Morley et al., 2014).

3.3.2. Model and data

From previous literature, the model considered in this chapter can be defined as:

$$LnTou_{ijt} = \beta_0 + \beta_1 LnGDPpc_{jt} + \beta_2 Pop_{jt} + \beta_3 LnDist_{ij} + \beta_4 Border_{ij} + \beta_5 Lang_{ij} + \beta_6 Colony_{ij} + \beta_7 Comcol_{ij} + \beta_8 Smctry_{ij} + \beta_9 ReligSim_{ij} + \beta_{10} RTA_{ijt} + \beta_{11} RLaw_{jt} + \beta_{12} Terrorism_{jt} + \beta_{13} WHS_{j} + \beta_{14} LnTemp_{j} + \beta_{15} LnLifeExp_{jt} + \gamma' DiseaseRisk_{j} + \lambda_{it} + \varepsilon_{ijt}$$

$$(3.1)$$

The dependent variable Tou is the number of international tourist arrivals from country of origin i to destination country *j* during year *t*. The dataset includes 208 origin countries and 196 destination countries for the period 2000-2013.

For a total of 40,365 possible country pairs, there exist positive tourism flows, with missing values, for 14,119 (35%).

The explanatory variables are defined as follows. *GDPpc* is the per capita real gross domestic product of the destination country; *Pop* is the population of the country of destination; *Dist* is the distance in kilometres between country of origin and destination country; *Border, Lang, Colony Comcol* and *Smctry* are dummy variables that take a value of one if both countries in the pair share a common geographical land border, a common language, a colonial background, and common colonizer and have been part of the same country respectively, and zero otherwise; *ReligSim* is a religious similarity index as defined by Fourie et al. $(2015)^2$; *RTA* is a dummy variable for being a signatory to the same regional trade agreement; Rlaw is a proxy for the quality of the institutions at the destination country³; *Terrorism* is a proxy for the instability and insecurity at the destination country measured as the number of



victims in terrorist attacks per 10,000 inhabitants; WHS is the number of World Heritage Sites (WHS) at the destination country, Temp is the average annual temperature in the destination country⁴; LifeExp is the life expectancy at birth in the destination country. Finally, ε is a well-behaved disturbance term. It should be noted that, as in similar exercises, the Tou, Dist, GDP, Pop, Temp and LifeExp variables are taken in natural logs (Ln), aiming to reduce heteroscedasticity and to capture any non-linear relationship between these variables. Therefore these coefficients can be interpreted as elasticities.⁵ The variable of interest is DiseaseRisk that includes a set of key travel-related diseases, namely Malaria, Dengue, Yellow Fever and Ebola. This variable is a dummy variable with value of unity when there exist disease risk in the destination country, and zero otherwise. Appendix 3.1 shows existence of these 4 diseases globally. This set of variables reflects the existence of a TRD risk of contagion for travellers when visit a particular country. It is important to mention that in the present research it is assumed that the key factor in the impact of infectious diseases on tourism is the existence of the disease in the destination country (and not prevalence ratio per year). Therefore, it is considered that tourists mainly focus on the existence of a moderate or high risk of contagion when they travel to a destination country, as opposed to the real number of cases. In particular, it is considered travel warnings about risk of contagion for travellers and these risks remains constant for the whole period under analysis (2000-2013). Even if a particular country does not experience any disease case, if it has existed in the past it can still present risk of contagious.

⁵ Table A1 in the Appendix presents the source of the data



²This variable is generated as $\text{ReligSim}_{ij} = \sum_{r=1}^{5} r_i r_j$ where \mathbf{r}_i and \mathbf{r}_j are the percentages of the population affiliated to each of the five major religions in the origin and destination country, respectively. See Fourie et al (2015) for variable definition.

³ The rule of law captures perceptions of the extent to which agents have confidence in and abide by the rules of society, and in particular the quality of contract enforcement, property rights, the police, and the courts, as well as the likelihood of crime and violence. This variable ranged from -2.5 (weak) to 2.5 (strong)

⁴ The average annual temperature for the period (1961-1990) is used since we are interested in climate not in weather.

Consequently, WHO recommendation for travellers regarding Yellow Fever vaccinations and details concerning the risk of Malaria per country (risks C and D) are used.⁶

This data are completed with information from the Center for Disease Control and Prevention (CDC, 2016). Specifically, in the CDC's Health Information for International Travel (commonly known as the Yellow Book), health risk levels for international travellers to different countries are published.⁷

Moreover, for Dengue and Ebola risk it has been considered countries where Dengue is Endemic and there exists a risk of infection and countries that have experience Ebola outbreaks in the past. In the empirical analysis, the following data on infectious diseases are considered: (i) the estimated moderate or high risk of Malaria for travellers⁸; (ii) Dengue risk areas where the disease is endemic, implying a high risk of contagion for travellers⁹; (iii) countries where a Yellow Fever vaccination is recommended before travelling there¹⁰; (iv) countries with Ebola outbreaks since 2000; (v) risk of any disease is also considered since one country can present more than one type of TRD Risk. The variables of interest, namely DiseaseRisk, is a vector of destination-specific time-invariant characteristic, so panel estimation techniques cannot be applied since the variable of interest would be dropped. Origin country



⁶ For Malaria and Yellow Fever risk: <u>http://www.who.int/ith/ITH_country_list.pdf</u>

⁷For Malaria and Yellow Fever risk: <u>http://wwwnc.cdc.gov/travel/yellowbook/2016/infectious-diseases-related-to-travel/yellow-fever-Malaria-information-by-country</u>

For Dengue risk: http://wwwnc.cdc.gov/travel/yellowbook/2016/infectious-diseases-related-to-travel/Dengue

For Ebola outbreaks: http://www.cdc.gov/vhf/Ebola/outbreaks/history/chronology.html

⁸Recommended prevention by the WHO is decided on the basis of the following factors: the risk of contracting Malaria; the prevailing species of Malaria parasites in the area; the level and spread of drug resistance reported from the country; and the possible risk of serious side-effects resulting from the use of the various prophylactic drug.

time-varying fixed effects (λ_{it}) are included to control for source country characteristic such as population or GDP per capita of the origin country. However, destination time varying (or, alternatively destination fixed effects and year fixed effects) cannot be included since they would not allow to estimate the variable of interest. The detailed description of variables and their sources are given in Appendix 3.2.

⁹Based on surveillance data, official reports, published research, and expert opinion, compiled by CDC Dengue Branch in collaboration with University of Oxford.

¹⁰WHO determines those areas where "a risk of Yellow Fever transmission is present" on the basis of the diagnosis of cases of Yellow Fever in humans and/or animals, the results of Yellow Fever zero-surveys and the presence of vectors and animal reservoirs. Yellow Fever vaccination is recommended for all travelers \geq 9 months old in areas where there is evidence of persistent or periodic Yellow Fever virus transmission.



	Tuble 5.1	Descriptiv	c bransnes		
	Obs	Mean	Std. Dev.	Min	Max
LnTou _{jt}	142,415	6.918	3.277	0.00	18.18
$LnGDPpc_{jt}$	142,415	8.488	1.447	4.91	11.36
LnPop _{jt}	142,415	16.052	2.040	9.86	21.06
LnDist _{ij}	142,415	8.492	0.954	2.35	9.90
<i>Border</i> _{ij}	142,415	0.038	0.191	0.00	1.00
<i>Language</i> _{ij}	142,415	0.190	0.392	0.00	1.00
Colony _{ij}	142,415	0.020	0.140	0.00	1.00
$Comcol_{ij}$	142,415	0.106	0.308	0.00	1.00
$Smctry_{ij}$	142,415	0.018	0.133	0.00	1.00
ReligSim _{ij}	142,415	0.190	0.235	0.00	0.99
<i>RTA</i> _{ijt}	142,415	0.191	0.393	0.00	1.00
$Rlaw_{jt}$	142,415	0.108	0.930	-1.95	2.00
$Terrorism_{jt}$	142,415	0.008	0.050	0.00	2.14
WHS_{jt}	142,415	7.063	9.622	0.00	53.00
$LnTemp_{jt}$	142,415	2.768	0.565	0.41	3.34
LnLifeExp _{jt}	142,415	4.262	0.127	3.71	4.43
Malaria _{jt}	142,415	0.147		0.00	1.00
$YellowFever_{jt}$	142,415	0.146		0.00	1.00
<i>Dengue_{jt}</i>	142,415	0.325		0.00	1.00
Ebola _{jt}	142,415	0.006		0.00	1.00
AnyTRD _{jt}	142,415	0.388		0.00	1.00

 Table 3.1 Descriptive Statistics

Therefore an extensive set of destination and country-pair controls are included in the regression. Consequently, equation [3.1] is estimated by pooled OLS including time-varying source country dummy variables (origin-year) fixed effects where standard errors are clustered on host/source country pairs.-Table 3.1 presents some descriptive statistics.

3.4. Results and discussion

3.4.1. Impact of infectious disease risk on tourist arrivals

According to Morley et al. (2014) the introduction of the time-dimension on tourism



demand makes possible to evaluate not only the structural nature of the determinants but also its dynamic evolution. However, since travel warnings about risk of contagion remains constant for the whole period, tourist arrivals to countries with and without a disease risk are being compared. Therefore, in this section the shortrun effect of eradication of a TRD is not evaluated but the impact of its existence on the tourists' destination choice. In general, it is expected that if there exist risk of infection/contagion when travelling to a particular country, tourist will choose an alternative destination with none or low risk. Consequently, a negative estimated coefficient for DiseaseRisk is expected.

Table 3.2 presents the estimated coefficients and different regression statistics for the five estimated equations (Equation 3.1), one for each considered TRD, i.e. Malaria, Dengue, Yellow Fever, Ebola and any TRD. From a medical point of view, policy and measures taken to eradicate each of these diseases can be different and, consequently separate equations to evaluate each of the diseases is estimated. Moreover, from an econometric point of view, when a joint estimation is carried out the high correlation between countries affected by different diseases gives non expected results or non-significance for some of the diseases.

Equation [3.1] is estimated by pooled OLS including origin-year fixed effects. The R-square values in Table 3.2 for all the disease equations show that a 77 % variation in international tourist arrivals has been explained. In general, the estimated parameters yield the expected signs and sizes, suggesting that the model is correctly specified. Estimate parameters are very similar in the four regressions for each disease risk under analysis.

The per capita GDP and population of the destination countries are significantly positive suggesting that tourists prefer travelling to richer and populated countries. The distance variable, which can be regarded as a proxy for the cost of the trip, is consistently negative and significant. This result is also confirmed by the significantly positive effect of the common border dummy variable, suggesting that tourists prefer to travel to closer countries.



		2000-2	013)		
	(A)	(B)	(C)	(D)	(E)
$LnGDPpc_{jt}$	0.405***	0.491***	0.452***	0.463***	0.404***
	(0.0191)	(0.0186)	(0.0183)	(0.0183)	(0.0184)
LnPop _{jt}	0.673***	0.664***	0.656***	0.658***	0.650***
	(0.0101)	(0.00998)	(0.01000)	(0.00996)	(0.00990)
LnDist _{ij}	-1.316***	-1.290***	-1.295***	-1.300***	-1.282***
·	(0.0234)	(0.0235)	(0.0235)	(0.0233)	(0.0235)
<i>Border_{ij}</i>	1.221***	1.269***	1.243***	1.244***	1.263***
·	(0.120)	(0.121)	(0.122)	(0.122)	(0.121)
Language _{ij}	0.875***	0.886***	0.875***	0.872***	0.900***
0 0 0	(0.0442)	(0.0443)	(0.0445)	(0.0444)	(0.0441)
Colony _{ij}	0.785***	0.774***	0.783***	0.789***	0.766***
	(0.113)	(0.114)	(0.115)	(0.114)	(0.115)
Comcol _{ij}	0.474***	0.419***	0.454***	0.453***	0.468***
	(0.0630)	(0.0634)	(0.0631)	(0.0633)	(0.0627)
Smctry _{ij}	0.0918	0.135	0.0910	0.0863	0.134
2-5	(0.142)	(0.143)	(0.144)	(0.144)	(0.143)
ReligSim _{ij}	1.080***	1.122***	1.102***	1.092***	1.134***
0 9	(0.0659)	(0.0663)	(0.0663)	(0.0663)	(0.0658)
<i>RTA</i> _{ijt}	0.747***	0.769***	0.777***	0.773***	0.777***
.y.	(0.0439)	(0.0440)	(0.0441)	(0.0439)	(0.0440)
<i>Rlaw_{jt}</i>	0.539***	0.414***	0.466***	0.467***	0.472***
<i>J</i> .	(0.0255)	(0.0261)	(0.0249)	(0.0249)	(0.0248)
Terrorism _{jt}	-2.059***	-2.260***	-2.225***	-2.146***	-2.378***
y.	(0.237)	(0.238)	(0.239)	(0.239)	(0.239)
WHS _{jt}	0.0202***	0.0178***	0.0192***	0.0189***	0.0197***
<i>J</i> .	(0.00195)	(0.00201)	(0.00199)	(0.00200)	(0.00197)
$LnTemp_{jt}$	0.735***	0.711***	0.709***	0.662***	0.854***
1 5-	(0.0294)	(0.0296)	(0.0325)	(0.0290)	(0.0336)
LnLifeExp _{jt}	-0.781***	-0.302**	0.185	0.127	0.0208
5 15	(0.162)	(0.152)	(0.154)	(0.155)	(0.152)
Malaria _{jt}	-0.629***		. ,	. ,	, ,
<u>.</u>	(0.0531)				
YellowFever _{jt}		-0.445***			
j.		(0.0406)			
Dengue _{jt}		× ,	-0.124***		
0 ,			(0.0343)		
<i>Ebola_{it}</i>			· /	-0.324*	
<i>j</i> .				(0.187)	
AnyTRD _{jt}				()	-0.464***
. <i>J</i> = <i>J</i> t					(0.0373)
Observations	142,415	142,415	142,415	142,415	142,415
R-squared	0.770	0.770	0.768	0.768	0.766

Table 3.2 Effect of TRD Risk on international tourist arrivals (Pooled OLS
2000-2013)

Note: Robust standard error clustered by host/source country pairs in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Constant and origin-year fixed effects are not reported.



Cultural factors such as colonial links, sharing a common language or a religious similarities display significantly positive coefficients in the estimates. Hence, a cultural gap is a relevant explanatory factor in international tourism demand. As expected, countries with coast (or not being a landlocked country) has a positive effect on the number of tourist arrivals. Being member of a common regional trade agreement, used as a proxy for the intensity of the economic relations between countries yields a positive effect.

Destination specific characteristics such as the rule of law and number of fatalities in terrorist attacks per 10,000 inhabitants present the expected signs. That is, tourists prefer travelling to safer countries and with a higher quality of their institutions.

Finally, variables that might affect the tourist attractiveness of the destination are significant and with the expected sign. A higher annual average temperature and the number of World Heritage Sites at the destination country have a positive effect on tourist arrivals. The estimated impact of life expectancy at birth differs depending on the disease risk considered in the regression, although it is not significant in three of the five models estimated.

As for the variable of interest, all the parameters related to TRD are significant and show negative signs, evidencing the expected negative relationship between the existence of the disease and the level of tourist arrivals. That is, countries with a TRD risk, receive a lower number of international tourists. In particular, countries with Malaria risk receive 47% fewer tourists than countries where this disease is not endemic. Similarly, countries with Yellow Fever receive 36%, while countries with a risk of Dengue and Ebola receive 12% and 28% fewer tourists, respectively. Observing the parameter of the variable of having risk of any TRD, it is also significantly negative implying that countries with TRD risk receive 37% fewer inbound tourists. Therefore, it seems clear that TRD risk implies a barrier for tourism sector to develop since the risk of infection is taken into account when people decide the tourist destination. Moreover, Malaria is the TRD that presents the highest impact



on tourism.

There are reasons to assume that travellers from highly developed countries are more sensitive to these diseases, than tourist from developing countries. Therefore, the impact of TRD risk on different subsamples of origin countries is explored as a robustness check. The sample is disaggregated by level of development of the origin countries using the Human Development Index (HDI). So, Developed countries (114) are countries that present very high or high HDI while developing countries (94) are countries with medium or low HDI. Table 3.3 presents results of the impact of TRD on inbound tourism according to the development level of the origin country.

		level		
	Malaria _{jt}	YellowFever _{jt}	Dengue _{jt}	Ebola _{jt}
Developed	-0.738***	-0.511***	0.0161	-0.468***
(114 countries)	-0.0643	-0.0489	-0.0421	-0.143
Developing	-0.409***	-0.331***	-0.402***	-0.316
(94 countries)	-0.0874	-0.0686	-0.0562	-0.435

Table 3.3 Effect of TRD Risk by group of origin development level

Note: Robust standard error clustered by host/source country pairs in parentheses. *** p<0.01.

It is observed how the impact of Malaria, Yellow Fever and Ebola is larger when tourists arrive from developed countries while the opposite happens for Dengue. Interestingly, Dengue risk is not significant for tourist arrivals from developed countries while Ebola risk is not significant for tourist arrivals from developing countries.

To sum up, it can be generally concluded that tourists from developed countries, where TRD are eradicated, are more sensitive to infectious diseases risk when they decide the tourist destination.



3.4.2. Impact of eradication of TRD risk on tourism expenditure. simulation analysis

In this section, the direct economic impact of eradicating a TRD risk is calculated. In a first stage, predicted tourism gains of removing a TRD risk are obtained. Firstly, the predicted gains of tourist arrivals due to the eradication of each disease risk are obtained. Then, a counterfactual model is estimated considering that the TRD risk does not exist in any country, and predicted tourist arrivals are generated.

Finally, predicted total tourist arrivals from the baseline model and the counterfactual model are compared to obtain gains, in terms of inbound tourism, due to the complete eradication of a disease risk. It should be noted that the total number of arrivals to a particular destination can be obtained as the sum of tourist arrivals from

all origin countries as $TOU_j = \sum_i Tou_{ij}$. In a second stage, we quantify the impact of the increase in total tourist arrivals to a particular country where there exists a disease risk. This assessment of the economic consequences of the TRD eradication is obtained assuming that there is a linear relationship between the total number of inbound tourists and tourist expenditure by foreign tourists in a destination country.

¹ Note that since the dependent variable is in logarithm, the parameter of *DiseaseRisk* is interpreted as a semielasticity, that is $Exp(\gamma)$ -1.



Analytically, this is done by estimating the following equation:

$$LnEXP_{jt} = \varphi_0 + \varphi_1 LnTOU_{jt} + \omega_t + \upsilon_j$$
[3.2]

Where *EXP* is the total tourism expenditure by foreign tourists in a destination country *j* during period *t*; *TOU* is total international tourist arrivals in destination *j* at year *t*; ϕ_1 , is the parameter to be estimated; ω_t is year fixed effects; and υ_{jt} is a well-behaved disturbance term. This simple model presented in equation [3.2] is estimated for the 196 destination country for the period 2000-2013 using panel fixed effects. Total tourist expenditure *EXP* (in US\$) is defined as expenditures by international inbound visitors, including payments to national carriers for international transport.

Variables *EXP* and *TOU* are obtained from the World Development Indicators (The World Bank Group, 2016). At this point, it is important to point out that through this procedure only the direct effect of the eradication of travel-related diseases is obtained.

Thus, it could be argued that an increase in tourism expenditures (receipts) in the destination country could increase GDP in that country and, as expressed in equation [3.1], the GDP at the destination could act in itself as an attractor of international tourists (in the sense that a higher GDP could also be related to higher levels of development, public services etc., which might attract more tourists). Thus the multiplying effects of an increase in the GDP on tourism are not considered in this study. Moreover, displacement effects are also not considered in this analysis.

A specific reference year is not going to be considered to calculate the impact on tourist arrivals and tourist expenditure of a TRD eradication but the average for the period 2005-2008.

¹²For simplicity in the counterfactual analysis is assumed that the TRD is completed eradicated (DiseaseRisk=0 for all countries)



This year span is selected because is the period before the world economic crisis.¹³ For the simulation analysis, equation [3.1] is re-estimated as a cross-section for the average values for 2005-2008 and results are presented in Table 3.4. As can be observed, estimate parameters are similar to the ones presented in Table 3.2. In particular, countries with risk of Malaria presents 48% fewer inbound tourism, with risk of Yellow Fever a 39%, with Dengue risk a 7% and with Ebola risk a 45%. Moreover, having any type of TRD risk implies a decrease of tourist arrivals of 36% than countries without any disease risk.

The estimated equation [3.2], linking international tourism and the tourism expenditures, is presented in Table 3.5. The high level of the R-square shows that tourism arrivals are a good predictor of the tourism expenditures in the destination countries. Therefore, this result confirms the link between the international tourism demand and the economic impact in the destination countries. The estimated parameter of the tourist flow variable shows that a 1% increase in tourist arrivals to a representative country implies a 0.69% increase in the tourist expenditures.

	(A)	(B)	(C)	(D)	(E)
Malaria _{jt}	-0.649***				
	(0.0573)				
$YellowFever_{jt}$		-0.484***			
		(0.0461)			
Dengue _{jt}			-0.0750**		
			(0.0372)		
Ebola _{jt}				-0.592***	
				(0.213)	
AnyTRD _{jt}					-0.444***
					(0.0414)
Observations	12,106	12,106	12,106	12,106	12,106
R-squared	0.791	0.792	0.790	0.790	0.792

¹³Results of the simulation analysis are robust to alternative periods/years of reference.



	LnExp _{jt}
$LnTOU_{jt}$	0.692 ***
	(0.025)
Observations	2310
Within R-squared	0.6354

Table 3.5 Relationship between tourist	S
arrivals and tourist GDP	

Estimate by panel fixed effect.

Constant and year fixed effects are not reported.

Robust standard errors in parentheses. *** p<0.01,

The simulated effects of the eradication of any TRD on tourism arrivals and tourist expenditure are presented in Table 3.6 while Tables A2, A3, A4 and A5 in the appendix present the direct economic effect of eradicating Malaria, Yellow Fever, Dengue and Ebola, respectively. In this section we are focusing on the effect of eradicating all TRD risks, since more than one infectious disease might exist in a country. However, the results presented in the appendix are relevant for policymakers when they are evaluating the economic impact of eradicating a specific TRD. In any case, this estimate are for guidance only since, as previously mentioned, only direct effects are taken into account as well as displacement/substitution effects are not quantify. For instance, eradicating Ebola in Uganda would suppose an increase on inbound tourism but also can positively or negatively affect tourist arrivals to neighbouring countries like Tanzania or Kenya without Ebola risk.

The first two columns in Table 3.6 present predicted total tourist arrivals with TRD risk (benchmark) and without TRD risk (counterfactual). Third and fourth columns present increases in inbound tourism figures if TRD risk is eradicated, in thousands and in percentage change, respectively. In the fifth column, total tourist receipts in each country are presented, while last column presents the predicted gains in terms of tourism expenditure if all TRD are eradicated. For instance, is TRD are eradicated, tourist arrivals are expected to increase a 15.3% in Angola which implies an increase on tourist receipts of 19.1 million of US\$ per year (=0.153*0.69*180)



Table 3.6			dication on	tourism	and tourism	<u>n expenditur</u>
	Predicted	Predicted				Impact on
	tourism	tourism	Tourism	Tourism	Tourist	Tourist
	With	without			Expenditure	
	Disease	Disease	Increase (the surger day)	Increase	(million	Expenditure
	Risk	Risk	(thousands)	(%)	US\$)	(million
	(thousands)	(thousands)				US\$)
	× ,	. ,	Africa			
Angola	123.3	142.2	18.9	15.3%	180	19.08
Benin	1114.8	1153.2	38.5	3.5%	170	4.05
Burkina Faso	958.3	921.1	- 37.2	- 3.9%	61	-1.63
Cabo Verde	358.8	445.4	86.5	24.1%	318	52.84
Cameroon	761.1	786.2	25.2	3.3%	220	5.03
Central African						
Rep.	77.8	74.8	- 3.0	- 3.8%	10	-0.27
Chad	139.3	141.2	1.9	1.4%		0.00
Comoros	214.9	240.0	25.1	11.7%	30	2.37
Congo	3047.3	3472.1	424.8	13.9%	46	4.46
Congo, Dem.						
Rep.	6734.6	7082.3	347.7	5.2%	2	0.07
Cote D'ivorie	453.1	461.1	8.0	1.8%	111	1.35
Eritrea	76.2	76.6	0.4	0.5%	58	0.22
Ethiopia	301.5	305.5	4.0	1.3%	790	7.15
Gambia	285.1	302.7	17.6	6.2%	74	3.15
Ghana	714.9	765.0	50.1	7.0%	935	45.23
Guinea	329.2	318.1	- 11.1	- 3.4%	2	-0.04
Guinea-Bissau	53.9	57.1	3.2	5.9%	18	0.71
Kenya	737.0	746.7	9.7	1.3%	1268	11.47
Madagascar	120.4	126.4	6.0	5.0%	453	15.68
Mali	977.7	933.2	- 44.5	- 4.6%	213	-6.68
Mauritius	1136.7	1511.4	374.6	33.0%	1500	341.12
Mozambique	258.0	277.0	19.0	7.3%	170	8.62
Niger	582.7	549.1	- 33.6	- 5.8%	53	-2.12
Nigeria	1941.4	2114.3	172.9	8.9%	413	25.35
Rwanda	534.7	567.8	33.1	6.2%	154	6.59
Senegal	1606.5	1653.0	46.6	2.9%	480	9.60
Seychelles	701.9	927.2	225.3	32.1%	350	77.52
Sierra Leone	156.8	159.3	2.5	1.6%	36	0.39
Sudan	375.5	398.7	23.2	6.2%	250	10.64
Tanzania	868.0	895.9	27.9	3.2%	1083	23.99
Togo	527.3	538.3	10.9	2.1%	33	0.47
Uganda	746.0	765.0	18.9	2.5%	418	7.31
Zambia	525.7	568.2	42.5	8.1%	125	6.94
Zimbabwe	194.4	201.5	7.1	3.7%	275	6.93
			Americas	S		
Antigua &						
Barbuda	1047.1	1386.2	339.0	32.4%	328	73.17
Argentina	1939.4	2460.1	520.7	26.8%	4350	805.78
Aruba	1204.7	1642.1	437.4	36.3%	1200	300.64
Bahamas	491.0	663.1	172.1	35.0%	2150	519.91
Barbados	2529.4	3418.6	889.2	35.2%	1175	285.00
Belize	99.5	118.2	18.7	18.8%	260	33.66
Bolivia	194.5	210.1	15.6	8.0%	328	18.09
Brazil	1637.0	1959.8	322.8	19.7%	5050	687.11
Colombia	1724.2	1938.3	214.0	12.4%	2450	209.85
Costa Rica	1330.0	1568.9	238.9	18.0%	2100	260.24

المنارات المعنية المستشارات

Table 3.6 Effects of all disease eradication on tourism and tourism expenditure

$\begin{array}{c c c c c c c c c c c c c c c c c c c $	Cuba	250.9	297.3	46.4	18.5%	2425	309.30
Dominican Rep. 762.8 927.7 165.0 21.6% 3925 585.68 Ecuador 453.8 520.1 66.3 14.6% 590 59.50 El Salvador 1472.3 1659.6 187.2 12.7% 713 62.52 Grenada 720.7 917.3 196.5 27.3% 106 19.99 Guatemala 1182.9 1307.7 124.8 10.6% 1028 74.82 Guyana 54.2 60.8 6.6 12.2% 45 3.81 Haiti 250.6 270.6 20.0 8.0% 170 9.34 Jamaica 413.8 509.3 95.5 23.1% 2050 326.39 Mexico 3405.3 4250.1 844.8 24.8% 13750 2353.64 Nicaragua 578.8 613.8 35.1 6.1% 625 10.45 Paraguay 139.1 151.0 12.0 8.6% 114 6.77 Peru 608.3 <td></td> <td></td> <td></td> <td></td> <td></td> <td></td> <td></td>							
Ecuador 453.8 520.1 66.3 14.6% 590 59.50 El Salvador 1472.3 1659.6 187.2 12.7% 713 62.52 Grenada 720.7 917.3 196.5 27.3% 106 19.99 Guatemala 1182.9 1307.7 124.8 10.6% 1028 74.82 Guyana 54.2 60.8 6.6 12.2% 45 3.81 Haiti 250.6 270.6 20.0 8.0% 170 9.34 Honduras 940.0 1020.0 80.0 8.5% 540 31.73 Jamaica 413.8 509.3 95.5 23.1% 2505 326.39 Mexico 3405.3 4250.1 844.8 24.8% 13750 255.3 10.45 Paraguay 139.1 151.0 12.0 8.6% 114 6.77 Peru 608.3 717.6 109.3 18.0% 1900 235.46 St. Lucia 1214.6 1538.4 323.9 26.7% 320 58.88 St. Vicents & Gre. 969.5 1							
El Salvador 1472.3 1659.6 187.2 12.7% 713 62.52 Grenada 720.7 917.3 196.5 27.3% 106 19.99 Guatemala 1182.9 1307.7 124.8 10.6% 1028 74.82 Guyana 54.2 60.8 6.6 12.2% 45 3.81 Haiti 250.6 270.6 20.0 8.0% 170 9.34 Honduras 940.0 1020.0 80.0 8.5% 540 31.73 Jamaica 413.8 509.3 95.5 23.1% 2050 326.39 Mexico 3405.3 4250.1 844.8 24.8% 13750 235.45 Panama 371.8 433.1 61.3 16.5% 1625 184.73 Paraguay 139.1 151.0 12.0 8.6% 114 6.77 Peru 608.3 717.6 109.3 18.0% 1900 235.46 St. Vicents & Gree. 969.5 1216.5 247.0 25.5% 104 18.28 Suriname<	_						
Grenada 720.7 917.3 196.5 27.3% 106 19.99 Guatemala 1182.9 1307.7 124.8 10.6% 1028 74.82 Guyana 54.2 60.8 6.6 12.2% 45 3.81 Haiti 250.6 270.6 20.0 8.0% 170 9.34 Honduras 940.0 1020.0 80.0 8.5% 540 31.73 Jamaica 413.8 509.3 95.5 23.1% 2050 326.39 Mexico 3405.3 4250.1 844.8 24.8% 13750 2353.64 Nicaragua 578.8 613.8 35.1 6.1% 250 10.45 Paraguay 139.1 151.0 12.0 8.6% 114 6.77 Peru 608.3 717.6 109.3 18.0% 1900 235.46 St. Lucia 1214.6 1538.4 323.9 26.7% 320 58.88 St. Vicents & Gre. 969.5 1216.5 247.0 25.5% 104 18.28 Suriname <td></td> <td></td> <td></td> <td></td> <td></td> <td></td> <td></td>							
Guatemala 1182.9 1307.7 124.8 10.6% 1028 74.82 Guyana 54.2 60.8 6.6 12.2% 45 3.81 Haiti 250.6 270.6 20.0 8.0% 170 9.34 Honduras 940.0 1020.0 80.0 8.5% 540 31.73 Jamaica 413.8 509.3 95.5 23.1% 2050 326.39 Mexico 3405.3 4250.1 844.8 24.8% 13750 2353.64 Nicaragua 578.8 613.8 35.1 6.1% 250 10.45 Panama 371.8 433.1 61.3 16.5% 1625 184.73 Paraguay 139.1 151.0 12.0 8.6% 114 6.77 Peru 608.3 717.6 109.3 18.0% 1900 235.46 St. Vicents & Gre. 969.5 1216.5 247.0 25.5% 104 18.28 Suriname 59.9 71.6 11.6 19.4% 91 12.12 Trinida &				196.5			
Haiti 250.6 270.6 20.0 8.0% 170 9.34 Honduras 940.0 1020.0 80.0 8.5% 540 31.73 Jamaica 413.8 509.3 95.5 23.1% 2050 326.39 Mexico 3405.3 4250.1 844.8 24.8% 13750 2353.64 Nicaragua 578.8 613.8 35.1 6.1% 250 10.45 Panama 371.8 433.1 61.3 16.5% 114 6.77 Peru 608.3 717.6 109.3 18.0% 1900 235.46 St. Kitts & Nevis 778.2 1045.4 267.2 34.3% 123 29.02 St. Lucia 1214.6 1538.4 323.9 26.7% 320 58.88 St. Vicents & Gre. 969.5 1216.5 247.0 25.5% 104 18.28 Suriname 59.9 71.6 11.6 19.4% 91 12.12 Trinida & 7.0% 75 3.62 3.62 111.67 Venezuela			1307.7				
Haiti 250.6 270.6 20.0 8.0% 170 9.34 Honduras 940.0 1020.0 80.0 8.5% 540 31.73 Jamaica 413.8 509.3 95.5 23.1% 2050 326.39 Mexico 3405.3 4250.1 844.8 24.8% 13750 2353.64 Nicaragua 578.8 613.8 35.1 6.1% 250 10.45 Panama 371.8 433.1 61.3 16.5% 1625 184.73 Paraguay 139.1 151.0 12.0 8.6% 114 6.77 Peru 608.3 717.6 109.3 18.0% 1900 235.46 St. Kits & Nevis 778.2 1045.4 267.2 34.3% 123 29.02 St. Lucia 1214.6 1538.4 323.9 26.7% 320 58.88 St. vicents & Gre. 969.5 1216.5 247.0 25.5% 104 18.28 Suriname 59.9 7	Guyana	54.2	60.8	6.6	12.2%	45	3.81
Jamaica413.8509.395.523.1%2050326.39Mexico3405.34250.1844.824.8%137502353.64Nicaragua578.8613.835.16.1%25010.45Panama371.8433.161.316.5%1625184.73Paraguay139.1151.012.08.6%1146.77Peru608.3717.6109.318.0%1900235.46St. Kitts & Nevis778.21045.4267.234.3%12329.02St. Lucia1214.61538.4323.926.7%32058.88St. Vicents & Gre.969.51216.5247.025.5%10418.28Suriname59.971.611.619.4%9112.12Trinidad &71.6100.216.1%908100.54Menzuela624.2724.4100.216.1%908100.54Bangladesh431.6461.830.27.0%753.62Brunei477.4646.6169.235.4%22053.81Cambodia211.1219.07.93.8%9000568.20Indonesia651.0733.082.012.6%6000521.30Lao125.9133.57.76.1%1938.08Malaysia3169.93681.2511.316.1%91370.01Pakistan762.2852.585.311.1%91370.01		250.6	270.6	20.0	8.0%	170	9.34
Mexico 3405.3 4250.1 844.8 24.8% 13750 2353.64 Nicaragua 578.8 613.8 35.1 6.1% 250 10.45 Panama 371.8 433.1 61.3 16.5% 1625 184.73 Paraguay 139.1 151.0 12.0 8.6% 114 6.77 Peru 608.3 717.6 109.3 18.0% 1900 235.46 St. Kitts & Nevis 778.2 1045.4 267.2 34.3% 123 29.02 St. Lucia 1214.6 1538.4 323.9 26.7% 320 58.88 St. Vicents & Gre. 969.5 1216.5 247.0 25.5% 104 18.28 Suriname 59.9 71.6 11.6 19.4% 91 12.12 Trinidad & $ -$ Venezuela 624.2 724.4 100.2 16.1% 908 100.54 Bangladesh 431.6 461.8 30.2 7.0% 75 3.62 Brunei 477.4 646.6 169.2 35.4% 220 53.81 Cambodia 211.1 219.0 7.9 3.8% 1133 29.37 India 7439.7 8058.5 618.8 8.3% 9900 568.20 Indonesia 651.0 733.0 82.0 12.6% 6000 521.30 Lao 125.9 133.5 7.7 6.1% 193 8.08 Malaysia <t< td=""><td>Honduras</td><td>940.0</td><td>1020.0</td><td>80.0</td><td>8.5%</td><td>540</td><td>31.73</td></t<>	Honduras	940.0	1020.0	80.0	8.5%	540	31.73
Nicaragua 578.8 613.8 35.1 6.1% 250 10.45 Panama 371.8 433.1 61.3 16.5% 1625 184.73 Paraguay 139.1 151.0 12.0 8.6% 114 6.77 Peru 608.3 717.6 109.3 18.0% 123 29.02 St. Lucia 1214.6 1538.4 323.9 26.7% 320 58.88 St. Vicents & Gre. 969.5 1216.5 247.0 25.5% 104 18.28 Suriname 59.9 71.6 11.6 19.4% 91 12.12 Trinidad &	Jamaica	413.8	509.3	95.5	23.1%	2050	326.39
Panama371.8433.161.316.5%1625184.73Paraguay139.1151.012.08.6%1146.77Peru608.3717.6109.318.0%1900235.46St. Kits & Nevis778.21045.4267.234.3%12329.02St. Lucia1214.61538.4323.926.7%32058.88St. Vicents & Gre.969.51216.5247.025.5%10418.28Suriname59.971.611.619.4%9112.12Trinidad &TTobago961.91233.9271.928.3%573111.67Venezuela624.2724.4100.216.1%908100.54AsiaBangladesh431.6461.830.27.0%753.62Brunei477.4646.6618.88.3%9900568.20India7439.78058.5618.88.3%9900568.20Indonesia651.0733.082.012.6%6000521.30Lao125.9133.57.76.1%19370.01Philippines555.5629.874.313.4%3950364.68Sri Lanka189.4233.243.823.1%753119.98Thailand1794.42123.1328.718.3%80002274.83Timor-Leste33.536.02.57.6%201.05Vietnam <td>Mexico</td> <td>3405.3</td> <td>4250.1</td> <td>844.8</td> <td>24.8%</td> <td>13750</td> <td>2353.64</td>	Mexico	3405.3	4250.1	844.8	24.8%	13750	2353.64
Panama 371.8 433.1 61.3 16.5% 1625 184.73 Paraguay 139.1 151.0 12.0 8.6% 114 6.77 Peru 608.3 717.6 109.3 18.0% 1900 235.46 St. Kitts & Nevis 778.2 1045.4 267.2 34.3% 123 29.02 St. Lucia 1214.6 1538.4 323.9 26.7% 320 58.88 St. Vicents & Gre. 969.5 1216.5 247.0 25.5% 104 18.28 Suriname 59.9 71.6 11.6 19.4% 91 12.12 Trinidad & T 724.4 100.2 16.1% 908 100.54 Asia Bangladesh 431.6 461.8 30.2 7.0% 75 3.62 Brunei 477.4 646.6 169.2 35.4% 220 53.81 Cambodia 211.1 219.0 7.9 3.8% 1133 29.37 India 7439.7 8058.5 618.8 8.3% 9900	Nicaragua	578.8	613.8	35.1	6.1%	250	10.45
Peru608.3717.6109.318.0%1900235.46St. Kitts & Nevis778.21045.4267.2 34.3% 12329.02St. Lucia1214.61538.4323.926.7%32058.88St. Vicents & Gre.969.51216.5247.025.5%10418.28Suriname59.971.611.619.4%9112.12Trinidad &724.4100.216.1%908100.54AsiaBangladesh431.6461.830.27.0%753.62Brunei477.4646.6169.235.4%22053.81Cambodia211.1219.07.93.8%113329.37India7439.78058.5618.88.3%9900568.20Indonesia651.0733.082.012.6%6000521.30Lao125.9133.57.76.1%1938.08Malaysia3169.93681.2511.316.1%147501641.54Pakistan767.2852.585.311.1%91370.01Philippines555.5629.874.313.4%3950364.68Sri Lanka189.4233.243.823.1%753119.98Thailand1794.42123.1328.718.3%180002274.83Timor-Leste33.536.02.57.6%201.05Vietnam864.8938.9 <td< td=""><td>-</td><td>371.8</td><td>433.1</td><td>61.3</td><td>16.5%</td><td>1625</td><td>184.73</td></td<>	-	371.8	433.1	61.3	16.5%	1625	184.73
Peru608.3717.6109.318.0%1900235.46St. Kitts & Nevis778.21045.4267.234.3%12329.02St. Lucia1214.61538.4323.926.7%32058.88St. Vicents & Gre.969.51216.5247.025.5%10418.28Suriname59.971.611.619.4%9112.12Trinidad &7724.4100.216.1%908100.54Venezuela624.2724.4100.216.1%908100.54Bangladesh431.6461.830.27.0%753.62Brunei477.4646.6169.235.4%22053.81Cambodia211.1219.07.93.8%113329.37India7439.78058.5618.88.3%9900568.20Indonesia651.0733.082.012.6%6000521.30Lao125.9133.57.76.1%1938.08Malaysia3169.93681.2511.316.1%147501641.54Pakistan767.2852.585.311.1%91370.01Philippines555.5629.874.313.4%3950364.68Sri Lanka189.4233.243.823.1%753119.98Thailand1794.42123.1328.718.3%180002274.83Timor-Leste33.536.02.57.6%<	Paraguay	139.1	151.0	12.0	8.6%	114	
St. Kitts & Nevis 778.2 1045.4 267.2 34.3% 123 29.02 St. Lucia 1214.6 1538.4 323.9 26.7% 320 58.88 St. Vicents & Gre. 969.5 1216.5 247.0 25.5% 104 18.28 Suriname 59.9 71.6 11.6 19.4% 91 12.12 Trinidad &Tobago 961.9 1233.9 271.9 28.3% 573 111.67 Venezuela 624.2 724.4 100.2 16.1% 908 100.54 AsiaBangladesh 431.6 461.8 30.2 7.0% 75 3.62 Brunei 477.4 646.6 169.2 35.4% 220 53.81 Cambodia 211.1 219.0 7.9 3.8% 1133 29.37 India 7439.7 8058.5 618.8 8.3% 9900 568.20 Indonesia 651.0 733.0 82.0 12.6% 6000 521.30 Lao 125.9 133.5 7.7 6.1% 193 8.08 Malaysia 3169.9 3681.2 511.3 16.1% 14750 1641.54 Pakistan 767.2 852.5 85.3 11.1% 913 70.01 Philippines 555.5 629.8 74.3 13.4% 3950 364.68 Sri Lanka 189.4 233.2 43.8 23.1% 753 119.98 Thailand 1794.4 21		608.3	717.6	109.3	18.0%	1900	235.46
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St. Vicents & Gre. 969.5 1216.5 247.0 25.5% 104 18.28 Suriname 59.9 71.6 11.6 19.4% 91 12.12 Trinidad & 70bago 961.9 1233.9 271.9 28.3% 573 111.67 Venezuela 624.2 724.4 100.2 16.1% 908 100.54 Asia Bangladesh 431.6 461.8 30.2 7.0% 75 3.62 Brunei 477.4 646.6 169.2 35.4% 220 53.81 Cambodia 211.1 219.0 7.9 3.8% 1133 29.37 India 7439.7 8058.5 618.8 8.3% 9900 568.20 Indonesia 651.0 733.0 82.0 12.6% 6000 521.30 Lao 125.9 133.5 7.7 6.1% 193 8.08 Malaysia 3169.9 3681.2 511.3 16.1% 14750 1641.54 Pakistan 767.2 852.5 85.3 11.1%	St. Lucia	1214.6	1538.4	323.9		320	58.88
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Venezuela 624.2 724.4 100.2 16.1% 908 100.54 Bangladesh 431.6 461.8 30.2 7.0% 75 3.62 Brunei 477.4 646.6 169.2 35.4% 220 53.81 Cambodia 211.1 219.0 7.9 3.8% 1133 29.37 India 7439.7 8058.5 618.8 8.3% 9900 568.20 Indonesia 651.0 733.0 82.0 12.6% 6000 521.30 Lao 125.9 133.5 7.7 6.1% 193 8.08 Malaysia 3169.9 3681.2 511.3 16.1% 14750 1641.54 Pakistan 767.2 852.5 85.3 11.1% 913 70.01 Philippines 555.5 629.8 74.3 13.4% 3950 364.68 Sri Lanka 189.4 233.2 43.8 23.1% 753 119.98 Thailand 1794.4<	Trinidad &						
Venezuela 624.2 724.4 100.2 16.1% 908 100.54 Bangladesh 431.6 461.8 30.2 7.0% 75 3.62 Brunei 477.4 646.6 169.2 35.4% 220 53.81 Cambodia 211.1 219.0 7.9 3.8% 1133 29.37 India 7439.7 8058.5 618.8 8.3% 9900 568.20 Indonesia 651.0 733.0 82.0 12.6% 6000 521.30 Lao 125.9 133.5 7.7 6.1% 193 8.08 Malaysia 3169.9 3681.2 511.3 16.1% 14750 1641.54 Pakistan 767.2 852.5 85.3 11.1% 913 70.01 Philippines 555.5 629.8 74.3 13.4% 3950 364.68 Sri Lanka 189.4 233.2 43.8 23.1% 753 119.98 Thailand 1794.4<	Tobago	961.9	1233.9	271.9	28.3%	573	111.67
Bangladesh431.6461.830.27.0%753.62Brunei477.4646.6169.235.4%22053.81Cambodia211.1219.07.93.8%113329.37India7439.78058.5618.88.3%9900568.20Indonesia651.0733.082.012.6%6000521.30Lao125.9133.57.76.1%1938.08Malaysia3169.93681.2511.316.1%147501641.54Pakistan767.2852.585.311.1%91370.01Philippines555.5629.874.313.4%3950364.68Sri Lanka189.4233.243.823.1%753119.98Thailand1794.42123.1328.718.3%180002274.83Timor-Leste33.536.02.57.6%201.05Vietnam864.8938.974.18.6%3225190.66DecemiaGuinea48.952.83.97.9%50.30Solomon Islands30.934.33.410.9%251.90Vanuatu82.798.315.618.8%13517.55Any Disease affected countries	Venezuela	624.2	724.4	100.2	16.1%	908	100.54
Brunci 477.4 646.6 169.2 35.4% 220 53.81 Cambodia 211.1 219.0 7.9 3.8% 1133 29.37 India 7439.7 8058.5 618.8 8.3% 9900 568.20 Indonesia 651.0 733.0 82.0 12.6% 6000 521.30 Lao 125.9 133.5 7.7 6.1% 193 8.08 Malaysia 3169.9 3681.2 511.3 16.1% 14750 1641.54 Pakistan 767.2 852.5 85.3 11.1% 913 70.01 Philippines 555.5 629.8 74.3 13.4% 3950 364.68 Sri Lanka 189.4 233.2 43.8 23.1% 753 119.98 Thailand 1794.4 2123.1 328.7 18.3% 18000 2274.83 Timor-Leste 33.5 36.0 2.5 7.6% 20 1.05 Vietnam 864.8<				Asia			
Brunei477.4646.6169.235.4%22053.81Cambodia211.1219.07.93.8%113329.37India7439.78058.5618.88.3%9900568.20Indonesia651.0733.082.012.6%6000521.30Lao125.9133.57.76.1%1938.08Malaysia3169.93681.2511.316.1%147501641.54Pakistan767.2852.585.311.1%91370.01Philippines555.5629.874.313.4%3950364.68Sri Lanka189.4233.243.823.1%753119.98Thailand1794.42123.1328.718.3%180002274.83Timor-Leste33.536.02.57.6%201.05Vietnam864.8938.974.18.6%3225190.66OcceaniaPalau115.4150.835.430.6%6313.32Papua NuevaGuinea48.952.83.97.9%50.30Solomon Islands30.934.33.410.9%251.90Vanuatu82.798.315.618.8%13517.55Any Disease affected countries	Bangladesh	431.6	461.8	30.2	7.0%	75	3.62
India 7439.7 8058.5 618.8 8.3% 9900 568.20 Indonesia 651.0 733.0 82.0 12.6% 6000 521.30 Lao 125.9 133.5 7.7 6.1% 193 8.08 Malaysia 3169.9 3681.2 511.3 16.1% 14750 1641.54 Pakistan 767.2 852.5 85.3 11.1% 913 70.01 Philippines 555.5 629.8 74.3 13.4% 3950 364.68 Sri Lanka 189.4 233.2 43.8 23.1% 753 119.98 Thailand 1794.4 2123.1 328.7 18.3% 18000 2274.83 Timor-Leste 33.5 36.0 2.5 7.6% 20 1.05 Vietnam 864.8 938.9 74.1 8.6% 3225 190.66 Guinea 48.9 52.8 3.9 7.9% 5 0.30 Solomon Islands		477.4	646.6	169.2	35.4%	220	53.81
Indonesia651.0733.082.012.6%6000521.30Lao125.9133.57.76.1%1938.08Malaysia3169.93681.2511.316.1%147501641.54Pakistan767.2852.585.311.1%91370.01Philippines555.5629.874.313.4%3950364.68Sri Lanka189.4233.243.823.1%753119.98Thailand1794.42123.1328.718.3%180002274.83Timor-Leste33.536.02.57.6%201.05Vietnam864.8938.974.18.6%3225190.66OceaniaPalau115.4150.835.430.6%6313.32Papua NuevaGuinea48.952.83.97.9%50.30Solomon Islands30.934.33.410.9%251.90Vanuatu82.798.315.618.8%13517.55Any Disease affected countries	Cambodia	211.1	219.0	7.9	3.8%	1133	29.37
Lao125.9133.57.76.1%1938.08Malaysia3169.93681.2511.316.1%147501641.54Pakistan767.2852.585.311.1%91370.01Philippines555.5629.874.313.4%3950364.68Sri Lanka189.4233.243.823.1%753119.98Thailand1794.42123.1328.718.3%180002274.83Timor-Leste33.536.02.57.6%201.05Vietnam864.8938.974.18.6%3225190.66OceaniaPalau115.4150.835.430.6%6313.32Papua Nueva48.952.83.97.9%50.30Solomon Islands30.934.33.410.9%251.90Vanuatu82.798.315.618.8%13517.55Any Disease affected countries	India	7439.7	8058.5	618.8	8.3%	9900	568.20
Malaysia3169.93681.2511.316.1%147501641.54Pakistan767.2852.585.311.1%91370.01Philippines555.5629.874.313.4%3950364.68Sri Lanka189.4233.243.823.1%753119.98Thailand1794.42123.1328.718.3%180002274.83Timor-Leste33.536.02.57.6%201.05Vietnam864.8938.974.18.6%3225190.66OceaniaPalau115.4150.835.430.6%6313.32Papua Nueva48.952.83.97.9%50.30Solomon Islands30.934.33.410.9%251.90Vanuatu82.798.315.618.8%13517.55Any Disease affected countries	Indonesia	651.0	733.0	82.0	12.6%	6000	521.30
Pakistan767.2852.585.311.1%91370.01Philippines555.5629.874.313.4%3950364.68Sri Lanka189.4233.243.823.1%753119.98Thailand1794.42123.1328.718.3%180002274.83Timor-Leste33.536.02.57.6%201.05Vietnam864.8938.974.18.6%3225190.66OceaniaPalau115.4150.835.430.6%6313.32Papua NuevaGuinea48.952.83.97.9%50.30Solomon Islands30.934.33.410.9%251.90Vanuatu82.798.315.618.8%13517.55Any Disease affected countries	Lao	125.9	133.5	7.7	6.1%	193	8.08
Philippines 555.5 629.8 74.3 13.4% 3950 364.68 Sri Lanka 189.4 233.2 43.8 23.1% 753 119.98 Thailand 1794.4 2123.1 328.7 18.3% 18000 2274.83 Timor-Leste 33.5 36.0 2.5 7.6% 20 1.05 Vietnam 864.8 938.9 74.1 8.6% 3225 190.66 Oceania Palau 115.4 150.8 35.4 30.6% 63 13.32 Papua Nueva Guinea 48.9 52.8 3.9 7.9% 5 0.30 Solomon Islands 30.9 34.3 3.4 10.9% 25 1.90 Vanuatu 82.7 98.3 15.6 18.8% 135 17.55 Any Disease affected countries Any Disease affected countries 14.5 14.5 14.5	Malaysia	3169.9	3681.2	511.3	16.1%	14750	1641.54
Sri Lanka 189.4 233.2 43.8 23.1% 753 119.98 Thailand 1794.4 2123.1 328.7 18.3% 18000 2274.83 Timor-Leste 33.5 36.0 2.5 7.6% 20 1.05 Vietnam 864.8 938.9 74.1 8.6% 3225 190.66 Oceania Palau 115.4 150.8 35.4 30.6% 63 13.32 Papua Nueva Guinea 48.9 52.8 3.9 7.9% 5 0.30 Solomon Islands 30.9 34.3 3.4 10.9% 25 1.90 Vanuatu 82.7 98.3 15.6 18.8% 135 17.55	Pakistan	767.2	852.5	85.3	11.1%	913	70.01
Thailand 1794.4 2123.1 328.7 18.3% 18000 2274.83 Timor-Leste 33.5 36.0 2.5 7.6% 20 1.05 Vietnam 864.8 938.9 74.1 8.6% 3225 190.66 Oceania Palau 115.4 150.8 35.4 30.6% 63 13.32 Papua Nueva Guinea 48.9 52.8 3.9 7.9% 5 0.30 Solomon Islands 30.9 34.3 3.4 10.9% 25 1.90 Vanuatu 82.7 98.3 15.6 18.8% 135 17.55		555.5	629.8	74.3	13.4%	3950	364.68
Timor-Leste 33.5 36.0 2.5 7.6% 20 1.05 Vietnam 864.8 938.9 74.1 8.6% 3225 190.66 Oceania Oceania Oceania Oceania Oceania Oceania Oceania Oceania Palau 115.4 150.8 35.4 30.6% 63 13.32 Papua Nueva Guinea 48.9 52.8 3.9 7.9% 5 0.30 Solomon Islands 30.9 34.3 3.4 10.9% 25 1.90 Vanuatu 82.7 98.3 15.6 18.8% 135 17.55 Any Disease affected countries Countries Oceanita Oceanita Oceanita	Sri Lanka	189.4	233.2	43.8	23.1%	753	119.98
Vietnam 864.8 938.9 74.1 8.6% 3225 190.66 Oceania Palau 115.4 150.8 35.4 30.6% 63 13.32 Papua Nueva Guinea 48.9 52.8 3.9 7.9% 5 0.30 Solomon Islands 30.9 34.3 3.4 10.9% 25 1.90 Vanuatu 82.7 98.3 15.6 18.8% 135 17.55 Any Disease affected countries	Thailand	1794.4	2123.1	328.7	18.3%	18000	2274.83
Oceania Oceania Palau 115.4 150.8 35.4 30.6% 63 13.32 Papua Nueva 50.6% 63 13.32 Guinea 48.9 52.8 3.9 7.9% 5 0.30 Solomon Islands 30.9 34.3 3.4 10.9% 25 1.90 Vanuatu 82.7 98.3 15.6 18.8% 135 17.55 Any Disease affected countries	Timor-Leste	33.5	36.0	2.5	7.6%	20	1.05
Palau 115.4 150.8 35.4 30.6% 63 13.32 Papua Nueva	Vietnam	864.8	938.9	74.1	8.6%	3225	190.66
Papua Nueva 52.8 3.9 7.9% 5 0.30 Guinea 48.9 52.8 3.4 10.9% 25 1.90 Solomon Islands 30.9 34.3 3.4 10.9% 25 1.90 Vanuatu 82.7 98.3 15.6 18.8% 135 17.55 Any Disease affected countries					L		
Guinea48.952.83.97.9%50.30Solomon Islands30.934.33.410.9%251.90Vanuatu82.798.315.618.8%13517.55Any Disease affected countries	Palau	115.4	150.8	35.4	30.6%	63	13.32
Solomon Islands 30.9 34.3 3.4 10.9% 25 1.90 Vanuatu 82.7 98.3 15.6 18.8% 135 17.55 Any Disease affected countries	Papua Nueva						
Vanuatu 82.7 98.3 15.6 18.8% 135 17.55 Any Disease affected countries		48.9	52.8	3.9	7.9%	5	0.30
Any Disease affected countries							
	Vanuatu	82.7	98.3	15.6	18.8%	135	17.55
Total 73664.2 84295.3 10631.1 14.4% 120460.2 11995.45					d countries		
	Total	73664.2	84295.3	10631.1	14.4%	120460.2	11995.45

One of the most remarkable outcomes is that there is a predicted increase of 10.6 million tourist arrivals (14.4%) after TRD are eradicated from the countries listed in the table, leading to a rise in tourism expenditures of 12 billion US\$ worldwide. Specifically, countries in the Americas such as Aruba, Bahamas and Barbados are the ones that would see the highest growth in tourist arrivals. Countries whose tourist



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sector's have a higher level of tourism expenditures, like Thailand, Malaysia, Mexico and India would largely benefit from the eradication of Malaria.

On the other hand, African countries would experience very low or even negative (i.e. in Niger, Mali, Burkina Faso and Central African Republic) gains in inbound tourism if TRD risk disappear. This can be explained since the African countries suffer from several TRD risk which make the problem more complex as well as from very important structural barriers that impede the tourism sector to develop.

3.5. Conclusion

Literature shows that health and macroeconomics are strongly correlated, as good health in a population improves the country's economic outcomes, since it boosts economic wellbeing through higher levels of labour productivity, education and investment, and through demographic change. However, all these issues are often observed in the long run, jointly with the improvement of health statistics, and in many cases it is hard to establish the true causal relationship. Countries' resources are limited, and decisions have to be made in the short run as to whether investing resources in an eradication programme is preferable to their use in projects unrelated to healthcare or even in alternative health intervention programmes.

Using a gravity model, this chapter has evaluated the effects of the eradication of Malaria, Yellow Fever, Dengue and Ebola on international tourism arrivals and its national economic impact at destinations through their tourist industries. This is the first empirical attempt to study the association between infectious disease risk and international tourism flows using a global database. However, since the variable of interest is time-invariant, causal effects cannot be explored.

The results show Malaria and Yellow Fever to be the diseases that play the most decisive role in explaining tourist destination choices. In any case, the risk of TRD is



associated to a decrease of 37% in inbound tourism figures.

In this research, a simulation analysis to explore the impact on tourist arrivals and expenditure of eradication of infectious disease risks is implemented. As mentioned before, the figures presented are for guidance only but can help to evaluate one dimension of the impact of policies that aim to eradicate TRD.

Specifically, the eradication of Malaria can be associated with an increase of 6.2 million tourists and 3,532 million US dollars in the affected countries per year, figures that represent an average 19.8% growth in total tourist arrivals of the affected economies. In the case of Dengue, its eradication would imply an increase of 2.5 million tourists, an increase in expenditure of 2,861 million US dollars, and an average growth of 3.7 % in the affected destinations' inbound tourists.

At a secondary level, the eradication of Yellow Fever would lead to 8.1 million more tourists, representing an increase of 4,975 million US dollars and a 30.1%% average growth in the tourist arrivals to affected economies. Finally, Ebola's eradication in the four affected countries during the period of our analysis would imply an increase of 5 million international tourists, representing an increase of 375 million US dollars and an average growth of 76 %.

By analysing the economic benefits of the eradication of Dengue, Ebola, Malaria, and Yellow Fever for the tourist sector - a strategic economic sector for many of the countries where these TRD are present -, this chapter explores a new aspect of the quantification of health policies which should be taken into consideration in future international health assessment programmes. Consequently, results of this work should be taken into account not only at international level to promote international research programs aiming the eradication of these diseases but also at country level to evaluate the economic benefits in terms of tourist expenditures for a specific country to reduce the incidence or eliminate the disease.

It is important to note that the results must be interpreted within the context of a study of these characteristics, and thus an analysis is only made of the direct impact of the diseases' eradication. The multiplicative effects of a growth in the GDP, in



terms of tourism attractiveness, are not evaluated. Consequently, the economic results can be considered to be skeleton ones. Another important point is the fact that data at a national level was used for the analysis and this can be imprecise, especially in the case of some big countries where some of the aforementioned diseases tend to be limited to certain areas. However, tourism data is available at a national level and, for this reason, regional information could not be used.

Future research should try to take into account for neighbourhood effects (country with a high disease risk may negatively affect tourism in neighbouring countries) and to incorporate the latest available data, particularly in the case of Ebola, since it should be used to confirm whether the influence of the social media, following the 2014-2015 outbreak of Ebola, changed the impact on the affected countries. In particular to investigate the causal effect of the outbreak of some specific diseases (Ebola, SARS, ...) on tourism flows it would be desirable to use the difference in differences approach since these disease could have mainly a temporal effect. Moreover, this research only addresses the impact of infectious disease risk at the host country and tourist arrivals. However, the gravity model would make it possible to study the associations between tourism and disease risk in both the source and origin country since a disease in the origin country may prevent people from travelling abroad.



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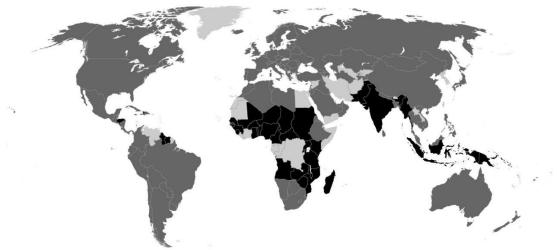
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APPENDIX-3

APPENDIX 3.1

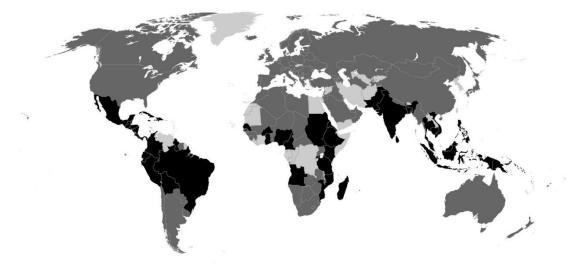
1. Risk of Malaria



Note: black color implies countries with moderate and High risk of Malaria, dark grey implies no risk and light grey means that the country is not included in the sample

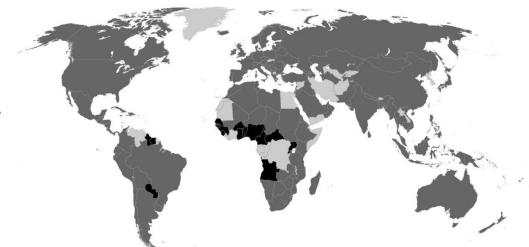


2. Dengue Risk



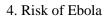
Note: black color implies countries where Dengue is endemic, dark grey implies no risk and light grey means that the country is not included in the sample

3. Risk of Yellow Fever



Note: black color implies countries where yellow fever vaccination is recommended, dark grey implies no risk and light grey means that the country is not included in the sample





Note: black color implies countries where there was a ebola outbreak during the period 2000-2010, dark grey implies no risk and light grey means that the country is not included in the sample



APPENDIX 3.2

	Data sources	
Variable	Definition	source
LnTou _{jt}	Log of Tourist arrivals to destination country from the origin country	UNWTO (2015)
LnGDPpc _{jt}	Log of Real GDP per capita of the destination country	The World Bank Group
LnPopjt	Log of population of the destination country	(2016)
LnDist _{ij}	Log of the distance (in km) between the origin and the destination country	
Border _{ij}	Dummy variable that takes the value 1 if both countries in the pair share a common landborder, 0 otherwise	
Language _{ij}		
Colony _{ij}	Dummy variable that takes the value 1 if both countries in the pair have ever had a colonial link, 0 otherwise	Mayer and Zignago (2011)
Comcol _{ij}	Dummy variable that takes the value 1 if both countries in the pair have had a common colonizer after 1945, 0 otherwise	
<i>Smctry</i> _{ij}	Dummy variable that takes the value 1 if both countries in the pair were/are the same country, 0 otherwise	
ReligSim _{ij}	Religious similarity Index	Johnson and Grim (2008)
RTA _{ijt}	Dummy variable that takes the value 1 if both countries in the pair	World Trade Organization
KI Aijt	belong to the same regional trade agreement, 0 otherwise	(2016)
<i>Rlaw</i> _{jt}	Rule of Law of the destination country	The World Bank Group. (2015)
Terrorism _{jt}	Number of fatalities in terrorist attacks at the destination country	National Consortium for the Study of Terrorism and Responses to Terrorism (2016)
WHS _{jt}	Number of World Heritage Sites at the destination country	UNESCO (2016)
<i>LnTemp</i> _{jt}	Logaritm of the annual average temperature (in Celsius) at the destination country	Mitchell (2004)
LnLifeExp _{jt}	Life expectancy at birth	United Nations (2016)
<i>Malaria_{jt}</i>	Dummy variable that takes the value 1 if there is risk of Malaria at the destination country, 0 otherwise	
YellowFev er _{jt}	Dummy variable that takes the value 1 if there is risk of Yellow Fever at the destination country, 0 otherwise	
Dengue _{jt}	Dummy variable that takes the value 1 if there is risk of Dengue in the destination country , 0 otherwise	World Health Organization. (2016)
Ebola _{jt}	Dummy variable that takes the value 1 if there is risk of Ebola at the destination country, 0 otherwise	
AnyTRD _{jt}	Dummy variable that takes the value 1 if there is risk of any TRD at the destination country, 0 otherwise	



4

NEW INSIGHTS INTO THE ROLE OF PERSONAL INCOME ON INTERNATIONAL TOURISM

Abstract: This study aims to investigate the role of personal income in the income elasticity of tourism demand and, more specifically, the hypothesis proposed by Morley (1998), who suggested that, in travel decisions, the richest and poorest individuals both tend to react less to changes in income than middle-class individuals, who tend to be more sensitive. To that end, this study applies different strategies within the context of a gravity model, using yearly data from 1995 to 2016 and bilateral flows between 200 countries. The results show that income elasticity behaviours are determined to a significant extent by per capita income in the origin country and they confirm the inverted U relationship between income elasticity and personal income. The study indicates that middle-income countries are more elastic than low and high-income ones, while high-income countries display an inelastic or non-significant relationship.

Keywords: international tourism, income elasticity, gravity model, demand analysis.



4.1. Introduction

Tourism demand modelling can be tackled from different perspectives. Numerous surveys on the subject have shown that aggregate tourism demand modelling has been the most popular method to do that (Song and Li, 2008; Peng et al., 2015; G Li et al., 2006; Crouch, 1994; Morley, 1992). Generally speaking, with this approach, different regression models are built to explore the correlation between bilateral tourism flows (origin-destination) and a set of determining variables in order to accurately quantify the relationship (normally in terms of elasticities) between the change in the aggregate level of tourism flows and the change in any of the explanatory variables. The final goal is often to forecast tourism demand, a key issue for the industry (Song and Li, 2008). Whatever the case, from a literature review, the income in source markets has been demonstrated to be a dominant explanatory variable and it is the most widely discussed determinant of international tourism demand (Peng et al. 2014).

Although studies of tourism demand modelling usually assume that income's effect on tourism demand remains stable, irrespective of changes in the remaining factors, more recently an increasing body of literature has started to draw attention to the variability of the estimated income elasticity, striving to explain why the relationship between tourism and income can vary as a result of different factors. Empirical literature has just started to identify various factors that could explain the variability of the income elasticity, such as financial and economic crises (Smeral, 2008), the point in the business cycle (Smeral and Song, 2013; Gunter and Smeral, 2016), structural changes (Song et al., 2009), different time periods (Gunter and Smeral (2016), different destination-origin pairs (Peng et al., 2014) and the income level at the destination country/continent (Martins et al., 2017).

However, controversy over the income elasticity's assumed constancy is nothing new. According to the hypothesis put forward by Morley (1998), low-income and



high-income countries are expected to have a low elasticity, while medium-income countries are thought to be the most elastic. In other words, people in the wealthiest countries would not relinquish their holiday in the event of an economic recession (and neither would they significantly increase their travel activities in the event of economic growth) because they would understand travel to form part of their regular consumption (a necessary good). That is, they might adjust their travel expenses but they would continue to travel. However, people in medium-income countries would be the most sensitive, reacting significantly to changes in income levels because they understand tourism to be a luxury good. Finally, people in the poorest countries would not have enough money for international travel. So, since they demand for tourism is limited, they would not react to changes in income levels.

The objective of this study is to investigate the relationship between personal income and the income elasticity of tourism demand and to evaluate the veracity of the hypothesis put forward by Morley (1998). Although various empirical applications that have explored variability in income elasticities (Gunter and Smeral, 2016; Rosselló et al., 2005; Smeral and Song, 2013; Song and Wong, 2003; Song and Li, 2008; Song et al., 2010) seem to point to the validity of Morley's hypothesis, none of these papers has directly attempted to confirm the hypothesis that personal income determines the income elasticity of tourism demand, in the sense that the richest and poorest people tend not to react very much to changes in income, while the middle classes are the most sensitive individuals. It is worth noting that an in-depth analysis of the special relationship between income and tourism is an issue of strategic importance in long-term tourism forecasts. Thus, in a world where future predictions of the world GDP point to a positive trend in coming decades (PwC, 2015), if the GDP is acknowledged to play a key role in long-run tourism projections (UNWTO, 2011), then an accurate insight into how income determines tourism flows is crucial for strategic planning by both public administrations and private-sector tourism stakeholders.

To achieve the above objective, this research study proposes the application of various different strategies, using aggregate tourism demand models for international



tourism in the context of a gravity model. The models are estimated for different income and timing subsets, using interactions between the income elasticity and level of income in the source market. Yearly data from 1995 to 2015 and for bilateral flows between 200 countries was used to estimate a gravity model.

The rest of the study is organized as follows. The next section reviews some previous papers that have explored and quantified the relationship between tourism demand and income. Section 4.3 presents the methodology and data used to make an in-depth analysis of the special relationship of the national income variable and its effect on tourism demand. Section 4.4 presents the empirical application and, finally, section 4.5 summarizes the results, before going on to present the general conclusions, point out the limitations of the study and propose research ideas to extend the analysis in the future.

4.2. Income and tourism demand: a recent literature review

Economic utility theory has led economists to specify demand as a function of determining variables, with a decisive influence for individuals. According to the microeconomic theory of tourism demand, the independent variables in the models should include measures of income, fares, prices and other variables that tourists encounter at a destination (Morley, 1992). The empirical results have shown that the dynamics of tourism demand are mainly determined by income and prices and, more specifically, past research has demonstrated that income in the source market is a dominant explanatory variable and it is the most widely discussed determinant of international tourism demand (Crouch, 1992, 1994 and 1995; Lim, 1999; Peng et al., 2014 and 2015).

In empirical exercises using aggregate data, the nominal or real GDP or their per capita form are the most popular proxies of tourist income (Greenidge, 2001; Turner and Witt, 2001). Whichever income variable is used, most of the empirical studies



demonstrate that, in accordance with economic theory, income has a positive effect on tourism demand. Crouch (1996) shows that, in empirical exercises, multiple values are obtained in estimates of the income elasticity of tourism demand modelling. The point is that international tourism should be considered a luxury product, as indicated by the fact that most studies have estimated an income elasticity of demand of over 1, showing that, as income rises, tourism consumers spend an increasing amount of their income on international travel (Peng et al., 2014). However, in the meta-analysis by Crouch (1996), although the mean income elasticity was 1.86, the standard deviation was 1.78, showing that many empirical applications obtained a value of between 0 and 1 (indicating that tourism is a necessary good), with some of them even obtaining a negative value for the income elasticity (indicating that tourism can be an inferior good). Consequently, although in estimations of tourism demand, the income elasticity is considered to remain constant, it has been agreed that many determinants can cause the value of this elasticity to differ.

Song et al., (2010) proposed the use of confidence intervals in the estimation of tourism demand elasticities. They argued that point estimates give a single value for the parameter of interest, but that it provides no information about its degree of variability. Hence, point estimations could provide biased estimations of true elasticities if it is assumed that this elasticity is a non-linear function of other parameters in the model. In a study that pays particular attention to income elasticities, Peng et al., (2014) show that income elasticities can differ considerably across different origin–destination pairs, depending on how deluxe the destinations are. For example, the estimated income elasticity of the tourism demand for Aruba varies from 1.43 for American tourists to 2.52 for Dutch visitors (Croes and Vanegas, 2005). Along the same lines, Dogru, et al., (2017) point out that a Giffen good (a good for which the demand grows as its price increases, and vice versa) should be related to an inferior good, and hence this type of destination is lacking in quality and it will be chosen by tourists when they have no other alternative.

Economic theory suggests that time can also influence elasticity values. In the short



term, tourists' responses to income and price changes may be constrained by existing travel arrangements. However, in the long run, tourists have enough time to adjust as necessary and they are likely to display more income-elastic behaviour (Peng et al., 2014). According to these last authors, the estimated long-run income and (absolute) price elasticities of international tourism demand are expected to be higher than the short-run estimates. In their empirical framework, Song et al., (2009) show that tourism demand modelling exercises have often failed to consider long-run co-integration relationships and short-run dynamics. However, in many empirical studies that have calculated the elasticities in both the short and long run, the values of both the long-run income and own-price elasticities are higher than their short-run counterparts, showing that tourists are more sensitive to income/price changes in the long term (Pesaran, 1997; Pesaran et al., 2001; Li et al., 2005; Mervar and Payne, 2007; Seetaram et al., 2016).

It is also important to add that divergences in income elasticity estimations can also be explained by the way in which tourism demand is measured. Martins et al., (2017) used the inbound visitor population and on-the-ground expenditures as tourism demand measures, showing that the per capita world GDP is more important in explaining arrivals, although relative prices become more important when expenditures are used as a proxy for tourism demand. They also showed that an increase in the per capita world GDP, the depreciation of the national currency, and a decline in relative domestic prices help to boost tourism demand.

It has also been suggested that the economic environment can also determine income elasticities. Using a global panel data set of 208 destination countries and 7 origin countries between 1985 and 2002, Eugenio-Martin et al., (2008) found that economic development makes a difference to tourist decision-making, showing that in countries with high GDPs, differences in economic development are not significant, whereas in developing countries they are. Gunter and Smeral (2016) showed that structural change does not remain constant in the long term and its positive impact on certain goods, such as international travel, slows down or disappears, also leading to a decline in income elasticities from period to period. Additionally, the reaction of



tourism demand to income changes could be asymmetric during different phases of the business cycle (Smeral and Song, 2013; Smeral 2018). Overall, it could be argued that the economic environment can be captured by income indicators (like the per capita GDP) and, consequently, these studies could be considered to be specific case studies of the more general hypothesis explored in this chapter, which proposes that the income elasticity will depend on the level of personal income.

Martins et al., (2017) recently conducted an empirical analysis of world tourism demand of special interest for the purposes of this research study. Using an unbalanced panel of 218 countries over the period 1995-2012, they analysed the role of the per capita world GDP on tourism demand (among other variables), partitioning the data by the income level (at the destination) and finding robust results of the existence of differences in the estimated value of the income elasticity, depending on the per capita GDP at the destination. In some way, our study expands the study by Martins et al., (2017), focusing on income's effect on tourism demand and taking into account not just differences in personal income at the destination but also in the origin country, thus linking current discussion on income's effect on tourism demand with Morley's hypothesis (1998) on the differing income elasticity of tourism demand, depending on the countries' level of income.

4.3. Methodology and data

4.3.1. Methodology

Because personal income at a national level is expected to have a high structural component, a gravity equation was used to explain tourism flows, while also taking into consideration the potential time variability of the determinants. The gravity equation suggests that different bilateral international flows (i.e. trade, tourism, migrations, foreign direct investment, etc.) are expected to increase with the economic size of a country and to decrease as the distance between country pairs



grows. Additionally, a set of other determining variables, such as origin and destination characteristics, can be included.

The gravity model has been extensively used in empirical exercises to explain international trade due to its goodness of fit (Deardorff, 1998; Anderson and Wincoop, 2003; Vietze, 2012). Since tourism is a special type of trade in services, gravity equations have also been used to estimate the magnitude of tourism flows in different contexts (Eilat and Einav, 2004; Kimura and Lee, 2006; Santana-Gallego et al., 2010; Fourie and Santana-Gallego, 2011; Falk, 2016). Although the use of the gravity equation method has been backed up by international trade theory for many years, only recently has its use been justified in the field of tourism, based on consumer theory (Morley et al., 2014).

Given the aim of this chapter–which focuses on the specific effect of personal income on the income elasticity–, the gravity equation that was used considered the fixed effects between country pairs and destination-period pairs and so it centred its attention on structural factors relating to the origin country which determine the outbound tourism demand. Analytically, the baseline model can be written as:

$$\ln(Tou_{ijt}) = a + b \ln(GDPpc_{it}) + c_k X_{it}^k + \alpha_{ij} + \delta_{jt} + \varepsilon_{ijt}$$

$$[4.1]$$

Where the dependent variable, Tou_{ijt} reflects tourism demand from origin country *i* to destination country *j* during period *t*; $GDPpc_{it}$ is the personal income indicator of the origin country; X_{it}^k is a set of determining variables relating to the origin country during period *t*; and *a*, *b* and *c*, are parameters to be estimated. Moreover, a set of fixed effects that control for dyadic (α_{ij}) and destination-year (δ_{jt}) characteristics was added to equation [4.1]. Finally, ε_{ijt} is a well-behaved disturbance term. It should be noted that the *Tou* and *GDPpc* variables are taken in natural logs, so coefficient *b* can be interpreted as an elasticity.

From the initial Equation [4.1], the dependence of the income elasticity or, in other words, the specific function f between *Tou* and *GDPpc* is evaluated following different strategies. First, we consider the 4th order Taylor polynomial of the



relationship between tourism demand and the income variables. Analytically:

$$\ln(Tou_{ijt}) = a + b_1 \ln(GDPpc_{it}) + b_2 [\ln(GDPpc_{it})]^2 + b_3 [\ln(GDPpc_{it})]^3 \quad [4.2]$$
$$+ b_4 [\ln(GDPpc_{it})]^4 + c_k X_{it}^k + \alpha_{ij} + \delta_{it} + \varepsilon_{ijt}$$

Thus, assuming that f is derivable and continuous, with the estimation of b_1 , b_2 , b_3 and b_4 , it is possible to evaluate the function's behaviour within the range of the observed *GDPpc* variable from a specific dataset. The existence of a maximum can be found through the first derivative of Equation 2 in relation to ln(GDPpc), after verifying that the second derivative takes a negative value within the income variable's range.

The second strategy considers different subsamples of origin countries, selected according to the ordered values of the *GDPpc* variable, and it estimates different (*b*) parameters for equation [4.1] for the different subsamples. The effect of personal income on the income elasticity of tourism demand is derived, in this case, from the different estimations of the *b* parameters. Analytically, we divide the sample into *w* groups with the same number of countries in each group, four in our case $w = \{1,2,3,4\}$, where 1 represents the group of countries with the lowest incomes and 4 the countries with the highest.

For both strategies, we evaluate general estimations, with two different subsamples interacting with the proposed one. On the one hand, we consider the differences in the level of development at the destinations since, according to Martins et al., (2017), the level of development at a destination can be a significant determinant of the income elasticity. On the other hand, according to previous results on how the economic crisis has affected tourism demand (Gunter and Smeral 2016; Papatheodorou et al, 2010; Smeral and Song, 2013; Smeral, 2008 and 2018), we consider different subsample periods for the years before and after the international economic crisis.

Finally, for estimation purposes, we use a standard OLS estimator with fixed effects as benchmark estimation (OLS-FE). In addition, the Poisson pseudo-maximum-



likelihood (PPML) estimator proposed by Silva and Tenreyro (2006 and 2011), which correctly accounts for the existence of heteroscedastic residuals, is also used. PPML also allows for zeros in the dependent variable. However, one drawback to tourism data is the fact that it is not possible to discriminate between zero tourism flows and missing values. For this reason, as proposed by Neumayer and Plumper (2016), the PPML estimator is only applied for positive bilateral tourism flows.

4.3.2. Data

In accordance with previous literature, the dependent variable Tou_{ijt} used in this study consists of the number of international tourist arrivals from origin country *i* to destination country *j* during year *t*, using data from the United Nations' World Tourism Organization (UNWTO, 2017). As mentioned earlier, one of the main limitations of this database is the fact that it does not report zero tourism flows between country pairs. Missing data can stem from gaps in the data collection procedure or because bilateral tourism flows between some country pairs are recorded only if they are above a certain threshold. Marginal tourism flows from origin countries to destinations are grouped together by the UNWTO under the "other countries" label. Although we acknowledge that the estimates can suffer from a sample selection bias because no zeros are reported, only positive tourism flows are considered in the analysis. The dataset includes 200 countries for the period 1995-2016.

The personal income indicator $GDPpc_{it}$ is measured through the real per capita GDP of each origin country, and is taken from the World Development Indicators. As mentioned in the methodological section, because the variable of interest is origin specific, we should consider how the control variables are related to the origin country too, while other potential determining variables referring to country pairs (like the distance) or to the destination (the coastline, visa restrictions etc.) will be captured by the fixed effects.



The control/explanatory variables (X_{it}^k) were taken from the World Economic Indicators. More specifically, we take into consideration *Pop*, the population of the origin country in thousands; *R-Law*, the rule of law, which is a proxy for the origin country's law and governance system, which captures perceptions of the extent to which agents have confidence in and abide by the rules of society and, in particular, the quality of contract enforcement, property rights, the police, and the courts, as well as the likelihood of crime and violence. This variable ranged from -2.5 (weak) to 2.5 (strong). *Terrorism* was used as a proxy for the level of instability and insecurity in the origin country, measured as the number of victims of terrorist attacks per 10,000 inhabitants. The data was obtained from the Global Terrorism Database (2016), which defines terrorism as 'the threatened or actual use of illegal force and violence by a non-state actor to attain a political, economic, religious, or social goal through fear, coercion, or intimidation'.

The main descriptive statistics relating to these variables are presented in Table 4.1.

Table 4.1 Descriptive Statistics					
	Obs	Mean	Std. Dev.	Min	Max
Tou _{ijt}	211,073	74372.76	860131	0	7.90e+07
<i>GDPpc</i> _{ijt}	804,351	14921.96	21,356	170.6	192,989
Pop _{ijt}	824,051	3.34e+07	1.30e+08	4,377	1.40e+09
Rlaw _{ijt}	808,882	.090	.971	-2.17	2.10
<i>Terrorism</i> _{ijt}	853,798	.0211	.140		3.9

4.4. Empirical application

The estimation results of the baseline model, Equation [4.1], are presented in Table 4.2 using the whole sample first and then two different periods relating to the precrisis period (1995-2007) and the crisis and post-crisis period (2008-2016). In general, the estimated parameters of the control variables yield the expected signs and sizes, suggesting that the model is correctly specified.



As expected, countries with bigger populations generate more international tourists. Despite the clear evidence that this result provides, it should be highlighted that, if we focus on PPML estimations, the parameter for the post-crisis period is lower than the pre-crisis one (and significant only at a 10% level).

Table 4.2 Baseline Model						
	All Sample 1995-2007 2008-2016					
	OLS-FE	PPML	OLS-FE	PPML	OLS-FE	PPML
$Ln(GDPpc_{ijt})$	0.774***	0.910***	0.623***	0.886***	0.748***	1.057***
	(0.0327)	(0.164)	(0.0459)	(0.170)	(0.0457)	(0.252)
$Ln(Pop_{ijt})$	0.449***	0.803***	0.143	1.171***	0.698***	0.395*
	(0.0605)	(0.260)	(0.0988)	(0.229)	(0.0858)	(0.236)
<i>Rlaw</i> _{ijt}	0.0569	0.140***	0.171*	-0.111	0.0403	0.146***
	(0.0375)	(0.0533)	(0.0964)	(0.142)	(0.0274)	(0.0516)
<i>Terrorism</i> _{ijt}	0.0684***	-0.189**	0.00932	-0.157*	0.0757***	-0.0251
	(0.0198)	(0.0825)	(0.0241)	(0.0941)	(0.0244)	(0.0512)
Observations	205,998	205,998	103,211	103,211	102,296	102,296
R-Square	0.968		0.973		0.981	

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Destination-year and countrypair fixed effects are included but not reported

This should be tied in with the higher propensity to travel domestically during and after the crisis period, an option that is more easily available in big countries. The coefficient for terrorism at the origin country is very low or even insignificant in most of the regressions. However, the positive sign, when it is significant, shows that if there are attacks in the origin country, people tend to travel abroad more. Additionally, a good law and governance system in the origin country is also related to a higher propensity to travel internationally.

As for the variable of interest, personal income, all the estimated parameters show a positive significant sign, highlighting the expected positive relationship between income and tourism demand. Moreover, the income elasticities estimated by the PPML model are always greater than the ones for the OLS-FE estimates. Focusing specifically on the results of the PPML model, the values of the coefficients show a mean income elasticity of around one, which is in line with previous estimates found in past literature (Peng et al., 2015; Li et al., 2006; Lim 1997 and 1999; Crouch, 1994, 1995 and 1996, among others). The pre-post crisis analysis shows an increase in the income elasticity values in the most recent period. Again, this coincides with



the related literature, which propounds relatively higher income elasticities during sluggish growth periods as compared with fast ones (Smeral, 2014 and 2018). As a possible explanation for this, Smeral (2014) suggests that consumers behave like loss averters. That is, consumers will not reduce their consumption and travel plans during the slowdown period when they expect a recession.

However, as argued in the methodological section, the variability of the income elasticity can be related to the country's income level, and this issue is analysed by considering a 4th order Taylor polynomial, in accordance with Equation 4.2, whose estimated parameters are shown in Table 4.3. Thus Table 4.3 shows that the coefficients of the polynomial of the GDPpc variable confirm the existence of a complex (nonlinear) relationship between personal income and the income elasticity at a country level. Additionally, according to the estimated coefficients of the polynomial, an inverted U-shape relationship is found, providing evidence of Morley's hypothesis that low-income and high-income countries tend to be lowelastic while medium-income countries are the most elastic.

	All Sample	1995-2007	2008-2016
Method	-		
PPML			
$Ln(Pop_{ijt})$	1.160***	1.354***	0.504**
	(0.137)	(0.247)	(0.202)
<i>Rlaw</i> _{ijt}	0.122**	-0.091	0.148**
	(0.0519)	(0.135)	(0.0575)
Terrorism _{ijt}	-0.138**	-0.142*	-0.012
	(0.0643)	(0.0849)	(0.0420)
$Ln(GDPpc_{ijt})$	23.67**	8.545	39.94**
	(11.93)	(18.79)	(19.20)
$Ln(GDPpc_{ijt})^2$	-4.667**	-1.714	-8.315**
	(2.144)	(3.434)	(3.436)
$Ln(GDPpc_{ijt})^3$	0.417**	0.164	0.756***
	(0.169)	(0.273)	(0.268)
$Ln(GDPpc_{ijt})^4$	-0.0137***	-0.00565	-0.0247***
2 V ·	(0.00489)	(0.00797)	(0.00770)
Observations	205,998	103,211	102,296

 Table 4.3 Non-Linear Model

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Destination-year and country-pair fixed effects are included but not reported.



Further insights into these results can be obtained by calculating the turning points. That is, the *GDPpc*, where it is expected that, on average, a country will display a higher income elasticity. If we focus on the PPML estimations, we get the maximum *GDPpc* at US\$ 40,134. Thus, when a country's per capita GDP exceeds this threshold, its income elasticity is expected to become less elastic. According to data for 2017, 29 countries exceeded this value. It is important to note that for the postcrisis period, this threshold has rised to 59,874 US\$. Furthermore, again the income elasticity is found to be larger for the crisis and recovery period from 2008 to 2016.

Finally, the income elasticity's variability and its relationship with a country's income level are also evaluated by considering different subsamples (according to the income level) and the estimations of the income elasticity parameter. In this case, the results are presented in Table 4.4.

Table 4.4 Income Groups of Origin Countries						
	Income Level at origin					
	w=1	w=2	w=3	w=4		
	(low)	(low-medium)	(high-medium)	(high)		
Method PPML						
$Ln(GDPpc_{ijt})$	0.414*	0.413***	0.961***	-0.023		
	(0.235)	(0.155)	(0.182)	(0.179)		
$Ln(Pop_{ijt})$	1.055*	0.997**	0.256	1.305***		
	(0.639)	(0.509)	(0.378)	(0.178)		
<i>Rlaw_{ijt}</i>	-0.083	0.239***	0.548**	-0.363**		
	(0.081)	(0.063)	(0.228)	(0.164)		
<i>Terrorism_{ijt}</i>	0.162	0.214	0.292***	-0.105		
	(0.118)	(0.134)	(0.078)	(0.079)		
Countries	47	47	47	47		
Observations	35,117	39,955	52,068	77,166		

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Destination-year and countrypair fixed effects are included but not reported.

Again, Table 4.4 shows that there are different income elasticities according to the income level in the origin country. It seems clear that low and higher-income countries are less elastic than middle-income countries. First, it is noteworthy that the



coefficient of the income variable is highly significant in lower-to-middle-income and middle-to-upper-income countries with striking differences in elasticity values. Low-income countries have a less elastic value which, additionally, is only significantly different from 0 at a 10% confidence interval. In the case of highincome countries, the elasticity coefficient is statistically equal to zero. Thus, the results indicate that income only has a clear significantly positive impact on tourism in the case of medium-income countries. Additionally, middle-to-upper-income countries are more income elastic when compared with lower-to-middle-income ones. This definitely shows that the former are more sensitive to an increase in income and ultimately to tourism demand. In other words, it was found that people from high-income origin countries do not relinquish their holiday (or do not significantly increase/decrease their travel behaviour in the event of economic growth/an economic crisis) because they understand travel to be part of their regular consumption (a necessary good), whereas people from medium-income origin countries are the most sensitive ones, reacting significantly to changes in income levels because they understand tourism to be a luxury good. In the case of people from the poorest countries, they do not have enough money to make international trips so they do not react to changes in income levels.

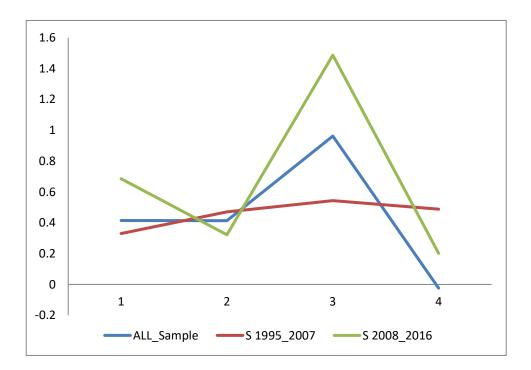
Again, it is possible to explore this relationship further, considering the pre-crisis period (S 1995-2007) and crisis and post-crisis period (S 2008-2016). For simplicity, here we focus our attention on the income elasticity estimations. Figure 4.1 shows that there are differences in the behaviour of the elasticity, attributable to the different time periods under consideration and the income groups (=1; low income, =2 low-medium income; =3 high-medium income; =4 high income) of the origin countries. The estimates for the full sample reproduce the results for the whole period, shown previously in Table 4.5. In this case, it is important to note that, in keeping with the previous strategy, the inverted U-shape is clearer for the crisis and post-crisis period (2008-2016). During this period, a maximum of 1.49 was estimated for the income elasticity for medium-to-high-income countries.

The final segmentation considered in this chapter explores the role of income in the



destination country as an additional determinant of the income elasticity. For this purpose, we divided the sample into two main groups. The first one (low development destinations - LDD) includes low-income and lower-to-middle-income destinations while the second one (high development destinations - HDD) includes middle-to-upper and high-income countries. The reason for this division is to see whether, according to previous literature (Martins et al., 2017), differences in income elasticity values exist due to the level of income at the destination.

Figure 4.1 Income elasticity: Different income groups and different time periods





	Income Level Origin countries				
	w=1 w=2		w=3	w=4	
	(low)	(low-medium)	(high-medium)	(high)	
Method PPML			-		
All Sample	0.414*	0.413***	0.961***	-0.023	
	(0.235)	(0.155)	(0.182)	(0.179)	
Observations	35,117	39,955	52,068	77,166	
Less developed	0.406**	0.375***	0.693	-0.418***	
	(0.195)	(0.146)	(0.543)	(0.083)	
Observations	15,099	16,300	20,856	34,768	
High developed	0.427	0.420**	1.079***	0.990***	
	(0.325)	(0.193)	(0.146)	(0.175)	
Observations	20,018	23,655	31,212	42,398	

Table 4.5 Income Groups of Origin / Destination Countries

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Destination-year and countrypair fixed effects are included but not reported.

Table 4.5 shows the interaction between the income level of the origin country (*w*) and the destination's income level. In general, we observe a higher income elasticity for tourism demand in the case of destinations with a higher level of development. However, significant differences in the estimated income elasticities cannot be observed when origin countries with low and low-to-medium-incomes are analysed, with an income elasticity below 0.5 in all cases. Hence it seems that outbound tourism is inelastic in countries with a low income, whatever the level of development at the destination. In other words, in the case of poor countries, changes in income levels do not lead to big changes in outbound flows, neither to destinations with a high level of development nor to less developed ones. As in previous cases, countries with medium-to-high incomes are characterized by the highest income elasticities. However, the maximum elasticity corresponded to origin countries with high-to-medium incomes visiting destinations with a high level of development.

The most interesting case was high-income origin countries. Although on average these countries are income inelastic in behaviour, when their inhabitants travel to more developed countries, the income elasticity becomes positive and significant. Thus it seems that in the case of origin countries with high incomes, on the one hand, travel to high-income destination countries is not regarded as a necessary good, since the elasticity is increasingly close to one and, on the other hand, travel to less



developed countries is seen as an inferior good. In other words, in situations of economic expansion (crisis), high-income countries would reduce (increase) their trips to less developed countries and increase (reduce) them to more developed ones. Thus there seem to be clear variations in the income elasticity depending on the income in both the origin and destination countries.

4.5. Conclusion

Due to the tourism sector's substantial economic relevance and public administrations' expectations that this sector will boost the growth and development of economies, extensive literature can be found that deals with the evaluation of the determinants of tourism demand. The identification, analysis, and measurement of the impacts of the determinants of tourism demand are central to any attempt to understand and explain past changes and to anticipate possible trends in future tourism flows. In this context, from a literature review, it can be seen that tourist income, which is often assessed by taking the GDP in the origin country, is a dominant explanatory variable in tourism demand modelling.

This chapter conducted an in-depth analysis of the relationship between tourism and income by investigating heterogeneity in the nexus between income elasticity and tourism demand, reviving Morley's hypothesis (1998) that low-income and high-income countries tend to have a low income elasticity, while medium-income countries are the most income elastic. Using yearly data for 208 origin countries and 196 destination countries for the period 1995–2016, different gravity models were estimated for different income and time subsets, based on the pre and post-financial crisis and using interactions with the level of income at the destination market.

The results show that the income elasticity is significantly determined by per capita income in the origin country, verifying the inverted U-relationship between income elasticity and personal income proposed by Morley (1998). Thus, outbound tourists



from middle-income countries are found to be the most elastic, while tourists from high and low-income countries show a lower (sometimes not significant) relationship. The segmentation analysis further qualifies these results. On the one hand, the inverted U relationship seems to be more significant and the peak in the income elasticity is higher during the crisis and post-crisis period (2008-2016). On the other hand, when the segmentation analysis was based on income at the destination countries, the results for the wealthiest origin countries reflect very different behaviours depending on whether tourists from these countries travel to high-income countries or to the poorest ones.

If income in source markets is acknowledged to play a key role in generating tourism demand, then long-term forecasts needed for strategic planning by public and private tourism managers must be made with as much precision as possible. The results of this study should be useful in facilitating more accurate research into long-term tourism projections.

Further studies should explore different ways to extend this research. On the one hand, at an aggregate level, different segmentations could be considered that might offer a further insight into the specific relationship between income and tourism demand. On the other hand, the relationship between income and tourism consumption could also be explored, using survey data and microeconometric techniques to examine income elasticities at an individual level. In this way, our knowledge of this particular relationship could be enhanced, using different case studies of destination and/or origin countries.



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5

AN OVERVIEW OF "NEW CONTRIBUTIONS ON THE DETERMINANTS OF INTERNATIONAL TOURISM DEMAND: WEATHER, TRAVEL DISEASES AND INCOME"

Previous literature has proved that climate, weather conditions and other macroeconomic variables affect the demand for tourism. The impact of temperature on tourism demand (or, tourist destination choice) has been examined intensively (see Gómez Martín, 2005; Bigano et al., 2006; Hamilton and Tol, 2007; Tol, 2007; Álvarez-Díaz et al., 2010; Falk, 2014; Michailidou et al., 2016). In addition, Altalo and Hale (2002), Gómez Martín (2005), Álvarez-Díaz et al. (2010), and Falk (2014) illustrate that the demand for tourism hinges negatively on precipitation. Gómez Martín (2005), Álvarez-Díaz et al. (2010) point out that a windy day or a storm pushes tourists to change their scheduled outdoor activities. Bigano et al. (2006), Rosselló et al. (2011), and Falk (2014) show that the more the sunshine hours, the



more the tourists. Although, a lot have been done in this area of knowledge, but relatively little is known about the extent if weather effects are present in the step of destination decision choice. With current shorter booking lead times, new determinants of tourist trips could have emerged.

In this context, Chapter 2 explores meteorological conditions as new short-run factors determining tourist travel choices, investigating the role of weather variables in explaining short-term variability in Google searches relating to Majorca by its two main tourist markets: Germany and UK. The estimated statistical models provide evidence that the weather conditions in both the country of origin and at the destination are related to data recorded by Google Trends. Bearing in mind the limitations of this kind of models, which can only capture average tourist behaviors, results show clearly how as weather conditions improve at the destination or as they worsen in the country of origin, more searches relating to Majorca are reported by Google Trends. Additionally results show how the effect seems more evident for last data. This work will significantly contribute to short term forecasting literature in international tourism demand.

As our objective was also to cover long-term issues of tourism demand, influences of macroeconomic conditions on the demand for tourism have attracted much interest from researchers. The favourable climate conditions for tourism often also imply favourable conditions for infectious diseases, with the ensuing development constraints on countries' tourist sectors. There was breaking news on CNN in 2014 that "Air Europa will not fly to Africa due to Ebola. Moreover, Ebola outbreak: Asky (major West African Airline) bans flights in West Africa (BBC, 2014). Going through the literature, we found that, generally, the work on infectious disease risk in tourism literature was very limited, or they focused on a specific country or single disease.

Chapter 3 presents an analysis on the effect of infectious diseases on international tourism movements. Using a gravity model, this chapter has evaluated the effects of the eradication of Malaria, Yellow Fever, Dengue and Ebola on international tourism arrivals and its national economic impact at destinations through their tourist



industries. This is the first empirical attempt to study the association between infectious disease risk and international tourism flows using a global database. The results show Malaria and Yellow Fever to be the diseases that play the most decisive role in explaining tourist destination choices. In this research, a simulation analysis to explore the impact on tourist arrivals and expenditure of eradication of infectious disease risks is implemented. This chapter explores a new aspect of the quantification of health policies which should be taken into consideration in future international health assessment programmes. Consequently, results of this work should be taken into account not only at international level to promote international research programs aiming the eradication of these diseases but also at country level to evaluate the economic benefits in terms of tourist expenditures for a specific country to reduce the incidence or eliminate the disease.

Hamilton and Tol (2005) have shown how income is more important variable than climate variables. The relationship between income and demand is one of the main concerns in economics. Furthermore, one of the most important macro-economic variables for international tourism demand is Income. Finally, Chapter 4 focuses on long term issues of tourism demand, specifically on Income. Meta-analyses reveal an extensive body of research on this relationship in tourism demand (Crouch, 1995; Peng et al., 2014 and 2015), air travel demand (Gallet and Doucouliagos, 2014), and other areas, such as residential water demand (Dalhuisen et al., 2003). Regarding tourism, income in origin markets is recognized as a dominant explanatory variable of international tourism demand by many authors (Crouch, 1994; Lim, 1997; Peng et al., 2015).

The study of the relationship between income and recreation demand relationship started in the 19th century, explained with Engel's law. Since then, a number of studies have been undertaken on the relationship between income and tourism demand. Knowing tourism demand, its characteristics and relationship with income is of great importance to researchers and practitioners especially because of the perishability of tourism products. Indeed, Forsyth and Dwyer (2010) highlight that the understanding of tourism demand and its forecasting is essential for tourism mar-



keters, managers, planners and public agencies.

The relationship between income and tourism demand is usually estimated with the income elasticity of tourism demand-based macroeconomic data using time data series as well as panel data. Furthermore, studies on consumer surveys were undertaken lately to assess the relationship between income and tourism spending (Bronner and Hoog, 2016). Reviews of studies on the income elasticity of tourism demand (Crouch, 1995; Song and Li, 2008; Peng et al., 2015) show that explanatory and dependent variables, time periods of data, methodologies and origin/destination pairs influence the income elasticity of tourism demand.

According to the hypothesis proposed by Morley (1998), it is expected that lowincome and high income countries tend to be low-elastic while medium income countries are the most elastic ones. People in the richest countries would not be able to give up to their holidays in case of an economic recession (or they would not increase significantly their travel behavior in case of economic growth) because they would understand travelling as a part of their regular consumption (necessary good). That is, they might adapt travel expenses but they will continue travelling. However, people in medium income countries would be the most sensitive ones, reacting significantly to changes in income levels because they understand tourism as a luxury good; and, finally, people in poorest countries could not have enough money to undertake international trips, so they would not react to changes in income levels. Unfortunately, the empirical evidence of Morley (1998) was limited and based on only the seven major source countries of tourists to Australia were evaluated.

This chapter has gone in deep in the knowledge of the relationship between tourism and income by investigating the parameter heterogeneity in the income elasticity– tourism demand nexus. Thus it has recovered the hypothesis proposed by Morley (1998) where it is proposed that low-income and high income countries trend to be low-income elastic while medium income countries are the most income elastic ones. Using yearly data from 208 origin countries and 196 destination countries for the period 1995–2016, different gravity models have been estimated for different income and time subsets according to the pre and post financial crisis and using interactions



with the level of income in the destination market.

Results evidence that income elasticity is significantly determined by per capita income in the origin country and verifies the inverted-U relationship between income elasticity and personal income proposed by Morley (1998). Thus, outbound tourism from middle-income countries is found the most elastic one while tourism from high and low income countries shows a lower even sometimes a not significant relationship. The segmentation analysis aims qualifying these results. On the one hand, the inverted-U relationship seems more significant and the peak in the income elasticity is higher in the crisis and post crisis period (2008-2016). On the other hand, when segmentation analysis is carried out in terms of the income in the destination results for the richest origins show a very different behavior when tourists from these countries are travelling to high income countries or poorest ones.

These results should be useful to investigate more accurately long term forecasts of tourism. If we acknowledged that income in source markets plays a key role in generating tourism demand, long term forecasts that are essential for the strategic planning for both public and private tourism managers should be projected in a more accurate way.

In summary, this thesis covers climate change and long term issues of tourism demand. First chapter, focus on short-term forecasting of tourism demand using climate variables of both origins and destination. By using Google trend data, this chapter is preliminary in this regard, and it will be significant addition due to growing trend of online searches. Moving toward long-term issues, as favorable climate conditions are also favorable for diseases, next chapter addresses very important issue by focusing on disease threat for tourism demand. There was very limited work on this vital long-term issue, either it was country specific or single disease. This work is first empirical attempt to study the relationship using global data. We take four very important diseases (Malaria, Yellow Fever, Dengue, and Ebola), mostly from mosquitos, results show their importance in explaining tourist destination choice. Finally, we come up with eradication model for these diseases, hence; increase in future arrivals and tourism GDP of destinations.



highlights on most important variable of tourism demand i.e. Income, as literature shows how income is more important than climate variables, as for as tourism demand is concern. This chapter concludes that income elasticity of tourism varies with income level of both the origin and destination. Middle income countries are the most elastic to income as compared to low and high income origins. Moreover, elasticity values significantly differ with income level of the destinations. All these chapters will significantly contribute to tourism literature.

Re-search always have limitations that leads toward future recommendations. So, chapter 2 extended previous research by showing that beliefs about weather, however, the meteorological effects in origins have been considered at national level. The importance of differing regional climates (or even microclimates) for tourism decision-making and behaviour could have its relevance as it has been evidenced in Hartz et al., (2006), Wilson and Becken (2011) or Rutty and Scott (2014). Consequently, future research would try to consider the regionalization of the tourism data. The chapter 2 ensures that no spurious regression and that the captured effect is related to weather and not to climate. However, on the other hand, reduces the statistical significance of weather effects longer than a week. Thus, if a heat or a cold wave persists during some weeks, and, precisely this persistence motivates the interest on a tourist destination, the relationship between weather variables and tourism will be covered by the autoregressive terms. Future research would try to solve this dilemma.

In chapter 3, future research should try to take into account for neighbourhood effects (country with a high disease risk may negatively affect tourism in neighbouring countries) and to incorporate the latest available data, particularly in the case of Ebola, since it should be used to confirm whether the influence of the social media, following the 2014-2015 outbreak of Ebola, changed the impact on the affected countries. In particular to investigate the causal effect of the outbreak of some specific diseases (Ebola, SARS, ...) on tourism flows it would be desirable to use the difference in differences approach since these disease could have mainly a temporal effect. Moreover, chapter 3 only addresses the impact of infectious disease risk at the



host country and tourist arrivals. However, the gravity model would make it possible to study the associations between tourism and disease risk in both the source and origin country since a disease in the origin country may prevent people from travelling abroad.

In chapter 4, further studies should explore different ways to extend this research. On the one hand, at an aggregate level, different segmentations could be considered that might offer a further insight into the specific relationship between income and tourism demand. On the other hand, the relationship between income and tourism consumption could also be explored, using survey data and microeconometric techniques to examine income elasticities at an individual level. In this way, our knowledge of this particular relationship could be enhanced, using different case studies of destination and/or origin countries.



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