The effect of politically motivated violence on international tourists' choices: an interaction model for Colombia

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Abstract

International tourism is an essential economic activity for several developed and developing countries. To attract overseas tourists, governments and other tourism stakeholders place vital importance on the determinants that most influence tourists' choices, including security associated factors. This study examines the impact of politically motivated violence (PMV) on the demand for international tourism in Colombia, including its interactive effects with tourists' income and international trade. A dynamic panel-data multinomial logit model is estimated using the first-differenced Generalized Method of Moment approach. The dependent variable of international tourism demand is approached through the empirical probability of visiting an international tourist destination, following probabilistic choice theory. The likelihood ratio of travelling to Colombia is calculated from 29 countries over the period 1995-2013. A group of 53 nations is included as other tourists' set of alternatives. The estimates confirm the adverse impact of PMV incidents on international tourists' choice for travelling to Colombia. Notwithstanding, this effect tends to be lower when international tourists' income and the relative bilateral trade between tourists' country of origin and Colombia increases. The results suggest that wealthier holiday visitors and business tourists are less likely to shift their choice for Colombia, even under the PMV incidents. To raise tourists' preferences for Colombia, the number of PMV acts must decrease in absolute and relative values. Based on the findings, suggestions for Colombia's tourism marketing policy can be realised.

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3.1 Introduction

The increasing number of inbound visitor arrivals across the world in the last five decades (see UNWTO, 2014) has boosted study in the field of international tourism demand. Since the seminal works of Guthrie (1961), the number of studies has risen significantly: from 5 in the 1960s, as noted by Crouch (1994) to more than 300 articles in the first decade of the current century, according to Scopus statistics. The reason seems to depend on the willingness governments and other tourism stakeholders keep in understanding international visitors' preferences among tourist destinations, the determinants behind tourists' decision-making, and the most common practices utilised in international travel demand estimates. A comprehensive review of works have been carried out by Brida and Scuderi (2013); Crouch (1994); Divisekera (2013a); Li, Song, and Witt (2005); Lim (2006); and Song and Li (2008).

For predicting and forecasting the demand for an international tourist destination, several proxy response variables have historically been used. One of them, the number of inbound visitor arrivals, has been utilised in numerous studies, including Su and Lin (2014), Ridderstaat, Oduber, Croes, Nijkamp, and Martens (2014), De Vita and Kyaw (2013), and Tadesse and White (2012). In spite of its high popularity (also noted by Crouch, 1994; Lim, 2006; Song & Li, 2008), this absolute frequency measure has not yet been employed as a normalised variable, with which the empirical probability of visiting a country of destination can be approached. Based on the theory of discrete choice (see Train, 2009), the relative frequency of visitor arrivals is an aggregate measure of revealed preferences capable of capturing all the characteristics tourists' choice set of alternatives must fulfil.

The demand of an international tourism destination has been demonstrated to depend on diverse factors,[1] including variables that directly or indirectly threat tourists' lives when travelling there. Amongst them, Political instability (PI) (Yap & Saha, 2013), terrorism (TE) (Drakos & Kutan, 2003), and/or politically motivated violence (PMV) (Neumayer, 2004) have been found as destination attributes that adversely influence international tourists' demand. The latter being the bridge between some PI actions, such as guerrilla warfare, civil war, or internal conflict, and TE attacks. To date, politically motivated violence (against combatant and non-combatant targets) has not yet been captured as a relative measure, with

[1] Tourists' characteristics, destination attributes, spatial pattern associated factors, budget and time constraints, and external events, are classifications where most tourism demand explanatory factors are likely to belong to.

which tourists' risk perception of PMV actions in a country of destination (compared to other county alternatives) can be approached.

The adverse impact of PMV incidents (against combatant and non-combatants) on the demand for international tourism has been interactively analysed with UNESCO's listed heritage sites (Yap & Saha, 2013), country size (Neumayer, 2004), and terrorism for the case of political instability (Saha & Yap, 2014). Although further interaction terms may accompany these violent actions, tourists' income and international trade seem to be of interest. Ultimately, wealthier people tend to travel more (Schiff & Becken, 2011; Serra, Correia, & Rodrigues, 2014; Thompson, 2013), and more international trade leads to further business tourists' trips (Kulendran & Wilson, 2000; Turner & Witt, 2001).

The aim of this chapter is to estimate the impact created by changes in the relative number of PMV incidents in a country of destination on changes in tourists' choice for travelling there, including its interactive effects with tourists' income and relative international trade. A dynamic panel-data multinomial logit (PDMNL) model is estimated using the first-differenced Generalized Method of Moment (GMM) estimator. Hypotheses to be estimated are as follows:

- More visitor arrivals in a destination country reflect higher international tourists' preferences for travelling there
- Further relative PMV incidents in a country adversely influence overseas visitors' choices for going there
- An increase in tourists' income tends to lower the impact that further relative PMV incidents in the country of destination cause on travellers' choices
- A rise in relative bilateral trade between tourists' country of origin and destination tends to lower the impact that more relative PMV incidents in the country of destination cause on (business) tourists' choices

These hypotheses can be tested by looking at Colombia over a 19 year period (between 1995 and 2013). In Colombia, there have been PMV incidents for several years that seem to affect tourists' preferences for travelling there. The events have arisen amid the armed conflict between Colombia's military force, guerrilla insurgents (mainly Fuerzas Armadas Revolucionarias de Colombia (FARC) and Ejercito de Liberacion Nacional (ELN)), and rightwing paramilitary groups (primarily Autodefensas Unidas de Colombia (AUC) and Convivir).[2] Although the average number of PMV incidents was lower during the period 2003-2013 than 1995-2002, in relative terms, it was not (the numbers in other destinations between 2003 and 2013 was on average lower) (see Appendix A). This fact suggests that tourists' risk perception of PMV in Colombia is higher than in other destinations.

On the other hand, tourists who most visit Colombia come from countries where above average real per capita income has grown, and where the relative bilateral trade with Colombia has slightly increased in most of the studied years. From an experimental perspective, it seems that these increments tend to lessen the effects that further PMV incidents in Colombia - relative to the numbers recorded in other tourists' destination countries, cause on visitors' choice for travelling to Colombia.

The remaining of this chapter is organised as follows. Section 3.2 provides a literature review on relative measures commonly used in international tourism demand studies, as well as on the effects that PMV actions cause on the demand for an international destination. In section 3.3, the research methodology followed in this study is presented. Section 3.4 presents empirical results from econometric estimates. In Section 3.5, the conclusions and policy implications are presented.

3.2 Literature review

3.2.1 Relative measures of international tourism demand

According to the theory of discrete choice (see Ben-Akiva & Lerman, 1985; Train, 2009), when decision makers' choice set is discrete (not continuous as typically observed in the demand for products), the number of alternatives is finite, exhaustive and mutually exclusive. When a person travels abroad, his/her choice set on where to go for a period and spend in tourism-related products fulfils these characteristics. There is a countable number of countries

[2] The incidents perpetrated within this non-international armed conflict should remain under the category of PMV against combatants; however, a plethora of these actions remains as terrorist acts in reality. This is because of the assassination of civilians, which are non-combatants (see ICRC, 2015); the merge with drug trafficking activities by the rebels; the proliferation of landmines; and other human rights violations (see Nagle, 2015; Paredes Z., 2003; US-Department-of-state, 2014). Terrorist actions are emphatically condemned by the International Humanitarian Law (ICRC, 2015); however, their coexistence amid the Colombian armed conflict is irrefutable.

where tourists can travel to, all countries are potential destinations for them, and only one country can be visited at a time.[3]

The relative frequency of visitor arrivals (rfa), an aggregate data measure calculated from revealed-preference data at a macro level, satisfies all these characteristics. Finiteness and exhaustiveness are fulfilled, as all countries (finite) available to be visited by the travellers from a country s are included ($C_s\colon\{1,\dots,N\}$). Hence, tourists' trade-off between alternatives is captured exhaustively. Furthermore, since each arrival corresponds to one inbound tourism trip, and the arrivals in each country are recorded separately (UNWTO, 2015), the characteristic of mutual exclusion between alternatives is automatically embedded; that is, $c_1c_2 = c_1c_3 = \cdots = c_kc_n = 0$.

There are three relative measures close to rfa in studies on international tourism demand. The first is the market share of visitor arrivals (rma), which is calculated by dividing the number of arrivals in country i over the total number of visitor arrivals in the analysed countries (Drakos & Kutan, 2003). The second is the relative share of visitor arrivals obtained from two ways: i) the ratio between the number of visitor arrivals in country i from country s and the total number of visitor arrivals from country s (rsa) (Tsai & Wang, 1998), and ii) the quotient between the number of visitor arrivals in country i from country s and the total number of tourist departures from country s ($rsad$) (McKercher, Chan, & Lam, 2008).

As rfa, rma and rsa are continuous with limits between zero and one; a strength that has enabled studies to capture country competitiveness in the international travel arena from the demand side ($rsad$ is excluded, as the quotient can be greater than one). rsa has also served as a proxy dependent variable of the relative share of tourism expenditures, with which the AIDS model of Deaton and Muellbauer (1980) adapted to international tourism can be estimated (both in static and dynamic versions). In spite of their features, the following misspecification problems can be identified among these measures, when the characteristics that tourists' choice set must satisfy are taken into account:

i) Since rma has been calculated with the number of visitor arrivals in each country of destination, the representative tourist (and the country where he/she comes from) turns to be

[3] The last characteristic suggests that "humans are not omnipresent" in Papatheodorou's (2006, p. 75) words.

unknown. This practice inevitably creates a problem of decision maker's identification, which is crucial in any consumer demand studies.

ii) As rsa has not been calculated over the whole set of alternatives tourists may choose from, the characteristic of exhaustiveness stated in the theory of probabilistic choice tends to be skipped. As a result, the estimated level of substitutability between countries is likely biased toward the group of destinations chosen in the studies. Song, Dwyer, Li, and Cao (2012) have already referred to the problem of including a small number of destinations in tourism demand works. In their view, "further studies should consider a theoretically justified demand system involving a large number of interactive destinations…" (p.1659). The authors' solution relies on predicting the relative share of tourism expenditures (rse) under an AIDS specification using VAR techniques; however, this may also be covered by regressing rfa under a linear or non-linear probabilistic choice method, including logit.[4] As noted by Theil (1969), the effects of infinitesimal changes in explanatory variables on the probability of choosing one alternative are similarly interpreted to consumer demand models where the relative share of expenditures is used as the response variable.

As opposed to rsa, $rsad$ includes almost all destinations tourists can travel to; however, the ratio assumes that all visitor departures from country $\mathcal{s}$ equal the number of arrivals recorded in the countries of destination (one-by-one relation). Although this can be the case, the measure should take into account that tourists who depart from any country $\mathcal{s}$ can visit more than one destination during their trip; e.g., ten departures from country $\mathcal{s}$ may represent a total of twenty arrivals anywhere by tourists from the country $\mathcal{s}$. Therefore, countries' outbound tourism flows (calculated on visitor arrival) is different to departures data provided by each country of reference (see UNWTO, n.d).

iii) The variables rma and rsa have not been regressed on explanatory factors associated with both personal and business/professional tourism activities, despite the ratios having been calculated from statistics on arrivals that aggregate all tourism purposes. As a result of this practice, their prediction and/ forecasts are probably accompanied by omitted variable problems. Arguably, if the tourism object lies on personal activities -as conceptualised by the

[4] In the light of the higher reliability that data on visitor arrivals present over tourism expenditures (Barry & O'Hagan, 1972; O'Hagan & Harrison, 1984), and the way rfa is calculated, it might be expected to see more efficient predictions in international tourism demand studies conducted with rfa.

World Tourism Organization (UNWTO, 2010a), consumer choice theories need to be followed; if the trip is for business/professional activities, producer choice theories should rather be embraced. If both activities are inherent in the measure, the determinants for both tourism purposes must be included. As noted by Train (2009), it is the ability of researchers in including the set of explanatory variables, what ultimately makes the error term to be an independent and identically distributed random variable.

rfa can be linked to consumer or producer choice theories, as the decision for a country of destination can be made for personal or business/professional activities (UNWTO, 2010a), respectively. The optimisation, in either case, is held as a corner solution due to the discrete nature of the choice.[5] From the consumer theory perspective, rfa reveals those destinations the representative international tourist most prefers, as probabilistic choice works directly with utility functions (Ben-Akiva & Lerman, 1985). Thus, rfa can be associated with the consumer's primal problem: the maximisation of utility (U) - as an indirect function (V), which depends on explanatory factors observed by the researcher, plus a random term ε. In brief:

$$Max\ U_{\bar{n}\mathscr{s}} \equiv U_{\mathscr{s}} = c_1, c_2, \dots, c_N$$

Subject to:

$$c_i = \begin{cases} 1\ if\ country\ i\ is\ chosen \\ 0 \qquad otherwise \end{cases}$$

If $U_{\mathscr{s}i} > U_{\mathscr{s}j}$, country i is chosen against the j-th alternative.

As $U = V + \varepsilon$, then:

$$rfa_{\mathscr{s}i} \equiv P_{\mathscr{s}i} = Pr\left[V_{\mathscr{s}i} + \varepsilon_{\mathscr{s}i} \geq V_{\mathscr{s}j} + \varepsilon_{\mathscr{s}j},\ \forall\ j \in C_{\mathscr{s}}\right]$$

From the producer theory viewpoint (in tourism for business/professional activities), rfa is likely to show companies' preferable destinations to do businesses; places where employees are appointed to travel to (the representative business tourist, $\bar{n}$).[6] Arguably, business visitors'

[5] "Discrete responses are the result of optimization of payoffs to decision makers: utility for consumers, profit for firms" (McFadden & Train, 2000, p. 448).

[6] "(a) Employees of non-resident entities (of the country or region visited), as well as self-employed persons staying for a short period of time (less than a year) to provide a service such as the installation of equipment, repair, consultancy, etc., where there is no implicit employer-employee relationship with a resident entity; (b) Travellers entering in business negotiation with resident entities (in the country or region visited) or looking for business opportunities, including buying and selling" (UNWTO, 2010a, p. 25).

trade-off between countries is the voice of companies' opportunity cost for doing business in a country rather than in others. From this perspective, rfa might be indirectly associated with the primal problem of the representative world-trade oriented firm ($\bar{m}$): the maximisation of production constrained to costs to get maximum benefits ($\vec{\mathcal{B}}_j$).[7] rfa is, thereby, an indirect function of companies' international trade associated actions (T),[8] as well as of unobserved factors (ε). The representation is:

$Max\ \vec{\mathcal{B}}_{\bar{m}s} \equiv \vec{\mathcal{B}}_{s} = c_1, c_2, \dots, c_N.$

If $\vec{\mathcal{B}}_{si} > \vec{\mathcal{B}}_{sj}$, country alternative i is chosen for international trade operations.

As $\vec{\mathcal{B}} = T + \varepsilon$,

$$rfa_{si} \equiv P_{\bar{n}s}(i|C_s) = f\left(P_{\bar{m}s}(i|C_s)\right)$$

$$rfa_{si} \equiv P_{\bar{n}si} = Pr\left[T_{si} + \varepsilon_{si} \geq T_{sj} + \varepsilon_{sj},\ \forall\, j \in C_s\right]$$

Finally, another measure near rfa is the quotient between the number of visitor departures (or tourist flows) to a destination and the population size of tourist' country of origin (Dritsakis & Athanasiadis, 2000; Eilat & Einav, 2004; Hamilton, Maddison, & Tol, 2005). Since each arrival corresponds to one inbound tourism trip, and the arrivals in each country are recorded separately (UNWTO, 2015), the rational number should be interpreted as the number of outbound trips per capita from the country of origin, and not as a relative frequency measure capable of comparing choices, as Eilat and Einav (2004) did.

3.2.2 Politically motivated violence as a determinant

The determinants of the demand for international tourism have been studied from diverse theories and economic models (see Crouch, 1994; Li et al., 2005; Lim, 2006). Based on Lancaster's (1966) model of characteristics, some studies have investigated destination attributes that attract international visitors (Rosselló-Nadal, 2014; Rugg, 1973; Su & Lin, 2014). Amongst the strand of country qualities, tourists' risk associated factors, including terrorism (TE),[9] politically motivated violence (PMV), and political instability (PI) have been investigated; they have been found nefarious for international tourism demand.

[7] The statement is based on Nadiri (1993, p. 448).

[8] These are: exports and imports (Kulendran & Wilson, 2000; Turner & Witt, 2001), and international capital movements (Divisekera, 2013b).

[9] Against tourists (Pizam & Smith, 2000; Tarlow & Muehsam, 1996) or other targets that indirectly permeates the tourism sector (Teye, 1988; Wall, 1996).

In a study conducted with global data, Yap and Saha (2013) found that a one-unit increase in the score of PI causes an average decline in tourist arrivals and revenues of between 26 and 33%, respectively. In line, Neumayer (2004) found that tourism demand is more severely affected by PMV in the long-run than the short-run. The impacts tend to vary between countries, according to Drakos and Kutan (2003). Some nations are more sensitive than others and can lose market share individually (within the region they belong to) or collectively (compared to other geographic areas), depending on the intensity of attacks; that is: low, moderate, or high.

While the impact of PI actions on the demand for international tourism consensually remains negative, interestingly, the effect of TE acts does not. The study of Saha and Yap (2014) found that TE incidents do not affect the demand for tourism. Their result argues that countries perceived as low-to-moderate politically risky tend to witness tourism gains from terrorist incidents. In their study on tourists' perception of TE and PI, Sönmez and Graefe (1998) found the opposite. In their findings, more than half of the respondents (57%) were discouraged to travel abroad in the presence of terrorist episodes. Moreover, a high number of those surveyed (88%) believe that politically unstable countries should be avoided.

Terrorism is "politically motivated violence perpetrated against non-combatant targets by subnational groups or clandestine agents" (Title 22 USC 222656f(a) and 222656f(d), cited by the US Department of State (2014)). The concept has been treated as a component of political instability (Hall & O'sullivan, 1996), or as a separate deterring factor (Ingram, Tabari, & Watthanakhomprathip, 2013; Saha & Yap, 2014; Yap & Saha, 2013). The former perspective has been advocated by Neumayer (2004), Sönmez (1998), and Sönmez and Graefe (1998), for whom political instability and terrorism are bridged by political violence. The latter was justified by Saha and Yap (2014) based on Page, Song & Wu's (2012) study.

The concept of political instability seems to have evolved through time from a general one to a multi-dimensional one. As argued by Gupta (1990) and Jong-A-Pin (2009), the factors of political instability (25 in total) must be framed in 4 dimensions. They are politically motivated violence (PMV), mass political violence (MPV), instability within the political regime (IWPR), and instability of the political regime (IOPR). Arguably, the first dimension (PMV) is likely perpetrated against combatant targets, as the category aggregates guerrilla warfare, civil war and internal conflict. However, the presence of civilian assassinations amid the armed conflict (international or non-international as classified by the International Committee of the Red Cross (ICRC, 2008)), and other incidents against the International Humanitarian Law (condemned by the ICRC (ICRC, 2015)), makes it difficult to separate from terrorism.[10] Thus, politically motivated violence against combatants and non-combatants should be subsumed within some armed conflicts, guerrilla warfare, or civil wars.

Any forms of violence have something in common: they provide potential inputs for media companies, which have the control to influence on tourists' risk perception (Hall & O'sullivan, 1996). Violent acts have the power of discouraging travellers' trips toward intended destinations when perceived risk is critical for the decision-making (Maser & Weiermair, 1998). It is the news issued by media companies the form of adverse communication that convinces prospectus tourists to consider other alternatives. As noted by Sönmez (1998), violent actions perpetrated by terrorists are capable of reaching a broad audience through mass media. Due to media coverage, violent actions affect the country's image and reputation; a fact that is usually followed by marketing campaigns to improve tourists' risk perception (Sönmez, Apostolopoulos, & Tarlow, 1999). Depending on the situation, visitors' reactions are delayed by months (Enders & Sandler, 1991; Enders, Sandler, & Parise, 1992), or even by years (Mansfeld, 1999). The effects can be lengthy, taking time for the sector to bounce back (Baral, Baral, & Morgan, 2004; Neumayer, 2004).

The impacts of risk factors in tourism on visitors' choice for an international destination have been estimated from different theoretical perspectives, and with a variety of data. For TE and PI, the studies have relied on history-base (Lea, 1996) and sociology-base (Ingram et al., 2013) theories. Another group has worked on tourism demand associated models (Drakos & Kutan, 2003; Enders et al., 1992; Saha & Yap, 2014; Sönmez & Graefe, 1998; Yap & Saha, 2013). The statistics of terrorism have remained on count data or indices that assess political violence in the destination. The scores have been collected from the International Country Risk Guide (ICRG). PI has also been approached through tourists' perceptions in other pool of studies (Ingram et al., 2013; Sönmez & Graefe, 1998).

[10] The concept of terrorism has not yet reached consensus among the international community (Aksenova, 2015), although for authors such as Ramsay (2015), this is "largely unnecessary and irrelevant to the effective use of the term in the heterogeneous contexts within which it is employed" (p.211). The lack of agreement is mainly explained by the frequent changes of the term over the last two centuries (Hoffman, 1998), and permanent conflicts of interest between state authorities and their opponents (Ruby, 2002).

A drawback that arises from indices (scale measures) is the level of subjectivity in the answers, as "data is assessed and coded by experts into an ordinal scale of instability magnitude" (Neumayer, 2004, p. 268). Another is related to comparability, as the gap between two levels in an ordinal scale is not similar to the difference between two other levels (Weiss, 2016). To have a complementary view, Neumayer (2004) used both variables (count data and scores) together with own scaled measures of conflict intensity, human rights violation, and repressive political regime.

Research methodologies have rested on descriptive analyses (Hall & O'sullivan, 1996; Wall, 1996), as well as on econometric estimates. The latter has included panel-data techniques for static (Saha & Yap, 2014; Yap & Saha, 2013) and dynamic (Neumayer, 2004) models, such as Least Squares and GMM, respectively. Other techniques, including VAR (Enders & Sandler, 1991), ARIMA with the transfer function (Enders et al., 1992), and the Seemingly Unrelated Regression Equations (SURE) (Drakos & Kutan, 2003) have also been estimated. In light of the research methods recorded in the literature, it seems that multinomial logit (MNL) models have not yet been employed.[11] By specifying tourists' choices within an MNL model, the number of PMV incidents turns into a relative measure, with which visitors' risk of PMV incidents in the destination can be approached.

The interaction effects of TE, PMV, and PI with other tourism demand explanatory factors have been included in some of the studies. This practice is meaningful, as the elasticity of a dependent variable respect to a regressor might also depend on the magnitude of another explanatory variable (Wooldridge, 2005). The work carried out by Yap and Saha (2013) created interactions for PI and TE with UNESCO's listed heritage countries. The aim was to test whether countries are chosen even under the presence of these deterrent actions. The result demonstrated that a one-unit increase in PI reduces the number of arrivals in 31% under the presence of UNESCO's heritage sites. Saha and Yap (2014) tested whether the impact of PI on international tourism demand differs among levels of TE (taken as a proxy variable of political risk). The result confirmed that PI negatively affects the demand for tourism at any level of TE. Finally, Neumayer (2004) created an interaction between PMV and country area

[11] An attempted was made by Eilat and Einav (2004); notwithstanding, some comments are important. The first one is related to the response variable, as their proxy measure is a ratio of two integers that does not show any intrinsic comparison between tourist alternatives. The second one is based on the specified model, as they ultimately estimated a binary logit model using the outside alternative rather than a MNL model.

to observe whether the impact of PMV on the demand of international tourism depends on the size of the country. In the study, any statistical evidence to support the statement was found.

Further explanatory variables may interactively join the nefarious actions of PMV (against combatant and non-combatant targets). Among them, its interaction with tourists' income and international trade seems to be of interest for international tourism demand studies. One the one hand, travellers' income has been accepted as a significant determinant of travel demand (Mat Som, Ooi, & Hooy, 2014). Some studies have found an income-elasticity of demand higher than one; a fact that places tourism - for personal activities- in the category of luxury products (Altmark, Mordecki, Santiñaque, & Adrián Risso, 2013; Divisekera, 2003; Ledesma-Rodriguez, Navarro-Ibanez, & Perez-Rodriguez, 2001; Li, Song, & Witt, 2004; Schiff & Becken, 2011; Serra et al., 2014; Thompson, 2013). There are some exceptions where tourism is fitted into the category of "normal goods"; that is when the income-elasticity of demand has rested between zero and one (Divisekera, 2003).

On the other hand, it has been accepted that more international trade (imports and exports) tends to be accompanied by further business tourists' trips (Kulendran & Wilson, 2000; Turner & Witt, 2001). A similar statement has been mentioned for the case of international capital movements (Divisekera, 2013b). The few studies conducted with trade as one of the determinants of tourism demand have confirmed the hypothesis: overseas tourists are more likely to visit countries with which international businesses exist (Balli, Balli, & Cebeci, 2013; Kulendran & Wilson, 2000). It seems that "bilateral trade captures the stable unobserved links between pairs of countries" (Eilat & Einav, 2004, p. 1325).

If tourists' risk associated factors determine the demand for an international destination, and visitors' income plays an active role in international tourism, it would be expected to seeing different reactions from wealthier tourists. Arguably, an increase in tourists' income may lessen the effect caused by relative PMV incidents on visitors' choices. A similar situation may occur for the case of international trade; that is, an increase in the likelihood ratio of trade between tourists' country of origin and destination might lower the impact of relative PMV on (business) tourists' choice. As noted by Cook (1990), cited by Sönmez (1998), it is less plausible to see business travellers shifting their trip plans as a result of adverse actions, although it can be different if business executives are the terrorists' targets (Hartz, 1989, cited by Sönmez, 1998).

3.3 Methodology

As the response variable rfa is continuous with limits between zero and one, and the explanatory variables for each tourism purpose (personal or business/professional) are likely to take arbitrary real values, the prediction of rfa can be realised from two specifications. The first is through a logit transformation of binomial (see Berkson, 1953; Warner, 1962) or multinomial (see Theil, 1969) choices. The method is enabled to linearize the non-linear relation between the response variable and regressors and estimate the equation through the generalized least squares method (GLS), or generalized method of moments (GMM). In math terms, $E(Logit_{\mathcal{s}i}) = \varepsilon_{\mathcal{s}i} = f(X\beta)$, where: i) $E(Logit_{\mathcal{s}i})$ is the expected value of the transformed measure ($Logit_{\mathcal{s}i} = \log[P_{\mathcal{s}i}/P_{\mathcal{s}j}]$), where $i, j \in C_{\mathcal{s}}$ ($C_{\mathcal{s}}$ is tourists' set of alternatives); if only two options are available, $P_{\mathcal{s}j} = 1 - P_{\mathcal{s}i}$; ii) $X\beta$ is a linear predictor; and iii) f is an identity link function (linear-response data).

The second is through generalised linear models (GLM) or generalised estimation equations (GEE) for non-linear specifications. In both settings, the response variable is allowed to fit into any exponential distribution covered in the so-called "exponential family" by Pitman, Darmois & Koopman (1935), cited by Myers, Montgomery, Vining, and Robinson (2012). They can be estimated through the ML method, interactive methods (such as the Gauss-Newton method, and the nonlinear least square), or others (Hardin & Hilbe, 2012; Myers et al., 2012). Overall, $E(P_{\mathcal{s}i}) = \varepsilon_{\mathcal{s}i} = g^{-1}(X\beta)$, where: i) $E(P_{\mathcal{s}i})$ is the expected value of the continuous response variable ($P_{\mathcal{s}i}$); ii) $X\beta$ is the linear predictor; and iii) g is the link function of the exponential family. The identity, log, or power functions can be the link; they are suitable for models with continuous response variables that assume a Gaussian, an inverse Gaussian, or a Gamma distribution (Hardin & Hilbe, 2012).

In order to estimate the research hypotheses stated in the introduction, the linear multinomial logit (MNL) model of Theil (1969) will be followed in an unbalanced panel data structure.

3.3.1 The linear MNL model for international tourism

After extending the original binary choice model presented by Warner (1962) to a multinomial one, and placing logs in the equation to capture infinitesimal changes through first-order differentiation, Theil (1969) arrived at the following linear multinomial logit (MNL) model:

$$d(\log P_i) = \sum_{h=1}^{m}\left(\beta_{hi} - \sum_{j=1}^{N} P_j \cdot \beta_{hj}\right) \cdot d(\log x_h) + \sum_{k=1}^{n} \gamma_k \cdot \left\{ d(\log y_{ki}) - \sum_{j=1}^{N} P_j \cdot d\big(\log y_{kj}\big) \right\} \quad (1)$$

Where $d(\log P_i)$ is the change in the probability of choosing alternative i against other alternatives that belong to decision maker's choice set; $d(\log x_h)$ is the change in the h-*th* decision maker's characteristic; and $d(\log y_{ki}) - \sum_{j=1}^{N} P_j \cdot d\big(\log y_{kj}\big)$ is the variation in the k-*th* attribute of the alternative chosen (i) relative to the variation in the k-*th* attribute of other alternatives that belong to decision maker's choice set $C\colon \{1, 2, \dots, N\}$. The specification was noted to exhibit similarities with other consumer demand models, in which the response variable is the relative share of the i-*th* commodity in total expenditures, and the regressors are the common consumer demand determinants (Theil, 1965).

The above model applied to international tourism demand suggests that changes in the probability that a representative tourist chooses country i against other countries j (that belong to his/her set of alternatives) is explained by changes in tourists' characteristics (including their income) and relative changes in destination attributes. But the choice of an international tourist destination i can be made by travellers from different countries (s), whose choice can vary through time (t). By including these characteristics and rearranging equation (1) for practicality (see Appendix B), a linear panel-data multinomial logit (PDMNL) model can be specified.[12]

$$lP_{s\underline{i}t} = \alpha + \beta_1 lINCOME_{st} + \gamma_1 lPVIOLENCE_{\underline{i}t} + \gamma_2 lTRADE_{s\underline{i}t} + \sum_{k=3}^{n=5} \gamma_k \cdot ly^{*}_{k\underline{i}t} + u_{s\underline{i}t} \qquad (2)$$

Where $P_{s\underline{i}t}$ is the probability that a representative tourist from country s travels to country i at time t. $INCOME_{st}$ accounts for tourists' income at time t. $PVIOLENCE_{\underline{i}t}$ denotes the relative number of PMV incidents in country i at time t. $TRADE_{s\underline{i}t}$ captures relative trade between tourists' country of origin and destination. $y^{*}_{k\underline{i}t}$ depicts the remaining international tourism

[12] Panel data settings are more advantageous than those of cross section and time series, as they include the time dimension of analysed cross-sectional units, capture the complexity of humans' behaviour more accurately (by controlling for omitted variables; capturing dynamic relationships; testing more complicated hypotheses; and others), and simplify computational and statistical inference (Hsiao, 2007).

demand determinants included in this study: relative prices in country i adjusted to exchange rate at time t ($PRICE_{\underline{i}t}$), and relative transport cost between visitors' place of origin and destination at time t ($TRANSPORT_{\mathscr{s}\underline{i}t}$). The latter factor is also taken in its quadratic shape to identify the transport cost's breakpoint (${TRANSPORT_{\mathscr{s}\underline{i}t}}^2$). An intercept is included. All variables are in log form denoted by l.

As noted in section 3.2.2, destination attributes associated with tourists' risk have been studied from different visions and measure delimitations. Overall, PMV incidents have been found nefarious for international tourists' choices. When the actions of PMV (against combatant and non-combatant targets) in a country of destination are included in a relative context - as the MNL model suggests, a measure of tourists' risk of PMV incidents emerges. Likewise, if the relative number of PMV incidents is included interactively with other explanatory variables, such as tourists' income and relative bilateral trade, an experimental study can be realised. The equation for these interactions can be worked out within the PDMNL model (equation 3).

$$lP_{\mathscr{s}\underline{i}t} = \alpha + \beta_1 lINCOME_{\mathscr{s}t} + \gamma_1 lPVIOLENCE_{\underline{i}t} + \gamma_2 lTRADE_{\mathscr{s}\underline{i}t} + \phi_1 lINCOME_{\mathscr{s}t} \cdot lPVIOLENCE_{\underline{i}t} + \phi_2 lTRADE_{\mathscr{s}\underline{i}t} \cdot lPVIOLENCE_{\underline{i}t} + \sum_{k=3}^{n=5} \gamma_k \cdot ly^{*}_{k\underline{i}t} + u_{\mathscr{s}\underline{i}t} \quad (3)$$

The interaction terms are set up for understanding if wealthier tourists are less likely to change their choice for travelling to a destination that faces PMV incidents, and if an increase in relative bilateral trade between tourists' country of origin and destination tends to lower the impact of relative PMV on (business) tourists' choice.

3.3.2 Data

For hypotheses testing, Colombia is taken as the case for analysis. The study period is between 1995 and 2013 using annual data. The empirical probability that a tourist from country $\mathscr{s}$ travels to Colombia (i) at a time t is calculated using the number of visitor arrivals published by the World Tourism Organization in the yearbooks of tourism statistics. For most of the countries, code 1 or 2 are employed; that is, Arrivals of non-resident tourists at national borders, by nationality or country of residence, respectively. For the European countries, data under code 3 are the primary source; which is Arrivals of non-resident tourists in hotels and similar establishments, by nationality.

The calculation is as follows: the number of visitor arrivals (inbound trips) in Colombia from travellers' country of origin ($a_{\mathcal{s},i}$), which equals the number of outbound trips from the same countries to Colombia ($de_{\mathcal{s},i}$), is divided by the total number of outbound tourism trips from tourists' country of origin ($De_{\mathcal{s}}$). The latter is calculated following the World Tourism Organization, for whom outbound tourism trips are based on "data supplied by each of the destination countries and, therefore, corresponds to arrivals in these countries (and not to Departures data provided by the country of reference and compiled in the Compendium of Tourism Statistics ($De_{\mathcal{s}}^{*}$))" (UNWTO, n.d).[13] The equation is:

$$rfa_{\mathcal{s}\underline{i}} \equiv P_{\mathcal{s}}(i|C_{\mathcal{s}}) = a_{\mathcal{s}\underline{i}}/De_{\mathcal{s}} \qquad (4)$$

Where $P_{\mathcal{s}}(i|C_{\mathcal{s}})$ is the actual probability that a tourist from country $\mathcal{s}$ chooses Colombia (i) among his/her country alternatives $C_{\mathcal{s}}:\{1,\ldots,N\}$; $De_{\mathcal{s}} = \sum_{\mathcal{s}}\sum_{c=1}^{N} a_{\mathcal{s}c}$ is equivalent to $\sum_{\mathcal{s}}\sum_{c=1}^{N} de_{sc}$. In all cases, the addition of tourists' choice probabilities must equal one ($\sum_{\mathcal{s}}\sum_{c=1}^{N} P_{\mathcal{s}} = 1$). Twenty-nine (29) countries of origin are taken for the likelihood ratio calculation; they are the most important markets for Colombia regarding inbound visitor arrivals, accounting for 93% of Colombia's inbound tourism market. Moreover, fifty-three (53) countries are included as tourists' set of alternatives. These destinations are chosen based on geographic closeness from the source market and data availability. An initial matrix of 551 rows (29 countries x 19 years) and 53 columns (destination countries) is worked out, although non-reported data on arrivals at some countries prevents us from reaching the international tourism trips' balanced origin-destination matrix of 29,241 observations (excluding diagonal data). After a data treatment, a final matrix of 23,643 observations is used.

Non-reported data on the number of visitor arrivals in a country of destination arises when they have not been recorded in some years, or have not been reported whatsoever. For the first situation, the figures are forecasted through linear, exponential, logarithmic, or polynomial functions. The functional form is chosen based on the best-fitted regression line. Extrapolation and moving average techniques are also used for forecasting when missed data

[13] Appendix C extends this matrix calculation.

is in the middle of two series, or when data trend is not clear, respectively. For the second situation, a value equivalent to 0.05% of visitor arrivals is added for all the countries of origin in another column called “others 1”.[14] This procedure is followed under the assumption that all important destinations for tourists from each country $\mathscr{s}$ have been included in the 53-country sample. The percentage is drawn by dividing the total number of arrivals in countries that do not report any data of arrivals (called z) from country $\mathscr{s}$ ($\sum_{\mathscr{s}} \sum_{z=1}^{Z} a_{\mathscr{s}z}$) over the total number of arrivals from country $\mathscr{s}$ across the world ($\sum_{\mathscr{s}} \sum_{c=1}^{N} a_{\mathscr{s}c}$). $a_{\mathscr{s}z}$ is one-step ahead forecasted after predicting $a_{\mathscr{s}c}$ on the following exponential function from visitor arrivals data: $a_{\mathscr{s}c} = \theta e^{-\beta c}$, where θ and β are parameters, and c accounts for the countries that report data (they are organised in descendent form).

The non-inclusion of other country alternatives, where tourists from the 29-country sample are also likely to travel to, prevents us from reaching the characteristic of exhaustiveness stated in the theory of discrete choice. To approach the value of arrivals in the other group of destinations (called q), the average ratio between $De_{\mathscr{s}}$ and $De_{\mathscr{s}}^{*}$ is taken into consideration. Axiomatically, this ratio is equal to or greater than one. The reason is that the number of visitor arrivals from country $\mathscr{s}$ across the world should be at least equal to the number of visitor departures from the same country. A value greater than 1 indicates that tourists who depart from country $\mathscr{s}$ visit more than one nation in the same trip. When the result is lower than one, an increment in the number of visitor arrivals from country $\mathscr{s}$ is included in another column called “others 2”. The percentages used in 12 out of 29 countries are 3, 5, or 10%, which are assigned depending on the gap between the two figures.

For understanding the extent to which the missed data - from non-reported years and non-included countries - affect the calculation of tourists’ probability for travelling across the world, the following measure is estimated: $z_{\mathscr{s}j\underline{t}} = \sum_{j=1}^{N} P_{\mathscr{s}j\underline{t}}{}^{e} / \sum_{j=1}^{N} P_{\mathscr{s}j\underline{t}}{}^{c}$. The denominator accounts for the cumulative probability of travelling to countries $j = 1, \dots N$, at time $\underline{t}$, from country $\mathscr{s}$. The year $\underline{t}$ is chosen whenever the number of destinations recorded for tourists from country $\mathscr{s}$ is the highest. The numerator is the denominator multiplied by the percentage share of complete data on country j between 1995 and 2013 (cd_j); so $P_{\mathscr{s}j\underline{t}}{}^{e} = P_{\mathscr{s}j\underline{t}}{}^{c} \cdot cd_j$.

[14] For instance, arrivals in Argentina are reported only for a few countries: Brazil, Uruguay, Chile, the USA, and Bolivia. The empirical probability calculation that a tourist from, say, Austria travels to Argentina cannot be realized. Since Austrian tourists’ likelihood ratio of travelling to other countries makes up 99.95% of the total, the calculation for the Argentinian case (and other countries that do not report arrivals from Austria) is not significant. This situation repeats in the group of 29 countries.

When data on any country j are reported for all years, $cd_j = 1$; for 5 years, $cd_j = \frac{5}{19} = 0.2632$, and so forth. When the ratio $z_{\mathcal{s}j\underline{t}}$ is equal to one (the upper limit), there is no missed data for any year, so $\sum_{j=1}^{N} P_{\mathcal{s}j\underline{t}}{}^{e} = \sum_{j=1}^{N} P_{\mathcal{s}j\underline{t}}{}^{c}$. The latter is an ideal scenario of complete data. As the results obtained here are always above 95% (except for Belgium, whose value is 91%), it can be argued that non-reported data and non-included countries do not significantly affect the calculations.

When the likelihood ratio of travelling to Colombia is compared to the number of visitors who arrive there, some comments can be highlighted. First, a high number of visitor arrivals in Colombia do not necessarily reflect high likelihood ratios of travelling there. That is the case of the USA, Spain, Mexico, Argentina, and Brazil, whose average probability of visiting Colombia is lower than 0.90% each, although the number of visitors travelling there is within Colombia's top 10 countries. An opposite situation occurs for countries such as Panama and Costa Rica, whose likelihood ratios of going to Colombia are high (10.90 and 4.48%, respectively), but their number of arrivals in Colombia are relatively small (see Appendix D).

Second, both figures have similar shapes before 2003, but not afterwards. Between 1995 and 1997, a significant drop in both variables occurred (-30.71 and -40.82%, respectively); between 1998 and 2002, the values slightly fell on average by 2 and 5%, respectively; and from 2003 to 2013, the number of visitor arrivals in Colombia significantly increased on average by 11.4% per annum, although the probability of travelling only grew by 3% (see Appendix E). Arguably, the percentage change in the number of visitor arrivals is not necessarily reflected in tourists' preferences for the country of destination. Colombia, as an alternative destination for overseas tourists, has lost the position it used to hold in 1995.[15]

The gross domestic product (GDP) per capita of each tourist's country of origin is taken as a proxy variable of tourists' income ($INCOME_{\mathcal{s}t}$). The figures are collected in USA dollars and presented in constant prices of 2005 (2005=100). Data is taken from the World Bank (World Development Indicators).

[15] When compared to tourists' probability of travelling to other destinations near Colombia, it appears that tourists' trade-offs have mainly favoured Peru and Brazil, whose likelihood ratios jumped from 0.86 and 2.68% in 1995 to 3.12 and 3.50% in 2013, respectively.

$PVIOLENCE_{\underline{i}t}$ is calculated from data supplied by the National Consortium for the Study of Terrosrism and Responses to Terrorism (START) (2015).[16] This institution sorts incidents into the categories of assassination, hijacking, kidnapping, barricade incident, bombing/explosion, armed assault, unarmed assault, and facility/infrastructure attacks for most of the countries in the world. The targets are: companies (gas/oil, banks, MNC, and others), government (general and diplomatic), police, military, airports and aircraft, education institutions, infrastructure (food/water supply, telecommunication, utilities, port/marine facilities), tourists (buses, tours), journalists/media, private citizens/properties, and unknown. Since some nations have not faced any incidents in some years, but equation (2) requires non-zero numbers in the relative variables (destination attributes), a transformation of the measure is carried out. A simple average between the number of incidents in t and $t-1$ is calculated to get asymptotic results. Thus, $PVIOLENCE_{\underline{i}t} = \frac{PMV_{\underline{i}t}}{\prod_{t=1}^{T}\prod_{j=1}^{N} PMV_{jt}{}^{P_{\mathcal{s}jt}}}$, where $PMV_{\underline{i}t} = (inc_{\underline{i}t} + inc_{\underline{i}t-1})/2$ and $PMV_{jt} = (inc_{jt} + inc_{jt-1})/2$. The variable inc stands for incidents recorded from the year 1971. The procedure allows for capturing the lagged pattern of the violent incidents that occurred before 1995.

The number of PMV incidents recorded for countries placed in "others 1", which are observed in the denominator of $PVIOLENCE_{\underline{i}t}$, is the average number of PMV incidents that occurred in the countries that do not report data on the number of visitor arrivals from country $\mathcal{s}$. The figures are powered to the probability of travelling from the country $\mathcal{s}$ to "others 1", which was set at 0.05%. Moreover, the number of PMV incidents recorded for countries placed in "others 2" is set up depending on the analysed country $\mathcal{s}$, and powered to the probability of travelling from the country $\mathcal{s}$ to "others 2" as defined earlier. These two procedures are also replicated on the forthcoming relative variables.

The relative bilateral trade between tourists' country of origin and destination ($TRADE_{\mathcal{s}\underline{i}t}$) is calculated employing data supplied by Colombia's Administrative Department of National Taxes (DIAN). The equation is: $TRADE_{\mathcal{s}\underline{i}t} = btrade_{\mathcal{s}\underline{i}t}/(1 - btrade_{\mathcal{s}\underline{i}t})$, where $btrade_{\mathcal{s}\underline{i}t} = xm_{\mathcal{s}\underline{i}t}/XM_{\mathcal{s}t}$. In the latter expression, the numerator accounts for trade exchange

[16] The inclusion of "perceptions on the likelihood of political instability and/or politically-motivated violence, including terrorism" (statistics published by the World Bank in the Worldwide Governance Indicators) was intended. Nevertheless, the way data is collected creates biased estimates in the current study. Inevitably, we should assume that perceptions on security from over 30 individual sources (institutes, think tanks, NGOs, international organizations and firms) are the same for tourists from all over the world.

between each representative tourist's country of origin and Colombia; that is, $xm_{s\underline{i}t} = x_{s\underline{i}t} + m_{s\underline{i}t}$, where x and m are exports and imports, respectively. The denominator makes up the total trade recorded in the country of origin; that is, $XM_{st} = XT_{st} + MT_{st}$, where XT and MT are total exports and imports, respectively. Thus $TRADE_{s\underline{i}t}$ accounts for the odds ratio of doing international trade with Colombians versus not doing trade with them, or doing international trade with other country alternatives; that is, $\{1 - [btrade_{s\underline{i}t}/(1 - btrade_{s\underline{i}t})]\} = \sum_{t=1}^{T}\sum_{j=1}^{N} TRADE_{sjt}$.

For $PRICE_{\underline{i}t}$, the consumer price index (cpi) of each country (2010=100) is used together with the nominal exchange rate (er) between tourists' country of origin and destination. Data are drawn from the World Bank (World Development Indicators, n.d.). The equation is: $PRICE_{\underline{i}t} = \frac{price_{\underline{i}t}}{\prod_{t=1}^{T}\prod_{j=1}^{N} {price_{jt}}^{P_{sjt}}}$, where $price_{\underline{i}t} = cpi_{\underline{i}t} \cdot er_{s\underline{i}t}$ and $price_{jt} = cpi_{jt} \cdot er_{sjt}$. The exchange rates between Colombia and tourists' country of origin are calculated based on the nominal exchange rate of each country against the USA dollar. Since cpi comprises a basket of goods rather than single tourism-related products, and indices do not measure absolute values, the reading of $PRICE_{\underline{i}t}$ must be in terms of relative prices changes; so the direction in the change of $PRICE_{\underline{i}t}$ is the only characteristic we can interpret. Undoubtedly, the price of a bundle of tourism characteristic products adjusted to exchange rate would have been a more accurate proxy variable; nevertheless, the lack of stats on this matter makes it difficult to work them out.

Finally, relative transport costs between tourists' country of origin and destination ($TRANSPORT_{s\underline{i}t}$), a proxy measure of airfare, is approached as follows: $TRANSPORT_{s\underline{i}t} = \frac{transp_{\underline{i}t}}{\prod_{t=1}^{T}\prod_{j=1}^{N} {transp_{jt}}^{P_{sjt}}}$, where $transp_{\underline{i}t} = (boil_{s\underline{i}} \cdot oilp_t) \cdot er_{s\underline{i}t}$ and $transp_{jt} = (boil_{sj} \cdot oilp_t) \cdot er_{sjt}$. The variable $boil$ stands for the number of barrels of fuel that an aircraft uses to travel between two nodes. Since a Boeing 747-8 burns roughly 5 gallons per mile (almost 12 litres per kilometre),[17] and 1 barrel is 159 litres, the equation is extended to $boil_{s\underline{i}} = (dis_{s\underline{i}} \cdot 12)/159$. The Euclidean distance between tourists' country of origin and destination ($dis_{s\underline{i}}$) is taken from the website Timeanddate. The distance calculator estimates the air or the great

[17] This aircraft is taken as a reference for medium and long-haul trips (see Wikipedia, 2015); however, other aircrafts and models could be included.

circle distance between any two cities; that is, the shortest and most direct distance between them. In this study, the assumption that the representative tourist travels from and to the most populated cities is followed. Oil prices ($oilp_t$) are sourced by Global Financial Data in USD dollars, per year. The exchange rates er are taken as for relative prices.

3.4 Econometric estimates

Equation 2 and 3 are initially estimated through standard methods for static panel data models. The results are summarized in table 1. A Panel LS (Least Squares) is initially estimated for equation 2 (baseline). Although the adjusted R^2 is high, the Durbin-Watson (DW) statistic is very low, suggesting the presence of autocorrelation. Moreover, the majority of coefficients estimated are not statistically significant at 1 or 5% significance level. A pairwise sample spearman-rank correlation test is included to test for the level of correlation between independent variables. The outcome ranges between -0.77 and 0.72. Since the pairwise correlation TRADE-INCOME and PVIOLENCE-PRICE reach two extreme values (-0.77 and 0.72, respectively), a Variance Inflation Factor (VIF) test is carried out to test for multicollinearity. The outcomes of 3.57 and 2.21, respectively, suggest no signs of multicollinearity.

Table 1 Static panel-data estimations

	Panel LS	**Panel EGLS**				
Variable	**Baseline**	**1**	**2**	**3**	**4**	**5**
C	-0.787	-9.2282***	-8.8615***	-9.019***	-8.767***	-10.58***
$lINCOME_{st}$	-0.014	0.8451***	0.7902***	0.817***	0.796***	1.063***
$lPVIOLENCE_{it}$	0.086*	-0.1053***	-0.096***	-0.0077	-0.187***	0.2227*
$lTRADE_{sit}$	0.917***	0.2923***	0.2866***	0.286***	0.345***	0.4651***
$lPRICE_{it}$	-0.081	0.3782***	0.3543***	0.362***	0.341***	0.3273***
$lTRANSPORT_{sit}$	0.268*	0.2753***	0.4480***	0.447***	0.459***	0.5033***
$lTRANSPORT_{sit}^2$	-0.223***		-0.1248**	-0.1316***	-0.116**	-0.1619***
$lINCOME_{st} \cdot lPVIOLENCE_{it}$				-0.0106		-0.070***
$lTRADE_{sit} \cdot lPVIOLENCE_{it}$					-0.020	-0.060***
Observations	476	476	476	476	476	476
$Adj\ R^2$	0.8196	0.9890	0.9891	0.9891	0.9894	0.9903
$Prob\ F-test$	0.000	0.000	0.000	0.000	0.000	0.000
$Durbin-Watson$	0.1326	1.036	1.046	1.010	0.992	1.021
Wald test (p-value)				0.000	0.000	0.000

*, **, and *** on the parameters indicates whether the coefficient is significant at 10%, 5%, and 1%, respectively
Wald test for joint hypotheses:

As found in some studies, time-invariant country characteristics are likely to be present in the demand for international tourism (see Balli et al., 2013). The redundant fixed-effects likelihood ratio test is carried out in equation 2 for checking whether this is the case for Colombia. The null hypothesis that the cross-section effects are redundant (there is only a single intercept) is rejected. Moreover, the null hypothesis on uncorrelated random effects ($Ho: b_{fe} = b_{re}$) is rejected through the Hausman (1978) test. To capture these fixed effects in equations 2 and 3, a static panel data model with a within-group transformation is estimated. The Feasible Generalized Least Squares (EGLS) method is used to control for heteroscedasticity, which was found through a White general test. The results shown from column 1 to 5 are more robust than the estimated with panel LS, confirming the presence of time-invariant factors.[18] Notwithstanding, the DW near one and the high adjusted R^2 of 0.9890 still mark autocorrelation issues. The presence of an autoregressive term of order one is found.

In spite of the presence of autocorrelation, some results obtained through the panel EGLS method can be taken as a starting point. The negative coefficient found in column 2 suggests that the higher the number of PMV incidents in Colombia - relative to the number recorded in tourists´ alternatives, the lower the likelihood ratio of travelling there. The Wald test applied for the interaction terms (columns 3, 4 and 5) seems to reject the joint hypothesis that the effect of relative PMV incidents in Colombia on visitors' choice for travelling there does not depend neither on tourists' income nor relative bilateral trade. Moreover, the inclusion of a quadratic shape for the case of relative transport cost turns to be significant (columns 2 and 5). The turning point is observed when the relative transport cost reaches 1.79 (in logs).[19] It means that tourists' choice for Colombia turns down when the transport cost of travelling there exceeds six times the transport cost of flying to other destinations. Based on the sample, most European tourists would enter in this category (except for Spanish) and Uruguayan visitors.

The Im, Pesaran and Shin test is conducted for all variables with individual constant, and both individual constant and trend, to check for unit roots. The method is suitable for dynamic heterogeneous balanced or unbalanced panels, where the null hypothesis is that the autoregressive coefficient of each cross-section unit equals zero (the variable is not trend-

[18] Appendix F extends this finding

[19] $lRTRAN_{sit} = 0.4480/(2 * 0.1248) = 1.79487$

stationary) (see Im, Pesaran, & Shin, 2003). The null hypothesis is not rejected for the case of tourists' income, relative prices, and relative transport cost; they are integrated variables of order 1. For relative trade, the null hypothesis is rejected at a 5% significance level.

Under the presence of time-invariant country-specific factors; a first-order autocorrelation; unit roots in levels in some of the explanatory variables (no strict exogeneity), but no in the response variable; and an unbalanced panel data structure, the first-differenced panel Generalized Method of Moment (GMM) estimator seems to be appropriated for the estimates.[20] Since the series are not highly autoregressive and the time dimension is not short, lagged levels of the series can be utilised as instruments for predetermined and endogenous variables in first differences (see Blundell, Bond, & Windmeijer, 2001).[21] The Arellano and Bond's (1991) specification tests of no serial correlation in the errors is employed, as any "estimator that uses lags as instruments under the assumption of white noise errors would lose its consistency if in fact the errors are serially correlated" (p.278).

The equations to be estimated, without and with interactions terms, are the following:

$$\Delta lP_{s\underline{i}t} = \theta_1 \Delta lP_{s\underline{i}t-1} + \beta_1 \Delta lINCOME_{st} + \gamma_1 \Delta lPVIOLENCE_{\underline{i}t} + \gamma_2 \Delta lTRADE_{s\underline{i}t} + \sum_{k=3}^{n=5} \gamma_k \cdot \Delta ly^*_{k\underline{i}t} + \Delta u_{s\underline{i}t} \tag{4}$$

$$\begin{aligned}\Delta lP_{s\underline{i}t} = {} & \theta_1 \Delta lP_{s\underline{i}t-1} + \beta_1 \Delta lINCOME_{st} + \gamma_1 \Delta lPVIOLENCE_{\underline{i}t} + \gamma_2 \Delta lTRADE_{s\underline{i}t} \\ & + \phi_1 \Delta\left(lINCOME_{st} \cdot lPVIOLENCE_{\underline{i}t}\right) + \phi_2 \Delta\left(lTRADE_{s\underline{i}t} \cdot lPVIOLENCE_{\underline{i}t}\right) + \sum_{k=3}^{n=5} \gamma_k \cdot \Delta ly^*_{k\underline{i}t} \\ & + \Delta u_{s\underline{i}t}\end{aligned} \tag{5}$$

The results are summarised in Table 2. The first- differenced panel GMM estimator is obtained using the White weighting matrix updated with the continuously updating method; this is a routine to get accurate β's from iterations. The Arellano-Bond **serial correlation** testing show that the first-order correlation AR(1) is statistically significant (with a negative coefficient), whereas the second-order correlation AR(2) is not. The outcome is expected if

[20] GMM estimators are expected to be consistent and asymptotically normal distributed if stationary and ergodic variables are used (Hansen, 1982). The recognition on whether the first-differenced GMM estimator is identified or not under the presence of unit roots is crucial to define whether other appropriate estimators need to be utilized (Bond, Nauges, & Windmeijer, 2002, p. 4).

[21] As noted by Ahn and Schmidt (1995), the use of the dependent variable lagged two or more periods in the first-differenced GMM estimator, as conducted by Anderson and Hsiao (1998), Holtz-Eakin (1988), Holtz-Eakin, Newey, and Rosen (1998), Arellano and Bover (1990), and Arellano and Bond (1991), leads to consistent and efficient estimates; though they can improve if all the available moment conditions are used.

the model error terms are serial uncorrelated in levels. Therefore, there is no evidence from the serial correlation test that the AR(1) specification is inconsistent for the series. The p-values achieved for the J-statistic (the Sargan test) do not reject the hypothesis that the instruments and the model are correctly specified; therefore, since the over-identifying restrictions are valid, the instruments are not correlated with the errors and are not omitted variables in the models.

Table 2 Dynamic panel data model

	First difference GMM				
Variable	**1**	**2**	**3**	**4**	**5**
$\Delta lP_{\underline{s}it-1}$	0.658***	0.654***	0.6297***	0.7281***	0.6872***
$\Delta lINCOME_{\underline{s}t}$	0.2839***	0.2928***	0.5141***	0.7879***	1.063***
$\Delta lPVIOLENCE_{\underline{i}t}$	-0.020**	-0.017**	0.2336	-0.1708***	0.3225*
$\Delta lTRADE_{\underline{s}it}$	0.1341***	0.1240***	0.1059**	0.3129***	0.4076***
$\Delta lPRICE_{\underline{i}t}$	0.1109***	0.1073***	0.1002***	0.099***	0.066***
$\Delta lTRANSPORT_{\underline{s}it}$	0.2061***	0.2227***	0.2261**	0.1014	0.1955**
$\Delta lTRANSPORT_{\underline{s}it}^2$		-0.027	-0.007	0.1893**	0.087
$\Delta(lINCOME_{\underline{s}t} \cdot lPVIOLENCE_{\underline{i}t})$			-0.0287		-0.075**
$\Delta(lTRADE_{\underline{s}it} \cdot lPVIOLENCE_{\underline{i}t})$				-0.039***	-0.072***
Observations	397	397	397	397	397
J-statistic	23.28	20.23	25.32	16.41	21.25
Estimated coefficients	6	7	8	8	9
Instrument rank	30	32	30	30	29
Prob (J-statistic)	0.5027	0.7344	0.2816	0.7949	0.3820
Wald test (p-value)			0.002	0.000	0.000
AR(1) (p-value)	0.000	0.000	0.000	0.000	0.000
AR(2) (p-value)	0.6547	0.5152	0.5065	0.9676	0.6146

*, **, and *** on the parameters indicates whether the coefficient is significant at 10%, 5%, and 1%, respectively
Wald test for joint hypotheses:

The findings shown in column 1 suggest that a 1% change in the relative number of PMV incidents causes an average change in the probability of travelling to Colombia of -0.02%. The outcome is significant at a 5% significance level, and shows the relative number of PMV incidents as a factor that slightly affects tourists' choice for Colombia (although its conversion to absolute values may account for a significant number of tourists). The results also confirm hypotheses associated with income and trade. The likelihood ratio of visiting Colombia increases on average by 0.2839% for each 1% increase in tourists' income. Since the outcome is between 0 and 1, the income-elasticity of demand places Colombia as a "normal destination". For trade, the probability of travelling to Colombia rises by 0.1341% for each 1% increase in the odds ratio of trading with Colombia.

When the outcomes obtained in both the static and dynamic models are compared (columns 1 and 2 in Tables 1 and 2), the difference between coefficients is evident. As found in some studies (see Arellano & Bond, 1991; Blundell et al., 2001), the outcomes from static panel data models through the Least Squares method (the panel EGLS) tend to be biased upward. That is why the inclusion of the response variable as an autoregressive term (dynamics) allows for capturing consistent estimates of other parameters of interest (Bond, 2002). For the variable of relative PMV, the result obtained in table 2 shows a negative impact on tourists' choice for Colombia lower than the one obtained in table 1 (-0.02% and -0.096%, respectively).

Applying a joint F-test (Wald test) in equation 5, the null hypothesis that the effect of more relative PMV incidents in Colombia on tourists' choice does not depend on tourists' income is rejected (column 3). The negative coefficient of -0.028 suggests that the impact of more relative PMV incidents in Colombia on visitors' choice for travelling there decreases (gets smaller) as tourists' income gets larger. In other words, wealthier (HLR) tourists are less likely to change their choice of travelling to Colombia under relative PMV incidents. Replacing in $\Delta lP_{\mathscr{s}\underline{i}t}/\Delta lPVIOLENCE_{\underline{i}t} = 0.2336 - 0.0287\,\Delta lINCOME_{\mathscr{s}t}$, a 1% increase in $PVIOLENCE_{\underline{i}t}$ decreases the probability of travelling to Colombia by -0.034 standard deviations of the sample mean of tourists' income (9.36 in logs).

Similarly, the joint F test used in equation 4 rejects the null hypothesis that the effect of more relative PMV in Colombia on tourists' choice for travelling there does not depend on relative bilateral trade between tourists' country of origin and Colombia. The coefficient of -0.039 proposes that the effect of more relative PMV incidents in Colombia on (business) visitors' choice for travelling there decreases (gets smaller) as the odds ratio of trading with Colombia increases. The result advocates Cook's (1990) remark on the role of vexing actions on business tourism, cited by Sönmez (1998), as (business) tourists seem to be less likely to change their choice for Colombia under RPMV incidents. When replacing in $\Delta lP_{\mathscr{s}\underline{i}t}/\Delta lPVIOLENCE_{\underline{i}t} = -0.1708 - 0.039\,\Delta lTRADE_{\mathscr{s}\underline{i}t}$, a 1% increase in relative PMV incidents increases business tourists' probability of travelling to Colombia by 0.048 standard deviations of the sample mean of relative bilateral trade (-5.6 in logs).

Other results from the equation 4 can be analysed. Variations on the choice for Colombia are highly explained by previous choices, which confirm habit persistence (long-term inertia in tourists who choose Colombia). Moreover, a 1% change in Colombia's relative prices adjusted to exchange rate causes a 0.11% change in the probability of travelling there. The direct relationship between these two variables can be split into two stages: between 1995 and 2002 there was an average drop in both variables; whereas between 2003 and 2013 an average increase in both factors was noted. The reasons might lie on the affordability of tourism-related products in Colombia due to its highly devaluated currency compared to other countries.[22]

Finally, a 1% increase in the relative transport cost seems to cause a rise in tourists' preferences for Colombia of 0.22% average. Although the coefficient of the quadratic shape variable is negative, the parameter estimated is not significant at any significance level; therefore, the analyses of the effects of total transport cost on tourists' choice turns to be meaningless in the dynamic model.

3.5 Conclusion and policy implications

Calculations on tourists' likelihood ratio for travelling to a country of destination turn to be advantageous in tourism demand studies. First, the measure allows for exploiting existing revealed-preference data at a macro level, such as the number of inbound visitor arrivals. Second, it complies with the characteristics tourists' choice set of alternatives must fulfil following discrete choice theory; they are: finiteness, exhaustiveness, and mutual exclusion. Third, the relative measure allows tourism stakeholders to elucidate how preferable their country is for tourism purposes (among a set of alternatives), and how much tourists' preferences evolve.

More visitor arrivals in a country do not necessarily reflect higher international tourists' preferences for travelling there. The statement was confirmed for the case of Colombia, whose statistics showed that: a) North Americans, Spanish, Mexicans, Argentinians, and Brazilians' preferences for Colombia remain, on average, very low (less than 0.90%), even

[22] The Colombian Peso is between the ten least valuable currencies in the world, according to The Telegraph (2016); it has been undervalued against the American dollar for several years, according to the Big Mac Index worked out by The Economist (see D.H & R.L.W, 2016).

though they are in the top-10 countries where tourists who most visit Colombia come from; b) Although the number of visitor arrivals grew by 11.4% between 2003 and 2013, tourists´ preferences for Colombia fluctuated around 2% during the same period.

Based on the previous paragraphs, the Colombian government is advised to include in the aim of Colombia's tourism marketing policy (MCIT, 2009) not just the number of inbound visitor arrivals, but also tourists' likelihood ratios for travelling there. The former measure is more useful to identify the most important source markets, forecast their figures, and plan infrastructure. The latter is more advantageous to capture international tourists' preferences and their evolution; ultimately, tourists' trade-offs between alternatives are included in the probability measure, as consumer choice theories would suggests.

The adverse impact that further PMV incidents in a country of destination causes on tourists' choices was confirmed in Colombia. The likelihood ratio of travelling to this country dropped on average by 0.02% for each 1% increase in the relative number of PMV incidents. For overcoming this situation, the Colombian government is advised to keep working toward the cutback in the number of PMV incidents that occur there, not just in absolute but also in relative terms. From tourists' perspective, the reduction of PMV incidents in Colombia, whether through peace dialogues or belligerent actions, ought to be higher than those observed in other country alternatives.

Judging by the data, tourists' choice for Colombia seems to improve under the latter strategy (belligerent), but not under the former one (peace dialogues). The most notable attempt at peace ever witnessed between the Colombian government and the largest guerrilla group, FARC, officially occurred between 1999 and 2002; in contrast, the most committed efforts for tackling the number of PMV incidents in Colombia from belligerent actions was held between 2003 and 2010. The former strategy ended up with a drop in the average number of PMV incidents (from 333 cases recorded between 1995 and 1998 to 139 incidents), and a decline in the average likelihood ratio of travelling to Colombia (from 3.22% to 1.67%). The latter strategy finished with a fall in the average number of PMV incidents (from 139 to 84 cases), and a recovery in the average probability of travelling to Colombia (from 1.67% to 2.10%).

Without loss of generality, these facts seem to show tourists as agents that prefer actions aligned with personal security than long-term engagements that do not guarantee their security while staying there. From the perspective of tourism, the government is advised to bear in mind these results in the current peace process held with the same guerrilla group since 2011. As the statistics suggest, between 2011 and 2013 there was a surge in the average number of PMV incident (from 84 to 115 cases), an increase in the relative number of PMV incidents (from 78 to 349), and a decline in the average probability of travelling to Colombia (from 2.10% to 2.05%).

The results suggested that tourists who visit Colombia tend to be less sensitive to the number of relative PMV there when their income increases. The reasons might be numerous. First, as wealthier people tend to travel more, their choice for Colombia likely increases when this is an unvisited destination, and the more countries visited, the better. Second, since wealthier people tend to escape from their hometown cold weather (usually in subtropical countries) to warm-temperature places (usually tropical areas), Colombia is likely included in their list of destinations. Third, as wealthier people tend to enjoy exotic and diverse culture, they may see Colombia very attractive for its diverse folklore (music, dancing, food, and so forth). Forth, due to the presence of hotel chains in some cities in Colombia, including Marriot, Radisson, Hyatt, Hilton, and Holiday Inn, wealthier tourists are likely targeted as potential visitors by travel agencies; ultimately, these hotel brands make them feel less exposed to PMV incidents.

The results also showed that businesses tourists tend to be less vulnerable to relative PMV incidents in Colombia when the odds ratio of trading with Colombia increases. The reasons could be following. First, companies located in tourists' country of origin set up long-term businesses with Colombian companies (based on opportunity costs) that need workers to displace between the two nodes whenever is needed. As noted earlier, it is less plausible to see business tourists shifting their trip plans as a result of tense actions (Cook, 1990, cited by Sönmez, 1998), unless they are the terrorists' targets (Hartz, 1989, cited by Sönmez, 1998). Second, under further PMV incidents, the nominal exchange rate tend to devaluate against the American dollar; therefore, some multinational corporations based in Colombia tend to be willing to expand exporting operations there.

If the relative number of PMV incidents in Colombia persists, and tourists' income keeps its upward trend, the government (and other tourism stakeholders) is advised to hold their marketing campaigns in cities of wealthy people - mainly located in subtropical climates -, showing Colombia's climate strengths, its cultural uniqueness, and the existence of international hotel chains there. The Colombian government is also advised to increase the relative trade with tourists' country of origin, if the relative number of PMV in Colombia remains; preferably through new companies that may be interested in doing international trade businesses with Colombian firms.

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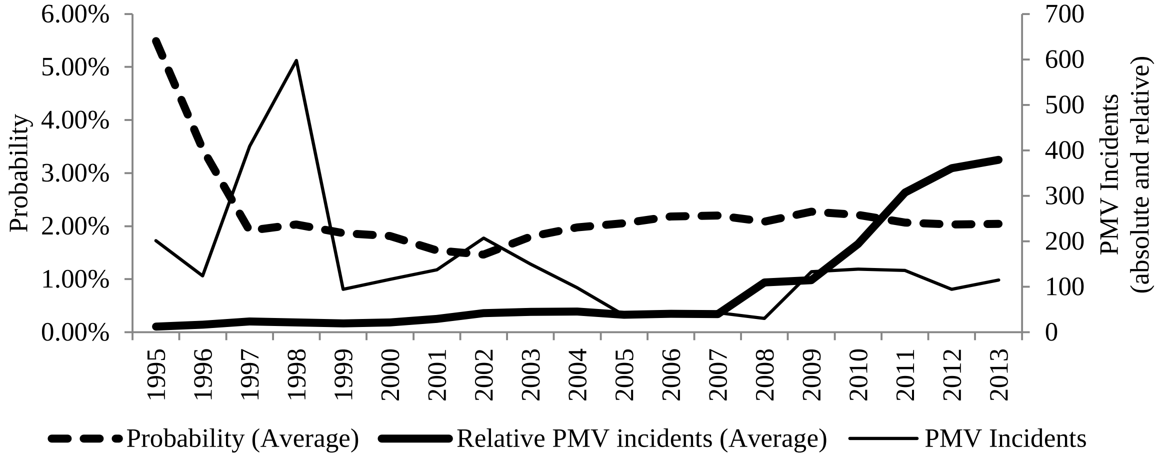
Appendix A. The average probability of travelling to Colombia Vs the number of PMV incidents in Colombia in absolute and relative values (period 1995-2013).



Source: World Tourism Organization and START.

Appendix B. Extension of the linear MNL model

Theil's (1969) linear MNL model equation was defined as follows:

$$d(\log P_i) = \sum_{h=1}^{m}\left(\beta_{hi} - \sum_{j=1}^{N} P_j \cdot \beta_{hj}\right) \cdot d(\log x_h) + \sum_{k=1}^{n} \gamma_k \cdot \left\{d(\log y_{ki}) - \sum_{j=1}^{N} P_j \cdot d\left(\log y_{kj}\right)\right\} \quad (A1)$$

Leaving equation (A1) in levels, fixing $h = 1$, and assuming that $k = 1, \dots 5$ we get:

$$\log P_i = \alpha + \left(\beta_{1i} - \sum_{j=1}^{N} P_j \cdot \beta_{1j}\right) \cdot \log x_1 + \sum_{k=1}^{5} \gamma_k \cdot \left\{d(\log y_{ki}) - \sum_{j=1}^{N} P_j \cdot d\left(\log y_{kj}\right)\right\} \quad (A2)$$

Where:

$\beta_{1i} - \sum_{j=1}^{N} P_j \cdot \beta_{1j} = \beta_1$; and

$$\sum_{k=1}^{5} \gamma_k \cdot \left\{d(\log y_{ki}) - \sum_{j=1}^{N} P_j \cdot d\left(\log y_{kj}\right)\right\} = \gamma_1 \left[\log\left(\frac{y_{1i}}{\prod_{j=1}^{N} y_{1j}^{P_j}}\right)\right] + \cdots + \gamma_5 \left[\log\left(\frac{y_{5i}}{\prod_{j=1}^{N} y_{5j}^{P_j}}\right)\right]$$

The right-hand side of the above expression can be written as: $\gamma_k \left[\log\left(\frac{y_{ki}}{\prod_{j=1}^{N} y_{kj}^{P_j}}\right)\right] = \gamma_k(\log y_{ki}^*)$

Thus, by simplifying equation A2 we arrive to:

$$lP_i = \alpha + \beta_1 \cdot lx_1 + \gamma_1 \cdot ly_{1i}^* + \gamma_2 \cdot ly_{2i}^* + \sum_{k=3}^{n=5} \gamma_k \cdot ly_{k\underline{i}}^* + u_i \quad (A3)$$

Where:

$x_1 = INCOME$
$y_{1i}^* = PVIOLENCE.$
$y_{2i}^* = TRADE$
l stands for logs

By placing equation A3 in a panel data context, including the new variables, we have equation A4 (or equation 2) as follows:

$$lP_{s\underline{i}t} = \alpha + \beta_1 lINCOME_{st} + \gamma_1 lPVIOLENCE_{\underline{i}t} + \gamma_2 lTRADE_{s\underline{i}t} + \sum_{k=3}^{n=5} \gamma_k \cdot ly_{k\underline{i}t}^* + u_{s\underline{i}t} \quad A4$$

Where $u_{s\underline{i}t} = \mu_s + e_{s\underline{i}t}$; μ_s accounts for time invariant-country specific factors, and $e_{s\underline{i}t}$ is the error term.

NB: applying Euler to equation A3, we get the nonlinear model A5 (a Cobb-Douglas function):

$$P_{s\underline{i}t} = \emptyset \cdot {x_{1st}}^{\beta_1} \cdot \prod_{k=1}^{5} {y_{k\underline{i}t}^*}^{\gamma_k} \cdot e^{u_{s\underline{i}t}} \quad (A5)$$

Appendix C. Probability calculations

	Countries of destination										
Country of origin ($\mathscr{s}$)	Col (i)	j_1	j_2	j_3	$\cdots$	j_{29}	$\cdots$	j_{53}	j_{ot1}	j_{ot2}	Total
$\mathscr{s}_1$	$a_{1,i}$	$-$	$a_{1,2}$	$a_{1,3}$	$\cdots$	$a_{1,29}$	$\cdots$	$a_{1,53}$	$a_{1,ot1}$	$a_{1,ot2}$	$\sum_1 \sum_{c=1}^{N} a_{1,c} = De_1$
$\mathscr{s}_2$	$a_{2,i}$	$a_{2,1}$	$-$	$a_{2,3}$	$\cdots$	$a_{2,29}$	$\cdots$	$a_{2,53}$	$a_{2,ot1}$	$a_{2,ot2}$	$\sum_2 \sum_{c=1}^{N} a_{2,c} = De_2$
$\mathscr{s}_3$	$a_{3,i}$	$a_{3,1}$	$a_{3,2}$	$-$	$\cdots$	$a_{3,29}$	$\cdots$	$a_{3,53}$	$a_{3,ot1}$	$a_{3,ot2}$	$\sum_3 \sum_{c=1}^{N} a_{3,c} = De_3$
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$
$\mathscr{s}_{29}$	$a_{29,i}$	$a_{29,1}$	$a_{29,2}$	$a_{29,3}$	$\cdots$	$-$	$\cdots$	$a_{29,53}$	$a_{29,ot1}$	$a_{29,ot2}$	$\sum_{29} \sum_{c=1}^{N} a_{29,c} = De_{29}$
Total	A_i	A_1	A_2	A_3	$\cdots$	A_{29}	$\cdots$	A_{53}	A_{ot1}	A_{ot2}	$\sum_{\mathscr{s}=1}^{29} \sum_{c=1}^{N} De_{\mathscr{s},c}$

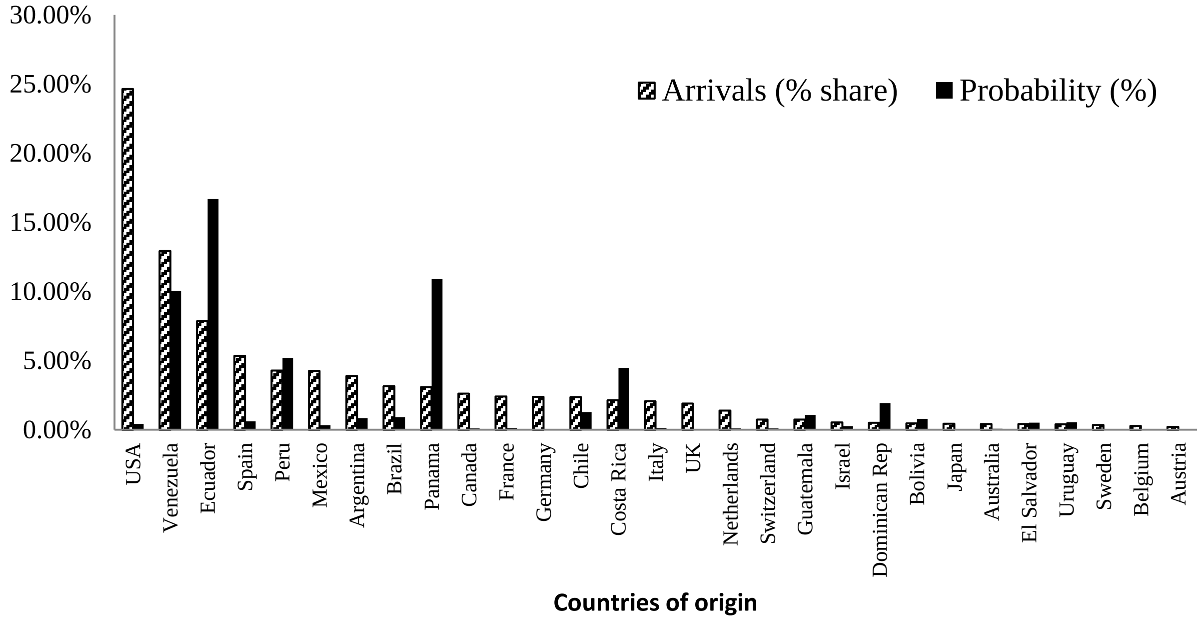
Table C1. Visitor arrivals from countries $\mathscr{s}$ to destinations i and j
Where i: Colombia, and j: 1,…,N other alternatives ($N = 53 + others$); $A_i = \sum_i \sum_{\mathscr{s}=1}^{29} a_{\mathscr{s}}$
The country alternatives are: Venezuela, Argentina, Ecuador, Brazil, Peru, Mexico, Chile, Panamá, Bolivia, Uruguay, Paraguay, Dominican Republic, Honduras, Guatemala, Nicaragua, El Salvador, Costa Rica, Canada, the USA, Aruba, Bahamas, Cuba, Curacao, Jamaica, Japan, China, Vietnam, Sri Lanka, New Zealand, Australia, Israel, Turkey, Spain, Italy, France, Hungary, Poland, Germany, Switzerland, Czech Republic, Netherland, Austria, Belgium, Denmark, Norway, Ireland, the UK, Indonesia, Croatia, Egypt, Korea, and Greece

Table A2. Tourists' choice probabilities

	Countries of destination										
Country of origin ($\mathscr{s}$)	Col (i)	j_1	j_2	j_3	$\cdots$	j_{29}	$\cdots$	j_{53}	j_{ot1}	j_{ot2}	Total
$\mathscr{s}_1$	$P_{1,i}$	$-$	$P_{1,2}$	$P_{1,3}$	$\cdots$	$P_{1,29}$	$\cdots$	$P_{1,53}$	$P_{1,ot1}$	$P_{1,ot2}$	$\sum_1 \sum_{c=1}^{N} P_1 = 1$
$\mathscr{s}_2$	$P_{2,i}$	$P_{2,1}$	$-$	$P_{2,3}$	$\cdots$	$P_{2,29}$	$\cdots$	$P_{2,53}$	$P_{2,ot1}$	$P_{2,ot2}$	$\sum_2 \sum_{c=1}^{N} p_2 = 1$
$\mathscr{s}_3$	$P_{3,i}$	$P_{3,1}$	$P_{3,2}$	$-$	$\cdots$	$P_{3,29}$	$\cdots$	$P_{3,53}$	$P_{3,ot1}$	$P_{3,ot2}$	$\sum_3 \sum_{c=1}^{N} P_3 = 1$
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$
$\mathscr{s}_{29}$	$P_{29,i}$	$P_{29,1}$	$P_{29,2}$	$P_{29,3}$	$\cdots$	$-$	$\cdots$	$P_{29,53}$	$P_{29,ot1}$	$P_{29,ot2}$	$\sum_{29} \sum_{c=1}^{N} P_{29} = 1$
Average	$\bar{P}_i$	$\bar{P}_1$	$\bar{P}_2$	$\bar{P}_3$	$\cdots$	$\bar{P}_{29}$	$\cdots$	$\bar{P}_{53}$	$\bar{P}_{ot1}$	$\bar{P}_{ot2}$	

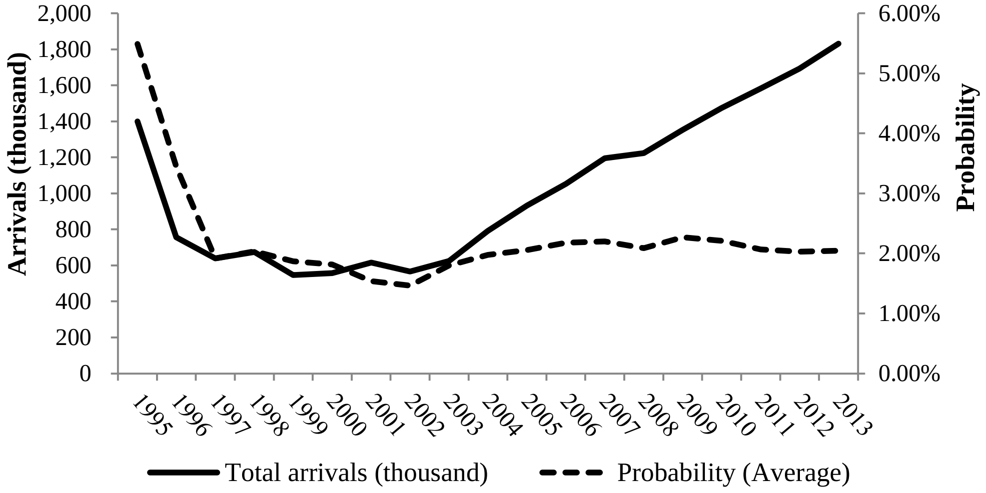
$N = 53 + others$; $P_{\mathscr{s},i} = a_{\mathscr{s},i}/De_{\mathscr{s}}$; $\bar{P}_i = \mathscr{s}^{-1} \sum_i \sum_{\mathscr{s}=1}^{29} P_{\mathscr{s}}$

Appendix D. Average percentage share of visitor arrivals in Colombia Vs Probability ratios of travelling to Colombia (period 1995-2013)



Source: World Tourism Organization. The number of arrivals for visiting friends and relatives is excluded.
Own calculus for probability ratios

Appendix E. Visitor arrivals in Colombia Vs Probability ratio of travelling to Colombia (period 1995-2013)



Source: World Tourism Organization and MCIT. The average probability of travelling to Colombia is the average of the relative frequency of outbound trips (as conceptualized by the UNWTO, n.d) done by tourists from countries s.

Appendix F. The presence of time-invariant country-specific factors

The presence of time-invariant country-specific factors (μ_{sit}) in the choice of travelling to Colombia was captured is included in the error term: $u_{sit} = \mu_{sit} + e_{sit}$. To capture the fixed effects from equation 2, a panel EGLS method was used with cross-section weights (see table F1).

Table F1

Dependent Variable: LNPROBI
Method: Panel EGLS (Cross-section weights)
Date: 05/18/16 Time: 17:10
Sample: 1995 2013
Periods included: 19
Cross-sections included: 29
Total panel (unbalanced) observations: 476
Linear estimation after one-step weighting matrix

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-9.228279	1.213265	-7.606150	0.0000
LNWJCONS	0.845152	0.113548	7.443149	0.0000
LNSEI_	-0.105390	0.015036	-7.009237	0.0000
LNXMI_	0.292321	0.024926	11.72733	0.0000
LNPI_	0.378213	0.045255	8.357418	0.0000
LNTC2JI_	0.275392	0.066962	4.112685	0.0000

Effects Specification

Cross-section fixed (dummy variables)

Weighted Statistics

R-squared	0.989814	Mean dependent var	-6.954917
Adjusted R-squared	0.989053	S.D. dependent var	4.186472
S.E. of regression	0.226309	Sum squared resid	22.63733
F-statistic	1301.490	Durbin-Watson stat	1.036183
Prob(F-statistic)	0.000000		

Unweighted Statistics

R-squared	0.985402	Mean dependent var	-5.444724
Sum squared resid	22.89901	Durbin-Watson stat	0.992116

Countries	Fixed effect
Ecuador	3.899822
Venezuela	3.298282
Panama	3.127392
Peru	2.755133
Costa Rica	2.630698
Dominican Rep	2.242600
Bolivia	1.633509
Guatemala	1.606992
Brazil	1.502622
Chile	1.140478
El Salvador	0.791692
Mexico	0.554870
Uruguay	0.507453
Argentina	0.490710
Spain	0.019982
USA	-1.07787
Israel	-1.12393
Italy	-1.71196
France	-1.75573
Australia	-1.80431
Canada	-1.83338
Netherlands	-2.15732
Germany	-2.59557
Switzerland	-2.61947
Sweden	-2.79139
Austria	-2.79626
UK	-2.80431
Belgium	-3.16831
Japan	-3.54982

As expected, the correlation between the fixed effects obtained and the Euclidean distance between tourists' country of origin and destination (see table F2) confirms the existence of time-invariant country-specific-factors. The effects are higher for the countries located near

Colombia. The Spanish case is excluded, as closeness between both countries is likely related to language/culture matters. As observed in Fig F1, the probability of travelling to Colombia is between 10 and 17% for tourists from countries such as Ecuador, Panama and Venezuela, whose Euclidean distance from Colombia is an average of 930 Kms; it is between 4 and 6% for tourists whose nations are, on average, 1,563 Kms away from Colombia; and it is in the range of 0.3 and 2% in those with 3,747 Kms of distance from Colombia. For the remaining nations, which are on average 9,717 Kms distanced from Colombia, the probability ratio falls under 0.3%. In the Spanish case, the probabilistic choice for travelling to Colombia is the highest among other non-Latin American countries, even though the Euclidean distance to get there is above 8,000 Kms. The short cultural distance between them prevails.

Table F2. Fixed effects estimated vs Euclidean distance

No of cross-section	Country of Origin	Fixed-effect Coefficient (log)	Euclidean Distance to Colombia (Kms)	Euclidean Distance to Colombia (Average Kms)	Language(s) in country of origin
1	Ecuador	3.8998	996		
2	Venezuela	3.2982	1025	930	Spanish
3	Panama	3.1273	770		
4	Peru	2.7551	1250	1,563	Spanish
5	Costa Rica	2.6306	1875		
6	Dominican Rep.	2.2426	1599		
7	Bolivia	1.6335	2428		
8	Guatemala	1.6069	2114		
9	Brazil	1.5026	4314		
10	Chile	1.1404	4229	3,747	Spanish
11	El Salvador	0.7916	1941		
12	Mexico	0.5548	3173		
13	Uruguay	0.5074	4757		
14	Argentina	0.4907	4645		
15	Spain	0.0199	8021		
16	USA	-1.0778	3996		Spanish/English
17	Israel	-1.1239	11547		Hebrew/Arabic/English
18	Italy	-1.7119	9118		Italian
19	France	-1.7557	8629		French
20	Australia	-1.8043	14336		English
21	Canada	-1.8333	4354		English/French
22	Netherlands	-2.1572	8853		Dutch
23	Germany	-2.5955	9430	9,717	German/English
24	Switzerland	-2.6194	9079		German/French/Italian
25	Sweden	-2.7913	9688		Swedish
26	Austria	-2.7962	9662		German
27	UK	-2.8043	8499		English
28	Belgium	-3.1683	8799		Dutch/French/German
29	Japan	-3.5498	14328		Japanese

These outcomes are consistent with the work of McKercher et al. (2008), who argue that “all destinations located in close proximity to source markets should have an inherent advantage over more distant destinations. When measured by share, therefore, all proximate destinations should record higher shares than any more distant one” (p.208). Following the distance decay theory (identified as the first law geography by Eldrigde and Jones, 1991, cited by McKercher et al. (2008)), they found that 8 out of 10 international trips are done in countries within 1,000 kms of tourists’ country of origin.

In this study, the correlation between distance and tourists’ choice for Colombia lies on almost 60%. If tourists’ choice for Colombia were judged only by distance, countries such as El Salvador, Bolivia, Mexico, the USA, Canada, the UK, and Austria would hold higher probability ratios; however, there are other determinants behind tourists’ decision-making.

ea	Tourists’ countries of origin	Probability of travelling to Colombia (%) (Average 1995-2013)	Average Distance to Colombia (Kms)
	Ecu, Ven, Pan	$10 < P_i < 17$	930
	Per, CR	$4 < P_i < 6$ (excludes countries in red area)	1,563
	DR, Chi, Gua Bra, Arg, Bol, Spa, Uru, ES, USA, Mex	$0.3 < P_i < 2$ (excludes countries in red and green areas)	3,747
it f a	Isr, Ita, Fra, Can, Net, Swi, Ausl, Swe, Ger, UK, Aus, Bel, Jap	$P_i < 0.3$ (excludes countries in red, green, and yellow areas)	9,717

Fig. F1. Probability of travelling to Colombia Vs Euclidean distance
Source: map from google maps; coloured areas from own calculus