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Does happiness drive tourism decisions?

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A B S T R A C T

This research examines the role that happiness plays in affecting tourism flows. While most previous studies are country-specific, our analysis is performed with panel data on 142 countries from 2005 to 2019. This allows us to implement a structural gravity model that includes both domestic and international tourism flows, which is a novel approach in this branch of the literature. Our empirical strategy enables us to correctly identify happiness when multilateral resistance terms are included. The results show that happiness at a destination is a significant tourist attractor, although the link follows an inverted U-shaped pattern. This suggests that tourists associate happiness with the quality of life at a destination but after a threshold, it becomes less important. Moreover, when cultural distance is greater, the effect of happiness on tourism arrivals is smaller. Therefore, tourists can better interpret happiness when origin and destination cultures are similar.

1. Introduction

Extensive research on the determinants of tourism flows has been conducted during the last two decades. When the analysis of tourism flows goes beyond pure forecasting, economic research in the field mainly focuses on quantifying the determinants of tourism demand. In particular, the empirical literature focuses on estimating the effect of economic determinants (e.g., income, exchange rate, relative prices, etc.) or on assessing the impact of a particular economic policy (e.g., tourist tax, visa policy, events, etc.). Indeed, the bulk of the literature on the factors that affect tourism demand has been dominated by analyses of economic determinants of inbound tourism (Song et al., 2019). In recent years however, the role of non-economic factors, such as cultural distance, climate, and security threats, has been studied, and such factors have been revealed to be important determinants of destination choice.

In the present research we hypothesize that people might decide to travel and to select the tourist destination based on non-economic determinants. In particular, this paper explores the effect of happiness on international tourism movements, since tourists might travel in search of emotional experiences. Additionally, tourists could perceive happy countries to be attractive destinations. Therefore, if people at the destination are happy, there are likely some reasons behind such a feeling. However, the effect of happiness on tourism flows using worldwide bilateral tourism data and estimating a structural gravity model including domestic tourism flows, has not yet been explored.

The database used in the empirical analysis includes tourist arrivals to destination countries disaggregated by origin for a sample of 142 countries from 2005 to 2019. We apply the most recent econometric techniques to estimate gravity models, which correct known biases, and we use a more accurate proxy for happiness than the ones considered in previous research in terms of data availability and consistency of the sample. Furthermore, we test for novel hypotheses on this link such as non-linearities and the role of cultural distance on the effect of happiness on worldwide tourism demand.

We aim to make two relevant contributions to tourism-economic literature. From a theoretical point of view, we explore the role played by the aggregate level of happiness as a determinant of tourism flows. To the best of our knowledge, this is the first attempt to comprehensively analyze the impact of happiness on worldwide bilateral tourism movements. To this end, we use data from the World Happiness Report, which provides a homogeneous index of revealed happiness of countries around the world. Furthermore, we study whether the effect of happiness on tourism depends on the cultural distance (measured in terms of linguistic proximity) between countries.

From an empirical point of view, we apply the methodology developed by Larch and Yotov (2016) and Heid et al. (2021) to estimate tourism demand with the structural gravity equation, controlling for multilateral resistance terms (MRTs) and country-pair fixed effects and including domestic (intra-national) tourism in the dependent variable. According to Yotov (2022), considering domestic flows in the dependent variable has theoretical and empirical benefits. Specifically, we can

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hedge the collinearity between country-specific variables and the country fixed effects required to control for multilateral resistance. Moreover, we provide results from three alternative approaches to measuring domestic tourism flows, which can be used as a guidelines for future research estimating structural gravity models for tourism demand.

The rest of the paper is organized as follows. In the next section, the literature review is presented. Then, the data and methodology we use are discussed, and after that, the results of the empirical analysis are presented. Finally, we make some conclusions and discuss their economic implications.

2. Background

Previous research has studied how tourism enhances happiness. Chen and Li (2018) provide an interesting literature review on this topic. In general, empirical research on the effect of tourism on happiness shows that going on vacation can significantly increase people's overall life satisfaction (McCabe and Johnson, 2013). Moreover, the degree of happiness derived from tourism varies depending on the type of tourism and the activities carried out at the destination. For instance, Bimonte and Faralla (2012) found that park visitors in Italy are happier than beach tourists. Therefore, how tourism enhances happiness is a topic that has been extensively analyzed, but research is virtually nonexistent when it comes to studying how happiness at the destination affects tourism flows.

Some antecedents on the effect of happiness on international movements of people can be found in the literature on migration (Simpson, 2013; Hendriks, 2015; Hendriks and Bartram, 2019). Hendriks and Bartram (2019) conclude that happiness should be considered when the consequences of migration on migrants are evaluated. Moreover, Hendriks (2015) reveals that migrants can become happier by migrating, but they typically do not reach levels of happiness similar to those of natives. Polgreen and Simpson (2011) hold that an individual will migrate if the utility of living abroad exceeds the utility of staying home net of migration costs (including distance, language differences, and family left behind). Their paper studies the migration-happiness link between 84 countries worldwide and finds a U-shaped relationship in which emigration rates fall as happiness increases in relatively unhappy countries, but rise in relatively happy countries. With a sample of net migration flows from all over the world into OECD countries (plus Russia), Marques et al. (2018) estimate the impact of happiness on movements of people across borders using a gravity model. Finally, Paniagua et al. (2021) explore the role of well-being differentials on asylum migration flows to the OECD, finding a robust association. These authors also highlight the necessity of differentiating between objective and subjective measures of well-being.

Objective measures are typically computed as composite indicators made up of a variety of dimensions, such as income, education, environmental quality, health, safety, and community support. The most well-known indicator is the Human Development Index (United Nations), which includes income, education, and life expectancy. More recent initiatives, such as the Better Life Index (OECD) and the Social Progress Index (Social Progress Imperative), are more comprehensive and consider a broader set of aspects. Nevertheless, a notable drawback of these indices is their need to aggregate their various dimensions (see, for instance, Peiró-Palomino and Picazo-Tadeo, 2018; Paniagua et al., 2021; Pritchett, 2022). As a result, the final value of the index largely depends on the decisions made in the aggregation process, such as the weight given to each dimension or the aggregation technique used.

In contrast, subjective measures are based on citizens' perceptions, which are proxied by indicators of life satisfaction or happiness. These two concepts are often used interchangeably in economic literature (MacKerron, 2012), although they are not perfect substitutes. In fact, subjective well-being is the scientific term for happiness, which is an evaluation of a person's life based primarily on three components: life satisfaction, positive affect, and negative affect. However, we follow the common nomenclature in the economic literature, as we consider this is an issue to be discussed in a different forum. Both personal and socio-economic factors condition these perceptions (Helliwell, 2003). Some of them, particularly those from the second group, are considered using composite objective indicators (see Mizobuchi, 2017). So, it is not surprising to find strong correlations between objective and subjective well-being indicators (Peiró-Palomino, 2019). However, not all objective factors are equally relevant to happiness, with health being one of the most critical (Mizobuchi, 2017). In any case, subjective measures are potentially more representative than objective ones when it comes to capturing life satisfaction/happiness. While it is true that objective conditions may influence satisfaction with life, there can be many other elements that are challenging to measure or even difficult to identify but which could affect people's happiness.

The literature supporting the use of subjective measures is abundant. For example, Krueger and Schkade (2008) suggest that, while subjective measures can be less reliable than many objective ones such as education or income, they are reliable enough for studies making use of aggregate data, that is, when group means are compared. Oswald and Wu (2010) use household data in the USA and conclude that subjective measures provide a good reflection of quality of life. Other studies such as Kingdon and Knight (2006) are critical of objective measures. The authors provide evidence for South Africa, arguing that an approach that focuses on the individual's own perception of well-being is less imperfect than other potential approaches, more quantifiable, or both. More recently, in a meta-analysis of 357 studies, Tan et al. (2020) report a moderate but highly significant association between subjective well-being and socio-economic status. All in all, it seems that objective measures do not capture all possible factors.

As for how subjective well-being matters to tourism, Chen and Li (2018) study how destination choice can determine tourist happiness, and they find that destination attributes, measured by destination image and service quality, are associated with tourist happiness. The authors highlight that destination competitiveness can be enhanced by projecting a positive image of a destination by using accurate measures of tourist happiness. Gholipour et al. (2016) investigate whether the happiness level of a country attracts more tourists and/or generates higher tourism revenues. By applying panel data techniques to a sample of data on 63 countries from the period 1999 to 2014, they explore whether tourists travel more to happier destinations. Their results show that tourists prefer to travel to and spend more money in happier destinations. Huang and Wei (2018) explore different socio-economic drivers of Chinese outbound tourism, and they find that happier residents are less likely to travel abroad. Huang et al. (2021) examine the impact of happiness level on travel choice by studying whether Chinese tourists take into account the level of happiness in a country when they decide on their destination. Using a database for Chinese tourist departures to 113 destination countries over the period 2012–2017, the empirical analysis suggests that the level of happiness at the destination positively affects Chinese outbound tourism. However, this positive influence reduces when cultural distance increases, perhaps because feelings of happiness in the destination country are more difficult to perceive due to cultural differences.

These previous papers on the effect of happiness on tourism demand use aggregate data on total arrivals (or departures) or focus solely on specific countries. Beyond these few antecedents, the demand-generating effect of happiness remains under-researched. As discussed by Polgreen and Simpson (2011) regarding migration, factors in both the source and destination countries, including differences in income, costs of migration, cultures, and immigration policies, can affect the flow of people between countries. These authors hold that the migration-happiness link might work in two ways: (i) people in unhappy countries are motivated to migrate to happier ones, and (ii) people in happier countries have fewer incentives to migrate.

Migrants and tourists share common travel traits; the difference between them has to do with time and attitude. Usually, migrants stay longer or permanently and have different motives, but a migrant, like a tourist, travels to a foreign destination. Therefore, some channels proposed by Polgreen and Simpson (2011) for the migrant-happiness relationship could help to explain bilateral tourism flows. That is, tourists might decide to travel abroad if the utility of going on vacation is higher than staying at home (or travelling domestically) net of travel costs. Therefore, if happiness affects utility, and tourists decide to travel based on the utility obtained, we can expect that happiness affects the decision to travel and the tourist destination choice.

To some extent, and based on the few previous studies in the area, we test whether tourists might prefer travelling to happier destinations, as they could attain higher levels of utility (Gholipour et al., 2016). Moreover, following Polgreen and Simpson (2011), we test for non-linearities in the effect of happiness on tourism and whether the effect of happiness on tourism flows depends on cultural distance between countries.

Additionally, this research contributes to the literature by applying the methodology developed by Larch and Yotov (2016) and Heid et al. (2021) to estimate tourism flows with a structural gravity model. This procedure includes domestic and international tourism flows on the left-hand side of the gravity equation. Yotov (2022) demonstrates the advantages of estimating structural gravity equations with domestic, in addition to international, trade flows. In our case, the most important reason to consider domestic tourism is to be able to identify the variable of interest, aggregate happiness at the destination country, while including the theory-consistent destination fixed effects (Heid et al., 2021). Anderson et al. (2018) include intra-national trade in services to estimate a structural gravity model in order to identify barriers to trade across service sectors, including travel. Using OECD data from the balance of payments, they find a decrease in border effects for services trade, although transportation and travel are among the sectors that faced the smallest decreases. As far as we are aware, our research is the first attempt to estimate a structural gravity model for bilateral tourism including domestic tourism flows and MRTs to identify the effect of a country-specific variable.

3. Methodology and data

3.1. Methodology

The gravity model has been used extensively to explain trade (e.g., Anderson and van Wincoop, 2003; McCallum, 1995; Rose, 2000; Santana-Gallego et al., 2016), migration (e.g., Gallardo-Sejas et al., 2006; Beine et al., 2016), and foreign direct investment (e.g., Bergstrand, 1985; Head and Ries, 2008; Nguyen et al., 2020) between countries. Such models are based on the notion that bilateral flows between a given pair of countries (*i*–the origin and *j*–the destination) are related to their economic size (i.e., population and GDP) and the frictions (i.e., distance, common language, and common borders) between the countries. The gravity model is also a popular methodology for modelling bilateral tourism demand (Neumayer, 2010; Vita and Kyaw, 2013; Fourie et al., 2015).

A key advantage of the gravity model is its solid theoretical foundation (see Arkolakis et al., 2012; Allen et al., 2020). The gravity equation is derived from a general equilibrium setup, and two main theoretical results need to be translated into the empirical analysis to deliver consistent estimates (Larch and Yotov, 2016). The first element of a structural gravity model is multilateral resistance terms (MRTs). According to Felbermayr et al. (2020), MRTs serve to translate partial equilibrium effects to country-specific effects on consumers and prices. Regarding gravity models for bilateral tourism flows, Santana Gallego and Paniagua (2022) show that outward multilateral resistance gives the origin's effect on tourism costs, and inward multilateral resistance represents the host's effect on tourism costs. For tourism flows, multilateral resistances imply that tourists' decision to visit a particular destination also depends on the remoteness of the destination (Santana Gallego and Paniagua, 2022; Harb and Bassil, 2018). For example, the tourism between Malta and Cyprus would be very different if they were isolated in the middle of the Pacific Ocean instead of being Mediterranean islands.

The second main element of structural gravity is domestic flows. Standard gravity models are closed by imposing market-clearing conditions. This means that all the tourism demand, both domestic and international, is perfectly satisfied in equilibrium. Therefore, estimates of tourism demand with gravity should include domestic flows in order to capture these theoretical conditions. By including domestic tourism, we also contribute to the "border effect" literature, which seeks to understand the difference between domestic and international flows. Moreover, as discussed in the following subsection 3.2, three alternative measures of domestic tourism are considered on the left-hand side of the equation.

Therefore, we first estimate a structural gravity model as defined by equation (1):

$$Tou_{ijt} = \psi INTL_{ij} + \alpha' Control_{ij} + \sigma RTA_{ijt} + \lambda_{it} + \lambda_{jt} + e_{ijt} \quad (1)$$

where dependent variable Tou_{ijt} refers to bilateral tourist arrivals from origin country *i* to destination country *j* at year *t*. Equation (1) includes MRTs at the origin (λ_{it}) and destination (λ_{jt}) countries as well as a set of bilateral time invariant controls ($Control_{ij}$) such as the log of distance ($LnDist_{ij}$), linguistic proximity (LP_{ij}), and dummy variables for having common land borders ($Contig_{ij}$) or a colonial link ($Colony_{ij}$). Additionally, a time-varying bilateral variable, i.e., belonging to a common bilateral trade agreement (RTA_{ijt}), is added to the specification to control for the intensity of the economic relationships between country pairs. The term $INTL_{ij}$ is a dummy variable for international tourism that takes a value one for international tourism ($i \neq j$) and zero for domestic tourism ($i = j$).

As discussed by Santos Silva and Tenreyro (2006, 2010), log-linearized equations cannot be consistently estimated because the conventional OLS estimation of the gravity equation is biased due to the likely existence of heteroscedastic residuals and zeros in the dependent variable. So, they suggest a non-linear Poisson estimator (pseudo-maximum likelihood estimation [PPML]) to overcome these biases.[1] The iterative PPML algorithm developed by Correia et al. (2019) flexibly accounts for multilateral resistance, pair-specific heterogeneity, and correlated errors across countries and time. Standard errors are adjusted by clustering by pairs. Therefore, a structural gravity estimated by PPML is the preferred gravity estimation method for our empirical analysis.

Fally (2015) shows that MRTs can be perfectly identified by including origin and destination fixed effects as regressors with PPML. Therefore, the model includes MRTs with origin-year (λ_{it}) and destination-year (λ_{jt}) fixed effects as well as country-pair fixed effects (λ_{ij}). Thus, any unobservable heterogeneity at the country level that varies with time is controlled for (such as GDP, population, financial crises, or other types of country-specific events). However, the drawback of including λ_{jt} is that aggregate happiness in the host country would also be removed from the estimate. A simple way to include MRTs and to estimate the parameters of the variable of interest is to use the methodology developed by Larch and Yotov (2016) and Heid et al. (2021). These authors propose a method that allows for the identification of the effects of country-specific variables, such as aggregate happiness at the destination, even in the presence of destination fixed effects, to estimate the following structural gravity model:

$$Tou_{ijt} = \beta(Happy_{jt-1} \times INTL_{ij}) + \sigma RTA_{ijt} + \lambda_{it} + \lambda_{jt} + \lambda_{ij} + e_{ijt} \quad (2)$$

[1] A drawback of tourism data compiled by UNWTO (2021) is that it is not possible to discriminate between zero tourism flows and missing values. For this reason, as proposed by Santana Gallego and Paniagua (2022), the PPML estimator is only applied to positive bilateral tourism flows.

In order to approximate perceived delays in tourists' interpretation of the happiness index, we use the lagged value of the variable of interest ($Happy_{jt-1}$) in our analysis.[2] In equation (2), the interaction variable $Happy_{jt-1} \times INTL_{ij}$ results in a new country-specific time-varying term that can be estimated even in the presence of destination-year fixed effects (Larch and Yotov, 2016). Consequently, adding domestic tourism to the left-hand side of the equation resolves the perfect multicollinearity problem if country-specific variables and MRTs are simultaneously included in the gravity model. The idea behind the introduction of the *INTL* dummy variable is that it captures international border effects that drive a wedge between domestic and international tourism (Larch and Yotov, 2016; Beverelli et al., 2018; Felbermayr et al., 2020). Therefore, the interaction variable ($Happy_{jt-1} \times INTL_{ij}$) captures the differential impact of happiness at the destination on international tourism relative to domestic tourism.[3]

Equation (2) is estimated by the PPML procedure after including all possible fixed effects (destination-year, origin-year, and dyadic), and it is our preferred model. In order to explore the relevance of considering MRTs and domestic tourism when the structural gravity model for tourism demand is estimated, we take the following steps. First, we estimate a baseline equation (2) considering only international tourist arrivals on the left-hand side of the equation, and destination-year λ_{jt} fixed effects are replaced by a set of time-varying destination-specific controls such as the log of GDP per capita ($LnGDPpc_{jt}$), a proxy for the quality of institutions measured in terms of the rule of law (RL_{jt}), relative prices at the destination country compared to the origin country ($Price_{ijt}$), the number of terrorist attacks with fatalities ($Terror_{jt}$), hosting a major sporting event ($Event_{jt}$), and a dummy variable for episodes of financial crisis ($Crisis_{jt}$).

Secondly, domestic tourism, along with international tourism, are considered as dependent variables. When the full set of fixed effects are included, the only control variable that can be estimated is RTA_{ijt}, since the rest of the explanatory variables are absorbed by the fixed effects. Finally, as in Beverelli et al. (2018) and Larch and Yotov (2016), we introduce time-varying border dummies $INTL_{ij} \times Year_t$ to capture any effect of globalization, which would imply a decline in international tourism-related costs relative to domestic tourism during the sample period.

3.2. Data

The dependent variable in equations (1) and (2) is the number of tourist arrivals from origin country i to destination country j in year t. Moreover, the database includes data on domestic tourism that occurs when $i = j$. Data on international tourist arrivals by country of origin was obtained from the World Tourism Organization (UNWTO, 2021) and covers tourist arrivals to and from 142 countries from 2005 to 2019.

The United Nation World Tourism Organization (UNWTO) defines a domestic visitor as a visitor who travels within his/her country of residence; this person is a domestic visitor, and his/her activities are part of domestic tourism. However, it is not straightforward to collect homogeneous data for domestic tourism across countries. Therefore, we make use of three different approaches to measure domestic tourism.

The first approach (*Guests*) uses data on domestic tourism as provided by the UNWTO (2021). This variable refers to "total guests in all commercial accommodation services." Thus, it reflects the number of resident guests that use services provided by commercial accommodations. Regarding the second and third approaches, we can assume that any country's citizens could be considered "potential" domestic tourists. So, for the second approach, we use the total population of the destination country (*Population*) as a measure for domestic tourism. Finally, the third approach (*Capacity*) consists of the population of the destination country weighted by the hotel capacity of the destination country, measured in terms of "bed-places per 1000 inhabitants." In doing this, we also control for the capacity of the tourism sector of a country to host domestic tourists. The number of bed-places per 1000 inhabitants was collected from the UNWTO (2021), while the population in the destination country was taken from the World Development Indicators (WDI, 2021).

Drawbacks of the *Guests* approach are that it only considers domestic tourists that stay in commercial accommodations and it is available for a limited number of countries (81). Accommodation capacity (*Capacity*) is available for 125 countries, and *Population* is available for 142 countries.[4] Table 1 provides descriptive statistics of the variables used in the empirical analysis. It is worth mentioning that correlations between the three approaches reaches nearly 60%, or more. Furthermore, the mean value of domestic tourism, regardless of the approach considered, is much higher than it is for international tourism flows.

As discussed in the previous subsection 3.1, different control variables are used. $Control_{jt}$ includes time-varying destination-specific characteristics such as the log of GDP per capita (*LnGDPpc*); the rule of law (*RL*), which captures perceptions of the extent to which agents have confidence in and abide by the rules of society (quality of contract enforcement, property rights, the police, and the courts, as well as the likelihood of crime and violence), and serves as a proxy for the institutional quality; the number of fatalities (per 100,000 inhabitants) in terrorist attacks *Terror*; hosting a major sporting event *Event*; and a proxy for the relative price competitiveness of the destination country (*LnPrice*). This last variable is measured by the log of prices in the destination country relative to those in the origin country. It is generated as the ratio of the price level ratio of the purchasing power parity (PPP) conversion factor to market exchange between destination countries and origin countries.

The set $Control_{ij}$ includes time-invariant country-pair characteristics such as the log of the distance between countries (*LnDist*) and a set of dummy variables that take a value one if countries share a common land border (*Contig*) or a common colonial link (*Colony*), and zero otherwise. Moreover, a proxy for cultural distance, measured in terms of linguistic proximity (*LP*), is included. This variable is defined as a continuous index over [0, 1], that measures how similar the languages spoken by the populations of two countries are. Finally, a time-varying bilateral variable that controls for the intensity of the economic relationships between countries is included by adding a dummy variable that takes a value of one if both countries belong to the same trade agreement (*RTA*).

Data on GDP per capita and relative price competitiveness were obtained from the World Development Indicators (WDI, 2021), data on regional trade agreements were obtained from Mario Larch's Regional Trade Agreements Database (Egger and Larch, 2008), and data on the rule of law were obtained from the Worldwide Governance Indicators (WGI, 2021). In contrast, data on distance and dummy variables for having common borders or a colonial link were taken from Mayer and Zignano (2011). Data regarding linguistic proximity was taken from Gurevich et al. (2021). Data related to terrorism were obtained from the Global Terrorism Database (GTD, 2017), and data on sports events, a dummy variable that takes a value of one if the destination country hosted a large sporting event, were compiled from different sources, following Fourie and Santana-Gallego (2011). Finally, the dummy variable for episodes of financial crisis was compiled from the classification

[2] Estimates of the lagged value of the happiness index are similar to the ones obtained if the contemporaneous value is used. These estimates are available upon request.

[3] Note that since we have a symmetric dataset that includes the same countries as origin and destination, we are also controlling for the happiness level at the origin country.

[4] The UNWTO (2021) also provides information about the number of domestic trips but data availability is even lower.

Table 1
Summary statistics.

Dependent Variable	Correlation		Obs.	Countries	Mean (millions)
Guest	1		1094	81	18.1
Capacity	0.874	1	1772	125	27.3
Population	0.608	0.593	2130	142	45.4
International			134,276	142	1.02
Explanatory Variables	**Obs.**	**Std. Dev.**	**Mean**	**Min**	**Max**
Happy	230,892	5.536	1.121	2.687	8.019
RTA	302,460	0.2468	0.431	0	1
LnDist	294,000	8.642	0.858	1.870	9.894
LP	302,460	0 .099	0.189	0	1
Contig	294,000	0.0219	0.146	0	1
Colony	294,000	0 .0133	0.115	0	1
LnGDPpc	298,910	8.683	1.474	5.455	11.625
RL	302,460	0.0145	0.985	−2.322	2.100
Price	289,564	−1.17e-10	3.753	−11.206	11.206
Terror	302,460	0.150	1.040	0	23.082
Event	302,460	0.003	0.052	0	1
Crisis	262,132	0.567	0.232	0	1

elaborated by Laeven and Valencia (2012).[5]

Regarding the variable of interest, $Happy_{jt}$ is a measure of the average (subjective) level of happiness of a country. This variable is proxied by life ladder (explained hereafter) and is taken from the World Happiness Report (WHR) (Helliwell et al., 2020). The primary source used to compute this subjective well-being (SWB) is the 2020 version of the Gallup World Poll (GWP) covering the years from 2005 to 2020 where respondents were asked to think of a ladder with the best possible life for them being a 10 and the worst possible life being a 0. Then, the national average of the responses to the question of life evaluations is presented. The rankings are from nationally representative samples, and they are based entirely on the survey scores, using the Gallup weights to make the estimates representative.

Previous studies such as Gholipour et al. (2016) and Huang et al. (2021) used data from the World Values Survey (WVS), which provides a happiness index of the same nature (also measured on a 0–10 scale). However, the WVS is published approximately every five years, while the WHR reports yearly data. Moreover, the countries participating in the WVS vary from one wave of the survey to another. For countries missing from some WVS editions, we should either use average data from other WVS waves or eliminate the country, which would reduce our sample size. Therefore, given that the WHR and the WVS are similar, but the WHR provides yearly data, we consider the WHR index a more reasonable choice.

Table 5 in the appendix provides the list of countries included in the sample and average happiness levels for the period 2005–2019. It is relevant to mention that although the life ladder index ranges from 0 to 10, the average reported happiness among countries in the sample ranges from 3.5 (Central African Republic) to 7.7 (Denmark).

Figs. 1 and 2 show average international tourist arrivals and happiness indices for the sample period (2005–2019). We can see that the happiest countries are located in Northern Europe, in addition to Australia and New Zealand, while these are not the countries that necessarily receive the highest number of tourists. Indeed, the two main tourist destinations in the world, in 2015, reported average happiness indices of 7.09 (the USA) and 4.99 (China).

4. Empirical results

As presented in the literature review, previous papers have addressed the issue of how travelling enhances tourists' happiness and life satisfaction. Consequently, concerns over endogeneity and reverse-causality may arise. To this respect, two potential sources of endogeneity might exist: endogeneity due to omitted variables and endogeneity due to reverse causality. The first source of endogeneity stems from the omission of relevant determinants. However, as discussed by Baier and Bergstrand (2007) and Larch and Yotov (2016), including country-pair fixed effects in the structural gravity model, in addition to the MRTs in the form of destination-year and origin-year fixed effects, allows for endogeneity bias to be accounted for, as these sets of fixed effects help reduce the bias caused by incorrectly specifying or omitting multilateral tourism resistance. Moreover, we apply the test by Oster (2019) to evaluate robustness to omitted variable bias, and the results indicate that there is no reason to suspect that there is any notable omitted variable bias.

The second source of endogeneity stems from reverse causality. If we consider that happier people tend to travel more, reverse causality could be a problem. However, evidence supporting this direction of causality is poor and its rationalization relies on multiple factors. For instance, the fact that tourism flows have substantially increased in recent times while happiness levels, as with other social variables such as generalized trust, have barely changed in the short or medium run. Accordingly, we should not expect an increase in travel propensity due to changes in aggregate happiness. In this sense, the use of aggregate data helps to reduce this possibility even more, as dramatic changes in individual happiness are smoothed out when aggregating at the country level.

Furthermore, in the specifications containing domestic tourism flows, the happiness variable is interacted with the border dummy ($Happy_{jt-1} \times INTL_{ij}$). It is safe to assume that the $INTL_{ij}$ dummy variable is exogenous since it captures whether the tourist flow is international or domestic. The interaction between happiness and the international border controls for endogeneity with a triple difference approach. This coefficient captures the difference between domestic and international tourism and the country-pair fixed effects, which essentially deliver a diff-in-diff estimation. This argument is formalized by Nizalova and Murtazashvili (2016), who show that the interaction between an exogenous variable and a potentially endogenous variable is exogenous. Under the assumption that the nature of endogeneity bias affects both domestic and international tourism, the interaction coefficient should be unbiased. We acknowledge that this second source of endogeneity is a challenging issue, given the difficulty of finding an appropriate instrument for happiness. In subsection 4.3, as a robustness check, we estimate the baseline model using dynamic panel data to address this potential endogeneity.

[5] Episodes of crisis are only reported up to 2017.

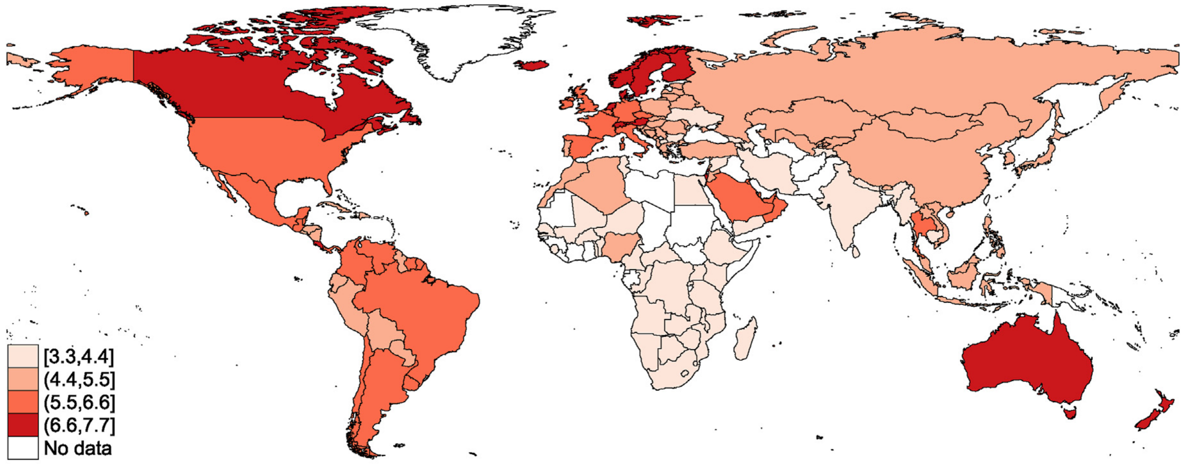

Fig. 1. Average happiness index 2005–2019.

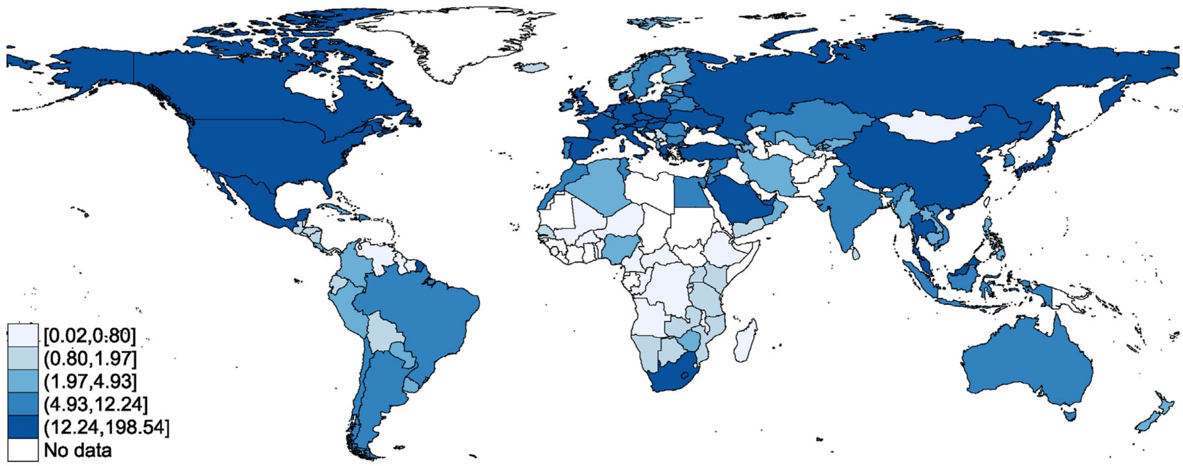

Fig. 2. Average international tourist arrivals 2005–2019.

Moreover, we check for cross-sectional dependence (CD) by applying a CD test, as described by Pesaran (2004, 2015). The main insight of Pesaran (2004) is that a transformation of the sum of pairwise correlations between panel units is standard normally distributed. The CD test rejects the null hypothesis of cross-sectional independence.[6] However, according to Baltagi (2015), CD in gravity models stems from three sources: (i) general equilibrium or resource constraints, (ii) strategic interaction, and (iii) unobservable determinants. These authors argue that the inclusion of country-year and country-pair fixed effects should control for the first and third sources of CD respectively. Other sources of cross-sectional dependence (strategic interaction and cross-sectional dependence through unobservable determinants of outcome captured by the disturbances) seem not to be relevant in our dataset as they are partially controlled by the country-pair fixed effects.

4.1. Border effect and domestic tourism

Before estimating the effect of levels of happiness on tourism movements, we aim to estimate the border effect (*INTL*) by comparing the three alternative approaches (*Guest*, *Capacity*, and *Population*) to measuring domestic tourism. To this end, we estimate equation (1) by considering on the left-hand side each of these three alternative approaches.

In Table 2 we show the results of regressing tourism flows on the dummy variable for the international border effect $INTL_{ij}$ and controlling for origin-year (λ_{it}) and destination-year (λ_{jt}) fixed effects. One can argue that domestic tourist flows would be larger for more populated countries, and so countries like China and India might act as outliers. Therefore, as a robustness check, we remove from the sample the five most populated countries (specifically, Brazil, China, India, Indonesia, and the United States). These estimates are reported in columns (2), (4), and (7). Moreover, since data availability for the variable *Guest* is limited to 81 countries, the sample size is considerably reduced when this approach is taken. In columns (5) and (8) in Table 2 we also estimate equation (1) using the *Capacity* and *Population* approaches, respectively, but with a restricted sample that only includes the same number of countries as *Guest* and only after removing the most populated countries to ensure comparability.

In general, all columns show that the estimated parameters of the control variables are similar in sign and significance for the three approaches to domestic tourism. Belonging to a common regional trade agreement (RTA_{ijt}) yields a positive effect on tourist arrivals. Geographic distance ($LnDist_{ij}$) presents the expected negative sign, while sharing a common land border ($Contig_{ij}$) has a positive effect. So, tourists prefer travelling to closer destinations. Finally, sharing a colo-

[6] We used the stata command xtcsd written by Hoyos and Sarafidis (2006). P-values close to zero indicate data are correlated across panel groups. The results of the CD test = 6,481.6 and $p - value = 0.000$, indicate that we should reject the null hypotheses of cross-sectional independence.

Table 2
International border effect.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
RTA_{ijt}	0.933***	0.951***	0.873***	0.894***	0.843***	1.071***	1.293***	1.380***
	(0.0876)	(0.0959)	(0.0780)	(0.0808)	(0.0890)	(0.0923)	(0.0894)	(0.109)
$LnDist_{ij}$	−0.842***	−0.836***	−0.893***	−0.918***	−0.936***	−0.587***	−0.718***	−0.807***
	(0.0572)	(0.0608)	(0.0507)	(0.0580)	(0.0605)	(0.137)	(0.0677)	(0.0687)
LP_{ij}	0.973***	1.017***	0.863***	0.865***	1.031***	1.211***	0.332**	0.400**
	(0.180)	(0.190)	(0.131)	(0.140)	(0.160)	(0.339)	(0.163)	(0.198)
$Contig_{ij}$	0.690***	0.642***	0.792***	0.755***	0.647***	1.035***	1.047***	0.783***
	(0.121)	(0.129)	(0.104)	(0.112)	(0.116)	(0.269)	(0.140)	(0.141)
$Colony_{ij}$	0.406***	0.437***	0.456***	0.395***	0.370***	0.629***	0.302**	0.0578
	(0.132)	(0.136)	(0.123)	(0.119)	(0.125)	(0.172)	(0.148)	(0.171)
$INTL_{ij}$	−2.955***	−2.935***	−3.943***	−3.859***	−3.591***	−4.635***	−4.766***	−4.183***
	(0.178)	(0.185)	(0.158)	(0.161)	(0.176)	(0.268)	(0.180)	(0.186)
Domestic	Guest	Guest	Capacity	Capacity	Capacity	Population	Population	Population
Most populated	Yes	No	Yes	No	No	Yes	No	No
Pair FE	No	No	No	No	No	No	No	No
Origin*year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Dest*year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	73,493	68,810	115,935	104,471	68,851	133,763	119,442	68,909

Notes: Robust standard errors clustered by pair in parentheses. ***1%, **5%, *10%.

nial link ($Colony_{ij}$) and speaking a similar language (LP_{ij}) have a positive effect on inbound tourism. These results suggest that cultural distance also matters when it comes to tourism flows.

Regarding the border effect, it is always significantly negative but its magnitude varies depending on the proxy used. Moreover, estimates are robust to the sample size considered. According to Larch and Yotov (2016), $INTL_{ij}$ can be interpreted as a home-bias effect that captures (exogenous) variables that affect international tourism differentially. Therefore, the negative border effect provides evidence of home bias, suggesting that domestic tourism is larger than international tourism. This is an expected result according to the information presented in Table 1 that shows how domestic tourism flows are larger than those of international tourism.

This evidence of home bias, obtained from the significantly negative effect of the dummy variable $INTL_{ij}$, contrasts with the results presented by Anderson et al. (2018) on the travel sector. These authors estimate a negative effect for the same country (*SMCTR*) dummy variable that would positively impact our *INTL* dummy variable. However, it should be noted that Anderson et al. (2018) use data on balances of payments (so, they measure trade in services in monetary terms) while in the present research, we use the number of tourists. Moreover, they use a restricted database that only includes 28 OECD countries during 2000–2007.

4.2. Baseline model

In this section we estimate equation (2) following the steps described in subsection 3.1 for a sample of 142 countries during the period 2005–2019. First, the baseline model is estimated with PPML, considering only international tourist arrivals on the left-hand side of the equation. Since the variable of interest is destination-specific ($Happy_{jt}$), destination-year fixed effects (λ_{jt}) cannot be included. Therefore, this destination resistance term is replaced by a set of destination-specific controls. Results are reported in column (1) of Table 3. Then, in columns (2) to (7), domestic tourism, along with international tourism, are considered in the dependent variable. This allows us to estimate the effect of happiness at the destination, considering theory-consistent fixed effects (Larch and Yotov, 2016; Heid et al., 2021). Columns (2) to (4) report estimates of the structural gravity model for tourism demand under the three alternative approaches to considering domestic tourism, and in columns (5) to (7) we also control for the effect of globalization.

Estimates in column (1) show that average happiness at the destination is not significant. However, domestic flows are not included and destination-year fixed effects are not controlled for in this regression. Then, the interaction term ($Happy_{jt} \times INTL_{ij}$) is added to the regression in columns (2) to (4). Now, happiness is consistently estimated by PPML after including both types of MRT (destination-year and origin-year) and country-pair fixed effects. It is worth mentioning that the parameter of the interaction term is significantly positive when *Capacity* and *Population* are used to measure domestic tourism, while it yields a negative but non-significant effect when *Guest* is considered. The significantly positive estimated parameter should be interpreted as the differential impact of happiness on international tourism relative to domestic tourism. Precisely, increasing the happiness index by 1% would increase international tourist arrivals (relative to domestic tourism) by 0.11–0.13%. This effect of happiness on tourism is in line with the results obtained by Gholipour et al. (2016), and it demonstrates that the level of happiness of a country is an asset capable of attracting tourists from other countries. Then, it should be considered when creating marketing campaigns to promote the tourist destination.

Columns (5) to (7) provide estimates of the globalization effect. Due to perfect collinearity, we need to drop one of the $INTL - Year$ dummies, and we set the border-effect base year to 2006. Thus, the international border effect estimates were interpreted as deviations from the average border effect that year. Specifically, a negative sign on the $INTL - Year$ variable indicates an increase in the border effect while a positive sign implies a decrease (Anderson et al., 2018). As presented in Fig. 3, the estimate parameters of the globalization effects are always negative and have relatively similar magnitudes across the sample period when *Guest* is used as a proxy for domestic tourism. Conversely, border barriers fall significantly, mainly after 2011, for *Capacity* and *Population* as proxies of domestic tourism. In these cases, the globalization effect can be interpreted as a decline in international tourism-related costs, since travelling internationally has become more affordable, accessible, and convenient.

After including globalization effects, the estimated impact of the interaction term on tourism is still positive when *Capacity* and *Population* are used as approaches to measure domestic tourism, but it is significantly negative when *Guest* is considered. So, holding other factors constant, happiness has a significant and lower effect on international tourists than on domestic guests (Table 3, column 5). However, when *Capacity* and *Population* are used, the coefficient of interest

Table 3
Effect of happiness on tourism. Baseline model.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
RTA_{ijt}	0.0877**	0.162***	0.209***	0.264***	0.166***	0.179***	0.126***
	(0.0429)	(0.0614)	(0.0447)	(0.0338)	(0.0624)	(0.0484)	(0.0364)
$Happy_{jt-1}$	0.0113						
	(0.0143)						
$Happy_{jt-1} \times INTL_{ij}$		−0.0348	0.124***	0.104***	−0.0764***	0.127***	0.132***
		(0.0253)	(0.0255)	(0.0327)	(0.0286)	(0.0276)	(0.0241)
$INTL_{ij} \times 2007$					−0.182***	0.0463	−0.140***
					(0.0580)	(0.0606)	(0.0382)
$INTL_{ij} \times 2008$					−0.0755***	0.00317	−0.0679***
					(0.0206)	(0.0202)	(0.0219)
$INTL_{ij} \times 2009$					−0.200***	−0.104***	−0.115***
					(0.0379)	(0.0167)	(0.0189)
$INTL_{ij} \times 2010$					−0.204***	−0.0439**	−0.0223
					(0.0418)	(0.0207)	(0.0213)
$INTL_{ij} \times 2011$					−0.196***	−0.0270	0.0123
					(0.0386)	(0.0203)	(0.0205)
$INTL_{ij} \times 2012$					−0.163***	−0.00874	0.0484**
					(0.0388)	(0.0207)	(0.0205)
$INTL_{ij} \times 2013$					−0.153***	0.0165	0.0896***
					(0.0387)	(0.0203)	(0.0219)
$INTL_{ij} \times 2014$					−0.171***	−0.00358	0.127***
					(0.0366)	(0.0202)	(0.0195)
$INTL_{ij} \times 2015$					−0.196***	0.0123	0.165***
					(0.0382)	(0.0213)	(0.0193)
$INTL_{ij} \times 2016$					−0.211***	0.0175	0.215***
					(0.0370)	(0.0225)	(0.0210)
$INTL_{ij} \times 2017$					−0.199***	0.0469*	0.291***
					(0.0377)	(0.0246)	(0.0235)
$INTL_{ij} \times 2018$					−0.188***	0.0579**	0.337***
					(0.0380)	(0.0261)	(0.0262)
$INTL_{ij} \times 2019$					−0.133***	0.119***	0.344***
					(0.0392)	(0.0238)	(0.0262)
Domestic tourism	No	Guests	Capacity	Population	Guests	Capacity	Population
Pair FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Origin*year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Dest*year FE	No	Yes	Yes	Yes	Yes	Yes	Yes
Observations	84,613	59,437	88,806	102,646	59,437	88,806	102,646

Notes: Robust standard errors clustered by pair in parentheses. Column (1) includes destination controls (GDPpc, RL, Price, Terror, Events and Crisis). ***1%, **5%, *10%.

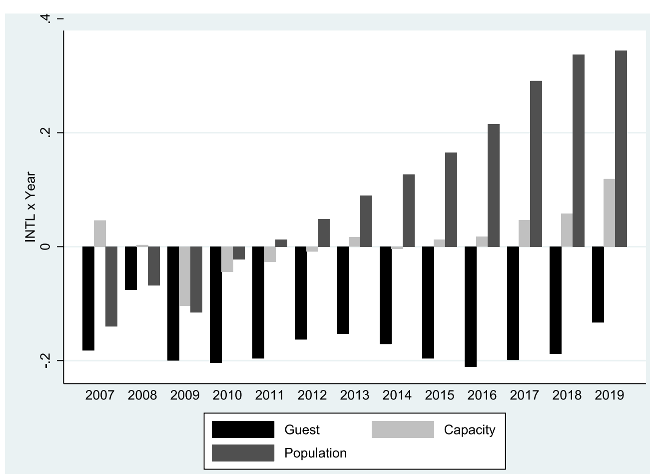

Fig. 3. Globalization effect.

Table 4
Non-linearity, cultural distance, and endogeneity.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
RTA_{ijt}	0.172***	0.186***	0.133***	0.158***	0.176***	0.122***	0.306***
	(0.0629)	(0.0480)	(0.0363)	(0.0568)	(0.0460)	(0.0342)	(0.0223)
$LnTou_{jt-1}$							0.855***
							(0.00325)
$Happy_{jt-1}$							0.0263***
							(0.00652)
$Happy_{jt-1} \times INTL_{ij}$	0.348	0.931***	0.692***	−0.178***	0.0788**	0.0652**	
	(0.382)	(0.287)	(0.229)	(0.0405)	(0.0378)	(0.0301)	
$Happy^2_{jt-1} \times INTL_{ij}$	−0.0351	−0.0692***	−0.0482**				
	(0.0305)	(0.0233)	(0.0188)				
$Happy_{jt-1} \times INTL_{ij} \times LP_{ij}$				0.320***	0.137*	0.208***	
				(0.101)	(0.0827)	(0.0714)	
Globalization	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Domestic tourism	Guests	Capacity	Population	Guests	Capacity	Population	No
Pair FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Origin*year FE	Yes	Yes	Yes	Yes	Yes	Yes	No
Dest*year FE	Yes	Yes	Yes	Yes	Yes	Yes	No
Method	PPML	PPML	PPML	PPML	PPML	PPML	GMM
Maximum	4.96	6.73	7.18				
Observations	59,437	88,806	102,646	59,437	88,806	102,646	81,846

Notes: Column (7) includes controls (GDPpc, RL, Price, Terror, Events and Crisis). Robust standard errors clustered by pair in parentheses. ***1%, **5%, *10%.

presents the expected significant and positive effect.[7] It also worth to mention that the coefficient of the *RTA* is significantly positive in all regressions. Campos et al. (2021) reported that the choice of domestic trade had little effect on FTA estimates. However, we find that choice of domestic tourism flows seems to matter for other variables, happiness in our case. This finding might be useful for future studies that apply structural gravity with domestic flows.

Two main findings stand out from the estimates in columns (2) to (7). First, we show that we can estimate the impact of a destination-specific variable ($Happy_{jt}$) in the presence of a full set of MRTs. This is a novel result in the empirical literature on tourism demand, since we are estimating country-specific variables by defining a theoretically consistent gravity model for tourism. It is also possible to explore the differential impact of any country-specific variable on international tourism relative to domestic tourism. In particular, we find that average happiness has a positive effect on international tourism. Secondly, we estimate a border effect for international tourism. However, due to globalization, this home bias decreases over time. A similar result has been found in the travel sector by Anderson et al. (2018) in their exploration of trade in services.

4.3. Non-linearity, cultural distance, and endogeneity

As a robustness check, we test two different hypotheses about the relationship between happiness and tourism. First, following Polgreen and Simpson (2011), a quadratic term ($Happy^2_{jt} \times INTL_{ij}$) is introduced into equation (2) to test for non-linearities in the relationship between happiness and tourist arrivals. As presented in column (1) in Table 4 when *Guest* is used as a proxy for domestic tourism, now the interaction term becomes positive and the quadratic term negative, but none of them are significant. However, when *Capacity* and *Population* are considered in columns (2) and (3), the interaction term yields a significantly positive effect and the quadratic term is significantly negative. Therefore, we find a significant non-linear relationship between tourism and aggregate happiness in the last two specifications.

The quadratic term's negative effect suggests an inverted U-shaped link between tourism flows and happiness level. This type of relationship was also found by Polgreen and Simpson (2011) for migration and happiness. Thus, increasing the average level of happiness in a destination country increases tourist arrivals, but this associated increase is lower after a threshold (around 6.73–7.18). As can be seen in Table 5, 120 (129) out of 142 countries have an average happiness index below 6.73 (7.18). The intuition behind such an inverted U-shaped relationship is not straightforward, and many factors could be related to the abovementioned objective versus subjective measures. On the one hand, tourists could associate happiness at the destination with a certain level of development that encompasses a set of conditions such as safety, certain levels of institutional quality, or income levels that guarantee relatively high-quality services. These might include a sound health system or adequate protection from the police. On the other hand, there are destinations, such as many Caribbean and South American countries, where these aspects could be largely improved upon, but people still report remarkably high levels of happiness, i.e., there must be other sources of happiness. These countries are, however, characterized by having a good climate, a certain environmental quality, warm and open people, and a more relaxed lifestyle.

Happiness indicators may capture these sorts of attributes, even if related aspects are included as controls in our models. Accordingly, there are different factors that tourists might take into account until relatively high levels of happiness at the destination are reached. After this threshold, increasing happiness is associated with lower increases in tourist arrivals. We can find potential explanations by looking at our sample. There are certainly a few countries above such a high threshold, particularly the Nordic countries in Europe plus a few others, including Australia, New Zealand, Austria, Switzerland, and Luxembourg. Despite the association of happiness with a higher quality of life—indeed the happiest countries in our sample are among those with the highest qualities of life and most developed welfare states—tourists know that they are not going to enjoy the qualities of life reserved for citizens, along the lines of Hendriks (2015) who look at the case of migration. Then, it is likely that tourists look for a *sufficiently high* quality of life at the destination, given that they only plan to stay there for a short period.

[7] There are fewer countries that report domestic guests (81 countries) than *Capacity* (125) and *Population* (142). If this selection of countries is correlated with our variable of interest, the negative result of happiness using *Guests* as a proxy could be attributed to measurement error that stems from country selection bias. Indeed, if we use the same country selection in columns 6 and 7 of Table 3 as in column 5, the effect of happiness is downward biased.

The second hypothesis that we explore is whether cultural distance affects the happiness-tourism link. This idea was presented by Huang et al. (2021), who studied whether the effect of levels of happiness on Chinese outbound tourism might be reduced by the cultural distance between China and the destination country. These authors argue that Chinese tourists are sensitive to cultural distance when deciding the tourist destination, since individuals from diverse cultural backgrounds tend to have different attitudes and behaviors. They hold that if a tourist believes the level of happiness that he/she will experience at the destination country is feasible in his/her home country, the destination becomes more attractive. However, this belief may be reduced when cultural differences increase. To measure cultural distance, they use Hofstede's five-dimension index where a higher value implies a greater cultural distance between countries (Hofstede et al., 2010). Their results suggest that after the inclusion of an interaction term between happiness and cultural distance, the influence of happiness on outbound tourists is still positive and significant. Moreover, they find an adverse effect of the interaction term, which implies that the positive effect of happiness decreases as cultural distance increases.

A limitation of the Hofstede index used in Huang et al. (2021) is that it is only available for 70 countries. Therefore, in our research, we use linguistic proximity (LP_{ij}) as a measure of cultural distance, and this variable is interacted with happiness level and the border effect ($Happy_{jt} \times INTL_{ij} \times LP_{ij}$). In our case, higher values of LP_{ij} imply lower cultural distance (or higher cultural similarity) between countries, so a positive sign of this interaction term indicates that cultural distance reduces the positive impact of happiness on tourism.

Columns (4) to (6) in Table 4 show that the influence of happiness on international tourism relative to domestic tourism ($Happy_{jt} \times INTL_{ij}$) is positive and significant when the *Capacity* and *Population* approaches are used, while it is significantly negative when *Guest* is considered. Regarding the interaction term with linguistic proximity ($Happy_{jt} \times INTL_{ij} \times LP_{ij}$), it is significantly positive under the three approaches. Indeed, the magnitude of this term when *Guest* is used is the largest, and so the total effect of happiness is positive for the three specifications.

Our estimates are in line with Huang et al. (2021). We also find that the impact of aggregate happiness on tourism is larger for culturally similar countries. Following Liu et al. (2021), cultural communication improves mutual understanding and friendship between trading partners, which would help to reduce information asymmetry. Since we measure cultural distance using a linguistic proximity index, our results might also indicate that it is easier for tourists to interpret and appreciate the level of happiness at a destination country if they share a common (or similar) language. Therefore, it is easier for locals to communicate their feelings and to facilitate cross-cultural communication if they can speak the tourists' language.

Finally, to explore dynamics and address potential endogeneity we estimate the baseline model with an Arellano-Bover/Blundell-Bond linear dynamic panel-data estimation, applying a generalized method of moments (GMM) estimator. Here, we treat all observable variables as potentially endogenous, so all the lagged differentiated variables are used as instruments. As shown in last column in Table 4, the coefficient of our variable of interest is still positive and significant. Although this method has some caveats—particularly, it cannot address zeros in the dependent variable or the inclusion of multilateral resistance terms—it has been used in the gravity literature as a common remedy against endogeneity (Busse et al., 2010; Myburgh and Paniagua, 2016).

5. Conclusions

Exploring the determinants of international tourism demand is a relevant topic within the tourism-economic literature. To this respect, extensive research has been carried out to analyze how various economic and non-economic factors determine international tourism movements. However, the role of a subjective variable such as happiness has been scarcely explored in previous literature. Moreover, estimates of gravity models for tourism demand seem to be a step beyond the empirical advances in structural gravity models applied to international trade. In this regard, the present research aims to provide two main contributions.

First, the role of aggregate happiness on worldwide tourism flows is explored and different hypotheses are tested. Secondly, we estimate a structural gravity model that includes both theory-consistent fixed effects, and domestic and international tourism movements (Heid et al., 2021; Larch and Yotov, 2016). Furthermore, we provide three alternative measures of domestic tourism that can be used as guidelines for future research estimating structural gravity models for tourism demand.

Results reveal that happiness matters in explaining tourism flows, and the results are sensitive to the proxy of domestic tourism considered. Moreover, we find evidence that the relationship between tourism and happiness is non-linear. Indeed, we find an inverted U-shaped link between tourism and happiness, obtaining a turning point in the positive effect of happiness on tourism at around 6.73–7.18. This result illustrates not only that tourists value a relatively high level of happiness at the tourist destination, but also that they might associate happiness with quality of life at the destination and, once a certain level is reached, it could be sufficient for them.

Moreover, the effect of happiness at the destination is higher for culturally similar countries (measured in terms of linguistic proximity), as we find that the positive influence of happiness on tourism decreases as cultural distance increases. This result suggests that cultural similarity facilitates cross-cultural communication, and so it is easier for tourists to perceive and appreciate the level of happiness at the tourist destination, leading to a larger effect on tourism flows.

The results we obtained are relevant since understanding travelers' motivations can help to define tourist strategies to promote the sector. For instance, marketing campaigns to promote a particular tourist destination can emphasize the level of happiness of that destination. This is especially important for culturally different countries, where it is more difficult for tourists to interpret levels of happiness.

Declaration of competing interest

None.

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A Appendix

Table 5
Average happiness (2005–2019) level by country

Denmark	7.69	El Salvador	5.99	Tajikistan	4.91
Finland	7.57	Poland	5.91	North Macedonia	4.90
Switzerland	7.55	Korea, Rep.	5.88	South Africa	4.87
Norway	7.54	Mauritius	5.84	Iran	4.86
Netherlands	7.46	Malaysia	5.80	Tunisia	4.76
Iceland	7.43	Uzbekistan	5.79	Gambia, The	4.73
Canada	7.40	Lithuania	5.79	Ukraine	4.73
Sweden	7.37	Kazakhstan	5.78	Nepal	4.69
New Zealand	7.31	Ecuador	5.77	Mozambique	4.68
Australia	7.29	Bolivia	5.75	Namibia	4.63
Austria	7.24	Jamaica	5.70	Cameroon	4.58
Israel	7.21	Nicaragua	5.63	Egypt	4.53
Costa Rica	7.18	Moldova	5.60	Zambia	4.53
United States	7.09	Peru	5.59	Eswatini	4.49
Ireland	7.07	Belarus	5.57	India	4.49
Luxembourg	7.05	Estonia	5.57	Bulgaria	4.48
Belgium	6.99	Paraguay	5.56	Congo, Dem. Rep.	4.47
United Kingdom	6.93	Croatia	5.55	Senegal	4.44
Oman	6.85	Greece	5.53	Armenia	4.44
United Arab Emirates	6.83	Russian Fed.	5.53	Angola	4.42
Germany	6.81	Romania	5.53	Myanmar	4.41
Mexico	6.75	Hong Kong	5.46	Kenya	4.39
Panama	6.68	Cuba	5.42	Ethiopia	4.38
France	6.67	Portugal	5.41	Congo, Rep.	4.35
Brazil	6.66	Honduras	5.39	Sri Lanka	4.31
Qatar	6.57	Algeria	5.39	Uganda	4.28
Czech Republic	6.56	Latvia	5.37	Niger	4.25
Saudi Arabia	6.54	Vietnam	5.31	Mali	4.25
Spain	6.51	Jordan	5.30	Cambodia	4.24
Singapore	6.50	Montenegro	5.28	Georgia	4.22
Malta	6.42	Turkey	5.27	Burkina Faso	4.17
Chile	6.37	Hungary	5.25	Sierra Leone	4.11
Argentina	6.34	Indonesia	5.23	Malawi	4.05
Colombia	6.29	Philippines	5.22	Syria	4.02
Trinidad & Tobago	6.28	Dominican Rep.	5.22	Benin	4.02
Kuwait	6.27	Maldives	5.20	Lesotho	4.00
Italy	6.27	Bhutan	5.20	Botswana	4.00
Suriname	6.27	Serbia	5.18	Madagascar	3.98
Uruguay	6.26	Bosnia & Herzegovina	5.16	Haiti	3.95
Guatemala	6.25	Kyrgyz Republic	5.09	Comoros	3.94
Belize	6.20	Morocco	5.04	Zimbabwe	3.93
Venezuela, Rb	6.12	China	5.00	Yemen, Rep.	3.91
Thailand	6.10	Albania	4.99	Tanzania	3.69
Cyprus	6.09	Lebanon	4.98	Rwanda	3.65
Slovak Rep.	6.02	Mongolia	4.98	Togo	3.56
Slovenia	6.02	Nigeria	4.97	Central African Rep.	3.51
Japan	6.01	Lao	4.97		
Guyana	5.99	Azerbaijan	4.94		

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